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# ECONOMIC ANALYSIS OF U.S. ETHANOL EXPANSION ISSUES

By

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# ABSTRACT

## ECONOMIC ANALYSIS OF U.S. ETHANOL EXPANSION ISSUES

By

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The dependency of the U.S. economy on crude oil imported from politically unstable countries, escalating energy demand world wide, growing nationwide environmental consciousness, and the Renewable Fuels Standards (RFS) government mandates are some of the primary factors that have provided a favorable environment for the growth and development of the U.S. ethanol industry.

The first essay derives decision rules for a discrete-time dynamic hedging model in a multiple commodity framework under expected utility maximization and basis risk. It compares hedging performance of three types of hedging models, namely constant hedging, time-varying static hedging model and the new dynamic hedging rule derived in this study. Findings show that natural gas futures contracts were effective instruments for hedging ethanol spot price risk before March, 2005, when ethanol futures trading was initiated on the CBOT. However, post-March, 2005, corn and ethanol futures contracts proved to be efficient hedging instruments. Results also indicate that ethanol producers may effectively decrease variance of cumulative cash flows by hedging using ethanol, natural gas and corn futures prices using the traditional techniques. The study concludes that using the new dynamic hedge model in a three period and two commodity set up, producers can effectively reduce variance of cumulative cash flow by 13.2% as compared to the 'no hedge' scenario.

In my second essay, I use choice based, conjoint analysis methods to estimate consumers' willingness to pay (WTP) for alternative transportation fuels in the U.S. In this study, I consider unleaded gasoline and ethanol, which may be derived from corn or three different sources of cellulosic biomass as alternative transportation fuels. Results suggest that age and household income are some of the socioeconomic variables that significantly influence consumer's choice behavior. Results indicate considerable consumer preference heterogeneity. Welfare effects are analyzed when consumers are faced with restricted choice sets. Results suggest that possible government mandates on the consumption of E-10 and E-85 diminish welfare of individuals belonging to the segment 'Conventional Gasoline Acceptor'. Similarly, individuals belonging to 'Ethanol Acceptor' segment experience welfare losses if corn grain ethanol is not available as an alternative transportation fuel.

Ethanol is increasingly being used as a gasoline oxygenate and a volume extender in the refinery and blender industry in the U.S. This paper estimates refinery and blender factor demand and evaluates price responsiveness of inputs. The study also develops and tests hypotheses regarding existence of structural change in the industry's demand for inputs. It determines whether there is a common shift point and adjustment rate for structural change in all the refinery and blender inputs by using gradual switching multivariate regression techniques and maximum likelihood methods. Results suggest a structural change in factor demand for inputs in the industry that occurs at different points and rates. Results also suggest that the demand for inputs, except for capital and unfinished oil, has become more inelastic over time.

*To my family, who offered me unconditional love and support throughout this journey.*

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## Optimal Futures Market Hedging by Ethanol Producers

### 1.1 Introduction

In the ethanol industry, profit depends on a set of commodity prices (corn, natural gas, ethanol and distiller's dried grain with solubles (DDGS)). Of these, ethanol has an illiquid futures market and DDGS does not have a futures market at all. With volatile input and output prices, ethanol plant owners face significant challenges in protecting profit margins given the unpredictability of commodity prices (CARD, 09). Additionally, with the financial risk stemming from initial capital outlays and increasing competition for resources, existing and future ethanol producers may consider hedging as a risk management tool. Hedging may allow market participants to increase the predictability of future cash flows, lock-in profit margins, and reduce downside risk (Varangis, Thigpen and Satyanarayan, 1994). Contractual agreements like futures contracts for ethanol were introduced in March, 2005 (Funk et al., 2008). Given their relative newness, these markets are comparatively illiquid and thinly traded (Franken and Parcell, 2002). However, assuming that contracting in cash markets alone may leave ethanol producers subject to price risk exposure, participation in the futures market may provide valuable risk management strategies for ethanol producers.

This paper uses dynamic programming to develop a multiple-commodity, multiple-period hedging model (henceforth referred to as Generalized Dynamic Hedge

(GDH) model) to manage ethanol profit risk. We extend the current prevailing literature (i.e. Myers and Hanson, 1996) by considering multiple commodities and multiple maturities, and at the same time utilizing some of the standard features like dynamic and cross hedging strategies. The intertemporal hedging model assumes that a typical ethanol producer faced with unpredictable input and output prices hedges in the futures market to mitigate price risk. He initiates a multiple period hedging strategy at an initial time period for the next $T$ periods of production. As he moves to the next period, he completes all cash market transactions and liquidates the futures contract that has the closest maturity date lying beyond the current month. With the advent of additional information, he updates the futures position for the remaining futures contracts. We derive the sequence of optimal hedging positions at each time period that maximizes utility of cumulative cash flow of the ethanol producer at the end of period $T$.

The hedging effectiveness of three types of hedging techniques is compared. The first technique is the constant hedge strategy where the hedge ratio is obtained by regressing the returns from the spot market transaction on the returns to holding the hedging instruments over the entire sample period. The second strategy is the time varying static hedge technique where we use simple twelve month lagged historical volatility to obtain the time varying hedging rule. We assume that at any given point, the spot price of a commodity is a function of its futures prices and that of other related commodities along with time to expiration of the nearest futures contract. In the third case, we obtain the dynamic hedging rule based on the solution to the GDH model described above. Next we compare results across the three hedging techniques.

The remainder of the paper is organized as follows. Section 1.2 explains the rationale for hedging by the ethanol producers. Section 1.3 gives an overview of the literature on the methodology utilized and relevant research on hedging in the ethanol market. Section 1.4 describes the dynamic hedging model. Section 1.5 presents the preliminary summary statistics of the data. Section 1.6 illustrates the empirical application of the generalized dynamic hedging model and a comparison with constant and time varying hedging model and also presents the empirical results. Section 1.7 concludes.

## 1.2 Rationale for Hedging

Ethanol producers are exposed to an array of risks, namely price risk, basis risk, yield risk, storage risk, institutional risk, financial risk and transportation cost risk (Coltrain, 2004). Price risk arises due to price volatility of the inputs and outputs related to ethanol production. More specifically, price risk may arise due to the possibility of negative profitability due to unfavorable combinations of input prices (corn, natural gas) and output prices (ethanol, distiller's dried grain with solubles (DDGS)). Each of these commodity prices present varying degrees of risk depending on their respective price volatility, the relative amount of each commodity used or produced, and the risk management tools available to the respective producers. Basis is defined as the difference between the spot price of a hedged asset and the price of an underlying futures contract. Basis risk is the risk associated with imperfect hedging using futures contracts (Castelino, 1992). It arises when the settlement prices on the futures contracts at expiration are correlated with, but not equal to, actual cash prices at which the producer makes transactions (Lapan and Moschini, 1994). With high degrees of volatility in input and output prices, producers may be exposed to significant basis risk from multiple commodities.

Institutional risk arises due to government intervention in the form of subsidies, taxes and regulations. Adoption of unfavorable government policies may inject greater degree of volatility in the profit margin. Financial risk may also be significant since it limits the firm's access to capital and the latest technology. Given the current technology, yield risk is not a major concern for ethanol producers.[1] Ethanol producers usually haul corn from elevators, or directly from corn farmers, to their plants and deliver ethanol and DDGS to end users. Thus any uncertainties in freight rates expose the ethanol producers to transportation price risk. In this paper, however, we assume that the producers are primarily exposed to price and basis risk. Other categories of risk (i.e. yield and storage risk, institutional and financial risk and transportation risk) will be relatively less important in the case of ethanol production and are left as topics for future research.

Ethanol producers may actively trade in the futures, swaps and options markets as well as engage in forward contracts to manage risk. Ethanol currently has only two such securities available for risk management, a futures contract traded on the Chicago Board of Trade and another on the Brazilian Mercantile and Futures exchange (Paddrik and Davis, 2008). The ethanol futures market lacks liquidity due to comparatively low volume of contracts traded. However, with time, the ethanol market is increasingly gaining efficiency with additional new entrants from producers as well as financial firms trading actively (CBOT, 2009). Currently hedgers in the ethanol markets are able to hedge nearly two years of production. This enables them to create more long-term protection and take on more leverage (EAR, 2008).

In a futures market transaction, delivery, or the possibility of delivery, promotes convergence of the spot price and the futures price at the delivery point at expiration. However, according to the CBOT, the predominant economic function of ethanol futures contracts is risk transfer and price discovery, rather than merchandising or title transfer for the underlying commodity. The CBOT's ethanol futures contracts are designed to

[1] 1 bushel of corn and 165 thousand British thermal units of natural gas are needed to create 2.7 gallons of ethanol and 17 pounds of DDGS (Hart, 2005).

provide high degrees of flexibility for market participants throughout the delivery process. For example, once the shipping certificate has been issued, there is no specified timeframe in which the buyer and seller must exchange physical ethanol.[2] Moreover, small ethanol production cycles (i.e. 40 to 75 hours) and monthly ethanol futures contracts might induce basis risk between the futures and cash markets.

Standard & Poor's conducted a risk analysis of all the major factors of ethanol production (government, yield margins, margin volatility, industry growth, and industry dynamics). The report concluded that typical ethanol plants demonstrated characteristics of a "B" rated entity, where "B" indicates that even though the ethanol industry primarily has a strong foot hold it still has an appreciable margin of risk in its pricing (Paddrik and Davis, 2008). Thus capital market imperfections coupled with high price volatility provide incentives to ethanol producers to use hedging instruments to hedge against price risk (Simmons, 2002; Panell et al. 2008).

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[2] CBOT Ethanol Futures, The delivery Process, url: http://www.cbot.com/cbot/docs/74401.pdf, viewed on 07/04/08

## 1.3 Background Literature

Historically, hedging has been one of the most effective risk management strategies used by competitive firms to deal with price uncertainty (Peck, 1975; Johnson, 1960). An optimal hedge ratio is usually defined as the proportion of a cash position that should be covered with an opposite position on a futures market (Myers, 1991). Static hedge ratios are obtained by regressing returns in the spot market on the return in the futures market. Given the restrictive assumptions underlying static hedging, several dynamic hedging strategies have been developed where hedgers may be able to improve hedging performance. Anderson and Danthine (1983) generalize the static hedging model to a dynamic framework that allows the hedger to update the hedge as new information arrives. The cash-holding period is divided into discrete time intervals such that at the end of each interval, futures positions are 'marked to market' and the size of the hedge may be adjusted. At the end of the final period, the cash position is liquidated along with any remaining futures positions. However, this study assumes no basis risk and negative exponential utility with normally distributed random variables. Duffie and Jackson (1987) solve the optimal futures hedging problem in continuous time settings such that a hedge is defined as a vector stochastic process specifying a futures position in each futures market. A hedge is considered optimal if it maximizes the expected utility of terminal wealth, which is the sum of the market value of a committed portfolio of spot market assets and the value of the margin account on termination. Mathews and Holthausen (1991) developed a multiperiod hedging model that allows for periodic adjustment of the hedge while minimizing the producer's profit variance. The study concluded that simple models may perform better for simple hedges, while the multi-period model with adjustable hedges may perform better under complex hedging situations such as those involving cross hedges. Karp (1987) developed a dynamic hedging problem with stochastic production. Myers and Hanson (1996) derived an optimal dynamic hedging rule where futures positions can be updated at regular intervals over a cash-holding period. The paper assumes cash positions to be nonstochastic and current futures price to be an unbiased predictor of upcoming futures prices.

To account for commodity price volatility, the possibility of autocorrelation in spot and futures prices, and to investigate the effect on hedging strategy with the arrival of new information, dynamic hedging methods may be more appropriate in many applications. The commonly used approaches for estimating time-varying optimal hedge ratios on futures markets are the moving sample variances and covariances approach and generalized autoregressive conditional heteroscedasticity (GARCH) model of Bollerslev (1986). Over the last decade, several studies on dynamic hedging have demonstrated that hedging models, particularly GARCH, which factors in the dynamic relationship between spot and futures contracts, outperforms traditional hedging models in hedging effectiveness (Cecchetti, Cumby and Figlewski, 1988; Kroner and Sultan, 1991; Park and Switzer, 1995). Baillie and Myers (1991) adopted the bivariate GARCH to estimate the optimal hedge ratio. They found that the resulting optimal hedge ratio varies with time and its effectiveness is better than those of the OLS constant hedge ratio models.

To avoid losing long-run information when dealing with the issues of nonstationarity, Krehbiel and Adkins, (1993) utilized cointegration to illustrate the long-run relationship between variables, as suggested by Engle and Granger (1987). If the spot and futures price series are nonstationary in levels, but stationary in first differences and additionally if a linear combination of the series is stationary, then the series are said to be cointegrated. An Error correction model (ECM) combines the long run, cointegrating relationship between the levels variables and the short run relationship between the first differences of the variables (Banerjee et al., 1993).

### 1.3.1 Background Literature on Hedging in the Ethanol Industry

Ethanol was introduced in the CBOT futures trading list in March, 2005. According to Funk et al. (2008), CBOT ethanol contracts may add efficiency to the cash ethanol market. CBOT futures contracts are a source of pricing information for producers, marketers, and purchasers of ethanol. Dahlgram (2009) examines the effectiveness of one-through eight-week ethanol hedges between 2005 and 2008. The study concludes that ethanol inventory hedging effectiveness is significant for two-week and longer hedges and increases with the hedging horizon. The analysis also concludes that ethanol futures are significantly superior to gasoline futures for hedging ethanol price risk for two-week and longer hedges. The study by Franken and Parcell (2002) estimated the cross-hedge relationship between New York Mercantile Exchange (NYMEX) unleaded gasoline futures price and Michigan spot ethanol price. The cross-hedge ratios varied from 0.175 to 0.418 depending on the hedging period. The hedging effectiveness increased for longer cross-hedging periods. The study also concludes that considerably fewer gallons of unleaded gasoline futures are required to hedge a particular amount of ethanol. However, with a typical 50 million gallon/year ethanol producing plant, the quantities of gasoline futures required to implement an effective cross-hedge ratio should not be a major deterrent for the producers to engage in cross hedging. A study by Brinker et al. (2007) used four locations for cash DDGS prices, namely Atlanta, Boston, Buffalo and Chicago markets. The estimated hedge ratios for the four locations are similar in value with very little variation in both the corn and soybean hedge ratios. The study suggests that a combination of both corn and soybean meal futures contracts provides a hedge that effectively manages DDGS price risk.

## 1.4 Generalized Dynamic Hedging Model

Consider an ethanol plant operating with fixed production capacity. Corn and natural gas are the main inputs used in the production process, with ethanol and Distiller's Dried Grains with Solubles (DDGS) being the primary outputs. Other than DDGS, all the commodities are traded in futures markets.

The producer faces a non-stochastic production process (i.e. no yield risk) with fixed scale of production. As discussed in the previous section, the producer is exposed to price and basis risk. Suppose the producer has a fixed cash position for corn, natural gas, ethanol and DDGS. The cash position for the agent represents a commitment to buy inputs or sell outputs, in known quantities, in the future. Future prices of the products are stochastic at earlier periods so there is price risk over the cash-holding period (Myers and Hanson, 1996). Producers may hedge price risk by establishing futures contracts. Even though ethanol has been produced and traded in the cash market in the U.S. for the last couple of decades, futures have been traded on the CBOT only since March, 2005. Given the high correlation between ethanol spot and gasoline and crude oil futures prices, producers may cross-hedge ethanol price risk by establishing futures contracts in these commodities. Similarly, DDGS is not traded in the futures market but the producer may be able to reduce price risk through cross-hedging cash DDGS with any actively traded futures market commodity (Anderson and Danthine, 1981).

Assuming the cash positions for corn, natural gas, ethanol and DDGS to be fixed and the futures positions of corn, natural gas, ethanol, crude oil and gasoline to be stochastic, the decision process for an ethanol producer can be illustrated as follows:

| t-i | t | t +j |
|---|---|---|
| Establish anticipatory hedges with corn, ethanol, natural gas, crude oil and gasoline futures contracts. | Close out existing hedges for inputs (corn and natural gas), buy corn and natural gas in cash market and consider updating ethanol, crude oil and gasoline futures contract position. | All hedges are closed out, ethanol and DDGS are sold in the cash market. |

where $t-i$ is the initial time period, $i$ is the time span before the production process starts and $j$ is the time required in the production of ethanol. The first stage $(t-i)$ corresponds to the initial decision making stage where the producer initially makes decisions regarding futures positions. The second stage $(t)$ corresponds to the beginning of the production process when the inputs are acquired in the cash market. The third stage $(t+j)$ corresponds to the end of the production process where the final outputs have been produced and sold in the cash market.

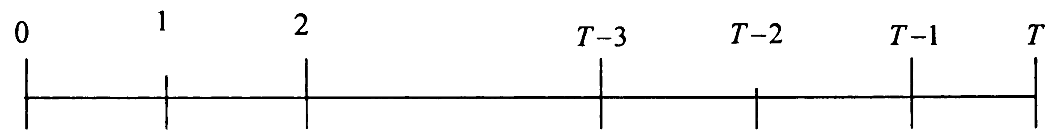
With small production cycles ($j = 40$ to 75 hours) and monthly futures contracts, multiple production cycles are completed between any two consecutive terminations of futures contracts. We assume that the firm completes 10 production cycles in a month and the entire spot market transactions are completed on the first day of the month. The decision process for the ethanol producer is therefore reduced to a two-period model:

| t | t +i+j |
|---|---|
| Establish anticipatory hedges with corn, ethanol, natural gas, crude oil and gasoline. | All hedges are closed out, corn and natural gas are bought from the cash market; ethanol and DDGS are sold in the cash market. |

We assume no transaction costs and that the firm does not have a liquidity constraint. However it is important to note that even with small production cycles, anticipatory hedging by the ethanol producers is a rational risk management strategy given the considerable sunk cost of building the plant (Schmit et al, 2008).

### 1.4.1 Multi-Period Model Specification

Consider an ethanol producer hedging in the ethanol, natural gas, corn, crude oil and gasoline futures markets. Since DDGS is not traded in the futures market, the producer may mitigate DDGS spot price risk by cross-hedging using futures contracts of related commodities. To keep the analysis simple, we model the optimal hedging strategy for ethanol producers assuming ethanol to be the primary output. Let the producer initiate a multiple period hedging strategy starting at $t=0$ for input requirements and expected outputs from time period $t=1$ onwards, for the next $T$ periods of production. The producer establishes hedging positions for commodity bundles at each period against a portfolio of futures contracts with maturities over each of the next $T$ periods. We may restrict our model by assuming that $m$ inputs are being used to produce $n=1$ output. Thus at $t=0$, the producer establishes positions in $T\times(m+1)$ futures contracts for $m+1$ commodities for the next $T$ periods. However, as he moves to the next period (i.e. $t=1$), he completes all cash market transactions (i.e. buys inputs and sells output in the spot market), liquidates the futures contract that has the closest maturity date lying beyond the current month and updates the futures position for the remaining $(T-1)\times(m+1)$ futures contracts with additional available information. The following timeline illustrates the futures positions established and updated at each period where $\mathbf{b}_{t,\tau}$ is a vector of futures positions held at time $t$ for maturity at $\tau$.[3]




| | | | | | |
|---|---|---|---|---|---|
| $\mathbf{b}_{0,1}$ | $\mathbf{b}_{1,2}$ | $\mathbf{b}_{2,3}$ | | | |
| $\mathbf{b}_{0,2}$ | $\mathbf{b}_{1,3}$ | $\mathbf{b}_{2,4}$ | | | |
| $\vdots$ | $\vdots$ | $\vdots$ | | | |
| $\mathbf{b}_{0,T-2}$ | $\mathbf{b}_{1,T-2}$ | $\mathbf{b}_{2,T-2}$ | $\mathbf{b}_{T-3,T-2}$ | | |
| $\mathbf{b}_{0,T-1}$ | $\mathbf{b}_{1,T-1}$ | $\mathbf{b}_{2,T-1}$ | $\mathbf{b}_{T-3,T-1}$ | $\mathbf{b}_{T-2,T-1}$ | |
| $\mathbf{b}_{0,T}$ | $\mathbf{b}_{1,T}$ | $\mathbf{b}_{2,T}$ | $\mathbf{b}_{T-3,T}$ | $\mathbf{b}_{T-2,T}$ | $\mathbf{b}_{T-1,T}$ |

Let $\mathbf{f}_{t,\tau}$ be the $1\times(m+1)$ vector of futures prices corresponding to $\mathbf{b}_{t,\tau}$ at time $t$ with expiration at $\tau$.

$$\mathbf{f}_{t,\tau} = \left[ f_{t,\tau}^{y}, f_{t,\tau}^{z1}, f_{t,\tau}^{z2}, \ldots\ldots, f_{t,\tau}^{zm} \right]_{[1\times(m+1)]} \tag{1.1}$$

$$\mathbf{b}_{t,\tau} = \left[ b_{t,\tau}^{y}, b_{t,\tau}^{z1}, b_{t,\tau}^{z2}, \ldots\ldots, b_{t,\tau}^{zm} \right]_{[1\times(m+1)]} \tag{1.2}$$

where $y$ and $(z_1,\ldots,z_m)$ represent output and inputs respectively. Let $\mathbf{P}_t$ be the vector of stochastic cash prices for the commodities at time $t$ (positive for outputs and negative for inputs), $\mathbf{A}_t$ be the vector of spot positions of the commodities at period $t$ (assumed given) and $C_t(.)$ be the non-stochastic cost function at $t$ that depends on all inputs that

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[3] For example, $\mathbf{b}_{2,T}$ represents the vector of futures positions held at time 2 maturing at $T$ for all the commodities that the producer is interested in hedging.

cannot be hedged (i.e. labor, capital etc). Futures prices of the commodities at all maturity dates ($\mathbf{f_t}$), hedge positions at all maturity dates ($\mathbf{b_t}$), cash prices ($\mathbf{P_t}$) and quantities ($\mathbf{A_t}$) at period $t$ are represented as follows:

$$\mathbf{f_t} = \left[\mathbf{f_{t,t}}, \mathbf{f_{t,t+1}}, \mathbf{f_{t,t+2}}, \ldots, \mathbf{f_{t,T}}\right]_{[1\times(m+1)\times(T-t+1)]} \tag{1.3}$$

$$\mathbf{b_t} = \left[\mathbf{b_{t,t+1}}, \mathbf{b_{t,t+2}}, \ldots, \mathbf{b_{t,T}}\right]_{[1\times(m+1)\times(T-t)]} \tag{1.4}$$

$$\mathbf{P_t} = \left[P_t^y, -P_t^{z1}, -P_t^{z2}, \ldots\ldots, -P_t^{zm}\right]_{[1\times(m+1)]} \tag{1.5}$$

$$\mathbf{A_t} = \left[y_t, z_t^1, z_t^2, \ldots\ldots, z_t^m\right]_{[1\times(m+1)]} \tag{1.6}$$

The futures position is negative for a short hedge and positive for a long hedge. We assume that there is no initial cost of establishing futures positions because margin requirements can be satisfied with interest-bearing government securities. Let us define $\mathbf{f_t^L}$ as:

$$\mathbf{f_t^L} = \left[\mathbf{f_{t-1,t}}, \mathbf{f_{t-1,t+1}}, \mathbf{f_{t-1,t+2}}, \ldots, \mathbf{f_{t-1,T}}\right]_{[1\times(m+1)\times(T-t+1)]} \tag{1.7}$$

The producer's realized cumulative cash flow ($\pi_t$) at period $t$ is given by:

$$\pi_t = (1+r)(\pi_{t-1} - C_{t-1}) + \Delta\mathbf{f_t}\mathbf{b'_{t-1}} + \mathbf{P_t}\mathbf{A'_t} \tag{1.8}$$

where $r$ is a constant per period interest rate representing the hedger's opportunity cost of funds, $\pi_{t-1}$ is the producer's cumulative cash flow in period $t-1$ and $\Delta\mathbf{f_t} = \mathbf{f_t} - \mathbf{f_t^L}$. The producer's objective is to choose a sequence of futures positions $\{\mathbf{b_{t-1}}\}_{t=1}^{T}$ to maximize the expected utility from cumulative cash flow at the end of period $t = T$,

$$\underset{\{\mathbf{b_{t-1}}\}_{t=1}^{T}}{Max} \quad E_0 u(\pi_T) \tag{1.9}$$

where $E_0$ denotes the expectation operator conditional on information available at $t = 0$, and $u$ is an increasing and strictly concave von Neumann-Morgenstern utility function. The maximization is subject to the cash flow constraint (1.8) and can be solved using stochastic dynamic programming. Consistent with Myers and Hanson (1996), we make the following four assumptions:

Assumption 1 (A1): The futures market is unbiased in that prices follow a martingale, $\mathbf{f_t} = \mathbf{f_t^L} + \mathbf{e_t}$ where $\mathbf{e_t}$ is a vector of zero mean random shocks which cannot be predicted and $\dim(\mathbf{e_t}) = [1 \times (m+1) \times (T - t + 1)]$. This implies that on an average, hedgers cannot predict upcoming futures prices more efficiently than the aggregate market prediction. Given that most studies have found little or no systematic bias in futures market, this assumption is reasonable for practical applications (Martin and Garcia, 1981).

Assumption 2 (A2): Expectations of cash prices at each period evolve according to $\mathbf{P_\tau} = E_t(\mathbf{P_\tau}) + \mathbf{v_{t,\tau}}$, $\tau > t$ where $\mathbf{v_{t,\tau}}$ is a zero mean random shocks which cannot be predicted and $\dim(\mathbf{v_{t,\tau}}) = [1 \times (m+1)]$. This is a very general assumption and implies that expectations are consistent. Let us define $\mathbf{v_t}$ as

$$\mathbf{v_t} = \left[(1+r)^{T-(t+1)} \mathbf{v_{t,t+1}}, \ldots, (1+r)\mathbf{v_{t,T-1}}, \mathbf{v_{t,T}}\right] \tag{1.10}$$

such that $\dim(\mathbf{v_t}) = [1 \times (m+1) \times (T-t+1)]$. This might seem arbitrary, but will help us in the following sections to obtain a more tractable form of the final solution.

Assumption 3 (A3): Expectations of innovations in cash prices given by:
$E_{t+h}\left[\mathbf{v_{t,\tau}}\right] = \mathbf{v_{t,\tau}} + \boldsymbol{\eta}_{\mathbf{t+h,\tau}}$, $\tau > t+h$ where $\boldsymbol{\eta}_{\mathbf{t+h,\tau}}$ is a zero mean random shocks which cannot be predicted and $\dim(\boldsymbol{\eta}_{\mathbf{t+h,\tau}}) = [1 \times (m+1)]$.

Assumption 4 (A4): The innovations in futures prices and expectations of cash prices are related according to $\mathbf{v_t} = \mathbf{e_t}\boldsymbol{\delta}_\mathbf{t} + \boldsymbol{\varepsilon}_\mathbf{t}$, where $\boldsymbol{\varepsilon}_\mathbf{t}$ is a vector of zero mean random shocks which cannot be predicted and is independent of $\mathbf{e_t}$ at all lags, and $\boldsymbol{\delta}_\mathbf{t}$ is a matrix of parameters that may vary over time. Note that $\dim(\boldsymbol{\varepsilon}_\mathbf{t}) = 1 \times (m+1) \times (T-t+1)$ and $\boldsymbol{\delta}_\mathbf{t}$ is a $[(m+1)(T-t) \times (m+1)(T-t+1)]$ matrix. This assumption allows for a wide set of basis relationship between the cash and futures price. Specifically, it does not require the futures price to be an unbiased predictor of the cash price at maturity.

We determine the optimal hedge ratio using backward recursion. At the last decision period, $T-1$, the hedging problem reduces to a one period problem:

$$\underset{\mathbf{b_{T-1}}}{Max}\ E_{T-1}[u(\pi_T)]$$

$$\text{s.t. } \pi_T = (1+r)[\pi_{T-1} - C_{T-1}] + \Delta\mathbf{f_T}\mathbf{b'_{T-1}} + \mathbf{P_T}\mathbf{A'_T} \qquad (1.11)$$

Second order conditions for maximization are satisfied by the concavity of the utility function and the first order condition is given by:

$$E_{T-1}\left[u'(\pi_T) * \mathbf{e_T}\right] = 0 \tag{1.12}$$

where $\Delta\mathbf{f_T} = \mathbf{e_T}$ according to assumption (A1). If $\pi_T$ and $\mathbf{e_T}$ are independent, then their joint density factorizes and equation (1.12) may be written as:

$$E_{T-1}\left[u'(\pi_T)\right] * E_{T-1}(\mathbf{e_T}) = 0 \tag{1.13}$$

Thus we need to obtain an optimal decision rule for $\mathbf{b_{T-1}}$ which makes $\pi_T$ independent of $\mathbf{e_T}$. Using assumptions (A1) through (A4), the cumulative cash flow constraint may be written as (for details please refer to Appendix A1.1):

$$\pi_T = (1+r)(\pi_{T-1} - C_{T-1}) + \mathbf{e_T b'_{T-1}} + \left[E_{T-1}(\mathbf{P_T}) + \mathbf{e_T \delta_T} + \boldsymbol{\varepsilon}_\mathbf{T}\right]\mathbf{A'_T} \tag{1.14}$$

In equation (1.14), $\mathbf{e_T}$ and $\boldsymbol{\varepsilon}_\mathbf{T}$ are the stochastic components and by construction, $\boldsymbol{\varepsilon}_\mathbf{T}$ is independent of $\mathbf{e_T}$. Let $\mathbf{b'_{T-1}} = -\boldsymbol{\delta}_\mathbf{T}\mathbf{A'_T}$; this renders cumulative cash flow independent of movement of futures prices. Therefore $\mathbf{b'_{T-1}} = -\boldsymbol{\delta}_\mathbf{T}\mathbf{A'_T}$ is the optimal hedging rule for the two period problem. Note that it can be demonstrated that in a two-period scenario, $\boldsymbol{\delta}_\mathbf{T}$ is the matrix of the ratios of the covariance between one-period innovations in cash and futures prices to the variance of one-period futures prices innovation, conditional on information available at $t = T-1$. This is the standard one period cross hedging formula that has been used previously in the literature (Kahl, 1983; Benninga, Eldor and Zilcha, 1984).

Following the dynamic programming algorithm, we move sequentially backwards from the terminal decision date to derive decision rules for earlier periods. Assuming an optimal strategy will be followed at $T-1$, the $T-2$ period problem may be expressed as:

$$\underset{\mathbf{b_{T-2}}}{Max}\ E_{T-2}\left[u\left((1+r)(\pi_{T-1}-C_{T-1})+\left[E_{T-1}(\mathbf{P_T})+\boldsymbol{\varepsilon}_\mathbf{T}\right]\mathbf{A}'_\mathbf{T}\right)\right]$$

$$\text{s.t. } \pi_{T-1}=(1+r)(\pi_{T-2}-C_{T-2})+\Delta\mathbf{f_{T-1}}\mathbf{b}'_\mathbf{T-2}+\mathbf{P_{T-1}}\mathbf{A}'_\mathbf{T-1} \tag{1.15}$$

Assuming the second-order condition is satisfied, the necessary condition for the optimal $\mathbf{b_{T-2}}$ is given by:

$$(1+r)E_{T-2}\left[u'(\pi_T)*\mathbf{e_{T-2}}\right]=0 \tag{1.16}$$

The objective is to find any $\mathbf{b_{T-2}}$ which makes $\pi_T$ independent of $\mathbf{e_{T-2}}$ will satisfy (1.16) and therefore be optimal. Let us consider the cumulative cash flow in period $T$ assuming the optimal one-period rule is used in period $T-1$, given by equation (1.14).

$$\pi_T=(1+r)(\pi_{T-1}-C_{T-1})+\left[E_{T-1}(\mathbf{P_T})+\boldsymbol{\varepsilon}_\mathbf{T}\right]\mathbf{A}'_\mathbf{T} \tag{1.17}$$

Substituting the expression for $\pi_{T-1}$ from equation (1.15),

$$=(1+r)\left[(1+r)(\pi_{T-2}-C_{T-2})+\Delta\mathbf{f_{T-1}}\mathbf{b}'_\mathbf{T-2}+\mathbf{P_{T-1}}\mathbf{A}'_\mathbf{T-1}-C_{T-1}\right]+\left[E_{T-1}(\mathbf{P_T})+\boldsymbol{\varepsilon}_\mathbf{T}\right]\mathbf{A}'_\mathbf{T}$$

$$\begin{aligned}&=(1+r)^2\pi_{T-2}-\sum_{i=1}^{2}(1+r)^iC_{T-i}+(1+r)\mathbf{e_{T-1}}\mathbf{b}'_\mathbf{T-2}+(1+r)\mathbf{P_{T-1}}\mathbf{A}'_\mathbf{T-1}\\&\qquad+\left[E_{T-1}(\mathbf{P_T})+\boldsymbol{\varepsilon}_\mathbf{T}\right]\mathbf{A}'_\mathbf{T}\end{aligned} \tag{1.18}$$

Following assumption (A2), we substitute $\mathbf{P_{T-1}}=E_{T-2}(\mathbf{P_{T-1}})+\mathbf{v_{T-2,T-1}}$ and $\mathbf{P_T}=E_{T-2}(\mathbf{P_T})+\mathbf{v_{T-2,T}}$ into (1.18) yielding:

$$\begin{aligned}&=(1+r)^2\pi_{T-2}-\sum_{i=1}^{2}(1+r)^iC_{T-i}+(1+r)\mathbf{e_{T-1}}\mathbf{b}'_\mathbf{T-2}+(1+r)E_{T-2}(\mathbf{P_{T-1}})\mathbf{A}'_\mathbf{T-1}\\&\quad+(1+r)\mathbf{v_{T-2,T-1}}\mathbf{A}'_\mathbf{T-1}+E_{T-1}\left[E_{T-2}(\mathbf{P_T})+\mathbf{v_{T-2,T}}\right]\mathbf{A}'_\mathbf{T}+\boldsymbol{\varepsilon}_\mathbf{T}\mathbf{A}'_\mathbf{T}\end{aligned} \tag{1.19}$$

Following the rule of iterated expectations we have:

$$= (1+r)^2 \pi_{T-2} - \sum_{i=1}^{2}(1+r)^i C_{T-i} + (1+r)\mathbf{e_{T-1}b'_{T-2}} + (1+r)E_{T-2}(\mathbf{P_{T-1}})\mathbf{A'_{T-1}}$$
$$+ (1+r)\mathbf{v_{T-2,T-1}A'_{T-1}} + E_{T-2}(\mathbf{P_T})\mathbf{A'_T} + E_{T-1}\mathbf{v_{T-2,T}A'_T} + \boldsymbol{\varepsilon}_\mathbf{T}\mathbf{A'_T} \quad (1.20).$$

Following assumption (A3), we substitute $E_{T-1}\lfloor \mathbf{v_{T-2,T}} \rfloor = \mathbf{v_{T-2,T}} + \boldsymbol{\eta}_\mathbf{T-1,T}$ and obtain

$$= (1+r)^2 \pi_{T-2} - \sum_{i=1}^{2}(1+r)^i C_{T-i} + (1+r)\mathbf{e_{T-1}b'_{T-2}} + (1+r)E_{T-2}(\mathbf{P_{T-1}})\mathbf{A'_{T-1}}$$
$$+ (1+r)\mathbf{v_{T-2,T-1}A'_{T-1}} + E_{T-2}(\mathbf{P_T})\mathbf{A'_T} + (\mathbf{v_{T-2,,T}} + \boldsymbol{\eta}_\mathbf{T-1,,T})\mathbf{A'_T} + \boldsymbol{\varepsilon}_\mathbf{T}\mathbf{A'_T}$$
$$= (1+r)^2 \pi_{T-2} - \sum_{i=1}^{2}(1+r)^i C_{T-i} + (1+r)\mathbf{e_{T-1}b'_{T-2}} + (1+r)E_{T-2}(\mathbf{P_{T-1}})\mathbf{A'_{T-1}}$$
$$+ \boldsymbol{\varepsilon}_\mathbf{T}\mathbf{A'_T} + E_{T-2}(\mathbf{P_T})\mathbf{A'_T} + \lfloor(1+r)\mathbf{v_{T-2,T-1}},\ \mathbf{v_{T-2,T}}\rfloor \begin{bmatrix} \mathbf{A'_{T-1}} \\ \mathbf{A'_T} \end{bmatrix} + \boldsymbol{\eta}_\mathbf{T-1,T}\mathbf{A'_T} \quad (1.21).$$

Let us define $\mathbf{A_t^T}$ as:

$$\mathbf{A_t^T} = \lfloor \mathbf{A_t}, \mathbf{A_{t+1}}, \ldots, \mathbf{A_T} \rfloor_{[1\times(m+1)(T-t+1)]} \quad (1.22).$$

Substituting $\mathbf{v_{T-1}} = \lfloor(1+r)\mathbf{v_{T-2,T-1}},\ \mathbf{v_{T-2,T}}\rfloor$ and $\mathbf{A_{T-1}^{T}}' = \begin{bmatrix} \mathbf{A'_{T-1}} \\ \mathbf{A'_T} \end{bmatrix}$ into (21) yields

$$= (1+r)^2 \pi_{T-2} - \sum_{i=1}^{2}(1+r)^i C_{T-i} + (1+r)\mathbf{e_{T-1}b'_{T-2}} + (1+r)E_{T-2}(\mathbf{P_{T-1}})\mathbf{A'_{T-1}}$$
$$+ \boldsymbol{\varepsilon}_\mathbf{T}\mathbf{A'_T} + E_{T-2}(\mathbf{P_T})\mathbf{A'_T} + \mathbf{v_{T-1}A_{T-1}^{T}}' + \boldsymbol{\eta}_\mathbf{T-1,T}\mathbf{A'_T} \quad (1.23)$$

Following assumption (A4), we substitute $\mathbf{v_{T-1}} = \mathbf{e_{T-1}}\boldsymbol{\delta}_\mathbf{T-1} + \boldsymbol{\varepsilon}_\mathbf{T-1}$ yielding

$$= (1+r)^2 \pi_{T-2} - \sum_{i=1}^{2}(1+r)^i C_{T-i} + (1+r)\mathbf{e_{T-1}b'_{T-2}} + (1+r)E_{T-2}(\mathbf{P_{T-1}})\mathbf{A'_{T-1}}$$
$$+ \boldsymbol{\varepsilon}_\mathbf{T}\mathbf{A'_T} + E_{T-2}(\mathbf{P_T})\mathbf{A'_T} + (\mathbf{e_{T-1}}\boldsymbol{\delta}_\mathbf{T-1} + \boldsymbol{\varepsilon}_\mathbf{T-1})\mathbf{A_{T-1}^{T}}' + \boldsymbol{\eta}_\mathbf{T-1,T}\mathbf{A'_T} \quad (1.24)$$

Thus to make $\pi_T$ independent of $\mathbf{e_{T-1}}$, we let

$$\mathbf{b}_{\mathbf{T-2}}^{'\ *} = -(1+r)^{-1}\boldsymbol{\delta}_{\mathbf{T-1}}\mathbf{A}_{\mathbf{T-1}}^{\mathbf{T}\ '}$$

More generally, considering a multi-period model, we have:

$$\mathbf{b}_{\mathbf{t-1}}^{'\ *} = -(1+r)^{t-T}\boldsymbol{\delta}_{\mathbf{t}}\mathbf{A}_{\mathbf{t}}^{\mathbf{T}'} \qquad (1.25).$$

These decision rules make terminal wealth independent of futures price movements at every $t$, assuming optimal rules will be followed in the future when positions are updated. According to equation (1.25), the optimal hedging rule is a function of $\boldsymbol{\delta}_{\mathbf{t}}$, the matrix of the ratios of covariance to variance weighted by a discount factor, $(1+r)^{t-T}$ and a matrix of cash positions. This reflects the fact that profits or losses from futures price movements are marked to market in every period. Moreover, the hedging rule obtained generalizes the dynamic hedging rule obtained by Myers and Hanson (1996) by considering multiple commodities, accommodating for multiple cash market transactions and allowing for cross-hedging. It is to be noted that if we reduce the multivariate set up to a single commodity frame work with single cash market transaction at the terminal period, dynamic hedge rule obtained in equation (1.25) reduces to that obtained by Myers and Hanson (1996) (page 16).

## 1.5 Data and Preliminary Statistics

Monthly price data from January 1993 to May 2009 has been used in the analysis. Ethanol spot price data has been obtained from official Nebraska Government website (Nebraska Government Website, 2009). The data source for corn and DDGS spot price is the United States Department of Agriculture (USDA, 2009). Futures price data for corn, natural gas, gasoline and crude oil has been obtained from Commodity Research Bureau (CRB, 2009). Spot price data for natural gas and futures price data for ethanol was obtained from Reuters (Reuters, 2009). At any given point of time, ethanol and natural gas has twelve outstanding futures contracts and corn has five futures contracts. Since multiple contracts usually trade simultaneously for a given commodity, futures prices form multiple time series corresponding to different contracts. Researchers usually follow 'nearbys' or 'constant-maturity price series' to convert discontinual futures price data into continual time series (Holton, 2003). Following Park and Switzer (1995) and Myers and Thompson (1989), to estimate the constant hedge ratio and the time varying static hedge ratios, we consider the closing price of the nearby futures contract on the first Wednesday of the month. Historic monthly risk free rate of return was obtained from Wharton Research Data Services (WRDS, 2009).

Analyses of the time series properties of the historic price data are important in choosing the best model specification (Koutmos and Pericli, 1999). Descriptive statistics for the price series are reported in table (1.1). Initial data analysis revealed high correlation between crude oil and gasoline futures price, even in first differences. Thus, to avoid the problem of multi-collinearity, our analysis does not include crude oil futures contracts. The estimated skewness and kurtosis for the times series indicate departure from normality. Corn spot and futures price series exhibit evidence of fat tails, since the kurtosis exceeds 3, which is the value under normality. The time series data, in general, exhibits positive skewness, which implies that the right tail is particularly extreme.

The Shapiro-Wilk test examines non-normality in small to medium sized samples. Table (1.1) reports the test statistics (W). Normality is strongly rejected for the spot as well as the futures price data of all commodities. The Anderson-Darling test for normality is also designed to detect departures from normality. According to the test statistics reported in table (1.1), with the exception of ethanol futures price series, the rest of the time series data are likely to be from non-normal distributions. Non-normality may be due to temporal dependencies in the return series. Next we also conduct the Ljung-Box test that tests whether there is any autocorrelation in the series or whether the observations are just a set of random, identically distributed variables (Baillie and Bollerslev, 2002). Table (1.1) presents the Ljung- Box test statistic(Q). According to the P- value, we can say that there is autocorrelation in the series.

Several diagnostic checks on the distributional properties of the data were performed to test for stationarity and presence of unit root for each of the price series. The Durbin-Watson Test for serial correlation assumes that the disturbances are stationary and normally distributed with mean zero. Since the reported Durbin-Watson test statistics are far from 2, there is strong evidence that the errors are strongly autocorrelated.

Next, we conduct the augmented Dickey-Fuller test (ADF) and the Phillips-Perron Test (PP) to test for presence of unit root in the univariate time series. Table (1.2) reports the results for the spot and futures price series data for levels and the first differences. According to the ADF test results, some of the price series have unit roots and become stationary on first differencing. The Phillips-Perron test is a test of a unit root hypothesis on a data series. It reports three types of test statistics corresponding to zero mean, single mean and trend. According to the Phillips-Perron test statistics, all the price series are non-stationary in their levels and that with first differencing, price series are rendered stationary. Thus the PP test confirms the presence of unit root in the time series data. The results, in general, suggest that all variables are integrated of order one (i.e. $I(1)$).

Prior to testing the existence of cointegration in the model, we conduct pair wise cointegration test among spot and futures prices while accounting for time to maturity $(T-t)$ (Engle and Granger, 1987). Time to maturity is included in the equilibrium relationship to reflect the fact that cash and futures prices are expected to converge at maturity (Moschini and Myers, 2002). Table (1.3) presents the results of these tests. According to the trace statistics and maximal eigen value statistics, with the exception of ethanol, natural gas, and corn spot against DDGS spot; and corn spot against gasoline futures, the rest of the spot and futures price series are cointegrated at the 5% significance level. To further explore possibility beyond pair wise cointegration, we test the hypotheses whether spot and futures prices are cointegrated, sharing a common stochastic trend (Engle and Granger, 1987).

Table (1.4) reports the Johansen Cointegration Test Results among the spot and futures price series. The first row tests the null hypothesis $r=0$ against $r>0$ where $r$ represents the number of linearly independent cointegrating vectors; similarly the second row tests $r \leq 1$ against $r > 1$.The trace test statistics and the maximal eigen value statistics are reported in columns 2 and 4 respectively. Results reported in Table (1.5) indicate that there is one cointegrating relationship among the seven price series. According to the results there is a feedback relationship between ethanol and gasoline futures and ethanol spot, corn and ethanol futures, significant at 1% level of significance. Causal relationships have also been revealed between corn spot and natural gas futures, natural gas spot against DDGS spot, ethanol spot and natural gas futures at 5% level of significance. The rest of the feedback relationships may be interpreted accordingly.

## 1.6 Empirical Application and Results

### 1.6.1 Constant Hedge Model

Following Chiu et al. (2005) and Myers and Thompson (1989), the traditional regression-based hedging model may be represented as:

$$\Delta P_t^x = \alpha_0^x + \alpha_1^x \mu_{t-1} + \delta \, \Delta f_t^x + \rho_x \Delta P_{t-1}^x + \sum_h \gamma_h \Delta f_t^h(T) + \upsilon_{x,t} \qquad (1.26)$$

where $\Delta P_t^x$ and $\Delta f_t^x$ represents the rate of return for the spot and futures market for the $x^{th}$ commodity at period $t$, respectively, $T$ represents the nearby expiration date, $\mu_{t-1}$ is the error correction term, $\upsilon_{x,t}$ is the prediction error, $\delta$ is the hedge ratio, and $\alpha_0^x, \alpha_1^x, \rho_x, \gamma_h$ are parameters to be estimated.

While estimating the constant hedge ratio, we partition the data set such that the first set corresponds to the time period when ethanol futures contracts were not available to the producers to hedge risk (i.e. January, 1991 to March, 2005) and is referred to as 'Regime 1'. The second data set refers to data from April, 2005 onwards, when ethanol futures contracts are available and is referred to as 'Regime 2'. We assume that the ethanol producer may cross hedge ethanol spot price risk using natural gas, corn and gasoline futures contracts in both the regimes.

Once the cointegrating relationships and the time to maturity effects have been evaluated, we estimate equation (1.26) (Krehbiel and Adkins, 1993). We derive the hedge ratio for ethanol, corn and natural gas assuming that in addition to the commodity's own futures contracts, the ethanol producer can also cross hedge ethanol spot price against gasoline futures contracts.[4] Results from constant hedge models are displayed in table (1.6). In regime 1, we cross hedge returns from ethanol spot market against returns from natural gas, corn and RBOB gasoline futures markets. After correcting for autocorrelation, the constant cross-hedge ratio to hedge returns from ethanol spot market using returns from natural gas futures market is 0.0842, significant at 1% level of significance. This implies that for every gallon of ethanol produced and sold in the spot market in regime 1, on an average, the producer may engage in 0.0842 thousand cubic feet of natural gas futures contracts. Effect of error correction term with respect to natural gas futures is significant at 1% level of significance. Results also indicate that lag of ethanol spot price and natural gas futures price series are important in hedge ratio determination, significant at 1% level of significance.

In the second regime ( i.e. April, 2005 to May, 2009), the ethanol producers may use returns from ethanol futures market as the additional hedging instrument to hedge against returns from the ethanol spot market. The constant hedge ratio using ethanol and corn futures markets are 0.3018 and 0.0015 respectively, both significant at 5% level of significance. This implies that for every gallon of ethanol produced and sold in the spot market in regime 2, on an average, the producer may engage in 0.3018 gallons of ethanol futures contracts and 0.0015 bushels of corn futures contracts. Since 1 bushel of corn yields 2.7 gallons of ethanol, the cross-hedge ratio using corn futures contratcs is expected to be much less than unity (Hart, 2005). Results are consistent with those in

[4] No significant difference in results was observed when the analysis was conducted using crude oil futures contracts instead of gasoline futures contracts.

Dahlgram (2009) and Brinker et al. (2007). Effect of lag ethanol spot price is also significant at 1% level of significance implying the persistence in spot prices (table 1.6). It is to be noted that there is a sudden drop in constant cross-hedge ratio for hedging ethanol spot prices against natural gas futures contracts from 0.0842 to 0.0167 as we move across regimes (figure 1.2). This coincides with the time period when ethanol futures contracts were introduced in the CBOT commodity trading list. Moreover, the constant hedge ratio estimates for hedging returns from natural gas spot market against natural gas futures contracts jumps up from 0.3798 in regime 1 to 0.6849 in regime 2, both significant at 1% level of significance (figure 1.5). Similarly, results indicate that there has been an increase in constant hedge ratio estimates for hedging returns from corn spot prices against corn futures prices from 0.0025 in regime 1 to 0.009 in regime 2, both significant at 1% level of significance (figure 1.6).

### 1.6.2 Time Varying Static Hedge Model

To estimate the time varying static hedge model, we estimate equation (1.26) for different sample periods of twelve month windows starting from January, 1991 to May, 2009 (Myers, 1991). For example, the first estimate is obtained by estimating equation (1.26) for the time period of January, 1991 to December, 1991. Similarly, the second estimate is obtained by estimating equation (1.26) for the time period of February, 1991 to January, 1992.

Consistent with constant hedge ratio estimation, we derive the time varying static hedge ratio for ethanol, corn and natural gas assuming that in addition to the commodity's own futures contracts, the ethanol producer can also cross hedge ethanol spot price against gasoline futures contracts. Figure (1.2) illustrates estimated optimal cross-hedge ratio paths for hedging ethanol spot prices against natural gas futures contracts using moving sample variances and covariances over the first and second regime. Similarly, figure (1.3) illustrates the optimal hedge ratio paths for hedging ethanol spot prices using nearby corn futures contracts. Given that corn futures contracts provide effective hedging instrument to hedge ethanol spot price risk in the second regime (i.e. April, 2005 to May, 2009), for analysis of cross-hedge ratio using corn futures contracts, we focus our attention exclusively on the second regime. Results indicate that the time varying static hedge ratio towards the beginning of the second regime is large and volatile. However, from end 2008 onwards, the hedge ratios seem to converge to the corresponding constant hedge ratio estimate, (i.e. 0.0015). Figure (1.4) displays the time varying hedge ratio path to mitigate ethanol spot price risk using nearby ethanol futures contracts in regime 2. Even though the constant hedge ratio over the sample period is 0.3018, the time varying static hedge ratios to hedge returns from ethanol spot market using returns from ethanol futures market exhibits variability over time. This may be due to the volatility in ethanol futures trading volume over the time period (Reuters, 2009).

Figure (1.5) and (1.6) illustrates the optimal hedge ratio path for hedging natural gas and corn spot price series against near-by natural gas and corn futures contracts respectively. Results suggest a change in hedging strategy by ethanol producers to hedge its input and output spot price risk.

### 1.6.3 Generalized Dynamic Hedge Model

For a simple illustration of the GDH rule derived in this paper (equation 1.25), we restrict our empirical analysis to two commodities (i.e. ethanol, the primary output and natural gas, one of the primary inputs) and a three period time frame. Given that ethanol futures contracts are available for trading only since March, 2005, we restrict our analysis in regime 2. Consistent with equation (1.3), let us define $\mathbf{f_t} = \lfloor \mathbf{f_{t,t+1}}, \mathbf{f_{t,t+2}} \rfloor$ where $\mathbf{f_{t,t+1}} = \lfloor f_{t,t+1}^{ethn}, f_{t,t+1}^{ng} \rfloor$. Thus,

$$\mathbf{f_t} = \lfloor f_{t,t+1}^{ethn}, f_{t,t+1}^{ng}, f_{t,t+2}^{ethn}, f_{t,t+2}^{ng} \rfloor_{[1\times 4]} \qquad (1.27).$$

In deriving the optimal hedging rule for the GDH model, key assumptions made are given by (A1) through (A4). During empirical estimation, it may be desirable to impose these assumptions. In a two commodity-three period framework, assumption 1 (A1) may be written as:

$$\lfloor \Delta f_{t,t+1}^{ethn}, \Delta f_{t,t+1}^{ng}, \Delta f_{t,t+2}^{ethn}, \Delta f_{t,t+2}^{ng} \rfloor = \mathbf{e_t}. \qquad (1.28).$$

The price vector given by equation (1.5) may be restated as:

$$\mathbf{P_t} = \lfloor P_t^{ethn}, -P_t^{ng} \rfloor_{[1\times 2]} \qquad (1.29).$$

Following assumption 2 (A2), we can restate price in period $t+1$ and $t+2$ as

$(1+r)\,\mathbf{P_{t+1}} = E_t((1+r)\,\mathbf{P_{t+1}}) + (1+r)\,\mathbf{v_{t,t+1}}$ and

$\mathbf{P_{t+2}} = E_t(\mathbf{P_{t+2}}) + \mathbf{v_{t,t+2}}$.

Combination of the two price vectors may be stated as:

$$[(1+r)\,\mathbf{P_{t+1}}, \mathbf{P_{t+2}}] = E_t[(1+r)\,\mathbf{P_{t+1}}, \mathbf{P_{t+2}}] + \lfloor (1+r)\,\mathbf{v_{t,t+1}}, \mathbf{v_{t,t+2}} \rfloor$$

$$\left[\tilde{\mathbf{P}}_{\mathbf{t}}\right] = E_t\left[\tilde{\mathbf{P}}_{\mathbf{t}}\right] + \mathbf{v}_{\mathbf{t}} \tag{1.30}$$

where $\tilde{\mathbf{P}}_{\mathbf{t}} = \left[(1+r)\mathbf{P}_{\mathbf{t+1}}, \mathbf{P}_{\mathbf{t+2}}\right]$ and $\mathbf{v}_{\mathbf{t}} = \left[(1+r)\mathbf{v}_{\mathbf{t,t+1}}, \mathbf{v}_{\mathbf{t,t+2}}\right]$.

Utilizing the relationship between $\mathbf{v}_{\mathbf{t}}$ and $\mathbf{e}_{\mathbf{t}}$ under assumption 4 (A4), equation (1.30) may be written as:

$$\left[\tilde{\mathbf{P}}_{\mathbf{t}}\right] = E_t\left[\tilde{\mathbf{P}}_{\mathbf{t}}\right] + \mathbf{e}_{\mathbf{t}}\boldsymbol{\delta}_{\mathbf{t}} + \boldsymbol{\varepsilon}_{\mathbf{t}} \qquad (1.31).$$

A more appropriate way of expressing equation (1.30) would be to include an additional set of control variables that include additional information available. More specifically, equation (1.31) may be written as:

$$\left[\tilde{\mathbf{P}}_{\mathbf{t}}\right] = E_t\left[\tilde{\mathbf{P}}_{\mathbf{t}}\right] + \alpha\, X_{\mathbf{t}} + \Delta\mathbf{f}_{\mathbf{t}}\boldsymbol{\delta}_{\mathbf{t}} + \boldsymbol{\varepsilon}_{\mathbf{t}} \tag{1.32}$$

where $X_{\mathbf{t}}$ is a set of variables in the information set predicting $\tilde{\mathbf{P}}_{\mathbf{t}}$, $\alpha$ is a vector of unknown parameters and $\boldsymbol{\delta}_{\mathbf{t}}$ is a $4 \times 4$ matrix. This is a very general representation of the estimated model that has been implemented in this paper and can incorporate any particular model explaining spot prices. For example, to model spot prices with AR(1) specification, we model $E_t\left[\tilde{\mathbf{P}}_{\mathbf{t}}\right]$ in the following way:

$$\tilde{\mathbf{P}}_{\mathbf{t}} = \beta\tilde{\mathbf{P}}_{\mathbf{t-1}} + \boldsymbol{\gamma}_{\mathbf{t}} \qquad (1.33).$$

Then the estimated model would be

$$\tilde{\mathbf{P}}_{\mathbf{t}} = \beta\tilde{\mathbf{P}}_{\mathbf{t-1}} + \alpha\, X_{\mathbf{t}} + \Delta\mathbf{f}_{\mathbf{t}}\boldsymbol{\delta}_{\mathbf{t}} + \mu_{\mathbf{t}}$$

The OLS estimate of $\boldsymbol{\delta}_t$ may then be substituted in equation (1.25) to obtain the optimal dynamic hedge $\mathbf{b}_{t-1}^{*}$ in period $t-1$.

Next we attempt to empirically examine the GDH model developed in this paper. Figures (1.7) and (1.8) reports the persistence in ethanol and natural gas spot price. The persistence in ethanol spot price ranges from 0.1 to 0.89. However, the persistence in natural gas spot price has a bigger range (i.e. from 0.07 to 1.2). Figure (1.9) illustrates the dynamic path of hedge positions ethanol producers may establish to hedge returns from ethanol spot market using returns from natural gas and ethanol futures contracts. Results indicate that paths representing dynamic hedge positions set in period 0 with maturity in period I (the graph represented by *) and hedge positions set in period 0 with maturity in period II (the graph represented by +) follow each other closely. However, the optimal hedge path representing updated hedge position set by the producer in period I with maturity in period II (the graph represented by #) deviates from the former two graphs. This may reflect the effect of new information arrival on the optimal hedge path, assuming no transaction cost for updating hedge positions. Similarly, figure (1.10) illustrates the optimal path of hedge positions to mitigate natural gas spot price risk using natural gas and ethanol futures contracts. In this time period, the static hedge ratios to mitigate ethanol and natural gas spot price risk are -1.1 and .03 respectively.

Figure (1.11) compares the cumulative cash flow earned by the ethanol producers using different hedging techniques. The graph (represented by '*') illustrates the cumulative cash flow path under the three-period dynamic hedging model. Similarly, the graphs (represented by 'x' and '#') represent the cumulative cash flow under no-hedge and constant hedge strategies respectively.

### 1.6.4 Performance Test

Performance test results for constant hedge model, time varying static hedge model and GDH model as compared to a 'no hedge' scenario are reported in table (1.7). Given the fluctuations in cumulative cash flow caused by volatility in ethanol, natural gas and corn spot prices, the ethanol producer establishes futures contracts to minimize spot price risk. The producer's wealth at the end of the period equals the sum of net gain on futures transactions and net cash value from spot market transactions. The futures positions can be adjusted on a monthly basis. Performance is evaluated in terms of effects on the variance of the producer's cumulative cash flow position for the three types of hedging techniques compared to 'no hedge' strategy.

#### 1.6.4.1 Constant Hedge Model

Results indicate that in regime 1, producers may utilize constant hedging technique to hedge returns from ethanol spot market using natural gas futures contracts. This decreases variance of cash flow returns by 0.2902%. Interestingly, in regime 2, utilizing corn and ethanol futures contracts as hedging instruments, the producer may be able to decrease variance of cash flow returns by 3.2819%. However, magnitude of variance reduction and direction of change varies across natural gas and corn. If the producer engages in constant hedging technique to hedge natural gas spot price against natural gas futures contracts, variance of cumulative cash increases by 3.0354% in regime 1. However, it decreases by 2.2805% in regime 2. Similarly, utilizing constant hedge strategy, the producer may mitigate returns from corn spot market using returns from corn futures contracts. Results indicate a decrease in variance of cumulative cash flow returns by 3.7722 and 8.7670 percentage points in regime 1 and 2 respectively.

Next we consider the effect of hedging on the portfolio comprising of ethanol as the primary output and natural gas and corn as the two primary inputs. Under constant hedge strategy, variance of cumulative cash flow decreases by 2.1216% and 0.9978% in regime 1 and 2 respectively.

#### 1.6.4.2 Time Varying Static Hedge Model

According to the analysis, in regime 1, hedging ethanol spot price using time varying static hedge strategy decreases the variance of cash flow returns by 0.2315%. Similarly, utilizing this strategy to mitigate natural gas spot price risk using natural gas futures contracts, the producer is able to decrease variance of cumulative cash flow by 0.0944 and 1.0155 percentage points in regime 1 and 2 respectively. Results for hedging corn spot prices may be similarly interpreted. Next we analyze the performance of time varying static hedge strategy while considering the portfolio of commodities (i.e. ethanol, natural gas and corn). Variance of cumulative cash flow decreases by 1.9514 and 4.1662 percentage points in regime 1 and 2 respectively.

#### 1.6.4.3 Generalized Dynamic Hedge Model

Next we analyze the performance of the GDH model developed in this paper. To demonstrate a simple application of the model and test its effectiveness, we consider two commodities, namely ethanol and natural gas and limit the analysis to three periods. Results indicate that producers can effectively reduce variance of cash flow return by

13.2105% by engaging in the three period hedging strategy as opposed to the 'no hedging' technique. Similarly, the producer may reduce the variance by 11.4222% under the constant hedge rule, assuming no transaction costs.

## 1.7 Conclusion and Policy Implications

This study develops a discrete-time dynamic hedging model for ethanol producers in a multiple commodity-period framework under expected utility maximization and basis risk. The basic assumptions made are futures markets to be unbiased and the size of the cash positions to be nonstochastic. A typical ethanol producer, to mitigate price risk for inputs and outputs, initiates a multiple period hedging strategy at initial time period for the next $T$ periods of production. As he moves to the next period, he completes all cash market transactions and liquidates the futures contract that has the closest maturity date lying beyond the current month. With new information available, he updates the futures position for the remaining futures contracts. We derive the sequence of optimal hedging positions at each time period that minimizes the variance of cumulative cash flow of the ethanol producer at the end of period $T$. The model concludes that the optimal dynamic hedge depends on interest rates, the length of time remaining in the cash-holding period, and a particular covariance-to-variance ratio. The hedging rule obtained generalizes the dynamic hedging rule obtained by Myers and Hanson (1996) by considering multiple commodities, accommodating for multiple cash market transactions and allowing for cross-hedging.

Next the study compares dynamic hedge ratios and hedging effectiveness using the optimal hedging rule derived in this paper and the dynamic error-correction hedging model utilizing moving sample variances and covariances. Given that ethanol was included in the CBOT futures trading list on March, 2005, the ethanol producers has the option to hedge against ethanol futures contracts from March, 2005 onwards. Empirical results show that natural gas futures contracts may have been a good cross-hedging instrument prior to this time period. However, post March, 2005, ethanol producers may effectively hedge using ethanol futures contracts and cross hedge using corn futures contracts. Natural gas spot and corn spot price risk may be hedged effectively using their respective futures contracts. The performance test results indicate in regime 1, under dynamic hedge strategy, variance of cumulative cash flow of the portfolio decreases by 1.9514%, where as, it decreases by 2.1216% under constant hedging strategy. However, in the second regime, with ethanol futures contracts being the additional hedging instrument available, the variance decreases by 4.1662% and 0.9978% under dynamic and static hedge strategies respectively.

Dynamic hedging model performs better than the 'no hedge' scenario in reducing the producer's variance of cumulative cash flow. For a simple illustration of the hedging model derived in this paper, we consider a three-period and two commodity framework. Performance analysis indicates a 13.2105% decreases in variance of cumulative cash flow compared to the no-hedge scenario where the producer only engages in cash market transactions. Similarly, the producer may effectively 11.4222% in variance of cumulative cash flow employing static hedging strategy. Given the data limitations, results are very encouraging.

The solution to the dynamic hedging model derived under the generalized set up is most effective provided there is little or no uncertainty surrounding the size of the cash position being hedged and also if the assumption of an unbiased futures market is a good approximation. We also assume no transaction cost for setting up and updating hedge positions. An extension of the current work may be to derive the optimal dynamic hedging rule relaxing the above assumptions. The empirical analysis is restricted to the commodity set related to the ethanol industry. The effectiveness of the hedging strategy may be tested using a wider set of commodities. Moreover, this paper considers futures contracts as the risk management tool. Future research work may consider discussion and analysis of options and forward contracts as alternative risk management tools by the agricultural producers and analyze relative efficiency of each of these contracts with respect to futures contracts.

# Chapter 1 Appendix

## A1.1 Derivation of Cumulative Cash Flow

The culumlative cash flow in terminal period $T$ is given by equation (1.11):

$$\pi_T = (1+r)[\pi_{T-1} - C_{T-1}] + \Delta\mathbf{f_T}\mathbf{b}'_{\mathbf{T-1}} + \mathbf{P_T}\mathbf{A}'_{\mathbf{T}} \tag{1.11}$$

Using assumptions (A1) and (A2), the cumulative cash flow constraint may be expressed as:

$$\pi_T = (1+r)(\pi_{T-1} - C_{T-1}) + \mathbf{e_T}\mathbf{b}'_{\mathbf{T-1}} + [E_{T-1}(\mathbf{P_T}) + \mathbf{v_{T-1,T}}]\mathbf{A}'_{\mathbf{T}} \tag{1.11a}$$

$$\pi_T = (1+r)(\pi_{T-1} - C_{T-1}) + \mathbf{e_T}\mathbf{b}'_{\mathbf{T-1}} + [E_{T-1}(\mathbf{P_T}) + \mathbf{v_T}]\mathbf{A}'_{\mathbf{T}} \tag{1.11b}$$

Using assumptions (A4), equation (1.11b) may be restated as:

$$\pi_T = (1+r)(\pi_{T-1} - C_{T-1}) + \mathbf{e_T}\mathbf{b}'_{\mathbf{T-1}} + [E_{T-1}(\mathbf{P_T}) + \mathbf{e_T}\boldsymbol{\delta}_{\mathbf{T}} + \boldsymbol{\varepsilon}_{\mathbf{T}}]\mathbf{A}'_{\mathbf{T}} \tag{1.14}$$

Table 1.1
Summary Statistics

| | Spot Prices | | | | Futures Prices | | | |
|---|---|---|---|---|---|---|---|---|
| | Corn | Natural gas | Ddgs | Ethanol | Corn | Natural gas | Gasoline | Ethanol |
| Mean | 2.6931 | 4.0319 | 104.7700 | 1.4862 | 271.5355 | 4.1254 | 0.9919 | 2.1593 |
| Standard Deviation | 0.8686 | 2.6934 | 34.2236 | 0.5133 | 89.0637 | 2.7403 | 0.6385 | 0.4434 |
| Minimum | 1.6100 | 1.1575 | 46.0000 | 0.9000 | 180.5000 | 1.1890 | 0.3463 | 1.4900 |
| Maximum | 6.7300 | 13.6907 | 190.0000 | 3.5800 | 748.7500 | 14.1830 | 3.5494 | 3.7000 |
| Skewness | 2.0016 | 1.2307 | 0.3851 | 1.4828 | 2.2801 | 1.2315 | 1.6484 | 0.9249 |
| Kurtosis | 4.4673 | 1.1198 | -0.4120 | 1.6493 | 6.2115 | 1.2029 | 2.1677 | 1.9641 |
| Normality Tests | | | | | | | | |
| Shapiro-Wilk (W) | 0.7909*** | 0.8445*** | 0.9666*** | 0.8224*** | 0.7516*** | 0.8524*** | 0.7790*** | 0.9396** |
| Anderson-Darling | 14.0121** | 12.0114** | 2.4050** | 14.4583** | 16.5201** | 10.9208** | 18.2766** | 0.4844 |
| Ljung-Box test Q(12) | 1137.80*** | 1540.59*** | 934.81*** | 1521.95*** | 1089.13*** | 1518.51*** | 1824.22*** | 46.78*** |
| Tests for Serial Correlation | | | | | | | | |
| Durbin–Watson test | 0.078 | 0.022 | 0.134 | 0.092 | 0.133 | 0.109 | 0.054 | 0.559 |

*, ** and *** represents significance at 10%, 5% and 1% levels respectively

Table 1.2

Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Test Results for Unit Roots

| | ADF Test results | | | | PP Test results | | | |
|---|---|---|---|---|---|---|---|---|
| | Level | | First Differences | | Level | | First Differences | |
| | Intercept | Intercept & Trend | Intercept | Intercept & Trend | Intercept | Intercept & Trend | Intercept | Intercept & Trend |
| Spot Price data | | | | | | | | |
| Corn | -2.62* | -2.86 | -7.71*** | -7.71*** | -1.71 | -1.94 | -10.39*** | -10.37*** |
| Natural gas | -1.53 | -3.60* | -8.99*** | -8.97*** | -1.07 | -2.36 | -10.02*** | -10.00*** |
| DDGS | -2.09 | -1.98 | -8.12*** | -8.24*** | -2.37 | -2.16 | -10.67*** | -10.68*** |
| Ethanol | -3.09* | -4.23** | -12.11*** | -12.08*** | -2.25 | -3.09 | -10.98*** | -10.96*** |
| Futures Price data | | | | | | | | |
| Corn | -1.97 | -2.25 | -9.53*** | -9.52*** | -2.56 | -2.86 | -18.41*** | -18.38*** |
| Natural gas | -2.51 | -3.94* | -11.22*** | -11.21*** | -2.48 | -3.85* | -14.91*** | -14.89*** |
| Gasoline | -1.89 | -3.30* | -8.46*** | -8.45*** | -1.61 | -2.87 | -12.71*** | -12.68*** |
| Ethanol | -2.64* | -3.35* | -5.25*** | -5.13*** | -2.84* | -3.51* | -7.08*** | -7.08*** |

*, ** and *** represents significance at 10%, 5% and 1% levels respectively

Table 1.3
Johansen Test Results for pair wise Cointegration between Spot and Futures Prices, accounting for 'Time to Maturity'

| Pair of prices | Number of lags in VAR | Null hypothesis | Trace Statistics | Maximal Eigen Value Statistics |
|---|---|---|---|---|
| Ethanol Spot/ Ethanol futures | 2 | $r = 0$ | 47.3809** | 38.0423** |
| | | $r \leq 1$ | 9.3386 | 8.9990 |
| | | $r \leq 2$ | 0.3395 | 8.9990 |
| Ethanol spot/ DDGS spot | 2 | $r = 0$ | 10.0418 | 9.6158 |
| | | $r \leq 1$ | 0.4260 | 0.4260 |
| Ethanol spot/ Gasoline futures | 2 | $r = 0$ | 42.9541** | 38.2552** |
| | | $r \leq 1$ | 4.6989 | 4.5759 |
| | | $r \leq 2$ | 0.1230 | 0.1230 |
| Ethanol Spot/ Natural gas futures | 2 | $r = 0$ | 46.8761** | 35.0760** |
| | | $r \leq 1$ | 11.8001 | 11.6121** |
| | | $r \leq 2$ | 0.1880 | 0.1880 |
| Ethanol Spot/ Corn futures | 2 | $r = 0$ | 75.2361** | 65.0783** |
| | | $r \leq 1$ | 10.1578 | 10.0958 |
| | | $r \leq 2$ | 0.0620 | 0.0620 |
| Natural gas Spot/ Natural gas futures | 2 | $r = 0$ | 67.9993** | 51.6840** |
| | | $r \leq 1$ | 16.3152** | 16.0424** |
| | | $r \leq 2$ | 0.2728 | 0.2728 |
| Natural gas Spot/ Ethanol futures | 2 | $r = 0$ | 49.2950** | 40.2994** |
| | | $r \leq 1$ | 8.9956 | 8.7722 |
| | | $r \leq 2$ | 0.2234 | 0.2234 |
| Natural gas Spot/ Corn futures | 2 | $r = 0$ | 65.4804** | 60.8380** |
| | | $r \leq 1$ | 4.6424 | 4.6138 |
| | | $r \leq 2$ | 0.0285 | 0.0285 |
| Natural gas Spot/ DDGS spot | 2 | $r = 0$ | 4.7151 | 4.7073 |
| | | $r \leq 1$ | 0.0078 | 0.0078 |
| Corn Spot/ Corn futures | 2 | $r = 0$ | 132.7806** | 86.0461** |
| | | $r \leq 1$ | 46.7345** | 46.5533** |
| | | $r \leq 2$ | 0.1812 | 0.1812 |
| Corn Spot/ DDGS spot | 2 | $r = 0$ | 22.3451 | 18.6640 |
| | | $r \leq 1$ | 3.6811 | 3.5583 |
| | | $r \leq 2$ | 0.1229 | 0.1229 |
| Corn Spot/ Gasoline futures | 2 | $r = 0$ | 15.9986 | 11.2633 |
| | | $r \leq 1$ | 4.7354 | 4.6665 |
| | | $r \leq 2$ | 0.0689 | 0.0689 |
| Corn Spot/ Ethanol futures | 2 | $r = 0$ | 42.5180** | 40.1154** |
| | | $r \leq 1$ | 2.4027 | 2.3425 |
| | | $r \leq 2$ | 0.0601 | 0.0601 |
| Corn Spot/ Natural gas futures | 2 | $r = 0$ | 35.8036** | 28.7524** |
| | | $r \leq 1$ | 7.0512 | 6.9845 |
| | | $r \leq 2$ | 0.0667 | 0.0667 |

** implies significance at 5% level

Table 1.4

Johansen Cointegration Test Results among the Spot and Futures Price Series, accounting for 'Time to Maturity'

| Null Hypothesis | Trace Statistics | 5% Critical Value | Maximal Eigen Value Statistics | 5% Critical Value |
|---|---|---|---|---|
| $r = 0$ | 143.4892** | 140.74 | 52.3455** | 47.99 |
| $r \leq 1$ | 91.1436 | 109.93 | 30.6705 | 41.51 |
| $r \leq 2$ | 60.4731 | 82.61 | 22.5775 | 36.36 |
| $r \leq 3$ | 37.8956 | 59.24 | 17.9234 | 30.04 |
| $r \leq 4$ | 19.9723 | 39.71 | 10.8647 | 23.80 |
| $r \leq 5$ | 9.1075 | 24.08 | 6.3021 | 17.89 |
| $r \leq 6$ | 2.8054 | 12.21 | 2.3242 | 11.44 |
| $r \leq 7$ | 0.4813 | 4.14 | 0.4813 | 3.84 |

** implies significance at the 5% level

Table 1.5

Temporal Causality Results Based on Vector Error-Correction Model (VECM)

| Dependent Variable | Δ Corn Spot | Δ Natural Gas Spot | Δ DDGS Spot | Δ Ethanol Spot | Δ Corn Futures | Δ Natural Gas Futures | Δ Gasoline Futures | Δ Ethanol Futures |
|---|---|---|---|---|---|---|---|---|
| Δ Corn Spot | - | -0.0400 | 0.0098* | 0.4384 | -0.0034 | -0.1142** | -0.1922 | -0.2373 |
| Δ Natural Gas Spot | -0.0734 | - | -0.0146** | 0.8883** | -0.0040 | 0.1456** | -0.2691 | -0.2721 |
| Δ DDGS Spot | 8.0521 | -0.6117 | - | 10.9884 | 0.0070 | -2.0916 | -5.9638 | -4.5373 |
| Δ Ethanol Spot | -0.1878 | -0.0547 | -0.0009 | - | 0.0012 | -0.0978** | 0.0936 | -0.7273*** |
| Δ Corn Futures | 14.5515 | -6.7438 | 0.1078 | 56.2799*** | - | 2.0814 | -37.1504** | -50.8101** |
| Δ Natural Gas Futures | -0.6866 | 0.4672 | -0.0433 | 1.1094 | 0.0004 | - | -0.7667 | -0.3546 |
| Δ Gasoline Futures | -0.0665 | -0.0002 | -0.0011 | 0.7596*** | 0.0014 | -0.0477 | - | -0.4743** |
| Δ Ethanol Futures | 0.2958 | -0.0593 | 0.0062 | 1.1932*** | -0.0008 | -0.0239 | -0.1209 | - |

*, ** and *** represents significance at 10%, 5% and 1% levels respectively

## Table 1.6
## Constant Hedging Models

| | |
|---|---|
| **Hedging ethanol spot price using Near-by futures contracts** | |
| **(1991, January – 2005, March)** | |
| Intercept | 0.8436*** |
| Error correction term with respect to natural gas futures price | 0.8716*** |
| Difference in natural gas futures price | 0.0842*** |
| Difference in corn futures price | 0.0000 |
| Difference in RBOB gasoline futures price | -0.0337 |
| Lag ethanol spot price | -0.8232*** |
| Lag natural gas futures price | 0.0637*** |
| **(2005, April – 2009-May)** | |
| Intercept | -0.0129 |
| Lag ethanol spot price | 0.3491*** |
| Difference in ethanol futures price | 0.3018** |
| Difference in natural gas futures price | 0.0167 |
| Difference in corn futures price | 0.0015** |
| Difference in RBOB gasoline futures price | 0.0022 |
| Lag natural gas futures price | 0.0167 |
| **Hedging corn spot price using Near-by futures contracts** | |
| **(1991, January – 2005, March)** | |
| Intercept | 1.8598*** |
| Error correction term with respect to natural gas futures price | 0.7030*** |
| Difference in corn futures price | 0.0025*** |
| Difference in natural gas futures price | -0.0330*** |
| Lag corn spot price | -0.9051*** |
| Lag corn futures price | 0.2088*** |
| Lag natural gas futures price | -0.0440*** |
| **(2005, April – 2009-May)** | |
| Intercept | 0.1697 |
| Difference in corn futures price | 0.0090*** |
| Difference in natural gas futures price | -0.0159 |
| Lag corn spot price | -1.0539*** |
| Lag corn futures price | 0.9989*** |
| **Hedging natural gas spot price using Near-by futures contracts** | |
| **(1991, January – 2005, March)** | |
| Intercept | 3.4625*** |
| Error correction term with respect to natural gas futures price | 0.3489*** |
| Error correction term with respect to corn futures price | 0.2531*** |
| Difference in natural gas futures price | 0.3798 *** |
| Difference in corn futures price | -0.0019*** |
| Lag natural gas spot price | -0.6602*** |
| Lag natural gas futures price | 0.3793*** |
| Lag corn futures price | -0.1819*** |
| **(2005, April – 2009-May)** | |
| Intercept | 0.0850 |
| Difference in natural gas futures price | 0.6849*** |
| Difference in corn futures price | 0.0012 |
| Lag natural gas spot price | -0.6418*** |
| Lag natural gas futures price | 0.4135 |
| Lag corn futures price | 0.0255 |

*, ** and *** represents significance at 10%, 5% and 1% levels respectively

Table 1.7
Comparison of the Effects of Hedging on Cumulative Cash Flow across Models*

| **Conventional Hedge Models** | | |
|---|---|---|
| | Moving Sample Hedge | Constant Hedge |
| **Regime 1 (January-1991 to March, 2005)** | | |
| Ethanol Spot | -0.2315 | -0.2902 |
| Natural Gas Spot | -0.0944 | 3.0354 |
| Corn Spot | -1.1748 | -3.7722 |
| All commodities | -1.6814 | -2.1216 |
| **Regime 2 (April, 2005 to May, 2009)** | | |
| Ethanol Spot | -7.4565 | -3.2819 |
| Natural Gas Spot | -1.0155 | -2.2805 |
| Corn Spot | -2.4579 | 8.7670 |
| All commodities | -4.1662 | -0.9978 |
| **Dynamic Two Period Hedge Model (Three Periods) (April, 2005 to May, 2009)** | | |
| | Dynamic Model | Constant Hedge |
| Variance in Cash Flow | -13.2105 | -11.4222 |

*Represents percentage change in variance of cumulative cash flow using different hedging techniques compared to 'no hedge' scenario

Figure 1.1
Cross Hedging Ethanol Spot against Near-by Natural Gas Futures Contracts, January-1991 to May, 2009

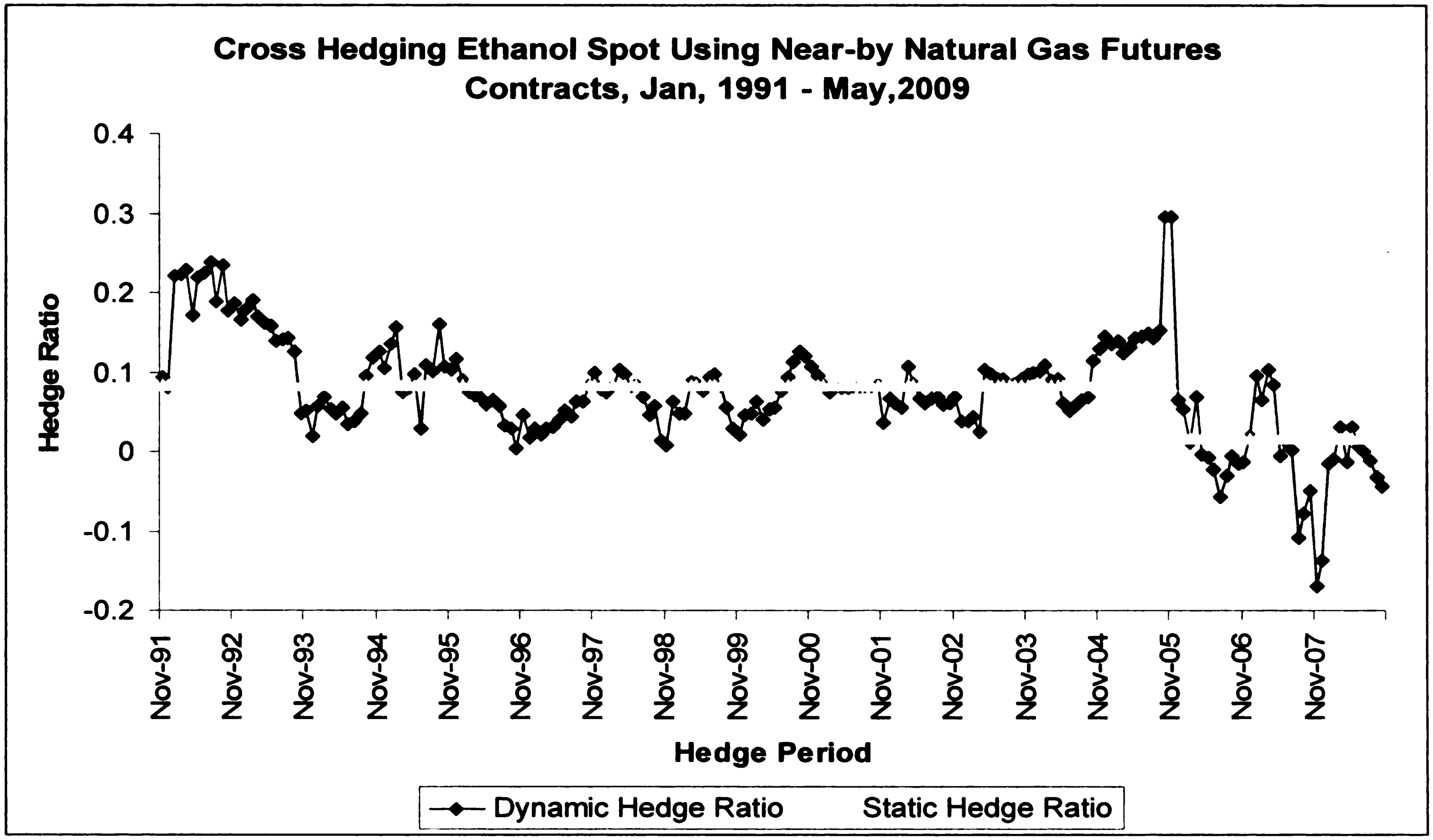


Figure 1.2

Cross Hedging Ethanol Spot against Near-by Corn Futures Contracts, April-2005 to May, 2009

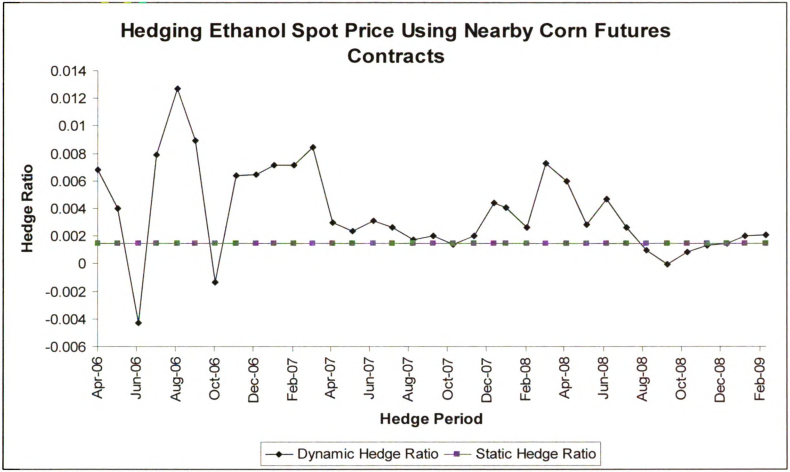


Figure 1.3

Hedging Ethanol Spot Price against Nearby Ethanol Futures, April, 2005 to May, 2009

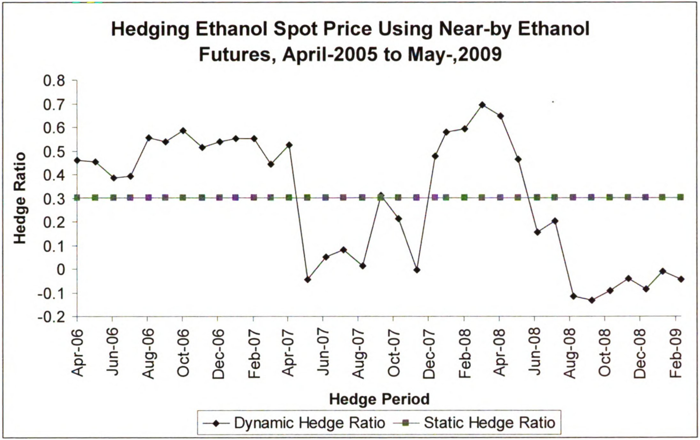


Figure 1.4
Hedging Natural Gas Spot Price against Nearby Natural Gas Futures contracts

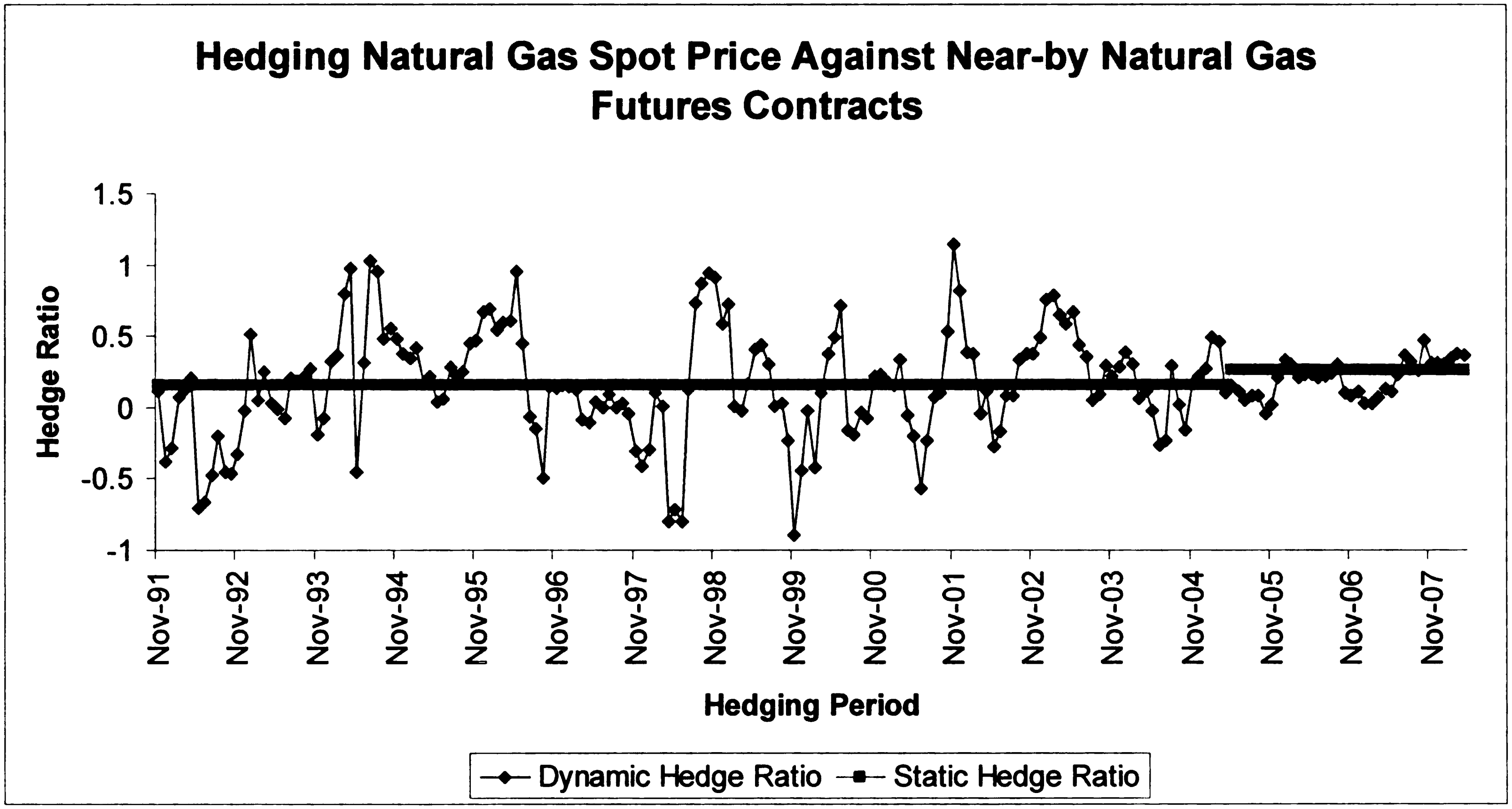


Figure 1.5
Hedging Corn Spot Price against Nearby Corn Futures contracts

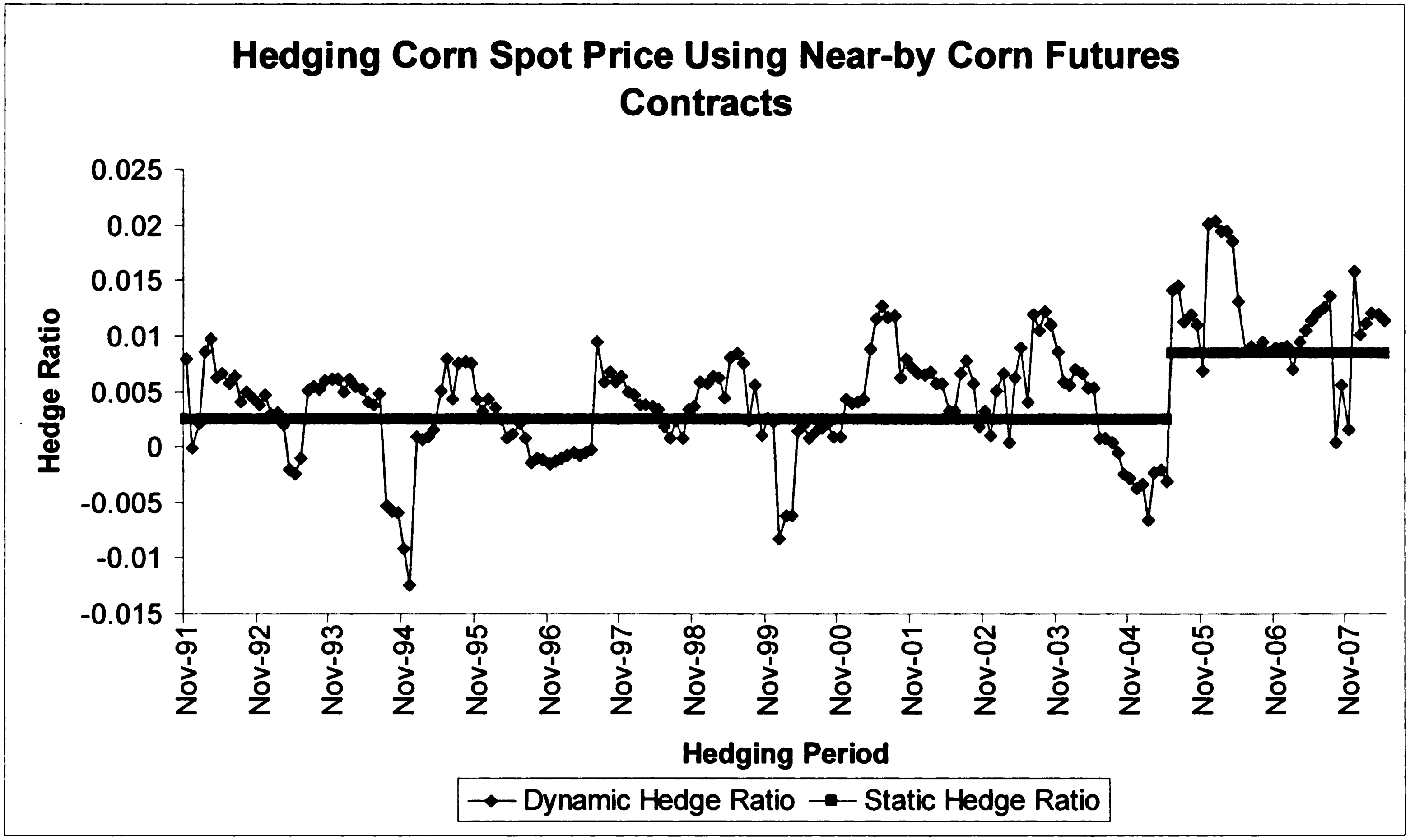


Figure 1.6
Persistence in Ethanol Spot Price in Second Regime

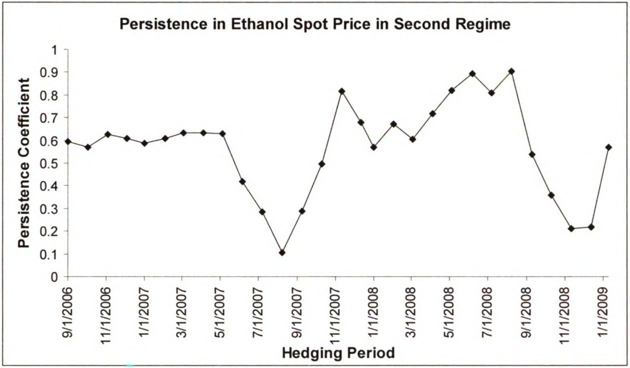


Figure 1.7

Persistence in Natural Gas Spot Price in Second Regime

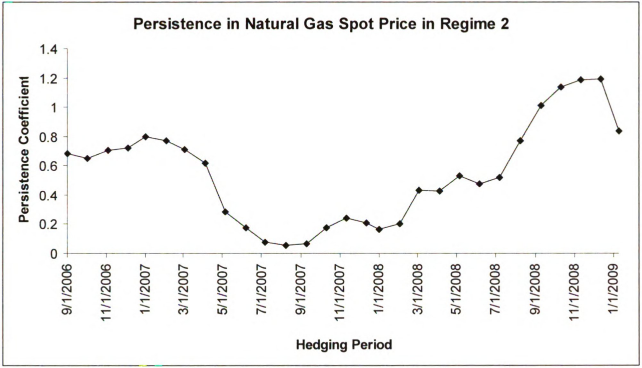


Figure 1.8
Ethanol Hedge Positions in Period I and II

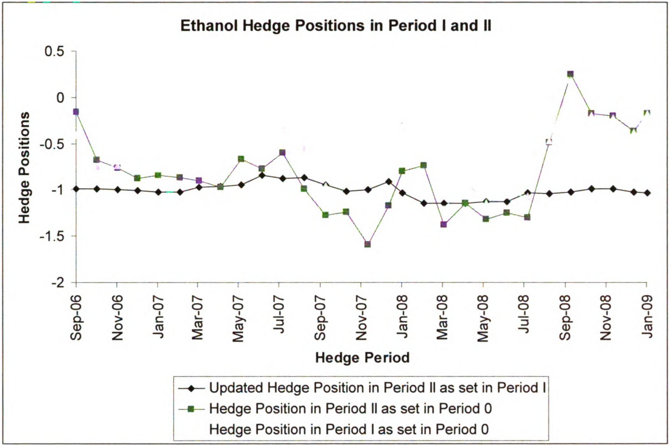


Figure 1.9
Natural Gas Hedge Positions in Period I and II

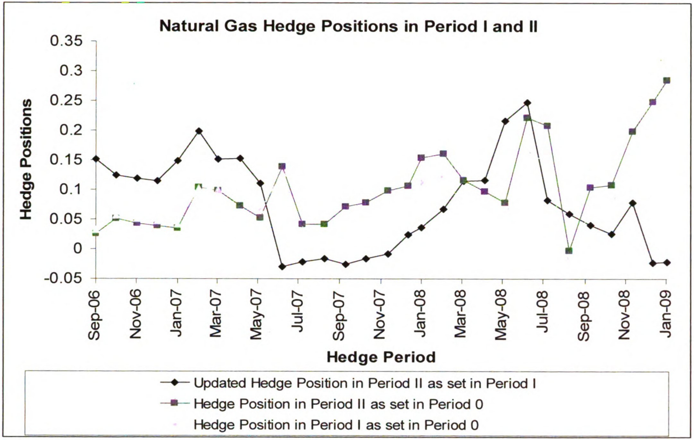
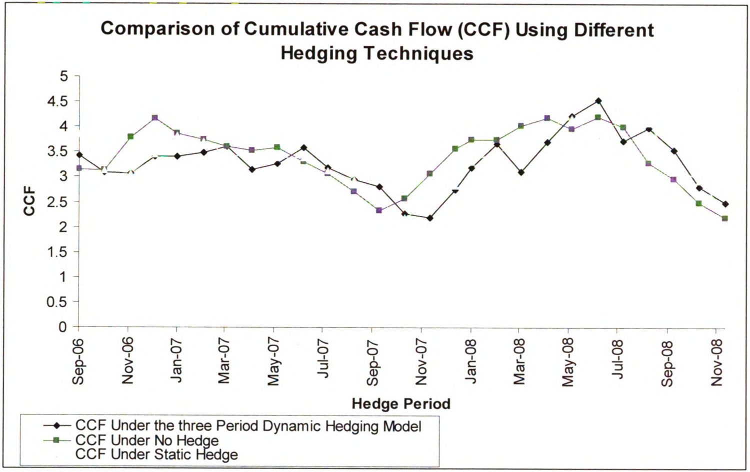


Figure 1.10
Comparison of Cumulative Cash Flow across Hedging Techniques



# Chapter 2

## Consumer Preference for Alternative Transportation Fuels: A Conjoint Analysis

### 2.1 Introduction

Recent decades have witnessed persistent effort by the U.S. government to enhance ethanol production and promote ethanol blended gasoline as an alternative transportation fuel (Rask, 1998; Yacobucci 2006, 2008). Successful implementation of such mandates and market acceptance of fuel alternatives may aid the government in solving ongoing energy crises by slowing U.S. gasoline demand growth rates. Use of ethanol, considered the cleanest liquid fuel alternative to fossil fuels, may also reduce greenhouse gas (GHG) emissions, help prevent radical climate change and bolster local economies (Lin and Tanaka, 2005; Niven, 2004). However, less energy efficiency and limited availability as compared to conventional gasoline are some of the major drawbacks of alternative fuels. The pros and cons of ethanol blended gasoline as an alternative transportation fuels may result in consumers holding heterogeneous preferences. Thus for policy prescriptions and for strategic product positioning in the U.S. market, analyses of consumer preference for alternative transportation fuels and welfare analyses are of vital importance.

We evaluate the characteristics of consumer preferences for alternative transportation fuels with differing fuel attributes including fuel cost and availability, emission level, bio-feedstock source, and purchase and maintenance cost of the appropriate vehicle. Alternative transportation fuels considered in this study are E-10 and E-85 where E-x implies motor fuel blends of x% ethanol with (100 - x) % gasoline. Ethanol may be derived from corn or cellulosic biomass including corn stalks, wood stalks and switch grass. Thus the choice set consists of a set of hypothetical fuels and a set of real transportation fuel alternatives available in the market. We employ choice based conjoint analysis to estimate consumer willingness to pay (WTP) to switch from conventional gasoline to alternative transportation fuels in a U.S. based survey (Louviere, 1988; Lusk et al., 2003; Alfnes and Rickertsen, 2003). A latent segmentation approach is employed to allow for and evaluate consumer preference heterogeneity (Boxall and Adamowicz, 2002). Our analyses of consumers' WTP for alternative transportation fuels uses observed variables (i.e. the demographic and socio-economic characteristics) as well as unobserved or latent variables. We also evaluate whether willingness to pay for alternative fuels varies across consumer segments and how availability of alternative fuels impacts social welfare. Three particular hypothetical situations are considered where due to varied reasons, either conventional gasoline, corn grain based ethanol or cellulosic ethanol is not available for consumption. We identify welfare effects across consumer segments in each of these three cases.

The remainder of the paper is organized as follows. Section 2.2 gives an overview on the existing research on alternative fuel vehicles and the methodology. Section 2.3 describes the latent class model. Section 2.4 presents a description on the research design. Section 2.5 gives the empirical specifications. Section 2.6 presents the empirical results and Section 2.7 concludes.

## 2.2 Previous Studies

Studies on consumer demand for alternative transportation fuels are few and limited in scope. Bhattacharjee et al. (2008) measured willingness to pay for E-10 fuel by U.S. consumers employing a contingent valuation (CV) technique in a simultaneous latent variable equation framework. The authors found self-described liberals have significantly higher WTP, WTP is higher for males, and WTP increases as familiarity with ethanol increases. However, supporters of alternative fuels, but who are not sympathetic to ethanol, have significantly lower WTP for E-10. Results show that the mean WTP for E10 is almost .049 cents higher than the prevailing national average price of regular gasoline during the time of survey ($2.55/gallon,).

Several studies on the potential demand for alternative fuel vehicles have been conducted over the last decade using discrete choice analyses (Ahn et al., 2008; Horne et al., 2005;). Potoglou and Kanaroglou (2007) examined the potential demand for alternative fuelled vehicles in Canada. The study concluded that purchase tax reliefs and low emission levels may attract potential buyers whereas limited fuel availability may prove to be a major deterrent factor. Ewing and Sarigollu (2000) assessed preferences for clean-fuel vehicles in Canada using a discrete choice experiment. The study concluded that even though consumers value the environmental impact, vehicle performance characteristics are critical decision variables. It also concluded that government regulations are not sufficient to create a market for clean-fuel vehicles.

Following Boxall and Adamowicz (2002) and Greene and Hensher (2008), we use a latent segmentation model to analyze consumer preference heterogeneity for alternative transportation fuel in the U.S. using an internet based survey and employing choice based conjoint analysis. This is the first known study to assess U.S. consumer preference for alternative transportation fuels besides conventional gasoline.

Choice experiments present respondents with the task of choosing one alternative among multiple product profiles, each described in terms of a generally common attribute set. Traditionally, resulting choice data are modeled through models such as the Multinomial Logit (MNL), Nested MNL, and Probit models (Swait and Adamowicz, 2001). However, each of these models suffers from several shortcomings. The MNL has an error structure assuming Independence from Irrelevant Alternatives (IIA). The IIA property states that 'the relative odds of one alternative being chosen over a second should be independent of the presence or absence of unchosen third alternatives' (McFadden, 1974). Moreover, conventional MNL assumes homogeneity in consumer preference. That is, all respondents have the same preferences across alternative fuel attributes (Lusk et al., 2003). To account for consumer preference heterogeneity, Boxall and Adamowicz (2002) use a latent class model and introduces sociodemographic variables to understand systematic heterogeneity. The approach assumes that consumers can be grouped into discrete segments where each segment is characterized by homogenous preferences while preferences are heterogeneous across segments (Swait, 1994). The model simultaneously assesses the influence of latent variables such as attitudes, perceptions, socioeconomic effects and choice-based attributes in the estimation of the latent segments and predicting product choice (McFadden, 1986; Swait 1994).

Internet surveys offer the possibility of large sample sizes allowing the researcher to investigate a range of methodological questions (Berrens, 2003). Internet-based data collection method has the potential to yield higher-quality data with lower nonresponse rates and is less costly than traditional methods (Fleming and Bowden, 2009). According to Lindhjem and Navrud (2008), data quality and welfare estimates are not significantly different or substantially biased using Internet as the data collection mode of choice compared to in-person interviews. A study by Kypri et al. (2004) deals with nonresponse bias in internet surveys of alcohol use. The findings from the study indicate that the bias resulting from nonresponse is arguably too small to be of concern with respect to estimating other important attributes such as consumption levels, the incidence of alcohol-related problems etc.

In response to the need for more rapid and iterative feedback on customer preferences, researchers are increasingly employing web-based adaptive conjoint analysis (ACA) methods that adapt the design of conjoint questions based on a respondent's answers to previous questions as opposed to the traditional non-adaptive design (Fixed). A study by Dahan et al. (2002) reveal that results from both methods exhibit a remarkable level of consistency and this finding holds across estimation methods.

## 2.3 Model of Fuel Choice

Random utility models are based upon the assumption that individual $i$ derives utility $U_{ij}(X_{ij})$ from selecting option $j$ where $X_{ij}$ is a vector of attributes of $j$ as perceived by individual $i$. The utility function, $U_{ij}(X_{ij})$ is composed of two components, the deterministic component that depends on the attributes of the alternatives $V_{ij}(X_{ij})$ and the random component represented by the error term, $\varepsilon_{ij}$ :

$$U_{ij} = V_{ij}(X_{ij}) + \varepsilon_{ij} \tag{2.1}$$

In this study, $V_{ij}$ is the systematic portion of the utility function determined by the alternative fuel attributes and their levels:

$$V_{ij} = \beta_i X_{ij} \ \forall\ j = A, B, C \tag{2.2}$$

$$V_{ij} = \delta \quad \forall\ j = D \tag{2.3}$$

where $X_{ij}$ is the vector of choice attributes, 'A', 'B' and 'C' are alternative choices available to the consumer, 'D' refers to the option of not purchasing either of the three alternatives and $\delta$ is a constant. The fuel attributes ($X_{ij}$) considered in the analysis are fuel cost, fuel availability, level of emission, purchase and maintenance cost, and bio-feedstock or not.

The latent class approach assumes that latent variables such as general attitudes and perceptions and observable variables such as socioeconomic characteristics influence segment membership and classifies the respondent into one of $S$ segments (Swait, 1994). The probability that a randomly chosen individual $i$ chooses $j$ and lies in segment $s$ where $s = 1, \ldots, S$ is given by (McFadden, 1974; Swait, 1994):

$$\pi_i(j) = \sum_{s=1}^{S} \left[ \frac{\exp(\alpha\lambda_s Z_i)}{\sum_{s=1}^{S} \exp(\alpha\lambda_s Z_i)} \right] * \left[ \frac{\exp(\mu_s \beta_s X_{ij})}{\sum_{j\in A,B,C,D} \exp(\mu_s \beta_s X_{ij})} \right] \tag{2.4}$$

where the first expression gives the probability of membership for respondent $i$ in segment $s$ (i.e. $\pi_{is}$) and the second expression gives the choice probabilities conditional on segment membership (i.e. $\pi_{i|s}(j)$). $\mu_s$ and $\beta_s$ are segment specific scale and utility parameters respectively, $\lambda_s$ are segment membership parameters and $Z_i$ is a vector of both the socioeconomic variables $(I_i)$ as well as latent characteristics. Socioeconomic characteristics used in this analysis are gender, age, level of education, income, employment, race, family size, state of residency, vehicle characteristics and willingness to buy a Flex Fuel Vehicle (FFV) in the next five years. This model permits choice attribute data and individual consumer characteristics to simultaneously explain choice behavior. Moreover, latent class approach relaxes the requirement of the analyst to make specific assumptions about the distributions of parameters across individuals (i.e. normality not assumed). The parameters, i.e. $\lambda_s, \beta_s, \mu_s, \alpha$ are estimated via maximum likelihood methods. The log likelihood function may be written as:

$$\ln L(\alpha, \beta \mid S) = \sum_{i=1}^{N} \sum_{m} \sum_{j\in A,B,C,D} \delta_{imj} \ln\left( \sum_{s=1}^{S} \pi_{i|s}(j) * \pi_{is} \right) \tag{2.5}$$

where $N$ is the total respondents who participated in the survey, $m$ represents the total number of choice sets per person for which the choice data were provided, $j$ represents the alternatives from the choice experiment and $\delta_{ij}$ equals 1 if individual $i$ chooses $j$ and

0 otherwise. The scale parameters $\alpha$ and $\mu$ s are set to unity (Boxall and Adamowicz, 2002).

## 2.4 Research Design

Our unique consideration of cellulosic biomass based fuel, which is not currently available to consumers, necessitates our use of hypothetical choice experiments. Following Gao and Schroeder (2009 AJAE), e-Rewards, Inc. a marketing research company conducted an internet based survey and collected complete response from 1,400 U.S. residents in January, 2009. Table (2.1) gives the descriptive profile of the stated choices sample versus the 2000 U.S. Census. As is evident from the table, the sample is a good representation of the population.

A questionnaire was developed that gathered information on the socio-demographic characteristics of the respondents, their degrees of awareness and their attitudes and perceptions on related issues such as the blender's credit offered by the government for every gallon of ethanol blended with gasoline, possibility of industry level production of cellulosic ethanol etc. The demographic characteristics include age, gender, education, annual income, number of adults and children in the family, state of residency, vehicle characteristics, average number of miles driven annually, average fuel cost etc.

Six additional pieces of information were collected that were used in the latent segment model. These involved a series of 22 statements (Appendix 2A.1) that represented reasons why individuals may favor the usage of ethanol as an alternative fuel based on environmental issues with reference to air pollution, level of GHG emission, and probable effects on climate change, deforestation and loss of grasslands. The other issues considered were the effect of production of corn based ethanol on the local economy in terms of job creation, income generation and opportunity for corn farmers. Some of the geo-political issues considered were the nation's dependency on foreign oil and the possibility of food price volatility injected in the system due to increased corn based ethanol production. Respondents were asked to rate the level of importance of each statement on a 5 point Likert scale ranging from "Strongly Agree" to "Strongly Disagree" (Crandall, 1980; Beard and Ragheb, 1983). The scores of the respondents were analyzed with factor analysis to measure consumer's attitude towards using ethanol as the alternative transportation fuel.

The second part of the survey was an application of a choice experiment where the respondents provide their choices among sets of alternative transportation fuels or opting out from choosing any of these products (Alfnes, 2004; Lusk et al., 2003). We personalized the survey to include choice experiments revealing resident preferences for alternative transportation fuels based on information provided by respondents (i.e., car type, miles driven per year, purchase/lease status) earlier in the survey. Table (2.1) lists the attribute-level specification for the alternative fuel choice experiment:

### 2.4.1 Attributes of Alternative Fuels and Their Levels:

1. *Fuel cost* refers to the total annual cost of buying transportation fuel. It is a function of fuel per gallon prices, fuel efficiency, and the average number of miles driven by the respondent annually. Price of fuel per gallon refers to the price of the transportation fuel per gallon. Fuel efficiency refers to the energy content/ mileage per gallon of alternative transportation fuels.

2. *Level of pollution and GHG emissions* refers to the amount of health-damaging and smog-forming airborne pollutants the vehicle emits and the level of green house gas emitted in terms of the annual tons of $CO_2$ due to combustion of given volume of ethanol blends as compared to gasoline.
3. *Fuel Availability*: Fuel availability is defined as the proportion of existing stations offering fuels other than gasoline in the area. It may be measured by the percentage of gas stations offering the alternatives within a 5 mile radius from the respondent's residence.
4. *Cost of buying and maintaining FFV*: Includes purchase price of a FFV, annual repair and maintenance cost.
5. *Feedstock*: Feedstock refers to the basic ingredient the alternative transportation fuel is derived from. At present, ethanol used in the commercial sector is predominantly corn based. Cellulosic ethanol may be produced from a wide variety of cellulosic biomass feedstocks including agricultural plant wastes (corn stover, cereal straws, sugarcane bagasse), plant wastes from industrial processes (sawdust, paper pulp) and energy crops grown specifically for fuel production, such as switchgrass (Moller, 2005).

**2.4.2 Cheap Talk:**

Current literature suggests willingness-to-pay is overstated in hypothetical valuation questions as compared to when actual payment is required (Lusk, 2003). We introduced cheap talk in our survey to eliminate the potential bias in hypothetical valuation questions. Cheap talk refers to process of explaining hypothetical bias to individuals prior to asking a valuation question.

The experience from previous similar surveys is that people often state a higher willingness to pay than what one actually is willing to pay for the good. It is important that you make your selections like you would if you were actually facing these fuel-vehicle choice decisions, noting that allocation of funds to these alternative fuels means you will have less money available for other purchases. **<u>Please place an "X" in the "I choose" box, below the option that you would choose from each of the following scenarios:</u>**

## 2.5 Empirical Specification

In this choice experiment, a typical choice scenario (Figure 2.1) consisted of four alternatives. The first three choices present the respondent with multiple different sets of hypothetical alternative transportation fuels and vehicle choice. The underlying assumption being that standard vehicles run on conventional gasoline or E-10 where FFVs have the choice of running on gasoline, E-10 or E-85. The fourth option gives the respondents an option to opt out. The conventional gasoline constituted the base alternative with the levels of the attributes being held constant, excepting that of respondent's fuel cost. Attributes of the rest of the alternatives were varied in the design. A design matrix was developed using SAS for designing discrete choice experiments and considering $3^3*2^4*2^4*2^4*2^4$ orthogonal main-effects design, yielding 31 scenarios (Louviere et al. 2000; Kuhfeld, 2005). The scenarios were randomly assigned into 4 blocks each consisting of 8, 8, 8 and 7 choice exercises respectively.

### 2.5.1 Factor Analysis:

The first step in developing the latent segmentation model involved a factor analysis of the 22 statements (motivational indicators) to provide estimates of the latent motivational constructs which enter the membership likelihood function. The scores from the 22 statements were factor analyzed using principal component analysis with varimax rotation (Sprotles And Kendall, 1986). We used confirmatory factor analysis to verify the factor structure of the set of observed variables (Suhr, 2006). The analysis identified four components of motivations for choice of alternative transportation fuels and the factor structure thus obtained explains 91.68% of the variance in the data. These motivational components were labeled based on magnitudes of the loadings of individual statements (Appendix 2A.1).

The first component was called "Economic and Environmental Effect" because statements related to the positive biofuel economic impact of production and usage of ethanol on the U.S. economy as well as the positive environmental effects loaded highly in this factor. The second factor was labeled "Positive intentions toward biofuel" because statements related to how positive individual effort may initiate changes towards adoption of eco-friendly transportation fuel and also make other individuals environmentally consciousness loaded highly in this factor. The third factor involved statements related to the impact of production of corn based ethanol on food supply and on the effect on food price volatility. This factor was labeled "Negative biofuel impact on food". The fourth factor was called "Crisis Overrated". Scores of the four latent factors were then calculated for each individual in the sample yielding four variables to be included in the $Z_i$ vector in equation (2.4), to explain latent segment membership.

### 2.5.2 Estimation of the Number of Latent Segments

In estimating the latent segment models, statistical criteria are used to select the 'optimal' number of segments in a set of estimations and the number of segments imposed varies across estimations. The underlying idea being that as the number of segments increase, the log likelihood value improves. However, the model fit gets compromised as the number of parameters increases due to additional segments. Following Kamakura and Russell (1989), this study uses two criteria to assist in determining the optimal number of segments, the minimum Akaike Information Criterion (AIC) and the minimum Bayesian Information Criterion (BIC) (Boxall and Adamowicz, 2002; Allenby, 1990).

### 2.5.3 Willingness-to-Pay Estimates and Welfare Measures

Consumer willingness to pay (WTP) estimates are of particular interest. Following Lusk et al. (2003) and Tonsor et al. (2009, CJAE), we quantify the value that consumers place on each of the fuel-vehicle attributes by taking the ratio of the attribute coefficients to the purchase and maintenance cost coefficient (multiplied by two if effects coding is applicable) (Boxall and Macnab, 2000). In order to consider statistical variability in parameter estimates, we utilize simulation techniques and generate 20,000 values of each WTP estimate using a bootstrapping procedure proposed by Krinsky and Robb (1986). More specifically, 20,000 observations were drawn from a multivariate normal distribution parameterized by using the coefficients and estimated variance-covariance matrix. The simulated WTP statistics from each model were utilized to empirically test for differences in WTP preferences across segments. First, mean WTP estimates and 95% confidence intervals were identified incorporating both statistical and preference variability in LCM. We repeat similar simulation procedure to obtain the mean WTP estimates and 95% confidence intervals for the MNL model.

We use the utility estimates to examine how restricted alternative fuel choice sets affect consumer welfare. Other than unleaded conventional gasoline, our choice experiment contains four different attribute levels for bio-feedstock: corn grain ethanol and also ethanol derived from cellulosic biomass (i.e. wood, corn stalks and switch grass). We estimate welfare impacts of government policies mandating the use of ethanol blended gasoline (i.e. unleaded conventional gasoline is no longer an option) and of banning usage of corn grain ethanol considering the controversy linking food price volatility with its increased production. Lastly, considering the fact that production of cellulosic ethanol is still in the experimental stage, we examine changes in consumer welfare if it never becomes available to consumers. Following Lusk et al. (2006), Small and Rosen (1978) and Tonsor, Olynk and Wolf (JAAE, forthcoming), expected maximum utility (EU) from consumer $i$'s choice set selection is given by:

$$EU_i = \ln\left(\sum_j \exp(V_{ij})\right) + K \tag{2.6}$$

where $K$ is Euler's constant and $V_{ij}$ is defined by equations (2.2) and (2.3). Under the assumption of no income effects, general welfare changes may be given by:

$$CV_i = \frac{1}{\gamma}\left[\ln\left(\sum_j \exp(V_{ij}^1)\right) - \ln\left(\sum_j \exp(V_{ij}^0)\right)\right] \tag{2.7}$$

where $CV_i$ is the compensating variation for individual $i$, $\gamma$ is the marginal utility of income, the $0$ subscript refers to the initial state and $1$ superscript refers to the new state following some change in $V_{ij}$ (Hanemann, 1982; Boxall and Adamowicz, 2002).

## 2.6 Results and Discussion

In estimating the latent segment models, 1 to 6-segment solutions were attempted. The log likelihood values at convergence reveal improvement in the model fit as segments are added to the procedure, particularly with the 2, 3 and 4 segment models. This is evident in the pseudo R-squared values which increase from the base of 0.074 to 0.341 with the 4 segment model. The minimum BIC and AIC statistics are clearly associated with the four segment model (Boxall and Adamowicz, 2002; McLachlan and Basford, 1988).

### 2.6.1 Characterizing the Segments and Comparing the Models

The segment membership parameters ($\lambda_S$) for the 4-segment solution are displayed in Table (2.3). According to the segment membership probabilities, segment 1 and 2 each had 20.9% members of the total 1400 respondents, 13.8% were members of segment 3, and the remaining 44.4% belong to segment 4. Only the second and fourth segments have significant, negative coefficients on the 'opt out' parameter. This indicates that the members who belong to the first and third segments (approximately one-third of consumers) are statistically indifferent to all options available.

The data revealed high correlation between the number of adults and number of children in the household and also number of vehicles owned by the household. It also revealed high correlation between age and employment status of the respondent. Thus we included age of the respondent, plans of buying a FFV in the next five years, number of adults in the household and annual pre-tax household income in the set of demographic factors used in the analysis. Note that the parameters for the fourth segment are normalized during estimation.

The utility function parameters for the multinomial logit (MNL) model and the 4-segment model are displayed in table (2.4). We labeled the segments based on their preferences (e.g., utility coefficients) as well as their demographic and socioeconomic characteristics (e.g., segment membership variables) displayed in tables (2.4) and (2.3) respectively. Segment one was labeled 'Cellulosic Ethanol Acceptor' since the members who belong to this segments exhibit significant preference for ethanol derived from cellulosic biomass (i.e. wood, corn stalk and switch grass). The second segment was labeled 'Corn Grain Ethanol Rejecter' because members lying in this segment exhibit disutility from the use of corn grain based ethanol. These segment members are however indifferent to the use of cellulosic ethanol. Finally the third segment was labeled 'Conventional Gasoline Acceptor' because members in this segment exhibit disutility from the consumption of wood and corn stalks based cellulosic ethanol. Members of this segment however are indifferent towards corn grain ethanol and switch grass based cellulosic ethanol. The fourth segment was labeled 'Ethanol Acceptor' since members who belong to this segment exhibit preference for ethanol as the alternative fuel, independent of the source for ethanol. They also exhibit sensitivity towards all the fuel attributes, significant at 1% level of significance. More specifically, the parameters on feedstock for production of ethanol (i.e. corn, wood, stalk and switch grass) are all uniformly positive and statistically significant unlike the other three segments.

According to the parameter estimates displayed in table (2.3), older individuals and those belonging to lower household income with higher number of adults in the household are more likely to reject corn grain ethanol. Based on the latent variables, individuals who have 'Positive intentions toward biofuel' (factor 2), 'Negative biofuel impact on food' (factor 3) and 'Economic and Environmental Effect' (factor 1) are also more likely to reject corn grain ethanol. However, individuals who believe that the biofuel related crisis is overrated (factor 4) are less likely to reject corn grain based ethanol. Similarly, individuals who have plans of buying or leasing a FFV in the next five years are less likely to lie either in segment 'Corn Grain Ethanol Rejecter' (segment 2) or in 'Conventional Gasoline Acceptor' (segment 3).

It is to be noted that there are some anomalies in results that may be attributed to data error. For example, everything else remaining the same, individuals characterized by 'Positive intentions toward biofuel' (factor 2) are more likely to lie in 'Ethanol Acceptor' (segment 4) as opposed to 'Conventional Gasoline Acceptor' (segment 3) or 'Corn Grain Ethanol Rejecter' (segment 2) as reflected in table (2.3). This could be due to poor factor analysis or poor random utility model setup or both and it may be difficult to separate out the effects. Moreover, our choice experiment requires the respondent to make tradoffs amongst multiple desirable alternatives. On the other hand, Likert scale requires them to agree or disagree with the statement. Given the inherent methodological differences, choice experiment results may not be completely at sink with Likert-scale judgments, though both are derived from a common data set.[5]

According to the preference information displayed in table (2.4), parameters for level of emission and purchase and maintenance cost are negative and statistically significant for both MNL and the 4-segment models. Similarly, parameters for fuel

[5] It is to be noted that we had similar conclusions from the latent class model run exclusively using the fuel-vehicle choice variables and ignoring the latent factors.

availability are positive and statistically significant across models. These results are consistent with economic theory. However, parameters for fuel cost are variable across the models and segments. Results from the 4-segment model imply that preference for alternative transportation fuel increases for 'Cellulosic Ethanol Acceptor' (segment 1), 'Corn Grain Ethanol Rejecter' (segment 2) and 'Ethanol Acceptor' (segment 4) with a decrease in fuel cost. However, the 'Conventional Gasoline Acceptor' (segment 3) set of respondents are indifferent towards fuel cost. Moreover, the 'Cellulosic Ethanol Acceptor' (segment 1) and 'Ethanol Acceptor' (segment 4) respondents have preference for cellulosic ethanol (i.e. ethanol derived from wood, corn stalks and switch grass). On the contrary, 'Conventional Gasoline Acceptor' (segment 3) exhibit disutility for wood and corn stalks based ethanol and is indifferent towards the rest. Similarly, 'Corn Grain Ethanol Rejecter' (segment 2) and 'Ethanol Acceptor' (segment 4) have reversed preference for corn grain ethanol with the later segment exhibiting a preference for the fuel. Differing magnitudes of estimates and degrees of significance across fuel attributes and segments suggest preference heterogeneity among respondents. These effects are absent in the single segment model which suggests that individuals would prefer alternative fuel with lower fuel cost universally. According to the MNL model estimates, consumers exhibit significant preference for cellulosic ethanol and derive disutility from consumption of corn grain ethanol.

### 2.6.2 Willingness to Pay

In the latent class model, WTP estimates for each attribute specific to each segment is simply the ratio of the parameter on the attribute to the corresponding parameter on the purchase and maintenance cost coefficient (multiplied by two because of effects coding, when ever applicable).[6] Table (2.5) presents the WTP estimates and corresponding 95% confidence intervals for fuel attributes. According to the MNL model estimates, the representative consumer is willing to pay 79 cents less in purchase and maintenance fees for every annual dollar spent in fuel cost. They are also willing to pay an additional $9,573.77 in purchase and maintenance cost for 100% increase in alternative fuels availability in the existing gas stations within 5 miles radius from their respective residence. Similarly, consumers reveal significant discount for level of emissions as they are willing to pay $205.1 less in purchase and maintenance fees for every additional pound of green house gas (GHG) emission caused by the combustion of unit gallon of fuel. Additionally, the MNL estimates reveal that consumers exhibit significant preference for cellulosic ethanol and derive disutility from consumption of corn grain ethanol. The representative consumer is willing to pay $1,698.02 and $2,299.81 more in purchase and maintenance cost for vehicles run on corn stalks and switch grass based ethanol relative to unleaded gasoline. On the other hand, they are willing to pay $1,243.17 less in purchase and maintenance fees for vehicles run on corn grain based ethanol relative to unleaded gasoline.

Examining preference heterogeneity using a latent class model lays out more intricate details. Even though mean WTP is consistently high across all segments, the WTP for all other fuel attributes vary significantly across segments. In particular, the latent class model indicates that the 'Ethanol Acceptor' (segment 4) exhibit preference towards consumption of corn based ethanol over gasoline. Individuals who belong to this segment are willing to pay an additional $1,074.49 in purchase and maintenance cost for

[6] Willingness-to-pay values are in $ per purchase and maintenance cost units.

vehicles run on corn grain ethanol over unleaded gasoline. However, 'Cellulosic Ethanol Acceptor' (segment 1), 'Conventional Gasoline Acceptor' (segment 3) and 'Corn Grain Ethanol Rejecter' (segment 2) exhibit indifference for corn grain ethanol over unleaded gasoline. Similarly, 'Cellulosic Ethanol Acceptor' (segment 1), 'Corn Grain Ethanol Rejecter' (segment 2) and 'Conventional Gasoline Acceptor' (segment 3) exhibit disutility from higher fuel cost (mean WTP of -\$10.59, -\$2.72 and -\$3.89 respectively) as opposed to 'Conventional Gasoline Acceptor' (segment 3) being indifferent towards the fuel attribute.

The four classes are also very diverse in their valuations for ethanol derived from cellulosic biomass over unleaded gasoline. Segments 'Cellulosic Ethanol Acceptor' (segment 1) and 'Ethanol Acceptor' (segment 4) exhibits high WTP for cellulosic ethanol (mean WTP of \$1,434.95 and \$2,186.39 for wood based ethanol, mean WTP of \$2,917.57 and \$3,404.62 respectively for corn stalks based ethanol and mean WTP of \$1,447.72 and \$3,891.97 respectively for switch grass based ethanol). 'Conventional Gasoline Acceptor' (segment 3) exhibit disutility from consumption of wood based and corn stalks based ethanol (mean WTP of -\$13,137.82 and -\$6,731.91 respectively) and indifferent towards the consumption of switch grass based ethanol. 'Corn Grain Ethanol Rejecter' (segment 2) is indifferent towards consumption of ethanol as alternative transportation fuel in general. The willingness-to-pay values also convey some important characteristics about consumer preferences for different fuel attributes. Consumers, in general, are willing to pay large premiums for higher fuel availability. Similarly, respondents who belong to 'Conventional Gasoline Acceptor' (segment 3) are willing to pay large negative premiums so as to prevent wood based and corn stalks based cellulosic ethanol from being viable options as alternative transportation fuel. Even though the estimated premiums appear large and reflect some overstatement of willingness to pay in a hypothetical setting, we can be more confident about their relative magnitudes assuming that hypothetical-bias is similar across attributes (Cummings et al., 1995; Fox et al., 1998; Fox et al., 2001).

### 2.6.3 Consumer Welfare Evaluation

Table (2.6) presents estimates of welfare impacts across segments of restricting alternative transportation choice sets in three distinct cases. The first scenario assumes a hypothetical situation where government policy mandates the use of E-10 or E-85 (i.e. ban use of unleaded conventional gasoline). Welfare estimates capture the change in welfare that would result from moving from a world where consumers could choose between conventional gasoline, E-10 or E-85 with ethanol derived either from corn grain or cellulosic biomass and none to a world where the choice was only between E-10, E-85 and none. The welfare estimates can be interpreted as the maximum amount consumers would pay to keep unleaded conventional gasoline in their choice set. The welfare estimates from the MNL model implies that restricted choice set results in welfare gain of approximately \$346.09 for the representative consumer. This implies that on an average, the consumers are willing to pay \$346.09 to prevent the consumption of unleaded conventional gasoline. Estimates for the four segments identified by the LCM reveal mixed welfare effect across segments. Segments 'Conventional Gasoline Acceptor' (segment 3), comprising approximately 14% of the population have significantly large welfare losses with restricted choice set (mean welfare loss being \$2,000.00). On the

contrary, 'Cellulosic Ethanol Acceptor' (segment 1) and 'Ethanol Acceptor' (segment 4), comprising approximately 65% of the population, experience welfare gain as a result of the ban (mean welfare gain being \$546.38 and \$1,089.53 respectively). However, the welfare impact for individuals belonging to 'Corn Grain Ethanol Rejecter' (segment 3) is not different from zero. It is to be noted that the above analysis assumes no income effect as the set of alternative transportation fuel available to the consumer changes.[7]

In the second scenario, we consider the case where due to controversial debate relating world food price volatility with the production of corn grain ethanol, the later ceases to be one of the options in the alternative transportation fuel choice set (Trostle, 2008; Leibtag, 2008). According to the estimates of the MNL model, the new restricted choice set leads to welfare enhancement for the representative consumer by approximately \$89.38. However, the 4 segments LCM portray a different story. Only the 'Ethanol Acceptor' segment, comprising of 44.44% of the population, experiences welfare loss (mean welfare loss being \$77.25). The welfare impacts for rest of the three segments when faced with the restricted choice set are not different from zero.

At present, in the U.S., ethanol is predominantly produced by fermentation of corn glucose. Given the nation's significant agronomic base, technology development for ethanol production from nonfood-plant sources, also known as cellulosic biomass, which can be converted into fuel ethanol, holds promise (Lin and Tanaka, 2006). However, current technology is still in the experimental stage. In the third scenario, we analyze consumer welfare if cellulosic ethanol never becomes available to consumers. The 1-segment model indicates significant welfare loss by the consumers if faced with the

[7] Another reason explaining consumer's gain in welfare when faced with restricted choice set may be reduction in search cost. Moreover, in reality, the assumption of no income effect might not hold well.

restricted fuel choice set (mean welfare loss being \$330.78). As expected, the variation in consumer welfare levels across the four segments reveals preference heterogeneity. 'Cellulosic Ethanol Acceptor' (segment 1) and 'Ethanol Acceptor' (segment 4), constituting 65% of the evaluated consumer population have preferences for cellulosic ethanol and hence experience welfare loss with the restricted choice set (mean welfare loss being \$362.64 and \$674.87 respectively). On the other hand, 'Conventional Gasoline Acceptor' (segment 3) experiences a welfare gain when exposed to the restricted choice set (mean welfare gain being \$1,420.00). The welfare impact for individuals belonging to 'Corn Grain Ethanol Rejecter' (segment 2) is not different from zero.

## 2.7 Summary and Conclusions

In recent years, production of fuel ethanol by corn grain fermentation or by conversion of cellulosic biomass has gained momentum. Use of ethanol blended gasoline is also a rapidly increasing alternative transportation fuel in the U.S. market. This study examines consumer preference heterogeneity and estimates consumers' willingness to pay (WTP) to switch from conventional gasoline to alternative transportation fuels by employing choice based conjoint analysis and applying latent segmentation approach.

Fuel-vehicle attributes used in the analysis are fuel cost and availability, emission level, bio feedstock and purchase and maintenance cost of the appropriate vehicle. Evaluated consumer base was segmented into four broad classes based on the socioeconomic characteristics, latent constructs of the consumers as well as their fuel attribute choice. Results from the latent class model indicate strong consumer heterogeneity for fuel attributes. Analysis of consumer preference heterogeneity and WTP may be of considerable value to policy makers.

Age, annual pre-tax household income and plans of buying or leasing a flex fuel vehicle (FFV) in the next 5 years are some of the socioeconomic variables that influenced the respondents' choice of alternative transportation fuels. Our analysis indicates that state of residency, specifically whether the respondent is from the Mid-West or from California did not have a significant impact on decision choice made by the respondent. Similarly, degree of awareness as indicated by the respondents did not play a significant role in their decision making process. According to the parameter estimates of the latent variables, individuals who are more economically and environmentally conscious are more likely to lie in the 'Corn Grain Ethanol Rejecter' segment. Similarly, individuals who believe that production of corn based ethanol adversely affects production of corn for human consumption and also affects overall food prices are more likely to belong either to the 'Cellulosic Ethanol Acceptor' or the 'Corn Grain Ethanol Rejecter' segment. Additionally, individuals who believe that the crisis involving production and usage of transportation fuels is overrated are less likely to lie either in 'Corn Grain Ethanol Rejecter' or in 'Conventional Gasoline Acceptor' segments.

The WTP estimates validate suspected consumer preference heterogeneity. Results from the MNL model and the 4-segment model indicate that on an average, consumers are willing to pay significantly higher amounts for higher fuel availability and pay less for fuel cost and Green House Gas (GHG) emissions. Moreover, the WTP for bio-feedstocks vary across the segments in the latent class model. Three particular hypothetical situations are considered where due to varied reasons, either conventional gasoline, corn grain based ethanol or cellulosic ethanol is not available for consumption. The consumer welfare estimates indicate notable diversity among consumers in each of the three cases. 'Conventional Gasoline Acceptor', comprising approximately 14% of the evaluated consumer population experiences welfare loss when faced with a restricted choice set with unleaded conventional gasoline being not an option, with mean welfare loss being $2,000.00. Individuals belonging to 'Ethanol Acceptor' segment, approximately 44.44% of the evaluated consumer population experiences welfare loss if corn grain ethanol is not made available in the U.S. market as alternative transportation fuel choice, with mean welfare loss being $77.25. On the other hand, if cellulosic ethanol is not available as the alternative transportation fuel, individuals lying in segments

‘Cellulosic Ethanol Acceptor’ and ‘Ethanol Acceptor’, constituting approximately 65% of the sample set experience welfare loss under the restricted choice set, with mean welfare loss being $362.64 and $674.87 respectively.

Thus analysis of consumer preference heterogeneity for alternative transportation fuel and their WTP estimates may be important in determining marketing opportunities for farmers and rural small businesses, biofuel producers, petroleum suppliers, and fuel marketers. Such analysis may also aid the policy makers. Future research work may consider some of the alternative transportation fuels available in the market, namely hydrogen, liquefied natural gas, Liquefied Petroleum Gas (LPG), Compress Natural Gas (CNG), Bio-diesel etc to estimate consumer preference structure and their WTP for various fuel-vehicle attributes.

# Chapter 2 Appendix

Table A2.1

Distribution and Factor Analysis of Attitudinal Statements

| | Economic and Environmental Effect | Positive intentions toward biofuel | Negative biofuel impact on food | Crisis Overrated |
|---|---|---|---|---|
| I am willing to pay more to buy transportation fuel that is more ecologically friendly. | 0.9683 | 0.0000 | 0.0000 | 0.6592 |
| I am willing to advertise/ campaign for consumption of eco-friendly transportation fuel. | 1.0359 | 0.0009 | 0.0000 | 0.6500 |
| My individual effort to increase the consumption of alternative transportation fuel will have some positive impact on the environment. | 1.1621 | 0.2503 | 0.2650 | 0.8021 |
| I believe that a nation wide effort to increase the consumption of alternative transportation fuel will effectively reduce air pollution and level of GHG Emission. | 1.0575 | 0.6086 | 0.6512 | 0.7515 |
| I believe that the net environmental effect in terms of air and water pollution of producing ethanol domestically and consuming it as compared to importing gasoline and consuming it is positive. | 0.8979 | 0.9074 | 0.8298 | 0.7573 |
| 'Food price volatility' is an issue overrated and I am not concerned about its effect. | 0.6748 | -0.1816 | -0.5915 | 0.4665 |
| Income generated by the ethanol plants has a trickle down effect on the local economy in terms of creation of job, generating income and demand for goods and services. | 0.9590 | 0.7096 | 0.6552 | 0.8937 |
| I do not support the government's financial support to the ethanol industry since its production induces food price volatility. | -0.2100 | -1.5687 | -1.0361 | -0.2970 |
| I do not support the government's financial support to the ethanol industry since its production leads to deforestation and loss of grasslands. | 0.3432 | -2.0574 | -1.7433 | -0.0415 |
| I do not support the government's financial support to the ethanol industry since its production leads to climate change and increased level of GHG emission. | 0.3691 | -2.0131 | -1.7693 | -0.1578 |

Table A2.1 Continued

| | | | | |
|---|---|---|---|---|
| High demand for corn generated for production of corn-based ethanol is good for the U.S. corn farmers. | 0.7318 | 0.8111 | 0.8091 | 0.7264 |
| Given the current trend in domestic demand for transportation fuel, I believe that a partial substitution of conventional gasoline with ethanol is sustainable. | 0.9016 | 0.9869 | 0.9339 | 0.8658 |
| I support the government's financial support to the ethanol industry since it is an eco-friendly fuel. | 1.0967 | 1.7711 | 1.4121 | 1.4415 |
| I support the government's financial support to the ethanol industry since its production is good for the local economy. | 1.0828 | 2.0416 | 1.6137 | 1.5854 |
| I support the government's financial support to the ethanol industry since its production is good for the corn farmers. | 1.0417 | 1.8852 | 1.4363 | 1.5298 |
| High demand in corn for production of corn-based ethanol is adversely affecting production of corn for human food consumption. | -0.4153 | 0.3530 | 1.1230 | 0.2883 |
| High demand in corn for production of corn-based ethanol is providing non-corn producing farmers incentives to switch production and grow more corn. | 0.3945 | 0.5960 | 0.9803 | 0.5922 |
| High demand in corn for production of corn-based ethanol is adversely affecting overall food prices. | -0.3928 | 0.5410 | 1.3607 | 0.4065 |
| I believe that nationwide consumption of alternative transportation fuels will help the nation to decrease its dependency on foreign oil (i.e. level of crude oil imported will decrease). | 0.8537 | 0.8144 | 0.9102 | 0.6584 |
| Pollution issue related to the use of alternative transportation fuel is overrated. | 0.0000 | 0.0000 | 0.0000 | 0.1968 |
| 'Dependency on foreign oil' is an issue overrated and I am not concerned about its effect. | 0.1935 | -0.4882 | -0.6722 | 0.2757 |
| I believe that the U.S. government's financial support to the ethanol industry will end the nation's dependency on foreign oil. | 0.9730 | 1.0909 | 0.6986 | 1.0913 |
| Variance Explained by Each Factor | | | | |
| Weighted | 7.3451 | 5.4049 | 1.7378 | 11.4391 |
| Unweighted | 2.5989 | 1.8718 | 0.7231 | 4.9966 |

## Table 2.1
## Descriptive Statistics

| Total Number of Household Respondents (1400) | | | |
|---|---|---|---|
| | | Survey Data Statistics | 2000 US Census |
| Gender | Females | 46.49 | 49.1 |
| | Males | 53.51 | 50.9 |
| Age | 20 years and less | 1.21 | 28.60 |
| | 21 – 30 years | 15.83 | 13.63 |
| | 31 – 40 years | 16.96 | 15.36 |
| | 41 – 50 years | 14.55 | 15.11 |
| | 51 – 60 years | 12.99 | 11.03 |
| | 61 – 70 years | 27.04 | 7.23 |
| | 71 – 80 years | 10.93 | 5.78 |
| | 81 years and over | 0.50 | 3.26 |
| Income | Less than $20,000 | 12.63 | 22.10 |
| | $20,000 to $39,999 | 25.05 | 25.29 |
| | $40,000 to $59,999 | 22.07 | 19.66 |
| | $60,000 to $79,999 | 14.83 | 13.34 |
| | $80,000 to $99,999 | 9.30 | 8.37 |
| | $100,000 to $119,999 | 4.90 | 11.24 |
| | $120,000 - $139,999 | 2.91 | |
| | $140,000 - $159,999 | 2.63 | |
| | $160,000 - $179,999 | 1.49 | |
| | $180,000 or more | 4.19 | |
| Education | Did not graduate from high school | 0.78 | 19.60 |
| | Graduated from high school, Did not attend college | 14.48 | 28.60 |
| | Attended college, no degree earned | 23.85 | 21.10 |
| | Attended college, associates or trade degree earned | 12.70 | 6.30 |
| | Attended college, Bachelor's (B.S. or B.A.) degree earned | 28.46 | 15.5 |
| | Graduate or advanced degree (M.S., M.A., Ph.D., Law School) | 17.89 | 8.90 |
| | Other | 1.85 | - |
| Race | White, Caucasian | 80.27 | 75.1 |
| | Black, African American | 9.01 | 12.3 |
| | Asian, Pacific Islander | 1.49 | 3.7 |
| | American Indian | 0.21 | .9 |
| | Other | 2.20 | - |
| | Mexican, Latino | 6.81 | 12.5 |
| Employment | Full-time employed | 44.22 | 63.9 |
| | Part-time employed | 10.50 | |
| | Unemployed | 4.26 | 36.1 |
| | House maker | 4.12 | |
| | Retired | 30.02 | |
| | Student | 4.47 | |
| | Other | 2.41 | |

Source: U.S. Census, 2000 ; url : http://factfinder.census.gov/home/saff/main.html?_lang=en.

Table 2.2
Attributes and Levels of Alternative Fuel Choice Experiment

| Experimental Design Attributes | Gasoline | E-10 | E-85 |
|---|---|---|---|
| Fuel Cost ($) | First level/ base calculated in the program based on available information on primary vehicle class, approximate miles driven per year and the average cost of fuel per gallon. The other 2 levels are 15% lower and higher than the base. | | |
| Fuel Availability(% of existing stations within 5 miles radius from the house) | 100% | (1) 90%<br>(2) 75%<br>(3) 50%<br>(4) 25% | (1) 90%<br>(2) 75%<br>(3) 50%<br>(4) 25% |
| Emission (pounds/gallon) | 19.40 pounds/gallon (base) | (1) -10% than the base<br>(2) -20% than the base<br>(3) -50% than the base<br>(4) -75% than the base | (1) -10% than the base<br>(2) -20% than the base<br>(3) -50% than the base<br>(4) -75% than the base |
| Feedstock | Not Applicable | (1) Corn<br>(2) Cellulose: Wood<br>(3) Cellulose: Corn Stalks<br>(4) Cellulose: Switch Grass | (1) Corn<br>(2) Cellulose: Wood<br>(3) Cellulose: Corn Stalks<br>(4) Cellulose: Switch Grass |
| Cost of buying and maintaining the vehicle ($) | $21,500 (base) | (1) -20% than the base<br>(2) -10% than the base<br>(3) base<br>(4) +10% than the base | (1) -20% than the base<br>(2) -10% than the base<br>(3) base<br>(4) +10% than the base |

Table 2.3
Segment membership variables for the four segment model[1]

| Variables | Segment 1[Ψ] (Cellulosic Ethanol Acceptor) | Segment 2 (Corn Grain Ethanol Rejecter) | Segment 3 (Conventional Gasoline Acceptor) | Segment 4 (Ethanol Acceptor) |
|---|---|---|---|---|
| Intercept | -3.7264*** | -6.0427*** | -5.6414*** | 0 |
| Age | -0.0112 | 0.0400*** | 0.0040 | 0 |
| Plans of buying/ leasing a FFV in the next 5 years | -0.2528 | -1.1224*** | -0.8360*** | 0 |
| Number of adults in the household | 0.0824 | 0.2623** | -0.0407 | 0 |
| Annual pre-tax household income | 0.0600 | -0.1467** | 0.0040 | 0 |
| Factor 1 (Economic and Environmental Effect) | 0.0571** | 0.0658** | 0.1487*** | 0 |
| Factor 2 (Positive intentions toward biofuel) | 0.0417 | 0.2008*** | 0.1869*** | 0 |
| Factor 3 (Negative biofuel impact on food) | 0.0546 | 0.0776** | -0.0621 | 0 |
| Factor 4 (Crisis Overrated) | -0.0080 | -0.1755*** | -0.2825*** | 0 |

*, **, *** indicates 10%, 5% and 1% level of significance respectively
1 Log likelihood at convergence (LL): -5,690.359
Ψ Average probabilities of lying in class 1, 2, 3 and 4 are .209, .209, .138 and .444 respectively.
Pseudo R-squared: 0.341
AIC: 11,517.72

Table 2.4
Utility Function Parameters on Fuel Attributes

| Variable | 1 segment model | 4 segment model | | | |
|---|---|---|---|---|---|
| | | Segment 1 (Cellulosic Ethanol Acceptor) | Segment 2 (Corn Grain Ethanol Rejecter) | Segment 3 (Conventional Gasoline Acceptor) | Segment 4 (Ethanol Acceptor) |
| Fuel cost | -0.0002*** | -0.0040*** | -0.0008*** | 5.30E-05 | -0.0010*** |
| Fuel availability | 2.0363*** | 6.6804*** | 0.8489*** | 4.6441*** | 1.5254*** |
| Emission | -0.0436*** | -0.0540*** | -0.0478*** | -0.0316** | -0.0736*** |
| Purchase & Maintenance Cost | -0.0002*** | -0.0004*** | -0.0003*** | -9.62E-05*** | -0.0003*** |
| Corn | -0.1322*** | 0.0401 | -0.2448** | 0.0706 | 0.1349*** |
| Wood | 0.0637*** | 0.2686** | -0.0125 | -0.6318*** | 0.2746*** |
| Corn Stalks | 0.1806*** | 0.41128*** | -0.0861 | -0.3238** | 0.4276*** |
| Switch Grass | 0.2446*** | 0.2710** | 0.0861 | -0.0466 | 0.4889*** |
| Opt Out Option | -3.7915*** | -37.6017 | -3.1863*** | 1.2239 | -7.6089*** |

*, **, *** indicates 10%, 5% and 1% level of significance respectively

Table 2.5

Consumer Willingness to Pay [95% Confidence Interval] for Transportation Fuel Attributes

| Variable | 1 segment model | 4 segment model | | | |
|---|---|---|---|---|---|
| | | Segment 1 (Cellulosic Ethanol Acceptor) | Segment 2 (Corn Grain Ethanol Rejecter) | Segment 3 (Conventional Gasoline Acceptor) | Segment 4 (Ethanol Acceptor) |
| Fuel Cost | -0.79 [-1.18 to -0.40] | -10.59 [-13.63 to -8.05] | -2.72 [-3.88 to -1.82] | 0.55 [-1.95 to 3.85] | -3.89 [-4.40 to -3.42] |
| Fuel Availability ($/percentage fuel availability) | 9,573.77 [8,527.00 to 10,738.00] | 17,847.64 [14,772.00 to 21,764.00] | 3,086.04 [1,211.00 to 5,281.00] | 48,281.77 [28,275.00 to 1.30E+05] | 6,072.07 [5,330.70 to 6,872.30] |
| Emission ($/pound) | -205.10 [-252.23 to -161.36] | -144.37 [-231.80 to -61.62] | -173.81 [-295.55 to -67.35] | -328.57 [-1,042.80 to 11.54] | -293.13 [-334.22 to -254.70] |
| Corn ($/vehicle) | -1,243.17 [-1,989.50 to -501.96] | 214.19 [-1,256.60 to 1,827.40] | -1,779.93 [-3,467.40 to 75.74] | 1,467.47 [-3,747.50 to 13,217.00] | 1,074.49 [516.42 to 1,663.20] |
| Wood ($/vehicle) | 598.88 [-110.15 to 1,298.50] | 1,434.95 [271.03 to 2,547.30] | -90.82 [-2,221.40 to 1,923.80] | -13,137.82 [-41,338.00 to -5,330.20] | 2,186.39 [1,551.00 to 2,848.30] |
| Corn Stalks ($/vehicle) | 1,698.02 [996.01 to 2,474.00] | 2,197.57 [1,021.00 to 3,488.70] | -625.69 [-2,356.10 to 1,173.90] | -6,731.91 [-19,222.00 to -1,997.40] | 3,404.62 [2,689.60 to 4,154.40] |
| Switch Grass ($/vehicle) | 2,299.81 [1,575.30 to 3,061.30] | 1,447.72 [133.15 to 2,869.40] | 626.27 [-1,165.30 to 2,470.30] | -969.70 [-7,467.00 to 5,216.90] | 3,891.97 [3,181.30 to 4,647.90] |
| Opt Out Option | -17,825.39 [-18,713.00 to -16,917.00] | -100,458.72 [-5.21E+06 to 4.95E+06] | -11,582.94 [-13,953.00 to -8,321.90] | 12,725.19 [-2,020.30 to 69,773.00] | -30,288.60 [-31,440.00 to -29,246.00] |

Table 2.6

Welfare Effects of Restricted Alternative Transportation Fuel Choice Sets under Various Assumptions

[95% Confidence Interval]

| Variable | 1 segment model | 4 segment model | | | |
|---|---|---|---|---|---|
| | | Segment 1 (Cellulosic Ethanol Acceptor) | Segment 2 (Corn Grain Ethanol Rejecter) | Segment 3 (Conventional Gasoline Acceptor) | Segment 4 (Ethanol Acceptor) |
| Scenario 1: Unleaded Conventional Gasoline not available ($/person) | 346.09 [250.73 to 450.69] | 546.38 [380.85 to 747.47] | -193.00 [-431.07 to 66.05] | -2.00E+03 [-5,121.00 to -1,186.70] | 1,089.53 [962.54 to 1,230.20] |
| Scenario 2: Corn grain ethanol not available ($/person) | 89.38 [36.57 to 142.09] | -15.40 [-129.51 to 91.531] | 127.97 [-5.7611 to 250.66] | -1.06E+02 [-973.74 to 264.15] | -77.25 [-119.35 to -36.71] |
| Scenario 3: Cellulosic ethanol not available ($/person) | -330.78 [-403.48 to -263.52] | -362.64 [-495.28 to -248.16] | 10.64 [-147.52 to 162.65] | 1.42E+03 [756.79 to 3,984.7] | -674.87 [-759.06 to -596.50] |

Figure 2.1
An example of choice scenario from the choice experiment

| | Gasoline | E-10 | E-85 | Not Purchase |
|---|---|---|---|---|
| Fuel Cost | $731.25 | $989.34 | $731.25 | I choose not to purchase either of these products. |
| Fuel Availability(% of existing stations) | 100% | 50% | 25% | |
| Emission (pounds/gallon) | 19.40 | 9.70 | 14.55 | |
| Bio-Feedstock | Not Applicable | Cellulose: Switch Grass | Cellulose: Corn Stalks | |
| Cost of buying and maintaining the vehicle | $21,500 | $19,350 | $19,350 | |
| I Choose | □ | □ | □ | □ |

# Chapter 3

## Factor Demand Analysis for Ethanol in the U.S. Refinery Industry

### 3.1 Introduction

The demand for ethanol as a complement to and substitute for gasoline has increased significantly in the last decade. This is primarily in response to government policies such as the Clean Air Acts, the Federal Reformulated Gasoline (RFG) programs, mandatory Renewable Fuel Standard (RFS), and a series of tax exemptions and subsidies targeted at the ethanol and gasoline industries. Other contributing factors influencing the demand for ethanol are high demand for fuel, volatile gasoline prices, technological advancement and environmental awareness. Methyl tertiary butyl ether (MTBE) was initially used as the primary petroleum-based oxygenate. However, given that MTBE is bio-accumulative and an active polluting agent, the major environmental hazard involved with its expanded use was ground water contamination (RFA, 2008). A gradual phase out of MTBE as an oxygenate and replacement by ethanol was initiated in 1999. This provided an additional boost to the factor demand for ethanol at the refinery industry in the U.S. (Miranowski, 2007). These policies may lead to short and long term effects on the U.S. economy and may even result in a permanent structural change in factor demand in the country's refinery and blender industry.

The objectives of this study are three fold. First, factor demand relationships for material inputs from the U.S. refinery industry are estimated using a static translog model. Second, we examine whether there has been a structural change in the factor demand of refinery inputs. Finally we examine whether the gradual switching process has been simultaneous for all factor inputs with a common adjustment rate or individual switching paths with unique adjustment rates.

In our analysis, we employ two alternative switching regression models. The first model is a gradual switching regression model that allows the independent factors affecting the share equations to shift at different change-points and at individual adjustment rates. The second model is a restricted version of the first model and assumes the shift point (or join point) and rate of adjustment for all independent factors to be identical for the set of share equations of the translog system. Results obtained across the two models are compared. We then proceed to obtain bootstrap distributions and confidence intervals of the common shift point and the rate of adjustment.

The remainder of the paper is organized as follows. Section 3.2 provides a discussion of the factors influencing the demand for ethanol in the refinery and blender industry. Section 3.3 gives an overview on the existing research on structural change analysis, specifically those using switching regression models. Section 3.4 describes the translog cost function, two alternative gradual switching regression methods and the associated assumptions. Section 3.5 describes the data. Section 3.6 presents the empirical results and Section 3.7 concludes.

## 3.2 Motivation

Federal and some state level governments have offered an array of tax credits, exemptions and investment incentives to boost the demand for and future development of the ethanol industry as well as the domestic production of ethanol (Duffield and Collins, 2006). Volumetric ethanol excise tax credit (VEETC) is a production-linked subsidy offered to the U.S. ethanol industry by the Federal government. It ranges from approximately \$4.5 to \$6.4 billion per year with no limit or dependence on the price of fuels for which ethanol may be considered to be a substitute (Koplow, 2006).

Blender's credit is an incentive policy offered by the government to the petroleum refining industry for every gallon of ethanol blended with gasoline. This provides an additional boost to the factor demand for ethanol. Initiated in 1980, refiners and blenders receive an income tax credit for every gallon of ethanol blended with gasoline (Energy Information Administration, 2008). Petroleum blenders currently receive 51 cents per gallon income tax credit, which is scheduled to expire in 2010.

Renewable Fuel Standard (RFS) is a mandatory requirement aimed at reducing the nation's dependence on foreign oil by increasing the supply of alternative fuel sources. Figure (3.1) demonstrates the effect of mandates on ethanol production. The government mandates and initiatives have successfully increased the production of ethanol by more than 400% over the last ten years (Anderson and Coble, 2008).

Crude oil is the major raw material used in the U.S. petroleum refining industry, with other inputs being capital, labor, liquefied petroleum gases (lpg), oxygenates, unfinished oils[8], motor gasoline blending components, etc. The factor demand for ethanol at the refinery level has increased from 1,857 thousand barrels in January, 2002 to 14,768 thousand barrels in May, 2008. At the same time, the factor demand for MTBE has decreased by 99.77% where as liquefied natural gases exhibited a cyclical pattern. However, the factor demand for crude oil has been comparatively stable experiencing only a 2.15% increase in this time period (Energy Information Administration, 2008).

The capital intensity of the U.S. refining industry, measured by the ratio of total capital expenditure to refinery capacity, registered a sharp rise between January, 2000 and January, 2002, reflecting the surge in investments in upgrading refineries. The industry registered a second phase of steady increase in investments from January, 2006 to January, 2007. The capital intensity in the interim period (i.e. 2002 to 2006) has fluctuated. Labor intensity in the petroleum refining industry, measured by the ratio of the total number of production workers to operating crude oil distillation capacity, registered a steady decrease from 1993 onwards. However, it has experienced an upward trend from 2006 onwards. Thus there is evidence to suggest structural change in the factor demand in the U.S. refinery and blender industry due to several contributing factors such as high demand for oil, volatile gasoline prices, governmental policies and environmental awareness (Rask, 1998).

[8] In the petroleum refining and processing industry, unfinished oil refers to all oils that require further processing, except those oil that require only mechanical blending. They are produced as a result of partial refining of crude oil. Naphthas and lighter oils, kerosene and light gas oils, heavy gas oils, and residuum fall under this category of unfinished oils (Energy Information Administration, 2008).

## 3.3 Literature Review

Extensive research has been conducted on identifying, measuring and testing the hypotheses of structural change in demand systems. Goodwin and Brester (1995) utilized gradual switching regression techniques to evaluate structural change in factor demand relationships in the U.S. food industry. Rickertsen (1995) investigated structural change in the Norwegian demand for meat and fish utilizing a dynamic switching specification of the almost ideal demand system. Stern et al (1979) analyzed evidence of structural change in the demand for aggregate U.S. imports and exports. Schafer (2005) illustrates structural change in the energy sector for eleven world regions using time series data and discusses their impact on the decline in energy intensity. This current paper evaluates the structural change in factor demand in the U.S. petroleum refinery industry, a study being conducted for the first time known.

Since Quandt (1958) proposed the switching regression model, it has often been utilized to test for structural change in demand systems. Tsurumi (1980) and Katayama et al (1987) considered the switching regression model assuming that structural change was gradual. Ohtani and Kakimoto (1989) and Ohtani and Katayama (1990) extended the switching regression model by setting a switching regression model with a transition path specified by a polynomial of time and considering a gradual switching regression model with autocorrelated errors respectively. Although the majority of the literature on switching regression models assumes that coefficients shift at a common shift point, Toyoda and Ohtani (1989) developed a less restrictive switching regression model such that the individual coefficients may have differing change-points. In this paper, we extend the literature by setting up a switching regression model where the inputs follow individual transitional paths characterized by unique shift points and adjustment rates for the U.S petroleum refinery industry.

## 3.4 Model Specification

### 3.4.1 Specification of the Translog Model

In this study, a static translog model is used to estimate factor demand of inputs for the U.S. petroleum refinery industry. We use time as a proxy for technological progress. Since the translog model provides a test for structural change while identifying the exact nature of any shifts, this empirical approach proves to be advantageous over other approaches given its flexible functional form and its representation of the cost structure of an industry (Goodwin and Brester, 1995; Fischer et al, 2001). The translog cost model may be expressed as:

$$\begin{aligned} \ln C_t^*(P_i, Q_t, t) &= \alpha_0 + \sum_{i=1}^{N} \alpha_i \ln P_{it} + \alpha_y \ln Q_t + \alpha_t t + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_{ij} \ln P_{it} \ln P_{jt} \\ &+ \sum_{i=1}^{N} \alpha_{iq} \ln P_{it} \ln Q_t + \sum_{i=1}^{N} \alpha_{it} t \ln P_{it} + \frac{1}{2}\alpha_{yy} \ln Q_t \ln Q_t + \alpha_{yt} t \ln Q_t + \frac{1}{2}\alpha_{tt} t^2 \end{aligned} \tag{3.1}$$

where $C_t^*(\ )$ is total cost; $P_{jt}$ is price of input $j$ in period $t$; $\alpha$ 's are parameters to be estimated and $Q_t$ is output in period $t$, measured by the total amount of gasoline produced in that period. The cost-share equations are estimated rather than the cost function to ease potential estimation problems and conserve degrees of freedom (Huang, 1991). The cost-minimizing factor demands are obtained by applying Shephard's lemma (Shephard, 1953),

$$x_i^* = \frac{\partial C^*(P_i, Q_t, t)}{\partial P_i} \qquad (3.2).$$

The input share equation is:

$$w_{it} = \alpha_i + \sum_{j=1}^{N} \alpha_{ij} \ln P_{jt} + \alpha_{iq} \ln Q_t + \alpha_{it} t; \quad i = 1, \ldots, N \qquad (3.3),$$

where $w_{it}$ is the cost share of input $i$ at time $t$ and subscript $i$ stands for $i = 1$ for crude oil ($co$), $i = 2$ for ethanol ($e$), $i = 3$ for MTBE ($mtbe$), $i = 4$ for liquefied petroleum gases ($lpg$), $i = 5$ for labor ($l$), $i = 6$ for capital ($k$) and $i = 7$ for unfinished oil($uo$).

### 3.4.2 Structural change identification allowing separate shift points & adjustment rates

Consider multiple regression models for each of the $N$ linear share equations as given by equation (3.3). A structural change can be interpreted as a shift in parameters from one regime to another. We allow the system of share equations to follow separate transition paths with respect to coefficients on each of the individual independent variables such that they may have different join points and adjustment rates. Building from equation (3.3) we assume that the parameters (i.e. $\alpha$ 's) shift gradually from one regime to the other along the transition path $trn_i(s_{it} / \eta_i)$ at an unknown join point ($t_i^*$) and rate of adjustment ($\eta_i$) such that the gradual switching translog demand system may be expressed as:

$$w_{it} = \alpha_i + \sum_j \alpha_{ij} \ln P_{jt} + \alpha_{iq} \ln Q_t + \alpha_{it} t + \alpha_i' trn_i(s_{it} / \eta_i)$$

$$+ \sum_j \alpha_{ij}' trn_i(s_{it} / \eta_i) \ln P_{jt} + \alpha_{iq}' trn_i(s_{it} / \eta_i) \ln Q_t + \alpha_{it}' trn_i(s_{it} / \eta_i) t + \varepsilon_{it}; \qquad (3.4)$$

$$i = 1, \ldots, N-1 \quad t = 1, \ldots, T$$

where

$$s_{it} = \begin{Bmatrix} 0 \; for \; t \le t_i^* \\ t - t_i^* \; otherwise \end{Bmatrix} \qquad (3.5).$$

The transition function, $trn_i(s_{it} / \eta_i)$ satisfies (Tsurumi, 1982)

$$\begin{aligned} &\lim_{s \to \infty} trn_i(s_{it} / \eta_i) = 1; \\ &\lim_{\eta \to 0} trn_i(s_{it} / \eta_i) = 1; \text{ and} \\ &\lim trn_i(0) = 0 \end{aligned} \qquad (3.6).$$

We assume that the error term is normally and independently distributed with zero mean and constant covariance $\sigma_i^2$ and remains constant over the whole period (i.e. $\varepsilon_{it} \sim NID(0, \sigma_i^2)$, $i = 1, \ldots, N$) (For more details on model specifications please refer to Appendix A3.1).

### 3.4.3 Structural change identification assuming common join point and rate of adjustment

In this section, we assume that that the parameters in equation (3.3) shift gradually from one regime to the other at an unknown join point $t^*$ and an unknown gradual rate of adjustment $\eta$ common to all shares (i.e. $t_i^* = t_j^*; \eta_i = \eta_j \; \forall \, i \ne j$ ). Here we use the transition function $trn(s_t / \eta)$ (i.e. $trn_i = trn_j \forall\, i \neq j$ ). Equation (3.3) being re-expressed as:

$$w = X\beta + trn(s_t / \eta)\, X\theta + \varepsilon, \quad t = 1,\ldots,T \tag{3.7},$$

where $w$ is an $T(N-1)\times 1$ vector of observations on the dependent variable; $X$ is an $T(N-1)\times k$ matrix of observations on the explanatory variables, $\beta$ and $\theta$ are $k \times 1$ vectors of unknown demand parameters and unknown transitional parameters respectively used to transform the parameters to their post-shift values. Since only $(N-1)$ of the share equations are independent, one equation is deleted. We impose the adding up constraints by eliminating the cost share equation for $uo$ (unfinished oil) and recovering these parameters post-estimation. Please refer to Tsurumi et al (1986), Tsurumi and Wago (1986) for details.

Following Goodwin and Brester (1995), we conduct an F-test on the joint significance of the transitional parameters to test for structural change. Assuming structural change on factor demand to be initiated at the optimal join point parameter $t^*$ at a slow adjustment rate $\eta$, we also test for structural change using the following multiple regression model:

$$w = Z^*\psi + Z^* d_t \gamma + \delta\, d_t + \varepsilon \tag{3.8}$$

where $Z^*$ is the matrix of price and output data, $\psi$ is the vector of unknown parameters, $\gamma$ and $\delta$ are the coefficient vectors and $\varepsilon$ is the vector of random disturbances. $d_t$ is a dummy variable such that

$$d_t = \begin{Bmatrix} 1 \; for \; t \geq t^* \\ 0 \; for \; t < t^* \end{Bmatrix} \tag{3.9}.$$

Defining $d_t$ by equation (3.9) implies that the coefficient vector shifts from $\psi$ to $\psi + \gamma$ at an unknown change interval given by $t^*$ (Toyoda and Ohtani, 1989). To test for structural change, we test the following hypothesis:

$$H_0 : \gamma = 0 \quad vs. \quad H_1 : \gamma \neq 0 \tag{3.10}$$

### 3.4.4 Transition function specifications

Estimation of the gradual switching translog system requires the selection of a specific functional form for the transition function, which satisfies the conditions given by equation (3.6). Since the choice of transition functional form is not believed to have a significant impact on the outcome, we represent the transition between alternative regimes with the hyperbolic tangent function given by equation (3.11) (Tsurumi and Wago, 1986):

$$trn(s_{it} / \eta_i) = \frac{\exp(s_{it} / \eta_i) - \exp(-s_{it} / \eta_i)}{\exp(s_{it} / \eta_i) + \exp(-s_{it} / \eta_i)} \tag{3.11}$$

Assuming that $\varepsilon$ is distributed as a multivariate normal distribution with mean 0 and variance-covariance matrix $\sigma^2 I_T$, the log-likelihood function is (Ohtani and Katayama, 1986):

$$L(\psi, \sigma \mid t^*, \eta^*) = -\left(\frac{T(N-1)}{2}\right)\log 2\pi - \left(\frac{T(N-1)}{2}\right)\log \sigma^2 - \frac{(w - Z\psi)'(w - Z\psi)}{2\sigma^2} \tag{3.12}$$

where $t^*$ and $\eta^*$ are the vectors of join point and rate of adjustment parameters respectively (i.e. $t^* = (t_1^*, ... t_7^*)$ and $\eta^* = \left(\eta_1^*, ...., \eta_7^*\right)$) and $\psi(t^*, \eta^*)$ is the set of regression coefficients and is a function of $t^*$ and $\eta^*$. Differentiating (3.12) with respect to $\psi(t^*,\eta^*)$ and $\sigma^2$, and equating resultant equations to zero, we obtain the maximum likelihood estimates (MLE) of $\psi(t^*,\eta^*)$ and $\sigma^2$ conditional on $t^*$ and $\eta^*$:

$$\hat{\psi} = (Z'Z)^{-1} Z'w \tag{3.13}$$

$$\hat{\sigma}^2 = \frac{\left(w - Z\hat{\psi}\right)'\left(w - Z\hat{\psi}\right)}{T(N-1)} \tag{3.14}$$

Substituting (3.13) and (3.14) into (3.12), we obtain the concentrated log-likelihood function:

$$L_{\max}(t^*,\eta^*) = -\left(\frac{T(N-1)}{2}\right)(1 + \log 2\pi) - \left(\frac{T(N-1)}{2}\right)\log\hat{\sigma}^2 \tag{3.15}$$

The MLE of $t^*$ and $\eta^*$, say $\hat{t}^*$ and $\hat{\eta}^*$ are obtained by a grid search over $t^*$ and $\eta^*$ that maximizes (3.15) (Toyoda and Ohtani, 1989; Moschini and Meilke, 1989). More specifically, let the inputs be characterized by distinctive join point (i.e. $t_i^*$) and rate of adjustment (i.e. $\eta_i^*$) for $i = 1,\ldots,7$. We use SAS program to conduct an extensive grid search over the sample data set to determine the unique combination of $t^*$ and $\eta^*$ for all the inputs that maximizes the value of the concentrated log-likelihood function given by equation (3.15).[9]

[9] The SAS program is available on request.

### 3.4.5 Imposing Concavity Constraints

The translog model has been noted to suffer from certain limitations. It may exhibit 'well behaved' results for only a restricted range of relative prices. However, outside this limited range, the model may fail to satisfy the theoretical regularity conditions of negative own-price elasticity (quasi-concavity) and positive shares (non-negativity) (Caves and Christensen, 1980, Lutton and LeBlanc, 1984). Moreover, given that the translog function's curvature property is data dependent, under typical estimation procedures, concavity is not guaranteed. Thus, we have imposed local concavity in the translog function following Ryan and Wales (1998, 2000). While this approach does not provide a global solution it improves the curvature property of the estimated function, while still preserving the flexibility of the translog functional form (Chua, Kew and Yong, 2005).

Let $X^* = \left(P^*, Q^*, t^*\right)$ denote the chosen normalization point. We scale the prices, state of nature variables, and output (but not the time and dummy variables) such that they are equal to one at $X^*$. The Hessian $(H)$ of the translog cost function will be negative semi-definite, providing $C^*(P,Q,t) > 0$ if and only if the matrix $G$ as defined by (16) below is negative semi-definite (Diewert and Wales, 1987). The $ij^{th}$ element of $G$, evaluated at $t^*$, is defined as

$$g_{ij} = \alpha_{ij} - \alpha_i * \kappa_{ij} + \alpha_i * \alpha_j \quad i, j = 1, \ldots\ldots, n \tag{3.16),}$$

where $g_{ij}$ denotes the $ij^{th}$ element of $G$ matrix, $\alpha_{ij}$, $\alpha_i$ and $\alpha_j$ are the estimated parameters shown in equation (3.3) and $\kappa_{ij} = 1$ if $i = j$ and $0$ otherwise. Imposing curvature at the reference point is attained by setting $G = -DD'$ with $D$ being a triangular matrix. Let $(DD')_{ij}$ denote the $ij^{th}$ element of $DD'$, and substituting $(DD')_{ij}$ into (3.16) and rearranging the terms, we obtain:

$$\alpha_{ij} = -(DD')_{ij} + \alpha_i * \kappa_{ij} - \alpha_i * \alpha_j \quad i,j = 1,.....,n \tag{3.17),}$$

where $\alpha_{ij}$ denotes the $ij^{th}$ element of $A$. The $\alpha_{ij}$ 's in (3.17) are replaced in the system of cost equation (3.1) and the cost share equations (3.3), thus guaranteeing that $G$, and hence $H$, is negative semi-definite. Negative semi-definiteness of $G$ guarantees concavity of the cost function at the reference point, $t^*$.

### 3.4.6 Symmetry and Adding-up Constraints

In order for the demand system to be consistent with neoclassical production theory, the following restrictions are imposed:

$$\alpha_{ij} = \alpha_{ji} \quad \forall\, i \neq j, i, j = 1,..., N; \tag{3.18),}$$

$$\sum_{i=1}^{N} \alpha_i = 1 \tag{3.19),}$$

$$\sum_{i=1}^{N} \alpha_{ij} = 0 \quad \forall\, i = 1,...., N \tag{3.20),}$$

$$\sum_{i=1}^{N} \alpha_{iq} = 0 \quad \forall\, i = 1,...., N \tag{3.21),}$$

$$\sum_{i=1}^{N} \alpha_{it} = 0 \quad \forall\, i = 1,...., N \tag{3.22).}$$

Equation (3.18) gives the symmetry condition, while equations (3.19)-(3.22) gives the necessary and sufficient adding up conditions ensuring that $C(.)$ is linearly homogeneous in input prices. In addition, for a well behaved technology, the cost function must be concave in input prices and the underlying technology must be monotonic. Concavity implies that the matrix of second derivatives of the cost function with respect to prices is negative semi-definite. Monotonicity requires that the predicted cost shares be positive (Goodwin and Brester, 1995).

## 3.5 Data

Monthly time series data, October, 1993 through May, 2008 was collected for crude oil, ethanol, liquefied petroleum gases (lpg), MTBE and unfinished oil used as refinery and blender net inputs. Historic price data of crude oil, lpg and unfinished oil were obtained from Energy Information Administration publications (Energy Information Administration, 2008). Monthly average ethanol rack prices and MTBE prices were collected from Nebraska website and Platts respectively (Nebraska Government Website, 2008; Platts, 2008). Labor costs were derived from the number of total production workers in the U.S. petroleum refinery industry and the average weekly earnings of production workers from the reports published by the U.S. Department of Labor Bureau of Labor Statistics (2008).

Capital expenditure was measured as the product of total capital stock and rental price of capital. In this study total productive capital stock in the petroleum refinery industry has been used as a proxy for measure of capital (Rasmussen, 1997). Productive capital stocks attempt to measure the total productive capacity of capital assets in existence at a point in time. However, the capital stock and cost of capital measure should be formed taking into account the loss in productive capacity of capital assets and the decline in asset prices as the age of the asset increases.

Total nominal investment in the petroleum refinery industry $(V_t)$ was assumed to be the sum of the additional property, plant, equipment and activity during the year and additional investment and advances made in the refinery industry in that year. The volume of investment in the asset $(I_t)$ was obtained by dividing the nominal investment series by the corresponding price series. Assuming that information regarding investments in a particular asset type was available for period $t-s$ to period $t$ such that $s = 0,1....,S$, the productive capacity of the asset in period $t$ that is now $s$ periods old is given by:

$$R_{t,s} = \phi_s I_{t-s} \tag{3.23}$$

where $\phi_s$ is the age-efficiency schedule representing the relative productive capacity of a $s$ period vintage asset to the productive capacity of a new asset. We also assumed that the life of the asset is ten years and the loss of productive capacity is linear. Thus the productive capital stock $K_t$ for a particular asset type in period $t$ was calculated as follows (McLellan , 2004; Diewert, 1990; Diewert and Lawrence, 2000):

$$K_t = \sum_{s=0}^{S} \phi_s I_{t-s} \qquad (3.24).$$

The depreciation rate used in the study was consistent with the petroleum refining industry depreciation rate as published by the Bureau of Economic Analysis (2008). Annual data on the cost of capital, the weighted average cost of equity and after-tax cost of debt, weighted by the market values of equity and debt, was used as the proxy for rental rate of capital (Value Line database, 2008). Data on additional property, plant, equipment and activity during the year and additional investment and advances made in the refinery industry in that year were available from Energy Finance (Energy Information Administration, 2002). Table 3.1 presents summary statistics with respective cost shares. Reviewing the statistics we observe that the expenditure on capital contributes to 75.3% of the total cost with expenditure on crude oil being the second largest component.

## 3.6 Results

Specification tests, such as the Wu-Hausman test was conducted to test for the exogeneity of prices and aggregate output in the translog system. Iterated SUR estimates and iterated 3SLS estimates were compared using the Hausman (1978) specification test. Instruments employed were lagged input prices, ending input and output stocks, lagged and contemporaneous refinery capacity, and crude oil accrual costs. Natural gas and corn are the major inputs for the production of ethanol while butane is the main input for MTBE production. Prices for natural gas, corn and butane were included in the list of instruments. The Hausman test suggests prices are endogenous, and hence iterated 3SLS are used.

### 3.6.1 Estimation of separate join points and rate of adjustments

Following the approach of Moschini and Meilke (1989), the separate join points and speed of adjustment parameters were estimated via a grid search over all possible values that maximized the concentrated log-likelihood function given by equation (3.15). Table 3.2 reports the separate individual shift points and rate of adjustments of the refinery inputs. The estimated change point for factor demand of capital was September, 1998, which led to a more capital intensive refinery and blending operation. This increased expenditure on capital may reflect the surge in investments made in the refinery industry to upgrade refineries to be able to respond to government mandates, implement technological changes and increase product yields (Rasmussen, 1997). The corresponding steady decline in the employment of labor in the industry over the last decade resulted in a structural shift in the demand for labor and the estimated shift point is January, 2001. With time, labor has been increasingly substituted by capital leading to a higher capital-labor ratio. The refinery industry also experienced a structural change in the demand for oxygenate with a fall in the demand for MTBE and a substantial increase in the demand for ethanol. The government policy of a gradual phase out of the use of MTBE as gasoline oxygenates was initiated in 1999 with a targeted deadline of December 2002. Given that the requirement was not effective immediately and the deadline was extended, the change in factor demand were observed with a lag. According to the estimates, structural change in the factor demand of ethanol occurred in November, 2003 followed by that of crude oil and MTBE in January, 2004 and March, 2004 respectively. Moreover, once the process of structural change has been initiated, the rate of adjustment has been consistently very slow for the refinery inputs. Results are in accordance with the findings of the American Petroleum Institute (API) which states that the phase down of MTBE use and increase in the use of ethanol as an oxygenate added to gasoline occurred on a time schedule that allowed refiners and marketers to make an 'orderly transition' (API, 2008). Additionally, the estimates indicate that the adjustment rate for capital is higher than the rest of the inputs.

So far, we have identified unique join points and rates of adjustment specific to each of the inputs using the gradual switching model. Even though this is the preferred model of estimation, to keep presentation practical, we have used a restrictive model in the following sections.

### 3.6.2 Estimation of common join points and rate of adjustments

We have used a restrictive version of the original model to estimate the common shift point and adjustment rates. It is assumed that refinery and blender inputs experienced a structural change in factor demand simultaneously. The estimated common shift point ($\hat{t}^*$) is March, 2004. The speed of adjustment ($\hat{\eta}^*$) has been estimated to be 0.0025. We would refer to regime 1 as the time period from October, 1993 to March, 2004 and to regime 2 as the time period from April, 2004 to May, 2008. Next we used bootstrap techniques to estimate the statistical properties of $t^*$ and $\eta^*$. After obtaining the MLE estimates of $\psi, \sigma^2, t^*, \eta^*$ the original data set is randomly sampled with replacement 10,000 times with each sample containing exactly 176 observations (our original sample size). The common joint point ($t^*$) and adjustment rate ($\eta^*$) have been estimated for each resulting bootstrap sample. Statistical properties of $t^*$ and $\eta^*$ have been estimated from the set of 10,000 bootstrap estimates generated (Krinsky and Robb, 1986). At 99% confidence interval, the joint point ranges from December, 2003 to June, 2004. The narrow width of the range of confidence interval suggests small standard error.

As a test for structural change, the hypothesis that the transitional parameters are jointly equal to zero is strongly rejected based on the results from F-test.[10] The hypothesis that the coefficient vector for the structural change model, $\gamma$ is equal to zero is strongly rejected based on the results from t-test. The significance of structural break was

[10] The F-test statistic for structural change is 2,180.7 and is significant at 1% level of significance.

confirmed by comparing the parameter estimates of iterated 3SLS in regime 1 and 2 (Appendix A.3.2). Confirmation of structural change indicates two regimes separated by a significant, gradually occurring structural shift.[11]

### 3.6.3 Own Price and Cross Price Elasticities

Own price and cross price elasticities of the two regimes were estimated using the restricted gradual switching regression model which assumes a common shift point and rate of adjustment.[12] The elasticity estimates provide valuable insights into the nature of the structural change. Own price elasticities were estimated at the normalized point by using Allen's partial elasticities of substitution for a translog function (Uzawa, 1962; Pindyck, 1979):

$$E_{ij} = \frac{\left(\gamma_{ii} + w_i w_j - \delta_{ij} w_i\right)}{w_i^2} \tag{3.25}$$

where $\delta_{ij}$ is the Kronecker delta, $\gamma_{ii}$ represents the estimated second order derivatives on the diagonal of Hessian Matrix and $w_i$ represents the fitted cost share for the $i^{th}$ input.

The bootstrap technique was used to estimate the statistical properties of the own price and cross price elasticities (Douglas, 1996; Douglas and Guilkey, 1996). With the common join point $t^*$ being identified as March, 2004, the original data set was split into two regimes as mentioned above. The original sample section pertaining to regime 1 was

[11] Structural change may also be detected by testing for the constancy of the parameters. Chow test, CUSUM test or the Cusum-of-squares test may be used to test for break points or structural changes in a model. Assuming a common shift point and adjustment rate, Chow test result indicates occurrence of structural change in July, 2002.

[12] Elasticity estimates for the seven inputs at different switch points and rates is difficult to illustrate and space consuming.

randomly sampled using the same bootstrap method as before with replacement 126 times for exactly 126 observations. Similarly, the original sample section pertaining to regime 2 was randomly sampled with replacement 50 times each containing exactly 50 observations using the bootstrap approach. Each of the bootstrap samples generated is normalized according to the following rule: the $i^{th}$ sample was normalized by choosing $X^* = (P^*, Q^*, t^* = i)$ as the normalization point and scale the prices, state of nature variables, and output (but not the time and dummy variables) such that they are equal to unity at $X^*$. For each of the resulting, normalized data sets, we estimated the system of equations using 3SLS and consequently estimate the elasticities, including cross-price and own-price elasticities. Thus regime 1 has 126 estimates of elasticities and regime 2 has 50 estimates of estimates, from where we obtain the statistical properties of the elasticities.

Table 3.3 reports the own-price elasticities and the Hicks-Allen cross price elasticities of the seven commodities for regime 1 and 2. We have reported the elasticities correct to two decimal places. In both the regimes, all the estimates are statistically significant at 10% level of significance or lower except Hicks-Allen cross price elasticity between labor and MTBE in regime 2. The absolute magnitude of own-price elasticities of all the inputs except capital and unfinished oil has decreased across regimes, implying that demand for these goods have become less responsive to own price changes. In particular, the demand for ethanol and MTBE has become less elastic with the absolute value of own price elasticity decreasing from 2.25 and 2.03 in the first regime to 2.03 and 1.91 in the second regime respectively. This has occurred at a time when MTBE's share of total production cost has fallen dramatically and that of ethanol increased substantially.

The decrease in ethanol and MTBE own price elasticity across regimes may be due to the compounded effect of the Federal Reformulated Gasoline programs, mandatory RFS set by the government and the ban on the use of MTBE has a gasoline oxygenate. Moreover, across regimes, the factor demand for capital and unfinished oil has become more responsive to own price changes with their respective own price elasticities increasing from -0.46 and -1.76 in the first regime to -0.59 and -1.82 in the second regime.

The cross-price effects suggest complementarity between labor and the set of inputs including crude oil, ethanol, MTBE and lpg in the first regime. However, in the second regime, estimates suggest complementarity between crude oil and labor, ethanol and labor, MTBE and labor only. The cross price elasticity estimates between ethanol and MTBE, lpg, labor and capital have decreased from the first regime to the second regime, implying that ethanol demand tends to be less elastic to the price changes of these inputs. On the other hand, the cross price elasticities between capital and crude oil, ethanol and unfinished oil have increased across regimes whereas that between capital and MTBE, lpg and labor have decreased over time. Additionally, the cross price elasticities between MTBE and the rest of the inputs, excepting labor and capital have increased across the regimes. Similarly, with the exception of capital, the cross price elasticities of all the inputs with respect to lpg have increased from regime 1 to regime 2. Thus according to the Hicks-Allen cross price elasticity estimates, with exceptions, the degree of substitutability across inputs in the refinery industry has increased as we move across regimes.

### 3.6.4 Morishima Elasticity of Substitution

The definition of factors as substitutes or complements based on the signs of the Hicks-Allen elasticities of substitution has been criticized (Goodwin and Brester, 1995). In a more-than-two factor scenario, a scalar measure of curvature and hence relative shares is inherently asymmetric. According to Blackorby and Russell (1989), Morishima elasticity of substitution (MES) yields a measure of the curvature of the isoquants, rendering itself to be a natural extension of the Hicksian two-variable elasticity. It measures the percentage change in a ratio of two factors in response to a 1% change in the corresponding relative price ratio. It is the logarithmic derivative of a factor quantity ratio with respect to the corresponding factor price ratio. The Morishima elasticity of substitution for the translog function is:

$$\sigma_{ij} = \left[\frac{(\gamma_{ij} + w_i w_j)}{w_i}\right] - \left[\frac{(\gamma_{ii} + w_i^2 - w_i)}{w_i}\right] \qquad (3.26).$$

Substitutability among factors in the refinery and blender industry as revealed by the Morishima elasticity of substitution for regime (1) and (2) has been reported in table 3.4. We have reported elasticity estimates correct to three decimal places and across regimes, the estimates are significant at 1% level of significance or lower. The elasticity estimates between labor, capital and unfinished oil against the set of the rest of the inputs indicate increasing substitutability between these inputs across regimes. However, the elasticity estimates between crude oil, ethanol, MTBE and lpg against the set of the rest of the inputs indicate decreasing substitutability with time. With the array of government policies and regulations imposing a ban on the use of MTBE as a gasoline oxygenate and simultaneously boosting the demand for ethanol as a gasoline oxygenate as well as a volume extender, the demand for ethanol has become less responsive to own and cross price changes. The Morishima elasticity of substitution estimate between capital and all other inputs in both the regimes are small compared to the rest of the estimates, implying significantly less degrees of substitutability between capital and the other inputs. Additionally, the Morishima elasticity of substitution estimates indicates labor and crude oil to be complementary inputs with the degree of complementarity decreasing over time.

## 3.7 Conclusion and Policy Implications

In this paper we have uniquely utilized the multivariate gradual switching regression techniques and translog factor demand model to estimate factor demand relationships for inputs used in the U.S. refinery and blender industry. Next we have identified structural changes in factor demand relationships in the industry and have evaluated separate shift points and rates of adjustment for the set of inputs. The underlying assumption of the model being that given external influencing factors such as government mandates, technological progress, changes in tastes and preferences, prices etc, the inputs tend to follow separate transitional path, each initiated at different join points with different rates of adjustment. The flexibility of the empirical method used allows the identification of the change for each of the inputs while allowing speed of adjustment between alternative regimes to be gradual and vary across inputs. We found structural change in factor demand of inputs to exist and occur for the seven inputs at different points and adjustment rates.

The structural change in the demand for capital and labor was initiated in late 1998 and early 2001 at slow rates of adjustment. There has been a gradual increase in the cost share of capital followed by a gradual decrease in the cost share of labor. This was reflective of the fact that the industry made additional capital expenditures to adhere to the heightened pollution abatement requirements for the refining operations. Structural change for the rest of the inputs was initiated only in late 2003 and early 2004 at typically slow rates of adjustment. The Renewable Fuels Standard (RFS) mandates ('02, '05 and '07) along with the 'Clean Air Act' and the phase out of the use of MTBE initiated in

1999 and be substituted by ethanol have played important roles in the demand for ethanol in the refinery industry. Even though government policy requiring the gradual phase out of the use of MTBE as the gasoline oxygenate was initiated in 1999, the requirement was not mandatory. Thus the change in factor demand was observed with a lag. More over, the time line of the change in factor demand in MTBE and ethanol occurred on a schedule that allowed refiners and marketers to make an 'orderly transition'.

We have used a restrictive version of the original model to estimate the common shift point and adjustment rates assuming that all the seven refinery and blender inputs experienced a structural change in factor demand simultaneously. The estimated common shift point is March, 2004 and the rate of adjustment is of gradual nature. Given the statistical significance of the common join point and adjustment rate, such an exercise is practical and relevant. The demand for capital is less elastic than for the other factor inputs. According to the own-price elasticity estimates, with the exception of capital and unfinished oil, demand responsiveness of inputs to price changes decreased across regimes. As we move across regimes, the own price elasticity of ethanol and MTBE have decreased. This may be a consequence of the compounded effect of the Federal Reformulated Gasoline programs, the mandatory Renewable Fuel Standard set by the government and the ban on the use of MTBE has a gasoline oxygenate. The Hicks-Allen cross price elasticity estimates suggest complementarity between labor and rest of the inputs including crude oil, ethanol, MTBE and lpg in the first regime and crude oil, ethanol and MTBE in the second regime. Morishima elasticity of substitution estimates suggests a decrease in the degree of substitutability among factors in the refinery industry across regimes in general. However, capital, labor and unfinished oil have been increasingly substituted by other inputs as we move from regime 1 to regime 2.

Results indicate that the array of government policies and mandates imposing a gradual phase out of the use of MTBE as a gasoline oxygenate and simultaneously encouraging the use of ethanol as the alternative oxygenate as well as the gasoline volume extender has successfully altered the structure of factor demand in the refinery and blender industry in U.S. Considerable decrease in the factor demand of MTBE was confirmed and can be expected to curb associated future environmental hazards. Simultaneously, the significant increase in the factor demand of ethanol is consistent with the goal of U.S. policies aimed at decreasing U.S. dependency on foreign oil.

This research work is the first known study that evaluates structural change in factor demand in the petroleum refining industry in the U.S. We use industry specific aggregate data in our analysis and impose the symmetry and homogeneity constraints in the cost function analysis. However, given the nature of the data, some constraints that are satisfied at the micro units may no longer be satisfied at the aggregate level. Hence following Illmakunnas (1986), an extension of the current research work may be to impose the constraints on the parameters stochastically in the system of cost share equations. Moreover, our methods can be applied in future work to identify separate switch points and rates of adjustment for individual factors used in other industries while evaluating structural changes in demand.

# Chapter 3 Appendix

## A3.1 Model details

Equation (3.4) may be represented as:

$$w^{*} = Z^{*}\psi + \varepsilon, \tag{3.27}$$

where $w^{*}$ is a $T(N-1)\times 1$ vector of shares, $\psi$ is the vector of unknown parameters and $\varepsilon$ is the vector of random disturbances (Tsurumi et al, 1986). Since only $N-1$ of the share equations are independent, one equation is deleted,

$$w^{*} = \left(w_1^{'}, w_2^{'}, \ldots, w_{N-1}^{'}\right)^{'}, \tag{3.28}$$

where $w_i = \left(w_{1i}, w_{2i}, \ldots, w_{Ti}\right)^{'}$, $i = 1, \ldots, N-1$. $Z^{*}$ is the matrix of price and output data given by the following equation:

$$Z^{*} = \begin{bmatrix} (X_1, trn_1 \circ X_1) & 0 & \ldots\ldots & 0 \\ 0 & (X_2, trn_2 \circ X_2) & & \\ . & . & & . \\ . & & & . \\ 0 & 0 & \ldots\ldots & (X_{N-1}, trn_{N-1} \circ X_{N-1}) \end{bmatrix}_{T(N-1)\times 2k} \tag{3.29}$$

$$\left(X_j, trn_j \circ X_j\right) = \begin{bmatrix} x_{j1} & trn_j \circ x_{j1} \\ x_{j2} & trn_j \circ x_{j2} \\ . & . \\ x_{jT} & trn_j \circ x_{jT} \end{bmatrix}_{T\times 2} \qquad j = 1,2,\ldots,7 \tag{3.30}$$

$$\text{Let } \psi = \begin{bmatrix} \beta_1 \\ \theta_1 \\ \beta_2 \\ \theta_2 \\ . \\ . \\ \beta_{N-1} \\ \theta_{N-1} \end{bmatrix}_{2k\times 1} \tag{3.31}$$

where $\beta_i$ and $\theta_i$ are vectors of regression coefficients such that

$\beta_i = (\beta_{1i},....,\beta_{ki})$ and $\theta_i = (\theta_{1i},.....,\theta_{ki})$, $\forall\ i = 1,...,N-1$ and

$\varepsilon = [\varepsilon_1\ \varepsilon_2........\varepsilon_{N-1}]'_{T(N-1)\times 1}$.

## Table A3.2
## Parameter Coefficients of the Translog model

| | Coefficient Estimates (Pooled model results) | Regime 1 (1993,October to 2004,March) | Regime 2 (2004,April to 2008, May) |
|---|---|---|---|
| $\alpha_1$ | 0.29* | 0.28* | 0.25* |
| $\alpha_2$ | 3.25E-3* | 1.37E-3* | -1.24E-2* |
| $\alpha_3$ | 1.25E-2* | 1.09E-2* | -2.93E-3 |
| $\alpha_4$ | 1.93E-3** | 4.27E-3* | 1.64E-2* |
| $\alpha_5$ | 7.00E-6* | 5.92E-6* | 1.71E-6*** |
| $\alpha_6$ | 0.67* | 0.69* | 0.75* |
| $\alpha_{crude\ oil,\ crude\ oil}$ | 0.12* | 0.11* | 0.18* |
| $\alpha_{crude\ oil,\ ethanol}$ | -1.92E-4 | -9.6E-4 | -3.09E-2** |
| $\alpha_{crude\ oil,\ lpg}$ | 2.92E-3 | 4.08E-3*** | -1.97E-2 |
| $\alpha_{crude\ oil,\ mtbe}$ | -4.98E-3* | -4.37E-3** | 1.28E-3 |
| $\alpha_{crude\ oil,\ unfinished\ oil}$ | 8.51E-4 | -2.85E-3 | -6.96E-3 |
| $\alpha_{crude\ oil,\ labor}$ | -2.53E-6* | -3.01E-6* | 6.76E-7 |
| $\alpha_{crude\ oil,\ capital}$ | -0.12* | -0.11* | -0.17* |
| $\alpha_{crude\ oil,\ gasoline}$ | 5.81E-4 | 6.72E-4 | -2.00E-5 |
| $\alpha_{crude\ oil,\ year}$ | 5.55E-4* | -4.41E-4* | -5.41E-4*** |
| $\alpha_{crude\ oil,\ month}$ | 3.00E-5 | -2.32E-4 | -5.58E-4 |
| $\alpha_{crude\ oil,\ month}$ | 3.00E-5 | -2.32E-4 | -5.58E-4 |
| $\alpha_{ethanol,\ ethanol}$ | 6.49E-3* | 2.47E-3* | 7.82E-3* |
| $\alpha_{ethanol,\ lpg}$ | -1.61E-4 | -9.11E-4 | 1.62E-4 |
| $\alpha_{ethanol,\ mtbe}$ | -3.72E-3* | -1.64E-3* | 9.9E-4** |
| $\alpha_{ethanol,\ unfinished\ oil}$ | 4.49E-3* | 3.23E-3** | 4.03E-4 |
| $\alpha_{ethanol,\ labor}$ | -2.47E-7 | -8.01E-7** | 8.759E-8 |
| $\alpha_{ethanol,\ capital}$ | -6.92E-3* | -2.19E-3* | -4.31E-3* |
| $\alpha_{ethanol,\ gasoline}$ | 1.00E-5 | -9.12E-6 | -1.3E-4** |

Table A3.2 Continued

| | Coefficient Estimates (Pooled model results) | Regime 1 (1993,October to 2004,March) | Regime 2 (2004,April to 2008, May) |
|---|---|---|---|
| $\alpha_{ethanol,\ year}$ | 8.61E-6 | 1.51E-5** | 1.28E-4* |
| $\alpha_{ethanol,\ month}$ | -2.00E-5 | -6.24E-6 | -4.21E-7 |
| $\alpha_{lpg,\ lpg}$ | 1.52E-2* | 1.33E-2* | 1.29E-2* |
| $\alpha_{lpg,\ mtbe}$ | -2.81E-3** | -1.91E-3** | -1.08E-3 |
| $\alpha_{lpg,\ unfinished\ oil}$ | -4.02E-3*** | -6.39E-3** | -3.58E-3** |
| $\alpha_{lpg,\ labor}$ | 2.05E-6 | 3.93E-7 | -2.04E-6** |
| $\alpha_{lpg,\ capital}$ | -1.21E-2* | -8.21E-3* | -6.52E-3* |
| $\alpha_{lpg,\ gasoline}$ | -6.03E-6 | -7.38E-6 | -1.41E-4** |
| $\alpha_{lpg,\ year}$ | -8.00E-5* | -7.00E-5* | 4.22E-5** |
| $\alpha_{lpg,\ month}$ | -8.4E-5** | 7.51E-5 | 9.81E-5*** |
| $\alpha_{mtbe,\ mtbe}$ | 6.78E-3* | 6.54E-3* | 3.63E-3* |
| $\alpha_{mtbe,\ unfinished\ oil}$ | -9.61E-4 | 6.01E-4 | -1.23E-3 |
| $\alpha_{mtbe,\ labor}$ | -1.6E-7 | -8.36E-8 | -4.32E-7 |
| $\alpha_{mtbe,\ capital}$ | 5.68E-3* | 7.79E-4 | -1.64E-3** |
| $\alpha_{mtbe,\ gasoline}$ | -2.05E-5 | -5.24E-6 | 1.22E-4* |
| $\alpha_{mtbe,\ year}$ | 1.71E-5* | 8.94E-6 | -1.11E-4* |
| $\alpha_{mtbe,\ month}$ | 1.64E-6 | -3.7E-6 | -2.13E-5 |
| $\alpha_{labor,\ unfinished\ oil}$ | 7.83E-7 | 8.98E-7 | -2.46E-7 |
| $\alpha_{labor,\ labor}$ | 1.81E-6* | 2.68E-6* | 5.15E-6* |
| $\alpha_{labor,\ capital}$ | -1.71E-6** | -7.71E-8 | -3.2E-6* |
| $\alpha_{labor,\ gasoline}$ | 3.69E-8** | 3.86E-8** | -2.86E-9 |
| $\alpha_{labor,\ year}$ | -2.97E-8* | -2.26E-8 | 6.08E-9 |
| $\alpha_{labor,\ month}$ | -7.27E-9 | -1.61E-8 | -3.22E-9 |
| $\alpha_{capital,\ unfinished\ oil}$ | -8.99E-3* | -2.61E-4 | -1.01E-2* |
| $\alpha_{capital,\ capital}$ | 0.14* | 0.12* | 0.19* |
| $\alpha_{capital,\ gasoline}$ | -3.01E-4 | -3.41E-4 | 6.13E-4 |
| $\alpha_{capital,\ year}$ | 6.34E-4* | 4.82E-4* | 4.14E-4 |
| $\alpha_{capital,\ month}$ | -3.4E-4 | -1.41E-4 | -1.03E-3 |

*, ** and *** represents 1%, 5% and 10% level of significance respectively

Table 3.1
Summary Statistics of Select Variables

| Commodity | | Mean | Standard Deviation | Max | Min | Average Input Cost Share |
|---|---|---|---|---|---|---|
| Crude Oil | Price ($ per Barrel) | 34.78 | 22.27 | 125.4 | 11.35 | 22.5% |
| | Quantity (Thousand Barrels) | 451,352.99 | 25,907.63 | 500,410 | 367,639 | |
| Ethanol | Price ($ per Barrel) | 62.40 | 21.87 | 150.36 | 37.8 | 0.33% |
| | Quantity (Thousand Barrels) | 3,708.27 | 3,870.57 | 14,768 | 220 | |
| MTBE | Price ($ per Barrel) | 51.25 | 25.82 | 143.85 | 19.16 | 0.41% |
| | Quantity (Thousand Barrels) | 5,322.56 | 2,706.15 | 8,845 | 15 | |
| LPG | Price ($ per Barrel) | 44.36 | 17.86 | 98.99 | 25.66 | 0.56% |
| | Quantity (Thousand Barrels) | 8,182.21 | 2,166.03 | 14,060 | 5,223 | |
| Unfinished Oil | Price ($ per Barrel) | 40.72 | 26.63 | 142.91 | 11.94 | 0.92% |
| | Quantity (Thousand Barrels) | 15,540.37 | 5,614.41 | 31,796 | 1,508 | |
| Labor | Price ($ per day) | 235.11 | 22.92 | 282.87 | 195.66 | .00045% |
| | Quantity (Thousand Workers) | 49.44 | 5.52 | 60.6 | 39.8 | |
| Capital | Price | 0.08 | 0.007 | 0.09 | 0.07 | 75.3% |
| | Quantity ($ thousand) | 625,931,972 | 244,417,797 | 1,160,732,569 | 375,437,751 | |

Table 3.2
Estimated Individual Join Points and Adjustment rates

| **Refinery and Blender Input** | **Individual Shift Point** | **Adjustment Rate** |
|---|---|---|
| Crude oil | January, 2004 | 0.0025 |
| Ethanol | November, 2003 | 0.0025 |
| LPG | September, 2003 | 0.0025 |
| MTBE | March, 2004 | 0.0025 |
| Unfinished Oil | January, 2004 | 0.0025 |
| Labor | January, 2001 | 0.0025 |
| Capital | September, 1998 | 0.0125 |

Table 3.3

Own and Cross-Price Elasticities

| Quantities | Crude oil | Ethanol | Liquified Petroleum Gas (lpg) | MTBE | Labor | Capital | Unfinished oil |
|---|---|---|---|---|---|---|---|
| **Regime 1 (1993,October to 2004,March)** | | | | | | | |
| Crude oil | -1.70* | 2.11E-3* | 9.02 E-3* | 7.89E-3* | -4.06E-3* | 1.56* | 1.42E-2* |
| Ethanol | 0.32* | -2.25* | 1.32E-2* | 4.09E-3*** | -2.66E-3* | 1.72* | 1.54E-2* |
| Liquified Petroleum Gas (lpg) | 0.33* | 1.73E-3* | -1.89* | 5.81E-3* | -5.09E-4* | 1.45* | 1.33E-2* |
| MTBE | 0.33* | 4.93E-4* | 6.53E-3* | -2.03* | -1.19E-3* | 1.56* | 1.42E-2* |
| Labor | -18.00* | -0.86* | -0.59* | -1.11* | -2.37* | 2.51* | 1.38E-2* |
| Capital | 0.42* | 3.51E-3* | 1.08E-2* | 1.01E-2* | 1.61E-5* | -0.46* | 1.39 E-2* |
| Unfinished oil | 0.38* | 3.10E-3* | 9.74E-3* | 9.02E-3* | 8.81E-6* | 1.36* | -1.76* |
| **Regime 2 (2004,April to 2008, May)** | | | | | | | |
| Crude oil | -1.54* | 1.45E-2* | 1.08E-2* | 2.44E-3* | -6.16E-5* | 1.41* | 2.53E-2* |
| Ethanol | 0.51* | -2.03* | 1.01E-2* | 2.37E-3* | -1.21E-5* | 1.43* | 2.58E-2* |
| Liquified Petroleum Gas (lpg) | 0.53* | 1.38E-2* | -1.81* | 2.02E-2* | 1.51E-4*** | 1.27* | 2.34E-2* |
| MTBE | 0.56* | 1.64E-2* | 8.15E-3*** | -1.91* | -4.24E-4** | 1.34 | 2.43E-2* |
| Labor | -9.61*** | 5.07E-2* | 0.47*** | -7.93E-3 | -2.25* | 0.97* | 2.55E-2* |
| Capital | 0.53* | 1.54E-2* | 1.01E-2* | 2.54E-3* | 3.87E-6* | -0.59* | 2.53E-2* |
| Unfinished oil | 0.49* | 1.43E-2* | 9.43E-3* | 2.28E-3* | 4.47E-6* | 1.29* | -1.82* |

*, ** and *** represents 1%, 5% and 10% level of significance respectively

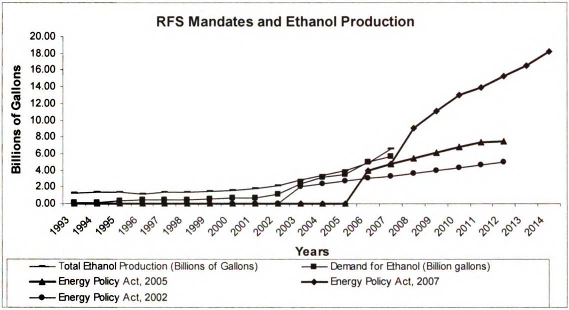
Table 3.4

Morishima Elasticities of Substitution

| Quantities | Crude oil | Ethanol | Liquified Petroleum Gas (lpg) | MTBE | Labor | Capital | Unfinished oil |
|---|---|---|---|---|---|---|---|
| **Regime 1 (1993,October to 2004,March)** | | | | | | | |
| Crude oil | | 1.702* | 1.709* | 1.708* | 1.700* | 3.261* | 1.714* |
| Ethanol | 2.575* | | 2.264* | 2.254* | 2.248* | 3.978* | 2.266* |
| Liquified Petroleum Gas (lpg) | 2.222* | 1.892* | | 1.896* | 1.890* | 3.346* | 1.904* |
| MTBE | 2.374* | 2.039* | 2.045* | | 2.037* | 3.605* | 2.053* |
| Labor | -15.628* | 1.513* | 1.782* | 1.266* | | 4.888* | 2.391* |
| Capital | 0.893* | 0.469* | 0.476* | 0.476* | 0.465* | | 0.479* |
| Unfinished oil | 2.147* | 1.769* | 1.776* | 1.775* | 1.766* | 3.129* | |
| **Regime 2 (2004,April to 2008, May)** | | | | | | | |
| Crude oil | | 1.558* | 1.555* | 1.546* | 1.544* | 2.952* | 1.569* |
| Ethanol | 2.543* | | 2.041* | 2.032* | 2.031* | 3.468* | 2.055* |
| Liquified Petroleum Gas (lpg) | 2.351* | 1.828* | | 1.816* | 1.814* | 3.093* | 1.837* |
| MTBE | 2.475* | 1.922* | 1.914* | | 1.905* | 3.246* | 1.931* |
| Labor | -7.358*** | 2.309* | 2.735* | 2.250* | | 3.229* | 2.284* |
| Capital | 1.133* | 0.608* | 0.603* | 0.595* | 0.593* | | 0.618* |
| Unfinished oil | 2.319* | 1.834* | 1.830* | 1.822* | 1.821* | 3.115* | |

*, ** and *** represents 1%, 5% and 10% level of significance respectively

Figure 3.1
Renewable Fuel Standard Mandates and Ethanol Production




Source: Energy Policy Act of 2002, Senate Amendment 2917,
http://energy.senate.gov/legislation/energybill/2917_analysis.pdf, Energy Policy Act Of 2005, url:
http://www.doi.gov/iepa/EnergyPolicyActof2005.pdf,
Energy Independence and Security Act of 2007, H.R.6, SEC. 202.
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