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Three Essays in Renewable Energy

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THREE ESSAYS ON RENEWABLE ENERGY

By

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THREE ESSAYS ON RENEWABLE ENERGY

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This dissertation studies three main issues related to renewable energy in the United States and in Sub Sahara Africa.

The first chapter seeks to provide answers to a very fundamental question for second generation biofuels: "How much crop residue can farmers harvest from their fields for sale to cellulosic ethanol companies without affecting current levels of production?" The model developed is applied to 101 counties from four Midwestern states in the United States (Colorado, Iowa, Nebraska and Wyoming). Results show that soil organic matter significantly contributes to explaining changes in technical efficiency and total factor productivity. Furthermore, average crop residue harvest potentials were 33%, 53%, 35% and 8% in Colorado, Iowa, Nebraska and Wyoming respectively.

The second chapter analyzes the market and welfare effects of foreign biofuel investments in Sierra Leone. A log-linear comparative static displacement model was used to carry out the analysis and a 30% demand shock was introduced into the system to represent an increase in biofuel demand. Results revealed large welfare enhancing gains for consumers of inedible biofuels but resulted in welfare losses in the staples and edible biofuel consumer markets. Producers generally reported welfare gains by virtue of owning factor inputs (land and other). Equilibrium quantities of inedible biofuels, edible biofuels and food increased by about 8.8%, decreased by 0.22% and increased by 0.6%

respectively. Prices for both inputs and outputs increased while quantities of inputs also increased.

The third chapter determines the degree of responsiveness of farm energy input prices and corn prices to changes in crude oil prices using time series techniques. An Error Correction Model (ECM) and a VAR (vector autoregressive model) was fitted. The VAR was used to deduced variance decompositions for the six variables considered (prices of crude oil, diesel, gasoline, natural gas, electricity and corn) to determine the various contributions to the respective error variances. Results showed that the variables converged to a long run stable equilibrium. The strongest relationship was estimated for crude oil prices and diesel and gasoline prices. Prices for natural gas, electricity and corn had small and negative association with crude oil prices.

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1.1: Introduction

With reported increases in production levels of corn and soybeans (USDA 2011), coupled with favorable policies and socio-economic factors, there has been rapid growth in the biofuel industry in the Midwestern states of the United States (Nebraska, Iowa, Colorado, Wyoming) over the last seven years. While this production-pull effect creates a ready market for corn farmers, there are concerns over how sustainable and environmentally efficient are the ensuing farming practices.

This issue has been increasingly debated lately after studies have shown that the current mode of producing biofuels (corn based biofuels) is not a panacea to the energy and environmental problems when compared to fossil fuels as had earlier been envisaged (Gorter H. et. al. 2009; U.S Energy Bill 2007). Advances in cellulosic ethanol production technologies are testimonies to the attempts by researchers to provide remedies to these shortcomings or possible complements to the current methods. With regards to policy, despite the Volumetric Ethanol Excise Tax Credit's (VEETC's[1]) support for second generation biofuels like cellulosic ethanol (through the $1.01 a gallon credit), some critics argue that, this policy created bottlenecks for the development of more cutting-edge technologies. With the subsidy expired at the end of 2011, the resulting repercussions are yet to be seen.

Assuming the commercial production of cellulosic ethanol comes to fruition, there would be an increase in the demand for all forms of biomass, including all post-harvest residues that are normally being reburied into the soil and contribute to the

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[1] VEETC = The Volumetric Ethanol Excise Tax Credit is a policy to subsidize the production of ethanol in the United States. The mandates have been continuously renewed but the subsidy expired in December of 2011.

formation of soil organic matter (SOM). Consequently, the question then becomes: what happens to agricultural productivity should crop residue be commercially harvested for the purpose of cellulosic ethanol? This issue would not be contentious if SOM had no effect on agricultural productivity. The optimum thing then to do would be to grow and market as much crop residue as profitable. However, what if SOM really affects agricultural productivity? Then the decision bundle that farmers face would be completely different. Should the latter scenario play out, the need to restrict the amount of crop residue harvested by farmers would become very crucial. Such policy determination would rely mainly on knowing the level of crop residue required to maintain current production levels. This scenario (SOM affects agricultural productivity) we hypothesize to be the most plausible and the progress made with second generation biofuel technologies creates a suitable platform for its realization. Agronomists and soil scientists, as summarized in W. W. Wilhelm et. al. (2004), see this as a solution to the energy, environmental and food problems faced globally. Wilhelm argues that despite their increasing scientific research efforts, there is still need to obtain a methodology that can be used to obtain that optimum crop residue harvest level.

This study aims at incorporating SOM characteristics when estimating agricultural performance. The reasons for doing this are threefold: i) Yields depend crucially on soil carbon content which is directly related to SOM, (FAO (2003)); ii) SOM contains sequestered carbon which becomes very important when greenhouse gases and climate change are currently important issues (A. Picollo et.al (1999)); iii) SOM enhances water holding capacity of soils which has implications for irrigation.

We initially test the effects of SOM on technical efficiency and agricultural productivity. We then use these SOM characteristic variables to determine the relative amount of crop residue harvest potentials that do not affect current production levels over the targeted regions for 2010. Our main hypothesis is that “soil organic matter significantly contributes to explaining changes in technical efficiency and total factor productivity”. This is mainly based on agronomic studies and long held beliefs that manure and other forms of crop residue improve yields. This fundamental question has not been answered in the literature from an economic standpoint. The inclusion of fertilizer in our model is very important because it helps us capture the contributions of SOM to explaining changes in technical efficiency and productivity change which might be confused with the effects of fertilizer had we chosen to exclude fertilizer.

Obtaining estimates of SOM across counties that go back as far as 1970 was one of the challenges faced by this research. This is because it has not been measured[2] consistently for all these years and in the respective geographic regions in the United States. The most referenced data source is the soil survey geographic database (SSURGO) hosted by the United States Department of Agriculture’s National Resource Conservation Service. The SOM values reported by SSURGO represent only current year estimates (2010). Also, because of variations in soil types across counties, a standard way of comparing SOM levels across counties was required. Therefore an SOM panel was constructed using available soil dynamic models in the literature. Initial values were obtained from SURRGO and adjusted for bulk density using GIS software methods. These methodologies would be discussed later in the paper.

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[2] SOM values are obtained by conducting soil sample tests in specific locations. There is no database that catalogs these values as far back as 1970 and at the county level.

This research has three main contributions. Firstly, we obtain SOM estimates for 101 counties from 1970 to 2010 and include SOM characteristic variables while characterizing productivity performance at the county level. Secondly, we develop a methodology that can be used by policy makers to determine relative amount of crop residue harvest potentials that do not affect current production levels at the county level. Lastly, the Malmquist productivity index is bootstrapped following the approach by Simar and Wilson (2000a, 200b, 2007.) This paper provides support about the ability of this semi-parametric approach to estimating technical efficiency and productivity by adding the possibility of making statistical inferences from the results.

The rest of the paper is presented in the following format: we first present a section (Section two) on relevant literature on the topic, methodology and documented trends from the states considered in this study. Section three outlines the methodology proposed for the study. Section four has all the relevant results and analytic discussions and lastly section five summarizes and concludes the study.

1.2: Literature Review

Three main sections are considered: a brief review on efficiency measures; an attempt to describe the relevance of SOM and its relationship to fertilizer application and agronomic practices; and an update on the state of county level agricultural performance in mid-western states of the US.

1.2.1: Efficiency Measures

Theoretical and empirical methodologies for the estimation of efficiency across economic units have come through decades of development tracing as far back as Farrell

(1957). Here (Farrell, (1957)), single output and multiple input efficiency measures were estimated. However, this methodology was criticized due to its extremely restrictive nature (Coelli, (2005)) and limited dimensionality. Some of the developments that have followed include the use of multiple outputs and multiple inputs in the estimation of efficiency; the estimation of scale efficiency; environmental efficiency; congestion under parametric, semi-parametric and non-parametric measure; the use of expenditure and revenue variables instead of the traditional input and output variables; to name a few. Technical Efficiency (TE) is a description of the success of a farm to produce maximum output from a given set of inputs, and Allocative Efficiency (AE), the success of a farm to optimize on the use of inputs given their respective prices (M. Graham (2004)). There are several efficiency measures in use and others are still being developed today. More specifically and in a non-parametric context, TE is an estimation of the distance a given allocation is from the production frontier relative to those of other decision making units (DMUs) (as defined by Farrell). Shepherd (1970), on the other hand, uses the inverse of the distance function to define TE. Allocations on the frontier are considered as being perfectly efficient and the degree of efficiency decreases moving away from the frontier (Färe, Grosskopff and Lovell (1996)).

1.2.2: Parametric vs Nonparametric

From the vast literature on methods of efficiency estimation, all the techniques that have been employed in the estimation of technical efficiency and productivity have fallen between these two extremes: parametric and non-parametric measures. The hybrid forms between these two extremes are referred to as semi-parametric methods. The main differences between the two extremes depend on assumptions of whether the enumerator has a reliable understanding of the distribution of the dataset. If so, parametric measures are the most preferred and if not, the safest next step is to use non-parametric techniques. These properties have their advantages and disadvantages depending on the problem being analyzed. Parametric methods, first introduced by Aigner, Lovell & Schmidt (1977) and Meeusen & Van den Broeck (1977), require the specification of a functional form (a process which introduces uncertainties into the modeling process – Hildreth et al (1998), R.C Griffin et al. (1998)) while nonparametric measures (Charnes & Rhodes (1978)) do not. Given the need for functional specificity and problems of data availability, parametric measures have been further divided into primal and dual methods.

Nonparametric measures assume that all deviations from the efficient allocation are due to inefficiency, while the stochastic parametric measures allow for statistical noise (Coelli (1995)). Therefore, a fundamental problem with non-parametric efficiency measures is that any measurement error, and any other source of stochastic variation in the dependent variable, is embedded in the one-sided component making the resulting TE estimates sensitive to outliers (Greene, 1993). Also, sampling errors occur as a result of best performers being excluded from the initial sample. Another characteristic of these Data Envelopment Analysis (DEA) methods is the potential sensitivity of efficiency scores to the number of observations as well as to the number of outputs and inputs (Nunamaker, 1985). As a way of correcting for these problems inherent in non-parametric methods, there have been growing uses of mid-way solutions. Some of these include the use of bootstrapping methods on the Malmquist total factor productivity and technical efficiency estimates obtained from DEA to account for the power or level of significance of these estimates. These bootstrapping procedures and software have been extensively studied by Simar and Wilson (1998, 2000a, 2000b). We use one of their smoothing methodologies to obtain bias corrected technical efficiency estimates and total factor productivity estimates as shown in Simar and Wilson (2000a, 2000b, and 2007), Hollingsworth, Harris and Gospodarevskaya (2002), and Gonzalez and Miles (2002). Furthermore, an alternative semi-parametric methodology commonly used in parts of the literature is the two-stage technique in which the efficiency estimates are obtained in the first stage and these estimates are regressed on covariances. Simar and Wilson (2007) show that the standard inference is invalid due to unknown serial correlation among the estimated efficiencies. They further propose the single or double bootstrap methods as preferable approaches. One of these we employ in this paper.

1.2.3: SOM: Measures, Fertilizer, Carbon Sequestration, and Agronomic Practices

There has been considerable inattention placed on the role that soil structure plays in determining agricultural performance. The United Nations' Food and Agricultural Organization describes SOM as the key to drought-resistant soil and sustained food production. SOM is an important input in agriculture because it helps reduce soil erosion, maintain the constitution of soils and support physiological processes that improve soil productivity. A good soil should have high soil carbon content. There is a linear relationship between SOM and soil carbon. Recent studies reveal a 2 to 1 approximate conversion ratio between the two. This means dividing SOM by two approximately yields the estimate of soil carbon (SOC) (A. Liska (2011)).

Organic matter enhances water and nutrient holding capacity of soils, which improves soil structure. This improves yields and environmental quality, while at the same time reduces the severity and costs of natural phenomena, such as droughts, floods, and diseases. In addition, increasing soil organic matter levels can reduce atmospheric CO_2 levels that contribute to climate change (STATSGO Database). By emphasizing organic matter management technology, soil loss can be reduced on those lands that still suffer excessive erosion. Moderate erosion rates can harm air quality, water quality, and wildlife habitat.

There has been growing evidence of the potentials to sequester soil organic carbon when no-tillage practices are employed and crop residue is reintroduced into the soil through minimum tillage (Rattan Lal et al. 2004). This has been particularly true for the top 10cm to 15cm soil depth region. This study, though it would not categorically provide relevant answers to the carbon sequestration question, would provide some insights into soil carbon holding capacities of soils (an integral component of carbon sequestration) at the county level which would be helpful for future research on SOM and Soil Carbon.

Some studies have suggested that the negative effects of biomass harvest on yields (Fahnestock et al. (1995)) may be nullified by increased fertilizer application while others argue that even with fertilizer application, SOM is still crucial in keeping soils compact, maintaining nutrients and preventing erosion. Although both inputs, to some extent, work as complements to one another, they also have their limitations in terms of production and environmental consequences. Also, since our focus is on capturing the contribution of SOM, it is important that we include fertilizer in our analysis.

1.2.4: Agricultural Productivity across mid-western states (NE, IA, WY and CO)

There are very few studies, if any, that have been conducted on agricultural efficiency and productivity at the county level in the mid-western regions of the United States. The few available ones have either targeted the state level, national level or the firm level. None have looked at what the trends are at the county level. We discuss the few available studies that have investigated issues of agricultural productivity in these states. These include the following: Ball et al 1994, 1997, 2004, Shaik and Perrin (1999); Fulginiti, and Plastina (2012); Ball, Wang, Fulginiti, and Plastina (2012); Rezek and Perrin (2004) and Shaik and Perrin (2001).

Ball et al (1994, 1997, and 2004): These studies made invaluable contributions towards creating an understanding of US agricultural productivity at the state level. Furthermore and in relation to our study, Ball et all 1994 and 2004 estimate Malmquist productivity indices for 48 states for a benchmark scenario with conventional and procured inputs and other Malmquist indices with environmental variables included. Compared to the proposed study, we estimate Malmquist indices with a similar benchmark case but use SOM as the environment variable for the alternative Malmquist index. Considering interstate productivity comparisons from their 2004 study, Nebraska reported TFP growth of 2.8%, Iowa a growth of 1.6%, Colorado 2.5% and Wyoming 0.8%. While our study follows their 2004 methodology closely, it however considers a different scale (county level), a different environmental variable, SOM, and uses a semi-parametric approach (Bootstrapping).

Shaik and Perrin (1999*)* - In this study, they directly estimate productivity changes non-parametrically using DEA, and also recover shadow prices of environmental variables from this approach to modify the traditional indexing measure of productivity changes. Their results showed that nonparametric productivity methods provide unrealistic measurements of environmentally-adjusted productivity gains, but do offer shadow prices that seem to be plausible values for adjusting the standard productivity index approach.

Shaik and Perrin (2001) - In this study they showed that Traditional TFP misrepresents the true change in agricultural productivity to the extent that environmental bads jointly produced with desirable outputs are unaccounted. Nonparametric productivity measures incorporating environmental bads are evaluated for Nebraska agriculture. The results indicate that prior to the 1980's the traditional TFP measures overstate productivity growth while it is underestimated afterwards, reflecting peak use of chemicals.

Rezek and Perrin (2004) -This study adjusts agricultural productivity gains in a panel of Great Plains states to account for the discharge of pesticide and nitrogen effluents into the environment. Using a translog distance function approach that allows for a comparison between traditional versus environmentally adjusted productivity gains, they showed that technical change has been increasingly biased towards environmentally friendly production. Adjusted productivity in the late 90’s outpaced the traditional measure, reflecting the pro-environment bias in technical change.

Plastina and Fulginiti (2012): This article develops a framework that can be used to obtain the returns to local public goods using the Rothbart’s concept of virtual prices. They estimate the internal rate of return to public investments in agricultural R&D for each of the 48 continental US states. From their results, they obtained an average own-state rate of 17% and a social rate of 29% that compare well to the 9 and 12% average returns of the S&P500 and NASDAQ composite indexes during the same period. Similar to the other studies mentioned, the Plastina and Fulginiti (2012) study is carried out at the state level while our research focusses at the county level.

Ball, Wang, Fulginiti, and Plastina (2012): This article alongside some of Alston and Pardew's (2010) work looks at the contributions of R&D to US agricultural productivity growth. Their key finding was that extension activities, road density, and R&D spill-ins play an important role in enhancing the benefit of public R&D investments.

Different from these studies, this research obtains productivity estimates at the county level. We also use SOM as an additional input in determining agricultural performance which has not been used in the efficiency and productivity literature. We use Simmer and Wilson (1998)'s bootstrapping procedures to obtained bias corrected technical efficiency estimates and total factor productivity change estimates.

1.3: Methodology

1.3.1: Brief Summary

This study initially uses DEA to estimate technical efficiency and total factor productivity. The effects of SOM characteristic variables on efficiency and productivity are then tested. This is used as a basis to estimate crop residue harvest potentials across counties. DEA approaches have the unique advantage of not having to make assumptions about specific functional forms but it is a deterministic approach. However, with the use of semi-parametric measures we are able to introduce an element of stochasticity.

We develop an output-based TE measure using DEA for three outputs and six inputs. These include corn, all hay and an index of all other outputs and fertilizer, irrigation area harvested, non-irrigated area harvested, chemicals, average temperature and SOM (either SOM-Liska or SOM-Martellato) as inputs. The first five inputs are the traditional inputs and the remaining two (alternative SOM proxies) are separately included to test their effects on TE and TFP variation.

Two SOM proxies were calculated and used in this study. They both characterize the level of SOM from 1970 to 2010. The methods used in obtaining the respective SOM values are discussed in detail below.

TFP change is being estimated by a Malmquist index approach and disaggregated into Pure Technical Change (TC) and Efficiency Change (EC). These two analyses are carried out including the SOM characteristic variables and excluding them to see clearly the contribution of SOM in the measurement of TFP and TE. Bootstrapping was then carried out on the TE estimates to obtain confidence intervals and correct them for the presence of bias using Wilson's FEAR software. Crop residue harvest potentials were then estimated for all the counties targeted and correct for the presence of bias. These estimates were only calculated for 2010.

Despite the deterministic nature of DEA methods, the efficiency scores computed are relative to an "estimated" frontier and not a "true" frontier. This makes them subject to sampling variation of the estimated frontier (Simar and Wilson, (1998)). It is in a bid to correct for this anomaly that we obtain bias corrected TE estimates as shown in Simar and Wilson (1998). Furthermore, since the estimates result from some data-generating process (DGP), the statistical properties of the estimated efficiency measures are essential for their interpretations. In the general multi-output multi-input framework, the bootstrap seems to offer the only means of inferring these properties (i.e. to estimate the bias and variance, and to construct confidence intervals). The bootstrap process will, therefore, generate values that mimic the distributions which would be generated from the unobserved and unknown DGP (Simar and Wilson (1998), (2000a, b)). The estimated TFP values were also bootstrapped using similar methods but accounting for time dependencies. The rest of this section describes the methods used in much detail.

1.3.2: Data Structure

This section describes the nature of the data set used in the study. Some of the variables were constructed and the processes and steps are described in this section.

1.3.2.1: Constructing SOM Panel

Obtaining a robust variable for SOM stock levels that go as far back as 1970 was a big challenge for the study. This is because there are no inventories of experiments conducted to capture the level of SOM across counties in the United States for all the years targeted. The closest that is available are point estimates from 1995 to 2003 which are not very useful when county level data are needed. For the purpose of this study, we constructed SOM variables using two different methodologies. Both methodologies share the same pattern of obtaining an initial stock level of SOM in period t (2010) and using a rate of carbon mineralization as a discounting rate to obtain the t-n SOM stock levels (n = 1 to 40). These methods are basically retroactive traces of the dynamics of SOM. Based on their pioneers/authors, these models we label as the Yang-Liska (2011) model and the Martellato (2010)/M. Milner (2010).

Soil carbon and hence soil organic matter dynamics have been studied extensively over the last five decades by soil scientists as evident in the literature. Some of these include Kortlevan J. (1963); Jenkinson D.J. (1977); Patron W.J. (1987); and more recently, Janssen and Yang (2000). Through their efforts, together with few others, the most commonly used models today are the MINIPa[3], MINIPb[4], CESAR[5], RECAFS[6], CNGRAS, ANIMO, NUCSAM and the CENTURY[7] models. These models are broadly categorized into two main groups. One group uses a single component as the main input substrate while the other uses multiple components. The single component forms (like CESAR) have faced criticism in the past because they used one fixed mineralization rate constant (k) depending on the substrate. The alternative, (like CENTURY) however, uses multiple rates of mineralization for the respective components used. However, the latter models have proved to be very large and case specific. Therefore, lots of assumptions are made in their development which cannot be easily generalized and adapted to represent other situations. In the MINIPb model however, Yang and Janssen (2000) developed a framework to obtain a mineralization rate k that changes across time and substrate. This is the version we adapt in this study to obtain one of the variables of SOM. The adaptations follow those of Liska et al. (2011) because it was modified for the agronomic and physical properties of the targeted region. We also use a fixed mineralization rate to obtain the second SOM variable for comparison purposes. These latter versions are different from MINIPa. It uses a rate obtained from experimental data across some regions in Nebraska (Martellato (2010)). This rate is then applied to current soil organic matter levels obtained from the SSURGO database and traced backwards. We describe these two methodologies in more detail in the following section.

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[3] Janssen 1984, 1986.
[4] Yang and Janssen 1996, 2000.
[5] Vleeshouwers and Verhagon 2001, 2002
[6] Conijin 1995
[7] Patron W.J. 1996

1.3.2.2: SOM Initial Values[8]

2010 SOM initial values were extracted at 10 m^2 map resolutions and at 30 cm soil depth. An initial SOM grid that had been corrected for bulk density and at the required soil depth and resolution was obtained from the National Conservation Resource Society NCRS (S. Waltman (2010)).This was then converted to a soil carbon (SOC) grid (S. Waltman and M. Milner (2010)). This grid was masked [9]over a crop-land area grid for 2010 from the same region making sure that the extents matched perfectly. The resulting grid was then clipped[10] by county to obtain the county level grids. The final SOC values where then extracted from these county level grids. Figure 1 below displays the values obtained. As can be seen, SOM levels increase from West to East.

1.3.2.3: SOM: Liska's adaptation of Yang-Jensen

Yang and Janssen (2000) developed a model for the mineralization of carbon from experimental data. Mineralization can be defined as the breakdown of organic residues by oxidation to form soluble or gaseous chemical compounds which may then take part in further soil processes or be utilized by plant life. In their model, they treated organic matter as a single component. The logarithm of the average relative mineralization rate, K, or rate constant, of a substrate considered as a whole was found to be linearly related to the logarithm of time, t, provided prevailing soil conditions remained unchanged. This relationship can be represented by:

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[8] M. Milner from the University of Nebraska was very helpful in computing these SOM initial values.
[9] In ArcGIS, Masking is a means of identifying areas to be included in analysis.
[10] In ArcGIS, Clipping is a means by which one extracts features from one feature class that reside entirely within a boundary defined by features in another feature class.

$$\log K = \log R - S \log t \quad \text{or} \quad K = Rt^{-s} \quad \ldots. \qquad 1.$$

where:

R (dimension t^{s-1}) represents K at t=1

S (dimensionless, 1>=S>=0) is a measure of the rate at which K decreases over time, also called the speed of aging of the substrate.

The quantity of the remaining substrate, Y_t, is calculated by:

$$Y_t = Y_0 \exp^{-Rt^{1-s}} \qquad 2.$$

where:

Y_o is the initial quantity of the substrate and

k is the actual relative mineralization rate.

The actual relative mineralization rate, k, at time t is proportional to K, according to:

$$k = (1 - S)K \qquad 3.$$

Using Liska's adaptations to the Yang - Jensen model, we get

$$Y_t = Y_0 \exp^{-R(Q10Ta - Tr/10 \bullet t)^{(1-s)}} \qquad 4$$

A more developed form of equation [2] is equation [4], which includes a "temperature coefficient" (Q10 = 2, chemical reaction rate increase per 10°C; Ta, daily average; Tr = 10°C, yearly average reference temperature) and has an exponential term (1-S) to adjust the intensity of R over time (to predict C level at any time point [t] the daily values for the temperature coefficient [Q10Ta-Tr/10 • t] must be summed). Multiple linear regression models were developed by Liska (2011) generalize daily modeled outputs from the simulation models. To estimate changes in SOC, initial soil carbon (Y_0) and carbon inputs from crop yields for all counties were used to develop a multiple linear regression equation for each crop with an annual time step. The calibrated relationships are:

$$\text{Soy Beans:} \quad \Delta SOC_{MLR} = -0.0815 - 0.00701{*}C_0 + 0.219{*}C_I \qquad 6.$$

$$\text{Wheat:} \quad \Delta SOC_{MLR} = -1.321 - 0.00134{*}C_0 + 0.937{*}C_I \qquad 7.$$

Where C_1 = annual carbon input and

C0 = initial carbon level.

Using crop residue data from crop yields reported by the National Agricultural Statistical Services database (NASS) 1970 to 2010, ΔSOC values were obtained. The graph below (figures two and three) represents plots of the calculated SOM values for some counties. In the Yang 2000 model, no account was taken of yearly SOM recharge. Therefore in constructing this series, we accounted for recharge at a rate of 40% of total crop residue (W. W. Wilhelm, (2007), Schlesinger, (1985)). Also, the assumption of constant physiological conditions over time is not a feasible condition in our targeted ecosystems particularly when we are using a 41 year time period. Figures two and three below gives plots of the values obtained at both the annual and daily steps respectively.

1.3.2.4: SOM: Martellato (2010)/M. Milner (2010)

A constant depreciation rate as defined by Martellato (2010) was applied to all 2010 SOM values and traced backwards up to 1970. The average rate of SOC change used was 0.046 SOC for corn and soybeans. This is the average of corn and soybeans values as described in the graph to the right on figure four below. This rate was obtained from Martellato (2010) who measured the rate of carbon change for corn and soybeans in Mead Nebraska. The results provide evidence of a declining trend in soil carbon over the years. Different from the SOM values obtained in the previous case, here the SOM values decrease steadily. This implies that these values predict a continuous decrease in net SOM levels for the coming years. The graphs in figure four show plots of SOM trends for two representative counties and SOC changes (right) of figure 4 from Martellato (2010).

1.3.3: Descriptive Statistics

The rest of the variables: corn, hay and other outputs; fertilizer, chemicals, irrigated and non-irrigated areas harvested and average annual temperature for inputs, are obtained from National Statistics (NASS) website and the Fulginiti-Perrin Research Group Database – University of Nebraska – Lincoln (FPRGD). Table 1 gives brief descriptive statistics of the variables.

1.3.4: Sample Area

Nebraska has a total of 93 counties, Iowa 99, Colorado 64 and 23 in Wyoming. Of these 279 counties, a sample of 101 counties was selected to carry out the research. This represents 36% of the total number of counties. This selection was based on earlier studies which showed that the degree of heterogeneity in physiological characteristics increases as one moves from east to west than from north to south. This can be seen by looking at the longitudinal and latitudinal length/width variations of the map shown below (figure 1).

1.3.5: Representation of the Technology

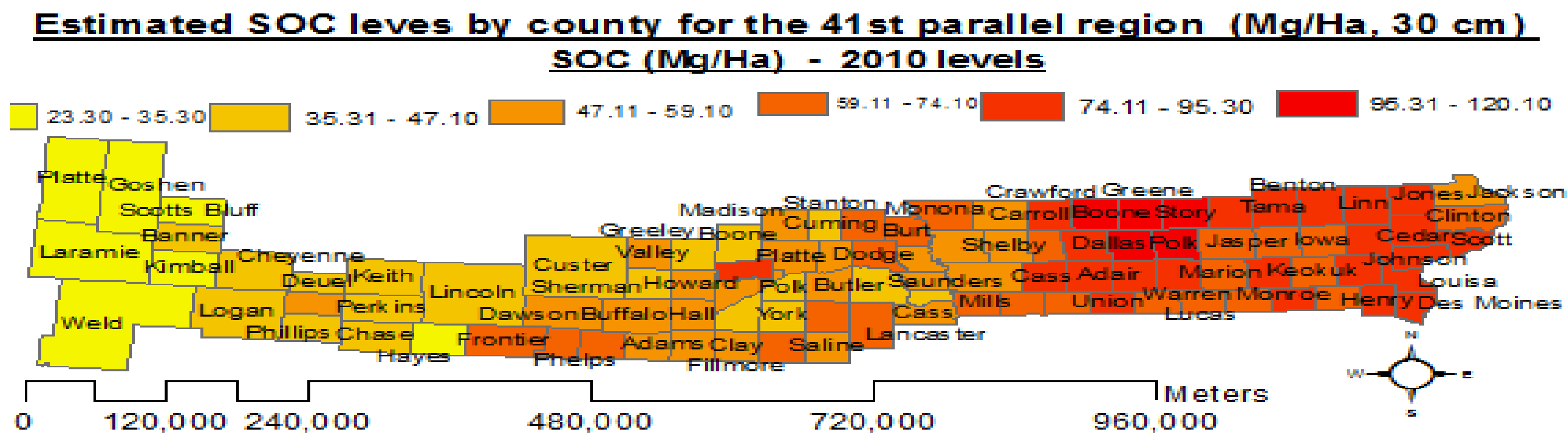
Farmers are constrained by a production technology transforming a vector of N inputs x = (x_1, x_2 … x_N) $\in \Re_+^N$ into a vector of M outputs u = (u_1, u_2,…,u_M) $\in \Re_+^M$ Observed combinations of inputs used and outputs produced (x_j,u_j) are taken to be representative points from the feasible production technology. In this study we use DEA to infer the boundaries of the feasible technology set from the observed points, as outlined in Färe, et al. (1994).

Observations from the technology consist of a sample of 101 DMUs producing outputs that have been categorized into three output variables (corn, hay and other) and using five conventional inputs in addition to SOM. These inputs are irrigated land area, non-irrigated land area, fertilizer, chemicals, average annual temperature, and the two types of SOM computed. The production technology can be represented by the graph denoting the collection of all feasible input and output vectors x and u:

$$GR = \{(x, u) \in \Re_+^{3+6} : x \in L(u)\} \quad 8.$$

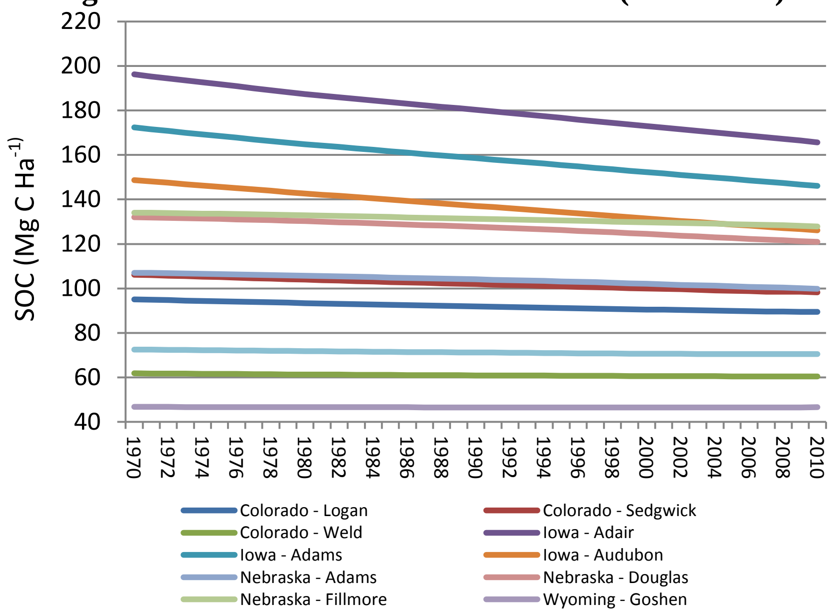
where L(u) is the input correspondence which is defined as the collection of all input vectors $x \in \Re_+{}^N$ that yields at least the output vector $u \in \Re_+{}^M$.

Figure 2 SOC Levels by county across 41st ||



Source: Author

Figure 1: SOC Levels From 1970 to 2010 (Martellato)



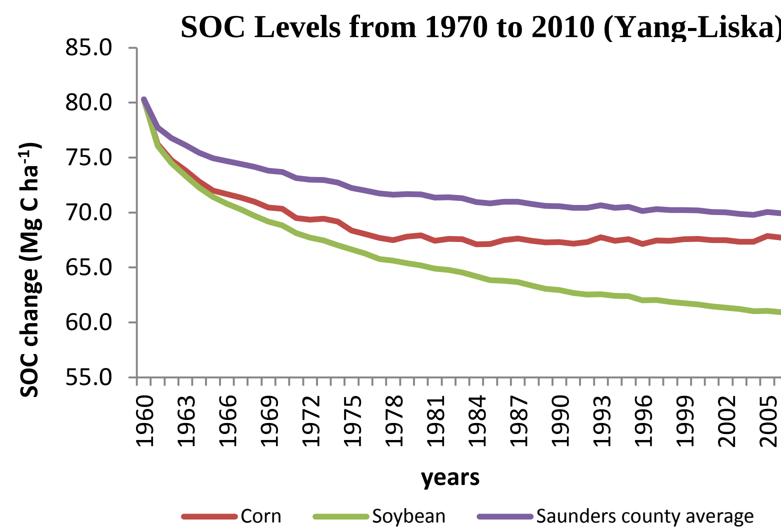
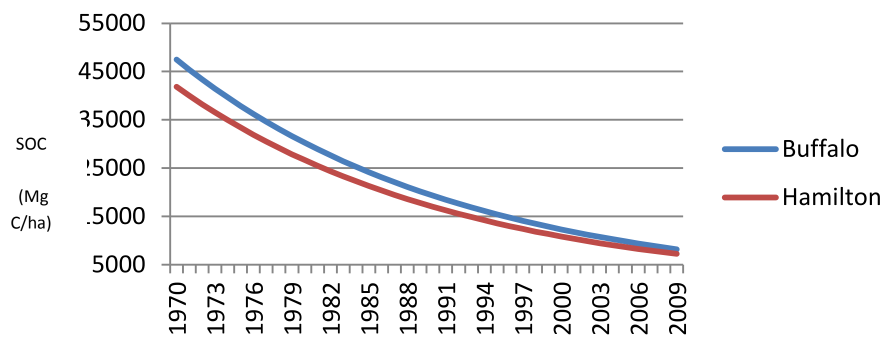


Figure 3: Graphs Showing SOM Change and Martellato's SOC change

From SSURGO database using Martellotto's average discount of 0.046

Change in SOM Milner/ Martellato: 1970 to 2010



Martellato: Annual rate of SOC Change

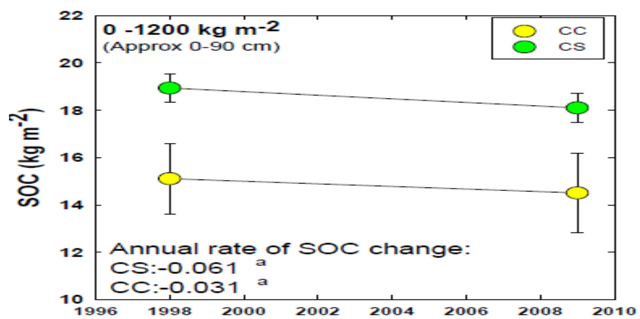
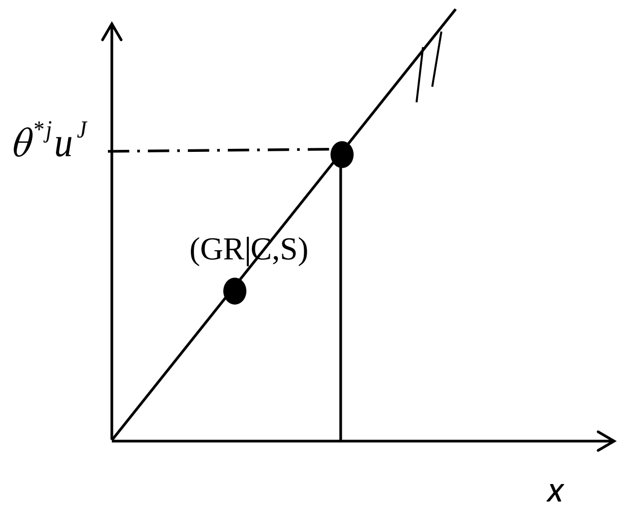


Table 1: Basic Descriptive Statistics for all Variables

Variables	N	Mean	Variance	Min	Max
Corn (Tons Ha -1)	4141	164080.57	9765569907	528.37	773810.5
Hay All (Tons Ha -1)	4141	29596.06	678452948.5	1375.93	243013.7
Other (Tons Ha -1)	4141	46955.44	1998939671	273.14	476343.3
Irrigated Area harvested (Hectares)	4141	61386.59	1427551194	0.01	190161.8
Non-Irrigated Area Harvested (Hectares)	4141	19821.49	784830363.2	0.01	162602.7
Fertilizer Index (Per hectare)	4141	20511.99	96446357.91	1263.49	65118.96
Chemicals Index (Per hectare)	4141	12186.15	47809450.78	318.7	65118.96
Mean Temp (oF)	4141	50.28	2.963948881	44.44	50.28
SOM1 (Mg C Ha -1)	4141	133.6	2187.47	46.55	298.87
SOM2 (Mg C Ha-1)	4141	244.51	12366.03	46.61	732.44

Figure 4: Graph Measure of TE with Constant Returns to Scale and Strong Disposability



1.3.6: Returns to Scale and Disposability

Throughout the literature, the choice of the prevailing returns to scale and disposability characteristics that represent the technology have always been dependent upon some knowledge that the researcher has about the technology set or for purposes of convenience in estimation. For this technology (shown in figure 5 above), we assume constant returns to scale mainly because there are no documented reasons why the size of a county affects the returns to scale. We also assume strong disposability because there are no laws levying fines against farmers producing less than the stipulated amount of biomass needed to produce soil organic matter. This means that there are no associated costs involved in the incorporation of SOM in the production process.

1.3.7: Technical Efficiency

There are several forms of TE measurements available in the literature. The version one uses depends on the type of data available and the particular problem investigated. For this analysis, we carry out an output based Shephard measure of TE as defined by Färe, Grosskopff and Lovell (1994). TE (output based), conditional on constant returns to scale technology and strong disposability, can be defined using the following linear programming relationship:

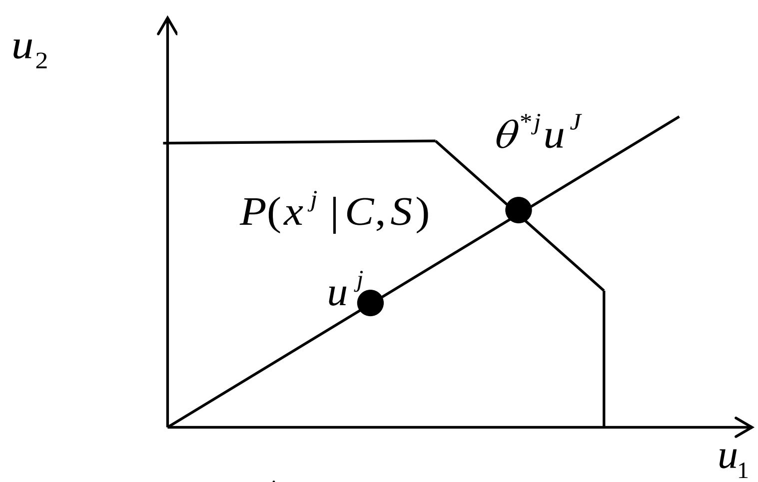
$$F_o(x^j, \delta u^j \mid C,S) = \delta^{-1} F_o(x^j, u^j \mid C,S), \delta \succ 0 \qquad 9.$$

$$F_o(x^j, u^j \mid C,S) = \max\left\{\theta : \theta u^j \in P(x^j \middle| C,S)\right\} \qquad 10.$$

for j = 1, 2 …J

This measure, as illustrated in Figure 6, measures the efficiency of u^j produced from x^j when the technology is assumed to satisfy constant returns to scale and strong disposability. It does so by radially expanding u^j as much as technologically possible and then by computing the ratio of the expanded to the observed output.

Figure 5: Output TE Measure



The intersection between u^j and the frontier is the *efficient level of output corresponding to input* x^j. That is

$$u^{j*} = u^J \theta^{*j} \qquad 11$$

As described in Fare, Groskopf and Lovell (1994), the properties of this output measure of technical efficiency are summarized below:

1) $F_o(x^j, \Theta u^j | C,S) = \Theta^{-1} F_o(x^j, u^j | C,S), \Theta > 0$ 12

2) $F_o(\lambda x^j, u^j | C,S) = \lambda F_o(x^j, u^j | C,S), \lambda \succ 0$ 13

3) $1 \leq F_o(x^j, u^j | C,S) \prec +\infty$ 14

4) $u^j \in WEff\, P(x^j | C,S) \Leftrightarrow F_o(x^j, u^j | C,S) = 1$ 15

5) $F_o(x^j, u^j | C,S)$ is independent of unit of measurement.

In other words, doubling all output quantities cuts the output efficiency measure into half, increasing one output while holding the others constant decreases the measure (Strict Monotonicity); the measure compares each feasible output to an efficient output vector.

More explicitly, the output measure of technical efficiency is obtained by finding a solution to the problem:

$$F_o(x^j, u^j | C,S) = \underset{\theta,z}{Max}\ \theta$$

Such that

$$\theta u^j \leq zM, x^j \geq zN and\ z \in \Re_+^{\ j} \quad 16$$

1.3.8: Malmquist Productivity Index

This is an index number that is used to measure total factor productivity (TFP) growth of an industry, firm or any economic agent over time. Productivity growth is defined as output per unit of input. It can be decomposed into two main sub categories which include technological change (TC) and efficiency change (EC).

The output based Malmquist index is used in this study and follows closely that developed by Färe and Grosskopff and Lovell (1994) and Lindgren and Roos (1992). The two contributors above used as their basis the pioneering works of Farrell (1957) and Christensen & Diewert (1982). Färe et al. (1992) merged efficiency theory as developed by Farrell (1957) with the Malmquist index of Caves et al. (1982) to propose a Malmquist index of productivity change that is now commonly used in the literature. Contrary to Färe et al. (1992), who considered an input based Malmquist index, we use an output based Malmquist index in the current paper.

We start by considering firms which use *n*-inputs to produce *m*-output. Denote $x \in R_+^n$ and $y \in R_+^m$ as, respectively, the input vector and output vector of those firms. The set of production possibilities of a firm at time *t* can be written as:

$$S^t = \{(x^t, y^t) \mid x^t \text{ can produce } y^t\}$$

Färe, Grosskopff, Norris & Zhang (1994) followed Shepherd (1970) to define the output distance function at time t as:

$$D_0^{\,t}(x^t, y^t) = \inf\{\theta \mid (x^t, y^t/\theta) \in S^t\} = (\sup\{\theta \mid (x^t, \theta y^t) \in S^t\})^{-1}$$

where the subscript o is used to denote the output-based distance function. Note that $D_0^{\,t}(x^t, y^t) \leq 1$ if and only if $(x^t, y^t) \in S^t$, and $D_0^{\,t}(x^t, y^t) = 1$ if and only if (x^t, y^t) is on the frontier of the technology.

To define the Malmquist index, Färe et al. (1994) defined distance functions with respect to two different time periods:

$$D_0^{\,t}(x^{t+1}, y^{t+1}) = \inf\{\theta \mid (x^{t+1}, y^{t+1}/\theta) \in S^t\} \qquad 17$$

and

$$D_0^{\,t+1}(x^t, y^t) = \inf\{\theta \mid (x^t, y^t/\theta) \in S^{t+1}\} \qquad 18$$

The distance function above measures the maximum proportional change in output required to make (x^{t+1}, y^{t+1}) feasible in relation to technology at time t. Similarly, the distance function in the last equation above measures the maximal proportional change in output required to make (x^t, y^t) feasible in relation to technology at time t + 1. The output Malmquist TFP productivity index can then be expressed as:

$$M_o(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \qquad 19$$

The term outside the brackets shows the change in technical efficiency while the geometric mean of the two ratios inside the brackets measures the shift in technology between the two periods t and t + 1; this could be called technological progress. Hence:

Efficiency change = $\dfrac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)}$ 20

Technical change = $\left[\dfrac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \dfrac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}}$ 21

In each of the formulas above, a value greater than one indicates an improvement and a value smaller than one represents deteriorations in performance over time.

To test the degree to which the SOM variables contribute towards variations in TE and TFP change, a benchmark run was carried out that includes only the five traditional inputs (Irrigated land area, non-irrigated land area, fertilizer, chemicals and average annual temperature). These estimates are represented as TE1 and TFPΔ1. Then the two different SOM variables are separately included as inputs and estimates obtained.

1.3.9: Amount of SOM That Does Not Affect Current Production Levels

The main hypothesis of this paper is that soil organic matter contributes to changes in technical efficiency and total factor productivity. Should the results fail to reject this hypothesis, the following question then becomes, at what level of SOM would output levels be maintained? That is, what minimum level of SOM would ensure that production levels are maintained while some of the crop residue is being harvested for the production of cellulosic ethanol?

Data Envelopment Analysis is used to shed light on these hypotheses. This we denote as the graph measure of SOM Efficiency.

1.3.9.1: Graph Measure of SOM Efficiency

The linear programming objective to solve this problem is given by the relationship below:

$$F_{SOM}\left(x^{all'}, x^{SOM}, u^j \middle| C, S\right) = \min_{\lambda,z} \lambda$$

Such that

$$u^j \leq zM,$$

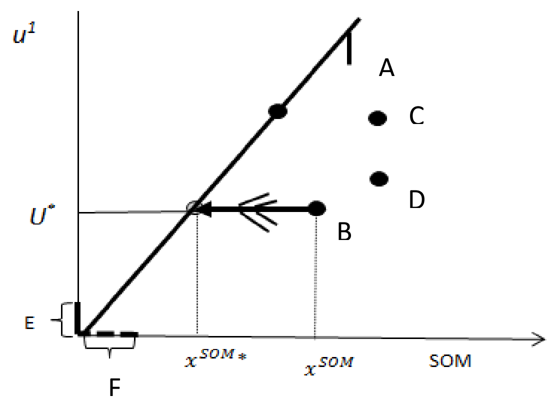
$$zN_{SOM} = \lambda x^{SOM},$$

$$zN_{all'} \leq x^{all'},$$

$$z \epsilon \Re_{+}^{J}$$

Sub-vector analysis as shown in Fare et al (1994) allows us to partition the input matrix into SOM and all other inputs. Also, mirroring the theory of undesirable outputs that allows one to obtain environmental efficiency, a similar method is employed to estimate SOM efficiency. In this case, we are only contracting x^{SOM} as shown in the second constraint above and leaving outputs and other inputs unchanged at their observed values.

Figure 6: Graph Measure of SOM Efficiency



In the graph above, A represents the most feasible frontier exhibiting constant returns to scale and strong disposability. B, C and D represent three observed levels of SOM and output for three counties. The farther away these points are from A (horizontally), the less efficient they are in the use of SOM. The horizontal distance to the frontier represents the amount of SOM that could be discarded and still produce the same level of output. So this measure, the ratio of the potential to the observed input-output pair, represents the percentage of SOM, hence crop residue, which can be harvested by a given county without affecting current production levels. An efficiency (“SOM Efficiency”) estimate λ (between 1 and 0) represent a (1- λ) % SOM harvest potential by that county. Counties on the frontier represent those counties that need all their current levels of SOM to produce their prevailing levels of output. Their biomass harvest potential is thus zero. This analysis suggests that counties that are relatively "SOM inefficient" have higher biomass harvest potentials than those that are relatively "SOM efficient".

1.3.10: Bootstrapping

The semi-parametric procedures developed by Simar and Wilson (1998) for the bootstrapping of distance functions were used in this study to obtain bias corrected TE estimates. A similar methodology was also used to bootstrap the Malmquist index estimates of TFP and their respective disaggregation accounting for the inherent time dependencies of the dataset. For a better insight into the theoretical basis for these approaches, we refer to Simar and Wilson (1998, 1999, 2000a, 2000b). In the next paragraph, we try to describe the most important components of the bootstrap algorithm in an output measure of TE framework and maintaining Fare et al (1994) notations.

The process is initiated by the estimation of the efficiency scores using the linear programming (LP) shown in equation 16. These estimates can be used to trace their respective levels as shown in equation 11 ($u^{j*} = u^{J}\theta_{k}^{*j}$). Using Monte Carlo techniques and selecting with replacement from the initial efficiency scores, a set of "Pseudo-samples" of efficiency scores are obtained θ_{k}^{*j}; say B= (1…n), where B is the number of pseudo-sample scores estimated. A smoothing operation is then carried out on these estimates to correct for distributional anomalies that are normally associated with high initial efficiency scores. These pseudo-samples are then used to obtain their respective efficiency levels (equation 11). Lastly, these estimates are used to construct their respective input-output data sets.

Once the number of desired samples is generated, the bias of the original estimate of theta is calculated as follows:

$$\textbf{\textit{Bias}}\ \theta_k = B^{-1}\sum_{b=1}^{B}\left(\theta_{kb}^{*j}\right) - \theta_k \qquad \text{---------} \quad 23$$

Where:

B= Number of pseudo-sample scores,

$\theta_{kb}{}^{*j}$ = Initial Efficiency Scores from pseudo sample or bootstrapped values as in Simar and Wilson 1998. The b subscript simply signifies that the estimate is biased, and

θ_{k} = Original estimator

Using Simmer and Wilson (2000), we can obtain our bias corrected technical efficiency estimates

$$\theta_k{}^{*j} = \theta_k - \text{bias } \theta_k \qquad 24$$

and plugging equation 23 into 24 yields

$$\theta_k^{*j} = 2\theta_k - B^{-1} \sum_{b=1}^{B}\left(\theta_{kb}^{*j}\right) \qquad - \qquad 25$$

The key assumption behind this approach is that the empirical bootstrap distribution will mimic the original unknown distribution if the assumed data generating process (DGP) is a consistent estimator of the unknown DGP.

We use Wilson's FEAR software to carry out this bootstrapping procedure. FEAR creates an opportunity to estimate TE and TFP estimates and performs bootstrapping from these estimates. It has a routine that generates confidence intervals, biases and bias corrected TE estimates. Results are presented in the next section.

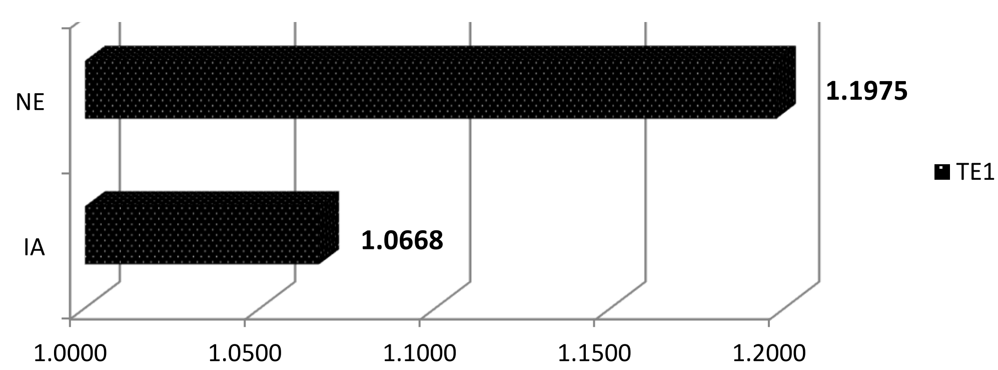
1.4: Results and Discussions

In this section we present results from the analysis carried out in the order as outlined in the methodology section above. That is, we first present results describing the state of agricultural productivity and technical efficiency along the four mid-western states targeted. Only state level comparisons are reported for the particular years. The rest of the results (county level) are presented in the appendix. We then present results with both SOM proxy variables in calculations of TE and TFP. For the former (TE), we present only bias corrected estimates. TFP estimates (TFP without SOM and with the two SOM variables) were tested for significant difference from one another at 90%, 95% and 99% levels. The reported values are those significant at the 90%. This was done only to accommodate more significant values. Lastly and most importantly, we present results for SOM efficiency and crop residue harvest potentials for 2010. This analysis was done with three different software packages, FEAR/R for the bootstrapping and bias correction estimates, GAMS for SOM efficiency and DEAP to confirm our Malmquist estimates. The respective codes are presented in appendix D.

1.4.1: Output Technical Efficiency

Three main statistical software packages were used to obtain TE and TFP

Figure 7: Benchmark (no SOM) Average Technical Efficiency, average for counties in NE and IA (Bias Corrected)



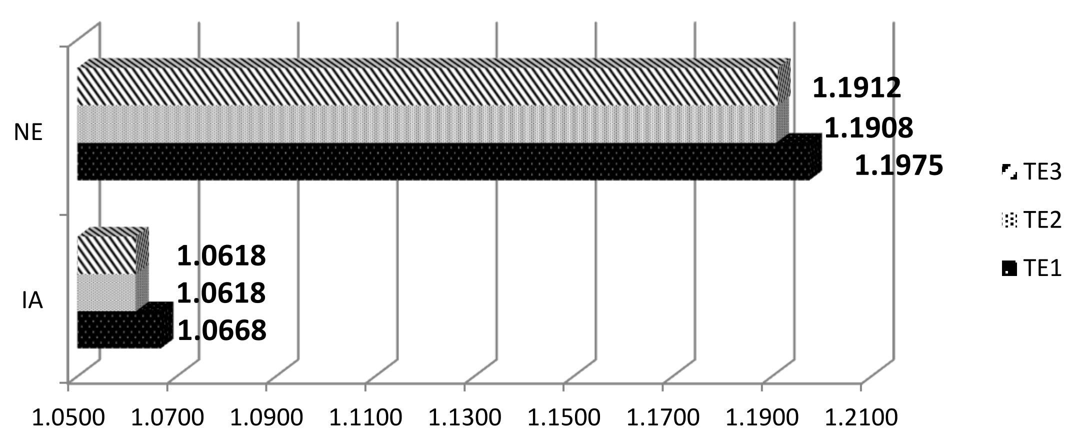
estimates for comparison purposes. These were the DEAP software from Coelli, GAMs (self-coded) and FEAR/R software from Simar and Wilson (1998). The results obtained from all three sources where exactly the same.

The results of TE are obtained from equation (13) above. Output technical efficiency estimates as defined by Shepherd (1970) are measures that are bounded downwards by 1 and are open ended upwards. An output efficiency measure of 1 represents the maximum production of outputs for the given set of inputs. Deviations from 1 represent the percentage by which outputs can be increased if production is reorganized, given the same level of inputs.

The technical efficiency estimates reported in figure 8 above have already been corrected for biases. In the graph, Shephard's output TE levels are reported at the state level. Because the samples used for Colorado and Wyoming are less representative we chose to compare only Nebraska and Iowa. Clearly, Iowa performed better than Nebraska on the basis of minimizing current year inputs to produce a given quantity of outputs. Please refer to the appendix for county level comparisons. Also, note that all means are geometric averages.

When SOM is included as an additional input we calculate three alternative

Figure 8: Three Measures of Technical Efficiency Compared, no SOM (TE1), SOM1 (TE2), SOM2 (TE3), average for counties in NE and IA



Shephard (1970) output oriented technical efficiency measures. TE1 represents technical efficiency in the absence of any measure of SOM. TE2 represents technical efficiency with SOM1, calculated following the procedure in Yang-Jansen-Liska, included as an input. TE3 represents the technical efficiency estimates including SOM2, calculated following Milner/Martellato. These results are shown in figure 9 below. Similar to the earlier graph (figure 8), only the average Nebraska and Iowa results were plotted. County level calculations can be seen in the appendix. The inclusion of an additional input to capture SOM leads to the efficiency measures tending towards the frontier. This means that the inclusion of this input has helped explain differential performance between the counties that defined the best practice frontier and those that do not. What appeared as inefficiency when SOM was not explicitly included (TE1) was, in part, due to differences in SOM levels across counties.

This can also be seen when all the county estimates are plotted, for the corresponding years, with SOM and without SOM. The graph below makes this analogy:

Figure 9: County TE estimates with (red) and without (blue) SOM, 1980

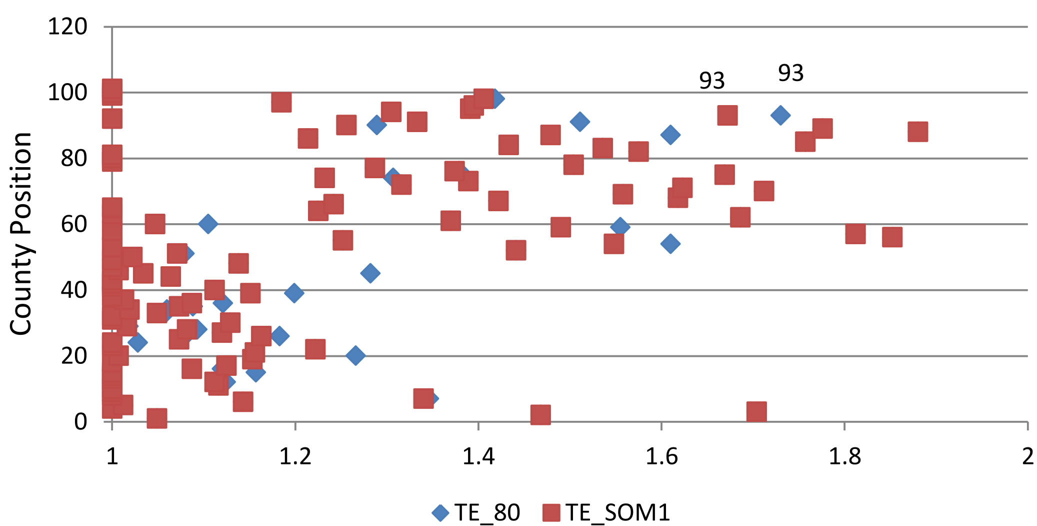


Figure10 above shows TE estimates with and without SOM for all 101 counties targeted for 1980. The spots in blue represent values without SOM and those in red represent those with SOM. Taking county # 93 (Seward county, Nebraska), the blue point is farther away from the frontier than the red point. This confirms our previous results, that when SOM is included as an additional input the counties are closer to the best practice frontier. Note that counties with TE estimates of 1 define the frontier. The table below shows the number of counties that lie on the frontier for 1970, 1980, 1990, 2000 and 2010. The efficiency scores for these years are presented in Appendix A.

Table 2: Number of Counties on the Frontier for TE1 (no SOM)

Number of Counties on the Frontier					
States	**1970**	**1980**	**1990**	**2000**	**2010**
Colorado	1	1	2	1	2
Iowa	15	16	22	25	5
Nebraska	10	8	12	8	15
Wyoming	2	3	3	2	2

Similarly, we present the number of counties on the frontier when SOM1 is in the model.

Table 3: Number of Counties on the Frontier for TE2 (SOM1)

Number of Counties on the Frontier					
States	**1970**	**1980**	**1990**	**2000**	**2010**
Colorado	3	1	1	1	2
Iowa	21	17	22	25	5
Nebraska	12	8	13	8	16
Wyoming	3	3	3	2	2

Table 4: Number of Counties on the Frontier for TE3 (SOM2)

Number of Counties on the Frontier					
States	**1970**	**1980**	**1990**	**2000**	**2010**
Colorado	3	1	1	1	2
Iowa	21	17	22	25	5
Nebraska	12	8	12	8	16
Wyoming	3	3	3	2	2

Tables 2, 3 and 4 above report the number of counties per state that define the frontiers of TE1, TE2 and TE3 for 1970, 1980, 1990, 2000 and 2010. Two distinct observations can be made. One is that the introduction of an additional input variable, SOM, to the model brings more counties to the frontier for all the years. This means that differential performance is better understood. Furthermore, Iowa's counties had better performance than Nebraska's from 1970 through 2000. From 2010 on, Nebraska's performance, on average, has been better than Iowa's. This can be attributed to the rapid adoption of irrigation technology in Nebraska over the last ten years that has significantly affected yield levels.

1.4.1: Total Factor Productivity, Efficiency Change and Technological Change

In this section, we report total factor productivity change estimates from the Malmquist indices computed from equation (19) above. Recall that productivity growth is defined as the growth rate of output minus the grow rate of inputs. Most of the literature on inter-country agricultural productivity performance has attributed growth in TFP for United States agriculture to strong technological change. Here we provide evidence of TFP change at the county level for a sample of 101 counties (DMUs) in Nebraska, Iowa, Wyoming and Colorado considering production data from 1970 to 2010. A TFP value greater than one represents productivity increases and a value less than one represents productivity decreases.

Table 5: Average Malmquist Total Factor Productivity, Technical Change and Efficiency Change Estimates, counties on the 41 parallel North, in IA, NE, Wyoming, and Colorado

States	Group	1970 – 1980			1980 – 1990			1990 - 2000			2000 - 2010		
		TFP	EFF	TECH	TFP	EFF	TECH	TFP	EFF	TECH	TFP	EFF	TECH
Co	No SOM	0.945	0.976	0.968	0.998	1.005	0.993	1.002	1.008	0.994	1.219	0.996	1.224
	SOM1	0.941	0.976	0.964	0.994	1.005	0.989	1.002	1.015	0.987	1.219	0.994	1.226
	SOM2	0.945	0.974	0.970	0.988	0.997	0.991	1.005	1.015	0.990	1.232	0.994	1.239
Wy	No SOM	0.9936	1	0.994	1.016	1	1.016	1.0074	0.9851	1.023	1.0577	1.0146	1.042
	SOM1	0.994	1	0.994	1.015	1	1.015	1.005	0.996	1.009	1.074	1.015	1.058
	SOM2	1.006	1	1.006	1.020	1	1.020	1.009	0.996	1.013	1.08	1.014	1.065
IA	No SOM	1.012	0.998	1.014	1.000	1.005	0.995	1.007	1	1.007	1.004	0.982	1.022
	SOM1	1.015	0.999	1.016	0.999	1.003	0.996	1.007	0.998	1.009	1.004	0.982	1.022
	SOM2	1.006	0.999	1.007	1.001	1.004	0.997	1.009	0.998	1.011	1.006	0.982	1.024
Ne	No SOM	0.99	1.003	0.987	1.006	1.017	0.989	0.983	0.995	0.988	1.083	1.004	1.079
	SOM1	0.988	1.003	0.985	1.006	1.017	0.989	0.984	1.002	0.982	1.083	1.004	1.079
	SOM2	0.971	1.002	0.969	1.005	1.017	0.988	0.984	1.002	0.982	1.092	1.006	1.085

Table 5 above shows total factor productivity change, technological change and efficiency change estimates without SOM and in the presence of both SOM measures. The county averages for the whole period are presented in Appendix B (B1, B2 and B3). These estimates are the original estimates that have not yet been corrected for biases. Table 6 represents the biased corrected version that reports significant estimates at 90% confidence interval. Both tables show only state level aggregations for ten year averages from 1970 to 2010 for the 101 counties considered in this study (41 parallel North in IA, NE, WY and CO). These are reported to show the contributions of technical change relative to efficiency change across time. It is important to remember that the best practice frontier is obtained from a subset of 101 counties in these four states (42 in Iowa, 42 in Nebraska, 4 in Colorado, and 3 in Wyoming, see list of counties in the appendix section). For the estimates without SOM, all the studied counties in all states show gradual improvements from the 70's into the 2000s. Counties under study for Colorado, Wyoming and Nebraska reported declines, on average, in TFP in the 70's but have enjoyed increasing TFP over the last three decades. Counties in Iowa, on the other hand enjoyed steady increases in TFP throughout the period targeted. On average, for all counties considered in these states, it is very clear that technical change has been the driver of growth.

Comparing Nebraska and Iowa over the last two decades, some interesting results emerge. In the last decade alone, counties in Nebraska have enjoyed, on average, a TFP growth increase of 8.3% (6.2% for 90% level of significance estimates) with the majority of this growth being attributed to technological change. It is important to note that this comes after a decade of declining growth for the counties in this state. Iowa on the other hand only continued to grow at its normal growth trajectory as had been the case in the past three decades. One possible reason for Nebraska's rapid growth can be the rapid degree of irrigation that was undertaken in the state during this period. For all four states, there has been an average growth in the counties considered in this study of 1.1% for the original estimates and 1.6% for bias corrected estimates (these estimates are without SOM). Both of these rates have been driven predominantly by technological change. Comparing the estimates of TFP with and without SOM in Table 6 below, it can be seen that accounting for SOM as a production input has resulted in a slight increase of the measured rate of growth of agricultural productivity in these counties.

Table 6: Average Malmquist Total Factor Productivity, Technical Change and Efficiency Change Estimates, Counties on the 41 parallel north, in IA, NE, Wyoming, and Colorado, biased corrected and significant at 90%

		No SOM			SOM1			SOM2		
States	Periods	effch	Techch	Tfpch	Effch	Techch	tfpch	effch	Techch	tfpch
Colorado	70/71-79/80	0.976	0.968	0.945	0.976	0.964	0.941	0.976	0.967	0.944
	80/81-89/90	1.005	0.994	0.998	1.005	0.990	0.994	1.005	0.993	0.997
	90/91-99/00	1.008	0.994	1.002	1.010	0.992	1.002	1.010	0.995	1.004
	00/01-09/10	0.996	1.203	1.198	0.994	1.205	1.198	0.994	1.213	1.206
Iowa	70/71-79/80	0.998	1.014	1.013	0.999	1.016	1.015	0.999	1.017	1.016
	80/81-89/90	1.005	0.995	1.000	1.003	0.996	0.999	1.003	0.997	1.001
	90/91-99/00	1.000	1.006	1.006	1.000	1.007	1.007	1.000	1.008	1.008
	00/01-09/10	0.982	1.022	1.004	0.982	1.023	1.004	0.982	1.024	1.005
Nebraska	70/71-79/80	1.003	0.987	0.990	1.003	0.985	0.988	1.003	0.986	0.989
	80/81-89/90	1.017	0.988	1.006	1.017	0.989	1.006	1.017	0.990	1.007
	90/91-99/00	0.995	0.988	0.983	0.995	0.989	0.984	0.995	0.990	0.985
	00/01-09/10	1.004	1.058	1.062	1.004	1.057	1.062	1.004	1.059	1.064
Wyoming	70/71-79/80	1.000	0.994	0.993	1.000	0.994	0.994	1.000	0.996	0.996
	80/81-89/90	1.000	1.016	1.016	1.000	1.015	1.015	1.000	1.017	1.017
	90/91-99/00	0.985	1.023	1.007	0.985	1.020	1.005	0.985	1.023	1.008
	00/01-09/10	1.015	1.043	1.058	1.015	1.059	1.074	1.015	1.064	1.079
Geometric Average >>		**0.999**	**1.017**	**1.016**	**0.999**	**1.017**	**1.017**	**0.999**	**1.020**	**1.019**

From the biased corrected Malmquist index results in Table 6 above, it is evident here too that the main contributing factors to agricultural productivity growth in the counties studied has been technological change. It includes innovations that allowed increased irrigation in states like Nebraska, Wyoming and Colorado, as well as the introduction of hybrid seeds, new pesticides, and several other ongoing innovations in the agricultural industry. Please refer to the appendix for the county level results.

1.4.2: SOM Efficiency and Crop Residue Harvest Potentials

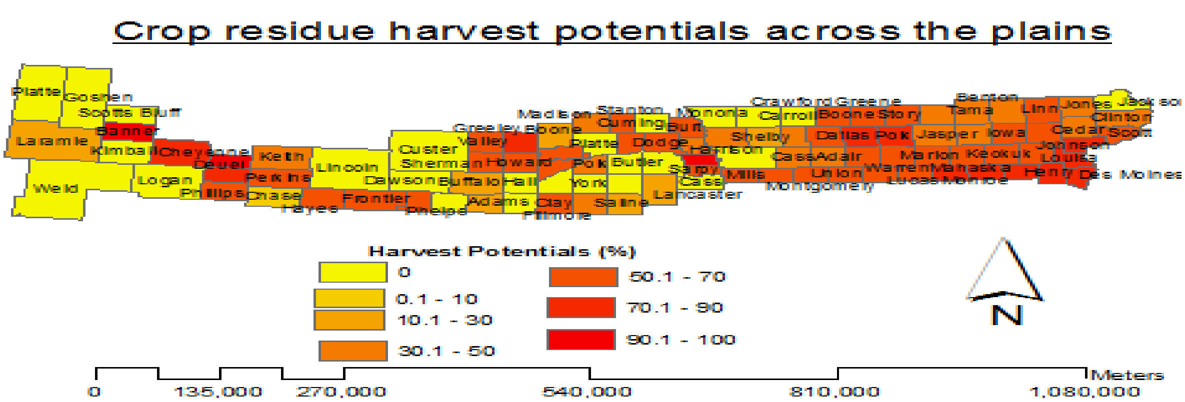
These results are obtained from equation (22) above. Tables 7 and 8 below show state level aggregated results for SOM efficiency estimates and hence crop residue harvest potentials obtained from the methodology outlined in the previous section. The county level estimates can be found in appendix C. Recall that harvest potential refers to the percentage by which one can further shrink SOM (hence harvest crop residue) without affecting production levels. Table 7 presents the percentage of counties that fall within certain harvest potential groups. The groups we identified are 0 to 10 %, 11% to 30%, 31% to 50% and above 50%. Although we report all four states, we focus our comparisons on Nebraska and Iowa for the same reasons outlined above. As can be seen from table 7, most Iowa counties have ample harvest potential.

Table 7: Percentage of counties in IA, NE, WY and CO (41 parallel North) in four harvest potential groups

% of Counties within given harvest potentials				
State	0 - 10%	11% - 30%	31%-50%	>50%
Co	50	0	0	50
Ia	10.64	2.13	27.66	59.57
Wy	66.67	33.33	0	0
Ne	34.78	13.04	13.04	39.13

:

Figure 10: Map Showing Crop Residue Harvest Potentials across the 41st Parallel



About 60% of the counties in Iowa have crop residue harvest potentials above 50% of their current SOM levels. For Nebraska, there is an even split between the two extreme groups (zero to ten, and above fifty); about one third of the counties fall within these two extreme categories. These represent 20% more than Iowa in the 0-10% group and the same proportion less than Iowa in the above 50% grouping. This means that Nebraska has 20% more counties than Iowa with almost zero SOM harvest potential. It also has about 20% less counties than Iowa with harvest potentials above 50% of their current SOM levels. Table 8 presents the average harvest potentials and the associated biomass quantities by state. As shown, the average crop residue harvest potentials were 33%, 53%, 35% and 8% in Colorado, Iowa, Nebraska and Wyoming respectively. Figure 11 above confirms that counties in Iowa reported higher harvest potentials while the counties studied in Wyoming reported the lowest.

Table 8: Crop Residue Harvest Potentials by state

State	HP	SOC(Mg C/Ha)	Crop Residue (Mg/Ha)
Co	32.45%	13.79	34.48
IA	53.16%	41.56	103.9
Ne	34.93%	17.55	43.87
Wy	7.97%	2.25	5.63
HP = Harvest Potential			

On average, 104 Mg per hectare of crop residue, in Iowa, was the highest quantity of crop residue that can be harvested while maintaining the same level of outputs and other inputs. This is equivalent to 42 Mg of SOC per hectare. The other states had values of crop residue available for extraction for given outputs and inputs, ranging from 104 Mg to 6 Mg. While the county level results fall within expected ranges for Iowa, Colorado and Wyoming, a few counties in western Nebraska have un-anticipated harvest potentials. Banner, Cheyenne and Deuel counties show high harvest potentials. A plausible explanation for this result is that low yields in these counties are as a result of having highly porous soils. As a consequence little farming activities are ongoing in these counties resulting to the low SOM levels needed to produce the prevailing low yields. In this sample, Iowa had the highest SOM harvest potentials while Wyoming had the lowest. Policy that targets crop residues policy should be county specific rather than state specific.

1.5: Conclusion

The main objective of this paper is to determine how much crop residue farmers can harvest from their fields on an annual basis without affecting negatively agricultural yields. The model developed was applied to 101 counties across four states in the mid-western region of the United States (41 parallel North of Nebraska, Iowa, Colorado and Wyoming). We first calculate technical efficiency and productivity growth at the county level with and without the inclusion of soil organic matter as an additional input in production.

We calculate soil organic matter by county as a proxy for crop residue and include this information in the calculation of technical efficiency and agricultural productivity growth rates. If productive efficiency is not affected by different SOM levels then a recommendation to farmers would be to harvest all crop residues for the production of cellulosic ethanol. If otherwise, there is need for information on which counties can afford, and to what degree, to harvest residuals while maintaining production levels. Once this information is available we obtain a measure of crop residue harvest potentials by county. This information is an important ingredient in the decision to supply biomass for second generation biofuels.

We also use this study as an opportunity to give an account of the status of inter-county agricultural productivity in this region. These calculations are novel as most productivity studies for the region have been done at state rather than county level and none has included SOM as a productive input.

From this analysis we conclude that including soil organic matter as an additional input in production does help explain variations in performance (technical efficiency) across counties. The inclusion of either of the two proposed SOM proxy variables in the model shows as a reduction in inefficiency. This means that SOM explains a portion of the heterogeneity in agricultural performance across counties. Including SOM also slightly changes the estimated rates of agricultural productivity growth for these counties. Over the years, counties in these three states have enjoyed a growth in TFP of 1.1%, the main driver being technological innovations. This is consistent with results obtained at the state and national level in the United States.

In summary, when SOM is included as an additional input in gauging county performance, technical efficiency (TE) shows that the performance of each county to those on the best practice frontier is better understood, while TFP growth rates do not change much.

Results suggest that the commercial harvest of biomass for cellulosic ethanol will be very much affected by the differential ability of each county to provide it with minimal effect on output produced, given the different levels of soil organic matter present. In this vein, the most important conclusion is that crop residue harvest potentials vary considerably across counties. On average, 35%, 50%, 11% and 67% of the counties in Nebraska, Colorado, Iowa and Wyoming respectively had zero crop harvest potentials. Iowa counties have the ability to produce the highest levels of biomass, on average 104 Mg per hectare, while maintaining yields. The harvest potentials for the other states ranged from under 104 Mg to 6 Mg per hectare of biomass. Our results indicate that Iowa had the highest SOM harvest potential while Wyoming had the least potential. These results should be of use when polies regarding second generation biofuels are designed or modified in the future.

Chapter 2: The New Frontier: Welfare Effects of Foreign Biofuel Investments in Africa (Case Study: Sierra Leone).

2.1: Introduction

Africa is the second largest continent by landmass and second most populous continent next to Asia. With an area of about 11.7 million sq. miles (about three billion hectares), it covers 6% of the earth's total surface area and 20.4% of the total land area (A.P World History 2008). 30.3% of the continent's land mass, which represents 906 million hectares of land, is potentially suitable for rain-fed agriculture. Unfortunately, only 10% of this land is considered prime land for rain-fed agriculture, leaving about 800 million hectares of non-prime land for agriculture. As Mckinsey (2010) puts it, about 60% of the world's available landmass suitable for rain-fed agriculture is from Africa. Such estimates may suggest that issues of land access for either agricultural purposes or other enterprises would not be such a big problem in the continent. However, recent studies have shown that land access inequality happens to be a major bottleneck for economic development in some African countries (ECA 2004). This reality has been attributed to several factors. One most commonly referred is the legacy of Africa's colonial system of land tenure.

While this communal land ownership system has the advantage of protecting communal welfare for current and future generations, it has been shown to hinder private sector investment, particularly foreign direct investment, as a result of poorly designed and enforced property rights.

With the world tending towards cleaner energies and a growing demand for biofuel products, has resulted in increases in the demand for land. This has resulted in food crops being substituted for biofuel crops (a politically sensitive option) and on seeking new land frontiers. Recent trends in Africa confirm that there is a growing shift towards the latter from both foreign investment companies and foreign government initiatives.

This interest in land investments in Africa has raised an even more sensitive question about the role western nations and stronger emerging economies are playing towards the development or demise of African nations in their search for these new frontiers. Countries like Switzerland in Sierra Leone, South Korea in Sudan, India and Saudi Arabia in Ethiopia, China in Zambia and Congo, to name a few (IFPRI 2009); land is being leased from the government or individuals to grow crops for biofuels like sugarcane, jatropha, palm oil and more, in land previously used to growfood crops like rice, wheat, cassava etc. In return, these companies/governments promise to provide jobs to these displaced farmers, build local infrastructure in addition to the taxes they pay to the government and the rent on the land leased.

Some African leaders see these investments as sources of foreign capital which would help their local economies not just in the short run but in the long term as well. An initial survey in Sierra Leone showed that farmers who lost their land to foreign investors but had rent acquisition rights see themselves better-off after giving up their land when compared to their status when they were farming the land. Farmers who had only farming rights (communal ownership or family ties) to the land but had no rights to claiming rents are upset because they have lost their main source of income in the process. This points towards the prevailing land tenure and property rights system having a significant role in determining the market and welfare effects of these investments. Given that these land acquisition leases are reported to be for long periods (40 to 50 years), the long term economic and environmental effects are crucial in understanding the true welfare effects of these investments.

For a better understanding of the implications of these investments and to adequately guide policy makers towards either encouraging more land investments or curtailing them, it is but proper to carry out country specific empirical studies to capture the likely market and welfare effects of these investments both in the short term and in the long-term.

In this research, the objective is to study the short-term positive and normative effects of an increase in the demand for biofuels in Sierra Leone.

To accomplish this, we use an equilibrium displacement model representing the agricultural economy of the country. Log-linear comparative static techniques are used to represent output and input markets. The model allows the introduction of different shocks to the system to test how equilibrium prices and quantities as well as the welfare of producers and consumers respond to these shocks. This model assumes that as a result of the biofuel investments (increased demand) farmers had to decide on reallocating their land to incorporate this increased biofuel demand and in the process increases the supply of biofuel products. Therefore several assumptions are made; we assume farmers do not lose their land forcefully. They make rational decisions to reallocate their inputs based on market forces. There is no “free” or unused land in Sierra Leone. This makes sure that all market effects are a result of reallocation of available resources due to the introduction of shocks such as an increase in the demand of biofuel crops

2.2: Literature Review

2.2.1: Background

Land tenure systems (land rights) are institutional laws that define a set of rules that determine the use of land, duration of tenure and under what conditions (ECA (2004)). There are different standards upon which these rules are based. For the most part, these benchmarks depend on sociopolitical and economic factors defining the prevailing human relationships between the different potential users and custodians. Land can be privately owned, communally owned or lack a clear definition of ownership -open access (D. Brautigam, (1992)). In developed countries, where the rights of land owners trump all other interests, very liberal systems like the “conveyance system” (U.S) and “conveyance with land registration system” (Germany, England, Australia etc.) have been in use for decades (Onsrud, Harlan J. (1989)). Both of these systems protect buyers from potential fraud through the use of title insurances in the case of the US and land registration regime for European countries (D. Brautigam, (1992)). These systems grant equal opportunity to its citizens to own land independent of status.

However, the case for Sierra Leone and other Sub-Saharan African countries is very different. Most African countries still carry a colonial heritage and customary traditions that strongly influence the laws of the land. There is a high degree of discrepancy over whether statutory rights should prevail over customary rights to owning physical property like land. In most urban cities in Africa, statutory rights prevail and define the ownership of land. However as one goes inland the degree of customary rights increases while statutory rights become less recognized. In between, this continuum exists a buffer region with conflicting and unclear land tenure rules. This creates room for opportunistic behavior for some risk lovers leading to land grabbing and the multiple sale of land from multiple owners to multiple potential users. This is made even worse in the absence of transparent enforcement regimes. The prevailing enforcement mechanisms tend to be biased towards the rich and powerful for urban-like settlements and towards chiefs and traditional elders for rural communities, with the ultimate victims being the poor and less influential. Most customary rules distribute land based on caste, seniority and gender (Lund C.(2001), prohibiting women from owning land in some African countries. This accounts for the prevailing inequality in land tenure across gender. Given that staggering averages of about 40% to 60% of households are headed by women, the situation is made even worse for women and children in the continent. Customary systems also create restrictions to commercial farming as land cannot be bought and sold freely because communal ownership does not clearly define rights to sell land. This accounts for the small farm holdings, low productivity and subsistence nature of the agricultural practices of most African countries. (E.H.P. Frankema 2006). For cases where provincial land is leased by the government to potential private users, chiefs and village elders insist on additional forms of payments from these new tenants before granting them permission to use the land. This to some extent discourages private sector investment in agriculture.

For most sub-Saharan African countries, agriculture is the main economic activity for households. This makes access to land a fundamental means whereby the poor can ensure household food supplies and generate income (Cotula L., Toulmin C. & Quan J., (2006)). Therefore land access is an issue of survival which in the absence of well-defined and enforced property rights, as is the case in Africa, can lead to continued civil unrest. This has been the reason for wars and civil and political unrests in countries like Zimbabwe, Chad, Ivory Coast, Uganda, etc. and for countries with better property rights like South Africa, Ghana, Botswana, etc., has been the engine of growth (E.H.P. Frankema, (2006)).

By the late 90s and increasingly so in recent years, due to changes in population dynamics, increasing urbanization of African societies, increased levels of privatization and a host of other factors, there have been growing calls for land reforms in different countries in Africa, including Sierra Leone. In Sierra Leone, the Chiefdom Councils Act, Section 28 (d) of the Local Government Act 1994 and the Provinces Lands Act (Cap 122) require a company wanting to lease land to pay surface rent to local authorities. This includes the paramount chief, the district Council and the land owners. Rents for these leases are renegotiated every seven years.

Given this shift, the future of land access in Africa is very promising should African leaders be empowered with accurate research to strike deals that would enhance welfare not just in the short-run but the long-run as well. About 70% of countries in Africa have adopted or are on the verge of adopting land reforms which are moving away from colonial ownership regimes. This has attracted substantial foreign direct investments. This is evident in the current flow of investment from emerging economies like China and India and some countries in Europe into different parts of Africa. These systems have led to Africa being seen as the new frontier for investments not just in the agriculture sector but most significantly in the industrial and service sectors.

2.2.2: Equilibrium Displacement Model: There has been a long list of contributions made towards the general equilibrium displacement model literature. The literature can be traced as far back as Buse (1958) who developed a system of reduced form elasticities from supply and demand equations for two commodities. He then contrasted his "total elasticities" with Marshallian ceteris paribus elasticities. Some reviews however pay more homage to Muth (1964) who developed the reduced forms for proportional displacements from equilibrium for a system of equations of supply and demand for a product dependent on two factors of production and exogenous shifters for each of the functions. Both of these contributions we think were very significant and paved the way for several other contributions to their methods.

Several developments have followed these pioneering contributions by Muth and Buse. Some of these include Perrin 1997's application of these techniques to develop a framework that can be used to obtain impacts of technological change, either ex ante or ex post.

This research follows closely the model developed in Perrin (1997) and in Perrin's updated class notes for the graduate course AECN 840 "Applied Welfare and Policy Analysis" at the University of Nebraska, Lincoln. The latter have been a widely used tool box for practitioners. In this research, we use a very simple multi-market model representing a system of demand and supply equations in a set of output and input markets. Using matrix algebraic methods and sensitivity analysis, we obtain calculate the market and welfare effects of increased demand of a biofuel crop in the agricultural sector in Sierra Leone

2.3: Methodology

2.3.1: The displacement model

In this paper the whole agricultural sector in Sierra Leone is modeled as consisting of three output markets and two input markets. The agriculture industry produces energy crops, and staple crops while using land and other inputs. We specify three main output markets; one for non-edible energy crops, one of edible energy crops and one for other staples; and two input markets; land and others

Consider a biofuel influenced farming industry producing three outputs, $Q_{b,}$ a product solely used as biofuel input, $Q_{f,}$ an edible oil product, and food staples, S, using two inputs, land L^Q and other O^Q. (Example of Q_b can be Jatropha while that for Q_f can be either sugar cane or palm oil). We model this farming industry as having one underlying technology that can be represented by the cost function $C(S,Q_b,Q_f,w^L,w^O)$, where the w's are prices of land and other inputs.

The equilibrium equations consist of demand equations for the three outputs:

$Q_b=f(p^{Qb},p^{Qf})$ + shock due to biofuel (β)

$Q_f=g(p^{Qf},p^S)$

$S= h(p^{Qf},p^S)$

and "supply" equations, production chosen so as to set marginal cost equal to price:

$C_{Qb} = p^{Qb}$,

$C_{Qf} = p^{Qf}$

$C_S = p^S$

Output-constant, derived demand equations for land and other inputs, using Shephard’s lemma, are:

$C_{wL} = L$,

$C_{wO} = O$,

And the input supply equations are:

$L = g(w^{L},)$,

$O = f(w^{L},)$

This system of 5 markets with 5 equilibrium conditions provides solutions to 10 unknowns ($dlnQ^b$, $dlnQ^f$, dlnS, $dlnP^{Qb}$, $dlnP^{Qf}$, $dlnP^S$, $dlnW^L$, $dlnW^o$, dlnL, dlnO). We introduce an increase in demand of inedible biofuel as a shock to the system. We then solve the system of equations to obtain the change in prices and quantities in the five markets as well as the producer and consumer welfare changes.

2.3.2: Log-linear comparative static equations:

The following is a key describing the variables presented in the equations below:

Q^b = Equilibrium quantity of Inedible Biofuel

Q^{fb} = Equilibrium quantity of edible biofuel

S = Equilibrium quantity of Staples

P^{Qb} = Equilibrium Price of inedible biofuel

P^R = Equilibrium Price of edible biofuel

P^S = Equilibrium Price for Staple

W^L = land prices

W^o = price of other inputs.

L = Total Land used by all three industries

O = other inputs used by all three industries

Demand Equations (H=Elasticity)

$dlnQ^{b} = H_{Qb/p}{}^{Qb}\, dlnP^{Qb} + H_{Qb/P}{}^{Qf} dlnP^{Qf} + H_{Qb/P}{}^{S} dlnP^{S} + \beta$ ---1

$dlnQ^{fb} = H_{Qfb/P}{}^{Qf} dlnP^{Qf} + H_{Qfb/P}{}^{Qb} dlnP^{Qb} + H_{Qfb/P}{}^{S} dlnP^{S}$ ------------ ------------------------------2

$dlnS = H_{S/P}{}^{Qf} dlnP^{Qf} + H_{S/P}{}^{S} dlnP^{S} + H_{S/p}{}^{Qb}\, dlnP^{Qb}$ --3

Equations one to three represent demands for biofuels, edible biofuels and staple products respectively.

Supply equations (∑=Elasticity)

$(\sum_{Qb}{}^{s}{}_{/P}{}^{Qb})^{-1} dlnQ^{bs} + (\sum_{Qf}{}^{s}{}_{/P}{}^{Qb})^{-1} dlnQ^{fs} + (\sum_{S}{}^{s}{}_{/P}{}^{Qb})^{-1} dlnS^{s} + (\sum_{W}{}^{L}{}_{/P}{}^{Qb})^{-1} dlnW^{L} + (\sum_{W}{}^{o}{}_{/P}{}^{Qb})^{-1} dlnW^{o} = dlnP^{Qb}$----4

$(\sum_{Qb}{}^{s}{}_{/P}{}^{Qf})^{-1} dlnQ^{bs} + (\sum_{Qf}{}^{s}{}_{/P}{}^{Qf})^{-1} dlnQ^{fs} + (\sum_{S}{}^{s}{}_{/P}{}^{Qf})^{-1} dlnS^{s} + (\sum_{W}{}^{L}{}_{/P}{}^{Qf})^{-1} dlnW^{L} + (\sum_{W}{}^{o}{}_{/P}{}^{Qf})^{-1} dlnW^{o} = dlnP^{Qf}$----5

$(\sum_{Qb}{}^{s}{}_{/P}{}^{S})^{-1} dlnQ^{bs} + (\sum_{Qf}{}^{s}{}_{/P}{}^{S})^{-1} dlnQ^{fs} + (\sum_{S}{}^{s}{}_{/P}{}^{S})^{-1} dlnS^{s} + (\sum_{W}{}^{L}{}_{/P}{}^{S})^{-1} dlnW^{L} + (\sum_{W}{}^{o}{}_{/P}{}^{S})^{-1} dlnW^{o} = dlnP^{S}$----------6

On the supply side, one cost function was used for all three crops and the first order conditions maintained (MC=P). The general forms for all three equations are: C_{Qb} (Q_b, Q_f, S, w^L, w^O) and. C_{Qf} (Q_b, Q_f, S, w^L, w^O), C_S (Q_b, Q_f, S, w^L, w^O).

Output Constant Derived Demand

$Z_{L/Qb}\, dlnQ^{bs} + Z_{L/Qf}\, dlnQ^{fs} + Z_{L/S}\, dlnS^{s} + Z_{L/W}{}^{L}\, dlnW^{L} + Z_{L/W}{}^{o} dlnW^{o} = dlnL$ ------------------------------ 7

$Z_{O/Qb}\, dlnQ^{bs} + Z_{O/Qf}\, dlnQ^{fs} + Z_{O/S}\, dlnS^{s} + Z_{O/W}{}^{L}\, dlnW^{L} + Z_{O/W}{}^{o} dlnW^{o} = dlnO$ ------------------------------ 8

Using Shephard's lemma, the above output constant equations were derived. The general forms are: $C_{wL} = L$; $C_{wO} = O$.

Supply and Market Clearing Conditions

$dlnL = \Omega_{L}{}^{T}{}_{/W}{}^{L}\, dlnW^{L} + \Omega_{L}{}^{T}{}_{/W}{}^{o}\, dlnW^{o}$ --9

$dlnO = \Omega_{O}{}^{T}{}_{/W}{}^{o}\, dlnW^{o} + \Omega_{O}{}^{T}{}_{/W}{}^{L}\, dlnW^{L}$ --10

$dlnQ_b = dlnQ_b{}^{s}$ --11

$dlnQ_f = dlnQ_f^s$ -- 12

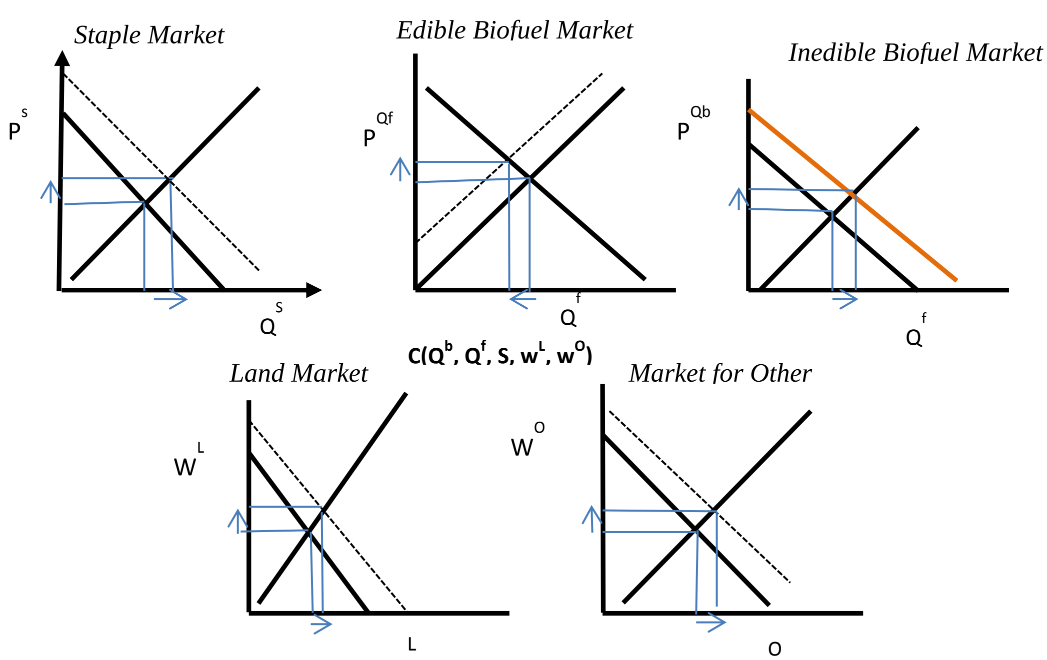
$dlnS = dlnS^s$ -- 13

Based on the above log-linear relationships, the graphs below try to describe the relationships with the shock introduced.

The graphs show the three output markets (staples, edible biofuel and inedible biofuel markets) and two input markets (land and other). The bolded black plots represent demand and supply curves describing the benchmark (that is, without the shock) while the other lines (dashed) represent the changes as a result of the shock (orange in graph).

2.3.3: Market Effects

Figure 11: Resulting Market Effects



And the matrix of elasticities corresponding to a system representing two input markets and three output markets is as shown below:

Table 9: Matrix Containing Elasticities and Shares for a System of Three Output and Two Input Markets

$dlnQ^{b}$	$dlnQ^{f}$	$dlnS$	$dlnP^{Qb}$	$dlnP^{Qf}$	$dlnP^{S}$	$dlnW^{L}$	$dlnW^{o}$	$dlnL$	$dlnO$			
-1	0	0	$-H_{Qb/p}^{Qb}$	$-H_{Qb/P}^{Qf}$	$-H_{Qb/P}^{S}$	0	0	0	0	$dlnQ^{b}$		B
0	-1	0	$-H_{Qf/P}^{Qb}$	$-H_{Qf/P}^{Qf}$	$-H_{Qf/P}^{S}$	0	0	0	0	$dlnQ^{f}$		0
0	0	-1	$-H_{S/P}^{Qb}$	$-H_{S/P}^{Qf}$	$-H_{S/P}^{S}$	0	0	0	0	$dlnS$		0
$(\Sigma_{Qb}^{s}/_{P}^{Qb})^{-1}$	$(\Sigma_{Qf}^{s}/_{P}^{Qb})^{-1}$	$(\Sigma_{S}^{s}/_{P}^{Qb})^{-1}$	-1	0	0	$(\Sigma_{W}^{L}/_{P}^{Qb})^{-1}$	$(\Sigma_{W}^{o}/_{P}^{Qb})^{-1}$	0	0	$dlnP^{Qb}$		0
$(\Sigma_{Qb}^{s}/_{P}^{Qf})^{-1}$	$(\Sigma_{Qf}^{s}/_{P}^{Qf})^{-1}$	$(\Sigma_{S}^{s}/_{P}^{Qs})^{-1}$	0	-1	0	$(\Sigma_{W}^{L}/_{P}^{Qf})^{-1}$	$(\Sigma_{W}^{o}/_{P}^{Qf})^{-1}$	0	0	$dlnP^{Qf}$	=	0
$(\Sigma_{Qb}^{s}/_{P}^{S})^{-1}$	$(\Sigma_{Qf}^{s}/_{P}^{S})^{-1}$	$(\Sigma_{S}^{s}/_{P}^{S})^{-1}$	0	0	-1	$(\Sigma_{W}^{L}/_{P}^{S})^{-1}$	$(\Sigma_{W}^{o}/_{P}^{S})^{-1}$	0	0	$dlnP^{S}$		0
$Z_{L/Qb}$	$Z_{L/Qf}$	$Z_{L/S}$	0	0	0	$Z_{L/W}^{L}$	$Z_{L/W}^{o}$	-1	0	$dlnW^{L}$		0
$Z_{O/Qb}$	$Z_{O/Qf}$	$Z_{O/S}$	0	0	0	$Z_{O/W}^{L}$	$Z_{O/W}^{o}$	0	-1	$dlnW^{o}$		0
0	0	0	0	0	0	$-\Omega_{L/W}^{L}$	$-\Omega_{L/W}^{o}$	1	0	$dlnL$		0
0	0	0	0	0	0	$-\Omega_{O/W}^{L}$	$-\Omega_{O/W}^{o}$	0	1	$dlnO$		0
				A						X		b

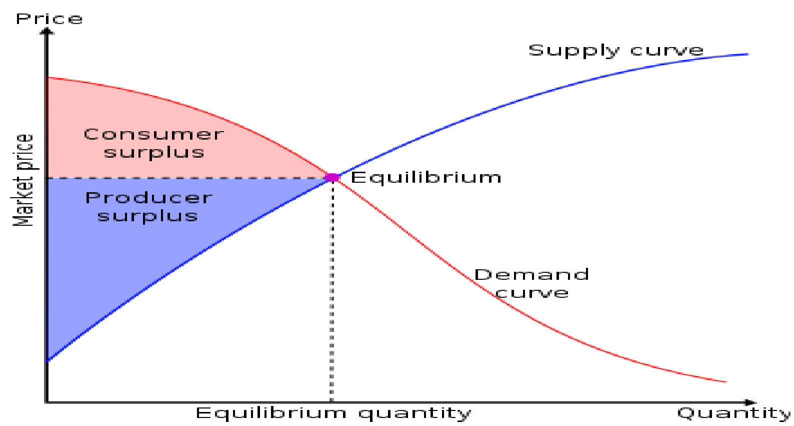
β represent the potential shock to the system, the increase in the demand of inedible biofuels. The inedible biofuel market is affected by an increase in foreign investments into Sierra Leone's biofuel industry and we represent this by an increase in demand (parallel outward shift of the demand curve). Solving the equation $A_{10x10}*X_{10x1}= b_{10X1}$ helps us characterize the market (positive) effects of the shock introduced on equilibrium prices and quantities in all five markets. The resulting estimates of X (market effects) represent the percentage by which the prices and quantities in the five market change as a result of exogenous shock**.** Given the linear relationship between X and b, doubling b_{11} (the shock) would double X_{11}. We therefore only introduced one shock to the system (30%) to illustrate. As the size of the shock increases, however the accuracy of the linear approximation of the system deteriorates.

2.3.3: Welfare Analysis

The measurement of welfare has seen decades of evolution particularly as practitioners' attempt to narrow the gap between theory and application. These tools have been central to most public policy applications. Slesnick D.T (1998) agrees that full consideration of policies like taxes, subsidies, transfer programs, health care reform and more, must ultimately address the question of how these policies affect the well-being of individuals. These welfare tools become very handy in conducting these types of policy analysis. Due to data limitations, we suggest the use of classic welfare measurement techniques "change in Consumer and Produce Surplus".

Consumer Surplus and producer Surplus

Figure 12: Graph Illustrating Consumer Surplus and Producer Surplus :



Consumer surplus is a measure of an individual consumer's willingness to pay for the consumption of a given good or service over what he/she actually pays to consume that good. This can be shown by area colored pink in figure 13 above. Similarly, producer surplus is a measure of a producer's willingness to produce a commodity or provide a service at a cost less than what h/she actually spends in producing that good or service (Varian (1992)). This can also be shown by the area colored purple in figure 13.

The welfare effects of an equilibrium change are generally approximated as the changes in consumer and producer surplus. In a multimarket framework using log-linear comparative static techniques as discussed in Perrin (1997) and in Perrin's updated class notes, welfare changes as a result of exogenous shocks can be expressed as fractions of the initial value of the good. If demand and supply curves are stationary, the relationship used to compute these welfare measures are as shown below:

Δ Consumer Welfare/ $P_i^0 Q_i^0 = (-dlnp_i^d(1+lnQ_i/2)$ - - - 14

Δ Producer Welfare/$P_i^0 Q_i^0 = (dlnp_i^s(1+lnQ_i/2)$ - - - 15

where:

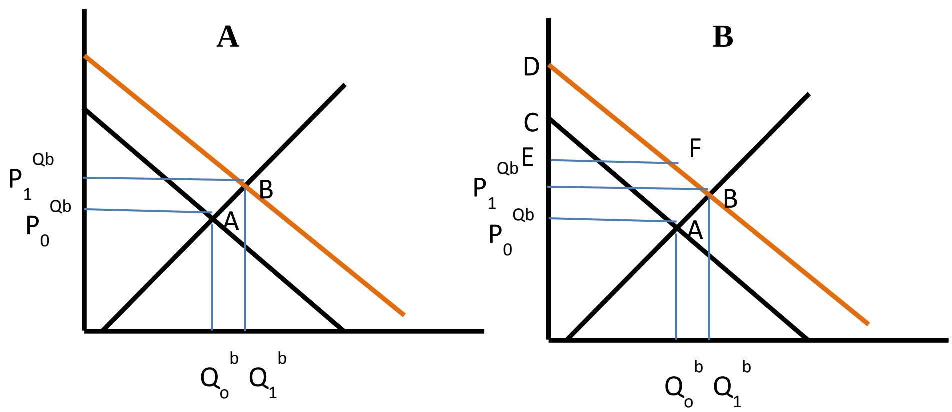
P^0=initial price before the shock was introduced for market i.

Q_i^0= initial quantity before the shock was introduced for market i.

This computation of change in consumer surplus is obtained by summing the rectangle measured by the change in equilibrium product price times initial quantity (area of rectangle) and the triangle measured by half of the change in price times the change in equilibrium quantity (area of triangle). Changes in producers' surplus in each of the input markets are measured by a comparable trapezoid under the new price for that input. To understand the computation of the welfare measures above, see figures 14a and 14b below. In 14a the change in producer surplus is represented by the area P_0P_1AB which is a trapezoid. In 14b the change in consumer surplus is represented by the trapezoid P_1EFB. The price change indicated by E - P_1 is calculated as dlnP= dlnQ/eta, where eta represents demand elasticities:

$$eta = \frac{\mathrm{dQ}}{\mathrm{dP}} x \ \frac{P}{Q} = \frac{\frac{dQ}{Q}}{\frac{dP}{P}} = \frac{dlnQ}{dlnP} \quad \text{Hence } \mathrm{dlnP_i=dlnQ/eta} \text{ -----------------------------16}$$

Figure 13: Illustrating Computation of Consumer Surplus and Producer Surplus.



Our welfare measures (changes in consumer surplus and producer surplus as percentages of the initial values of the respective products) are obtained considering the effects in the three output markets (for consumer surplus effects) and the effects in the two input markets (for producer surplus effects). That is, we obtain five welfare measures with three being percentage changes in consumer surplus from the three output markets while two being percentage changes in producer surplus from the two input markets.

2.3.4: Elasticities:

Three main methods that have been employed in the literature towards obtaining the elasticities and shares needed to populate the matrix of elasticities and shares above. These include an estimation of the elasticities through econometric methods, using secondary estimates from other studies in the literature or the use of micro economic theory and assumptions based on knowledge of the prevailing markets. Due to data limitations, we use a mixture of the last two methods to develop the elasticities and shares for the matrix. In the next section, we discuss all the considerations we considered to populate the different parts of this matrix.

Demand Elasticities

Homogeneous of degree zero in prices: i.e.: horizontal sum of elasticities should equal to zero. Because of downward sloping demands the own price elasticity of demands should be negative. By symmetry (Young's theorem) the signs of $H_{Qb/P}{}^{Qf}$ and $H_{Qf/P}{}^{Qb}$, $H_{Qb/P}{}^{S}$ and $H_{S/P}{}^{Qb}$, $H_{Qf/P}{}^{S}$ and $H_{S/P}{}^{Qf}$ are the same but comprise different magnitudes.

Table 10:Matrix of Demand Elasticities

$dlnP^{Qb}$	$dlnP^{Qf}$	$dlnP^{S}$	
-1	0	0	$dlnQ^{b}$
0	-1.5	1.5	$dlnQ^{f}$
0	0.375	-0.375	dlnS

The above matrix was populated using mainly our knowledge of the Sierra Leone food industry and some references from the literature. Some relevant references used in this vein include: FAO 2011 outlook on Rice in developing countries, an article by Ambiyah Abdullah 2009 on demand and supply elasticities for Indonesia palm oil sector and World Bank (D.R Larson -1996).

Supply

By constant returns to scale (CRS), cost is linearly homogenous with respect to output and supply is homogenous of degree 0 with respect to prices. Therefore inverse supply elasticities horizontally sum to zero. Also by young's theorem, we assume reciprocity. By CRS the following input cost shares of land and other inputs are obtained:

$$\frac{W^o O}{W^o O + W^L L} + \frac{W^L L}{W^o O + W^L L} = 1$$

The share of producer costs that goes towards expenses on land and other inputs were obtained from apriori knowledge of the land prices and expected costs on labor, machinery and other inputs needed to produce all three crops.

Table 11: Matrix of Supply Elasticities and Cost Shares of Inputs

Supply Elasticities				Shares		
$d\ln Q^b$	$d\ln Q^f$	$d\ln S$		$d\ln W^L$	$d\ln W^o$	
2.1	-0.5	-0.6	$d\ln P^{Qb}$	0.4	0.6	$d\ln P^{Qb}$
-0.22	2.12	-0.9	$d\ln P^{Qf}$	0.4	0.6	$d\ln P^{Qf}$
-0.34	-1.15	2.5	$d\ln P^{S}$	0.4	0.6	$d\ln P^{S}$

Input Demand Elasticities and Shares

By constant returns to scale, the first three elasticities in the input demand system represent output shares:

$$\frac{Q_b P_b}{Q_b P_b + Q_f P_f + SP_s} + \frac{Q_f P_f}{Q_b P_b + Q_f P_f + SP_s} + \frac{SP_s}{Q_b P_b + Q_f P_f + SP_s} = 1$$

The inputs derived demands are homogenous of degree zero in input prices. Therefore; the derived demand elasticities should sum to zero and reciprocity is imposed. The diagonal is negative because the cost function is assumed concave.

Table 12: Matrix of Input Demand Elasticities and Shares.

Input Demand Elasticities

dlnWL	dlnWo	
-0.3	0.3	dlnWL
0.2	-0.2	dlnWo

Shares

dlnQb	dlnQf	dlnS	
0.2	0.45	0.35	dlnWL
0.2	0.45	0.35	dlnWo

Elasticities of Inputs Supply

For the same reasons discussed above under output own supply elasticities, Input own elasticities are assumed positive.

Table 13: Matrix of Input Supply Elasticities

dlnWL	dlnWo	
0.1	0	dlnL
0	2	dlnO

Table 14: Matrix of Elasticities and Shares

$dlnQ^b$	$dlnQ^f$	dlnS	$dlnP^{Qb}$	$dlnP^{Qf}$	$dlnP^S$	$dlnW^L$	$dlnW^o$	dlnL	dlnO			
-1	0	0	-1	0	0	0	0	0	0	$dlnQ^b$		**-0.3**
0	-1	0	0	-1.5	1.5	0	0	0	0	$dlnQ^f$		0
0	0	-1	0	0.375	-0.375	0	0	0	0	dlnS		0
2.10	-0.50	-0.60	-1	0	0	0.4	0.6	0	0	$dlnP^{Qb}$		0
-0.22	2.12	-0.90	0	-1	0	0.4	0.6	0	0	$dlnP^{Qf}$	=	0
-0.34	-1.15	2.50	0	0	-1	0.4	0.6	0	0	$dlnP^S$		0
0.2	0.45	0.35	0	0	0	-0.3	0.3	-1	0	$dlnW^L$		0
0.2	0.45	0.35	0	0	0	0.20	-0.20	0	-1	$dlnW^o$		0
0	0	0	0	0	0	0.1	0	-1	0	dlnL		0
0	0	0	0	0	0	0	2	0	-1	dlnO		0

Description of Different Players

For a better understanding of the potential losers and winners of the 30% increase in demand of inedible biofuels, it is important to describe or identify the different players in both the input and output markets.

In the output market, the consumers of staples are mainly all Sierra Leoneans as this staple may include a crop, like rice, which is the main staple product of the country. Consumers of edible biofuels are also all Sierra Leoneans. This is because palm oil is used to produce most dishes that are being eaten with rice. That is, there is some complementarity in the consumption of rice and palm oil. Consumers of inedible biofuels are mainly owners of the biofuel industry. Given that the biofuel processing industry is not well developed in Sierra Leone, these biofuel products are being exported hence making foreign biofuels industry the end consumers of inedible biofuels. It is important to note that farmers are also consumers of staples and palm oil.

Producers of all three products are local Sierra Leonean farmers. These farmers are also the consumers of the inputs in the production of the three outputs. Identifying input suppliers may not be very easy as an input like land does not have well defined property right in some regions of Sierra Leone. The traditional communal land ownership regime makes it complicated. On average, most farmers in Sierra Leone have user rights to the land but may not have ownership rights (cannot sell the land.) Supplier of labor are farmers and other hired agricultural workers. The above should help us better understand potential winners and losers as discussed in the next section.

2.4: Analysis of Results

In this section, we present results obtained from the analysis and provide explanations for these results. We first present the market effects as a result of introducing a 30% increase in demand shock to the system. Following these, we then present results from our welfare measures (percentages change in consumer surplus and producer surplus).

2.4.1: Market Effects

This section presents results representing changes in equilibrium quantities and prices in the five markets in this analysis as a result of a shock, an increase in the demand for inedible biofuels introduced to the system. The primary focus in this analysis is to determine the directions of change in the prices and quantities in each market when the shock of interest is introduced into the system.

Introducing the Shock

As shown in equation one above and the matrix of elasticities (table 14), a 30% increase in demand of inedible biofuels was introduced. This represents a parallel outward shift of the demand curve in this market (as shown in figure 12). The ensuing market effects are shown in table 15 below:

Table 15: Market Effects from a 30% Demand Increase of Inedible Biofuel

Effects	β = 30%
$dlnQ^b$	8.76%
$dlnQ^f$	-0.22%
$dlnS$	0.06%
$dlnP^{Qb}$	21.24%
$dlnP^{Qf}$	0.31%
$dlnP^S$	0.16%
$dlnW^L$	5.10%

$dlnW^o$	1.22%
dlnL	0.51%
dlnO	2.45%

The results indicate that with a 30% increase in the demand of inedible biofuels, the equilibrium quantity of inedible biofuels increases by about 8.8%, the equilibrium quantity of edible biofuels decrease by about 0.22%, while the equilibrium quantity of staples increases by 0.6%. Furthermore, as a result of this shock, equilibrium prices for both inputs and outputs increase with the largest effects being a 21% increase in inedible biofuel prices and a 5% increase in land prices. Equilibrium quantities of inputs also increased, with that of land increasing by 0.5% and that of other inputs by 2.45%. Figure 12 above presents these shifts.

2.4.4: Consumer Surplus and Producer Surplus

This section presents results from the welfare analysis.

2.4.4.1: Consumer Surplus

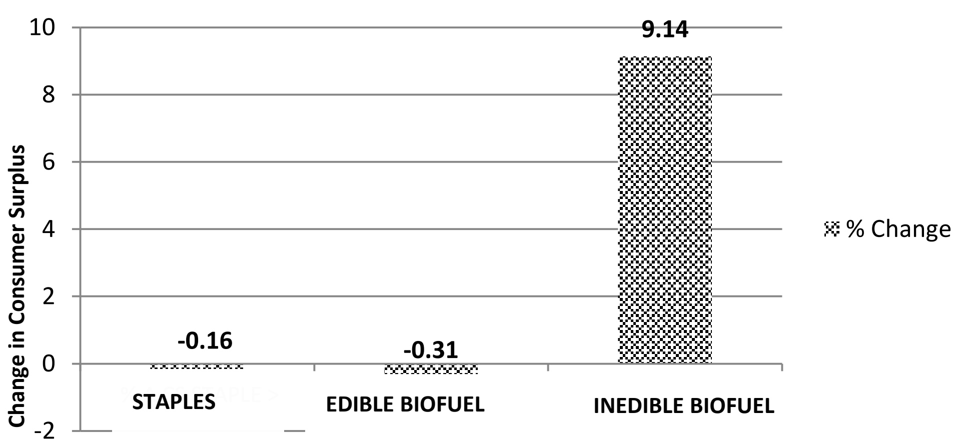
Results for changes in consumer surplus for the whole system, computed as shown in the methodology section above, are presented in this section. These expressed as a percentage of the initial market value of the commodity. They represent the consumer and producer welfare effects for the whole system. The results obtained are as shown below:

Table 16: Change in Consumer Surplus as a results of a 30% Increase in Demand for Inedible Biofuels, as a percent of the value of the commodity

	% Change
% ∆ CS STAPLE >	-0.16
% ∆ CS EDIBLE BIOFUEL >	-0.31
% ∆ CS INEDIBLE BIOFUEL >	9.14

Note that these percentage changes are relative to the value of the commodity. The results show that consumers of staples loose by 0.16% while consumers of edible biofuels loose by 0.31%. This means that the 30% shock to the inedible biofuel market is welfare dis-enhancing to consumers of staples and edible biofuels by 0.16% and 0.31% respectively. On the other hand, the consumers of inedible biofuels gained by 9.14% as a result of the shock. This means the shock to the inedible biofuel industry is welfare enhancing to consumers of inedible biofuels. We also graphically represent the results in figure 15 below:

Figure 14: Change in Consumer Surplus as a percentage of the value of commodity in Output Markets



2.4.5: Producer Surplus

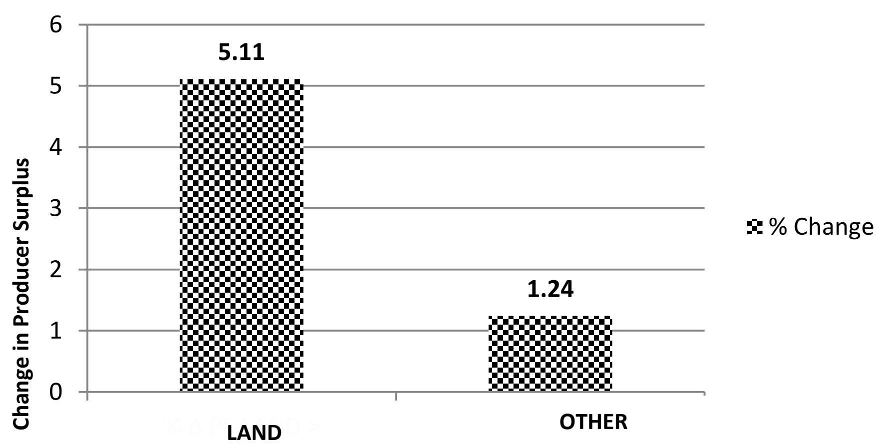
Here we present results from the estimation of the changes in producer surplus expressed as a percentage of the original output value. These represent the whole system’s producer welfare effects because changes in producer surpluses from the output markets are returns to inputs.

Table 17: Changes in Producer Surplus as a percentage of the value of commodity due to a 30% increase in demand for Inedible Biofuels

	% Change
% ∆ PS LAND >	5.11
%∆ PS OTHER >	1.24

The results reveal that the welfare effects on all producers (owners of land and of other inputs) were positive. This means that the demand shock to the biofuel industry enhanced welfares of all land owners and owners of other inputs, which are primarily labor. The magnitudes of these effects were however very different. The effects associated with land were welfare enhancing by 5% while those associated with other inputs enhanced welfare by 1.24 %

Figure 15: Graphs Showing Change In Producer Surplus in Input Markets



2.5: Discussion of Results and Conclusion

Over the last five to ten years, there has been an influx of foreign investments into Africa by different natural resource seeking industries. The worldwide increase in demand for energy, in particular for biofuels, has resulted in an induced increase in the demand for arable land. This trend continues to persist as western countries continue their investments on clean energy sources and as the rate of growth of developing countries like China continues strong. The induced increase in demand for land and other natural resources in the developing world in general, and in particular in Africa, has been a very contentions issue as the societal effects of these investments have not been thoroughly studied .

This paper attempts to answer a simple but fundamental question: what are the short run market and welfare effects in the agricultural sector of a developing country like Sierra Leone of an induced increase in the demand for arable land due to an increase in the demand of biofuels.

In achieving these objectives, a log-linear comparative static system is developed and used to measure market and welfare effects. One shock (an increase in demand of inedible biofuels) is applied to the system and the market and welfare effects measured. The magnitude of the shock tested is 30%. That is we investigate how prices and quantities in agricultural input and output markets would respond to a 30% increase in demand of inedible biofuels. We also trace out the effects of this increase on consumers and producers' welfare.

From the market effect estimates shown above, an increase of 30% in the demand of inedible biofuel, given representative elasticities for these markets, resulted in increased quantity demanded of both inedible biofuels (8.7%) and staples and a small reduction in the quantity demanded of edible biofuels (0.22%). Prices in all three output markets increased; the highest being in the inedible biofuel market (21%). Sierra Leoneans, who are mainly consumers of staples and edible oils, are affected negatively by these price increases. Farmers that are net producers of staples and of edible and inedible oils are benefited. The bigger price increase in the inedible biofuels market will induce a shift from production of staples and edible biofuels to that of inedible biofuels. Quantity demanded of all inputs used in production of these three outputs increased as well as their prices. In particular, land prices increased by 5%. This means that input costs have increased. Returns to landowners increase as well as returns to other productive inputs (labor) although much less than the increase of landowners.

From the welfare analysis carried out, percentage changes in consumer surplus were largely positive for the inedible biofuel industry (9%) but negative and very small for the consumers of edible oils and staples. This means that the shock to the inedible biofuel industry had large welfare enhancing effects on consumers of inedible biofuels but had small welfare dis-enhancing effects on the other two sets of consumers. From a food security stand point, the shock would have negative welfare effects on food consumers (every Sierra Leonean).

From the point of view of the owners of resources, changes in producer surplus of land and other input owners were welfare enhancing. However, as a result of the increase in demand for inedible biofuels (like Jathropa), land owners benefited more (welfare of land owners enhanced by 5%) than owners of other resources, like labor (where welfare of laborers enhanced by 1%).

Table 18: Winners and Losers from a Welfare Perspective

Welfare Effects		Winners and Losers
% Δ CS Staples	-0.16	Welfare of consumers of staples decreases. This includes all Sierra Leoneans
% Δ CS Edible Biofuels	-0.31	Welfare of consumers of edible biofuels decreasesmore than the welfare of staple consumers. Edible oil is a complement to staples in the Sierra Leoneans diet.
% Δ CS Inedible Biofuels	9.14	Welfare of consumers of inedible biofuels is largely enhanced. These consumers are mainly the biofuels industry. A large share is foreign demand.
% Δ PS Land	5.11	Welfare of owners of land is significantly enhanced. These are mainly farmers who own land.
%Δ PS Other	1.24	Welfare of owners of other inputs (like labor) is also enhanced but not as much as that of landowners.

Looking at the gains to consumers and producers (table 18); clearly there are winners and losers as a result of an increase in the demand for inedible biofuels. Welfare effects on farmers are dependent upon ownership of factor inputs. Land owners, in particular, gain the most while owners of other resources like labor gain but not as much as land owners. This means that farmers that own land that also work on their own farms and also produce inedible biofuels gain the most. The next tier down is those that own only land and produce inedible biofuels. The lowest category of winners is laborers that work on these inedible biofuel farms. For consumers, only those that demand inedible biofuels presumably for energy production can be considered winners. Consumers of staples and edible biofuels, mainly Sierra Leoneans, clearly have their welfare decreasing as a result of this increased demand in inedible biofuels. Given that majority of the inedible biofuel product is demanded by foreign companies, these gains go to foreigners. Given that some consumers are also producers, the gains as a result of owning some factors of production, can off-set the losses from consumption. Consumers that are not involved in the production process and producers that do not have ownership rights to factor inputs (like land) stand the loose the most.

Hence, for the average Sierra Leonean consumer, this increase in demand for an energy crop results in higher prices of staples and edible oils, main ingredients of their diet and a loss in their welfare, even though labor income might increase slightly. Sierra Leoneans farmers that are net producers gain as well as biofuel producers, most of them foreign companies. These results, that only consider the short run effects of the worldwide increase in demand of biofuels, indicate potential severe implications for food security in the country. It would be important to follow with a study of the long run implications for the resident country of foreign investments in extractive industries.

Chapter 3: Response of Farm Energy Input Prices and Food Prices to Crude Oil Prices (A Vector Error Correction Approach).

3.1: Introduction

Over the last five years, crude oil price spikes and fluctuations have been center stage in all attempts to revive the US and world economy (including those of developing countries). This has been mainly as a result of the inherent rippling effects crude oil price variations have on other commodity prices. Some of these include its influence on world food prices (Bhattacharya et al (2003); Cullen et al (2005); Gicheva et al (2010); Beatty et al (2011)), its influence on other energy prices, to name few. In a bid to reduce the US dependence on crude oil and with continued setbacks encountered on developing renewable energy, there have been renewed resilience and effort made by all actors in the biofuel industry in the United States towards the commercial production of cellulosic ethanol. This continues to be a contentious subject as researchers grapple with issues related to energy balance and the need to increase biofuel productivity (per unit of land and feedstock employed); D. Pimentel and T.W. Patzek (2005), Cassman (2008). The 2008 Food, Conservation and Energy Act (which has been extended through September 2013) and the Energy Independence and Security Act of 2007 have both been very instrumental in obtaining the current results and technological improvements observed in the US towards the attainment of economically viable biofuel products. However there are still significant milestones yet to be reached to see the complete realization of this objective. Khana (2008) argues that the success of all these government incentives to stimulate production of cellulosic biofuels will crucially depend on the price of gasoline, the costs at which it will be commercially viable to convert cellulosic feedstock into fuel and the costs of producing corn–based ethanol.

From a farmer’s stand point, energy costs have become a significant part of total farm expenditures (H.W. Downs et al 2011). Expenditures related to energy are now very important as farmers try to make optimal decisions on the farm. For instance, decisions about adoption of new technologies to be used on the farm will depend not only on the price of the new technology in comparison with the older technology, but also on the variations in the prices of fuel these technologies use. In the case of technologies that use forms of renewable energies, one should think of energy price effects as being carried over or passed on from the inputs in terms of the feedstock used to produce the biofuel and in terms of energy used for their production. Hence not only is the price of the feedstock important but also the price of the energy inputs used.

This research seeks to determine the degree of responsiveness of these farm energy prices (including corn prices), to crude oil prices both in the short run and in the long-run. We think this is important because in the absence of strong responses of farm energy prices to crude oil prices, farmers and other energy end users can safely make decisions furthering the use of such energy sources even as crude oil prices continue to rise. The reverse would be expected if otherwise. For the renewable energy industry, such results would guide the choice of feedstock used and the input energies used in the production of these renewable energy products. For instance, if some of these energy inputs happen to have large responses to crude oil prices, it would become wise for them to use energy inputs that may have lesser responses to crude oil price spikes.

The EIA reported in 2008 that given the then prevailing technologies for the production of cellulosic ethanol and with the prevailing government subsidies, cellulosic ethanol could compete commercially only if oil prices rose to $145.98/barrel. Given the technological change that has taken place in the last three years, that estimate has been reduced considerably. The Danish company Novozymes, in collaboration with M&G, is in the process of building the world's first commercially viable cellulosic ethanol producing plant and they expect to start production in 2012 at a price much cheaper than what earlier technologies suggested (below USD 2.00 per gallon for the initial commercial-scale plants). Knowledge of the degree of responsiveness of farm energy prices to crude oil prices would help other companies in the biofuel industry to better develop lesser crude oil dependent biofuel production systems or technologies.

As an addendum to this study, we also include corn prices in our system of prices to test how they respond to crude oil prices and other related farm input prices. We think the inclusion of corn prices is important because they affect feedstock supply, prices and hence energy prices. This represents the second objective of this analysis. Research on food prices and their relationship to energy prices in a world where food crops are increasingly being used for the production of biofuel, have seen great attention in the applied economics literature over the last five years.

Given that this analysis targets prices averaged over all states in the United States, cluster analysis is performed to study the energy price variations observed at a state level. This we think is very important because some unique information or trends get lost when the respective price variables are averaged over 51 states. Carrying out such an analysis would help support the other results in this study and provide relevant information for future studies.

3.1.1: Objectives:

- Determine the degree of responsiveness of farm energy input prices and corn prices to crude oil prices in the United States.
- Analyze state level clustering based on energy prices in the United States

3.2: Literature Review
3.2.1: Introduction

In this section, we review some relevant literature to this research. Areas we focus on include recent issues on the dynamics of crude oil prices in relation to food prices and other energy prices, renewable energies in relations to first and second generation biofuels and lastly on the intended methodology of choice, vector autoregressive models and vector error correction models.

Issues that have been investigated, similar to our research question, include questions like the role that the biofuel industry plays in rising food prices, the degree of substitutability between food and fuel, the economic effects of crude oil price shocks on food security and many others. On the drivers of food prices, very ambiguous results have been reported; while Wes Harrison (2009), P.C Timmer (2009) and some others have evidence of significant causation of demand for biofuels on food prices, Fortenbery et al. (2009), Power et al. (2009), Benjamin. et al. (2009), J . Dewbre et al. (2008) and others showed that the relationship is not clear-cut. Others like Baek and Koo (2009), Simla et al (2009), and Kimberly (2008); think this relationship can only be significant in the long run and not in the short-run. In retrospect, what can be gathered from these results is a confirmation that there are multiple factors accounting for the rise in food prices. However, some factors should have higher impacts than others. Although Timmer

(2009) argues that these factors are crop-specific, this claim can be questioned due to the fact that these price hikes were not for selectively few crops. For the most part, most of these scholars seem to be in agreement over the following drivers of food prices:

- Increased demand for biofuels as a result of rising prices of crude oil and growing world demand for energy.
- Increased demand for food due to high income growth from emerging economies like China and India.
- Exchange rate and world macroeconomic factors.

Other factors that have also been suggested include:

- Poor crop seasons (tight global supplies not matching growing demand).
- Speculative actions of future price changes.
- Increased marketing costs (R. Harisson (2009)) due to increased prices of crude oil.

Although this research asks a much more fundamental question, it contributes to this literature by providing estimates for the long run response of corn prices to crude oil and other farm energy prices. We also provide information on the percentage of the fluctuations in corn prices that can be attributed to crude oil price shocks and other farm energy price shocks in selected time horizons.

Over the last two years, several studies including Kilan (2007) and others have focused on the economic impacts of energy price shocks. In all these varying and very useful contributions, the choice of variables and the methodologies have been very different. Theirs focused on the use of panel data techniques including macroeconomic variables in their system while here our main focus is on energy prices. The few time series studies have selected variables that seem not to cointegrate. This has restricted most of these studies to the use of vector autoregressive models. On the other hand, in this study, a system of six equations is modeled, two long-run relationships are identified due to the presence of cointegration and a vector error correction model is fitted instead of the VAR levels.

3.2.2: VAR and VECM Models

Two main complementing time series analysis methodologies were applied in this study. We initially estimated a structural vector autoregressive (SVAR) model. However when cointegaration tests were carried out on the system, there was strong evidence of the variables cointegrating. A vector error correction model (VECM) was chosen then for the analysis. Within the framework of the VECM, the series of interest were then forecasted to obtain expected prices over a ten year period. This suggests that there is normally some *a priori* information about the number of cointegrating vectors and most practical work involves pre-testing to determine the cointegrating rank of the system as well as the lag order in the autoregressive component that embodies the system of equations. These order selection decisions can be made by sequential likelihood ratio tests (e.g. Johansen (1988), for rank determination) or the application of suitable information criteria (Phillips (1996)). The latter approach has several advantages such as joint determination of the cointegrating rank and autoregressive order, consistent estimation of both order parameters (Chao and Phillips, (1999)), robustness to heterogeneity in the errors, and the convenience and generality of semi-parametric estimation in cases where the focus is simply the cointegrating rank (Cheng and Phillips, (2010)).

The general forms of both equations that will be used in this analysis are as shown below:

VAR $Y_t = A_1 Y_{t-1} + e_t$ -------------------------------------- 1

VECM $\triangle y_t = \boldsymbol{\pi} y_{t-1} + \sum_{i=0}^{p} \acute{\Gamma}_i \Delta\, y_{t-i} + e_t$ --------------------------- 2

The structure of these equations would be discussed in detail in the methodology section.

3.2.3: Cluster Analysis

Cluster analysis groups data objects based only on information found in the data that describes the objects and their relationships. The goal is that the objects within a group be similar to one another and different from the objects in other groups. The greater the degree of homogeneity within a group and the greater the difference between these groups, the better or more distinct are the clusterings. This technique divides data into groups that are meaningful to the investigator. If meaningful groups are the goal, then the clusters should capture the natural structure of the data. The type of cluster analysis used in carrying out this study follows closely studies like Jože Rovan and Jože Sambt (2003), Brian G. Raub and William W. Chen (2005) and more.

These techniques have been used for different kinds of analysis from different disciplines and for different purposes. In some cases, cluster analysis is only a useful starting point for other purposes, such as data summarization. It helps give *a priori* information about the nature of the dataset that can be used for the main analysis. Some of the disciplines that have strongly used this methodology either for understanding data or utility include: Psychology and other Social Sciences, Biology, Statistics, Information Retrieval Data Mining, and more. In the applied economics literature, these techniques are increasingly being used also. Dos Santos et al, (2010) used this technique to group farmers, according to some relevant characteristics, as a pre-requisite for extrapolation and modeling their behavior from a sample to the whole population (Dos Santos et al, 2010).

3.3: Methodology

3.3.1: Introduction

This section provides a description of the methodology used to carry out this analysis. Firstly, a preliminary, descriptive statistics analysis was carried out. This analysis helped in fine tuning the dataset and getting it ready for the types of analysis that followed. A traditionally necessary step is to analyze the individual series using univariate time series analysis. Hence we carried out an initial univariate time series analysis using the ARIMA framework. Due to its limitations in achieving the objectives, multivariate techniques were employed. The sequence of methods described in this section is a discussion on the data structure and some descriptive statistics, univariate techniques (ARIMA), multivariate techniques (VAR and VEC) and lastly forecasting (impulse response and variance decomposition).

3.3.2: Data Structure

The main data sources for this study were the US Department of Energy and the Nebraska Department of Energy websites. The five energy variables of interest (Crude Oil, Diesel, Natural Gas, Gasoline and Electricity) were measured in Nominal Dollars per Million BTU. This is to enhance effective comparison of all the variables with the standard energy unit. The following conversions were used: Electricity: 1kilowatthour = 3412 BTU, crude oil: 1 barrel = 42 U.S gallons = 5800000 BTU and diesel fuel: 1 gallon = 138690 BMT. The series used was monthly over the period 1981 to 2010. Corn price data was obtained from the University of Wisconsin dairy market information website and was measures in dollars per bushel.

Table 18: Descriptive Statistics of all variables, all U.S. 1980-2010

Variable	N	Mean	Std Dev	Min	Max
Lngas	384	1.08	0.09	0.91	1.33
Lelect	384	1.58	0.06	1.47	1.72
Lgasol	384	1.28	0.12	1.05	1.58
Ldiesel	384	1.23	0.12	0.99	1.52
Lcrude	384	0.89	0.23	0.37	1.38
Lcorn	384	0.42	0.15	0.15	0.88

Figure 16: Plot of Log Energy Prices from 1980 to 2010

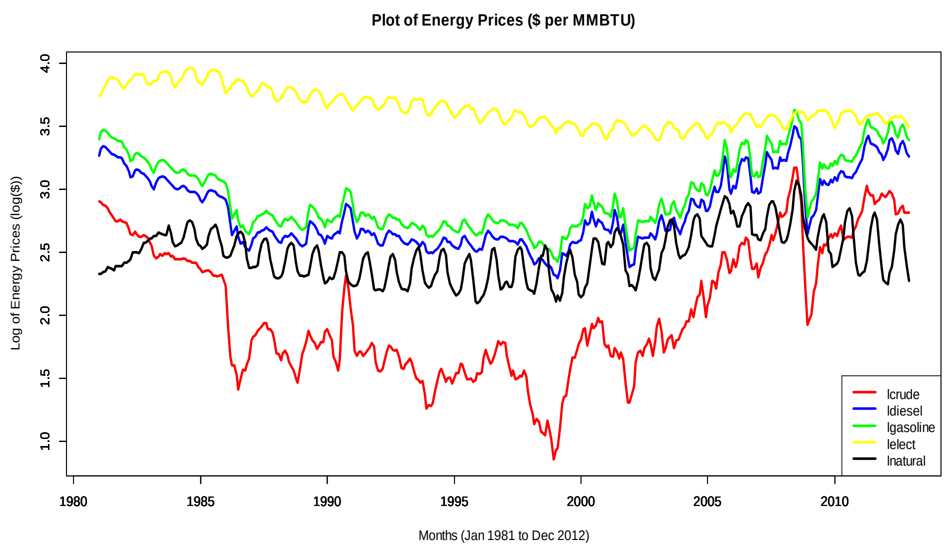
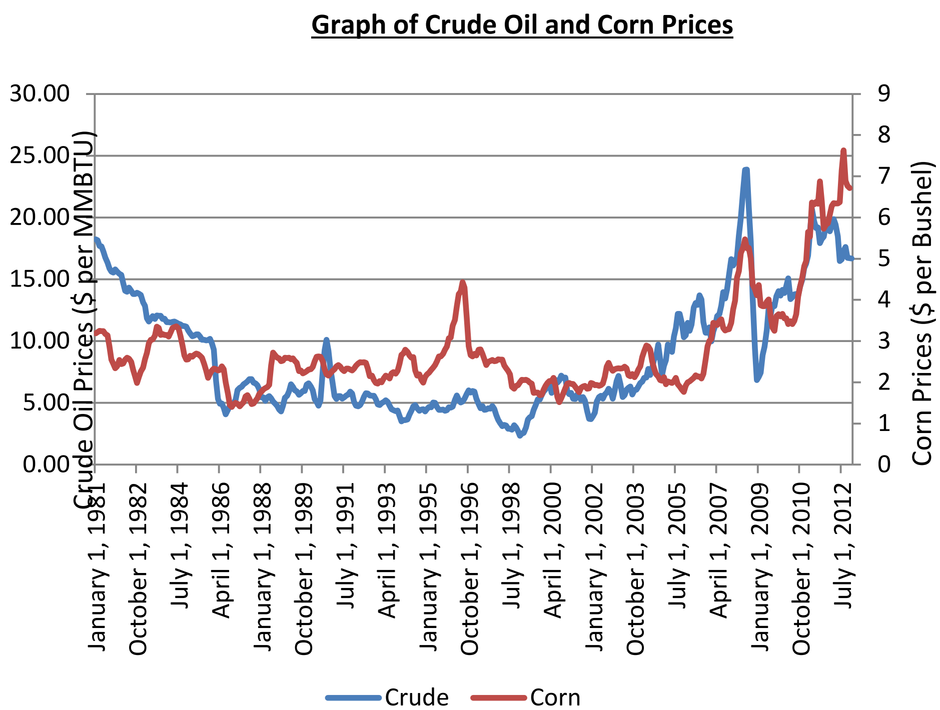


Figure 17: Graph Showing Monthly Crude Oil and Corn Prices from Jan 1980 to Dec 2012.



3.3.3: Correlations

The correlation matrix of the six variables is shown in Table 27. It reports a very high correlation amongst three of the six variables. It registers a correlation of 98% between crude oil and diesel prices. A similar average (98%) was also obtained for the correlation between crude oil and gasoline. Second higher correlations were observed for corn and gasoline/diesel followed by natural gas and diesel/crude. The lowest correlation was observed for corn and electricity.

Table 19: Table of Correlations of prices of gasoline, electricity, diesel, crude oil and corn, U.S. 1980-2010

Correlations (Spearman)						
	Lngas	Lelect	Lgasol	ldiesel	Lcrude	lcorn
Lngas	1					
Lelect	0.087	1				
Lgasol	0.548	0.135	1			
Ldiesel	0.548	0.135	1	1		
Lcrude	0.479	0.14	0.98	0.98	1	
Lcorn	0.199	-0.055	0.637	0.637	0.621	1

3.3.4: Univariate Time series Analysis

To obtain an initial impression of the dataset, a preliminary, univariate, time series analysis was carried out using a standard ARIMA (p,d,q) framework. ARIMA models are the most general class of models for forecasting a time series which can be stationarized by transformations such as differencing and logging.

The acronym ARIMA stands for "Auto-Regressive Integrated Moving Average." Lags of the differenced series appearing in the forecasting equation are called "auto-regressive" terms, lags of the forecast errors are called "moving average" terms, and a time series which needs to be differenced to be made stationary is said to be an "integrated" version of a stationary series. A nonseasonal ARIMA model is classified as an "ARIMA (p,d,q)" model, where:

- **p** is the number of autoregressive terms,
- **d** is the number of nonseasonal differences, and
- **q** is the number of lagged forecast errors in the prediction equation.

To identify the appropriate ARIMA model for a time series, you begin by identifying the order(s) of differencing needing to stationarize the series and remove the gross features of seasonality, perhaps in conjunction with a variance-stabilizing transformation such as logging or deflating. If you stop at this point and predict that the differenced series is constant, you have merely fitted a random walk or random trend model. However, the best random walk or random trend model may still have autocorrelated errors, suggesting that additional factors of some kind are needed in the prediction equation.

Given the existence of strong correlation amongst variables as reported in table 21 above, a multivariate approach seemed most preferable. Therefore two main complementing multivariate time series methodologies were applied: a vector autoregressive (VAR) model and a vector error correction model (VEC). From the augmented Dickey-Fuller (ADF) and Johansson cointegration (JC) test results obtained, a vector error correction (VEC) model was more appropriate than a vector auto regression (VAR) model to characterize the multivariate relationships among the six series (Engle and Granger, 1987; Enders, 1995). This was mainly due to the presence of cointegration amongst the variables.

3.3.5: Vector Autoregression

Two main complementing time series analysis methodologies were applied in this study. We initially estimated a Structural Vector Autoregressive (SVAR) model. However when cointegaration tests were carried out on the system, there was strong evidence of the variables cointegrating. In correcting for this anomaly, a vector error correction model (VECM) was preferred for the analysis.

According to Enders (1995), the general VAR form of the model can be written as:

$$\underbrace{\begin{bmatrix} 1 & -\alpha_{12} & -\alpha_{13} & -\alpha_{14} & -\alpha_{15} & -\alpha_{16} \\ -\alpha_{21} & 1 & -\alpha_{23} & -\alpha_{24} & -\alpha_{25} & -\alpha_{26} \\ -\alpha_{31} & -\alpha_{32} & 1 & -\alpha_{34} & -\alpha_{35} & -\alpha_{36} \\ -\alpha_{41} & -\alpha_{42} & -\alpha_{43} & 1 & -\alpha_{45} & -\alpha_{46} \\ -\alpha_{51} & -\alpha_{52} & -\alpha_{53} & -\alpha_{54} & 1 & -\alpha_{56} \\ -\alpha_{61} & -\alpha_{62} & -\alpha_{63} & -\alpha_{64} & -\alpha_{65} & 1 \end{bmatrix}}_{\textit{Contemporaneous Effects}} \begin{bmatrix} Cr_t \\ Dl_t \\ Gs_t \\ El_t \\ Ng_t \\ Cn_t \end{bmatrix} = \begin{bmatrix} 1 & \gamma_{12} & \gamma_{13} & \gamma_{14} & \gamma_{15} & \gamma_{16} \\ \gamma_{21} & 1 & \gamma_{23} & \gamma_{24} & \gamma_{25} & \gamma_{26} \\ \gamma_{31} & \gamma_{32} & 1 & \gamma_{34} & \gamma_{35} & \gamma_{36} \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & 1 & \gamma_{45} & \gamma_{46} \\ \gamma_{51} & \gamma_{52} & \gamma_{53} & \gamma_{54} & 1 & \gamma_{56} \\ \gamma_{61} & \gamma_{62} & \gamma_{63} & \gamma_{64} & \gamma_{65} & 1 \end{bmatrix} \begin{bmatrix} Cr_{t-1} \\ Dl_{t-1} \\ Gs_{t-1} \\ El_{t-1} \\ Ng_{t-1} \\ Cn_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{bmatrix}$$

This can be written as: $BY_t = \Gamma_1 Y_{t-1} + \varepsilon_t$,

and in more standard form: $Y_t = A_1 Y_{t-1} + e_t$ 3

where:

$A_1 = B^{-1}\Gamma_1$ and

$e_t = B^{-1}\varepsilon_t$

3.3.6: The Vector Error Correction Model

A VECM is a restricted form of a VAR model. The VECM restricts long-run behavior of the dependent variables so that they converge to their long run equilibrium and allow short run dynamics. It is particularly useful for forecasting purposes, more so when some degree of cointegration is suspected in the system. The General VEC model can be represented as shown below.

$$\triangle y_t = \boldsymbol{\pi} y_{t-1} + e_t \quad , \qquad 4$$

where:

$\triangle y_t = y_t - y_{t-1}$ and

π=pi-weights which account for vector error correction terms

The extended form can be written as:

$$\begin{bmatrix} \Delta Cr_t \\ \Delta Dl_t \\ \Delta Gs_t \\ \Delta El_t \\ \Delta Ng_t \\ \Delta Cn_t \end{bmatrix} = \begin{bmatrix} \pi_{11} & \pi_{12} & \pi_{13} & \pi_{14} & \pi_{15} & \pi_{16} \\ \pi_{21} & \pi_{22} & \pi_{23} & \pi_{24} & \pi_{25} & \pi_{26} \\ \pi_{31} & \pi_{32} & \pi_{33} & \pi_{34} & \pi_{35} & \pi_{36} \\ \pi_{41} & \pi_{42} & \pi_{43} & \pi_{44} & \pi_{45} & \pi_{46} \\ \pi_{51} & \pi_{52} & \pi_{53} & \pi_{54} & \pi_{55} & \pi_{56} \\ \pi_{61} & \pi_{62} & \pi_{63} & \pi_{64} & \pi_{65} & \pi_{66} \end{bmatrix} \begin{bmatrix} Cr_{t-1} \\ Dl_{t-1} \\ Gs_{t-1} \\ El_{t-1} \\ Ng_{t-1} \\ Cn_{t-1} \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \\ e_5 \\ e_6 \end{bmatrix}$$

Note that the above system assumes an optimum lag length of 1. For the more general form, see equation 2 above.

In equation 4 above, the π-weights represent the error correction term. The $\boldsymbol{\pi_{.1}}$ parameters represent the speed of adjustment parameters while the rest of the **π** contains the speed of adjustment parameters and the cointegrating equations. More explicitly, the cointegrating term would be ($Cr_{t-1} - \pi.2Dlt_{-1} - \pi_{.3}Gs_{t-1} - \pi_{.4}El_{t-1} - \pi_{.5}Ng_{t-1} - \pi_{.6}Cn_{t-1}$). This is the error correction term since the deviation from long run equilibrium is corrected gradually through short-run adjustments. In this framework Cr_t, Dl_t, Gs_t, El_t, Ng_t, and Cn_t are treated as being endogenous.

From the results, there were four cointegrating relationships (r=2). Hence the resulting π matrix can be divided into a 6x2 matrix of α s and a 2x6 vector of β s.

$$\alpha_{ij} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \\ \alpha_{31} & \alpha_{32} \\ \alpha_{41} & \alpha_{42} \\ \alpha_{51} & \alpha_{52} \\ \alpha_{61} & \alpha_{62} \end{bmatrix}_{6x2} \qquad \beta_{ij} = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} & \beta_{15} & \beta_{16} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} & \beta_{25} & \beta_{26} \end{bmatrix}_{2x6}$$

From equation 4 above, π can we written as $\alpha\beta'$

$$\triangle y_t = \boldsymbol{\pi} y_{t-1} + \sum_{i=0}^{p} \acute{\Gamma}_i \Delta\, y_{t-i} + e_t \quad \text{---------------------------------5}$$

$$6x1 \quad 6x6\ 6x1 \qquad 6x6\ 6x1 \quad 6x1$$

3.3.7: Impulse Response

Impulse response functions help to identify how variables in the system respond to a unit change/increase/shock in one of the variables. For our case, it would show how a unit increase in crude oil prices would affect the remaining five variables We use it to confirm nonstationarity of the system before running the model of choice and re-run the impulse functions. This should give us a notion of how stationary the forecasted part of the system is.

From our recovered VAR system, if the process yt is I(0), the effects of shocks in the variables of a given system are most easily seen in this moving average representation:

$Y_t = \phi_0 U_t + \phi_1 U_{t-1} + \phi_2 U_{t-2} + \ldots$

where:

$\Phi_0 = Ik$ and

$$\Phi s = \sum_{j=1}^{s} \left(\Phi_{s-j} Aj\right), \; s = 1,2, \ldots$$

The coefficients of this representation may be interpreted as reflecting the responses to impulses hitting the system.

3.3.8: Variance Decomposition:

There is some relationship between impulse response and variance decomposition. While impulse response functions trace the effects of a shock to one endogenous variable onto the other variables in the VAR, variance decomposition separates the variation in an endogenous variable into the component shocks to the VAR. Variance decomposition refers to the breakdown of the forecast error variance for a specific time horizon. Variance decomposition can indicate which variables have short-term and long-term impacts on another variable of interest. Basically, variance decomposition can tell a researcher the percentage of the fluctuation in a time series attributable to other variables at select time horizons.

Let's assume the h-step forecast error from a VAR to be

$$Y_{T+h} - Y_{T+h}| T = U_{T+h} + \varphi_1 U_{T+h-1} + \ldots + \varphi_{h-1} U_{t+1} .$$

The corresponding forecast variance is:

$$\sigma^2{}_k(\mathrm{h}) = \sum_{j=1}^{K} \left(\psi^2{}_{kj,0} \quad + \cdots + \psi^2{}_{kj,0}\right)$$

The term $\left(\psi^2{}_{kj,0} \quad + \cdots + \psi^2{}_{kj,0}\right)$ is interpreted as the contribution of variable j to the h-step forecast error variance of variable k. Dividing the preceding terms by the forecast variance above gives the percentage contribution of variable j to the h-step forecast error variance of variable k.

3.3.6: Cluster Analysis

There are different types of cluster models used to carry out cluster analysis. The choice of the model mainly depends on the type of dataset that the researcher is analyzing. Some common models include connectivity models, centroid models, distribution models, density models and graph based models, to name a few. Given our objectives, the model of choice was the graph based model that uses average hierarchical linkage clustering techniques to obtain the distances between clusters and form the clusters. The relationship is given as:

$$D(x,y) = \frac{1}{N_x \text{ X } N_y} \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} d(x_i y_j);$$

$$x_i \in X, y_j \in Y,$$

where:

- D(x,y) is the distance between objects x=X and y=Y,
- X and Y are two sets of objects (clusters) and
- N_x and N_y are the numbers of objets in clusters X and Y respectively.

3.4: Data Analysis

In this section, we present and discuss all the results from the analysis. We follow the order used in the previous section. Please note that this analysis was carried out in SAS and the codes are presented in appendix E1.

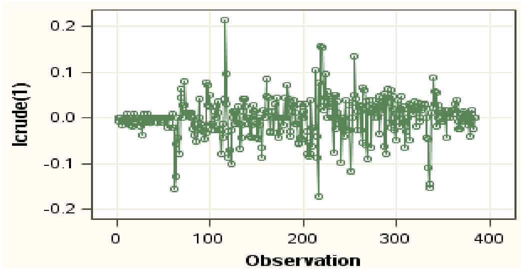
3.4.1: Univariate Analysis

As discussed above, to help understand the characteristics of the dataset, we initially performed a univariate ARIMA analysis. The Enders (1995) and Hendry (1986) ‘‘General to Specific’’ procedure was the basis for the identification process. Different models were tested and, based on the most suitable AIC and Schwartz criteria, the time series processes were identified. We used the Proc ARIMA procedure in SAS statistical software and followed the eye-ball method of viewing the ACF/PACF graphs to select by how much to difference the series to attain a stationary series. From the analysis carried out, the following results were obtained: The lcrude series was best characterized as ARIMA (3,1,1), the ldiesel series was an ARIMA (2,1,1), the lngas was ARIMA (2,1,0), the lelect was seasonal ARIMA (0,12,1) and the lnatural was also seasonal ARIMA (0,12,1). As evident from viewing the graphs of natural gas and electricity, they both proved to be seasonal. We then carried out a univariate Augmented Dickey Fuller test to test for the presence of unit roots. The test results showed that unit roots were very unlikely for all the series given that all of the *p*-values were small enough. Hence one cannot reject the null hypothesis that the series had unit roots and can be considered non-stationary.

Below we present plots of the different series after being stationarized by differencing.

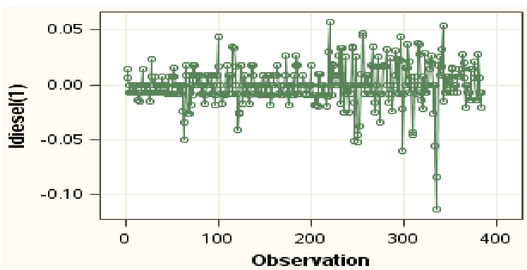
Figure 18: Stationary Time series

ARIMA(3,1,1)



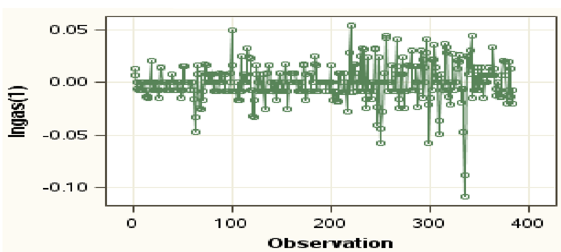
Autoregressive Factors	
Factor 1:	1 - 1.36892 B**(1) + 0.49691 B**(2) - 0.03979 B**(3)
Moving Average Factors	
Factor 1:	1 - 0.9277 B**(1)

ARIMA (2,1,1)



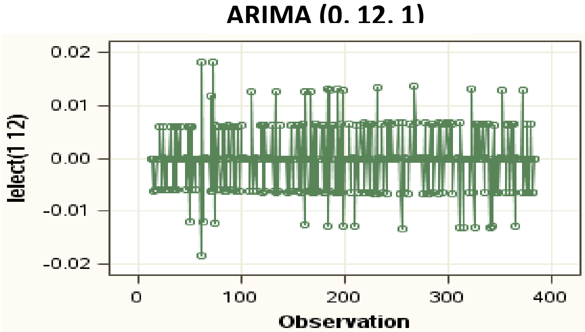
Autoregressive Factors	
Factor 1:	1 - 0.43446 B**(1) + 0.22978 B**(2)
Moving Average Factors	
Factor 1:	1 + 0.07987 B**(1)

ARIMA (2,1,0)



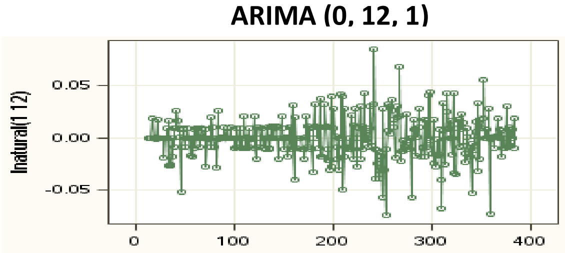
Autoregressive Factors	
Factor 1:	1 - 0.49171 B**(1) + 0.26849 B**(2)

ARIMA (0, 12, 1)



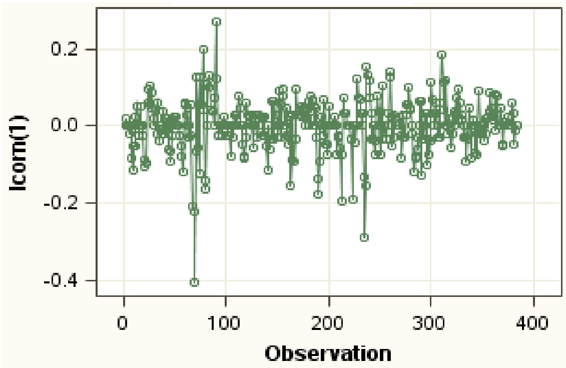
Moving Average Factors	
Factor 1:	1 - 0.32257 B**(1)
Factor 2:	1 - 0.79513 B**(12)

ARIMA (0, 12, 1)



Moving Average Factors	
Factor 1:	1 + 0.15728 B**(1)
Factor 2:	1 - 0.68543 B**(12)

ARIMA (2,1,1)



Autoregressive Factors	
Factor 1:	1 - 1.06024 B**(1) + 0.37848 B**(2)
Moving Average Factors	
Factor 1:	1 - 0.58333 B**(1)

Despite having stationary series from this univariate analysis, we had to use multivariate techniques to better address our research questions. The next section presents results from the multivariate analysis.

What we have done thus far is to initially test for stationarity of the univariate series. The results show that all the variables were non-stationary. We then performed ARIMA analysis on each variable to have them stationarized as shown in the figure 19 above. The next step is to treat these variables as a system and apply multivariate time series techniques to depict these relationships and trends.

3.4.2: Multivariate Time Series:

The main research question would not be answered adequately with univariate time series techniques. All the variables considered do have some relationship as theory suggests. Analyzing them in a system would either prove the presence of these relationships, describe their nature or would prove their independence. We therefore resorted to using multivariate time series techniques for our analysis. Analyzing and modeling the series jointly enables you to understand the dynamic relationships over time among the series and to improve the accuracy of forecasts for individual series by using the additional information available from the related series and their forecasts.

3.4.2.1: Vector Autoregressive Modeling:

VAR models are frequently used or better suited for systems that do not have some or all of the variables converging to some long term relationship (cointegration). Therefore a necessary first step to guide whether to use VAR models or Vector Error Correction is to test for the presence of cointegration amongst the variables. The VAR model basically represents the variables in their levels while the error correction model allows for differencing the system of variables in a bid to correct for cointegration.

3.4.2.2: Test for Cointegration (Dickey Fuller and Johansen Cointegration Tests)

Here we present results for both the Dickey-Fuller and the Johansen tests. The Dickey-Fuller test is a test for stationarity/non-stationarity while the Johansen test is the test for the presence of cointegration in the system of equations.

Table 20: Unit Root Test Results **(Dickey-Fuller Unit Root Tests)**

Variable	Type	Rho	Pr<Rho	Tau	Pr<Tau
Lcrude	**Zero Mean**	-9.41	0.0328	-2.17	0.0289
	Single Mean	-12.95	0.0643	-2.55	0.1041
	Trend	-14.4	0.2016	-2.81	0.1947
Ldiesel	**Zero Mean**	-3.22	0.2173	-1.31	0.1766
	Single Mean	-16.16	0.0287	-2.87	0.0499
	Trend	-18.53	0.0899	-3.23	0.0799
Lngas	**Zero Mean**	-2.11	0.3183	-1.07	0.2559
	Single Mean	-15.81	0.0314	-2.85	0.0524
	Trend	-18.18	0.0996	-3.22	0.083
Lelect	**Zero Mean**	-0.29	0.617	-0.60	0.4574
	Single Mean	-15.8	0.0314	-2.78	0.0625
	Trend	-50.23	0.0007	-5.00	0.0003
Lnatural	**Zero Mean**	-68.95	<0.0001	-5.84	<0.0001
	Single Mean	-137.82	0.0001	-8.20	<0.0001
	Trend	-149.22	0.0001	-8.44	<0.0001
Lcorn	**Zero Mean**	-2.41	0.2859	-1.15	0.2296
	Single Mean	-17.42	0.0209	-2.76	0.0658
	Trend	-22.43	0.0397	-3.33	0.0639

In the Dickey-Fuller test output above (test for non-stationarity of each series), the second column specifies three types of models, which are zero mean, single mean, or trend. The third column (Rho) and the fifth column (Tau) are the test statistics for unit root testing. Other columns are their p-values. Except for the zero mean model for electricity prices, the Rho estimates are smaller (more negative) than the Tau estimates. This implies that the series have unit roots meaning that they are all non-stationary.

Table 21: Cointegration Rank Testing

Cointegration Rank Test Using Trace						
H: Rank =r	H1: Rank>1	Eigenvalue	Trace	5% Critical Value	Drift in ECM	Drift in Process
0	0	0.1328	121.8456	82.61	Noint	Constant
1	1	0.0927	68.5586	59.24		
2	2	0.0572	32.1631	39.71		
3	3	0.0172	10.1172	24.08		
4	4	0.009	3.6124	12.21		
5	5	0.0006	0.2186	4.14		

When the system was tested for the presence of cointegration, it was clear that there are two cointegrated processes. This means the time series are cointegrated with rank = 2. In the cointegration rank test, the last two columns explain the drift in the model or process. Since the NOINT option is specified, the model is

$\triangle y_t = \boldsymbol{\pi} y_{t-1} + \acute{\Gamma}\Delta\ y_{t-1}\ \ e_t$

From table 23, the column drift in ECM means there is no separate drift in the error correction model, and the column drift in process means the process has a constant drift before differencing.

3.4.2.3 Vector Error Correction Model

A Vector Error Correction Model (VECM) can lead to a better understanding of the nature of any nonstationarity among the different component series and can also improve longer term forecasting over an unconstrained model.

Observing the schematic representations of the partial autoregression and partial cross correlations, it was revealed that the system was stationary after being differenced by 10. Therefore the p in VECM (p) was equal to ten, i.e. VECM (10).

Table 22: Partial Cross Correlation to Identify Stationary Lag Length

Schematic Representation of Partial Cross Correlations															
Variable/Lag	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
lcrude	+.....	---..+	....+.	.-....	......	.+..+.	....+.	..-...	......	......	-...-.	......	....-.	......	......
ldiesel	.++...	.--...	......	...+-.	......	..+.+.	....+.	......	......	......	......	......	......	......	......
lngas	.++...	+--...	..+...	......	......	......	......	......	......	......	.-....	......	......	......	......
lelect	...+..	...--.	....-.	.-.+-+	...++.	....++	...++.	...++.	...+..	......	....-.	......	...-..	...-..	......
lnatural	....+.	-..--.	......	....+.	..+++.	+.+.+.	...+..	....+.	...-+.	...-+.	......	......	....-.	......	......
lcorn	.....+	...-.-	......	..-...	......	......	......	......	......	......	......	......	......	......	......
+ is > 2*std error, - is < -2*std error, . is between															

Our best model to fit became the VECM (10) with order r=2.

$$\triangle y_t = \boldsymbol{\pi} y_{t-1} + \sum_{i=0}^{p=10} \acute{\Gamma}_i \Delta y_{t-i} + e_t \qquad \text{--------------------------------5}$$

6x1 6x6 6x1 6x6 6x1 6x1

3.4.3: Long run relationships

We chose to the ldiesel variable to normalize the system. As noted in the methods section, this normalization does not affect the intrinsic relationship between the different variables. The second beta estimates are 1s because they represent those of ldiesel which was used in the normalization. As a general rule, having beta = 1 means that, over the long run, those two variables follow each other on a one to one basis. Recall that the betas represent the cointegration parameters and ($Cr_{t-1} – \pi.2Dlt_{-1} - \pi_{.3}Gs_{t-1} - \pi_{.4}El_{t-1} - \pi_{.5}Ng_{t-}$

$_1$ - $\pi_{.6}Cn_{t-1}$) is the error correction term. Also recall that in the π matrix, the ".j" subscript represents the betas. The alpha coefficients capture the speed of adjustments towards the long run equilibrium path. It is also very important to note that the signs of the alpha estimates reveal departures from the equilibrium price gaps.

Table 23: Alpha and Beta Estimates

Long-Run Parameter Beta Estimates When RANK=2			Adjustment Coefficient Alpha Estimates When RANK=2		
Variable	**1**	**2**	**Variable**	**1**	**2**
Lcrude	-0.05146	-0.06192	**lcrude**	0.4436	0.56104
Ldiesel	1	1	**ldiesel**	-0.28856	-0.14811
Lngas	-0.98549	-0.92294	**lngas**	-0.2032	-0.06919
Lelect	0.09352	0.03388	**lelect**	-0.20099	0.18934
Lnatural	0.02881	0.09234	**lnatural**	-0.54892	-0.3998
Lcorn	0.00978	0.00744	**lcorn**	-1.25864	-1.27903

From the results obtained above, the following two long-run relationships were obtained from **β * yt:**

1) ldiesel = 0.05146 lcrude + 0.98549 lngas - 0.09352lelect – 0.02881lnatural – 0.00978lcorn
2) ldiesel = 0.06192 lcrude + 0.92294 lngas - 0.03388lelect – 0.09234lnatural – 0.00744lcorn

Table 26 below shows the intrinsic long run relationships between all of the variables.

Table 24: Long Run Equilibrium Relationships

	Ldiesel	Lcrude	lngas	lelect	Lnatural	Lcorn
Ldiesel	1	0.05146	0.98549	-0.09352	-0.0288	-0.0098
Lcrude	19.4326	1	19.1506	-1.81733	-0.5599	-0.1901
Lngas	1.0147	19.1506	1	-0.0949	-0.0292	-0.0099
Lelect	-10.6929	-0.5503	-10.5377	1	0.3081	0.1046
Lnatural	-34.7102	-1.7862	-34.2065	3.2461	1	0.3395
Lcorn	-102.25	-5.2618	-100.766	9.5624	2.9458	1

From these relationships, the following observations can be made (please recall that these are long-run relationships):

- A unit increase in crude oil prices would increase diesel prices by 19.4 units.
- A unit increase in crude oil prices would increase gasoline prices by about the same units as diesel (19.1 units).
- A unit increase in crude oil prices would decrease electricity prices by 1.8 units.
- A unit increase in crude oil prices would decrease natural gas prices by 0.6 units
- A unit increase in crude oil prices would decrease corn prices by 0.2 units.

It must be noted that the adjustment process does not occur quickly and it may take considerable amounts of time to converge to these long run equilibria. Also, the interpretations above represent only one of the cointegrating relationships. However, similar conclusions can be made for the second cointegrating relationship.

Table 25: Parameter Estimates for π

Variable	lcrude	Ldiesel	lngas	lelect	lnatural	Lcorn
Lcrude	-0.05757	1.00464	-0.95496	0.06049	0.06459	0.00851
Ldiesel	0.02402	-0.43667	0.42107	-0.032	-0.02199	-0.00392
Lngas	0.01474	-0.2724	0.26412	-0.02135	-0.01224	-0.0025
Lelect	-0.00138	-0.01165	0.02332	-0.01238	0.01169	-0.00056
Lnatural	0.053	-0.94872	0.90995	-0.06488	-0.05273	-0.00834
Lcorn	0.14397	-2.53767	2.42084	-0.16104	-0.15437	-0.02183

Table 28 above shows parameter estimates in terms of lag one coefficients, y_{t-1}, and the ten lags first differenced coefficients, are shown in the appendix section. "Alpha * Beta′" indicates the coefficients of y_{t-1} and is obtained by multiplying the "Alpha" and "Beta" estimates. From the coefficients presented in appendix 1, the parameter AR1_*i*_*j* corresponds to the elements in the "Alpha * Beta′" matrix. The t values and p-values corresponding to the parameters AR1_*i*_*j* are missing since the parameters AR1_*i*_*j* have non-Gaussian distributions. The parameter AR2_*i*_*j* corresponds to the elements in the differenced lagged AR coefficient matrix. The "D_" prefixed to a variable name implies differencing.

3.4.4: Model estimate VECM (10) r = 2:

Below we present some of the coefficient estimates (rest in the appendix.)

Table 26: Parameter estimates of VECM (10) r=2

Model Parameter Estimates						
Equation	**Parameter**	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**	**Variable**
D_lcrude	**AR1_1_1**	-0.05757	0.03193			lcrude(t-1)
	AR1_1_2	1.00464	0.55644			ldiesel(t-1)
	AR1_1_3	-0.95496	0.52975			lngas(t-1)
	AR1_1_4	0.06049	0.03782			lelect(t-1)
	AR1_1_5	0.06459	0.03938			lnatural(t-1)
	AR1_1_6	0.00851	0.00478			lcorn(t-1)
	AR2_1_1	0.57693	0.06602	8.74	0.0001	D_lcrude(t-1)
	AR2_1_2	-0.43344	0.69215	-0.63	0.5316	D_ldiesel(t-1)
	AR2_1_3	-0.1649	0.70486	-0.23	0.8152	D_lngas(t-1)
	AR2_1_4	0.16635	0.46166	0.36	0.7189	D_lelect(t-1)
	AR2_1_5	0.03732	0.12379	0.3	0.7632	D_lnatural(t-1)
	AR2_1_6	-0.00082	0.03413	-0.02	0.9809	D_lcorn(t-1)
	AR3_1_1	0.15505	0.07333	2.11	0.0353	D_lcrude(t-2)
	AR3_1_2	-0.56752	0.78177	-0.73	0.4684	D_ldiesel(t-2)
	AR3_1_3	0.23623	0.78793	0.3	0.7645	D_lngas(t-2)
	AR3_1_4	-0.26535	0.46631	-0.57	0.5697	D_lelect(t-2)
	AR3_1_5	-0.14955	0.12452	-1.2	0.2306	D_lnatural(t-2)
	AR3_1_6	-0.00905	0.03705	-0.24	0.8071	D_lcorn(t-2)
	AR4_1_1	-0.03613	0.07423	-0.49	0.6267	D_lcrude(t-3)
	AR4_1_2	-1.74049	0.82758	-2.1	0.0363	D_ldiesel(t-3)
	AR4_1_3	2.03325	0.85355	2.38	0.0178	D_lngas(t-3)
	AR4_1_4	-0.3874	0.45943	-0.84	0.3997	D_lelect(t-3)
	AR4_1_5	0.04804	0.12431	0.39	0.6994	D_lnatural(t-3)
	AR4_1_6	-0.0093	0.03677	-0.25	0.8006	D_lcorn(t-3)

When estimated, the model is as shown below:

$$
\begin{bmatrix} \Delta Cr_t \\ \Delta Dl_t \\ \Delta Gs_t \\ \Delta El_t \\ \Delta Ng_t \\ \Delta Cn_t \end{bmatrix}
=
\begin{bmatrix}
0.058 & 1.005 & -0.96 & 0.061 & 0.065 & 0.009 \\
(0.032) & (0.56) & (0.53) & (0.04) & (0.04) & (0.005) \\
 & & & & & . \\
 & . & & & & . \\
 & & . & & & 0.111 \\
 & & & & & (0.051)
\end{bmatrix}
\begin{bmatrix} Cr_{t-1} \\ Dl_{t-1} \\ Gs_{t-1} \\ El_{t-1} \\ Ng_{t-1} \\ Cn_{t-1} \end{bmatrix}
+
\begin{bmatrix}
0.577 & -0.433 & -0.165 & 0.166 & 0.037 & -0.0008 \\
(0.066) & (0.692) & (0.705) & (0.462) & (0.124) & (0.034) \\
 & & & & & . \\
 & . & & & & . \\
 & & & . & & 0.459 \\
 & & & & & (0.051)
\end{bmatrix}
\begin{bmatrix} \Delta Cr_{t-1} \\ \Delta Dl_{t-1} \\ \Delta Gs_{t-1} \\ \Delta El_{t-1} \\ \Delta Ng_{t-1} \\ \Delta Cn_{t-1} \end{bmatrix}
+\ldots+
\begin{bmatrix}
. & . & . & . & . & . \\
 & . & & & & \\
 & & . & & & \\
 & & & . & & \\
. & . & . & . & . & .
\end{bmatrix}
\begin{bmatrix} \Delta Cr_{t-9} \\ \Delta Dl_{t-9} \\ \Delta Gs_{t-9} \\ \Delta El_{t-9} \\ \Delta Ng_{t-9} \\ \Delta Cn_{t-9} \end{bmatrix}
+
\begin{bmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \\ e_5 \\ e_6 \end{bmatrix}
$$

The structure of this equation is exactly the same as that represented in equation 5. For parameter values, see the appendix section.

Its VAR (10) counterpart becomes:

$$\mathbf{Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_{10} Y_{t-10} + e_t}$$

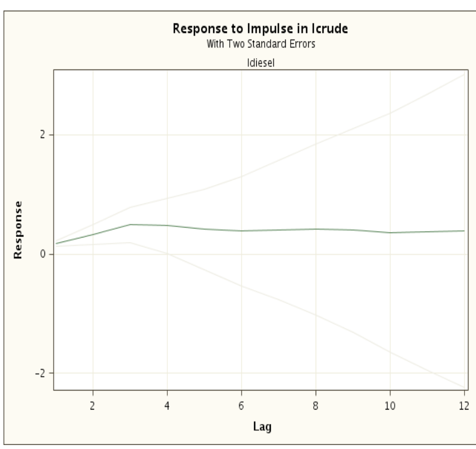
where the respective estimates can be found in Appendix E.

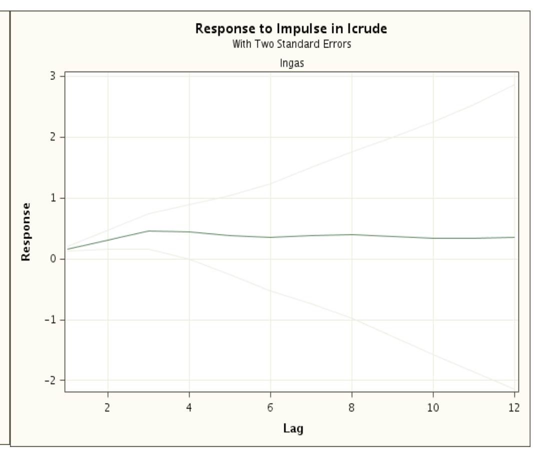
3.4.5: Impulse Response

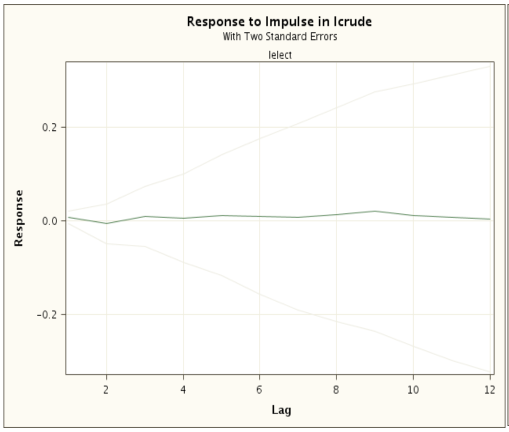
Here we present some of the results from the impulse response and forecast outputs. The rest of the results can be seen in the appendix. As shown in the table below and on the graphs below, a unit increase in crude oil prices would have increasing effects on all other variables except for corn in the first lag. The greatest effects are observed with diesel and gasoline. Electricity and natural gas responses are infinitesimally small and even negative in the second lag.

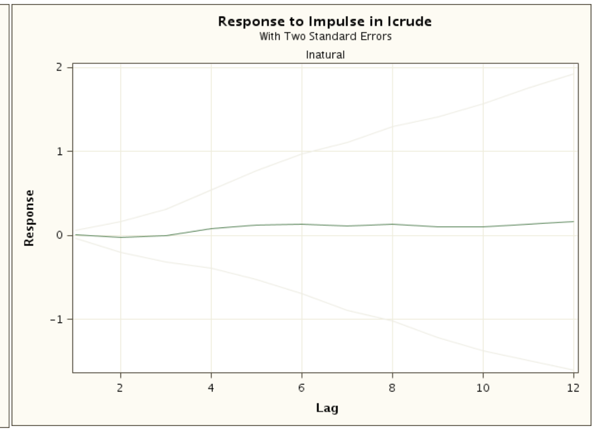
Table 27: Simple Impulse Response Outputs

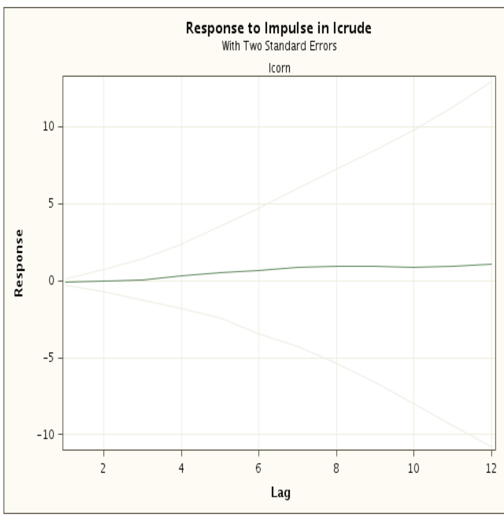
Simple Impulse Response							
Lag	**Variable Response\Impulse**	**Lcrude**	**Ldiesel**	**lngas**	**lelect**	**lnatural**	**lcorn**
1	**Lcrude**	1.51936	0.57119	-1.11986	0.22684	0.10191	0.0077
	Ldiesel	0.17895	0.75484	0.3667	-0.21821	-0.05764	0.01081
	Lngas	0.16548	0.67381	0.4259	-0.23645	-0.05654	0.01493
	Lelect	0.00823	0.02248	-0.03624	0.72127	0.04555	0.00231
	Lnatural	0.01128	-0.37983	0.47029	-0.72832	1.14234	-0.02507
	Lcorn	-0.0918	-1.02523	0.54328	-1.00286	-0.01987	1.43734
2	**Lcrude**	1.80579	0.36886	-1.52397	0.13478	0.12494	0.00194
	Ldiesel	0.32585	0.74392	-0.06286	-0.21668	-0.06059	0.01857
	Lngas	0.31281	0.56795	0.08458	-0.17498	-0.02221	0.01793
	Lelect	-0.00615	0.02473	-0.0331	0.6594	0.07864	-0.00176
	Lnatural	-0.02122	-0.58568	0.70466	-0.6794	1.04377	-0.03335
	Lcorn	-0.00173	-1.46593	0.64672	0.60091	-0.05557	1.52053

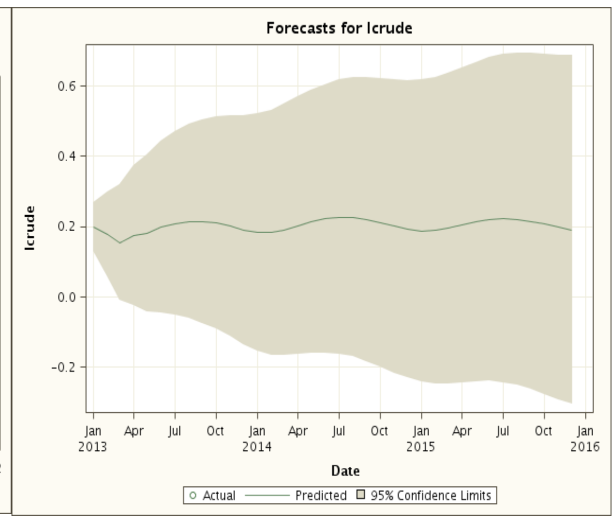












From the forecast results, crude oil prices are expected to drop briefly around the months of March and April 2013 and would increase slightly through the end of the year. A similar pattern would also be observed in 2014 and 2015. That is, there would be a brief fall in prices by the end and start of the New Year but would recover and get slightly higher after April.

3.4.6: Variance Decomposition:

Variance decomposition refers to the breakdown of the forecast error variance for a specific time horizon. Variance decomposition can indicate which variables have short-term and long-term impacts on another variable of interest. Basically, variance decomposition can tell a researcher the percentage of the fluctuation in a time series attributable to other variables at select time horizons.

Table 28: Innovation Contributions

Orthogonal Innovation Contribution						
Lcrude	ldiesel	lngas	lelect	lnatural	lcorn	VAR
16.39268	4.493282	10.35922	0.766927	0.064981	0.049438	32.12652
1.644242	2.626744	0.689593	1.648694	0.00491	0.018465	6.632648
1.479538	2.348898	1.694883	1.452412	0.005256	0.017105	6.998091
0.001085	0.00331	0.022065	2.700288	0.007242	0.000112	2.734101
0.117832	0.339345	3.153121	7.103953	3.222058	0.018325	13.95463
1.78878	1.623751	12.05932	35.4201	-6.0844	16.21019	61.01775

Table 30 above shows the different innovation contributions of all variables on their counterparts. The price of crude oil's own innovation contribution is 16.4 and the gasoline innovation contribution to the crude oil is 10.4.

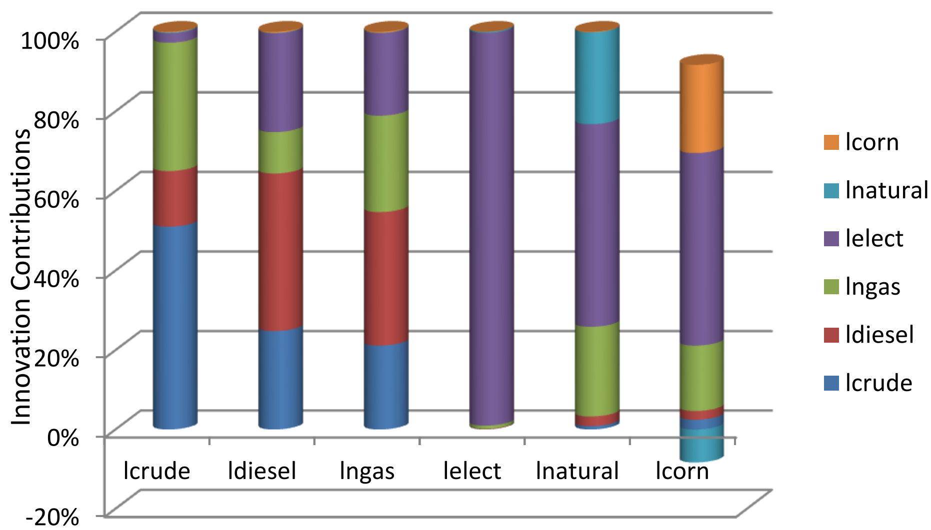
For an understanding of the contribution of innovations in the i th variable to MSE see table 31 below.

Table 29: Innovation Account

Innovation Account						
	lcrude	ldiesel	lngas	lelect	lnatural	lcorn
lcrude	51.03%	13.99%	32.25%	2.39%	0.20%	0.15%
ldiesel	24.79%	39.60%	10.40%	24.86%	0.07%	0.28%
lngas	21.14%	33.56%	24.22%	20.75%	0.08%	0.24%
lelect	0.04%	0.12%	0.81%	98.76%	0.26%	0.00%
lnatural	0.84%	2.43%	22.60%	50.91%	23.09%	0.13%
lcorn	2.93%	2.66%	19.76%	58.05%	-9.97%	26.57%

Innovations in the third variable (gasoline) explain 32.25% of the error variance of the first variable (crude oil), while the innovations in the fourth variable (electricity) explain 98.76% of its own error variance. For all the variables, the own contributions are the greatest. That is the error variances in all the variables are being explained by their own innovations the most. The results for corn seem interesting. Innovations in natural gas seem to serve as disincentive to corn prices. Innovations in electricity have a larger effect on the error variance on corn than all the other variables. As expected, innovations in diesel and gasoline account for the largest contributions to explaining the error variances of crude oil. The graph below presents these percentages.

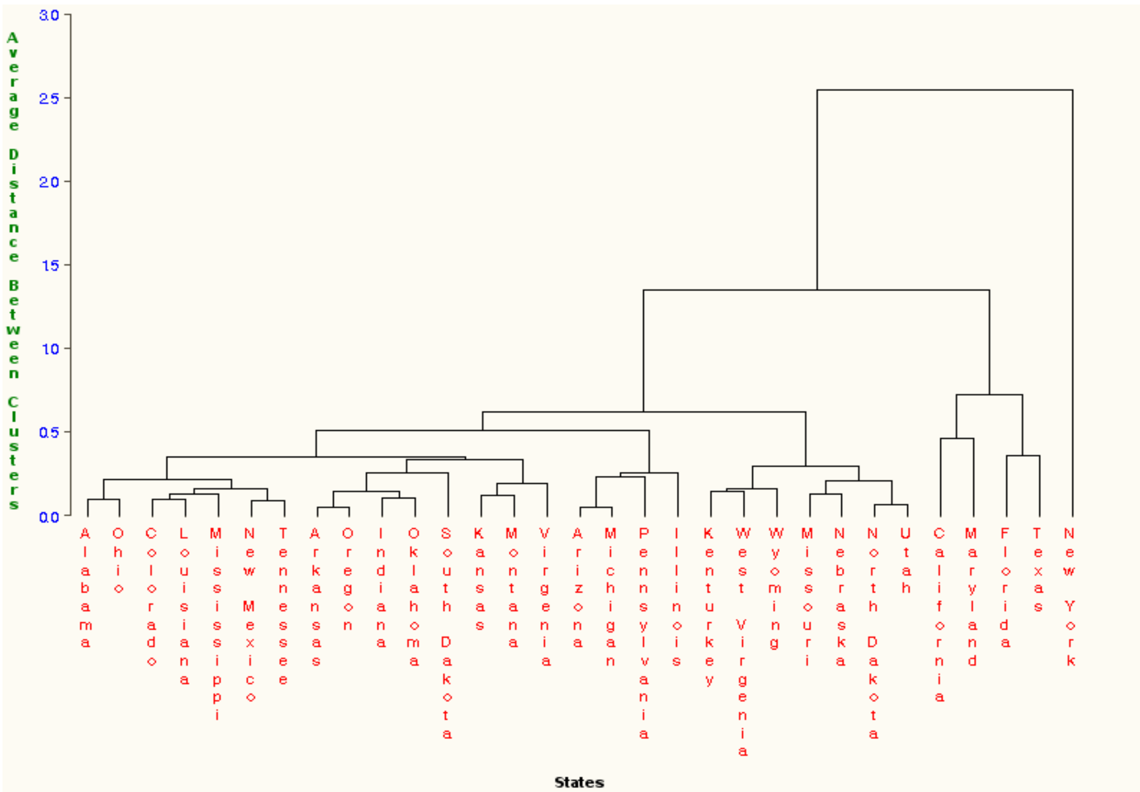
Figure 19: Graph of Innovations**:**



3.4.7: Cluster Analysis

Cluster analysis was performed on two sets of variables. The first was done on three energy price variables, namely, electricity, natural gas and diesel. The first two were both seasonal. We therefore wanted to see how these variables influenced clustering across states. If very clear clustering are observed, it means some vital variable or trend may be prevalent at the state level that might have been hidden as a result of averaging across states. The second sets of analyses were done on electricity prices for a four year period. This is mainly to see whether there were large price swings across states for these periods.

Figure 20: Dendrogram Showing Cluster of Electricity, Diesel and Natural Gas Prices



Although the Dendrogram above and table 39 reveal about 30 small clusters, we were able to identify four large clusters from which some inferences can be made. These clusters are shown in table 38 below. These clusters provide some very useful insights. Cluster one represent the states with the highest electricity, diesel and natural gas prices. One next step this research suggests is to understand the dynamics or drivers of these prices in these states. Cluster two represents the list of states with the lowest prices. These states, except Nebraska and Missouri, happen to be the leading producers of coal in the United States. This reveals that the inclusion of coal prices would help provide more information for any similar research in the future. The other two groups (3 and 4) certainly may have very good information that is worth investigating to producer improved results in the future.

Table 30 Clusters

No	Clusters
1	Texas, Florida, Maryland, California
2	Utah, North Dakota, Nebraska, Missouri, Wyoming, West Virginia and Kentucky
3	Illinois, Pennsylvania, Michigan, Arizona,
4	All other States

The next clustering, as shown in figure 25 below, uses only electricity prices for four different years (2006, 2007, 2008, 2009 and 2010). From the Dendrogram results shown below, it was observed that the second clustering identified above persisted even when electricity prices were considered singly over years.

Figure 21: Dendrogram Showing Clusters of States for Electricity Prices Over Five Year Period

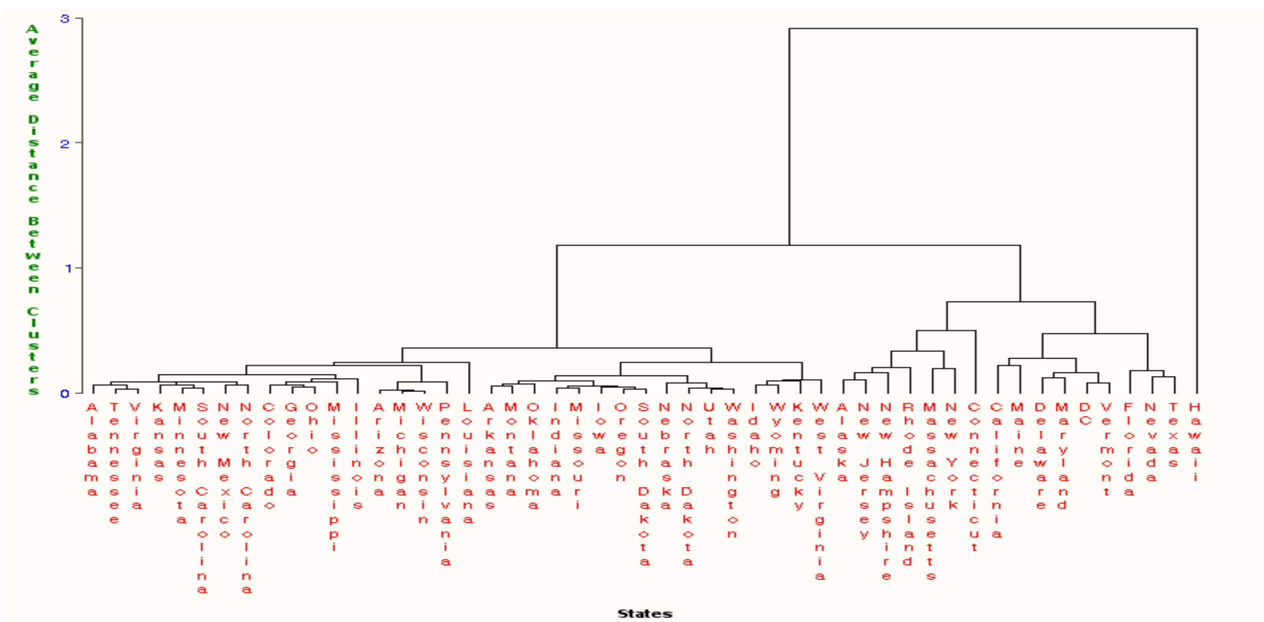


Table 31: Main Clusters

Cluster History					
Number of Clusters	**Clusters Joined**		**Freq**	**Norm RMS Distance**	**Tie**
30	Arizona	Michigan	2	0.0524	
29	Arkansas	Oregon	2	0.0542	
28	North Dakota	Utah	2	0.0652	
27	New Mexico	Tennessee	2	0.0933	
26	Colorado	Louisiana	2	0.0999	
25	Alabama	Ohio	2	0.1016	
24	Indiana	Oklahoma	2	0.1042	
23	Kansas	Montana	2	0.1224	
22	CL26	Mississippi	3	0.1284	
21	Missouri	Nebraska	2	0.1324	
20	Kentucky	West Virginia	2	0.1456	
19	CL29	CL24	4	0.1471	
18	CL22	CL27	5	0.163	
17	CL20	Wyoming	3	0.1652	
16	CL23	Virginia	3	0.1909	
15	CL21	CL28	4	0.2119	
14	CL25	CL18	7	0.219	
13	CL30	Pennsylvania	3	0.2347	
12	CL13	Illinois	4	0.2558	
11	CL19	South Dakota	5	0.2579	
10	CL17	CL15	7	0.2941	
9	CL11	CL16	8	0.3325	
8	CL14	CL9	15	0.3557	
7	Florida	Texas	2	0.3607	
6	California	Maryland	2	0.4645	
5	CL8	CL12	19	0.5079	
4	CL5	CL10	26	0.6217	
3	CL6	CL7	4	0.7243	
2	CL4	CL3	30	1.3483	
1	CL2	New York	31	2.5502	

Results from this chapter showed that a multivariate time series approach was preferable to analyzing such a research question than univariate forecast techniques. Two complementing multivariate time series techniques were used: Vector Autoregressive model – VAR(p) and Vector Error Correction Models (VECM). The starting point always is the development of the VAR system. However after testing for the presence of cointegration, it was clear that some form of cointegration existed. This means the variables converged to a long-run equilibrium or steady state. The order of the cointegrating relationships identified was two. This justified the use of a VEC model. After carrying out tests for stationarity in the VEC system, it was clear that the two seasonal variables had significant influence on the whole system. The system became stationary after the 10th difference. Therefore the model of choice was a VECM (10) with cointegration order 2. We learned that:

Long-run relationships

- A unit increase in crude oil prices would increase diesel prices by 19.4 units.
- A unit increase in crude oil prices would increase gasoline prices by about the same units and diesel (19.1 units).
- A unit increase in crude oil prices would decrease electricity prices by 1.8 units.
- A unit increase in crude oil prices would decrease natural gas prices by 0.6 units
- A unit increase in crude oil prices would decrease corn prices by 0.2 units.

Clearly, by virtue of the presence of cointegration, some long run equilibrium exists for the system of equations and the inherent price gaps are reported to be stable. The largest long-run effects on crude oil prices were reported for gasoline and diesel. The other three prices reported positive but with small effects.

Impulse response and forecasts

The forecast results showed that crude oil prices would have moderate increases in the next three years. Some seasonal pattern would be observed with prices falling slightly by the start of 2013, 2014 and 2015 and then starting to rise by April of these years. They would peak in the summer and then slowly decrease toward the end of the year and the start of the other year. A unit increase in crude oil prices would have increasing effects on all other variables except for corn in the first lag. The greatest effects are observed with diesel and gasoline. Electricity and natural gas responses are infinitesimally small and even negative in the second lag.

Variance Decomposition

Except for corn, the largest drivers of the error variances of all the variables were their own innovations. For corn, the largest driver happened to be electricity prices. For crude oil, innovations in diesel and gasoline happened to explain crude oil's error variance the most.

Cluster Analysis

The most important result that was rational and explainable in the context of this study was the cluster of states that produce coal the most. This is very revealing because this effect may be the reason why the variance decomposition results for corn had innovations in electricity as the largest driver. This would be a necessary next step to this research (the inclusion of coal prices to the current system of equations).

3.5: Conclusion

Crude oil price shocks have been shown to affect several sectors. Even in the growing biofuel industry, the use of crude oil products at several stages of the production of these biofuel products sometimes defeats the principle purpose of producing these biofuels both from an economic and crude oil substitutability standpoint as well as from an environmental standpoint. Also, these energy crude oil price shocks are increasingly affecting farmers' decisions with regards to technology adoption and other decisions related to the use of energy. These concerns can be better addressed with knowledge of the degree of responsiveness of farm energy prices to crude oil prices. This is the main objective of this paper. Multivariate time series techniques were employed and some cluster analysis carried out at the end to see how states cluster with respect to some variables that had produced peculiar results from the time series analysis. A vector error correction model was fitted; its associated levels were recovered by presenting its VAR counterpart and variance decomposition performed.

Clearly, diesel and gasoline had the greatest long-run relationship with crude oil prices. The other variables reported very small and sometimes infinitesimal effects. However these long run gaps were shown to be present and significant. For the impulse response function results, a unit increase in crude oil prices induces moderate increases in diesel and gasoline prices but no effects on the other variables. The forecast results showed that crude oil prices would have moderate increases in the next three years. Some seasonal pattern would be observed with prices falling slightly by the start of 2013, 2014 and 2015 and then starting to rise by April of these years. The variance decomposition results showed that apart from corn, own innovations accounted the most for variations reported in the error variance. For crude oil, the largest contributors of innovation to its error variance were diesel and gasoline. Electricity prices were completely driven by innovations in their own industry.

The general implication of these results in the broader context is that these price gaps are here for the long run and are stable. Crude oil price hikes will continue driving energy costs of industries that use diesel and gasoline as inputs. However, if substitution of these energy sources with gas were possible, those industries would protect themselves from the oil market price hikes. Electricity prices uniquely contribute very little to variations in crude oil prices. The inclusion of coal prices to this system is a necessary next step that the cluster analysis revealed. Corn prices happened to be influenced greatly by innovations in the electricity industry. This is a little less intuitive. However we think the inclusion of coal prices to the system would help fix this situation.

Potential next steps:

Two main necessary next steps were identified at the end of this study.

- **Introduction of Coal prices in the system and re-estimating model.**
    - As revealed by the across state cluster analysis, we think the inclusion of coal prices would help improve on the results obtained.
- **Seasonality.**
    - The way seasonality was addressed in this study may be inadequate. We therefore propose testing other techniques like the introduction of dummies as proposed in Lutkepohl (2007) or the use of spectral analysis.

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Appendix A: Bias Corrected Technical Efficiency Estimates for 1970, 1980, 1990, 2000 and 2010.

Table 32: Ten Years Interval Bias-Corrected Technical Efficiency Estimates (1970 to 2010)

State	County	No	TE_70	TE_80	TE_90	TE_00	TE_10
Colorado	Logan	1	1	1.049	1.385	1.019	1
Colorado	Phillips	2	1.01	1.468	1.284	1.339	1.364
Colorado	Sedgwick	3	1	1.704	1.233	1.167	1.393
Colorado	Weld	4	1	1	1	1	1
Iowa	Adair	5	1.017	1.012	1.053	1.008	1.014
Iowa	Adams	6	1.22	1.143	1.015	1	1.214
Iowa	Audubon	7	1	1.346	1.091	1	1.144
Iowa	Benton	8	1	1	1	1	1.017
Iowa	Boone	9	1	1	1.024	1.05	1.159
Iowa	Carroll	10	1	1	1	1	1
Iowa	Cass	11	1.009	1.116	1.035	1.006	1.057
Iowa	Cedar	12	1.212	1.124	1.006	1	1.149
Iowa	Clarke	13	1	1	1	1	1.035
Iowa	Clinton	14	1	1	1	1	1.031
Iowa	Crawford	15	1.178	1.157	1	1.078	1
Iowa	Dallas	16	1.029	1.12	1	1	1.326
Iowa	Des Moines	17	1.019	1.125	1	1.057	1.517
Iowa	Greene	18	1	1	1	1.033	1.135
Iowa	Guthrie	19	1.127	1.153	1.092	1	1.267
Iowa	Harrison	20	1.342	1.266	1.144	1.046	1.144
Iowa	Henry	21	1.155	1.156	1.099	1.08	1.642
Iowa	Iowa	22	1	1.222	1	1.057	1.299
Iowa	Jackson	23	1	1	1	1	1
Iowa	Jasper	24	1.011	1.028	1.053	1	1.167
Iowa	Jefferson	25	1.074	1.076	1.041	1	1.497
Iowa	Johnson	26	1.14	1.183	1.045	1.103	1.404
Iowa	Jones	27	1	1.12	1.027	1	1.036
Iowa	Keokuk	28	1.139	1.093	1.133	1.018	1.379
Iowa	Linn	29	1.062	1.018	1	1	1.155
Iowa	Louisa	30	1.106	1.129	1	1.076	1.631
Iowa	Lucas	31	1	1	1	1	1.276
Iowa	Madison	32	1	1	1.043	1.062	1.155
Iowa	Mahaska	33	1	1.058	1.035	1.008	1.439
Iowa	Marion	34	1.033	1.06	1	1	1.385
Iowa	Marshall	35	1	1.088	1.034	1	1.122
Iowa	Mills	36	1.121	1.121	1.03	1	1.117
Iowa	Monona	37	1.104	1	1	1	1

Iowa	Monroe	38	1	1	1	1	1.605
Iowa	Montgomery	39	1.175	1.199	1.034	1.005	1.185
Iowa	Muscatine	40	1.208	1.112	1.052	1.044	1.65
Iowa	Polk	41	1	1	1.04	1.02	1.751
Iowa	Pottawattamie	42	1	1	1	1	1
Iowa	Poweshiek	43	1	1	1	1	1.071
Iowa	Scott	44	1.245	1.064	1	1	1.6
Iowa	Shelby	45	1.036	1.282	1.059	1.075	1.083
Iowa	Story	46	1	1.007	1	1	1.199
Iowa	Tama	47	1	1	1.087	1.002	1.085
Iowa	Union	48	1.06	1.138	1.017	1.079	1.104
Iowa	Wapello	49	1.019	1	1	1.129	1.495
Iowa	Warren	50	1.02	1.022	1	1	1.183
Iowa	Washington	51	1.16	1.079	1.013	1.106	1.558
Nebraska	Adams	52	2.066	1.441	1.126	1.06	1
Nebraska	Banner	53	1	1	1.362	1	3.378
Nebraska	Boone	54	1.808	1.61	1.144	1.558	1.214
Nebraska	Buffalo	55	1	1.252	1.182	1.175	1.024
Nebraska	Burt	56	1.934	1.852	1.401	1.529	1.183
Nebraska	Butler	57	2.141	1.812	1.23	1.3	1
Nebraska	Cass	58	1	1	1	1	1
Nebraska	Chase	59	1.818	1.555	1.348	1.149	1.05
Nebraska	Cheyenne	60	1	1.105	1.381	1	2.488
Nebraska	Clay	61	1.98	1.37	1.06	1.414	1.168
Nebraska	Colfax	62	1.605	1.686	1.087	1.068	1.047
Nebraska	Cuming	63	1	1	1.034	1.211	1
Nebraska	Custer	64	1.019	1.225	1.06	1.014	1
Nebraska	Dawson	65	1	1	1	1	1
Nebraska	Deuel	66	1	1.242	1.353	1.08	2.232
Nebraska	Dodge	67	1.887	1.422	1.323	1.215	1.209
Nebraska	Douglas	68	1.546	1.618	1.183	1.397	2.049
Nebraska	Fillmore	69	2.398	1.558	1.381	1.259	1.096
Nebraska	Frontier	70	1.988	1.712	1.302	1.712	1.129
Nebraska	Gosper	71	1.764	1.623	1.252	1.513	1.11
Nebraska	Greeley	72	1.511	1.316	1.153	1.314	1.232
Nebraska	Hall	73	1.253	1.389	1	1	1
Nebraska	Hamilton	74	1.266	1.307	1	1.045	1
Nebraska	Hayes	75	1.239	1.669	1.508	1.46	1.264
Nebraska	Howard	77	1.001	1.287	1	1.399	1.22
Nebraska	Kearney	76	1.389	1.379	1.11	1.129	1.136
Nebraska	Keith	78	1.205	1.504	1.548	1.359	1.259
Nebraska	Kimball	79	1	1	1	1	1
Nebraska	Lancaster	80	1	1	1	1	1.115
Nebraska	Lincoln	81	1	1	1.131	1.003	1
Nebraska	Madison	82	1.439	1.575	1.149	1.621	1.157
Nebraska	Merrick	83	1.305	1.536	1.11	1.332	1.156
Nebraska	Nance	84	2.075	1.433	1.036	1.761	1.186
Nebraska	Perkins	85	1.247	1.757	1.325	1.218	1.149

Nebraska	Phelps	86	1.623	1.214	1	1.02	1
Nebraska	Platte	87	1.721	1.61	1.22	1.456	1.054
Nebraska	Polk	88	1.56	1.88	1.211	1.416	1.119
Nebraska	Saline	89	1.745	1.776	1.355	1.351	1.004
Nebraska	Sarpy	90	1.845	1.289	1.099	1.35	1.333
Nebraska	Saunders	91	1.862	1.511	1.119	1.135	1
Nebraska	Scotts Bluff	92	1	1	1	1	1
Nebraska	Seward	93	2.463	1.73	1.186	1.229	1
Nebraska	Sherman	94	1.217	1.305	1	1.224	1.124
Nebraska	Stanton	95	1.274	1.391	1	1.241	1.067
Nebraska	Valley	96	1.217	1.395	1.244	1.244	1.269
Nebraska	Washington	97	1	1.185	1.235	1.176	1.16
Nebraska	York	98	1.957	1.418	1	1.031	1
Wyoming	Goshen	99	1	1	1	1	1
Wyoming	Laramie	100	1	1	1	1.57	1.017
Wyoming	Platte	101	1	1	1	1	1

Appendix B: Average Malmquist Results Showing Total Factor Productivity Change and its Components (Efficiency Change and Technological Change).

B1: Average Malmquist Productivity Results without SOM

Table 33: Malmquist Results without SOM

State	County	Efficiency Change	Technological Change	Total Factor Productivity Change
Colorado	Logan	1	0.999	0.999
Colorado	Phillips	0.993	0.991	0.984
Colorado	Sedgwick	0.992	1.164	1.154
Colorado	Weld	1	0.998	0.998
Iowa	Adair	1	1.013	1.013
Iowa	Adams	1	1.015	1.015
Iowa	Audubon	0.997	1.004	1
Iowa	Benton	1	1.025	1.024
Iowa	Boone	0.996	1.007	1.004
Iowa	Carroll	1	1.006	1.006
Iowa	Cass	0.999	1.006	1.005
Iowa	Cedar	1.001	1.007	1.008
Iowa	Clarke	0.999	1.012	1.011
Iowa	Clinton	0.999	1.002	1.001
Iowa	Crawford	1.004	1.017	1.021
Iowa	Dallas	0.994	1.016	1.009
Iowa	Des Moines	0.99	1.008	0.998
Iowa	Greene	0.997	1.013	1.01
Iowa	Guthrie	0.997	1.003	1
Iowa	Harrison	1.004	1.01	1.014
Iowa	Henry	0.991	1.005	0.996
Iowa	Iowa	0.993	1.004	0.998
Iowa	Jackson	1	0.996	0.996
Iowa	Jasper	0.996	1.018	1.015
Iowa	Jefferson	0.992	1.011	1.002
Iowa	Johnson	0.995	1.006	1
Iowa	Jones	0.999	1.005	1.004
Iowa	Keokuk	0.995	1.011	1.006
Iowa	Linn	0.998	1.012	1.01
Iowa	Louisa	0.99	1.013	1.003
Iowa	Lucas	0.994	1.008	1.002
Iowa	Madison	0.996	1.009	1.005

Iowa	Mahaska	0.991	1.003	0.993
Iowa	Marion	0.993	1.013	1.006
Iowa	Marshall	0.997	1.005	1.002
Iowa	Mills	1	1.009	1.01
Iowa	Monona	1.002	1.007	1.01
Iowa	Monroe	0.988	1.013	1.001
Iowa	Montgomery	1	1.017	1.017
Iowa	Muscatine	0.992	1.008	1
Iowa	Polk	0.986	1.007	0.993
Iowa	Pottawattamie	1	1.015	1.015
Iowa	Poweshiek	0.998	1.001	1
Iowa	Scott	0.994	1.007	1.001
Iowa	Shelby	0.999	1.01	1.009
Iowa	Story	0.995	1.008	1.004
Iowa	Tama	0.998	1.022	1.02
Iowa	Union	0.999	1.009	1.008
Iowa	Wapello	0.99	1.011	1.001
Iowa	Warren	0.996	1.008	1.004
Iowa	Washington	0.993	1.008	1
Nebraska	Adams	1.018	0.998	1.016
Nebraska	Banner	0.97	0.987	0.958
Nebraska	Boone	1.01	0.998	1.008
Nebraska	Buffalo	0.999	1.001	1.001
Nebraska	Burt	1.012	1.004	1.016
Nebraska	Butler	1.019	0.984	1.003
Nebraska	Cass	1	1.203	1.203
Nebraska	Chase	1.014	0.997	1.011
Nebraska	Cheyenne	0.977	0.968	0.946
Nebraska	Clay	1.013	1.002	1.016
Nebraska	Colfax	1.011	0.992	1.002
Nebraska	Cuming	1	1.008	1.008
Nebraska	Custer	1	1.002	1.002
Nebraska	Dawson	1	1.001	1.001
Nebraska	Deuel	0.98	1.129	1.106
Nebraska	Dodge	1.011	0.992	1.003
Nebraska	Douglas	0.993	1.012	1.005
Nebraska	Fillmore	1.02	0.997	1.016
Nebraska	Frontier	1.014	0.99	1.005
Nebraska	Gosper	1.012	0.988	0.999
Nebraska	Greeley	1.005	0.998	1.003
Nebraska	Hall	1.006	1	1.006
Nebraska	Hamilton	1.006	1.001	1.007
Nebraska	Hayes	1	0.991	0.99
Nebraska	Howard	0.995	0.987	0.982
Nebraska	Kearney	1.005	1.005	1.01
Nebraska	Keith	0.999	0.99	0.989
Nebraska	Kimball	1	1.127	1.127
Nebraska	Lancaster	0.997	0.99	0.988

Nebraska	Lincoln	1	0.987	0.987
Nebraska	Madison	1.005	0.994	0.999
Nebraska	Merrick	1.003	0.992	0.995
Nebraska	Nance	1.014	0.988	1.002
Nebraska	Perkins	1.002	0.986	0.988
Nebraska	Phelps	1.012	1.004	1.016
Nebraska	Platte	1.012	0.986	0.998
Nebraska	Polk	1.008	0.995	1.003
Nebraska	Saline	1.014	0.981	0.995
Nebraska	Sarpy	1.008	1.008	1.016
Nebraska	Saunders	1.016	0.999	1.014
Nebraska	Scotts Bluff	1	1.198	1.198
Nebraska	Seward	1.023	0.993	1.016
Nebraska	Sherman	1.002	0.996	0.998
Nebraska	Stanton	1.004	0.997	1.002
Nebraska	Valley	0.999	1.008	1.007
Nebraska	Washington	0.996	1.006	1.002
Nebraska	York	1.017	1.002	1.019
Wyoming	Goshen	1	1.038	1.038
Wyoming	Laramie	1	0.996	0.996
Wyoming	Platte	1	1.022	1.022
Mean		1	1.01	1.011

B2: Average Malmquist Productivity Results with SOM 1 (Liska)

Table 34: Malmquist Results with SOM 1 (Liska)

SOM 1				
States	**Counties**	**Efficiency Change**	**Technological Change**	**Total Factor Productivity Change**
Iowa	Adair	1	1.013	1.013
Iowa	Adams	1	1.015	1.015
Nebraska	Adams	1.018	0.998	1.016
Iowa	Audubon	0.997	1.007	1.003
Nebraska	Banner	0.97	0.99	0.96
Iowa	Benton	1	1.024	1.024
Iowa	Boone	0.996	1.008	1.004
Nebraska	Boone	1.011	0.997	1.009
Nebraska	Buffalo	0.999	1.001	1.001
Nebraska	Burt	1.012	1.004	1.016

Nebraska	Butler	1.019	0.983	1.002
Iowa	Carroll	1	1.007	1.007
Iowa	Cass	0.999	1.007	1.006
Nebraska	Cass	1	1.204	1.204
Iowa	Cedar	1.001	1.012	1.013
Nebraska	Chase	1.014	0.997	1.011
Nebraska	Cheyenne	0.977	0.967	0.945
Iowa	Clarke	0.999	1.012	1.011
Nebraska	Clay	1.013	1.002	1.016
Iowa	Clinton	0.999	1.001	1
Nebraska	Colfax	1.011	0.992	1.002
Iowa	Crawford	1.001	1.019	1.02
Nebraska	Cuming	1	1.01	1.01
Nebraska	Custer	1	1.002	1.002
Iowa	Dallas	0.993	1.016	1.009
Nebraska	Dawson	1	1.001	1.001
Iowa	Des Moines	0.99	1.008	0.998
Nebraska	Deuel	0.98	1.129	1.106
Nebraska	Dodge	1.011	0.991	1.002
Nebraska	Douglas	0.993	1.012	1.005
Nebraska	Fillmore	1.02	0.997	1.016
Nebraska	Frontier	1.014	0.99	1.005
Wyoming	Goshen	1	1.042	1.042
Nebraska	Gosper	1.012	0.988	0.999
Nebraska	Greeley	1.005	0.998	1.003
Iowa	Greene	0.997	1.013	1.01
Iowa	Guthrie	0.997	1.004	1.001
Nebraska	Hall	1.006	0.999	1.005
Nebraska	Hamilton	1.006	1.003	1.009
Iowa	Harrison	1	1.018	1.018
Nebraska	Hayes	1	0.991	0.99
Iowa	Henry	0.991	1.005	0.997
Nebraska	Howard	0.995	0.987	0.982
Iowa	Iowa	0.993	1.006	0.999
Iowa	Jackson	1	0.996	0.996
Iowa	Jasper	0.996	1.017	1.013
Iowa	Jefferson	0.992	1.011	1.002
Iowa	Johnson	0.995	1.006	1.001
Iowa	Jones	0.999	1.005	1.005
Nebraska	Kearney	1.006	1.001	1.007
Nebraska	Keith	1	0.989	0.989
Iowa	Keokuk	0.995	1.012	1.007
Nebraska	Kimball	1	1.127	1.127
Nebraska	Lancaster	0.999	0.989	0.988
Wyoming	Laramie	1	1	0.999
Nebraska	Lincoln	1	0.987	0.987
Iowa	Linn	0.998	1.012	1.01
Colorado	Logan	1	0.998	0.998

Iowa	Louisa	0.99	1.013	1.003
Iowa	Lucas	0.994	1.008	1.002
Iowa	Madison	0.996	1.009	1.005
Nebraska	Madison	1.005	0.994	0.999
Iowa	Mahaska	0.991	1.004	0.995
Iowa	Marion	0.993	1.016	1.008
Iowa	Marshall	0.997	1.008	1.005
Nebraska	Merrick	1.003	0.992	0.995
Iowa	Mills	1	1.012	1.012
Iowa	Monona	1.002	1.006	1.009
Iowa	Monroe	0.988	1.013	1.001
Iowa	Montgomery	1	1.018	1.018
Iowa	Muscatine	0.992	1.009	1.001
Nebraska	Nance	1.014	0.988	1.002
Nebraska	Perkins	1.002	0.986	0.988
Nebraska	Phelps	1.012	1.003	1.016
Colorado	Phillips	0.993	0.99	0.983
Wyoming	Platte	1	1.023	1.023
Nebraska	Platte	1.014	0.984	0.998
Iowa	Polk	0.986	1.007	0.993
Nebraska	Polk	1.008	0.995	1.003
Iowa	Pottawattamie	1	1.017	1.017
Iowa	Poweshiek	0.998	1.003	1.001
Nebraska	Saline	1.014	0.98	0.994
Nebraska	Sarpy	1.008	1.009	1.017
Nebraska	Saunders	1.009	0.997	1.006
Iowa	Scott	0.994	1.007	1.001
Nebraska	Scotts Bluff	1	1.198	1.198
Colorado	Sedgwick	0.992	1.165	1.155
Nebraska	Seward	1.023	0.988	1.011
Iowa	Shelby	0.998	1.012	1.01
Nebraska	Sherman	1.002	0.996	0.998
Nebraska	Stanton	1.004	0.997	1.001
Iowa	Story	0.995	1.008	1.004
Iowa	Tama	0.998	1.021	1.018
Iowa	Union	0.999	1.009	1.008
Nebraska	Valley	0.999	1.008	1.007
Iowa	Wapello	0.99	1.011	1.002
Iowa	Warren	0.996	1.008	1.004
Iowa	Washington	0.993	1.01	1.002
Nebraska	Washington	0.997	1.004	1
Colorado	Weld	1	0.992	0.992
Nebraska	York	1.017	1.002	1.019
Mean		1	1.011	1.011

B3: Average Malmquist Productivity Results with SOM 2 (Martellato)

Table 35: Malmquist Results with SOM 2: (Martellato)

SOM 2				
States	Counties	Efficiency Change	Technological Change	Total Factor Productivity Change
Iowa	Adair	1	1.013	1.013
Iowa	Adams	1	1.015	1.016
Nebraska	Adams	1.018	0.998	1.016
Iowa	Audubon	0.997	1.009	1.006
Nebraska	Banner	0.97	0.991	0.961
Iowa	Benton	1	1.025	1.024
Iowa	Boone	0.996	1.008	1.004
Nebraska	Boone	1.011	0.999	1.011
Nebraska	Buffalo	0.999	1.001	1.001
Nebraska	Burt	1.012	1.004	1.016
Nebraska	Butler	1.019	0.983	1.002
Iowa	Carroll	1	1.009	1.009
Iowa	Cass	0.999	1.009	1.008
Nebraska	Cass	1	1.207	1.207
Iowa	Cedar	1.001	1.014	1.015
Nebraska	Chase	1.014	0.998	1.013
Nebraska	Cheyenne	0.977	0.969	0.948
Iowa	Clarke	0.999	1.012	1.012
Nebraska	Clay	1.013	1.002	1.016
Iowa	Clinton	0.999	1.003	1.002
Nebraska	Colfax	1.011	0.992	1.002
Iowa	Crawford	1.001	1.026	1.027
Nebraska	Cuming	1	1.016	1.016
Nebraska	Custer	1	1.002	1.003
Iowa	Dallas	0.993	1.017	1.01
Nebraska	Dawson	1	1.004	1.004
Iowa	Des Moines	0.99	1.008	0.998
Nebraska	Deuel	0.98	1.129	1.106
Nebraska	Dodge	1.011	0.991	1.002
Nebraska	Douglas	0.993	1.012	1.005
Nebraska	Fillmore	1.02	0.997	1.016
Nebraska	Frontier	1.014	0.99	1.005
Wyoming	Goshen	1	1.049	1.049
Nebraska	Gosper	1.012	0.988	0.999
Nebraska	Greeley	1.005	0.998	1.003
Iowa	Greene	0.997	1.013	1.01
Iowa	Guthrie	0.997	1.004	1.001
Nebraska	Hall	1.006	1.002	1.007
Nebraska	Hamilton	1.006	1.012	1.018
Iowa	Harrison	1	1.022	1.022

Nebraska	Hayes	1	0.991	0.99
Iowa	Henry	0.991	1.005	0.997
Nebraska	Howard	0.995	0.987	0.982
Iowa	Iowa	0.993	1.007	1.001
Iowa	Jackson	1	0.999	0.999
Iowa	Jasper	0.996	1.019	1.015
Iowa	Jefferson	0.992	1.011	1.003
Iowa	Johnson	0.995	1.007	1.002
Iowa	Jones	0.999	1.006	1.005
Nebraska	Kearney	1.006	1.004	1.01
Nebraska	Keith	1	0.99	0.99
Iowa	Keokuk	0.995	1.014	1.009
Nebraska	Kimball	1	1.128	1.128
Nebraska	Lancaster	0.999	0.996	0.994
Wyoming	Laramie	1	1.001	1.001
Nebraska	Lincoln	1	0.987	0.987
Iowa	Linn	0.998	1.012	1.01
Colorado	Logan	1	1	1
Iowa	Louisa	0.99	1.013	1.003
Iowa	Lucas	0.994	1.008	1.002
Iowa	Madison	0.996	1.009	1.005
Nebraska	Madison	1.005	0.994	0.999
Iowa	Mahaska	0.991	1.005	0.996
Iowa	Marion	0.993	1.018	1.01
Iowa	Marshall	0.997	1.01	1.007
Nebraska	Merrick	1.003	0.992	0.995
Iowa	Mills	1	1.013	1.013
Iowa	Monona	1.002	1.009	1.011
Iowa	Monroe	0.988	1.013	1.001
Iowa	Montgomery	1	1.019	1.019
Iowa	Muscatine	0.992	1.009	1.001
Nebraska	Nance	1.014	0.988	1.002
Nebraska	Perkins	1.002	0.986	0.988
Nebraska	Phelps	1.012	1.004	1.017
Colorado	Phillips	0.993	0.993	0.986
Wyoming	Platte	1	1.025	1.025
Nebraska	Platte	1.014	0.988	1.001
Iowa	Polk	0.986	1.007	0.993
Nebraska	Polk	1.008	0.995	1.003
Iowa	Pottawattamie	1	1.023	1.023
Iowa	Poweshiek	0.998	1.004	1.003
Nebraska	Saline	1.014	0.981	0.995
Nebraska	Sarpy	1.008	1.009	1.018
Nebraska	Saunders	1.01	1.003	1.013
Iowa	Scott	0.994	1.008	1.001
Nebraska	Scotts Bluff	1	1.199	1.199
Colorado	Sedgwick	0.992	1.166	1.156
Nebraska	Seward	1.023	0.99	1.013

Iowa	Shelby	0.998	1.017	1.015
Nebraska	Sherman	1.002	0.996	0.998
Nebraska	Stanton	1.004	0.997	1.002
Iowa	Story	0.995	1.009	1.004
Iowa	Tama	0.998	1.022	1.02
Iowa	Union	0.999	1.009	1.008
Nebraska	Valley	0.999	1.008	1.007
Iowa	Wapello	0.99	1.012	1.002
Iowa	Warren	0.996	1.008	1.004
Iowa	Washington	0.993	1.011	1.003
Nebraska	Washington	0.997	1.006	1.002
Colorado	Weld	1	1.001	1.001
Nebraska	York	1.017	1.003	1.02
Mean >>		1	1.012	1.012

Appendix C: SOM Efficiency and Harvest Potentials for 101 Counties across the 41st ||

C1: SOM Efficiency and Harvest Potential (One output dimension-(production))

Table 36: SOM Efficiency and Harvest Potential (One Output Dimension)

State	County	No	SOM Efficiency	Harvest potentials
Colorado	Logan	58	0.641	35.90%
Colorado	Phillips	75	0.256	74.40%
Colorado	Sedgwick	87	0.184	81.60%
Colorado	Weld	100	1	0.00%
Iowa	Adair	1	0.313	68.70%
Iowa	Adams	2	0.241	75.90%
Iowa	Audubon	4	0.425	57.50%
Iowa	Benton	6	0.513	48.70%
Iowa	Boone	7	0.309	69.10%
Iowa	Carroll	12	0.533	46.70%
Iowa	Cass	13	0.446	55.40%
Iowa	Cedar	15	0.517	48.30%
Iowa	Clarke	18	0.164	83.60%
Iowa	Clinton	20	0.601	39.90%
Iowa	Crawford	22	1	0.00%
Iowa	Dallas	25	0.273	72.70%
Iowa	Des Moines	27	0.15	85.00%
Iowa	Greene	36	0.323	67.70%
Iowa	Guthrie	37	0.29	71.00%
Iowa	Harrison	40	0.662	33.80%
Iowa	Henry	42	0.171	82.90%
Iowa	Iowa	44	0.441	55.90%
Iowa	Jackson	45	1	0.00%
Iowa	Jasper	46	0.551	44.90%
Iowa	Jefferson	47	0.16	84.00%

Iowa	Johnson	48	0.343	65.70%
Iowa	Jones	49	0.477	52.30%
Iowa	Keokuk	52	0.302	69.80%
Iowa	Linn	57	0.387	61.30%
Iowa	Louisa	59	0.195	80.50%
Iowa	Lucas	60	0.115	88.50%
Iowa	Madison	61	0.2	80.00%
Iowa	Mahaska	63	0.283	71.70%
Iowa	Marion	64	0.231	76.90%
Iowa	Marshall	65	0.49	51.00%
Iowa	Mills	67	0.342	65.80%
Iowa	Monona	68	1	0.00%
Iowa	Monroe	69	0.109	89.10%
Iowa	Montgomery	70	0.306	69.40%
Iowa	Muscatine	71	0.254	74.60%
Iowa	Polk	78	0.16	84.00%
Iowa	Pottawattamie	80	1	0.00%
Iowa	Poweshiek	81	0.467	53.30%
Iowa	Scott	85	0.299	70.10%
Iowa	Shelby	89	0.775	22.50%
Iowa	Story	92	0.312	68.80%
Iowa	Tama	93	0.544	45.60%
Iowa	Union	94	0.155	84.50%
Iowa	Wapello	96	0.145	85.50%
Iowa	Warren	97	0.17	83.00%
Iowa	Washington	98	0.309	69.10%
Nebraska	Adams	3	0.72	28.00%
Nebraska	Banner	5	0.042	95.80%
Nebraska	Boone	8	0.652	34.80%
Nebraska	Buffalo	9	0.676	32.40%
Nebraska	Burt	10	0.322	67.80%
Nebraska	Butler	11	0.551	44.90%
Nebraska	Cass	14	1	0.00%
Nebraska	Chase	16	0.503	49.70%
Nebraska	Cheyenne	17	0.091	90.90%
Nebraska	Clay	19	0.454	54.60%
Nebraska	Colfax	21	0.345	65.50%
Nebraska	Cuming	23	1	0.00%
Nebraska	Custer	24	1	0.00%
Nebraska	Dawson	26	1	0.00%
Nebraska	Deuel	28	0.043	95.70%
Nebraska	Dodge	29	0.432	56.80%
Nebraska	Douglas	30	0.056	94.40%
Nebraska	Fillmore	31	0.487	51.30%
Nebraska	Frontier	32	0.269	73.10%
Nebraska	Gosper	34	0.379	62.10%
Nebraska	Greeley	35	0.24	76.00%
Nebraska	Hall	38	0.933	6.70%
Nebraska	Hamilton	39	1	0.00%
Nebraska	Hayes	41	0.221	77.90%

Nebraska	Howard	43	0.346	65.40%
Nebraska	Kearney	50	0.663	33.70%
Nebraska	Keith	51	0.496	50.40%
Nebraska	Kimball	53	0.208	79.20%
Nebraska	Lancaster	54	0.658	34.20%
Nebraska	Lincoln	56	0.94	6.00%
Nebraska	Madison	62	0.467	53.30%
Nebraska	Merrick	66	0.279	72.10%
Nebraska	Nance	72	0.333	66.70%
Nebraska	Perkins	73	0.301	69.90%
Nebraska	Phelps	74	0.693	30.70%
Nebraska	Platte	77	0.813	18.70%
Nebraska	Polk	79	0.413	58.70%
Nebraska	Saline	82	0.618	38.20%
Nebraska	Sarpy	83	0.244	75.60%
Nebraska	Saunders	84	1	0.00%
Nebraska	Scotts Bluff	86	1	0.00%
Nebraska	Seward	88	1	0.00%
Nebraska	Sherman	90	0.393	60.70%
Nebraska	Stanton	91	0.461	53.90%
Nebraska	Valley	95	0.284	71.60%
Nebraska	Washington	99	0.604	39.60%
Nebraska	York	101	1	0.00%
Wyoming	Goshen	33	1	0.00%
Wyoming	Laramie	55	0.402	59.80%
Wyoming	Platte	76	1	0.00%

C2: SOM Efficiency and Harvest Potential Estimates (Three output dimensions)

Table 37: SOM Efficiency and Harvest Potentials (Three output Dimensions)

State	County	SOM Efficiency	Harvest Potential
Colorado	Logan	1	0.00%
Colorado	Phillips	0.479	52.10%
Colorado	Sedgwick	0.223	77.70%
Colorado	Weld	1	0.00%
Iowa	Adair	0.567	43.30%
Iowa	Adams	0.35	65.00%
Iowa	Audubon	0.556	44.40%
Iowa	Benton	0.517	48.30%
Iowa	Boone	0.335	66.50%
Iowa	Carroll	1	0.00%
Iowa	Cass	0.533	46.70%
Iowa	Cedar	0.529	47.10%
Iowa	Clarke	0.36	64.00%
Iowa	Clinton	0.658	34.20%
Iowa	Crawford	1	0.00%
Iowa	Dallas	0.285	71.50%
Iowa	Des Moines	0.204	79.60%

Iowa	Greene	0.342	65.80%
Iowa	Guthrie	0.32	68.00%
Iowa	Harrison	0.688	31.20%
Iowa	Henry	0.239	76.10%
Iowa	Iowa	0.494	50.60%
Iowa	Jackson	1	0.00%
Iowa	Jasper	0.6	40.00%
Iowa	Jefferson	0.25	75.00%
Iowa	Johnson	0.399	60.10%
Iowa	Jones	0.556	44.40%
Iowa	Keokuk	0.386	61.40%
Iowa	Linn	0.406	59.40%
Iowa	Louisa	0.211	78.90%
Iowa	Lucas	0.315	68.50%
Iowa	Madison	0.359	64.10%
Iowa	Mahaska	0.33	67.00%
Iowa	Marion	0.336	66.40%
Iowa	Marshall	0.52	48.00%
Iowa	Mills	0.468	53.20%
Iowa	Monona	1	0.00%
Iowa	Monroe	0.262	73.80%
Iowa	Montgomery	0.389	61.10%
Iowa	Muscatine	0.266	73.40%
Iowa	Polk	0.163	83.70%
Iowa	Pottawattamie	1	0.00%
Iowa	Poweshiek	0.58	42.00%
Iowa	Scott	0.307	69.30%
Iowa	Shelby	0.793	20.70%
Iowa	Story	0.327	67.30%
Iowa	Tama	0.571	42.90%
Iowa	Union	0.334	66.60%
Iowa	Wapello	0.244	75.60%
Iowa	Warren	0.326	67.40%
Iowa	Washington	0.342	65.80%
Nebraska	Adams	1	0.00%
Nebraska	Banner	0.056	94.40%
Nebraska	Boone	0.717	28.30%
Nebraska	Buffalo	0.706	29.40%
Nebraska	Burt	0.386	61.40%
Nebraska	Butler	1	0.00%
Nebraska	Cass	1	0.00%
Nebraska	Chase	0.931	6.90%
Nebraska	Cheyenne	0.108	89.20%
Nebraska	Clay	0.484	51.60%
Nebraska	Colfax	0.494	50.60%
Nebraska	Cuming	1	0.00%
Nebraska	Custer	1	0.00%
Nebraska	Dawson	1	0.00%

Nebraska	Deuel	0.061	93.90%
Nebraska	Dodge	0.493	50.70%
Nebraska	Douglas	0.087	91.30%
Nebraska	Fillmore	0.515	48.50%
Nebraska	Frontier	0.338	66.20%
Nebraska	Gosper	0.483	51.70%
Nebraska	Greeley	0.285	71.50%
Nebraska	Hall	1	0.00%
Nebraska	Hamilton	1	0.00%
Nebraska	Hayes	0.306	69.40%
Nebraska	Howard	0.358	64.20%
Nebraska	Kearney	0.77	23.00%
Nebraska	Keith	0.592	40.80%
Nebraska	Kimball	1	0.00%
Nebraska	Lancaster	0.876	12.40%
Nebraska	Lincoln	1	0.00%
Nebraska	Madison	0.575	42.50%
Nebraska	Merrick	0.373	62.70%
Nebraska	Nance	0.455	54.50%
Nebraska	Perkins	0.47	53.00%
Nebraska	Phelps	1	0.00%
Nebraska	Platte	1	0.00%
Nebraska	Polk	0.602	39.80%
Nebraska	Saline	0.806	19.40%
Nebraska	Sarpy	0.329	67.10%
Nebraska	Saunders	1	0.00%
Nebraska	Scotts Bluff	1	0.00%
Nebraska	Seward	1	0.00%
Nebraska	Sherman	0.424	57.60%
Nebraska	Stanton	0.488	51.20%
Nebraska	Valley	0.319	68.10%
Nebraska	Washington	0.695	30.50%
Nebraska	York	1	0.00%
Wyoming	Goshen	1	0.00%
Wyoming	Laramie	0.761	23.90%
Wyoming	Platte	1	0.00%

C3: Results of SOM Efficiency One Output Dimension

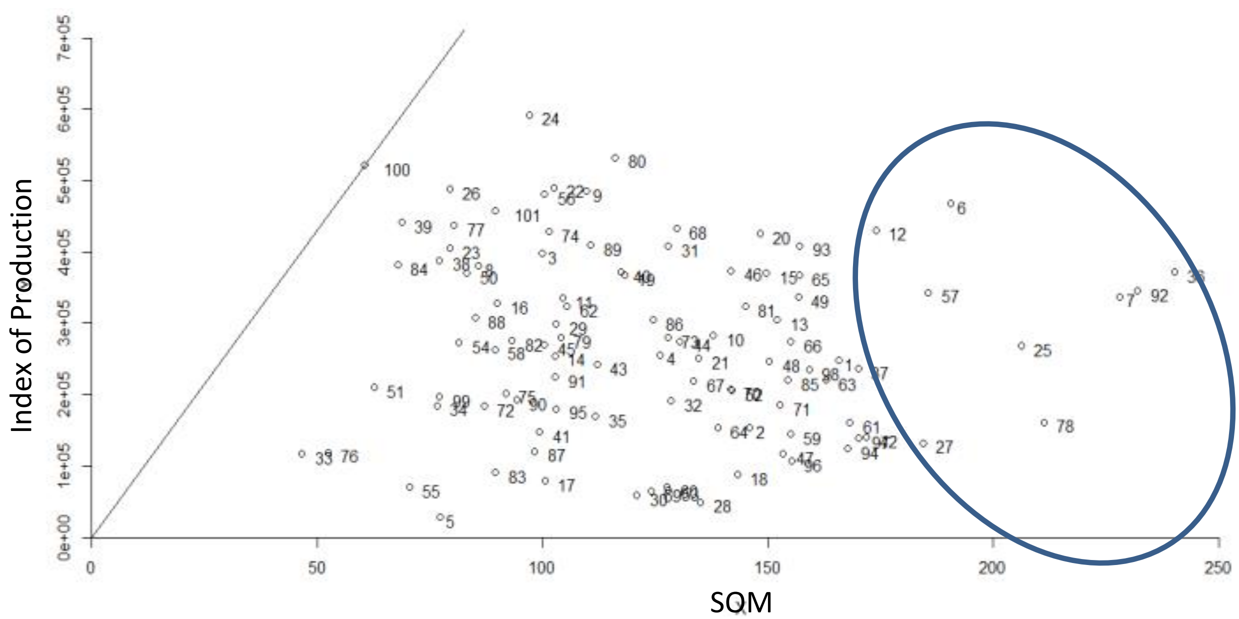
Table 38: Crop Residue Harvest Potentials and Associated Soil Carbon and Crop Residue by State (One output dimension)

State	HP	SOC(Mg C/Ha)	Crop Residue (Mg C/Ha)
Co	48%	20	51
IA	61%	47	119
Ne	45%	23	57
Wy	20%	6	14
HP = Harvest Potential			

Table 39: Percentage of Counties within selected harvest potential groups

% of Counties within given harvest potentials				
State	0 - 10%	11% - 30%	31%-50%	>50%
Co	25%	0%	25%	50%
Io	9%	2%	15%	74%
Ne	23%	4%	19%	54%
Wy	67%	33%	0%	0%

Figure 22: SOM Efficiency Scores in Two Dimensions (X-axis = SOM, Y-axis = Total Production Index)



Blue circle represents cluster of some IOWA counties (hence highest harvest potential)

Appendix D: Codes

D1: Bootstrap Malmquist Index with Confidence Intervals

library(FEAR) **#this line is introduced to mainly download the software FEAR into R**

malq1 <- read.table("c:/malq1.csv", header=T, sep=",") **#Here we are reading the dataset from a csv file**

#1970/1971 (Repeat this for every pair of years…. Please mind overlaps)
#The next set of code lines (8) tries to partition the dataset into matrices without SOM and including the two SOM variables. They also represent two periods (year t and year t+1).

```
xa1=t(matrix(c(malq1$x11,malq1$x21,malq1$x31,malq1$x41,malq1$x51),nrow=101,ncol=5))
xs11=t(matrix(c(malq1$x11,malq1$x21,malq1$x31,malq1$x41,malq1$x51,malq1$x61),nrow=101,ncol=6))
xs12=t(matrix(c(malq1$x11,malq1$x21,malq1$x31,malq1$x41,malq1$x51,malq1$x71),nrow=101,ncol=6))
y1=t(matrix(c(malq1$y11,malq1$y21,malq1$y31),nrow=101,ncol=3))
xa2=t(matrix(c(malq1$x12,malq1$x22,malq1$x32,malq1$x42,malq1$x52),nrow=101,ncol=5))
xs21=t(matrix(c(malq1$x12,malq1$x22,malq1$x32,malq1$x42,malq1$x52,malq1$x62),nrow=101,ncol=6))
xs22=t(matrix(c(malq1$x12,malq1$x22,malq1$x32,malq1$x42,malq1$x52,malq1$x72),nrow=101,ncol=6))
y2=t(matrix(c(malq1$y12,malq1$y22,malq1$y32),nrow=101,ncol=3))
```

 # the next two lines give unique identifications for periods. (Periods 1 and 2)

```
id1=c(1:101)
id2=c(1:101)
```

#The next three lines perform the malmquist and bootstrap operations for the three different scenarios

```
m1=malmquist.components(X1=xa1,Y1=y1,ID1=id1,X2=xa2,Y2=y2,ID2=id2,ORIENTATION=2,NREP=1000)
m2=malmquist.components(X1=xs11,Y1=y1,ID1=id1,X2=xs21,Y2=y2,ID2=id2,ORIENTATION=2,NREP=1000)
m3=malmquist.components(X1=xs12,Y1=y1,ID1=id1,X2=xs22,Y2=y2,ID2=id2,ORIENTATION=2,NREP=1000)
```

#The following three lines compute the confidence intervals at the 0.01, 0.05 and 0.1 significant levels

```
som1=malmquist(LIST=m1,alpha=c(0.1,0.05,0.01))
som2=malmquist(LIST=m2,alpha=c(0.1,0.05,0.01))
som3=malmquist(LIST=m3,alpha=c(0.1,0.05,0.01))
```

#the following three lines identifies parts of the output that are relevant to our research

```
outag1=t(matrix(c(som1$malm,som1$ci.malm,som1$eff,som1$ci.eff,som1$tech,som1$ci.tech),nrow=101,ncol=21))
outag2=t(matrix(c(som2$malm,som2$ci.malm,som2$eff,som2$ci.eff,som2$tech,som2$ci.tech),nrow=101,ncol=21))
outag3=t(matrix(c(som3$malm,som3$ci.malm,som3$eff,som3$ci.eff,som3$tech,som3$ci.tech),nrow=101,ncol=21))
```

#We then export three output files into CSS files

```
write.table(outag1,file="out1_00.csv")
write.table(outag2,file="out2_00.csv")
write.table(outag3,file="out3_00.csv")
```

D2.GAMS Code: SOM Efficiency (One Dimension)

The first eight lines are meant to declare all input-output variables to be used.

```
Set inout /y1,x1*x6/
Output(inout) /y1/
Input(inout) /x1,x2,x3,x4,x5/
Input1(inout)/x6/
Obs /1*200/
Subobs(obs) /1*101/
Actobs(obs);
Alias (subobs, subobs1)
```

 # Here we introduce the dataset

```
Table act(obs,inout) input output table

        y1              x1             x2            x3            x4            x5          x6

1       247672.44       83733.51       0.0001        18603.41      16702.43      49.06       165.68
 .          .               .              .             .             .            .           .
101         457869.49    16996.79696    105461.0783   27219.77      22330.53      48.6        89.47;
```

```
#We then describe the different variables
Variables
Lambda efficiency score
 Weight(obs) intensity variable;
 Positive variable weight;
 Equations
```

#Here we list the constraints

```
 Constr1(output,obs) DEA constraint for each output
 Constr2(input,obs) DEA constraint for each input
 Constr3(input1,obs) Dea constraint for som;
 Constr1(output,actobs).. sum(subobs,weight(subobs)*act(subobs, output)) =G= act(actobs,output);
 Constr2(input,actobs).. sum(subobs,weight(subobs)*act(subobs,input)) =L= act(actobs,input);
 Constr3(input1,actobs).. sum(subobs,weight(subobs)*act(subobs,input1)) =L= lambda*act(actobs,input1);

Parameter
 Score1(obs) efficiency scores;
 Model tedea /constr1, constr2, constr3/;
 Loop (subobs1,
 Actobs(obs)=no;
 Actobs(subobs1)=yes;
 Option LP=OSL;
 Solve tedea minimizing lambda using LP;
 Score1(subobs1)=lambda.l;
 );
 Display score1;
```

D3: Code GAMS Technical Efficiency

The first eight lines are meant to declare all input-output variables to be used.

```
Set inout /y1*y3,x1*x6/
Output(inout) /y1,y2,y3/
Input(inout) /x1,x2,x3,x4,x5/
Input1(inout)/x6/
```

```
Obs /1*200/
Subobs(obs) /1*101/
Actobs(obs);
Alias (subobs, subobs1)
```

#Here we call the data from a csv file

```
Table act(obs,inout) input output table
$ondelim
$include "SOMDATA.csv"
$offdelim
Variables
Lambda efficiency score
 Weight(obs) intensity variable;
 Positive variable weight;
 Equations
```

#Introduce constraints

```
 Constr1(output,obs) DEA constraint for each output
 Constr2(input,obs) DEA constraint for each input
 Constr3(input1,obs) Dea constraint for som;
 Constr1(output,actobs).. sum(subobs,weight(subobs)*act(subobs, output)) =G= act(actobs,output);
 Constr2(input,actobs).. sum(subobs,weight(subobs)*act(subobs,input)) =L= act(actobs,input);
 Constr3(input1,actobs).. sum(subobs,weight(subobs)*act(subobs,input1)) =L= lambda*act(actobs,input1);

Parameter
 Score1(obs) efficiency scores;
 Model tedea /constr1, constr2, constr3/;
 Loop (subobs1,
 Actobs(obs)=no;
 Actobs(subobs1)=yes;
 Option LP=OSL;
 Solve tedea minimizing lambda using LP;
 Score1(subobs1)=lambda.l;
 );  Display score1;
```

Appendix E: Results obtained from estimating Error Correction Model

Long-Run Parameter Beta Estimates When RANK=2		
Variable	**1**	**2**
lcrude	-0.05146	-0.06192
ldiesel	1	1
lngas	-0.98549	-0.92294
lelect	0.09352	0.03388
lnatural	0.02881	0.09234
lcorn	0.00978	0.00744

Adjustment Coefficient Alpha Estimates		
When RANK=2		
Variable	1	2
lcrude	0.4436	0.56104
ldiesel	-0.28856	-0.14811
lngas	-0.2032	-0.06919
lelect	-0.20099	0.18934
lnatural	-0.54892	-0.3998
lcorn	-1.25864	-1.27903

Coefficient of Granger Representation						
Variable	Lcrude	ldiesel	lngas	lelect	lnatural	lcorn
lcrude	0.66191	7.14049	-7.21258	0.83526	0.02734	0.07645
ldiesel	0.11771	-1.66549	2.74326	-0.36028	0.04144	-0.03045
lngas	0.06634	-1.55658	2.61634	-0.22408	0.03877	-0.01832
lelect	-0.0559	0.8134	-0.71758	0.99597	0.10875	0.00481
lnatural	0.27956	-6.14812	6.27926	-0.78502	1.04659	-0.06842
Lcorn	0.81181	-17.4045	17.65356	-2.10584	0.00788	0.8109
Parameter Alpha * Beta' Estimates						
Variable	Lcrude	ldiesel	lngas	lelect	lnatural	lcorn
lcrude	-0.05757	1.00464	-0.95496	0.06049	0.06459	0.00851
ldiesel	0.02402	-0.43667	0.42107	-0.032	-0.02199	-0.00392
lngas	0.01474	-0.2724	0.26412	-0.02135	-0.01224	-0.0025
lelect	-0.00138	-0.01165	0.02332	-0.01238	0.01169	-0.00056
lnatural	0.053	-0.94872	0.90995	-0.06488	-0.05273	-0.00834
Lcorn	0.14397	-2.53767	2.42084	-0.16104	-0.15437	-0.02183

AR Coefficients of Differenced Lag							
DIF Lag	Variable	lcrude	ldiesel	lngas	lelect	lnatural	lcorn
1	lcrude	0.57693	-0.43344	-0.1649	0.16635	0.03732	-0.00082
	ldiesel	0.15493	0.19151	-0.05437	-0.18621	-0.03565	0.01474
	lngas	0.15074	0.9462	-0.83821	-0.2151	-0.04429	0.01744
	lelect	0.00961	0.03413	-0.05957	-0.26634	0.03386	0.00286
	lnatural	-0.04172	0.5689	-0.43966	-0.66344	0.19507	-0.01672
	lcorn	-0.23576	1.51244	-1.87756	-0.84182	0.13449	0.45917
2	lcrude	0.15505	-0.56752	0.23623	-0.26535	-0.14955	-0.00905

	Idiesel	0.01657	0.01045	-0.33648	-0.06581	0.02576	0.00181
	lngas	0.02502	0.62318	-0.98688	-0.03554	0.0552	-0.00189
	lelect	-0.0133	0.06507	-0.07279	-0.09723	0.02607	-0.0025
	lnatural	-0.09913	0.37116	-0.33339	0.01508	-0.02988	0.01328
	lcorn	0.13596	1.99536	-1.99695	1.83497	0.15684	-0.08075
3	**lcrude**	-0.03613	-1.74049	2.03325	-0.3874	0.04804	-0.0093
	ldiesel	0.10558	-0.06325	-0.12698	0.12699	0.02742	0.02996
	lngas	0.0921	0.39843	-0.579	0.09068	0.03261	0.03422
	lelect	0.02097	-0.00427	-0.06865	-0.17738	0.0244	0.00291
	lnatural	-0.02485	0.197	-0.08108	0.49653	-0.12052	0.0051
	lcorn	-0.16821	2.33431	-1.90481	-0.51631	0.04962	-0.07968
4	**lcrude**	-0.06117	-1.63454	1.60251	0.16026	0.13783	-0.01371
	ldiesel	-0.02857	0.03225	0.02192	-0.21676	0.05693	-0.02581
	lngas	-0.02785	0.35628	-0.32478	-0.21382	0.04365	-0.01839
	lelect	0.00776	0.03868	-0.04893	-0.16947	0.00406	0.00364
	lnatural	0.02815	-0.1886	0.30024	-0.06316	-0.18776	-0.00174
	lcorn	0.08431	0.89247	-1.44334	-1.04856	0.10279	0.07928
5	**lcrude**	0.17515	-1.26819	0.80378	0.46665	-0.25827	0.08464
	ldiesel	0.0025	-0.09797	-0.14977	-0.20588	-0.00981	0.04233
	lngas	0.00994	0.1668	-0.42328	-0.18317	-0.0413	0.0322
	lelect	0.00236	0.04493	-0.0692	-0.18123	0.01289	0.00127
	lnatural	-0.05623	-0.33548	0.46785	-0.59806	-0.18453	-0.02059
	lcorn	-0.02233	0.60196	-0.11495	-0.70966	-0.04079	-0.0191
6	**lcrude**	0.01842	-0.68364	0.67764	-0.08113	-0.35889	-0.02539
	ldiesel	0.04493	0.24879	-0.35842	-0.10952	-0.10096	0.00914
	lngas	0.03275	0.50353	-0.6131	-0.10333	-0.09434	0.00657
	lelect	0.00154	-0.0208	0.00597	-0.35467	-0.0216	0.00225
	lnatural	-0.06769	-0.15473	0.17805	-0.83489	-0.04459	-0.00045
	lcorn	-0.22101	0.98454	-0.95446	0.46347	0.39617	0.06431
7	**lcrude**	0.07454	-0.47847	0.12158	-0.62173	0.38455	-0.01963
	ldiesel	0.03805	0.32081	-0.39485	-0.61356	0.09467	-0.00922
	lngas	0.04034	0.56003	-0.62448	-0.52958	0.08864	-0.00777
	lelect	0.00347	0.0318	-0.05869	-0.29873	-0.01477	-0.00199
	lnatural	-0.02765	0.06715	0.00099	-0.61631	-0.12649	0.01974
	lcorn	0.17705	0.63585	-1.00042	0.0325	-0.16658	0.07919
8	**lcrude**	0.07219	0.34498	-0.34094	0.05728	0.01368	0.03732
	ldiesel	-0.01373	0.48437	-0.6073	-0.17259	0.08717	-0.00342
	lngas	-0.00894	0.68453	-0.80486	-0.11715	0.10076	-0.00304
	lelect	0.00248	0.06738	-0.07734	-0.27356	0.02359	0.00135
	lnatural	0.0436	0.16909	-0.16666	-0.11244	-0.10462	0.0196
	lcorn	-0.02845	1.12354	-0.81028	1.4159	0.06783	-0.1844

9	**lcrude**	0.10532	-0.13465	-0.07616	-0.18751	-0.08183	-0.01845
	ldiesel	0.01584	0.14813	-0.23603	-0.31083	0.00104	0.00732
	lngas	0.00375	0.22931	-0.29037	-0.24715	-0.01505	-0.00062
	lelect	0.01082	-0.02968	-0.0115	-0.21278	0.07439	-0.00228
	lnatural	-0.0664	0.00675	0.0956	-0.35093	-0.1424	-0.02427
	lcorn	-0.2264	0.99744	-1.06712	0.81981	0.01739	0.11061

Schematic Representation of Parameter Estimates

Variable/Lag	AR1	AR2	AR3	AR4	AR5	AR6	AR7	AR8	AR9	AR10
Lcrude	******	+.....	+.....	.-+...	......	+...-+	....-.	....+.	......	......
Ldiesel	******	+.....	......	+....+	.....-	.....+	....-.	...-+.	.+-.+.	......
Lngas	******	++-...	.+-...	+.-..+	......	.....+	..-.-.	.+--+.	.+-.+.	......
Lelect	******	...-+.	......	+..-..	...-..	...-..	...-..	...-..	...-..	...-+.
lnatural	******	...-+.	-.....	...+-.	....-.	...--.	-..-..	...--.	....-.	-...-.
Lcorn	******	-....+	...+..	......	......	......	....+.	......	.....-	-....+

+ is > 2*std error, - is < -2*std error, . is between, * is N/A

Model Parameter Estimates

Equation	Parameter	Estimate	Standard Error	t Value	Pr > |t|	Variable
D_lcrude	**AR1_1_1**	-0.05757	0.03193			lcrude(t-1)
	AR1_1_2	1.00464	0.55644			ldiesel(t-1)
	AR1_1_3	-0.95496	0.52975			lngas(t-1)
	AR1_1_4	0.06049	0.03782			lelect(t-1)
	AR1_1_5	0.06459	0.03938			lnatural(t-1)
	AR1_1_6	0.00851	0.00478			lcorn(t-1)
	AR2_1_1	0.57693	0.06602	8.74	0.0001	D_lcrude(t-1)
	AR2_1_2	-0.43344	0.69215	-0.63	0.5316	D_ldiesel(t-1)
	AR2_1_3	-0.1649	0.70486	-0.23	0.8152	D_lngas(t-1)
	AR2_1_4	0.16635	0.46166	0.36	0.7189	D_lelect(t-1)
	AR2_1_5	0.03732	0.12379	0.3	0.7632	D_lnatural(t-1)
	AR2_1_6	-0.00082	0.03413	-0.02	0.9809	D_lcorn(t-1)
	AR3_1_1	0.15505	0.07333	2.11	0.0353	D_lcrude(t-2)
	AR3_1_2	-0.56752	0.78177	-0.73	0.4684	D_ldiesel(t-2)

	AR3_1_3	0.23623	0.78793	0.3	0.7645	D_lngas(t-2)
	AR3_1_4	-0.26535	0.46631	-0.57	0.5697	D_lelect(t-2)
	AR3_1_5	-0.14955	0.12452	-1.2	0.2306	D_lnatural(t-2)
	AR3_1_6	-0.00905	0.03705	-0.24	0.8071	D_lcorn(t-2)
	AR4_1_1	-0.03613	0.07423	-0.49	0.6267	D_lcrude(t-3)
	AR4_1_2	-1.74049	0.82758	-2.1	0.0363	D_ldiesel(t-3)
	AR4_1_3	2.03325	0.85355	2.38	0.0178	D_lngas(t-3)
	AR4_1_4	-0.3874	0.45943	-0.84	0.3997	D_lelect(t-3)
	AR4_1_5	0.04804	0.12431	0.39	0.6994	D_lnatural(t-3)
	AR4_1_6	-0.0093	0.03677	-0.25	0.8006	D_lcorn(t-3)
	AR5_1_1	-0.06117	0.07586	-0.81	0.4207	D_lcrude(t-4)
	AR5_1_2	-1.63454	0.84141	-1.94	0.053	D_ldiesel(t-4)
	AR5_1_3	1.60251	0.87169	1.84	0.0669	D_lngas(t-4)
	AR5_1_4	0.16026	0.44858	0.36	0.7211	D_lelect(t-4)
	AR5_1_5	0.13783	0.12382	1.11	0.2665	D_lnatural(t-4)
	AR5_1_6	-0.01371	0.03713	-0.37	0.7123	D_lcorn(t-4)
	AR6_1_1	0.17515	0.07543	2.32	0.0209	D_lcrude(t-5)
	AR6_1_2	-1.26819	0.84505	-1.5	0.1344	D_ldiesel(t-5)
	AR6_1_3	0.80378	0.87339	0.92	0.3581	D_lngas(t-5)
	AR6_1_4	0.46665	0.44452	1.05	0.2946	D_lelect(t-5)
	AR6_1_5	-0.25827	0.12331	-2.09	0.037	D_lnatural(t-5)
	AR6_1_6	0.08464	0.03709	2.28	0.0232	D_lcorn(t-5)
	AR7_1_1	0.01842	0.07553	0.24	0.8075	D_lcrude(t-6)
	AR7_1_2	-0.68364	0.82266	-0.83	0.4066	D_ldiesel(t-6)
	AR7_1_3	0.67764	0.85294	0.79	0.4275	D_lngas(t-6)
	AR7_1_4	-0.08113	0.44863	-0.18	0.8566	D_lelect(t-6)
	AR7_1_5	-0.35889	0.12541	-2.86	0.0045	D_lnatural(t-6)
	AR7_1_6	-0.02539	0.03807	-0.67	0.5053	D_lcorn(t-6)
	AR8_1_1	0.07454	0.07419	1	0.3158	D_lcrude(t-7)
	AR8_1_2	-0.47847	0.76752	-0.62	0.5335	D_ldiesel(t-7)
	AR8_1_3	0.12158	0.80069	0.15	0.8794	D_lngas(t-7)
	AR8_1_4	-0.62173	0.47284	-1.31	0.1895	D_lelect(t-7)
	AR8_1_5	0.38455	0.12432	3.09	0.0022	D_lnatural(t-7)
	AR8_1_6	-0.01963	0.03787	-0.52	0.6046	D_lcorn(t-7)
	AR9_1_1	0.07219	0.07266	0.99	0.3212	D_lcrude(t-8)
	AR9_1_2	0.34498	0.66742	0.52	0.6056	D_ldiesel(t-8)
	AR9_1_3	-0.34094	0.69029	-0.49	0.6217	D_lngas(t-8)
	AR9_1_4	0.05728	0.49748	0.12	0.9084	D_lelect(t-8)
	AR9_1_5	0.01368	0.12644	0.11	0.9139	D_lnatural(t-8)

	AR9_1_6	0.03732	0.03713	1.01	0.3156	D_lcorn(t-8)
	AR10_1_1	0.10532	0.07143	1.47	0.1414	D_lcrude(t-9)
	AR10_1_2	-0.13465	0.48766	-0.28	0.7826	D_ldiesel(t-9)
	AR10_1_3	-0.07616	0.51489	-0.15	0.8825	D_lngas(t-9)
	AR10_1_4	-0.18751	0.48293	-0.39	0.6981	D_lelect(t-9)
	AR10_1_5	-0.08183	0.12391	-0.66	0.5095	D_lnatural(t-9)
	AR10_1_6	-0.01845	0.03391	-0.54	0.5868	D_lcorn(t-9)
D_ldiesel	**AR1_2_1**	0.02402	0.01076			lcrude(t-1)
	AR1_2_2	-0.43667	0.18758			ldiesel(t-1)
	AR1_2_3	0.42107	0.17858			lngas(t-1)
	AR1_2_4	-0.032	0.01275			lelect(t-1)
	AR1_2_5	-0.02199	0.01328			lnatural(t-1)
	AR1_2_6	-0.00392	0.00161			lcorn(t-1)
	AR2_2_1	0.15493	0.02226	6.96	0.0001	D_lcrude(t-1)
	AR2_2_2	0.19151	0.23333	0.82	0.4124	D_ldiesel(t-1)
	AR2_2_3	-0.05437	0.23761	-0.23	0.8191	D_lngas(t-1)
	AR2_2_4	-0.18621	0.15563	-1.2	0.2324	D_lelect(t-1)
	AR2_2_5	-0.03565	0.04173	-0.85	0.3936	D_lnatural(t-1)
	AR2_2_6	0.01474	0.0115	1.28	0.2011	D_lcorn(t-1)
	AR3_2_1	0.01657	0.02472	0.67	0.5032	D_lcrude(t-2)
	AR3_2_2	0.01045	0.26354	0.04	0.9684	D_ldiesel(t-2)
	AR3_2_3	-0.33648	0.26561	-1.27	0.2062	D_lngas(t-2)
	AR3_2_4	-0.06581	0.15719	-0.42	0.6758	D_lelect(t-2)
	AR3_2_5	0.02576	0.04198	0.61	0.5398	D_lnatural(t-2)
	AR3_2_6	0.00181	0.01249	0.15	0.8848	D_lcorn(t-2)
	AR4_2_1	0.10558	0.02502	4.22	0.0001	D_lcrude(t-3)
	AR4_2_2	-0.06325	0.27898	-0.23	0.8208	D_ldiesel(t-3)
	AR4_2_3	-0.12698	0.28774	-0.44	0.6593	D_lngas(t-3)
	AR4_2_4	0.12699	0.15488	0.82	0.4129	D_lelect(t-3)
	AR4_2_5	0.02742	0.0419	0.65	0.5134	D_lnatural(t-3)
	AR4_2_6	0.02996	0.0124	2.42	0.0162	D_lcorn(t-3)
	AR5_2_1	-0.02857	0.02557	-1.12	0.2648	D_lcrude(t-4)
	AR5_2_2	0.03225	0.28364	0.11	0.9096	D_ldiesel(t-4)
	AR5_2_3	0.02192	0.29385	0.07	0.9406	D_lngas(t-4)
	AR5_2_4	-0.21676	0.15122	-1.43	0.1527	D_lelect(t-4)
	AR5_2_5	0.05693	0.04174	1.36	0.1735	D_lnatural(t-4)
	AR5_2_6	-0.02581	0.01252	-2.06	0.04	D_lcorn(t-4)
	AR6_2_1	0.0025	0.02543	0.1	0.9217	D_lcrude(t-5)
	AR6_2_2	-0.09797	0.28487	-0.34	0.7311	D_ldiesel(t-5)

	AR6_2_3	-0.14977	0.29442	-0.51	0.6113	D_lngas(t-5)
	AR6_2_4	-0.20588	0.14985	-1.37	0.1704	D_lelect(t-5)
	AR6_2_5	-0.00981	0.04157	-0.24	0.8136	D_lnatural(t-5)
	AR6_2_6	0.04233	0.0125	3.39	0.0008	D_lcorn(t-5)
	AR7_2_1	0.04493	0.02546	1.76	0.0786	D_lcrude(t-6)
	AR7_2_2	0.24879	0.27732	0.9	0.3703	D_ldiesel(t-6)
	AR7_2_3	-0.35842	0.28753	-1.25	0.2135	D_lngas(t-6)
	AR7_2_4	-0.10952	0.15124	-0.72	0.4695	D_lelect(t-6)
	AR7_2_5	-0.10096	0.04228	-2.39	0.0175	D_lnatural(t-6)
	AR7_2_6	0.00914	0.01283	0.71	0.4768	D_lcorn(t-6)
	AR8_2_1	0.03805	0.02501	1.52	0.1291	D_lcrude(t-7)
	AR8_2_2	0.32081	0.25874	1.24	0.2159	D_ldiesel(t-7)
	AR8_2_3	-0.39485	0.26992	-1.46	0.1445	D_lngas(t-7)
	AR8_2_4	-0.61356	0.1594	-3.85	0.0001	D_lelect(t-7)
	AR8_2_5	0.09467	0.04191	2.26	0.0246	D_lnatural(t-7)
	AR8_2_6	-0.00922	0.01277	-0.72	0.4705	D_lcorn(t-7)
	AR9_2_1	-0.01373	0.02449	-0.56	0.5756	D_lcrude(t-8)
	AR9_2_2	0.48437	0.22499	2.15	0.0321	D_ldiesel(t-8)
	AR9_2_3	-0.6073	0.2327	-2.61	0.0095	D_lngas(t-8)
	AR9_2_4	-0.17259	0.1677	-1.03	0.3042	D_lelect(t-8)
	AR9_2_5	0.08717	0.04262	2.05	0.0417	D_lnatural(t-8)
	AR9_2_6	-0.00342	0.01252	-0.27	0.7849	D_lcorn(t-8)
	AR10_2_1	0.01584	0.02408	0.66	0.511	D_lcrude(t-9)
	AR10_2_2	0.14813	0.16439	0.9	0.3682	D_ldiesel(t-9)
	AR10_2_3	-0.23603	0.17357	-1.36	0.1749	D_lngas(t-9)
	AR10_2_4	-0.31083	0.1628	-1.91	0.0571	D_lelect(t-9)
	AR10_2_5	0.00104	0.04177	0.02	0.9802	D_lnatural(t-9)
	AR10_2_6	0.00732	0.01143	0.64	0.5226	D_lcorn(t-9)
D_lngas	**AR1_3_1**	0.01474	0.01046			lcrude(t-1)
	AR1_3_2	-0.2724	0.18229			ldiesel(t-1)
	AR1_3_3	0.26412	0.17354			lngas(t-1)
	AR1_3_4	-0.02135	0.01239			lelect(t-1)
	AR1_3_5	-0.01224	0.0129			lnatural(t-1)
	AR1_3_6	-0.0025	0.00157			lcorn(t-1)
	AR2_3_1	0.15074	0.02163	6.97	0.0001	D_lcrude(t-1)
	AR2_3_2	0.9462	0.22674	4.17	0.0001	D_ldiesel(t-1)
	AR2_3_3	-0.83821	0.23091	-3.63	0.0003	D_lngas(t-1)
	AR2_3_4	-0.2151	0.15124	-1.42	0.1559	D_lelect(t-1)
	AR2_3_5	-0.04429	0.04055	-1.09	0.2756	D_lnatural(t-1)

	AR2_3_6	0.01744	0.01118	1.56	0.1198	D_lcorn(t-1)
	AR3_3_1	0.02502	0.02402	1.04	0.2984	D_lcrude(t-2)
	AR3_3_2	0.62318	0.2561	2.43	0.0155	D_ldiesel(t-2)
	AR3_3_3	-0.98688	0.25812	-3.82	0.0002	D_lngas(t-2)
	AR3_3_4	-0.03554	0.15276	-0.23	0.8162	D_lelect(t-2)
	AR3_3_5	0.0552	0.04079	1.35	0.1769	D_lnatural(t-2)
	AR3_3_6	-0.00189	0.01214	-0.16	0.8763	D_lcorn(t-2)
	AR4_3_1	0.0921	0.02432	3.79	0.0002	D_lcrude(t-3)
	AR4_3_2	0.39843	0.27111	1.47	0.1427	D_ldiesel(t-3)
	AR4_3_3	-0.579	0.27962	-2.07	0.0392	D_lngas(t-3)
	AR4_3_4	0.09068	0.15051	0.6	0.5473	D_lelect(t-3)
	AR4_3_5	0.03261	0.04072	0.8	0.4239	D_lnatural(t-3)
	AR4_3_6	0.03422	0.01205	2.84	0.0048	D_lcorn(t-3)
	AR5_3_1	-0.02785	0.02485	-1.12	0.2633	D_lcrude(t-4)
	AR5_3_2	0.35628	0.27564	1.29	0.1971	D_ldiesel(t-4)
	AR5_3_3	-0.32478	0.28556	-1.14	0.2563	D_lngas(t-4)
	AR5_3_4	-0.21382	0.14695	-1.46	0.1467	D_lelect(t-4)
	AR5_3_5	0.04365	0.04056	1.08	0.2827	D_lnatural(t-4)
	AR5_3_6	-0.01839	0.01216	-1.51	0.1316	D_lcorn(t-4)
	AR6_3_1	0.00994	0.02471	0.4	0.6877	D_lcrude(t-5)
	AR6_3_2	0.1668	0.27683	0.6	0.5473	D_ldiesel(t-5)
	AR6_3_3	-0.42328	0.28612	-1.48	0.14	D_lngas(t-5)
	AR6_3_4	-0.18317	0.14562	-1.26	0.2094	D_lelect(t-5)
	AR6_3_5	-0.0413	0.0404	-1.02	0.3074	D_lnatural(t-5)
	AR6_3_6	0.0322	0.01215	2.65	0.0085	D_lcorn(t-5)
	AR7_3_1	0.03275	0.02474	1.32	0.1867	D_lcrude(t-6)
	AR7_3_2	0.50353	0.2695	1.87	0.0626	D_ldiesel(t-6)
	AR7_3_3	-0.6131	0.27942	-2.19	0.029	D_lngas(t-6)
	AR7_3_4	-0.10333	0.14697	-0.7	0.4825	D_lelect(t-6)
	AR7_3_5	-0.09434	0.04108	-2.3	0.0223	D_lnatural(t-6)
	AR7_3_6	0.00657	0.01247	0.53	0.599	D_lcorn(t-6)
	AR8_3_1	0.04034	0.0243	1.66	0.0979	D_lcrude(t-7)
	AR8_3_2	0.56003	0.25144	2.23	0.0266	D_ldiesel(t-7)
	AR8_3_3	-0.62448	0.2623	-2.38	0.0179	D_lngas(t-7)
	AR8_3_4	-0.52958	0.1549	-3.42	0.0007	D_lelect(t-7)
	AR8_3_5	0.08864	0.04073	2.18	0.0303	D_lnatural(t-7)
	AR8_3_6	-0.00777	0.01241	-0.63	0.5317	D_lcorn(t-7)
	AR9_3_1	-0.00894	0.0238	-0.38	0.7074	D_lcrude(t-8)
	AR9_3_2	0.68453	0.21864	3.13	0.0019	D_ldiesel(t-8)

	AR9_3_3	-0.80486	0.22614	-3.56	0.0004	D_lngas(t-8)
	AR9_3_4	-0.11715	0.16297	-0.72	0.4728	D_lelect(t-8)
	AR9_3_5	0.10076	0.04142	2.43	0.0155	D_lnatural(t-8)
	AR9_3_6	-0.00304	0.01216	-0.25	0.803	D_lcorn(t-8)
	AR10_3_1	0.00375	0.0234	0.16	0.8726	D_lcrude(t-9)
	AR10_3_2	0.22931	0.15976	1.44	0.1522	D_ldiesel(t-9)
	AR10_3_3	-0.29037	0.16868	-1.72	0.0861	D_lngas(t-9)
	AR10_3_4	-0.24715	0.15821	-1.56	0.1192	D_lelect(t-9)
	AR10_3_5	-0.01505	0.04059	-0.37	0.711	D_lnatural(t-9)
	AR10_3_6	-0.00062	0.01111	-0.06	0.9552	D_lcorn(t-9)
D_lelect	**AR1_4_1**	-0.00138	0.00335			lcrude(t-1)
	AR1_4_2	-0.01165	0.05843			ldiesel(t-1)
	AR1_4_3	0.02332	0.05562			lngas(t-1)
	AR1_4_4	-0.01238	0.00397			lelect(t-1)
	AR1_4_5	0.01169	0.00414			lnatural(t-1)
	AR1_4_6	-0.00056	0.0005			lcorn(t-1)
	AR2_4_1	0.00961	0.00693	1.39	0.1669	D_lcrude(t-1)
	AR2_4_2	0.03413	0.07268	0.47	0.639	D_ldiesel(t-1)
	AR2_4_3	-0.05957	0.07401	-0.8	0.4215	D_lngas(t-1)
	AR2_4_4	-0.26634	0.04847	-5.49	0.0001	D_lelect(t-1)
	AR2_4_5	0.03386	0.013	2.6	0.0096	D_lnatural(t-1)
	AR2_4_6	0.00286	0.00358	0.8	0.4246	D_lcorn(t-1)
	AR3_4_1	-0.0133	0.0077	-1.73	0.0851	D_lcrude(t-2)
	AR3_4_2	0.06507	0.08209	0.79	0.4286	D_ldiesel(t-2)
	AR3_4_3	-0.07279	0.08273	-0.88	0.3796	D_lngas(t-2)
	AR3_4_4	-0.09723	0.04896	-1.99	0.0479	D_lelect(t-2)
	AR3_4_5	0.02607	0.01307	1.99	0.047	D_lnatural(t-2)
	AR3_4_6	-0.0025	0.00389	-0.64	0.5218	D_lcorn(t-2)
	AR4_4_1	0.02097	0.00779	2.69	0.0075	D_lcrude(t-3)
	AR4_4_2	-0.00427	0.0869	-0.05	0.9608	D_ldiesel(t-3)
	AR4_4_3	-0.06865	0.08962	-0.77	0.4443	D_lngas(t-3)
	AR4_4_4	-0.17738	0.04824	-3.68	0.0003	D_lelect(t-3)
	AR4_4_5	0.0244	0.01305	1.87	0.0625	D_lnatural(t-3)
	AR4_4_6	0.00291	0.00386	0.75	0.4519	D_lcorn(t-3)
	AR5_4_1	0.00776	0.00797	0.97	0.3307	D_lcrude(t-4)
	AR5_4_2	0.03868	0.08835	0.44	0.6619	D_ldiesel(t-4)
	AR5_4_3	-0.04893	0.09153	-0.53	0.5933	D_lngas(t-4)
	AR5_4_4	-0.16947	0.0471	-3.6	0.0004	D_lelect(t-4)
	AR5_4_5	0.00406	0.013	0.31	0.755	D_lnatural(t-4)

	AR5_4_6	0.00364	0.0039	0.93	0.3506	D_lcorn(t-4)
	AR6_4_1	0.00236	0.00792	0.3	0.766	D_lcrude(t-5)
	AR6_4_2	0.04493	0.08873	0.51	0.613	D_ldiesel(t-5)
	AR6_4_3	-0.0692	0.09171	-0.75	0.4511	D_lngas(t-5)
	AR6_4_4	-0.18123	0.04668	-3.88	0.0001	D_lelect(t-5)
	AR6_4_5	0.01289	0.01295	1	0.3203	D_lnatural(t-5)
	AR6_4_6	0.00127	0.00389	0.33	0.7452	D_lcorn(t-5)
	AR7_4_1	0.00154	0.00793	0.19	0.8461	D_lcrude(t-6)
	AR7_4_2	-0.0208	0.08638	-0.24	0.8098	D_ldiesel(t-6)
	AR7_4_3	0.00597	0.08956	0.07	0.9469	D_lngas(t-6)
	AR7_4_4	-0.35467	0.04711	-7.53	0.0001	D_lelect(t-6)
	AR7_4_5	-0.0216	0.01317	-1.64	0.1019	D_lnatural(t-6)
	AR7_4_6	0.00225	0.004	0.56	0.5747	D_lcorn(t-6)
	AR8_4_1	0.00347	0.00779	0.45	0.6559	D_lcrude(t-7)
	AR8_4_2	0.0318	0.08059	0.39	0.6934	D_ldiesel(t-7)
	AR8_4_3	-0.05869	0.08407	-0.7	0.4857	D_lngas(t-7)
	AR8_4_4	-0.29873	0.04965	-6.02	0.0001	D_lelect(t-7)
	AR8_4_5	-0.01477	0.01305	-1.13	0.2588	D_lnatural(t-7)
	AR8_4_6	-0.00199	0.00398	-0.5	0.6167	D_lcorn(t-7)
	AR9_4_1	0.00248	0.00763	0.33	0.7453	D_lcrude(t-8)
	AR9_4_2	0.06738	0.07008	0.96	0.3371	D_ldiesel(t-8)
	AR9_4_3	-0.07734	0.07248	-1.07	0.2868	D_lngas(t-8)
	AR9_4_4	-0.27356	0.05224	-5.24	0.0001	D_lelect(t-8)
	AR9_4_5	0.02359	0.01328	1.78	0.0765	D_lnatural(t-8)
	AR9_4_6	0.00135	0.0039	0.35	0.7297	D_lcorn(t-8)
	AR10_4_1	0.01082	0.0075	1.44	0.15	D_lcrude(t-9)
	AR10_4_2	-0.02968	0.0512	-0.58	0.5626	D_ldiesel(t-9)
	AR10_4_3	-0.0115	0.05406	-0.21	0.8317	D_lngas(t-9)
	AR10_4_4	-0.21278	0.05071	-4.2	0.0001	D_lelect(t-9)
	AR10_4_5	0.07439	0.01301	5.72	0.0001	D_lnatural(t-9)
	AR10_4_6	-0.00228	0.00356	-0.64	0.5232	D_lcorn(t-9)
D_lnatural	**AR1_5_1**	0.053	0.01318			lcrude(t-1)
	AR1_5_2	-0.94872	0.22975			ldiesel(t-1)
	AR1_5_3	0.90995	0.21873			lngas(t-1)
	AR1_5_4	-0.06488	0.01562			lelect(t-1)
	AR1_5_5	-0.05273	0.01626			lnatural(t-1)
	AR1_5_6	-0.00834	0.00197			lcorn(t-1)
	AR2_5_1	-0.04172	0.02726	-1.53	0.1269	D_lcrude(t-1)
	AR2_5_2	0.5689	0.28579	1.99	0.0474	D_ldiesel(t-1)

	AR2_5_3	-0.43966	0.29103	-1.51	0.1319	D_lngas(t-1)
	AR2_5_4	-0.66344	0.19062	-3.48	0.0006	D_lelect(t-1)
	AR2_5_5	0.19507	0.05111	3.82	0.0002	D_lnatural(t-1)
	AR2_5_6	-0.01672	0.01409	-1.19	0.2361	D_lcorn(t-1)
	AR3_5_1	-0.09913	0.03028	-3.27	0.0012	D_lcrude(t-2)
	AR3_5_2	0.37116	0.32279	1.15	0.2511	D_ldiesel(t-2)
	AR3_5_3	-0.33339	0.32533	-1.02	0.3063	D_lngas(t-2)
	AR3_5_4	0.01508	0.19254	0.08	0.9376	D_lelect(t-2)
	AR3_5_5	-0.02988	0.05141	-0.58	0.5615	D_lnatural(t-2)
	AR3_5_6	0.01328	0.0153	0.87	0.3862	D_lcorn(t-2)
	AR4_5_1	-0.02485	0.03065	-0.81	0.4181	D_lcrude(t-3)
	AR4_5_2	0.197	0.34171	0.58	0.5647	D_ldiesel(t-3)
	AR4_5_3	-0.08108	0.35243	-0.23	0.8182	D_lngas(t-3)
	AR4_5_4	0.49653	0.1897	2.62	0.0093	D_lelect(t-3)
	AR4_5_5	-0.12052	0.05133	-2.35	0.0195	D_lnatural(t-3)
	AR4_5_6	0.0051	0.01518	0.34	0.7372	D_lcorn(t-3)
	AR5_5_1	0.02815	0.03132	0.9	0.3696	D_lcrude(t-4)
	AR5_5_2	-0.1886	0.34742	-0.54	0.5876	D_ldiesel(t-4)
	AR5_5_3	0.30024	0.35992	0.83	0.4048	D_lngas(t-4)
	AR5_5_4	-0.06316	0.18522	-0.34	0.7333	D_lelect(t-4)
	AR5_5_5	-0.18776	0.05112	-3.67	0.0003	D_lnatural(t-4)
	AR5_5_6	-0.00174	0.01533	-0.11	0.9099	D_lcorn(t-4)
	AR6_5_1	-0.05623	0.03114	-1.81	0.072	D_lcrude(t-5)
	AR6_5_2	-0.33548	0.34892	-0.96	0.337	D_ldiesel(t-5)
	AR6_5_3	0.46785	0.36062	1.3	0.1955	D_lngas(t-5)
	AR6_5_4	-0.59806	0.18354	-3.26	0.0012	D_lelect(t-5)
	AR6_5_5	-0.18453	0.05092	-3.62	0.0003	D_lnatural(t-5)
	AR6_5_6	-0.02059	0.01532	-1.34	0.1797	D_lcorn(t-5)
	AR7_5_1	-0.06769	0.03119	-2.17	0.0307	D_lcrude(t-6)
	AR7_5_2	-0.15473	0.33968	-0.46	0.6491	D_ldiesel(t-6)
	AR7_5_3	0.17805	0.35218	0.51	0.6135	D_lngas(t-6)
	AR7_5_4	-0.83489	0.18524	-4.51	0.0001	D_lelect(t-6)
	AR7_5_5	-0.04459	0.05178	-0.86	0.3899	D_lnatural(t-6)
	AR7_5_6	-0.00045	0.01572	-0.03	0.977	D_lcorn(t-6)
	AR8_5_1	-0.02765	0.03063	-0.9	0.3673	D_lcrude(t-7)
	AR8_5_2	0.06715	0.31691	0.21	0.8323	D_ldiesel(t-7)
	AR8_5_3	0.00099	0.3306	0	0.9976	D_lngas(t-7)
	AR8_5_4	-0.61631	0.19524	-3.16	0.0018	D_lelect(t-7)
	AR8_5_5	-0.12649	0.05133	-2.46	0.0143	D_lnatural(t-7)

	AR8_5_6	0.01974	0.01564	1.26	0.2076	D_lcorn(t-7)
	AR9_5_1	0.0436	0.03	1.45	0.1472	D_lcrude(t-8)
	AR9_5_2	0.16909	0.27557	0.61	0.5399	D_ldiesel(t-8)
	AR9_5_3	-0.16666	0.28502	-0.58	0.5592	D_lngas(t-8)
	AR9_5_4	-0.11244	0.20541	-0.55	0.5845	D_lelect(t-8)
	AR9_5_5	-0.10462	0.05221	-2	0.0459	D_lnatural(t-8)
	AR9_5_6	0.0196	0.01533	1.28	0.2021	D_lcorn(t-8)
	AR10_5_1	-0.0664	0.02949	-2.25	0.025	D_lcrude(t-9)
	AR10_5_2	0.00675	0.20135	0.03	0.9733	D_ldiesel(t-9)
	AR10_5_3	0.0956	0.2126	0.45	0.6533	D_lngas(t-9)
	AR10_5_4	-0.35093	0.1994	-1.76	0.0794	D_lelect(t-9)
	AR10_5_5	-0.1424	0.05116	-2.78	0.0057	D_lnatural(t-9)
	AR10_5_6	-0.02427	0.014	-1.73	0.084	D_lcorn(t-9)
D_lcorn	**AR1_6_1**	0.14397	0.04761			lcrude(t-1)
	AR1_6_2	-2.53767	0.82977			ldiesel(t-1)
	AR1_6_3	2.42084	0.78997			lngas(t-1)
	AR1_6_4	-0.16104	0.0564			lelect(t-1)
	AR1_6_5	-0.15437	0.05873			lnatural(t-1)
	AR1_6_6	-0.02183	0.00713			lcorn(t-1)
	AR2_6_1	-0.23576	0.09846	-2.39	0.0172	D_lcrude(t-1)
	AR2_6_2	1.51244	1.03213	1.47	0.1438	D_ldiesel(t-1)
	AR2_6_3	-1.87756	1.05109	-1.79	0.075	D_lngas(t-1)
	AR2_6_4	-0.84182	0.68844	-1.22	0.2223	D_lelect(t-1)
	AR2_6_5	0.13449	0.1846	0.73	0.4668	D_lnatural(t-1)
	AR2_6_6	0.45917	0.05089	9.02	0.0001	D_lcorn(t-1)
	AR3_6_1	0.13596	0.10935	1.24	0.2147	D_lcrude(t-2)
	AR3_6_2	1.99536	1.16578	1.71	0.088	D_ldiesel(t-2)
	AR3_6_3	-1.99695	1.17496	-1.7	0.0902	D_lngas(t-2)
	AR3_6_4	1.83497	0.69536	2.64	0.0087	D_lelect(t-2)
	AR3_6_5	0.15684	0.18568	0.84	0.3989	D_lnatural(t-2)
	AR3_6_6	-0.08075	0.05525	-1.46	0.1449	D_lcorn(t-2)
	AR4_6_1	-0.16821	0.11069	-1.52	0.1296	D_lcrude(t-3)
	AR4_6_2	2.33431	1.2341	1.89	0.0595	D_ldiesel(t-3)
	AR4_6_3	-1.90481	1.27282	-1.5	0.1355	D_lngas(t-3)
	AR4_6_4	-0.51631	0.6851	-0.75	0.4516	D_lelect(t-3)
	AR4_6_5	0.04962	0.18537	0.27	0.7891	D_lnatural(t-3)
	AR4_6_6	-0.07968	0.05483	-1.45	0.1472	D_lcorn(t-3)
	AR5_6_1	0.08431	0.11313	0.75	0.4567	D_lcrude(t-4)
	AR5_6_2	0.89247	1.25472	0.71	0.4774	D_ldiesel(t-4)

	AR5_6_3	-1.44334	1.29987	-1.11	0.2677	D_lngas(t-4)
	AR5_6_4	-1.04856	0.66893	-1.57	0.118	D_lelect(t-4)
	AR5_6_5	0.10279	0.18464	0.56	0.5781	D_lnatural(t-4)
	AR5_6_6	0.07928	0.05537	1.43	0.1532	D_lcorn(t-4)
	AR6_6_1	-0.02233	0.11248	-0.2	0.8427	D_lcrude(t-5)
	AR6_6_2	0.60196	1.26014	0.48	0.6332	D_ldiesel(t-5)
	AR6_6_3	-0.11495	1.30241	-0.09	0.9297	D_lngas(t-5)
	AR6_6_4	-0.70966	0.66288	-1.07	0.2852	D_lelect(t-5)
	AR6_6_5	-0.04079	0.18389	-0.22	0.8246	D_lnatural(t-5)
	AR6_6_6	-0.0191	0.05531	-0.35	0.7301	D_lcorn(t-5)
	AR7_6_1	-0.22101	0.11263	-1.96	0.0506	D_lcrude(t-6)
	AR7_6_2	0.98454	1.22676	0.8	0.4228	D_ldiesel(t-6)
	AR7_6_3	-0.95446	1.27192	-0.75	0.4536	D_lngas(t-6)
	AR7_6_4	0.46347	0.669	0.69	0.489	D_lelect(t-6)
	AR7_6_5	0.39617	0.18702	2.12	0.0349	D_lnatural(t-6)
	AR7_6_6	0.06431	0.05677	1.13	0.2582	D_lcorn(t-6)
	AR8_6_1	0.17705	0.11063	1.6	0.1105	D_lcrude(t-7)
	AR8_6_2	0.63585	1.14454	0.56	0.5789	D_ldiesel(t-7)
	AR8_6_3	-1.00042	1.19399	-0.84	0.4027	D_lngas(t-7)
	AR8_6_4	0.0325	0.70511	0.05	0.9633	D_lelect(t-7)
	AR8_6_5	-0.16658	0.18539	-0.9	0.3696	D_lnatural(t-7)
	AR8_6_6	0.07919	0.05647	1.4	0.1618	D_lcorn(t-7)
	AR9_6_1	-0.02845	0.10835	-0.26	0.7931	D_lcrude(t-8)
	AR9_6_2	1.12354	0.99526	1.13	0.2598	D_ldiesel(t-8)
	AR9_6_3	-0.81028	1.02937	-0.79	0.4318	D_lngas(t-8)
	AR9_6_4	1.4159	0.74184	1.91	0.0572	D_lelect(t-8)
	AR9_6_5	0.06783	0.18855	0.36	0.7193	D_lnatural(t-8)
	AR9_6_6	-0.1844	0.05537	-3.33	0.001	D_lcorn(t-8)
	AR10_6_1	-0.2264	0.10652	-2.13	0.0343	D_lcrude(t-9)
	AR10_6_2	0.99744	0.72721	1.37	0.1712	D_ldiesel(t-9)
	AR10_6_3	-1.06712	0.76781	-1.39	0.1656	D_lngas(t-9)
	AR10_6_4	0.81981	0.72015	1.14	0.2558	D_lelect(t-9)
	AR10_6_5	0.01739	0.18477	0.09	0.9251	D_lnatural(t-9)
	AR10_6_6	0.11061	0.05057	2.19	0.0295	D_lcorn(t-9)

Information Criteria	
AICC	-50.8122
HQC	-49.7288
AIC	-51.1286
SBC	-47.603
FPEC	6.32E-23

Infinite Order AR Representation							
Lag	Variable	lcrude	ldiesel	lngas	lelect	lnatural	lcorn
1	Lcrude	1.51936	0.57119	-1.11986	0.22684	0.10191	0.0077
	Ldiesel	0.17895	0.75484	0.3667	-0.21821	-0.05764	0.01081
	Lngas	0.16548	0.67381	0.4259	-0.23645	-0.05654	0.01493
	Lelect	0.00823	0.02248	-0.03624	0.72127	0.04555	0.00231
	Lnatural	0.01128	-0.37983	0.47029	-0.72832	1.14234	-0.02507
	Lcorn	-0.0918	-1.02523	0.54328	-1.00286	-0.01987	1.43734
2	Lcrude	-0.42188	-0.13407	0.40113	-0.4317	-0.18687	-0.00824
	Ldiesel	-0.13836	-0.18107	-0.28211	0.1204	0.06142	-0.01293
	Lngas	-0.12572	-0.32302	-0.14867	0.17956	0.09949	-0.01933
	Lelect	-0.0229	0.03094	-0.01323	0.16912	-0.00779	-0.00536
	Lnatural	-0.05741	-0.19773	0.10627	0.67852	-0.22496	0.03
	Lcorn	0.37172	0.48292	-0.11939	2.67679	0.02235	-0.53992
3	Lcrude	-0.19118	-1.17297	1.79702	-0.12205	0.19759	-0.00024
	Ldiesel	0.08901	-0.07369	0.2095	0.1928	0.00165	0.02815
	Lngas	0.06707	-0.22476	0.40788	0.12622	-0.02259	0.03611
	Lelect	0.03427	-0.06934	0.00415	-0.08015	-0.00167	0.0054
	Lnatural	0.07428	-0.17416	0.25231	0.48145	-0.09064	-0.00818
	Lcorn	-0.30417	0.33895	0.09214	-2.35128	-0.10722	0.00107
4	Lcrude	-0.02503	0.10594	-0.43074	0.54766	0.08979	-0.00441
	Ldiesel	-0.13414	0.09549	0.1489	-0.34375	0.02951	-0.05577
	Lngas	-0.11994	-0.04215	0.25423	-0.3045	0.01104	-0.05261
	Lelect	-0.01321	0.04295	0.01972	0.00791	-0.02034	0.00074
	Lnatural	0.053	-0.3856	0.38132	-0.55969	-0.06724	-0.00684
	Lcorn	0.25252	-1.44184	0.46147	-0.53225	0.05317	0.15896
5	Lcrude	0.23632	0.36635	-0.79872	0.30639	-0.3961	0.09835
	Ldiesel	0.03107	-0.13022	-0.17168	0.01087	-0.06674	0.06814
	Lngas	0.03779	-0.18948	-0.0985	0.03066	-0.08495	0.05059
	Lelect	-0.0054	0.00625	-0.02027	-0.01176	0.00883	-0.00238

	Lnatural	-0.08437	-0.14688	0.16761	-0.5349	0.00323	-0.01886
	Lcorn	-0.10664	-0.29051	1.3284	0.33891	-0.14358	-0.09838
6	**Lcrude**	-0.15673	0.58455	-0.12615	-0.54778	-0.10062	-0.11003
	Ldiesel	0.04243	0.34676	-0.20865	0.09636	-0.09115	-0.03319
	Lngas	0.0228	0.33673	-0.18982	0.07984	-0.05304	-0.02563
	Lelect	-0.00082	-0.06573	0.07517	-0.17344	-0.03449	0.00098
	Lnatural	-0.01146	0.18075	-0.2898	-0.23683	0.13995	0.02014
	Lcorn	-0.19868	0.38258	-0.83951	1.17313	0.43696	0.08341
7	**Lcrude**	0.05612	0.20517	-0.55606	-0.5406	0.74343	0.00576
	Ldiesel	-0.00689	0.07202	-0.03643	-0.50404	0.19564	-0.01837
	Lngas	0.00759	0.0565	-0.01138	-0.42625	0.18298	-0.01433
	Lelect	0.00193	0.0526	-0.06466	0.05594	0.00684	-0.00424
	Lnatural	0.04003	0.22188	-0.17706	0.21858	-0.0819	0.0202
	Lcorn	0.39806	-0.34869	-0.04596	-0.43097	-0.56276	0.01488
8	**Lcrude**	-0.00234	0.82345	-0.46252	0.67901	-0.37087	0.05695
	Ldiesel	-0.05178	0.16355	-0.21245	0.44097	-0.0075	0.00581
	Lngas	-0.04928	0.1245	-0.18038	0.41243	0.01212	0.00473
	Lelect	-0.00099	0.03558	-0.01865	0.02517	0.03836	0.00334
	Lnatural	0.07125	0.10194	-0.16765	0.50387	0.02187	-0.00015
	Lcorn	-0.20549	0.48769	0.19014	1.3834	0.23441	-0.26359
9	**Lcrude**	0.03312	-0.47963	0.26479	-0.24479	-0.09551	-0.05577
	Ldiesel	0.02957	-0.33623	0.37127	-0.13824	-0.08613	0.01074
	Lngas	0.0127	-0.45521	0.51449	-0.13	-0.11582	0.00241
	Lelect	0.00834	-0.09706	0.06584	0.06078	0.0508	-0.00362
	Lnatural	-0.11	-0.16234	0.26225	-0.2385	-0.03778	-0.04387
	Lcorn	-0.19796	-0.1261	-0.25685	-0.59609	-0.05044	0.29501
10	**Lcrude**	-0.10532	0.13465	0.07616	0.18751	0.08183	0.01845
	Ldiesel	-0.01584	-0.14813	0.23603	0.31083	-0.00104	-0.00732
	Lngas	-0.00375	-0.22931	0.29037	0.24715	0.01505	0.00062
	Lelect	-0.01082	0.02968	0.0115	0.21278	-0.07439	0.00228
	Lnatural	0.0664	-0.00675	-0.0956	0.35093	0.1424	0.02427
	Lcorn	0.2264	-0.99744	1.06712	-0.81981	-0.01739	-0.11061
11	**Lcrude**	0	0	0	0	0	0
	Ldiesel	0	0	0	0	0	0
	Lngas	0	0	0	0	0	0
	Lelect	0	0	0	0	0	0
	Lnatural	0	0	0	0	0	0
	Lcorn	0	0	0	0	0	0
12	**Lcrude**	0	0	0	0	0	0
	Ldiesel	0	0	0	0	0	0
	Lngas	0	0	0	0	0	0

	Lelect	0	0	0	0	0	0
	Lnatural	0	0	0	0	0	0
	Lcorn	0	0	0	0	0	0
Simple Impulse Response							
	Variable						
Lag	**Response\Impulse**	**lcrude**	**ldiesel**	**lngas**	**lelect**	**lnatural**	**lcorn**
1	**Lcrude**	1.51936	0.57119	-1.11986	0.22684	0.10191	0.0077
	Ldiesel	0.17895	0.75484	0.3667	-0.21821	-0.05764	0.01081
	Lngas	0.16548	0.67381	0.4259	-0.23645	-0.05654	0.01493
	Lelect	0.00823	0.02248	-0.03624	0.72127	0.04555	0.00231
	Lnatural	0.01128	-0.37983	0.47029	-0.72832	1.14234	-0.02507
	Lcorn	-0.0918	-1.02523	0.54328	-1.00286	-0.01987	1.43734
2	**Lcrude**	1.80579	0.36886	-1.52397	0.13478	0.12494	0.00194
	Ldiesel	0.32585	0.74392	-0.06286	-0.21668	-0.06059	0.01857
	Lngas	0.31281	0.56795	0.08458	-0.17498	-0.02221	0.01793
	Lelect	-0.00615	0.02473	-0.0331	0.6594	0.07864	-0.00176
	Lnatural	-0.02122	-0.58568	0.70466	-0.6794	1.04377	-0.03335
	Lcorn	-0.00173	-1.46593	0.64672	0.60091	-0.05557	1.52053
3	**Lcrude**	1.78121	-0.89117	-0.06237	-0.08841	0.21056	-0.00571
	Ldiesel	0.48893	0.36147	-0.12015	0.02087	-0.01961	0.04076
	Lngas	0.45227	0.15505	0.11581	-0.02698	0.00579	0.04505
	Lelect	0.01004	-0.06877	0.01551	0.49268	0.09849	-0.00125
	Lnatural	-0.00645	-0.87627	1.03458	-0.16029	0.83266	-0.03238
	Lcorn	0.07332	-1.16762	0.6213	0.44242	-0.07314	1.4154
4	**Lcrude**	1.58109	-1.10712	0.59903	-0.15038	0.3833	-0.0275
	Ldiesel	0.47511	0.06985	0.23412	-0.25098	0.07006	0.02121
	Lngas	0.44066	-0.11038	0.43098	-0.26004	0.06585	0.03137
	Lelect	0.00605	-0.06711	0.03236	0.42373	0.09215	0.00017
	Lnatural	0.07638	-1.25043	1.47892	-0.08288	0.56784	-0.02862
	Lcorn	0.29726	-1.83415	1.02077	-0.80705	-0.16502	1.36112
5	**Lcrude**	1.5354	-0.99901	0.37576	0.25069	0.29589	0.0416
	Ldiesel	0.41054	-0.08853	0.38848	-0.50319	0.07881	0.03283
	Lngas	0.38643	-0.25172	0.55352	-0.45569	0.05122	0.03017
	Lelect	0.01229	-0.07609	0.04172	0.3492	0.0804	0.00145
	Lnatural	0.1204	-1.32556	1.54507	-0.52904	0.32916	-0.04977
	Lcorn	0.54197	-3.24601	2.27569	-1.9845	-0.40727	1.33601
6	**Lcrude**	1.45072	-0.60536	-0.19248	0.66994	-0.0136	0.11612
	Ldiesel	0.38436	-0.02218	0.22238	-0.46566	-0.07304	0.05926
	Lngas	0.35255	-0.10259	0.31937	-0.39683	-0.06925	0.05738
	Lelect	0.00921	-0.17055	0.16399	0.08597	0.02787	0.00059

	Lnatural	0.13555	-1.16336	1.209	-1.22191	0.23692	-0.06191
	Lcorn	0.62682	-3.27115	2.26997	-1.31397	-0.29228	1.37268
7	**Lcrude**	1.44195	-0.17267	-0.93185	0.61914	0.21218	0.15144
	Ldiesel	0.40623	0.17425	-0.03697	-0.4946	-0.08233	0.07501
	Lngas	0.38257	0.06698	0.11166	-0.45736	-0.08126	0.0744
	Lelect	0.00872	-0.09535	0.07933	-0.00908	-0.01443	-0.00248
	Lnatural	0.11018	-0.97572	0.99183	-1.62358	0.15987	-0.05021
	Lcorn	0.83937	-3.80834	2.56056	-1.00686	-0.27966	1.43907
8	**Lcrude**	1.38517	0.53584	-1.56442	0.33477	0.39697	0.15373
	Ldiesel	0.41469	0.47088	-0.38165	-0.39813	0.03088	0.05861
	Lngas	0.39329	0.32879	-0.21544	-0.43757	0.04965	0.05957
	Lelect	0.01385	-0.06544	0.05349	-0.09883	-0.00641	-0.00332
	Lnatural	0.13623	-0.77534	0.80286	-1.3489	0.12048	-0.01413
	Lcorn	0.92935	-4.20203	2.92435	0.89289	-0.40529	1.3268
9	**Lcrude**	1.38077	0.70591	-1.76602	-0.22196	0.40705	0.14798
	Ldiesel	0.39781	0.24413	-0.19616	-0.65299	0.05427	0.04577
	Lngas	0.36168	0.04607	0.03931	-0.60546	0.05108	0.03842
	Lelect	0.02008	-0.12373	0.1067	-0.11629	0.0497	-0.00537
	Lnatural	0.0976	-0.72517	0.78097	-1.09911	-0.00582	-0.01341
	Lcorn	0.94708	-4.08216	2.60724	2.7695	-0.59162	1.2962
10	**Lcrude**	1.355	1.30185	-2.23042	-0.16841	0.40103	0.16058
	Ldiesel	0.3625	0.07043	0.03691	-0.45962	0.00133	0.03996
	Lngas	0.34088	-0.09567	0.23212	-0.42726	0.00612	0.04194
	Lelect	0.01225	-0.08041	0.07544	0.06451	0.03594	-0.00597
	Lnatural	0.09825	-0.49369	0.50991	-0.33133	-0.04762	-0.02578
	Lcorn	0.89464	-4.90889	3.45849	3.0768	-0.61465	1.28546
11	**Lcrude**	1.36328	1.81263	-2.52166	0.1269	0.42597	0.17969
	Ldiesel	0.36542	0.29085	-0.03543	-0.08412	0.02011	0.04675
	Lngas	0.33914	0.11702	0.16371	-0.08049	0.02839	0.04562
	Lelect	0.00692	-0.05645	0.07151	0.24915	0.03096	-0.00551
	Lnatural	0.13362	-0.43606	0.40535	0.07443	0.16865	-0.04752
	Lcorn	0.95468	-5.67801	3.92668	2.85887	-0.35944	1.30552
12	**Lcrude**	1.32138	1.78392	-2.26964	0.16097	0.4216	0.17296
	Ldiesel	0.38651	0.47101	-0.13551	0.20409	0.0359	0.05628
	Lngas	0.36007	0.28513	0.05674	0.21568	0.04111	0.05467
	Lelect	0.0039	-0.02168	0.05759	0.48631	0.04112	-0.00653
	Lnatural	0.16043	-0.49149	0.40854	0.29319	0.49516	-0.0683
	Lcorn	1.06822	-5.97259	3.96293	2.58553	-0.21559	1.3021

Forecasts						
Variable	Obs	Time	Forecast	Standard Error	95% Confidence Limits	
lcrude	385	Jan-13	0.20003	0.03506	0.13131	0.26875
	386	Feb-13	0.17804	0.06112	0.05824	0.29784
	387	Mar-13	0.15504	0.08359	-0.0088	0.31888
	388	Apr-13	0.1751	0.10123	-0.0233	0.3735
	389	May-13	0.18171	0.11408	-0.04189	0.4053
	390	Jun-13	0.1988	0.12467	-0.04554	0.44315
	391	Jul-13	0.20865	0.13315	-0.05232	0.46961
	392	Aug-13	0.21489	0.14067	-0.06081	0.49059
	393	Sep-13	0.21405	0.14742	-0.07488	0.50299
	394	Oct-13	0.21027	0.15385	-0.09127	0.5118
	395	Nov-13	0.20114	0.16003	-0.11252	0.5148
	396	Dec-13	0.19119	0.16645	-0.13505	0.51742
	397	Jan-14	0.18321	0.17252	-0.15492	0.52134
	398	Feb-14	0.18316	0.17785	-0.16542	0.53175
	399	Mar-14	0.19072	0.18258	-0.16713	0.54857
	400	Apr-14	0.20271	0.18711	-0.16402	0.56944
	401	May-14	0.21407	0.1913	-0.16086	0.589
	402	Jun-14	0.22247	0.19516	-0.16003	0.60497
	403	Jul-14	0.22779	0.19882	-0.1619	0.61748
	404	Aug-14	0.22704	0.20248	-0.16982	0.62389
	405	Sep-14	0.22068	0.20609	-0.18325	0.62461
	406	Oct-14	0.2112	0.20954	-0.19948	0.62188
	407	Nov-14	0.20134	0.21287	-0.21588	0.61856
	408	Dec-14	0.19332	0.21616	-0.23035	0.617
	409	Jan-15	0.18855	0.2194	-0.24147	0.61858
	410	Feb-15	0.18947	0.22255	-0.24673	0.62566
	411	Mar-15	0.19591	0.22565	-0.24636	0.63818
	412	Apr-15	0.20498	0.22875	-0.24335	0.65331
	413	May-15	0.21406	0.23183	-0.24031	0.66843
	414	Jun-15	0.22077	0.2349	-0.23962	0.68116
	415	Jul-15	0.2237	0.23798	-0.24273	0.69014
	416	Aug-15	0.22177	0.24108	-0.25075	0.69428
	417	Sep-15	0.21577	0.24417	-0.2628	0.69434
	418	Oct-15	0.20733	0.24723	-0.27722	0.69189

	419	**Nov-15**	0.19842	0.25026	-0.29208	0.68892
	420	**Dec-15**	0.19127	0.25327	-0.30513	0.68766
Idiesel	**385**	**Jan-13**	0.35915	0.01182	0.33598	0.38231
	386	**Feb-13**	0.37053	0.02105	0.32927	0.41179
	387	**Mar-13**	0.36617	0.02732	0.31262	0.41972
	388	**Apr-13**	0.3711	0.03332	0.3058	0.4364
	389	**May-13**	0.37306	0.03835	0.29789	0.44823
	390	**Jun-13**	0.37434	0.04194	0.29214	0.45654
	391	**Jul-13**	0.37662	0.04476	0.28889	0.46434
	392	**Aug-13**	0.37478	0.0476	0.28148	0.46808
	393	**Sep-13**	0.36698	0.05018	0.26863	0.46532
	394	**Oct-13**	0.35764	0.05237	0.255	0.46028
	395	**Nov-13**	0.35312	0.05419	0.24691	0.45932
	396	**Dec-13**	0.35243	0.05623	0.24223	0.46264
	397	**Jan-14**	0.35307	0.05857	0.23827	0.46787
	398	**Feb-14**	0.35769	0.06083	0.23846	0.47692
	399	**Mar-14**	0.36506	0.06286	0.24185	0.48826
	400	**Apr-14**	0.37447	0.06476	0.24755	0.50139
	401	**May-14**	0.38087	0.06658	0.25038	0.51136
	402	**Jun-14**	0.3836	0.06831	0.24972	0.51748
	403	**Jul-14**	0.38205	0.06997	0.24491	0.51918
	404	**Aug-14**	0.37662	0.07162	0.23624	0.517
	405	**Sep-14**	0.36867	0.07323	0.22513	0.51221
	406	**Oct-14**	0.36019	0.07475	0.21367	0.5067
	407	**Nov-14**	0.35412	0.07619	0.20479	0.50345
	408	**Dec-14**	0.35144	0.07762	0.19931	0.50357
	409	**Jan-15**	0.35254	0.07903	0.19766	0.50743
	410	**Feb-15**	0.35774	0.08038	0.2002	0.51528
	411	**Mar-15**	0.3659	0.08169	0.20579	0.52601
	412	**Apr-15**	0.37447	0.08299	0.21181	0.53713
	413	**May-15**	0.38082	0.08428	0.21564	0.546
	414	**Jun-15**	0.38354	0.08555	0.21586	0.55122
	415	**Jul-15**	0.38209	0.08684	0.21189	0.5523
	416	**Aug-15**	0.37657	0.08814	0.20382	0.54932
	417	**Sep-15**	0.36869	0.08942	0.19344	0.54395
	418	**Oct-15**	0.36066	0.09065	0.18299	0.53833
	419	**Nov-15**	0.35444	0.09185	0.17442	0.53447
	420	**Dec-15**	0.35142	0.09303	0.16908	0.53376
Ingas	**385**	**Jan-13**	0.39365	0.01149	0.37114	0.41616
	386	**Feb-13**	0.40523	0.02036	0.36532	0.44514
	387	**Mar-13**	0.40318	0.02627	0.35168	0.45467

	388	**Apr-13**	0.40778	0.03186	0.34534	0.47023
	389	**May-13**	0.41003	0.03659	0.33831	0.48175
	390	**Jun-13**	0.41054	0.03998	0.33218	0.4889
	391	**Jul-13**	0.41248	0.04256	0.32906	0.4959
	392	**Aug-13**	0.41047	0.04535	0.32159	0.49935
	393	**Sep-13**	0.40306	0.04785	0.30928	0.49685
	394	**Oct-13**	0.39336	0.04981	0.29573	0.49099
	395	**Nov-13**	0.38973	0.05158	0.28864	0.49082
	396	**Dec-13**	0.38882	0.05351	0.28394	0.4937
	397	**Jan-14**	0.38932	0.05571	0.28014	0.49851
	398	**Feb-14**	0.39439	0.05781	0.28109	0.50768
	399	**Mar-14**	0.40195	0.05969	0.28496	0.51895
	400	**Apr-14**	0.41042	0.06148	0.28993	0.53091
	401	**May-14**	0.41648	0.06319	0.29263	0.54034
	402	**Jun-14**	0.41905	0.06481	0.29202	0.54608
	403	**Jul-14**	0.41721	0.06638	0.28711	0.54731
	404	**Aug-14**	0.41202	0.06795	0.27885	0.5452
	405	**Sep-14**	0.4043	0.06947	0.26815	0.54045
	406	**Oct-14**	0.3964	0.07089	0.25746	0.53534
	407	**Nov-14**	0.39058	0.07224	0.24899	0.53217
	408	**Dec-14**	0.3883	0.07359	0.24407	0.53253
	409	**Jan-15**	0.38947	0.07491	0.24264	0.5363
	410	**Feb-15**	0.39452	0.07619	0.24519	0.54385
	411	**Mar-15**	0.40237	0.07743	0.25062	0.55413
	412	**Apr-15**	0.41044	0.07865	0.25628	0.5646
	413	**May-15**	0.41633	0.07987	0.2598	0.57286
	414	**Jun-15**	0.41871	0.08107	0.25981	0.57761
	415	**Jul-15**	0.41716	0.08229	0.25587	0.57845
	416	**Aug-15**	0.4118	0.08352	0.24811	0.5755
	417	**Sep-15**	0.40432	0.08472	0.23827	0.57038
	418	**Oct-15**	0.39681	0.08588	0.22848	0.56514
	419	**Nov-15**	0.39102	0.08702	0.22047	0.56157
	420	**Dec-15**	0.38832	0.08813	0.21558	0.56106
lelect	**385**	**Jan-13**	0.41825	0.00368	0.41103	0.42546
	386	**Feb-13**	0.42098	0.00462	0.41193	0.43003
	387	**Mar-13**	0.42561	0.00542	0.41499	0.43623
	388	**Apr-13**	0.43232	0.00597	0.42063	0.44402
	389	**May-13**	0.43819	0.00636	0.42573	0.45066
	390	**Jun-13**	0.4442	0.00663	0.43122	0.45719
	391	**Jul-13**	0.44325	0.00668	0.43015	0.45634
	392	**Aug-13**	0.44166	0.0067	0.42852	0.45479

	393	Sep-13	0.43664	0.00673	0.42345	0.44983
	394	Oct-13	0.43043	0.00682	0.41706	0.4438
	395	Nov-13	0.42401	0.00687	0.41053	0.43748
	396	Dec-13	0.42017	0.00698	0.40649	0.43384
	397	Jan-14	0.41981	0.00727	0.40556	0.43406
	398	Feb-14	0.42206	0.00771	0.40694	0.43718
	399	Mar-14	0.42751	0.00821	0.41143	0.44359
	400	Apr-14	0.43437	0.00864	0.41744	0.45131
	401	May-14	0.44057	0.00894	0.42305	0.4581
	402	Jun-14	0.44458	0.0091	0.42674	0.46243
	403	Jul-14	0.4449	0.00917	0.42693	0.46288
	404	Aug-14	0.44236	0.00923	0.42427	0.46044
	405	Sep-14	0.43716	0.0093	0.41893	0.45539
	406	Oct-14	0.43071	0.00939	0.41231	0.44912
	407	Nov-14	0.42501	0.00947	0.40644	0.44358
	408	Dec-14	0.42131	0.00961	0.40248	0.44015
	409	Jan-15	0.4208	0.00986	0.40147	0.44013
	410	Feb-15	0.42351	0.01022	0.40348	0.44355
	411	Mar-15	0.42901	0.01062	0.4082	0.44982
	412	Apr-15	0.43571	0.01098	0.41419	0.45722
	413	May-15	0.44164	0.01124	0.41961	0.46367
	414	Jun-15	0.44528	0.0114	0.42293	0.46764
	415	Jul-15	0.44577	0.01151	0.42322	0.46833
	416	Aug-15	0.44306	0.0116	0.42032	0.4658
	417	Sep-15	0.43791	0.01171	0.41496	0.46086
	418	Oct-15	0.43169	0.01182	0.40851	0.45487
	419	Nov-15	0.42611	0.01195	0.40268	0.44954
	420	Dec-15	0.42262	0.01213	0.39885	0.4464
Inatural	385	Jan-13	-0.02667	0.01448	-0.05504	0.0017
	386	Feb-13	-0.02546	0.02213	-0.06884	0.01792
	387	Mar-13	-0.00385	0.02703	-0.05683	0.04912
	388	Apr-13	0.03326	0.02993	-0.0254	0.09192
	389	May-13	0.07277	0.03178	0.01049	0.13505
	390	Jun-13	0.1073	0.03319	0.04225	0.17235
	391	Jul-13	0.1296	0.0344	0.06218	0.19702
	392	Aug-13	0.13092	0.03542	0.0615	0.20035
	393	Sep-13	0.11348	0.03625	0.04244	0.18452
	394	Oct-13	0.07752	0.03677	0.00545	0.14959
	395	Nov-13	0.03899	0.03704	-0.0336	0.11159
	396	Dec-13	0.01008	0.03751	-0.06343	0.08359
	397	Jan-14	-0.00716	0.03879	-0.08318	0.06886

	398	**Feb-14**	-0.00509	0.04077	-0.085	0.07482
	399	**Mar-14**	0.01278	0.04279	-0.0711	0.09665
	400	**Apr-14**	0.04266	0.04455	-0.04466	0.12998
	401	**May-14**	0.07378	0.0459	-0.01619	0.16374
	402	**Jun-14**	0.10038	0.04693	0.00841	0.19235
	403	**Jul-14**	0.11457	0.04784	0.0208	0.20834
	404	**Aug-14**	0.11309	0.0488	0.01745	0.20873
	405	**Sep-14**	0.09494	0.0496	-0.00228	0.19215
	406	**Oct-14**	0.06625	0.05018	-0.0321	0.16459
	407	**Nov-14**	0.03571	0.05058	-0.06342	0.13483
	408	**Dec-14**	0.01185	0.05104	-0.08819	0.11189
	409	**Jan-15**	0.00098	0.05179	-0.10054	0.10249
	410	**Feb-15**	0.00593	0.05286	-0.09768	0.10954
	411	**Mar-15**	0.02461	0.05406	-0.08135	0.13056
	412	**Apr-15**	0.0516	0.05514	-0.05649	0.15968
	413	**May-15**	0.07932	0.05596	-0.03036	0.189
	414	**Jun-15**	0.1008	0.05657	-0.01007	0.21168
	415	**Jul-15**	0.11043	0.05715	-0.00158	0.22244
	416	**Aug-15**	0.10514	0.05778	-0.00812	0.21839
	417	**Sep-15**	0.08629	0.0584	-0.02816	0.20074
	418	**Oct-15**	0.05923	0.05889	-0.05619	0.17465
	419	**Nov-15**	0.03167	0.05928	-0.08451	0.14785
	420	**Dec-15**	0.0112	0.05967	-0.10576	0.12815
lcorn	**385**	**Jan-13**	-0.17832	0.05228	-0.2808	-0.07585
	386	**Feb-13**	-0.15553	0.0917	-0.33526	0.02421
	387	**Mar-13**	-0.15157	0.12133	-0.38938	0.08624
	388	**Apr-13**	-0.14929	0.14204	-0.42769	0.1291
	389	**May-13**	-0.15293	0.15922	-0.465	0.15915
	390	**Jun-13**	-0.18529	0.1753	-0.52887	0.1583
	391	**Jul-13**	-0.2127	0.19073	-0.58653	0.16113
	392	**Aug-13**	-0.23809	0.20691	-0.64363	0.16745
	393	**Sep-13**	-0.26204	0.22035	-0.69391	0.16983
	394	**Oct-13**	-0.27049	0.23276	-0.72668	0.18571
	395	**Nov-13**	-0.25623	0.2444	-0.73523	0.22278
	396	**Dec-13**	-0.22797	0.25585	-0.72943	0.27349
	397	**Jan-14**	-0.20549	0.26706	-0.72891	0.31793
	398	**Feb-14**	-0.17988	0.27818	-0.7251	0.36535
	399	**Mar-14**	-0.16883	0.28915	-0.73555	0.39789
	400	**Apr-14**	-0.17315	0.29973	-0.76061	0.41431
	401	**May-14**	-0.18815	0.31003	-0.7958	0.4195
	402	**Jun-14**	-0.21007	0.31988	-0.83702	0.41688

	403	**Jul-14**	-0.23595	0.32934	-0.88143	0.40954
	404	**Aug-14**	-0.25907	0.33851	-0.92253	0.40439
	405	**Sep-14**	-0.27054	0.34741	-0.95146	0.41038
	406	**Oct-14**	-0.26907	0.35608	-0.96698	0.42884
	407	**Nov-14**	-0.25469	0.36461	-0.96932	0.45994
	408	**Dec-14**	-0.23	0.37294	-0.96096	0.50095
	409	**Jan-15**	-0.20236	0.38105	-0.94921	0.54448
	410	**Feb-15**	-0.17846	0.38911	-0.9411	0.58418
	411	**Mar-15**	-0.16551	0.39714	-0.94389	0.61287
	412	**Apr-15**	-0.16629	0.40507	-0.96022	0.62763
	413	**May-15**	-0.17933	0.41275	-0.9883	0.62964
	414	**Jun-15**	-0.20088	0.42015	-1.02436	0.6226
	415	**Jul-15**	-0.22544	0.42731	-1.06296	0.61208
	416	**Aug-15**	-0.24708	0.43431	-1.09831	0.60415
	417	**Sep-15**	-0.25976	0.44118	-1.12446	0.60494
	418	**Oct-15**	-0.25955	0.44791	-1.13743	0.61834
	419	**Nov-15**	-0.24627	0.45449	-1.13705	0.64451
	420	**Dec-15**	-0.22321	0.46096	-1.12667	0.68024

E1: SAS Code for Time Series Analysis

***Please note that all bolded texts are notes describing parts of the code**
We initially define and import the dataset into SAS from an excel sheet.;

```
data final;
set work.series;
```

***We then transform all the variables to logs and view the dataset that has been transformed to logs.;**

```
lcrude=log(Crude);
ldiesel=log(Diesel);
lngas=log(Gasoline);
lelect=log(Electricity);
lnatural=log(Natural);
lcorn=log(Corn);

proc print data= final;
run;
```

***Univariate analysis: This is how we carry out the univariate ARIMA analysis. We use the Augmented Dickey Fuller test to test for stationarity and from the respective plots, using the eyeball method and AIC criteria, we identify the suitable ARIMA model;**

```
   ods graphics on;
  proc arima data=final plots;
 identify var=lcrude;
 identify var =ldiesel;
 identify var = lngas;
 identify var = lelect;
 identify var = lnatural;
```

```
 identify var = lcorn;
run;
proc arima data= final plots;
                    *IDENTIFY VAR=lcrude(1) stationarity=(adf=(1));
   *estimate p=3 q=1;
                    *identify var=ldiesel(1) stationarity=(adf=(1));
                    *estimate p=2 q=1;
                    *identify var=lngas (1) stationarity=(adf=(1));
                    *estimate p=2;
                    *identify var=lelect(1,12)stationarity=(adf=(1,12));
                    *estimate q=(1) (12);
                    *identify var=lnatural (1,12)stationarity=(adf=(1,12));
                    *estimate q=(1) (12);
                    *identify var=lcorn (1) stationarity=(adf=(1));
                    *estimate p=2 q=1;
run;
```

***Here we estimate relevant descriptive statistics;**

```
proc corr pearson spearman kendall;
    var lcrude ldiesel lngas lelect;
  run;
```

***In this section, we carry out vector autoregressing estimation. We initially test for the presence of cointegration in the code below.;**

*******VAR***************

***Cointegration Test: and test for the p (order);**

```
 proc varmax data=final;
    model lcrude ldiesel lngas lelect lnatural lcorn / p=10 print=(parcoef pcorr pcancorr) lagmax=15 noint dftest
cointtest=(johansen);
  run;
```

***Identification of lag-length;**

```
 ods graphics on;
 proc varmax data=crude   plots =(forecast model);
      id years interval=obs;
      model  ldiesel lcrude lngas lelect / p=1 print =(parcoef pcorr pcancorr) lagmax=6 noint cointtest=(johansen);
      run;
```

***Fitting the Error Correction Model;**

```
ods graphics on;
proc varmax data=final plot(unpack)=(residual model forecasts impulse);
 id Date interval=month;
   model lcrude ldiesel lngas lelect lnatural lcorn / p=10 noint lagmax=12
      ecm=(rank=2 normalize=ldiesel)

                    print=(iarr estimates);
output lead=36;
run;
```

/*Used to Compute Variance Decomposition*/

```
proc varmax data=crude plots=(model residual)plots = impulse(simple) plots = forecasts;
     id years interval=obs;

   *model lelect lngas ldiesel =lcrude / p=1 noint lagmax=3;
   *model lcrude lelect = ldiesel lngas/ p=1 noint lagmax=3;
    model lelect ldiesel lngas = lcrude/ p=1 noint lagmax=3

                ecm=(rank=3 normalize=lelect)
               print=(iarr estimates impulse (6)) ;

   output out=forecasts lead=10;
run;
```