INVESTIGATION OF ALTERNATIVE FUEL MARKETS

By

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INVESTIGATION OF ALTERNATIVE FUEL MARKETS

Abstract

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This dissertation investigates the economics of alternative fuels by combining the three areas of my interdisciplinary program – Economics, Marketing and Environmental Science. The first paper combines a spatial-econometric model of household demand for transportation fuels with Geographic Information Systems framework to analyze the spatial and temporal differences in the price-elasticity of demand for biofuels. In the second paper, I used a discrete choice modeling approach to investigating the link between consumers' socio-demographic characteristics and choice behavior. The third part investigates U.S. alternative fuel policies and market-based incentives for automobile manufacturers for investing in environmentally cleaner vehicles.

The chapter titled "Spatial and Temporal Differences in the Price-Elasticity of Demand for Biofuels" investigates consumers' demand-sensitivity to fuel price changes across the time and geographic space. Considering the spatial heterogeneity in household composition and demand preferences, using traditional econometric to explain the price-demand relationships

over a large geographic area may lead to biased results. I introduce an alternative, spatially weighted econometric model, which provides superior estimates over a global regression model. The geographic variation in the price-elasticity estimates suggests that the use of spatial-econometric technique provides more detailed empirical and policy relevant results.

The second chapter titled "Determinants of Consumer Choice for Biofuels," investigates the relationship between consumers' fuel choice (gasoline, cellulose- and corn-based ethanol), fuel attributes (price, emissions, and service), and a set of behavioral and socio-demographic variables. The results of our national survey revealed that economic incentives, such as cheaper prices and service availability exceed environmental incentives such as reduction in greenhouse gas emissions. The findings of this study contribute to predicting consumer's behavior, which increasingly became important in determining consumer demand. The results also provide important policy implications for the effective marketing of next generation clean transportation fuels.

The last chapter titled "A System-Dynamics Approach to Investigating Fuel-Economy and Alternative Fuel Policies" analyzes the market-based mechanisms that are designed to promote production of environmentally cleaner vehicles. The effects of several fuel-efficiency tax and rebate policies are simulated over time. The results shed light on the implementation issues of market-based mechanisms, such as revenue neutrality and a technological change over time.

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CHAPTER 1: SPATIAL AND TEMPORAL DIFFERENCES IN THE PRICE-ELASTICITY OF DEMAND FOR BIOFUELS

Abstract

The recent rise in public environmental awareness, concerns of national energy security, and high transportation fuel prices have all served to heighten the interest in alternative fuels. One of the fundamental issues influencing the economic viability of the ethanol industry is understanding consumers' demand-responsiveness to both gasoline and ethanol price changes. In this paper we present an alternative approach to this problem by estimating the geographic variation of price-elasticities of demand for ethanol across the study area, a departure from previous studies of ethanol demand, in which the price-elasticity of demand is identical across the space. Considering the spatial heterogeneity in household composition and demand preferences, using global estimates to explain the price-demand relationships over a large geographic area may lead to biased results. We demonstrate that the spatially weighted regression technique provides superior estimates over a global regression model. Resulting price-elasticities of demand for ethanol revealed significant geographic variation (ranging from -0.5 to -5.0), suggesting that the use of spatially disaggregated data provides more detailed empirical results and a more thorough understanding for policy determination related to the ethanol industry.

Introduction and Background

Alternative fuel policies are designed to increase the U.S. national energy independence and to reduce harmful environmental emissions from transportation fuels. According to the Renewable Fuel Standards (RFS),[1] biofuels production and use in the U.S. will reach 36 billion gallons by 2022 (EISA, 2007). To meet the RFS target, the U.S. Department of Energy (DOE) promotes the use of higher blends of ethanol (e.g., E85, 85% ethanol and 15% gasoline) by targeting specific regions and cities to establish high concentration of flexible fuel vehicles (FFV). The DOE also explores the possibility of using low-level blends of ethanol (e.g., E15 – 15% ethanol, 85% gasoline and E20 – 20% ethanol, 80% gasoline) in conventional vehicles. Understanding consumers' demand-responsiveness to ethanol and gasoline price changes at a specific geographical-level is imperative to implementing proposed renewable fuel policies.

In this paper I investigate consumers' demand-responsiveness to fuel price changes across the geographic space. In particular, I estimate the temporal and spatial variations for the own-price and cross-price elasticity of demand for ethanol in Minnesota. In previous studies of ethanol demand, the price-elasticity of demand for fuels was assumed to be constant across the study area (Anderson 2008; Hughes et al. 2008; Yatchew & No 2001; Schmalensee & Stoker 1999). I extend the model of household demand for close substitute transportation fuels (ethanol and gasoline) developed in Anderson (2008) to allow spatial variation of price-elasticity.

First, I use monthly price observations and sale volumes by individual E85 service stations in Minnesota to estimate own-price and cross-price elasticities of ethanol demand based on the initial model of household demand for transportation fuels. Then I motivate the problem of spatial non-stationarity in the data structure. The results from an exploratory data analysis

[1] The Renewable Fuel Standard is one of the key provisions of the Energy Independence and Security Act (EISA) of 2007, a government policy, which is designed to secure roughly one-third of the U.S. transportation fuel consumption.

show evidence for spatial autocorrelation in the regression residuals from the OLS and 2SLS specifications. The spatial structure in the data indicates that the value of the dependent variable in one spatial unit (a service station in our case) is affected by the independent variables in nearby units. Thus, the assumption of normally and independently distributed error terms when employing ordinary least squares regression is violated with the existence of spatial autocorrelation. This indicates that the non-spatial methods can lead to biased and inefficient parameter estimates. I extend and improve existing models by proposing an alternative model specification that accounts for spatial heterogeneity in data structure and provides superior estimates over global regression models.

I utilize data collected from ethanol service stations in Minnesota, which has been a leader in production and use of ethanol as an additive in gasoline over the last two decades. Prior to the 1990s Minnesota provided a tax credit for blending ethanol into gasoline. However, the tax credit negatively influenced funding for transportation. It was classified as ineffective in increasing ethanol production and was phased out in mid-1990s. Another state financial support program, which started in 1987, provided 20 cents per gallon to in-state ethanol processors for the first 15 million gallons of annual production. Currently, Minnesota provides tax incentives to increase E85 blending by taxing it at a lower rate than E10 or gasoline. Additionally, grants were provided to service station owners for installing E85 dispensing pumps. Many of these service stations that received E85 pump installation grants, participated in a monthly survey (conducted by Minnesota Department of Commerce and American Lung Association of Minnesota). Nearly all of the gasoline sold in Minnesota is required to contain 10% of ethanol (E10). By August 2013, this state law requirement will be increased to 20% (E20), conditional on the increase in the current "10% blending wall" established by the federal government. The combination of these state financial incentives and consumption mandates aim to achieve a broader goal of securing 25% of Minnesota's energy demand from renewable sources by 2025 (Yunker 2009).

The rest of the paper is organized as follows. The next section provides a brief overview of relevant literature. Theoretical Framework section introduces a basic model of household demand for close substitute fuels (gasoline and ethanol). This section also incorporates spatial patterns in consumer demand-responsiveness to fuel price changes into the model. In the section titled Empirical Framework I first motivate the problem of spatial dependence and spatial heterogeneity in data. The basic model of household demand for fuels is then extended into a spatial demand model. Data sources are detailed in the Data Sources and Description subsection, including a map that shows the distribution of service stations in relation to five ethanol blending terminals (racks) and major highways in Minnesota. The remaining sections report and compare the basic and spatial model results. The Geographically Weighted Regression (GWR) estimates were used to visualize the variation of price-elasticity estimates across time and space in our study area. I conclude by discussing the implication of our findings for state-level ethanol policies and for continued research in this realm at the national-level.

Relevant Literature

Due to the relatively short period of ethanol availability in the marketplace and consequent data limitations, the literature on demand estimation is minimal. Anderson (2008) shows that the household demand for ethanol as a close substitute to gasoline are sensitive to gasoline/ethanol relative prices. The gasoline-price (cross-price) elasticities of ethanol demand were estimated to be in the 2.5 – 3.0 range. The results were applied to study ethanol content standard related policies.

Recently, Bromiley et al. (2008) analyzed factors that influence consumer use of E85 in Minnesota. The authors argue that estimating household demand for ethanol for the purposes of understanding their responsiveness to price changes is an important component for the economic viability of the emerging ethanol industry. Schmalensee & Stoker (1999) argue that household composition, demographic characteristics, and demand preferences change considerably over time and geography, and that it is reasonable to expect that not only temporal but also spatial variations will influence the household demand for transportation fuel. Additionally, consumers' environmental perceptions regarding biofuels and their attitudes for prices and performance relative to imported, petroleum-based fuels may vary depending on where they live and purchase fuel (Bromiley et al. 2008).

In contrast, a great deal of attention has been paid to estimating price-elasticities of demand for gasoline. Hughes et al. (2008) analyze U.S. gasoline demand in two time periods – 1975 to 1980 and 2001 to 2006. The short-run elasticities varied from –0.31 to –0.34 for the first period, and from –0.034 to –0.077 for the second, thus providing evidence that short-run price-elasticity of gasoline demand is more inelastic in recent years. These results are consistent with those of recent meta-analytic studies (Espey 1996; Graham & Glaister 2002), which report –0.27 and –0.23 for the short-term price-elasticities, and –0.71 for the long-term. Some recent estimates reported in Brons et al. (2008) showed a slightly higher range, varying from –0.34 for short-run to –0.84 for long-run price-elasticities. Contrary to these findings of inelastic gasoline demand, Greene (1989) found own-price elasticity estimates to be over –15.0 (in absolute values).

However, none of these studies explicitly consider spatial attributes and/or provide a geographic comparison for the price-elasticities, which has important policy implications related to local governmental regulations for low-level vs. higher blend of ethanol. Bernstein and Griffin (2006) use a dynamic demand model to investigate the geographic differences in the price-demand relationships at the regional, state and sub-state level. The results showed that there are regional and state differences in the energy demand-responsiveness to price changes. However, their analyses only covered electricity and natural gas in the residential sector, and electricity use in the commercial sector.

Spatial regression techniques are widely used for analyzing data that has spatial characteristics (Case 1991), including hedonic house price spatiotemporal autoregressive models (R. Pace et al. 1998), and transportation spatial demand models (Henrickson and Wilson 2005). Henrickson and Wilson (2005) used a moving-window regression to estimate barge transportation demand elasticities. This approach is conceptually relevant to GWR technique as it produces spatially varying (to some extent) parameter estimates. However, the moving-window regression introduces so-called edge effects, because the data points within each local grid are given a weight equal to 1 (thus, are included in the regression), and those outside of the grid are given a weight of 0, which imposes limitations on capturing spatial variation between the two.

Theoretical Framework

In this section, I first introduce a basic model of household demand for close substitute fuels - gasoline and ethanol. I start with a basic model that reflects previous transportation fuel demand estimation models, (Rask, 1998; Anderson, 2008; Hughes et al., 2008). Following the notation in Anderson (2008) the household's utility function in terms of transportation fuels and other goods can be represented as $U = f(E, G, X)$, where E and G are consumption of close substitutes - ethanol and gasoline, and X represents the composite good. Since gasoline and ethanol are close substitutes, the household demand lands at the corner solution, such that the household will purchase ethanol only when $p_e < p_g/r$, where p_e and p_g are per gallon retail prices of ethanol and gasoline respectively, r (alternatively called fuel-switching price ratio) specifies the rate at which the consumer converts gallons of gasoline into ethanol-equivalent gallons, and p_g/r is ethanol-equivalent fuel price. Alternatively, the household will purchase gasoline when $p_e > p_g/r$. In other words, because ethanol has lower energy content (i.e., provides fewer miles per gallon), the fuel type decision is made based on the ethanol-equivalent price (Anderson 2008). The household demand for ethanol can be aggregated by assuming a fraction of households (ϕ) that own flexible fuel vehicles (FFV), and assuming that there are N such households. It is also assumed that each household owns a single vehicle. Further, it is assumed that fuel-switching price ratio r has differentiable cumulative distribution function $H(r)$, which is defined on $[0,\infty)$. Because $r < p_g/p_e$, i.e., households choose ethanol only when the switching ratio is less that the relative price, the portion of households that choose ethanol is the function evaluated at $H(p_g/p_e)$. The aggregate demand for ethanol takes the following form

(1)

$$E(p_e, p_g) = N\phi \int_0^{p_g/p_e} d(p_e)dH(r) = N\phi H\left(\frac{p_g}{p_e}\right) d(p_e)$$

where the total number of households, N, is multiplied by the fraction that own FFVs, ϕ, multiplied by the fraction of those FFV owners that choose ethanol (which is a function of relative prices), multiplied by the level of ethanol consumption by households that choose ethanol (which is a function of absolute price of ethanol). The logged aggregate demand is

(2)

$$lnE(p_e, p_g) = lnN\phi + lnH\left(\frac{p_g}{p_e}\right) + lnd(p_e)$$

The gasoline-price elasticity of aggregate ethanol demand can be derived by differentiating (2) with respect to p_g and multiplying by p_g

(3)

$$\xi_g = \frac{\partial lnE(p_e, p_g)}{\partial p_g} p_g = \frac{H'\left(\frac{p_g}{p_e}\right)}{H\left(\frac{p_g}{p_e}\right)} \frac{p_g}{p_e}$$

Similarly, the own-price elasticity of aggregate ethanol demand can be derived by differentiating (2) with respect to p_e and multiplying by p_e

(4)

$$\xi_e = \frac{\partial lnE(p_e, p_g)}{\partial p_e} p_e = \frac{p_e d'(p_e)}{d(p_e)} - \frac{H'\left(\frac{p_g}{p_e}\right)}{H\left(\frac{p_g}{p_e}\right)} \frac{p_g}{p_e}$$

Thus, the own-price elasticity (ξ_e) combines the effects of ethanol prices in terms of both reducing/increasing the demand for ethanol (the first term of equation (4)), and in terms of switching to/from gasoline.

The approach described above, however, does not incorporate considerations of spatial patterns in household demand into the model. Schmalensee and Stoker (1999) introduced a model of household demand for gasoline as a function of income, demographics and location. The authors argue that the demographic shift played an important role in increasing overall transportation fuel consumption over the last decades. The same source reports that household structure (number of drivers, household size, and household head age) has strong effects on gasoline demand. In addition to geographically varying household composition, the existence of spatial patterns in demand can be motivated by interdependent preferences. Yang and Allenby (2003) introduce a model of interdependent consumer preferences with data on automobile purchases, in which they found that preferences for Japanese-made cars are attributed to geographically and demographically defined networks. Based on these theoretical priorities, I extend the household demand model introduced above to account for geographic variations in household composition and demand preferences, which in turn influence price-elasticity of demand for fuels.

Empirical Framework

Basic Model of Consumer Demand for Ethanol

The econometric specification for estimating the ethanol demand basic model described above can be represented by the following equation

(5)

$$y_{it} = \beta_0 + \sum_m \beta_m X_{it} + \theta \mathrm{Z}_i + \gamma_t + \psi_t + \varepsilon_{it}$$

where y_{it} is time and location-specific dependent variable (fuel sales volume), X_{it} is a matrix of explanatory variables (county/station-specific characteristics, such as fuel prices, per-capita income, number of vehicles, and number of fueling stations that offer E85), Z_i represents time-invariant station-specific variables, e.g., station distance-to-rack and distance-to-highway, γ_t is the regional dummy (e.g., rural vs. urban), ψ_t represents monthly/seasonal dummy variables, and

ε_{it} is a random error term, assumed to be normally distributed. In a classical ordinary least squares specification, these parameters are assumed to be constant across the study area. According to this specification, any geographic variations of the relationships between y_{it} and the parameters are captured in the error term.

Motivating Spatial Heterogeneity

"There are spatial variations in people's attitudes or preferences or there are different administrative, political or other contextual issues that produce different responses to the same stimuli over space" (Fotheringham et al. 2002). The utilization of ethanol sales volume and price data across Minnesota for estimating price-elasticity of demand using traditional econometric methods (e.g., OLS regression) involves two types of problems. The first problem is the spatial dependence. In our case, spatial dependence is the extent to which the values of monthly sales volume at one service station depend on the values at another service station in the vicinity. Considering n geographic locations, the spatial dependence can be represented as the following equation

(6)

$$y_i = f(y_j), i = 1, \dots, n \quad j \neq i$$

where y is the value of the variable (e.g., sales volume), and i and j are locations (e.g., service stations). Spatial dependence violates the traditional Gauss-Markov assumption that explanatory variables are fixed in repeated sampling (Lesage and Pace 2009). One reason for the existence of spatial autocorrelation can be the measurement error. Another reason for the spatial dependence can be related to the E85 stations locations (e.g., the proximity to the ethanol blending terminal or to the major highways in the study area). The second problem is the spatial heterogeneity, which violates another Gauss-Markov assumption that a single linear relationship exists across the sample data observations. As shown in equation (7), local relationships can be modeled for each service station in the study area

(7)

$$y_i = X_i\beta_i + \varepsilon_i, \qquad i = 1, \dots, n$$

where y_i is the dependent variable at location i, X_i is a vector of explanatory variables, β_i is the associated set of parameters to be estimated, and ε_i is a stochastic disturbance term.

Spatial Extension Model of Consumer Demand for Ethanol

In this section I extend the econometric model (5) to a spatially weighted regression model. To address the traditional econometric restrictive assumption of identical or stationary relationships over the space, some of the papers reviewed earlier employed indicator variables. One of the specifications considered in Anderson (2008), restricted the data to two relationships by including urban vs. rural dummy variables to observe region effects. However, it is not known if only two dummies for the entire study area is appropriate disaggregation, or if additional sub-regional dummies should be included. Another approach, market segmentation, is used to reformulate data into small number of mutually exclusive and collectively exhaustive sub-samples (e.g., geographical samples – counties, states; socio-economic samples – income groups, education levels, etc.). Both of these strategies (dummy variables and market segmentation) introduce a problem of discontinuity in data, which eliminates the local spatial variations among different locations (for which data are available) in the study area.

One way to address this issue is to use a relatively recent spatial regression methodology that accounts for spatial non-stationarity in data – GWR (Fotheringham et al. 2002). The GWR methodology includes a spatial weighting matrix that assigns higher weights to the regressors in the near locations, and gradually decreases the weights as the distance from the regression point increases. In this spatially weighted model, the regression points are service stations. This approach allows estimating a "surface" of location-specific price-elasticity parameters. In our case, the GWR specification will produce local price-elasticity estimates of demand for ethanol throughout the study area. The estimates then can be mapped using Geographic Information Systems (GIS) software. Following the notation in Fotheringham et al. (2002), I represent the demand for ethanol fuel at each of the locations from which the data were drawn as the following

(8)

$$y_{it} = \beta_{ot}(\upsilon_i, \nu_i) + \sum\nolimits_m \beta_{mt}(\upsilon_i, \nu_i) X_{it} + \sum\nolimits_k \theta_k(\upsilon_i, \nu_i)\, \mathrm{Z}_i + \varepsilon_{it}$$

where y_{it} is the dependent variable (monthly ethanol sales volume) for each of the ith fueling stations in the study area, X_{it} is a matrix of time and location-specific explanatory variables discussed above, Z_i represents the time-invariant variables, and ε_i is the error term. Coefficients β and θ are to be estimated for each of the fueling station at (υ_i, ν_i) projected coordinates (i.e., converted from geographic coordinates). The expressions for parameters $\beta(\upsilon_i, \nu_i)$ and $\theta(\upsilon_i, \nu_i)$ indicate that the price-elasticity of demand for ethanol and the other estimates are location-specific. The estimator for this model has the following form

(9)

$$\hat{\beta}(\upsilon_i, \nu_i) = (X^{'} W(\upsilon_i, \nu_i) X)^{-1} X^{'} W(\upsilon_i, \nu_i) y$$

where $W(v_i, v_i)$ is a distance-based weighting matrix for expressing potential interaction among spatial units (e.g., fueling stations). The off-diagonal elements of the weighting matrix are zero, and the diagonals denote the geographical weighting of observed data for point i. Denoting the (v_i, v_i) coordinates as (u), the weighting matrix takes the following form

(10)

$$W(u) = \begin{pmatrix} w(u)_1 & 0 & 0 & \dots & 0 \\ 0 & w(u)_2 & 0 & \dots & 0 \\ 0 & 0 & w(u)_3 & \dots & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots \\ 0 & 0 & 0 & 0 & w(u)_n \end{pmatrix}$$

One way to assign weights to the diagonal elements in the weighting matrix in (10) is to let $w(u) = 1$ if $d_i(u) \leq h$, and $w(u) = 0$ otherwise, where $d_i(u)$ is a measure of Euclidean distance between the ith observation and the location (u) (i.e., a regression point or service station), h is some bandwidth. However, similar to the concept of moving window regression, this strategy introduces some extent of spatial discontinuity. To overcome that problem, we compute the weights as a continuous function of a distance $(d_i(u))$. One possible way of doing it is to calculate the diagonals of (10) according to a kernel that has a Gaussian shape:

(11)

$$w(u) = exp(-0.5 \left({}^{d_i(u)}/_{h} \right)^2$$

In this weighting scheme, the $d_i(u)$ is a measure of Euclidean distance as described above, and h is bandwidth. The bandwidth parameter for our distance-based weighting matrix is selected using the following cross-validation procedure

(12)

$$CV = \sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(h)]^2$$

where n is the sample size, $\hat{y}_{\neq i}$ denotes the fitted value of y_i with the observation for point i omitted from the calibration process (Fotheringham et al. 2002).[2] A value of h that minimizes the *CV* score is then used as the distance-weighting bandwidth. If the ith observation and the location (u) in weighting scheme (11) coincide, i.e., data were observed at location(u), the weight for that point will be unity. Then the weights of other locations around it will decrease according to a Gaussian curve as the distance between the two increases.[3] The spatial kernel represented in (11) avoids the discontinuity problem by assigning decreasing weights (according to a Gaussian shape curve) as the distance between two locations increases (Fotheringham et al. 2002).

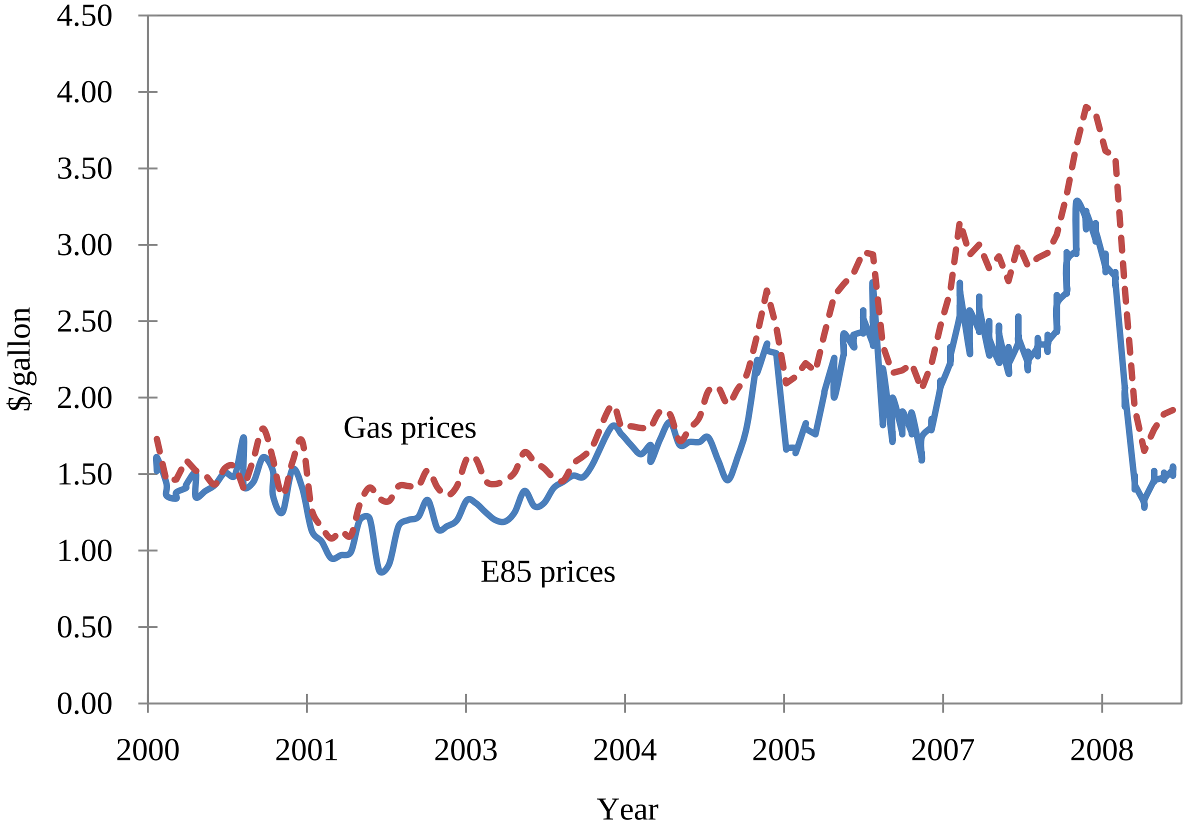
Data Sources and Description

Ethanol price information was obtained from a survey conducted by Minnesota Department of Commerce and American Lung Association of Minnesota. The data include monthly price observations and sale volumes by individual E85 service stations in Minnesota from 1997-2009. The number of participating E85 service stations was less than 10 in 1997, then steadily increased up to more than 330 as of mid 2009. As of September 2009, Minnesota had the highest number of E85 stations in the nation (351). This makes up more than 18% of the total

[2] In the CV equation, omitting the *i*th observation is necessary, otherwise the CV score will be minimized when $h = 0$, i.e., as $h \to 0$, $\hat{y}_i(h) \to y_i$, so the CV score is minimized when $h = 0$.
[3] The parameter estimation points are usually coinciding with the points from where data were drawn, but it is not a necessary condition (Fotheringham et al. 2002).

number of E85 stations in the U.S. (U.S. DOE Alternative Fuels and Advanced Vehicles Data Center).[4]

Figure 1: Gasoline and ethanol retail prices



This information was used to calculate the number of fueling stations (offering E85) in each county for each time period. Monthly observations of retail gasoline prices were averaged from the Minnesota Weekly Gasoline Retail Price Reports provided by the Energy Information Administration (EIA). Wholesale gasoline prices were obtained from the Minnesota Regular Gasoline Wholesale/Resale Price by Refiners database provided by the EIA.

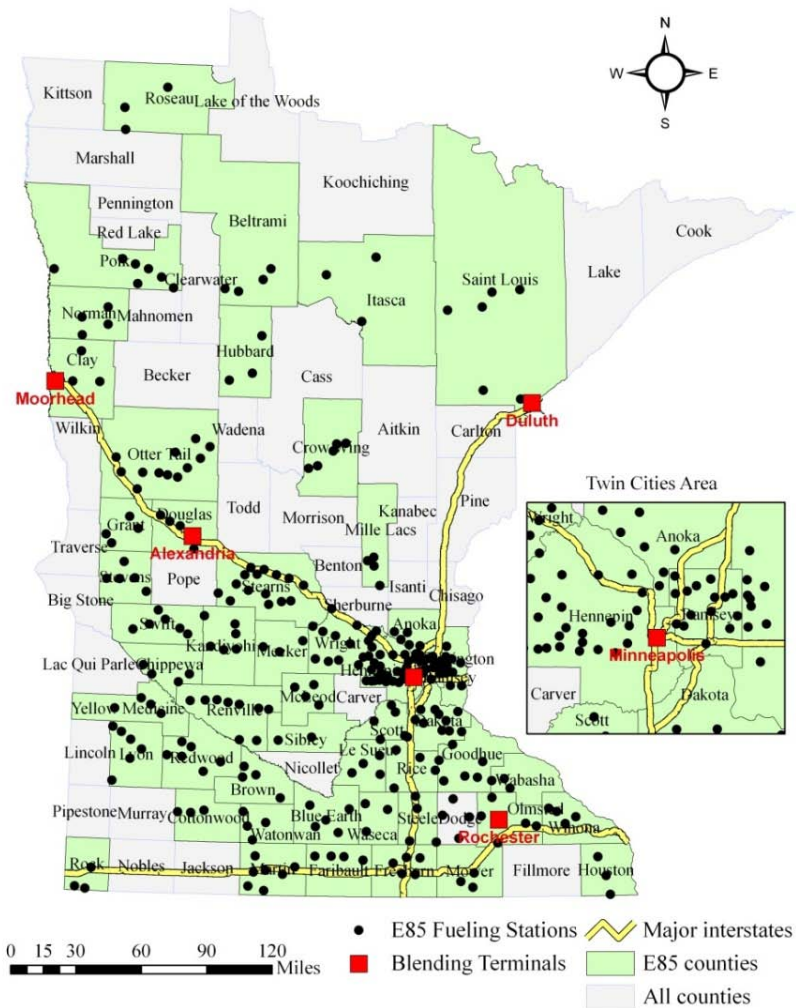
[4] For the distribution of all E85 service stations in the U.S. see Table 4 in the Appendix.

Figure 1 shows the relationship between ethanol and gasoline prices in Minnesota from 2000 to mid 2009 period. Using historical consumer price index from the Department of Labor, all prices were converted into real 2009 prices. In contrast to service station-level ethanol sales data, the gasoline prices were only available at a county-level, and for only 2000 – 2009. As a result, the number of observations was decreased from 13,339 (1997 – 2009) to 8,542 (2000 – 2008).

Per-capita income information (converted into 2009 dollars) was obtained from the Federal Reserve Economic Data (FRED) state/county-level database. Time series of the number of vehicles per county was obtained from the Driver and Vehicle Services at the Minnesota Department of Public Safety. A small portion of observations were dropped due to missing or not reported prices and sales volumes. The inclusion of the income and the vehicle stock variables restricted the number of usable observations further. As a result, the number of observations was decreased from 8,542 to 6,860. (i.e., the time period was restricted to 2003–2008.)

Figure 2 depicts the spatial distribution of E85 service stations included in our analysis, in which some level of local clustering can be observed around the Twin Cities area. Additionally, I used GIS to derive Manhattan distances (in miles) between ethanol fueling stations and five ethanol blending terminals in Minnesota (Minneapolis, Alexandria, Moorhead, Rochester and Duluth). The terminal location information was obtained from the Oil Price Information Service (OPIS) Rack Cities guide.

Figure 2: The geographic distribution of E85 service stations in Minnesota in 2009



I also used Minnesota's highway network GIS shapefile[5] and station locations available from the American Lung Association and Clean Air Choice organization.[6] Table 1 provides descriptive statistics for the data used in this paper.

[5] Minnesota road networks GIS shapefiles are available from the Minnesota Department of Transportation (http://www.dot.state.mn.us/maps/gisbase/html/datafiles.html)

[6] The map of E85 station locations can be found at: http://www.state.mn.us/mn/externalDocs/Commerce/State-wide_E-85_station_map_121302123133_MinnesotaE85StationsMap.pdf

Table 1: Descriptive Statistics

Variables	Mean	Stdev	Min	Max
Ethanol sales volume (gallons/month)	5,186	4,883	11	37,770
Income ($/per-capita)	39,565	6,783	27,274	49,196
Ethanol price (retail; $/gallon)	2.21	0.47	1.02	3.86
Gasoline price (retail; $/gallon)	2.66	0.60	1.64	3.87
Gasoline/ethanol price ratio (retail)	1.20	0.10	0.64	1.99
Gasoline price (wholesale; $/gallon)	1.75	0.61	0.92	3.35
Distance from nearest highway (miles)	22.44	24.51	0.28	144.00
Ethanol pumps in county (number/month)	6	4	1	17
Distance from nearest rack (miles)	34.15	26.32	1.00	100.00
Vehicle stock in county (number/month)	256,533	322,812	10,245	1,115,371

Basic Model Estimation and Results

First, I estimate the model of aggregate ethanol demand represented in equation (5). I let X_{it} denote ethanol and gasoline prices, per-capita income, number of vehicles, and number of stations offering ethanol, Z_i represents time-invariant distances to racks and to highways, γ_t and ψ_t represent regional and monthly dummy variables respectively. The equation (5) can be represented as the following

(13)

$$lnE_{it} = \beta_0 + \beta_1 \ln(PE_{it}) + \beta_2 \ln(PG_{it}/PE_{it}) + \beta_3 \ln(INC_{it}) + \beta_4 \ln(VEH_{it}) +$$
$$+\beta_5 \ln(NSTAT_{it}) + \theta_1 \ln(DISTR_i) + \theta_2 \ln(DISTH_i) + \gamma_1(TC_t) +$$
$$+\psi_2(M1) + \cdots + \psi_{11}(M11) + \varepsilon_{it}$$

where E_{it} is the monthly ethanol sales for all participating E85 stations throughout the time period, PE_{it} is the ethanol price (that was instrumented with wholesale gasoline prices in the 2SLS regression), PG_{it} is the gasoline price, INC_{it} is the per-capita income, VEH_{it} is the number of vehicles in each county, $NSTAT_{it}$ is the number of E85 stations (i.e., service stations having

E85 dispensers/pumps) in each county in each time period. $DISTR_i$ represents time-invariant distances from each of the E85 stations to the nearest ethanol blending terminal; $DISTH_i$ is time-invariant distance-to-highway variable representing the distance from each of the E85 stations to the nearest major highway node in the state. TC_t is a regional dummy variable controlling for Twin Cities area. Finally, $M1$ through $M11$ are 11 monthly dummy variables, and ε_{it} is the random error term.

Table 2 provides a summary of the OLS/2SLS estimates from the model described above.[7] I estimated the model for the whole time period, as well as for the prior and post Energy Independence and Security Act of 2007 periods (hereafter, prior to EISA and post EISA). The own-price elasticity of demand was found to be –3.33 for the 2003–2008 period, indicating a one percent increase in the price of ethanol leads to 3.33% decrease in the quantity of ethanol demanded.

One of the reasons that the change in the quantity of ethanol demanded is proportionately larger than the change in the price (i.e., the demand is elastic) is that consumers have quick access to the close substitute fuel – gasoline, at almost zero search cost (since every service station offers gasoline). Another reasonable explanation for the high elasticity estimate is consumers' concerns related to ethanol's corrosive characteristics. Some service stations in the Midwest advertised gasoline as "ethanol free" fuel, emphasizing that E85 results in a reduced range (miles per tank of fuel) and engine problems because of its moisture content (Galbraith 2008). Considering these conditions, consumers may show high sensitivity to small price increases by decreasing their consumption of fuel (ethanol) or by switching to gasoline. The

[7] Wholesale gasoline prices in Minnesota was used as an instrument for E85 prices. Ethanol sales represent a small portion of the gasoline consumption in Minnesota, therefore, wholesale gasoline prices can be considered as exogenous in our model.

estimate for the post EISA period (2007-2008) was estimated to be –4.09, much higher in absolute value compared to the prior to EISA period (2003– 2006) estimate of – 2.56.

Table 2: Basic Model Estimation Results

Dep. Var. = LN(ethanol monthly sales)	**2003-2008 (OLS)**	**2003-2006 (OLS)**	**2007-2008 (OLS)**	**2003-2008 (2SLS)**
Constant	–1.75***	–3.18***	–0.77	–1.84***
	(0.86)	(1.26)	(1.20)	(0.86)
LN(PE)	1.07***	2.11***	0.27***	0.94***
	(0.05)	(0.09)	(0.09)	(0.06)
LN(PG/PE)	4.35***	4.67***	4.36***	4.22***
	(0.12)	(0.17)	(0.18)	(0.12)
LN (INC)	0.41***	0.66***	0.17*	0.44***
	(0.08)	(0.12)	(0.11)	(0.08)
LN (VEH)	0.29***	0.22***	0.43***	0.27***
	(0.01)	(0.02)	(0.02)	(0.01)
LN (NSTAT)	–0.27***	–0.22***	–0.47***	–0.24***
	(0.02)	(0.02)	(0.03)	(0.02)
LN (DISTR)	(0.02)*	–0.01	0.03***	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
LN (DISTH)	0.02***	0.07***	–0.003	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Reg. Dummy	2.51***	2.19***	2.88***	2.49***
(Twin Cities area)	(0.05)	(0.07)	(0.09)	(0.02)
Month. Dummies	y	y	y	y
Own-price	-3.3	-2.6	-4.1	-3.3
elasticities	(0.06)	(0.08)	(0.08)	(0.06)
N	6860	3163	3697	6860
Adj. R-squared	0.43	0.47	0.45	0.43

***p<0.05, **p<0.1, *p<0.2. Standard errors are in parentheses. Dependent variable is the monthly ethanol sales volume in gallons. Prices are in 2009 dollars; income is the real per capita disposable income in 2009 dollars.

Gasoline-price elasticity of ethanol demand was estimated to be 4.35 for the whole period (2003 – 2008); 4.67 and 4.36 for the prior and post EISA periods, suggesting relatively stable, sensitive ethanol demand-responsiveness to gasoline prices changes throughout the study period. (All the logged prices used in the estimation were normalized as $ln(p^{*}) = ln(p/\bar{p})$, where $p^{*}$is the normalized price variable, p is the initial price variable, and $\bar{p}$ is the sample mean. Thus, $\hat{\beta}_2$ is interpreted as a gasoline-price elasticity of ethanol demand.)

Income-elasticity of demand for ethanol was found to be 0.41 for the 2003– 2008 period. This estimate is consistent with the results from a recent study that analyzed similar data (Bromiley et al. 2008). The authors found that the influence of income levels on E85 monthly sales is minimal in magnitude and statistically insignificant. These results are also comparable to the estimates found in Hughes et al. (2008), which reports income-elasticity of gasoline demand in the 0.47– 0.54 range.

The estimate for the vehicle stock variable (0.29) for the 2003– 2008 period suggests that every 10% increase in the vehicle stock will lead to only 2.9% increase in ethanol sales. Using the FFV stock variable, I would expect the estimate to be 1 or more, suggesting that doubling the FFV stock will at least double the E85 fuel consumption. However, due to data limitations I am using a conventional vehicle stock variable as a proxy for FFV stock in our analysis. I found the estimates to be 0.22 and 0.43 for the prior and post EISA periods. According to the Minnesota Department of Public Safety registration records, the total number of passenger vehicles in Minnesota reached 3.34 million in 2006, a slight increase from 3.4 million in 2008. Considering 125,000 FFV as of 2006 in Minnesota (as reported in Bromiley et al. (2008)), the ratio of FFV to conventional vehicles is less than 5%. Overall, the estimate is in accordance with our expectation of positive relationship between the stock of vehicles and fuel sales.

The number of ethanol stations per county estimate resulted in –0.27 for the 2003– 2008 period, and –0.22 and –0.47 for the prior and post EISA periods. Consistent with previous findings (Anderson 2008), the negative sign suggests that a 1% increase in the number of ethanol stations in a county will reduce per station E85 sales by 0.22–0.48%.

The distance to a major highway variable showed relatively weak (0.02) influence on the E85 sales volume. Generally, retail gasoline prices are positively correlated with the distances from the source of supply (i.e., refineries, blending terminals, pipelines, ports, etc.) as the distribution costs increase with the distance. However, retail ethanol is primarily shipped to service stations from regional blending terminals, which are usually located near to large consumption areas. Also, major highways are positively correlated with local clusters of regular gasoline stations and relatively dense traffic of conventional vehicles. This suggests that there is more demand for regular gasoline at locations around or in close proximities from major highways. Therefore, the ethanol stations that are near to the major highway may sell less E85 compared to those that are located further away.

The influence of the distances to the blending terminals in Minnesota on E85 monthly sales volume is slightly weaker than that of the distance to highway variable described above. All of the five blending terminals are located within a close distance from major highways in the state. The same reasoning – relatively dense traffic of conventional vehicles on major highways (i.e., higher demand for regular gasoline) may explain the positive influence of the distance to the racks variable on the E85 sales. The estimate for the regional dummy variable TC (Twin Cities) is positively correlated with the ethanol sales. Lastly, monthly dummy estimates reflect expected seasonal variation in transportation fuel demand.

Identification issues and spatial autocorrelation

Estimating demand functions that include price among the explanatory variables is often subject to endogeneity issues. In our model, the parameter estimates will be biased if the fuel prices are correlated with the unobserved characteristics embedded in the error term. Anderson (2008) argues that many ethanol retail stations in Minnesota price ethanol at a fixed discount to gasoline (specified in a contract with suppliers that lasts several months, and sometimes a year). This indicates that the correlation between ethanol prices and local, short-term ethanol demand shifts is less likely. This pricing behavior implies that the local ethanol demand shifts are not correlated with the individual (i.e., fueling station) price variations. Conditional on the argument above, the OLS estimation results will not be biased.

Another concern is the possible spatial autocorrelation in our data, under the assumption of normally and independently distributed error terms in the model. I calculated the Moran's I statistic (Moran 1950) for residuals from the OLS regression (13). The results showed a moderate spatial correlation in OLS residuals (Moran's I =0.17, Z–score =4.00, p–value =0.00). The GWR model, which allows spatial variation of the underlying processes, should largely eliminate the problem of spatial autocorrelation in the error term. To confirm the validity of the GWR approach, the Moran's I statistics for both OLS/2SLS and GWR model residuals are compared in the next section.

GWR Estimation and Results

In this section I estimate and visualize the spatial extension of the ethanol demand model described earlier. Considering the variable descriptions provided above, the GWR model (8) can be represented as[8]

(14)

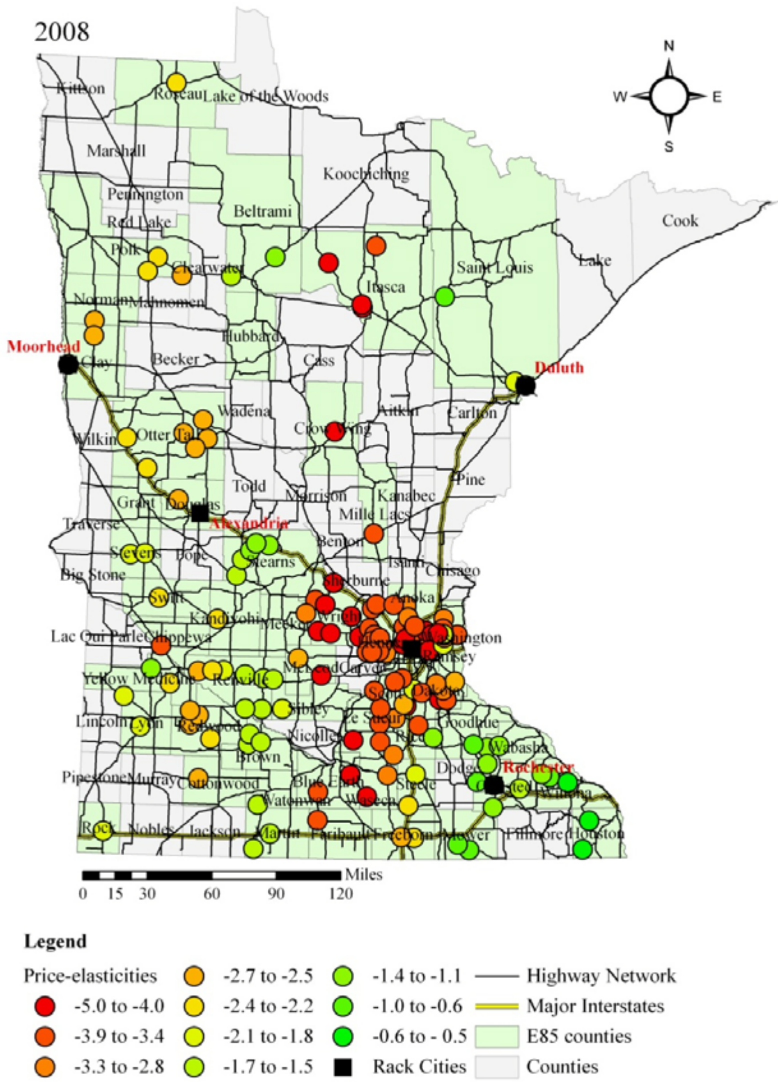
$$lnE_{it} = \beta_{ot}(v_i, \nu_i) + \beta_1 ln(v_i, \nu_i)PE_{it} + \beta_2 ln(v_i, \nu_i)(PG_{it}/PE_{it}) + \beta_3 ln(v_i, \nu_i)INC_{it} + $$

$$+\beta_4 ln(v_i, \nu_i)VEH_{it} + \beta_5 ln(v_i, \nu_i)NSTAT_{it} + \theta_1 ln(v_i, \nu_i)DISTR_{it} + \theta_2 ln(v_i, \nu_i)DISTH_{it} + \varepsilon_{it}$$

[8] Note that I did not include binary variables as the GWR allows explanatory variable coefficients to vary across the study area. Thus, the binary variables are not necessary, and their inclusion will introduce local collinearity.

The result of the GWR model is a "surface" of parameter estimates across the ethanol stations in Minnesota that were included in this study. Figure 3 illustrates the spatial changes in the magnitude of the price-elasticity of demand for ethanol for the year 2008.[9]

Figure 3: Spatial distribution of price-elasticity of demand for ethanol in Minnesota

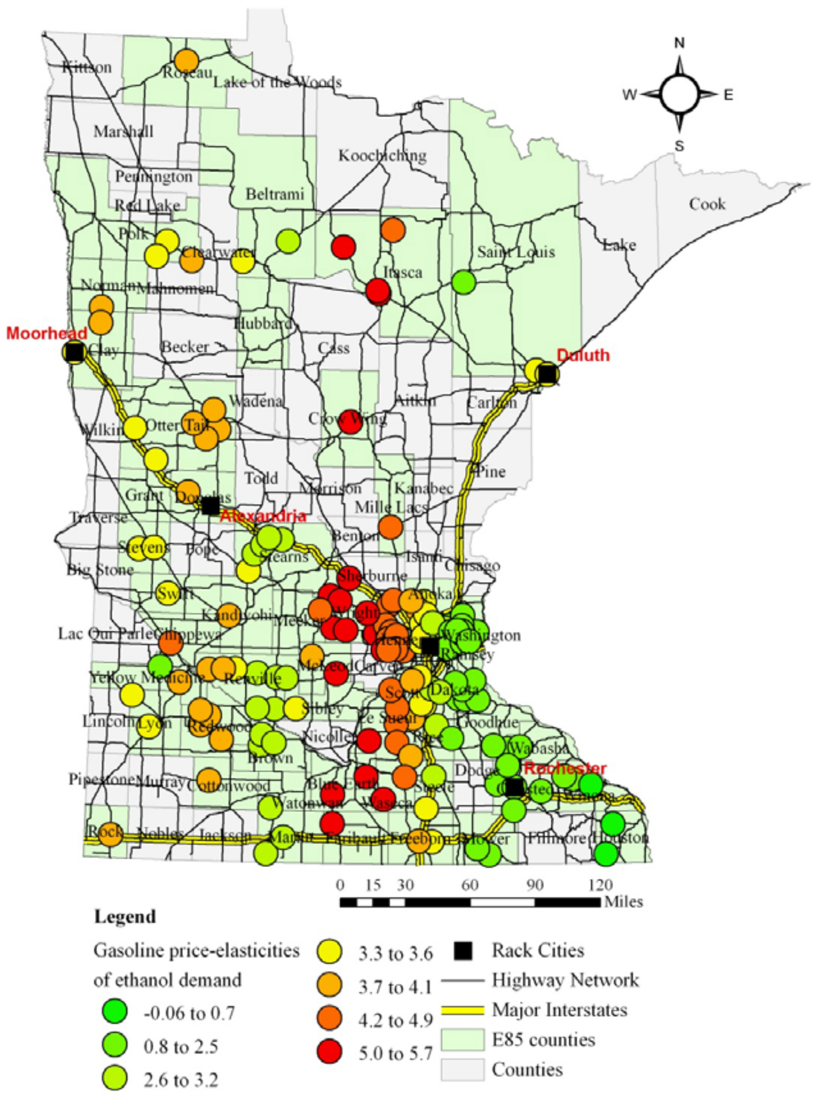


9 The estimates covering full time period are included in Figure 6 (a, b) of the Appendix (Ch. 1).

With a few outliers in the Itasca county in the Northern part of the state, the figure shows elastic ethanol demand cluster around the Twin Cities area (–5.0 to –2.2). Most of the estimates in the rural areas vary from –0.5 to –2.7. Overall, the estimated high elasticities are consistent with our expectations, explained by the availability of close substitute gasoline at almost zero search cost (since every service station where E85 is available also offers gasoline). The variation in the estimates also supports our motivation of the existence of spatial heterogeneity in the structure of the data. I have also visualized gasoline-price (cross) elasticities of ethanol demand (Figure 4). The estimates widely vary from –0.06 to 5.7 across the space. Because our analysis assumes only gasoline and ethanol fuels, the cross-price elasticity is comparable to the elasticity of Minnesota's ethanol's market share. The estimates in OLS/2SLS estimation showed that consumers are generally more sensitive to relative prices. However, our findings from the GWR model indicate that the consumers' demand-sensitivity to price changes widely varies geographically. In addition to visualizing the own- and cross-price elasticities in a map, Table 3 provides a summary of the estimates for comparing the GWR and OLS results side by side. As shown in the table, the OLS cross-price elasticity estimate (4.35) is found between upper quartile and maximum values of the GWR results. The own-price elasticity estimate from the OLS model (-3.3) falls between minimum and lower quartile values of the GWR estimates. Spatial distribution of the own-price and gasoline-price in Figure 3 and Figure 4 reveal that the OLS results represent only a portion of the geographic variation in gasoline-ethanol price-demand relationships.

Income-elasticities for the Twin-Cities area were found in the 1.4 to 2.5 range (Figure 5), indicating a positive relationship between income levels and ethanol consumption in the urban area.

Figure 4: Gasoline-price elasticities of ethanol demand



The estimates for the rest of the regions change from negative to positive sign, ranging from –2.1 to 1.3. According to the comparison in Table 3, the OLS estimate (0.41) for income-elasticity falls between lower quartile and median values of the GWR estimates.

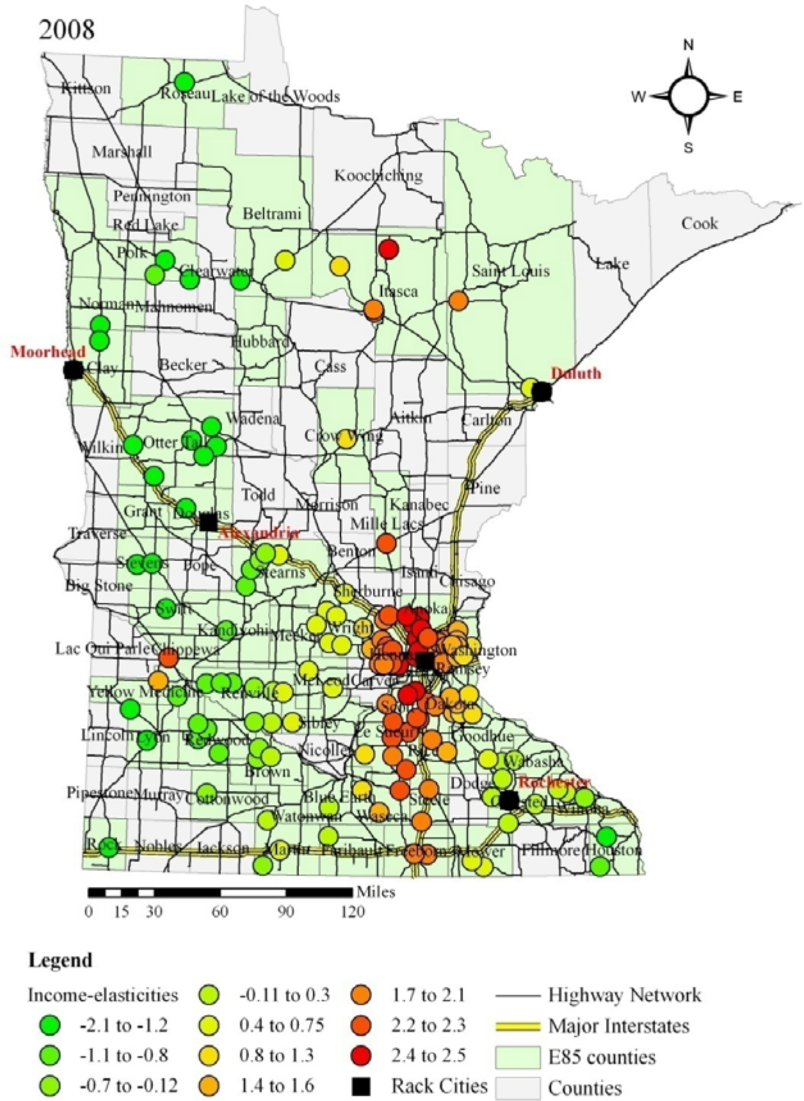
Table 3: GWR parameter summary and comparison with the global (OLS) model

Variables	Min	Lower Quartile (25th percentile)	Median (50th percentile)	Upper quartile (75th percentile)	Max	OLS (2003–2008)	Standard errors–OLS/2SLS (2003–2008)	GWR coefficients variability statistic $(\sqrt{\rho_i})$
ln(PE)	–5.00	–2.70	–2.08	–1.40	–0.50	1.07	0.05	1.06
ln(PG/PE)	–0.06	2.49	3.35	3.93	5.70	4.35	0.12	1.11
ln(INC)	–2.10	–0.48	0.95	2.02	2.50	0.41	0.08	1.36
ln(VEH)	–0.21	–0.02	0.13	0.33	0.59	0.29	0.01	0.21
ln(NSTAT)	–0.51	–0.39	–0.26	-0.14	0.06	–0.27	0.02	0.15
ln(DISTR)	–0.19	–0.08	–0.01	0.07	0.75	0.02	0.01	0.14
ln(DISTH)	–0.22	0.07	0.12	0.20	0.64	0.02	0.01	0.09

A close examination of the map provided in Figure 5 indicates that the OLS captured only part of the geographic area outside of the Twin Cities area (to the West and to the Southeast). Overall, as shown in Table 3, GWR estimates show substantial variation in contrast to the OLS estimates. Comparison of the estimates across all of the variables shows that the OLS results are representative of only a segment of the entire range of elasticity estimates.

I test the following hypothesis: $H_0\colon \beta(\upsilon_i, \nu_i) = \beta_{OLS}$ where i indexes the locations, against $H_1\colon \beta(\upsilon_i, \nu_i) \neq \beta_{OLS}$. To test this hypothesis, Brundson et al. (1998) suggest to measure the variability of the GWR coefficients (price-elasticities in our case) using the following statistics: $\rho_i = \sum_i (\beta(\upsilon_i, \nu_i) - \beta_{i.})^2 / N$, where a dot denotes averaging the GWR coefficients over N locations. The $\sqrt{\rho_i}$ for all of the variables in the model is then compared with the standard errors from the OLS/2SLS model (the last column of Table 3).

Figure 5: Spatial distribution of income-elasticity of ethanol demand in 2008



As shown in Table 3, all of the variability statistics are greater than the standard errors from the OLS/2SLS models suggesting an improvement upon the conventional estimation method. Additionally, I tested the residuals from the GWR for spatial dependence. The test statistics – Moran's I $_{GWR}$ = 0.07 with a Z-score = 3.33, and p-value = 0.008, compared to Moran's I $_{OLS}$ =

0.17 with a Z-score = 4.00 and p-value = 0.00 provide additional evidence for the advantage of estimating the price-elasticities with the GWR specification.

Concluding Remarks

The primary objective of this study was to estimate spatially extended version of ethanol demand model. The results of the GWR methodology showed significant spatial variation in the study area. The demand for ethanol was found to be elastic, with the estimates varying from -5.0 to -2.2 in the urban area. Most of the estimates for the rural areas of the state vary from -0.5 to -2.7 (although a few locations with high elasticity levels were found in the northern part of the state). Overall, the temporal variation in the price-elasticity of demand for ethanol was found to be less in magnitude. However, the post EISA (2007, 2008) period estimates showed significant variation, mostly increasing in absolute value around the Twin Cities area. The OLS/2SLS model estimates showed that consumers are more sensitive to relative prices. However, the comparison with the visualized GWR elasticity estimates showed that OLS model results can be attributed to only certain geographic areas.

Our findings of the spatial differences in price-elasticity of demand for ethanol fuel have several useful policy implications. Minnesota has joined several states in the Midwest in adopting the Energy Security and Climate Stewardship Platform Plan, an initiative designed to 1) produce commercially available cellulosic ethanol and other low-carbon fuels in the region by 2012, 2) increase E85 availability at retail fueling stations in the region, 3) reduce the amount of fossil fuel that is used in the production of biofuels by 50%, and 4) replace at least 50% of all transportation fuels consumed by the Midwest by locally-processed biofuels by 2025. As part of that plan, the Minnesota Environmental Quality Board (EQB) is studying the potential sources of biomass for cellulosic ethanol and other low-carbon fuels production. In contrast to corn-based ethanol, the cellulosic feedstocks are geographically dispersed. So, the cellulosic ethanol costs (and thus retail prices) are sensitive to feedstock transportation and processed fuel (pure ethanol) distribution costs (Khachatryan et al. 2009). The ethanol processors face plant location optimization problem. Should the processing plant be located near to feedstock sources or to end-use markets? One component that is necessary for solving this optimization problem is to understand consumers' location-specific demand-responsiveness. Second, knowing spatial patterns in household demand for ethanol is useful for decisions related to increasing the number of E85 dispensing pumps in the state, something that I found to be negatively correlated with station-specific demand for E85.

On a quantitative side, these findings have useful implications for state-level ethanol policy simulation experiments. Non-spatial econometric models emphasize similarities or regularities of data being analyzed. In contrast, spatially disaggregated estimation approach helps to reveal differences across the study area. Alternative fuel policy simulation requires consideration of a range of price-elasticity estimates to be used in a calibration. The use of disaggregated data in our study allowed obtaining more detailed estimates, which can be used in policy simulations with more certainty.

It is worth mentioning several limitations of this study. Although, our investigation aims to reveal spatial differences in the price-demand relationship, it is geographically bounded. Availability of ethanol fueling stations and price differences outside of Minnesota's borders may influence sales volumes observed in our data. Additionally, a portion of E85 sales can be attributed to the households not residing in Minnesota (since many E85 stations are close to major interstate highways).

In future research, I plan to simulate ethanol policy effects on environmental emissions reductions in Minnesota. From a methodological perspective, it will be useful for future research to develop and use a weighting scheme that accounts for both temporal and spatial effects simultaneously (i.e., spatiotemporal weighting matrix). In a spatiotemporal framework, spatial weights work in a same manner (e.g., decreasing the weights based on the distances between locations, or based on the number of nearest neighbors), however, the temporal weight gives more weight to more recent events, and gradually decreases the weights for previous years.

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Appendix (Ch. 1)

Table 4: The distribution of E85 service stations in the U.S. (as of September 2009)

State	Number of E85 Stations	State	Number of E85 Stations	State	Number of E85 Stations
Minnesota	351	N. Dakota	31	Idaho	5
Illinois	192	Tennessee	29	Connecticut	4
Iowa	123	Arizona	26	Louisiana	4
Wisconsin	121	Florida	26	Mississippi	4
Indiana	112	Pennsylvania	26	Utah	4
Missouri	95	N. Carolina	17	DC	3
Michigan	91	Washington	15	West Virginia	3
S. Carolina	85	Kentucky	14	Massachusetts	2
S. Dakota	80	Maryland	14	Delaware	1
Colorado	76	Nevada	14	Montana	1
Ohio	63	Alabama	11	Alaska	0
Nebraska	48	New Mexico	11	Hawaii	0
California	40	Oklahoma	11	Maine	0
Texas	40	Arkansas	8	New Hampshire	0
Georgia	37	Oregon	8	New Jersey	0
New York	35	Virginia	8	Rhode Island	0
Kansas	33	Wyoming	6	Vermont	0
Total	1928				

Source: U.S. Department of Energy, Alternative Fuels and Advanced Vehicles Data Center. http://www.afdc.energy.gov/afdc/fuels/stations_counts.html (Updated 09/24/2009)

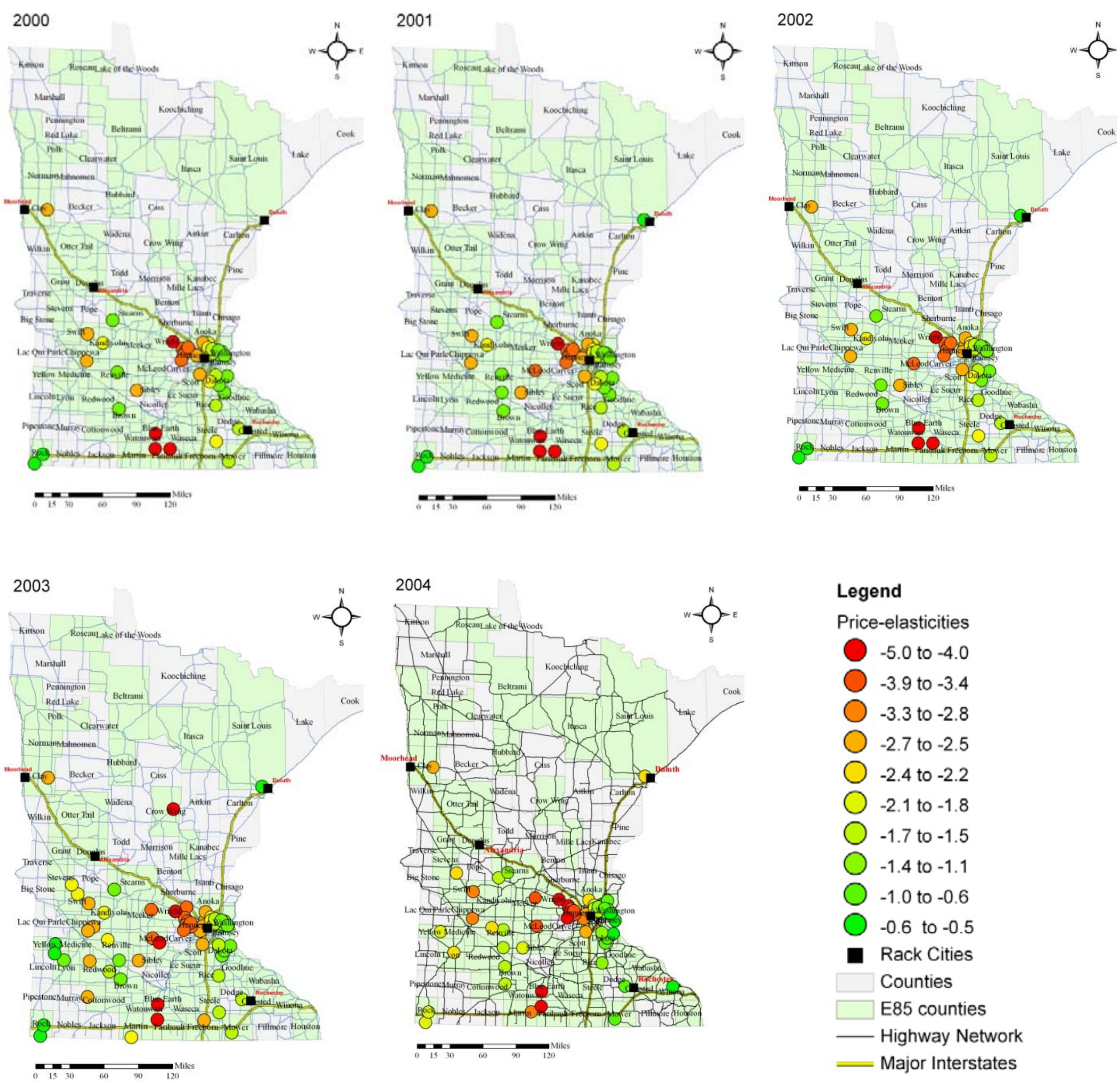
Table 5: Additional estimation results (OLS, linear model)

Dependent variable = LN(Ethanol monthly sales volume			
	2003 - 2008	**2003 - 2006**	**2007 - 2008**
constant	-6893.5***	-12065.7***	-3949.4***
	(622.8)	(915.1)	(1036.6)
PE	-6366.0***	-6160.6***	-6945.0***
	(322.2)	(421.9)	(471.7)
PG	6477.9***	9013.8***	5791.3***
	(261.2)	(400.9)	(383.0)
INC	0.07***	0.07***	0.07***
	(0.01)	(0.01)	(0.017)
VEH	0.002***	0.001***	0.005***
	(0.0003)	(0.0004)	(0.0005)
NSTAT	-142.8***	-66.3**	-347.8***
	(23.09)	(36.9)	(33.18)
DISTR	7.97***	-1.09	17.12***
	(2.58)	(3.44)	(3.59)
DISTH	-12.8***	-3.6	-19.8***
	(2.77)	(3.90)	(3.79)
Reg. Dummies			
GM	4878.6***	4071.0***	5513.3***
	(341.3)	(419.6)	(544.7)
TC	7993.7***	6451.9***	9111.9***
	(305.8)	(349.6)	(506.1)
Month. Dummies	y	y	y
N	6860	3163	3697
Adj. R-squared	0.31	0.36	0.32
Durbin-Watson statistic	1.99	2.17	2.03

***p<0.05, **p<0.1, *p<0.2. Standard errors are in parentheses. Dependent variable is the monthly ethanol sales volume in gallons. Prices are in 2009 dollars; income is the real per capita disposable income in 2009 dollars.

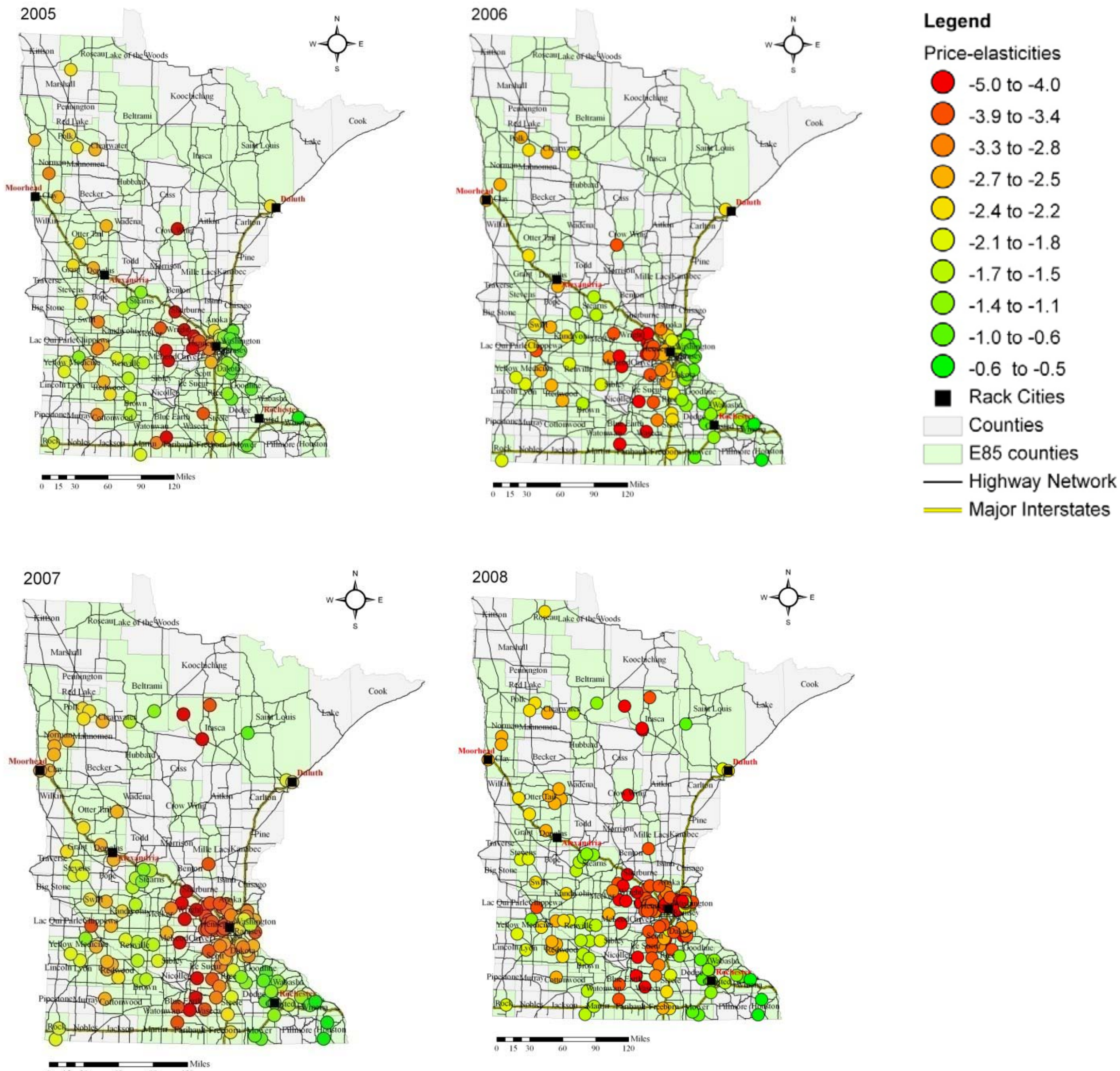
Figure 6: Spatial distribution of price-elasticity of demand for ethanol in Minnesota (2000-2008)

a)



Note: The parameter estimates for the 2000 – 2002 period were derived using a specification that does not include the vehicle stock variable (since the vehicle stock restricts our data to 2003-2008). Those maps were included to show the dynamics of the elasticities for the entire period.

b)


2005
2006
2007
2008
Legend
Price-elasticities
-5.0 to -4.0
-3.9 to -3.4
-3.3 to -2.8
-2.7 to -2.5
-2.4 to -2.2
-2.1 to -1.8
-1.7 to -1.5
-1.4 to -1.1
-1.0 to -0.6
-0.6 to -0.5
Rack Cities
Counties
E85 counties
Highway Network
Major Interstates
0 15 30 60 90 120
Miles

CHAPTER 2: DETERMINANTS OF CONSUMER CHOICE FOR BIOFUELS

Abstract

We use data from a national survey to investigate consumers' preference for cellulose- and corn-based ethanol using discrete choice modeling approach. Due to both positive and negative information about environmental footprints from the use of ethanol as a transportation fuel, consumers' fuel choice becomes complicated. We investigate the relationship between consumers' fuel choice and attributes, and a set of behavioral and socio-demographic variables. The results indicate that economic incentives, such as cheaper prices and service availability exceed environmental incentives such as reduction in environmental emission levels. The price attribute influenced consumers' choice decision making by 83% more than the emission levels attribute, and by 69% more than the service availability. We also find that the respondents with higher levels in proenvironmental norms not only prefer ethanol to gasoline, but they also prefer the environmentally cleaner alternative - cellulose-based ethanol. Increasing the extent to which individuals care about the future consequences from their current actions led to increased preference for environmentally cleaner fuels. Finally, we find that respondents' sensitivity to fuel attributes varies across several individual characteristics, such as proenvironmental norms, the consideration of future consequences, income, as well as across geography. The findings contribute to predicting consumer's behavior, which increasingly became important in determining consumer demand. The results also provide important policy implications for the effective marketing of next generation clean transportation fuels.

Introduction and Background

"Ethanol is a magic elixir. It allows politicians and political operations to promise voters that America can achieve energy independence" (Bryce 2007). Counterintuitive to the common sense that biofuels are environmentally friendly fuels, several massive displays in Oklahoma City advertised ethanol-free gasoline (Galbraith 2008): *"Why put corn in your tank? Increase MPG, buy 100% gas here!"* Today, consumers face increasing misinformation and disinformation about environmental and economic cost-benefits of biofuels. However, regardless of the ongoing speculation and surrounding political climate, biofuels' potential as an alternative to long-time dominated petroleum-based fuels has escalated. The Energy Independence and Security Act (EISA) of 2007 proposed to increase the Renewable Fuel Standard (RFS)[10] to meet the 36 billion gallons target by 2022 (EISA 2007; Sissine 2007). If successful, this will replace roughly one third of the U.S. transportation sector's fuel consumption. Further, to ensure sustainable energy and environmental future for the economy, starting in 2015, only advanced biofuels (i.e. those processed from cellulose[11]) will be counted toward the RFS target (EISA 2007). Under these conditions, will consumer's economic incentives (e.g., lower price or service availability) dominate environmental concerns (e.g., greenhouse gas emissions (GHG) or air pollution reduction) when choosing among different transportation fuels at the service station?

Consumers, including those considering themselves environmentally conscious, may have little or no knowledge about biofuels' net energy balance or feedstock types (cellulose vs. corn) that are used for ethanol processing. What attributes and to what extent will make the

[10] For comparison, the Renewable Fuel Standards for 2008 were only 9 billion gallons (EISA 2007; Sissine 2007).
[11] Cellulose refers to "non-food," cellulosic feedstocks, including dedicated energy crops, such as switchgrass, algae, poplar, etc., woody biomass, such as agricultural crop residue, forest residue, or animal manure, municipal solid waste, to name a few.

consumer to prefer biofuel to conventional gasoline? This initiates a question, about the determinants of the behavioral process that influences consumers' fuel choice decisions. Some of the past research investigating the environmental/economic cost-benefits argues about the positive aspects of biofuels (Farrell et al. 2006). In general, the proponents argue for biofuels' positive net energy balance and the contribution to the GHG emissions and air pollution reduction, sometimes overstating the actual environmental benefits. Only a few studies have tried to investigate possible adverse impact on the environment (Doornbosch & Steenblik 2007; Zah 2007)[12]. The uncertainty from these bipolar research-based recommendations can be misleading at the policy decision making level, as well as for an average consumer facing fuel choices at the service station. Therefore, an important dimension of research around biofuels involves an investigation of the behavioral process that influences consumers' fuel choice.

The primary objective of this paper is to investigate consumers' preferences for two types of biofuels – corn- and cellulose-based ethanol[13] using data from an online national survey. In particular, we quantify the influence of interactions of fuel attributes and behavioral/socio-demographic variables on consumer choice. In the online survey, we included the extended version of the consideration of future consequences scale, a measure which has been widely used in the peer reviewed research literature to measure the extent to which consumers care about the future consequences from their current choices. Additionally, we measure the weights that survey participants' assign to fuel attributes, including their willingness-to-pay (WTP) premium for the ethanol fuel. A discrete choice analysis is conducted, which involves both socio-economic (i.e., price and fueling station availability) and environmental (i.e., GHG emissions)

[12] (Zah 2007) reports that current ethanol processing from several feedstocks including U.S. produced corn, Brazilian soy, and Malaysian palm oil can lead to worse environmental consequences compared to fossil fuels, when the impact of the entire supply chain is considered.

[13] In this paper, ethanol refers to E85 fuel, which is a blend of 85 percent ethanol and 15 percent gasoline.

attributes of the fuel types under investigation – gasoline, corn- and cellulose-based ethanol. In contrast to the research investigating consumer's preferences through the direct effects of product attributes on choice, this paper incorporates behavioral variables that help understanding the process of choice decision making. Those behavioral variables include value orientations, environmental concerns, awareness of consequences, and proenvironmental personal norms.

The transition from petroleum-based fuels to alternative fuel consumption involves some understanding or concern about potential adverse impacts on the environment. Thus far, dominated by economic feasibility studies (Doornbosch & Steenblik 2007; Stiles et al. 2008; U.S. Government Accountability Office 2007) and environmental cost-benefit analysis (Doornbosch & Steenblik 2007; Farrell et al. 2006; Toman et al. 2008; Zah 2007), an in-depth investigation of the determinants of consumers' preferences for biofuels has been overlooked. A handful of studies investigated consumer preferences for alternative fuel vehicles (Ahn et al. 2008; Bhat & Sudeshna Sen 2006; Bhat et al. 2009; Fang 2008). In these studies that involved vehicle-specific attributes, the structure of consumers' preference formation is fundamentally different. This is because the product attributes are mostly related to the vehicles, i.e., annual maintenance cost, acceleration, body type, single passenger HOV line usage incentive, etc. Consequently, the experimental designs that are dominated by vehicle-oriented attributes do not identify and isolate the link between consumers' characteristics and fuel-specific attributes. Consumers may prefer a (flexible-fuel) vehicle that has the capacity to consume both gasoline and ethanol fuel. But regardless of that initial decision to buy a flexible-fuel car, their fuel choice decision can still be influenced by speculations about the benefits of using ethanol.

Additionally, research efforts in which the central focus is on the relationship between corporate proenvironmental behavior and consumer expectations, leaves out nuances of consumer-level heterogeneous behaviors (Brown & Dacin 1997; Creyer & Ross Jr. 1997; Sankar Sen & Bhattacharya 2001; Trudel & Cotte 2009) such as consumer sensitivity for greenhouse emissions (from the use of transportation fuels) across different age, income groups, or geography. Thus, to the best of our knowledge, none of the previous research investigated the consumers' heterogeneous preferences for biofuels by incorporating both economic and environmental attributes/incentives.

For purposes in this paper, the role of differentiating between the cellulose- and corn-based ethanol in the product choice set is essential. Besides its promising environmental benefits, the adoption of cellulosic feedstocks for ethanol processing provides potential to reduce the long-term economic feasibility issues. Driven by the global economic/financial crisis, the volatility in corn prices has recently caused many ethanol producers, including the biggest U.S. corn-based ethanol producer VeraSun Energy Corporation, to fill for bankruptcy (Biofuels Business 2008). Most notably, the use of cellulosic feedstocks for ethanol processing will enable flexibility to avoid some of the potential environmental problems related to substantive use of fertilizers for corn production (e.g. nitrogen runoffs into water sources). Finally, cellulosic feedstocks are resource abundant and do not contribute to the increasing food prices. Thus, with an increasing criticism for the use of corn as feedstock, cellulose-based ethanol gains considerable attention as a second-generation fuel, despite being under development stage. Given these different characteristics of the corn- and cellulose-based ethanol blends, the consumer choice decision requires considerations from both economic and environmental aspects, which presumably complicates the decision making process.

In addition to uncovering the behavioral process that leads to some choice outcome, the identification of important attributes and their interaction with individuals' characteristics has managerial implications. Responsible marketing action requires better understanding of the characteristics of the socially and environmentally conscious consumer. Therefore, to develop successful marketing strategies for the new product – cellulose-based ethanol (which is not marketed yet), in-depth understanding of the weights that consumers assign to product attributes is imperative. Additionally, consumers' environmental consciousness or an interest in environmental protection can be determined by their consideration of public consequences of current private consumption (Trudel & Cotte 2009; Webster 1975). The level of concern, or the way consumers treat current ecological problems can influence their actions to contribute or to further deteriorate the environment (Joireman et al. 2006; Kinnear & Taylor 1973). These considerations, coupled with the previous research findings disparity (arguing for both positive and negative economic/environmental consequences from the ethanol production and use) suggest an extra attention to investigating the consumer preferences for different alternative fuels. Additionally, at a macro level, a better understanding of consumers' behavioral process may contribute to the development and viability of an emerging ethanol industry.

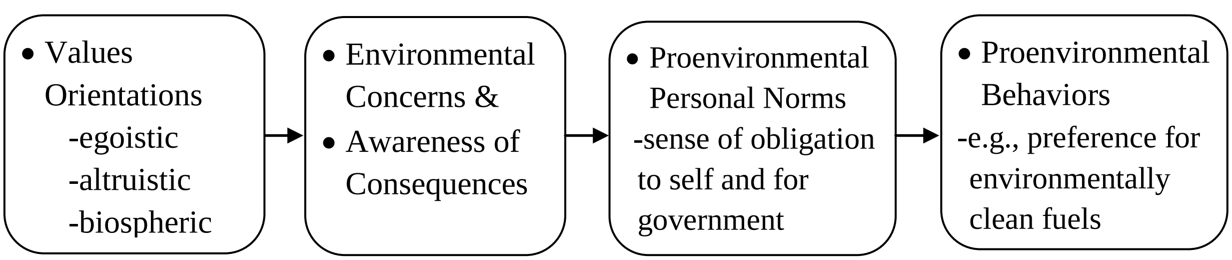
The rest of the paper is organized as follows. In the subsequent section, we review the relevant literature, by integrating them into the theoretical framework underlying this research. The section titled Theoretical Foundations discusses the elements of the Value-Belief-Norm theory (subsection Value-Belief-Norm Theory) that are integrated into the model, and provides the foundations for constructing the model. Subsection Consideration of Future Consequences discusses how the extent to which people consider potential future outcomes of their current actions may influence fuel choice decisions. Subsection titled Environmental Concerns and Consumer Preferences briefly reviews the relationship between environmental concerns and consumer preferences. Discrete Choice Modeling Approach subsection integrates the elements from the value-based theories with a random utility formulation for the consumer choice model. Methodology section describes the survey design, the empirical model, and the hypotheses. We conclude by discussing the results and implications of the current research in sections titled Model Estimation and Results and Discussion respectively.

Theoretical Foundations

Value-Belief-Norm Theory

Value-Belief-Norm (VBN) theory combines value and norm-activation theories, with the New Environmental Paradigm (NEP)[14] to create a causal or mediation chain, which leads to different behavioral outcomes. In the context of our research, we consider choice for alternative fuels as one such outcome. In particular, values (e.g., egoistic, altruistic, or biospheric) influence beliefs (e.g., NEP, awareness of consequences, and ascription of responsibility), which in turn activate proenvironmental personal norms (Figure 7). Finally, those personal norms result in a particular behavioral outcome (Stern 2000).

Figure 7: VBN in the framework of current research



Source: Adapted from (Stern 2000).

[14] For more information about the NEP scale used in the context of a social-psychological theory of attitude/behavior formation see (Stern et al. 1995)

However, in this paper we are not testing the validity of the VBN theory. The purpose of our investigation is to understand consumer's behavior when choosing among transportation fuel types, further focusing our attention on the consumer sensitivity for fuel attributes across different characteristic groups (attribute-consumer characteristic interaction effects).

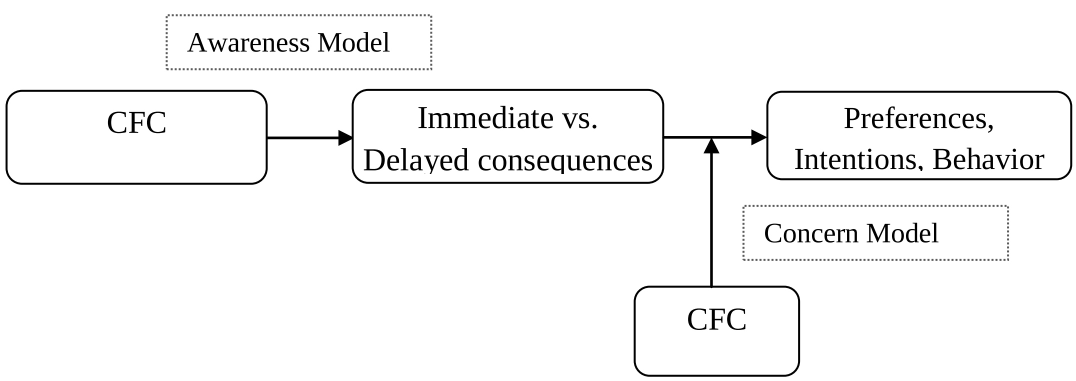
Under that framework, the primary role of the VBN theory for achieving our objectives is its well-established structure that we use to enrich the consumer choice model. For example, the VBN theory emphasizes that the proenvironmental behavior can be explained by a chain effect of individuals' values, awareness of consequences, and personal norms. These considerations are parallel to our investigation of transportation fuel choice, which includes biofuels, such as cellulose- or corn-based ethanol. Consumers' behavioral outcome in a form of a preference for biofuels vs. gasoline, or the choice between two different types of biofuels, may be influenced by the elements of the VBN theory.

Consideration of Future Consequences

Proenvironmental behavior has been found to be linked to the concept of a consideration of future consequences (CFC). Joireman et al. (2004) investigate preferences for commuting to work by different modes of transportation. The study reports higher preferences for public transportation among the survey participants with higher levels of environmental concern. The CFC scale was developed in Strathman et al. (1994), and refers to the extent to which people consider potential future outcomes of their current actions or behaviors. Generally, people scoring high in the CFC scale give high importance to the future consequences that might result from their current behavior, and low importance to immediate consequences. In contrast, those scoring low in the CFC are people who care less about the long-term consequences of their current behavior, but who give more importance to the immediate "payoffs." Additionally, the CFC construct has been used in applications, such as understanding fiscal responsibility behavior (Joireman et al. 2005), and for persuasiveness of health-related communication (Orbell & Hagger 2006), to name a few.

Joireman et al. (2006) discuss the awareness and concern models within the CFC construct. The awareness model represents a mediation model, in which individual differences in CFC influence immediate vs. delayed consequences of an action as depicted in the Figure 8. In turn, those consequences influence the outcomes – preferences, intentions and behavior. So, the path (initially) going from CFC to behavioral outcome becomes statistically insignificant after introducing the immediate vs. delayed consequences mediator. In the context of our model of fuel choice, an individual scoring low in the CFC scale may be seeking immediate payoffs from the use of gasoline in the form of lower per gallon prices, thus ignoring the long-term consequences in the form of higher emissions level.

Figure 8: Awareness and Concern Models of CFC



Source: Joireman et al. (2006)

Alternatively, the concern model of the CFC influences the effects of immediate vs. delayed consequences on the behavioral outcome. In other words, this moderation shows that the CFC can have influence on the relationship between the immediate vs. delayed consequences and preferences, intentions and behavior. In this case, both high and low in CFC individuals may equally accept the negative effects from gasoline usage, but those high in CFC are less likely to use it, since they give more importance to long-term consequences of the air pollution. Both the awareness (mediation) and concern (moderation) models can work simultaneously as discussed Joireman et al. (2006).

Environmental Concerns and Consumer Preferences

Over years, the relationship between individuals' value orientations and attitudes around environmental problems has been widely investigated (Joireman et al. 2004; Stern 2000; Stern et al. 1999; Stern & Dietz 1994; Stern et al. 1993; W. P. Schultz et al. 2005; P. Schultz 2001). A number of research papers in the field of environmental marketing that investigated consumer's environmental consciousness, emphasized its influence on advertising and merchandising strategies for "green" food products (Smith & Haugtvedt 1955; Sheth & Parvatiyar 1995; Shrum & McCarty 1995).

Cellulose-based ethanol is currently not marketed, because of the absence of commercial-scale cellulose-based ethanol processing plants in the country. However, there are many reasons that the cellulose-based fuels industry may benefit from the research investigating consumer preferences for transportation fuels. The identification of environmentally concerned consumers' characteristics or the identification of product attributes that consumers value most are some of the issues that the newly established industry may benefit from.

Discussions about biofuels' potential to replace part of the petroleum-based fuels date back to several decades. The situation with cellulose-based biofuels in the current marketplace is directly comparable with that of the gasoline with an F-310 additive introduced by Standard Oil Company of California in 1970 (Kassarjian 1971). Current ethanol marketers face similar conditions discussed in (Kassarjian 1971) – an introduction of pollution-reducing gasoline, population that is concerned with an increasing environmental pollution, substantial advertising campaigns, and considerable governmental support. Kassarjian (1971) examined the reactions of consumers to advertising for the gasoline with the new additive (F-310) that claimed to reduce automotive emissions. Counterintuitively, people with greater environmental awareness and receptivity for the emission-free fuel additive, and environmentally less concerned respondents revealed similar levels of WTP premium for the gasoline with the F-310 question. Advertising with promise of some mitigation of the environmental pollution was found to be an important factor for environmentally concerned consumers (Kassarjian 1971).

Webster (1975) analyzed the relationship between a socially conscious consumer index (CCI) and attitudinal, personality, social activity, socioeconomic, and demographic independent variables through the social involvement model. The CCI included questions about the usage of low-lead or lead-free gasoline, low-phosphate detergent, and beverages in returnable bottles. Findings revealed the possibility that the socially conscious consumer scores low on the measures of social responsibility. Using lead-free gasoline and boycotting certain products as examples, the results showed that the social consciousness and social responsibility measure two distinct phenomena. While, personality and attitude measures revealed a stronger relationship with the CCI than socioeconomic and demographic variables, the study found that the social involvement model was inadequate to explain the variation in socially conscious consumer behavior.

Discrete Choice Modeling Approach

Discrete choice experiments are broadly used to analyze consumer's preference structure in a number of disciplines, including marketing, applied economics, and transportation economics (Jordan J. Louviere et al. 2008; Small et al. 2005; Train & Wilson 2008). The underlying theory for discrete choice experiments is based on the random utility theory. Random utility models were developed for predicting individual-level choices, and assume that individuals prefer choices that maximize their utility. In the discrete choice modeling framework, the factors that influence consumers' utility and thus their choices, include attributes of the product, as well as individuals' characteristics represented by a set of behavioral and socio-economic variables.

One of the widely used discrete choice approaches to measure consumers' attitude toward environmental values is the contingent valuation method (Hanemann 1994). Contingent valuation allows capturing uncertainty measure in consumer attitude and perception for a product that has not been marketed before. Despite the wide use of discrete-choice methods for investigating preferences for both public and private goods, a number of relatively recent studies indicated possibility of bias between WTP responses and the actual purchasing behavior. It is natural (and is one the major limitations of the contingent valuation approach) that a survey participant will indicate a certain level of WTP, but will deviate from his/her "hypothetical commitment" when an actual purchase decision is made. As an alternative, the use of choice-based conjoint analysis (Jordan J. Louviere et al. 2008; Caparros et al. 2008) mitigates the deviations from respondents' "hypothetical commitment" by offering more realistic representation of market situation (Adamowicz et al. 1994).

The choice-based conjoint analysis refers to a method that estimates the structure of consumer's preferences by decomposing product attributers and valuing the utilities of each of those attributes (Green & Srinivasan 1978). Full profile, adaptive, self-explicated, and choice-based conjoint classes (same as discrete choice model) are some of the methodological variations of the conjoint analysis. The prevailing agreement is that the choice-based conjoint analysis provides improvement over contingent valuation method, making it an attractive alternative for measuring preference structures (Adamowicz et al. 1998).

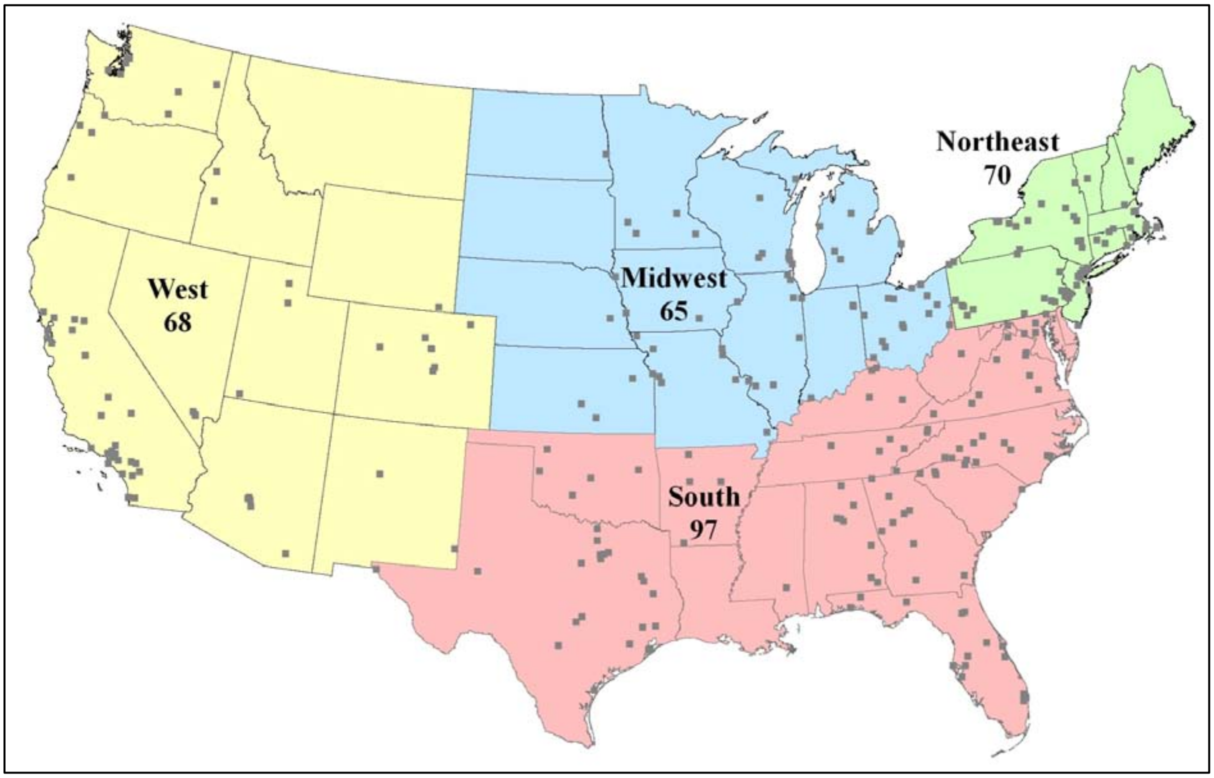
Methodology

Survey Design

The data were collected using online survey services provided by Qualtrics.com. The survey was conducted in November 2009, and responses from 463 participants were collected from different U.S. regions. After screening, 300 full responses were chosen for the analysis in this paper. The geographic distribution of the responses is shown in Figure 9. The full online survey questionnaire is provided in the Online Survey Template subsection of the Appendix (Ch. 2).

The participants of the online survey were asked to consider a scenario in which they are at a service station and have to choose between the three types of fuels – gasoline, cellulose-based ethanol, and corn-based ethanol. The participants were then asked to select their preferred fueling option from each of the 8 choice scenarios presented one after another on separate webpages. Each choice scenario contained a different combination of prices, emissions and service availability for the cellulose- and corn-based ethanol fuels. The price, emissions and service availability for gasoline, which is the reference fuel option, were the same in every choice scenario.

Figure 9: Survey participants' geographic distribution



The levels for the price attribute were based on retail gasoline sales data from 2007 – 2009 (Table 6). The emissions (carbon dioxide) attribute was developed based on Environmental Protection Agency's (EPA) transportation fuel emissions estimates (EPA 2009). The emission levels for cellulose- and corn-based ethanol were discounted from gasoline's CO2 emissions estimates by EPA. The service attribute shows the frequency of the service stations that own ethanol dispensing pumps.

Table 6: Attributes of Cellulose- and Corn-based Ethanol[15]

Fuel Attributes	Levels		Description
Price	2.50	3.00	\$/gallon
Emissions	14	16	lbs/gallon
Service	Every Service Station	Every 3rd Service Station	Fueling Stations that Sell Ethanol

* The reference option, gasoline, has price $2.75, emissions 20lbs/gallon, and every station service availability characteristics.

Following fractional factorial design procedures in (Kuhfeld 2009), 8 choice sets with orthogonal design were derived. Further, the respondents were asked to fill the rest of the questions in the survey. Demographic characteristics of the sample are shown in Table 7. The full summary statistics and variable descriptions are provided in the Data subsection of the Appendix (Ch. 2) - Table 12.

Table 7: Survey Sample Socio-Demographic Characteristics

Variable	Freq. (%)	Mean	St. Dev.
Gender		-	-
Male	50.0		
Female	50.0		
Age		50	13
Under 25 years	3.6		
25 to 44 years	26.9		
45 to 59 years	44.9		
60 to 78 years	24.6		
Annual Income		4.44	2.59

Variable	Freq. (%)	Mean	St. Dev.
Education		3.89	1.38
Less than High School	1.0		
High School	15.7		
Some College	30.1		
2-year College	14.1		
4-year College	26.1		
Master's Degree	11.4		
Doctoral Degree	1.0		
Professional Degree	0.7		

[15] Emissions and service attribute values for gasoline are constant at *20lb/gallon,* and *every gas station* respectively.

Below $20,000	15.7		
$20,000 - $29,999	14.7		
$30,000 - 39,999	12.0		
$40,000 - $49,000	12.0		
$50,000 - $59,999	10.0		
$60,000 - $69,999	9.7		
$70,000 - $79,999	5.4		
$80,000 - $89,999	14.7		
$90,000 and more	5.7		
Occupation		3.14	2.02
Full-time employed	34.7		
Part-time employed	12.3		
Self employed	9.0		
Unemployed	18.3		
Student	2.3		
Retired	20.3		
Other	3.0		

Marital Status		2.16	1.3
Married with children	47.8		
Married without child	14.7		
Divorced	15.1		
Single	18.4		
Widowed	4.0		
Race		-	-
African American	1.0		
Asian American	2.7		
Caucasian	91.9		
Hispanic	2.0		
Pacific Islander	0.3		
Other	2.0		
Region		2.46	1.08
West	22.7		
South	32.3		
Midwest	21.7		
Northeast	23.3		

Empirical Model for Discrete Choice Analysis

This section describes the discrete choice model and the VBN theory components that were incorporated into the model of consumer preferences for fuels. The use of VBN theory strengthens the model of consumer choice by providing better underlying behavioral rule that individuals use to make their choices. In doing so, it alleviates one of the maintained controversial assumptions made in discrete choice modeling that consumers act rationally. The VBN elements enter our model with the following components:

- Values with egoistic, altruistic and biospheric orientations; a 12-item scale adapted from de Groot & Steg (2008),
- Environmental Concerns with egoistic, altruistic and biospheric orientations; a 12-item scale from Schultz (2001),

- Awareness of Consequences with egoistic, altruistic and biospheric orientations; a 6-item scale adapted from (Stern et al. 1999),
- Proenvironmental Personal Norms (beliefs) with orientations related to self, to government, and to businesses; a 6-item scale adapted from (Stern et al. 1999).

In addition to these four constructs, the extended, 14-item version of the consideration of future consequences was used in the model. (The initial scale was developed in Strathman et al. (1994).)

In our model, consumers face with a set of fuel choice scenarios from which they have to select their preferred option. Attributes of the alternatives – per gallon prices, emissions levels and service availability varies over alternatives. Gasoline is the reference category and its attributes do not vary across choice scenarios. Additionally, the characteristics of the decision maker do not vary over alternatives. In other words, the model includes alternative-specific and case-specific variables. The alternative-specific variables are fuel attributes – per gallon prices, per gallon emissions and service availability. Case-specific variables include individuals' characteristics, which include behavioral and other socio-demographic variables.

Consider an individual i who faces a choice among j fuel alternatives (gasoline, cellulose-based ethanol and corn-based ethanol). By specifying the observed part of utility to be linear in parameters, the utility of individual i obtained from consuming alternative j can be represented as

(15)

$$U_{ij} = V_{ij}\left(w_{ij}\right) + \varepsilon_{ij}$$

where V_{ij} represents observed part of the utility, w_{ij} includes x_{ij} attributes for the j^{th} alternative for individual i, and z_i characteristics for individual i, i.e., $w_{ij} = \left[x_{ij}, z_i\right]$. The ε_{ij} is the unobserved term, and is independently, identically distributed (iid) extreme value. Variables in z_i do not change across alternatives (e.g., individual's age or race is the same across the choice alternatives). The attribute variables in x_{ij} have different values for each alternative, i.e., the fuel prices, emission levels and service availability is different across the choice alternatives (except for the reference category – gasoline). The probability of an individual i choosing alternative j from the choice set C_i can be modeled as conditional logit probabilities (McFadden 1974)

(16)

$$\boldsymbol{Pr(y_i = j) = \frac{e^{V_{ij}}}{\sum_j e^{V_{ij}}}, \qquad j \in C_i}$$

where y_i represents the choice outcome selected by individual i. Considering the observed part of the utility as a function of the product attributes (x_{ij}), the choice-specific constant (α_j), and assuming the V_{ij} to be linear in parameters, we can specify the following model

(17)

$$V_{ij} = \alpha_j + \beta' x_{ij}$$

The choice probability of an individual i choosing alternative j shown above becomes

(18)

$$\boldsymbol{Pr(y_i = j) = \frac{e^{\alpha_j + \beta' x_{ij}}}{\sum_j e^{\alpha_j + \beta' x_{ij}}}, \qquad j \in C_i}$$

This model in equation (17) allows investigating the effects of the product attributes - price, emissions, and service availability on consumers' choice decision (Model 1). The parameters of this specification can be estimated with conditional logit regression. Using this model we investigate whether the economic incentives such as lower prices and service convenience exceed environmental incentives such as GHG emissions reductions (Hypothesis 1). Additionally, the WTP for emissions reduction and service availability attributes can be calculated as the ratio of a given attribute to price attribute coefficient (Hensher et al. 2005; Revelt & Train 1998). The WTP premium for a reduction in emissions or an increase in service availability quantifies the importance of each fuel attribute that the consumers "assign" when making their choice decisions. Then the per gallon WTP premiums that consumers are willing to pay for the emissions reductions and service availability can be compared with each other.

Additionally, we are interested in determining whether the sensitivity to a particular fuel attribute varies across individuals with different behavioral and socio-demographic characteristics. For instance, if we are interested in examining whether price sensitivity of consumers varies across income levels, we need to include an interaction of the income variable with the price attribute. Thus, to account for these possible associations between individuals' characteristics and their fuel choices/attributes in a greater detail, we introduce interaction terms between attributes and individual characteristics (Model 2) and interactions between individual characteristics and fuel types (Model 3). To estimate these two models, we use a combination of conditional and multinomial logit models respectively. For Model 2, we specify the representative utility equation shown above as interactions between fuel attributes and individual characteristics $(x_{ij} \times z_i)$. The representative utility function becomes

(19)

$$V_{ij} = \gamma^{'}(x_{ij} \times z_i)$$

where γ is a vector of coefficients for the interaction terms. This specification allows estimating how individual demand for each attribute varies based on consumers' characteristics. By replacing V_{ij} s from equation (19) into (16) the probability of an individual i choosing alternative j becomes

(20)

$$Pr(y_i = j) = \frac{e^{\gamma'(x_{ij} \times z_i)}}{\sum_j e^{\gamma'(x_{ij} \times z_i)}}, \qquad j \in C_i$$

The probability estimates can also be treated as market shares for the fuel types under investigation. In a similar fashion, Model 3 can be estimated and choice probabilities can be derived by including interaction terms (this time between individual characteristics and fuel choices) into the equations (19) and (20).

Summary of Hypotheses

In Model 1 we test whether the economic incentives such as lower prices and service availability (i.e., convenience) exceed environmental incentives such as GHG emissions reductions (Hypothesis 1). In Model 2 we test whether consumers' sensitivity to price attribute is moderated by personal proenvironmental norms (Hypothesis 2). Under the framework of Model 2 we also test whether consumers' sensitivity to emissions varies across different levels of proenvironmental norms (Hypothesis 3), and whether consumers' sensitivity to price attribute varies across different income groups (Hypothesis 4). Lastly, in Model 3 we test whether consumers with higher levels in personal proenvironmental norms prefer biofuels over gasoline (Hypothesis 5), and whether consumers scoring high in the consideration of future consequences prefer biofuels over gasoline (Hypothesis 6).

Model Estimation and Results

Model 1 – the effects of attributes on consumer preferences for fuel

First we estimate Model 1, which specifies consumers' utility of a chosen fuel option as functions of the fuel attributes described in Table 6. The estimates for the alternative-specific attributes – price, emissions and service availability represent multiplicative effects of a unit change in that attribute variable on the probability of a given fuel alternative (i.e., either of the two types of biofuels). The estimates for the alternative-specific constants Cell (cellulose-based ethanol) and Corn (corn-based ethanol) represent, *ceteris paribus*, the relative likelihood of choosing cellulose- and corn-based ethanol versus gasoline – the reference group.

The results of the Model 1 are shown in Table 8. Increasing the price for a given fuel by one unit (the increment in our case is $0.25; see Table 6), decreases the probability of choosing that fuel by a factor of 0.005 (i.e., by 99.5%), holding the emissions and service attribute values constant for the other fuels. Similarly, increasing service availability by a unit for a given fuel (i.e., from *every station* to *every 3-rd station*), decreases the odds of using that fuel by a factor of 0.692, or by 30.8%.[16] In contrast, increasing the emissions levels by one unit (2 lbs/gallon) for a given fuel, decreases the probability of choosing that option by a factor of 0.838, or by only 16.2%. All of the attribute coefficients are statistically significant at $p < 0.01$ level.

Table 8: Conditional Logit Estimation Results (Model 1) - the effects of attributes on choice

Variables	Coeff.	z-value	p-value	e^{β}	WTP
Cell	-0.29	-1.24	0.214	0.746	
Corn	-0.48	-2.11	0.035	0.617	
Price	-5.30	-30.62	0.000	0.005	
Emiss	-0.18	-4.00	0.000	0.838	$0.03
Serv	-0.37	-9.88	0.000	0.692	$0.07
Number of observations	7,161			LR $\chi 2$ (5)	1714.2
Log-likelihood	-1,765.3			Prob > $\chi 2$	0.000
Pseudo R2	0.33				

Dependent variable is the choice for fuels with gasoline as a base alternative.

[16] Because the service attribute is ordered as 1) every station, 2) every 3rd station, in this case a unit increase in service attribute actually means less fuel availability. Thus, the negative sign/relationship between service availability and preference for that fuel is consistent with our expectations.

The results indicate that the economic incentive – the price attribute, influenced consumers' choice decision making by about 83% more than the emissions level attribute did, and by about 69% more than service availability. Further, the service availability influenced consumers' choice twice as much as the emissions levels. According to these results, we reject H_0 (Hypothesis 1) that the economic incentives in the form of price and service availability do not exceed environmental incentives such as decreased emissions levels. Other factors, such as the relationship between consumers' environmental concerns or awareness and fuel preferences will be discussed in the next two models, but these results indicated that the (low) prices have the most influence on consumers' preference for fuel.

Another support for rejecting the Hypothesis 1 can be observed by comparing the WTP estimates for emissions reduction and service availability attributes. The WTP estimates show that for every unit of reduction in emissions level, the consumers are willing to pay 3 cents premium. Meanwhile, for every unit change in the service availability, the WTP is 7 cents, which is more than twice the premium for the emissions attribute. According to the coefficient results reported in Table 8, the most important fuel attribute is the price, followed by the service attribute, and the least important attribute was found to be the emissions level. Consistent with those results, the WTP premium estimates showed that the emissions attribute was the least valued by the survey respondents, thus providing additional support for the Hypothesis 1. Although, higher weights assigned to service availability can be directly linked to consumers' preference for convenience, fuel service availability can also be associated with search costs, in terms of both time and money.

The estimates for the alternative-specific constants Cell and Corn indicate the relative likelihood of choosing cellulose- and corn-based ethanol versus gasoline, the reference group, assuming all of the attributes are constant. This means if the prices, emissions and service availability were the same for all fuels, the consumers would be 0.617 times (i.e., less) likely to purchase corn-based ethanol than gasoline. The same interpretation applies to the cellulose-based fuel coefficient. However, its coefficient is statistically significant at only $p < 0.3$ level.

The Likelihood Ratio (LR) statistics tests the hypothesis that all of the coefficients are statistically not significant from zero. The result (LR $\chi 2$ (5) = 1714.2, prob < 0.01) provides support for the overall significance of the model.

Model 2: the effects of attribute-individual characteristics interactions on consumers' fuel preference

Model 2 includes attribute interactions with value orientations, environmental concerns, awareness of consequences, proenvironmental norms (beliefs), the consideration of future consequences, income, and political orientation. Additionally, interactions with regional dummy variables were included for testing the extent to which consumers' preferences vary across U.S. regions. Values, environmental concerns and awareness of consequences variables were further divided into *egoistic*, *altruistic* and *biospheric* orientations. The proenvironmental norms variable was separated into personal (Bpers), for-government (Bgov), and for-businesses categories (Bbus).

The results in Table 9 show that the sensitivity to fuel attributes varies across several individual characteristics. In particular, respondents' with higher scores in personal beliefs (Bpers) category of proenvironmental norms showed more sensitivity to price attribute, thus supporting Hypothesis 2. Although in Model 1 we found that the prices had the biggest influence among the fuel attributes, this result provides evidence to argue that the influence of prices can be “fine-tuned” further by differentiating between different belief orientations. The coefficients for interactions of emissions with Bpers and Bgov belief orientations are statistically significant, with a negative sign indicating less sensitivity to emissions levels, while the positive coefficient of the Bbus category shows more sensitivity to emissions levels. These results support Hypothesis 3 that consumers’ sensitivity to emission levels changes across different levels of proenvironmental norms. Among the interactions with the service availability, only the Bpers category showed statistically significant results, with a positive sign indicating more sensitive to service availability.

Table 9: Mixed Logit Estimation Results (Model 2) – the effects of attribute×individual characteristic interactions on choice

Interaction Variables	Coeff.	Std. Err.	%
PRICE X			
CFC-F	-0.976***	(0.32)	-62.3
CFC-I	-0.123	(0.16)	-11.6
Vego	-0.551*	(0.31)	-42.4
Valt	0.540	(0.42)	71.7
Vbio	1.002**	(0.44)	172
ECego	-0.388	(0.31)	-32.1
ECalt	-0.782*	(0.45)	-54.2
ECbio	-0.804**	(0.38)	-55.3
ACego	0.546	(0.37)	72.7
ACalt	0.277	(0.56)	31.9
ACbio	-0.970**	(0.51)	-62.1
EMISS X			
CFC-F	-0.017	(0.02)	-1.7
CFC-I	0.005	(0.01)	0.5
Vego	0.110***	(0.02)	11.7
Valt	0.003	(0.03)	0.3
Vbio	-0.041	(0.03)	-4
ECego	0.030	(0.02)	3
ECalt	-0.024	(0.03)	-2.4
ECbio	0.044	(0.03)	4.5
ACego	0.073**	(0.03)	7.6

Interaction Variables	Coeff.	Std. Err.	%
PRICE X			
Bpers	1.929***	(0.26)	588.5
Bgov	-0.481	(0.31)	-38.2
Bbus	-0.270	(0.28)	-23.6
Income	0.035	(0.08)	3.6
Polit	-0.133	(0.14)	-12.5
West	-2.950***	(0.65)	-94.8
East	-0.242	(0.58)	-21.5
Midwest	-0.113	(0.59)	-10.6
EMISS X			
Bpers	-0.097***	(0.02)	-9.2
Bgov	-0.073***	(0.02)	-7
Bbus	0.053***	(0.02)	5.4
Income	-0.014**	(0.01)	-1.4
Polit	0.031***	(0.01)	3.1
West	0.012	(0.05)	1.2
East	0.044	(0.04)	4.5
Midwest	0.012	(0.04)	1.2

ACalt	-0.088**	(0.04)	-8.4
ACbio	0.005	(0.03)	0.5
SERV X			
CFC-F	0.016	(0.07)	1.6
CFC-I	-0.049	(0.03)	-4.8
Vego	-0.039	(0.06)	-3.8
Valt	-0.068	(0.08)	-6.6
Vbio	0.103	(0.09)	10.8
ECego	-0.042	(0.06)	-4.1
ECalt	0.006	(0.09)	0.6
ECbio	-0.064	(0.08)	-6.2
ACego	0.009	(0.08)	0.9
ACalt	0.016	(0.11)	1.6
ACbio	-0.084	(0.10)	-8.1
Log-likelihood			-1,240
LR $\chi 2$ (57)			2,010
Prob > $\chi 2$			0.00

SERV X			
Bpers	0.196***	(0.05)	21.6
Bgov	-0.048	(0.06)	-4.6
Bbus	-0.025	(0.05)	-2.5
Income	-0.017	(0.02)	-1.7
Polit	0.014	(0.03)	1.4
West	0.024	(0.13)	2.5
East	-0.041	(0.12)	-4
Midwest	-0.089	(0.13)	-8.5
Number of observations			6,132
Pseudo R2			0.45

$p < 0.01$ *** $p < 0.05$ ** $p < 0.1$ *

Dependent variable is the choice for fuels with gasoline as a base alternative.

The coefficient for sensitivity to price and service attributes across different income levels is statistically not significant. We fail to reject Hypothesis 4 that there is no price sensitivity variation across different income groups. Only the interaction of income with emissions attribute was found to be statistically significant – those in the higher income groups are less sensitive to emissions level/attribute when making fuel choice decision. Egoistic value orientation variable was found to be statistically significant with price (less sensitive) and emissions (more sensitive) interactions at $p < 0.05$ and $p < 0.01$ levels respectively.

Respondents with the CFC-future orientation are less sensitive or less concerned about prices when choosing among the fuel types. The CFC-future orientation with emissions and service interactions did not show statistical significance, indicating that the respondents' sensitivity for emissions and service attributes does not vary across individuals with different CFC orientations. In addition to the effects of interactions between fuel attributes and the CFC measure, we discuss the relationship between the CFC and biofuel choices using the estimates derived from Model 3 below.

The only geographic variation was found with the price attribute interaction with West regional dummy variable. Respondents from the West were found to be less sensitive to the price attribute. This spatial variation in the sensitivity to prices suggests that further investigation may be needed to analyze geographic patterns for consumer demand for fuels, as well as for several key variables included in the model.

Model 3: the effects of individual characteristics-fuel choice interactions

In Model 2 we estimated the influence of the interactions between fuel attributes and individual characteristics on choice. The purpose of the Model 3 is to understand whether respondents' fuel preference vary across different levels of consumer characteristics. To achieve that purpose, Model 3 incorporates interactions between fuel choices and individual characteristics such as values, environmental concerns, awareness of consequences, proenvironmental norms, the consideration of consequences, likelihood of purchasing flexible-fuel vehicle in the next 5 years, modal choices, and political orientations. In the initial model we also controlled for education, age, gender and race. However, none of these variables showed statistically significant results. The results of the Model 3 are shown in

Table 10.

The estimates for Bpers showed statistically significant results with a positive sign, thus supporting the Hypothesis 5. The positive sign of Bpers and Bgov categories for both cellulose- and corn-based fuels indicates that the higher is the score for the proenvironmental norms (both personal and for-government) the higher is the probability for those respondents to choose biofuels relative to the reference alternative – gasoline. Additionally, we observe that the magnitude of the coefficients for fuels differ between corn- and cellulose-based fuels.

Table 10: Mixed Logit Estimation Results (Model 3) – the effects of fuel type × individual characteristic interactions on choice

Interaction Variables	Coeff.	Std. Err.	%	Interaction Variables	Coeff.	Std. Err.	%
Cellulose-based ethanol X				**Corn-based ethanol X**			
Vego	-0.414***	(0.104)	-33.9	Vego	-0.494***	(0.107)	-39
Valt	-0.321**	(0.140)	-27.5	Valt	-0.321**	(0.143)	-27.4
Vbio	0.364***	(0.139)	43.9	Vbio	0.233*	(0.142)	26.3
ECego	-0.032	(0.100)	-3.2	ECego	0.087	(0.103)	9.1
ECalt	0.301**	(0.135)	35.1	ECalt	0.284**	(0.139)	32.8
ECbio	-0.312**	(0.124)	-26.8	ECbio	-0.180	(0.127)	-16.5
ACego	-0.317**	(0.140)	-27.1	ACego	-0.263*	(0.143)	-23.1
ACalt	0.187	(0.175)	20.6	ACalt	0.088	(0.181)	9.2
ACbio	0.078	(0.144)	8.1	ACbio	0.265*	(0.150)	30.3
Bpers	0.280***	(0.071)	32.3	Bpers	0.246***	(0.073)	27.9
Bgov	0.284***	(0.088)	32.9	Bgov	0.256***	(0.091)	29.2
Bbus	-0.163*	(0.088)	-15	Bbus	-0.247***	(0.090)	-21.9
CFC-F	0.271**	(0.105)	31.1	CFC-F	0.069	(0.107)	7.1
CFC-I	-0.117**	(0.059)	-11.1	CFC-I	0.005	(0.061)	0.5
FFV	0.179***	(0.044)	19.6	FFV	0.183***	(0.045)	20.1
drwork	-0.027	(0.151)	-2.6	drwork	-0.133	(0.156)	-12.5
drschool	0.069	(0.331)	7.1	drschool	0.137	(0.336)	14.7
drerrand	-0.564*	(0.290)	-43.1	drerrand	-0.509*	(0.303)	-39.9
polit	-0.147***	(0.050)	-13.7	Polit	-0.078	(0.052)	-7.5
Log-likelihood			-1,679.4	Number of observations			5,172
LR $\chi2$ (46)			429.1	Pseudo R2			0.11
Prob > $\chi2$			0.00				

$p < 0.01$ *** $p < 0.05$ ** $p < 0.1$ *

Dependent variable is the choice for fuels with gasoline as a base alternative.

The coefficients of Bpers (0.28) and Bgov (0.28) for cellulose-based fuel are relatively higher than those for the corn-based fuel – Bpers (0.25) and Bgov (0.26). This result provides evidence to argue that respondents with higher levels in proenvironmental norms (personal and for-government) not only prefer biofuels to gasoline in general, but they also give relatively more preference to environmentally cleaner alternative (cellulose-based). The same relationship is observed for the respondents with higher levels in the biospheric value orientation (Vbio) and altruistic environmental concerns (ECalt) variables. The coefficients are greater when interacted with the cellulose-based ethanol option for both variables (Table 10). The Bbus category showed negative relationship for both cellulose-based (-0.16, $p < 0.1$), and corn-based fuels (-0.25, $p < 0.01$).

Egoistic value orientations were found to be statistically significant with a negative sign for both cellulose- and corn-based fuels. As expected, the respondents with higher levels in egoistic value orientations care less about environmentally clean transportation fuels. The coefficients of the interactions between cellulose-based fuel and the CFC show statistically significant results for both future (0.27, $p < 0.05$) and immediate (-0.12, $p < 0.05$) orientations. Increasing the extent to which individuals care about the future consequences from their current actions (CFC-F category) leads to increased preference for environmentally cleaner fuels, thus supporting Hypothesis 6.

Another statistically significant positive relationship for both cellulose- and corn-based fuels was observed with the respondents' likelihood of purchasing a flexible fuel vehicle in the next 5 years variable. The respondents who indicated likelihood of purchasing a flexible fuel vehicle prefer both biofuel options to gasoline. Among modal choice variables, only "driving for daily errands" variable showed statistically significant negative relationship for both cellulose- and corn-based fuel interactions. Respondents who indicated that they drive their vehicles for daily errands versus walking, using public transportation or riding a bicycle, do not prefer biofuel options to gasoline. Political orientation variable showed statistically significant negative relationship when interacted with the cellulose-based ethanol variable. Respondents with more conservative political orientation tend to prefer gasoline to ethanol fuels.

Discussion

Investigation of factors that influence individual choice behavior remains as one of the fundamental concerns in many disciplines (McFadden 1974). Research efforts around the characteristics of environmentally conscious consumer date back to the early 1970's (Kinnear & Taylor 1973; Kassarjian 1971). Around the mid 1980's, contributions to understanding consumers' ecological awareness started to progress in several other disciplines, including sociology (Buttel 1987; van Liere & Dunlap 1981) , education (Hines et al. 1987) and psychology (Maloney et al. 1975; Arbuthnot 1977).

The primary focus of this paper was to investigate the link between consumers' environmental and socio-economic characteristics and their heterogeneous preferences for transportation fuels. We used data from the national online survey in which the participants were asked to consider a fuel choice scenarios, including gasoline, cellulose-based and corn-based ethanol options. Following the fuel choice scenarios, the respondents were asked to complete a set of behavioral and socio-demographic questions.

Findings from the Model 1 indicate that despite recent rise in public awareness about environmental issues, the economic incentives such as cheaper fuel prices and service availability exceeded environmental incentives such as reduction in the environmental emissions levels. The influence of the price attribute on consumers' choice during their decision making is 83% more than that of emissions level attribute. The Model 2 allowed isolating the effects of different orientations in proenvironmental norms, values, and the consideration of future consequences on the choice behavior. The sensitivity to fuel attributes varies across several individual characteristics, such as proenvironmental norms, the consideration of future consequences, income, as well as across the geography.

Today, companies are incurring additional costs to provide ethically produced goods, knowing that consumers “award” socially responsible marketers (Trudel & Cotte 2009). The results of the Model 3 showed that the respondents with higher levels in proenvironmental norms (personal; for-government), values (biospheric orientation) and environmental concerns (altruistic) not only prefer ethanol to gasoline in general, but they also prefer the environmentally cleaner alternative - cellulose-based ethanol. Corn-based ethanol has recently been criticized for its adverse impacts to the environment (through increased nitrogen fertilizers used in corn production), and for its contribution to the increasing food prices. It is possible that the choices of the respondents with above mentioned characteristics was influenced by the consideration that corn-based ethanol contributes to the national energy security in the short run, but harms the environment in the long run.

The consideration of future consequences concept is relevant in consumer choice for transportation fuels research context in a sense that it can be used to understand the structure of the thought (from the *temporal* point of view) that influences consumers’ intentions. In turn, these intentions lead to a behavioral outcome – choice for a specific type of fuel. In the Model 3 we found that increasing the extent to which individuals care about the future consequences from their current actions (CFC-F orientation) leads to increased preference for environmentally cleaner fuels. In contrast to corn-based ethanol, cellulosic biofuels are promising in terms of not interfering with the “food” feedstocks. (Cellulosic feedstocks are derived mainly from bio-waste - municipal, agricultural, or forest sources.) Essentially, cellulosic biofuels are beneficial for both short- and long-run. Thus, our findings are consistent with what we hypothesized – those respondents scoring high in the CFC scale, i.e., those more concerned in the future consequences from current actions will prefer ethanol to gasoline.

The possible link between consumers' environmental concerns and political interests has been often underestimated in the research literature (Torgler & Garcia-Valinas 2007). The results of the current research also showed that the respondents with conservative political orientation preferred gasoline to ethanol fuels. In examining consumer reactions to an advertising campaign for gasoline with a special additive that was claimed to reduce air pollution, Kassarjian (1971) found no significant results for political party preference variable. However, over time the situation with U.S. energy dependence on foreign sources may fundamentally change public views. Certainly, phrases, such as "energy security and independence" are keywords that are frequently heard during political debates. Additionally, politically active people tend to be better informed about the issues frequently discussed by the political world, including alternative transportation fuel policies. This may directly influence (positively or negatively) the level of their knowledge or concern about the current environmental problems.

These findings shed some light on the complexity of human choice behavior, by breaking down individual characteristics measuring environmental concerns or proenvironmental norms, etc., into egoistic, altruistic, and biospheric orientations. Predicting consumer's behavior increasingly became important in determining consumer demand for products yet to be marketed (e.g., cellulose-based ethanol). These results may also provide important policy implications for the alternative fuel marketers by revealing the consumer preference heterogeneity or geographic patters of the sensitivity to prices that we found in Model 2.

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CHAPTER 3: A SYSTEM-DYNAMICS APPROACH TO INVESTIGATING FUEL-ECONOMY AND ALTERNATIVE FUEL POLICIES

Abstract

During the last two decades the fuel economy standards have been the main policy tool to mitigate increasing fuel consumption in the US. Recently, a market-based alternative to fuel economy standards – a feebates program, has gained considerable interest among researchers and policy makers. According to the feebate system, manufacturers pay a fee for less fuel-efficient vehicles and receive refunds for vehicles that provide fuel efficiency that is above the national standard. Many researchers have investigated issues related to the feebates program, such as compliance costs, transparency, its influence and consequences on vehicle size changes, and most importantly – its revenue neutrality. In the previous studies of feebates the dynamic changes in the feebates rates that influence revenue-neutrality have been overlooked. In this paper, we use system dynamics approach, which allows simulating and controlling the effects of feebates programs over time. Our investigation includes three types of vehicles – conventional vehicles (CV), hybrid electric-gasoline vehicles (HGV) and alternative fuel vehicles (AFV). The results from several feebate program scenarios shed light on the implementation issues of the feebates, such as revenue neutrality.

Introduction and Background

A variety of policy reforms have been used in the U.S. to mitigate concerns about increasing fuel consumption and dependence on transportation fuels. The Corporate Average Fuel Economy (CAFE) standard is one such policy tool. The standard was established by Congress in 1975 for passenger cars and light trucks. The National Highway Traffic Safety Administration (NHTSA) has been delegated authority to establish and amend the standards in cooperation with the Environmental Protection Agency (EPA). The NHTSA is responsible for specifying the fuel economy standard – the sales-weighted harmonic average miles per gallon (MPG) that each auto manufacturer's fleet of passenger cars or light trucks must meet for any given model year. Since its establishment, the standard has contributed to considerable fuel consumption reductions.

Recently, with increasing concerns in energy security and imported oil dependence, the Energy Independence and Security Act (EISA) of 2007 mandated to increase the national fuel economy standard to 35 MPG by 2020. The EISA also proposed to increase the Renewable Fuel Standard (RFS) to meet the 36 billion gallons alternative fuel production 2022 (EISA 2007; Sissine 2007). However, findings from recent research provide evidence for ambiguity of the welfare effects of tighter U.S. Corporate Average Fuel Economy (CAFE) standards (Fischer 2008) and uncertainty in the economic feasibility of the RFS standard. Another concern regarding the major provisions of the CAFE standard is the incentive to downsize vehicles to meet the fuel economy mandates, which creates serious safety issues. Greene (2009) argues that market-based policies to promote higher fuel economy may increase the demand for smaller vehicles. The increase in imbalance of small and large vehicles has been linked to increased fatality rates from highway accidents, when large and small vehicles have a collision (Greene 2009).

In this paper we investigate an alternative mechanism to promote the production of fuel efficient vehicles while creating incentives to continually improve fuel economy over time – feebates. The feebates program is a relatively recent market-based mechanism that represents a sliding scale of fees and rebates (hence the term feebates) for the purchase of new vehicles (Ford 1995). Vehicles with a fuel economy lower than the MPG standard are charged taxes or fees, while vehicles providing fuel economy above the MPG standard (i.e., a pivot-point) receive a rebate. One of the main issues with the implementation of the feebate program is its revenue neutrality. A key consideration for the program to be revenue neutral is the accuracy of the estimated vehicle market shares. If the predicted market shares are close to the actual market shares, the feebate schedule (the amount of fees and rebates) can be adjusted such that the fees and rebates would balance one another over time.

Two scenarios follow. First, if it is relatively inexpensive for the majority of U.S. automobile manufacturers to increase fuel economy and exceed the pivot point (the MPG standard), then a net payment from the government funds to the manufacturers will exceed the rebates received from those who produced vehicles below the standard, thus creating negative balance. On the other hand, if the fuel economy adjustment is costly, many manufacturers will choose to produce below the pivot point, which will result in a net gain in the government funds. The outcome of the second option, of course, is not attractive to the automobile manufacturers.

Nevertheless, the feebates program is not without critics either. First, there is lack of experience from which researchers and potential practitioners can learn about the implementation effects of the feebates program. Further, the uncertainty in consumers' choice behavior complicates the prediction of the market shares, which is one of the key components for calculating feebates revenue neutrality. Second, for the same reason – lack of experience, there is minimal information on the manufacturer behavior after the introduction and implementation of a feebates program. Another issue is the consideration of the dynamics of the feebate program effects. In addition to the accuracy of market shares prediction, the revenue neutrality issue is also dependent on the dynamics of the feebate program effects (feedback loops). With the exception of Davis et al. (1995) study, previous research efforts do not consider the impact of the feebates schedule over years. This raises a question whether or not the feebates schedules should be or can be controlled and adjusted over time, based on the information from the feedback loops. A recent study by Greene (2009) argued that the implementation issues of the feebates program have received minimal attention thus far.

The revenue neutrality is influenced by consumers' heterogeneous preferences through the utility model/component of the feebates model/schedule. Consumer preference is an important element of the utility part of the model, which is used to estimate vehicle purchase probabilities – i.e., the market shares for the vehicle classes under investigation (Langer 2005). The net value to a consumer from improved fuel economy is the difference between future fuel savings and the vehicle price markup for its increased fuel efficiency (Greene et al. 2005). In theory, if that difference (tradeoff) is greater than the vehicle's price markup for fuel efficiency, *ceteris paribus*, the consumer will purchase the vehicle. However, as argued in Greene (2009), the extent to which the consumers value the future payoff (i.e., future fuel savings) largely varies depending on consumers' individual characteristics. A study of CAFE standards by NRC (2002) found that on average consumers undervalue the fuel savings by considering only 3 years payback period of savings, instead of the full lifetime period savings of the fuel efficient vehicle. As a result, the consumer undervaluation of the fuel economy improvements may negatively influence manufacturers' incentive to invest in fuel efficiency technology.

A parallel measure that has widely been used in the social-psychology research literature is the consideration of future consequences (CFC) construct (Strathman et al. 1994; Joireman et al. 2001). The CFC measure is the extent to which the consumers care about the future consequences from their immediate actions (e.g., the long-term savings from the purchase of a fuel efficient vehicle). Under the feebates framework, individuals scoring high in CFC scale may give high importance to the future savings that might result from their new vehicle choice and low importance to immediate payoffs (such as cheap price). This type of consumers will tend to have longer payback periods in their mind when purchasing a fuel efficient vehicle. In contrast, those individuals scoring low in the CFC scale are those who care less about the long-term consequences of their current behavior, but who give more importance to immediate payoffs. This type of individuals can be compared to those who consider only 3 years or less payback time for their savings from a fuel efficient vehicle. The CFC construct has also been used to understand individuals' fiscal responsibility behavior (Joireman et al. 2005).

The issues identified in the previous two paragraphs can be investigated by simulating different feebate schedule proposals using system dynamics methodology. Based on the "stock and flow" feebates model adapted from Ford (2009), we find a rate that ensures revenue neutrality. Additionally, we introduce an algorithm that searches for the optimal value of the rate. The simulations also include gasoline prices sensitivity analyses. Finally, our analysis incorporates individual differences in the consideration of future consequences measure into the utility subsection of the model.

The rest of the paper is organized as follows. In the next section we briefly discuss related literature and several feebates programs that have been considered or practiced in the past. Section titled Feebates – System Dynamics Model describes the structure of the system dynamics feebates model – fund balance, vehicle stock circulation, consumer utility/market shares, and feebates schedule subsections. Section Simulation of Feebates presents the simulation results of several feebate scenarios. The three subsections of the same section discuss the relationship between feebate rate and fund balance, the search for optimal value for the rate, and the revenue-neutrality sensitivity to fuel cost volatility.

Relevant Literature

Feebates Practices

Feebates practices and studies investigating their economic feasibility date back to the early 1990s. One of the first feebates program was implemented by the province of Ontario in the beginning of the 1990s, which considered a sliding scale of taxes based on vehicles' fuel consumption. According to the program, vehicles that had over 6.0 liters per 100 kilometer fuel efficiency paid taxes, while vehicles with less than 6.0 liters per 100 kilometer efficiency received rebates (HLB 1999). However, the program was not revenue neutral, and added $300 – 400 million to the government funds – something that Canadian auto industry, Canadian Auto Workers Union and car dealers did not benefit from. Although, SUVs are taxed differently, and light trucks and vans are excluded, the vast majority of the rest of the categories (90%) fall into the fee-paying segment of the feebate program. According to a report by Tellus Institute (Bernow 2002), this program did not influence consumer behavior, because of the low amount of fees that were imposed on the vehicles with fuel consumption below the standard. However, the manufacturers had no incentive to invest in alternative-fuel, electric or hybrid vehicle technologies.

Another feebates proposal, which in contrast was never actually implemented, was the California's DRIVE+ proposal. The program proposed the use of feebates for promoting demand for fuel efficient and thus environmentally cleaner vehicles in California (Greene et al. 2005). Representing sales tax deduction for the purchase of vehicles that have lower than average air pollutant emissions than CO_2 emissions, this program was proposed in the 1990 and reintroduced in 1991 and 1992. According to the proposal, to be eligible for a rebate, automobile manufacturers would be required to provide warranty that their vehicles will have reduced pollutant emissions for 50,000 miles.

Another feebates proposal was *The "Guzzler/Sipper" Bill* that was repealed in Maryland in 1993. The program proposed to provide sliding scale of credits to vehicles based on their fuel efficiency during the first two years of the implementation. Starting in 1995 and onwards, the program proposed to enforce tax on vehicles that provided less than 27 miles per gallon fuel efficiency. However, an investigation by the NHTSA found that states cannot enact laws that conflict with federal regulations, such as the CAFE standard. Accordingly to the NHTSA ruling, Maryland could not tax automobile manufacturers based on fuel economy, and the law was canceled. Several other unsuccessful attempts to introduce feebates (whether due to lack of political interest or economic feasibility) include proposals in Massachusetts (An Act to Promote Application of Scientific Principles and Technical Advances to Increase Automobile Efficiency and Reduce Global Warming, 1991 & 2001), in Arizona (1991 & 1993), in Wisconsin (Excess Gasoline Consumption Fee, 1991), and in Maine (1991).

Regardless their environmentally promising perspective, the feebates design issues, including legality compliance with federal regulations, revenue neutrality, and negative spillover effects[17], combined with political obstacles, complicate the establishment and implementation of feebates programs. Most of the program proposals described above did not proceed due to the public understanding of feebates as a tax on SUVs. This emphasizes the importance of the public outreach and education before the state proposals are discussed. Additionally, revenue neutrality is important for providing incentives to the automobile manufacturers that exercise powerful lobbying if necessary.

Feebates Research Studies

Research literature argues that by using the market rather government regulations, feebates programs will positively influence energy, environmental and long-term economic goals. Previous studies found that the effects of a national feebate program could reduce the carbon dioxide emissions and fuel consumption by about 20% (Langer 2005). The main response to a national feebate program will be observed from the manufacturers – by increasing the share of fuel efficient vehicles in their new models. It has also been found that changes in consumers' purchasing behavior will be minimal (Langer 2005).

One of the most thorough investigations of feebates is the study by Davis et al. (1995). The authors analyzed six alternative feebate programs, which included both consumer response (demand side) and automobile producer components (supply side). The consumer response component was designed to predict the vehicle choice by individual households, which was conditional on vehicle-specific and household-specific characteristics. The study found that low feebates (about 1-2% of the vehicle price) will result in a large reduction in fuel consumption, and thus in carbon dioxide emissions. Also, assuming that consumers are willing to pay for

[17] It is possible that consumers buy a vehicle in a neighboring state to avoid paying fees for the vehicle with fuel efficiency lower than the standard in their state.

increased fuel efficiency, the study found that the vehicle-owner household benefits from the purchase of fuel efficient vehicle largely outweigh the cost of feebates.

Another widely cited study of feebates was introduced by Greene et al. (2005), in which the authors investigated the effects of consumer undervaluation of fuel savings from increased fuel efficiency on the feasibility of feebates program. [18] The authors used a model, which did not include the gradual phasing in of a feebate system over time, but considered only a single future year. The utility model used in Greene et al. (2005), which generates vehicle market shares information included two attributes – fuel economy and vehicle price. It was also assumed that the manufacturers will not introduce new makes and models during the analysis period. The authors mentioned the importance of considering technological change – miles per gallon improvement over time when interpreting the effects of the feebates program. Considering consumers valuation of 3-year payback period for fuel savings, the study concluded that a feebate of $500 per 0.01 gallon per mile would improve new vehicle fuel consumption by 14%. The second scenario that considered $1000 per 0.01 gallon per mile resulted in fuel consumption reduction by 22%. Consistent with Davis et al. (1995) findings, the authors argue that the dominant effect of the feebates will be due to automobile manufacturers' response to fuel economy improvements, rather than through the change in consumers' purchasing preferences.

Langer (2005) analyzed several feebates proposals, including studies reviewed above and concluded that the models used to investigate feebate programs may not capture all of the components of manufacturer and consumer behavior. The author also mentioned that less attention has been paid to state-level feebates implementation issues. However, some of the recommendations of this study included to 1) keep the feebates schedule simple, 2) maintain the

[18] Greene et al. (2005) used information from industry surveys, which found an expectation of a 3-year payback time for investing in fuel efficient vehicle, instead of the full lifespan of the vehicle.

integrity of the model structure, 3) maintain detailed data collection, and 4) include all cars and light trucks under the program to maximize consumer attention and guarantee its educational value for the public. The last recommendation will help avoiding public perception of fees on fuel inefficient vehicles as “SUV taxes.”

Feebates programs may also initiate highway safety issues. Greene (2009) investigated the influence of feebates programs on consumers’ choice of vehicles sizes. Market-based policies, which promote higher fuel economy standards in terms of higher gasoline taxes, give consumers incentives for purchasing small-size vehicles. The manufacturers’ consequent response to consumer preferences increases the imbalance of small and large vehicles on highways. The increase in vehicle weight imbalance has been linked to increased fatality rates from highway accidents, when large and small vehicles have a collision (Greene 2009). Conditional on the assumptions made in their study, the results of the footprint (the product of vehicle’s wheel base and track width) based feebate program showed that manufacturer revenue losses are greatest in the first few years. Over the next few years, as the manufacturers develop better fuel economy technology, their revenue impact switches from negative to positive. The study also found that footprint-based feebates program is safety-neutral, i.e., does not significantly influence the vehicle size imbalance.

There are many psychological factors that influence consumers’ acceptance of financial incentives for switching to fuel efficient vehicles. Peters et al. (2008) investigated consumers’ incentives for switching to energy efficient vehicles by incorporating two different types of feebates – absolute (the pivot point is calculated based on energy consumption) and relative (the pivot point is based on the ratio of energy consumption to vehicle utility). The study found that consumers show moderate willingness to accepting a rebate incentive for switching to energy-efficient cars. While another study conducted in California by Agrawal et al. (2008) reported that the concept of fuel efficient transportation taxes and fees strongly appeals to the survey participants. Compared to flat-rate charges on fuel inefficient vehicles, more than 60% of the respondents supported the feebates system.

The review of recent literature revealed that the implementation issues of feebates program, such as revenue neutrality or the ability to control the feebate system based on manufacturer and consumer feedback remains less investigated. The utility component of the feebates program, which provides estimates for vehicle market share predictions is another key area that future research has to pay more attention.

Feebates – System Dynamics Model

This section describes the original feebates model and the modifications that allow testing several feebates scenarios discussed in recent feebates literature (Greene 2009; Greene et al. 2005). System dynamics models are constructed with the help of stock-and-flow 'visual' iThink software developed by isee systems (www.iseesystems.com). Our model is based on the feebates model developed by Andrew Ford (Ford 2009, 1999), the components of which are briefly described below.[19]

In the original feebates model (Ford 1999), vehicle attributes considered in the utility component for the derivation of market shares included purchasing price, emissions fraction, fuel cost, horse power, driving range, and fuel availability attributes. The coefficients for these attributes were adapted from a stated preferences survey by Bunch et al. (1993). The model introduced in this paper uses updated attributes and coefficients from a recent survey of

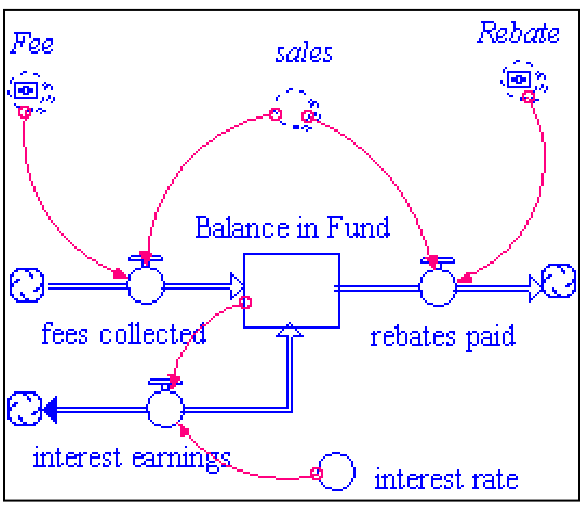
[19] Ford (1999), Ford (1995) and BenDor & Ford (2006) provide detailed discussions about the system dynamics software, and the basics of the feebates model using IThink software. The model adapted in this paper was first introduced in Ford (1999) as an interactive simulation tool.

consumer willingness to pay for clean vehicles by Potoglou & Kanaroglou (2007). In the new model the vehicle-attributes are purchasing price, maintenance cost, fuel cost, fuel availability, emissions fraction and driving range. The driving range is retained from the original feebates model.

Fund Balance and Vehicle Stock Components

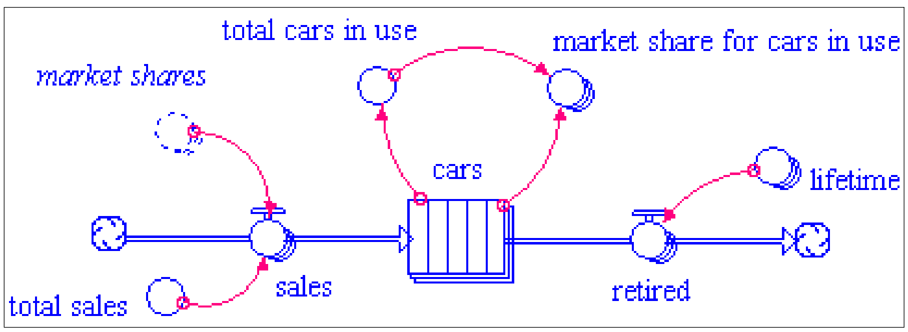
The feebates model consists of fund balance, consumer utility/market shares, and vehicle stock circulation model-components. The fund balance part of the feebates model is a stock-and-flow system that controls for the cash flow of the fund used to finance feebates programs – collected (fees) and received (rebates) from the purchase of new vehicles. The equations underlying the balance in the fund model inflate the fund by the interest earnings, or deflate it in case the balance in the fund drops below zero.

Figure 10: System Dynamics Representation of the Fund Balance Component of the Feebates Model



The vehicle stock circulation component is designed to simulate the number of vehicles in operation and their tailpipe emissions. Figure 11 shows only the vehicle circulation part, in which the number of vehicle sales is derived by multiplying the market shares by the total number of vehicle sales. The emissions levels are generated by using the emissions fraction estimate from the utility component of the model, annual travel per vehicle and emissions in gram per mile information.[20] The stock of vehicles is a conveyor, which is a function of the time of inflow and the length of vehicle lifespan (Ford 2009). The model assumes that vehicles would be in operation around 10 years before they retire. The vehicle lifetime information is also used to calculate per vehicle and total emissions for all three types of vehicles under investigation.

Figure 11: Vehicle Stock Circulation Component of the Feebates Model



Consumer Utility Component

The utility model is used to calculate the market shares of vehicle types under investigation, in this case conventional vehicles (CV), hybrid electric-gasoline vehicles (HGV), and alternative fuel vehicles (AFV). The utility that consumers receive from the purchase of a new vehicle is composed of six vehicle-specific attributes – purchase price, annual maintenance cost, annual fuel cost, driving range, fuel availability, and emissions fraction. The following equations were entered into the respective converters of the iThink software for the derivation of market shares for all three types of vehicles.

Total utility for received from the purchase of CVs, HGVs, and AFVs (indexed as j=1, 2, 3) is derived by summing part-worth utilities of the six attributes:

[20] For a full description of this component see Ford (2009).

- $U(vehicle_j) = U_{purc\,hase\ price} + U_{main\,t.cost} + U_{fuel\ cost} + U_{range} + U_{fuel\ avail.} + U_{emiss}$

Part-worth utilities are derived by multiplying attribute values with respective coefficients from multinomial logit regression:

  - $U(vehicle_j)_{pur\,hcase\ price} = coef1 \times purchase\ price(vehicle_j)/1000$
  - $U(vehicle_j)_{maint\ .cost} = coef2 \times maintenance\ cost(vehicle_j)$
  - $U(vehicle_j)_{fuel\ cost} = coef3 \times fuel\ cost(vehicle_j)$
  - $U(vehicle_j)_{range} = coef4 \times range(vehicle_j)$
  - $U(vehicle_j)_{fuel\ avail.} = coef5 \times fuel\ availability(vehicle_j)$
  - $U(vehicle_j)_{maint\ .cost} = coef6 \times emissions\ fraction(vehicle_j)$

The information from the total utility derived for each vehicle is used to calculated market shares for CVs, HGVs, and AFVs using the conventional conditional logit probabilities (McFadden 1974). [21] As a numerical illustration, the market share for CVs is found by the following equation

$$MS(CV) = \frac{e^{U_{CV}}}{\sum_{j=1}^{3} e^{U_j}} = \frac{e^{(U_{cv})}}{e^{(U_{cv})} + e^{(U_{HGV})} + e^{(U_{AVF})}}$$

$$= \frac{e^{-22.69}}{e^{-22.69} + e^{-24.91} + e^{-24.81}} = 0.814 \ \ or\ 81.4\ \%$$

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[21] Following McFadden (1974), Revelt & Train (1998), the utility that the consumer i derives from the purchase of new vehicles (CV, HGV, and AFV, indexed $j = 1, 2, 3$) can be represented as the following equation, $U_{ij} = V_{ij}(x_{ij}) + \varepsilon_{ij}$, where V_{ij} represents observed part of the utility with a matrix of variables x_{ij} that includes attributes for the j^{th} vehicle for individual i. The ε_{ij} is the unobserved term, and is independently, identically distributed (*iid*) extreme value. The probability of an individual i choosing alternative j from the choice set C_i can be modeled as conditional logit probabilities, $Pr(y_i = j) = \frac{e^{V_{ij}}}{\sum_j e^{V_{ij}}}$, $j \in C_i$, where y_i represents the choice outcome (CV, HGV, or AFV) selected by individual i. The left-hand side of the equation above represents market shares of the three vehicle types – CV, HGV, and AFV.

The market share information is then used to predict the sales for each of the three vehicle types. Further, the predicted sales are used in the fund balance component, which was described above. The *Fee* and *Rebate* values (the derivation of which is explained in the Feebates Schedule section below) are added and subtracted respectively from the purchasing price of vehicles.

In addition to the vehicle-specific attributes, the new model of feebates accounts for consumer taste heterogeneity. The importance that the consumers assign to different attributes of vehicle when making their purchasing decisions may vary across different age or income groups, or across individuals with different levels of environmental awareness or concern.

For example, the consumers who are willing to pay a premium for fuel efficient vehicles may have different expected time periods for the savings that they would receive from increased fuel efficiency (for which they would pay a premium). Greene et al. (2005) reports that government surveys reveal a consumer expectation of 3-year payback time, instead of a 14-year full lifespan of the vehicle. This situation is similar to the construct called consideration of future consequences (CFC), a measure which is largely used in the social-psychology literature (Joireman et al. 2008; Joireman et al. 2001; Strathman et al. 1994). The CFC measures the extent to which consumers care about the future consequences from their current behavior. Individuals scoring high in the CFC scale give high importance to the future consequences that might result from their current behavior, and low importance to immediate consequences. This category (CFC-future) can be associated with those who would consider full lifespan of a vehicle when thinking about the savings from increased fuel efficiency. In contrast, those scoring low in the CFC scale are people who care less about the long-term consequences of their current behavior, but who give more importance to the "immediate payoffs." This category (CFC-immediate) is characteristic to those individuals who would consider only 3-year payback period from their "investment" in fuel efficient vehicles.

The consumer taste heterogeneity can be accounted for by including an interaction terms of emissions fraction and fuel availability with both CFC-future and CFC-immediate variables. The representative utility equation shown above, in this case will be a function of vehicle attributes and interactions between selected vehicle attributes (emissions fraction and fuel availability) and individual characteristics.

Feebates Schedule

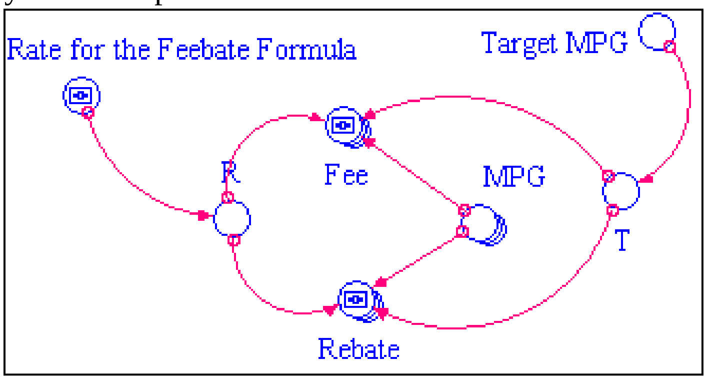
Multiple structures exist for the formulation of feebate schedules, some of which are explained in detail in Davis et al. (1995). The feebate system in this paper is based on the two critical components – fuel efficiency in MPG and a rate. The rate (R) and the pivot point (MPG_{target}), which determine how much the rebate or the fee will be, and what type of vehicles receive a rebate or pay a fee respectively:

(21)

$$F = R\left(\frac{1}{MPG_{target}} - \frac{1}{MPG}\right)$$

where F represents the rebate if $MPG > MPG_{target}$, or fee if $MPG < MPG_{target}$, R represents a dollar value per gallons per miles (GPM), which determines the size of the rebate/fee for any particular fuel economy. The MPG_{target} represents the fuel economy target, a pivot point above which a vehicle manufacturer receives a rebate (from the sale of that particular vehicle), and pays a fee when the fuel efficiency of its vehicles is lower than the target. In other words, the equation (21) will result in a negative dollar value if particular vehicle's fuel economy (MPG) is lower that the target fuel economy (MPG_{target}). Similarly, the formula provides positive value if the vehicle's fuel economy is above the target. Figure 12 shows the system dynamics representation of the feebates formula shown in equation (21) above. The described above, fee and rebate converters from this section are used in the market shares/utility and fund balance (Figure 10) components described above.

Figure 12: System Dynamics Representation of the Feebates Formula



As a numerical illustration, by assuming the rate of a particular feebates schedule to be \$500 per 0.01 GPM (or \$50,000 per GPM), we calculate the feebate for a scenario in which a vehicle provides 25MPG, and the target fuel economy is 40MPG. Based on the feebates formula above (equation (21), the 1/MPG difference is 0.025 – 0.04 = – 0.015. Because the $MPG <$ MPG_{target} , the fee in this case is \$750 (-0.015×\$50,000) per vehicle. Similarly, if a particular vehicle provides 50MPG, the same formula will result in a \$250 rebate. Consider a scenario in which the market shares of vehicles providing "above target" fuel efficiency (50MPG in this case) is for example 80 percent. Considering annual manufacturing of 10mln vehicles will result in \$2bln in rebates paid (\$250×8mln vehicles). While the fees collected from the reminding 20 percent of fuel inefficient vehicles (providing 25MPG) manufactured in the same year will result in \$1.5bln in total (\$750×2mln vehicles), leaving the operating fund in \$0.5bln negative balance.

This example shows the importance of the revenue neutrality of the feebates program, the achievement of which is one of the tasks of the next section.

Simulation of Feebates

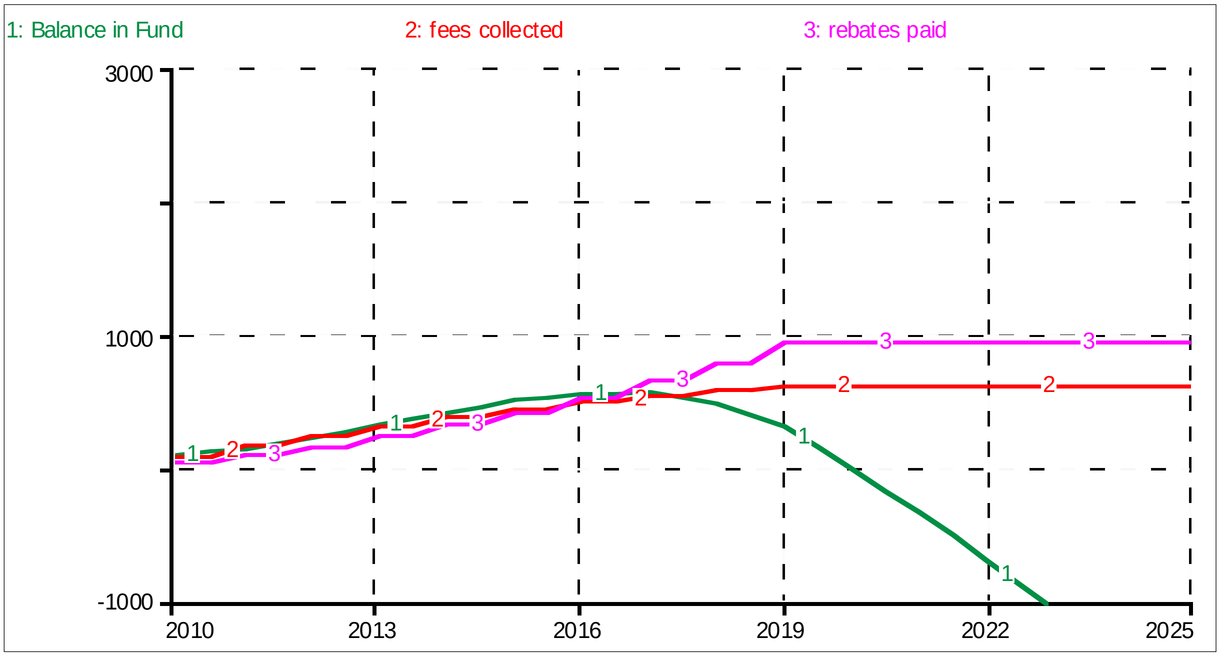
Feebate Rate & Fund Balance

In this section we use the feebates formula above to simulate several feebates scenarios. One of the goals of the simulations is to find a rate that guarantees revenue neutrality of the feebates program over time, the importance of which was numerically illustrated above. Additionally, we propose several scenarios in which we incorporate consumer taste heterogeneity – in this case, the extent to which the consumers consider future savings from their current purchase.

The feebate program is simulated using the structure of the equation (21), and assuming fuel efficiency of 25MPG for CVs, 60MPG for HGVs, 45MPG for AFVs, and 30MPG as target. The program is simulated for 2010 to 2025 period. To observe the trajectory of the fund balance under different fee and rebate combinations, we first simulate a feebates scenario with increasing values of rate (*R)* with $100 per 0.01 GPM increments. The relationship between increasing rates (from $100 to $1000 per 0.01GPM) and fund balance is depicted in Figure 13 below. The balance is growing with increasing rates until $700 per 0.01 GPM. After 2018, the fund balance declines at a higher rate and crosses the revenue-neutrality line (zero balance) by around 2020. The dynamic behavior of the fund balance trajectory under different rates helps to identify the approximate value for the rate that would ensure revenue-neutrality of the program.

In what follows, we simulate three feebate schedules with the rates equal to $250, $750 and $662 per 0.01 GPM.

Figure 13: The relationship between increasing rate and fund balance



The year-by-year implementation of these feebate scenarios allows observing not only the trajectory of the fund balance, but also market shares, fees, and rebates for each vehicle category in each year. The first rate results in market share of 77% for CVs, and 11.5% for both HGVs and AFVs. The fees collected for CVs are \$167, and rebates are \$417 and \$278 for HGVs and AFVs respectively (Table 11). At the end of the simulation period, the cash flow for hypothetical 10,000 vehicle sales resulted in \$1.28mln fees collected and \$0.79mln rebates paid. The resulted fund balance is positive, at around \$19mln. The second rate (\$750) significantly decreased the market share to 65% for CVs, and increased shares for HGVs and AFVs to 19% and 16% respectively. The fees and rebates combination in this scenario left the fund in a negative balance of around \$13.1mln.

Table 11: Illustration of different rate scenarios for feebates program

a) Initial simulation results

Policy Scenario		Fuel Economy				Feebate			Vehicle Type Mix			Government Expenditures					
	Rate level (per 0.01 GPM)	Target MPG	MPG			Fee ($/per vehicle)	Rebate ($/per vehicle)		Market Shares (%)			Cash Flow for 10k cars (1000 $)			Total Received/ Paid (1000 $)		Fund Balance (1000 $)
			CV	HGV	AFV	CV	HGV	AFV	CV	HGV	AFV	CV	HGV	AFV	Fee	Rebate	
Scenario A	250	30	25	60	45	167	417	278	0.77	0.115	0.115	1,286	480	320	1,286	799	19,440
Scenario B	750	30	25	60	45	500	1250	833	0.65	0.19	0.16	3,250	2,375	1,333	3,250	3,708	-13,180
Scenario C	662	30	25	60	45	441	1103	736	0.67	0.17	0.16	2,955	1,875	1,178	2,955	3,053	0

b) Simulation results for consumers with CFC-I value orientation

Policy Scenario		Fuel Economy				Feebate			Vehicle Type Mix			Government Expenditures					
	Rate level (per 0.01 GPM)	Target MPG	MPG			Fee ($/per vehicle)	Rebate ($/per vehicle)		Market Shares (%)			Cash Flow for 10k cars (1000 $)			Total Received/ Paid (1000 $)		Fund Balance (1000 $)
			CV	HGV	AFV	CV	HGV	AFV	CV	HGV	AFV	CV	HGV	AFV	Fee	Rebate	
Scenario A (CFC-I)	250	30	25	60	45	167	417	278	0.75	0.11	0.14	1,253	459	389	1,253	848	16,830
Scenario B (CFC-I)	750	30	25	60	45	500	1250	833	0.63	0.17	0.20	3,150	2,125	1,666	3,150	3,791	-21,300
Scenario C (CFC-I)	662	30	25	60	45	441	1103	736	0.65	0.16	0.19	2,867	1,765	1,398	2,867	3,163	-7,050

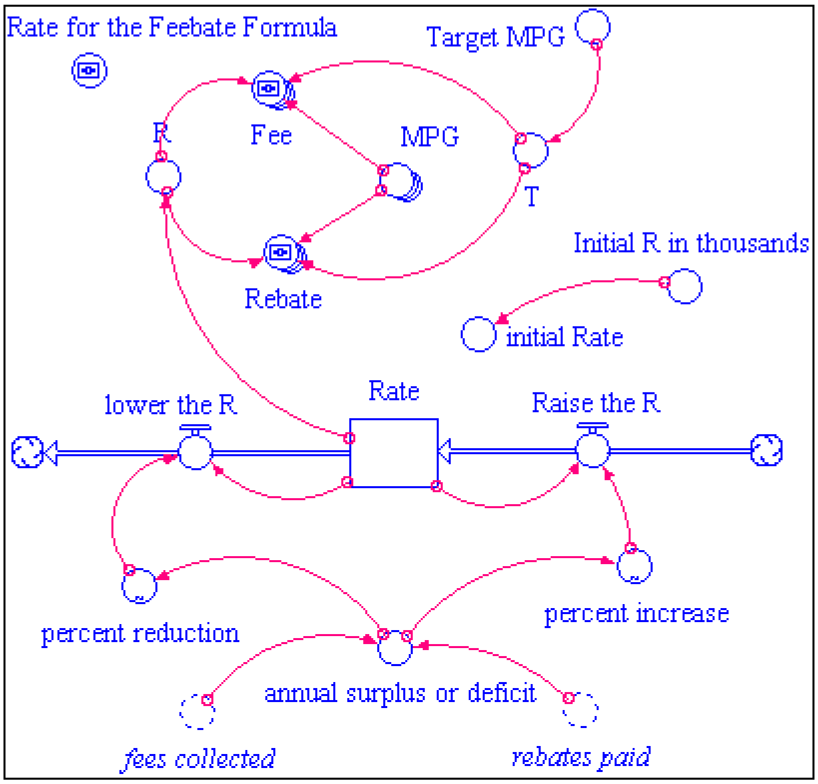
Using the insight gained from the relationship between the increasing rates and fund balance trajectory in the simulation above (Figure 13), we next simulate a rate scenario which leads the fund to balance at zero at the end of the simulation period. In this case, the rate is set to $662 per 0.01 GPM. The market share for CVs increased 2% from its previous level to 67%. The shares of HGVs decreased by 2% to 17%, and AFV shares stayed at the same level at 16%. The results of these three scenarios are summarized in Table 11.

In the next set of scenarios (Table 11, b) we incorporate interaction terms in the utility component of the feebates model. The coefficients for the emissions fraction and fuel availability are replaced with the coefficients of interaction terms between emissions fraction and fuel availability with CFC-immediate (CFC-I) variable. The most significant change in the fund balance is observed for the second ($750 per 0.01 GPM) and third ($662 per 0.01 GPM) rate scenarios. The distortion of the revenue-neutrality condition reached in this set of simulations above shows the importance of accounting for the consumer taste heterogeneity in the utility component of the feebates model, which generates the vehicle market shares information. Under these conditions, a new rate is required to achieve revenue-neutrality, a system dynamics model for which is investigated in the next section.

Search for Optimal Rate

In this section, we introduce a system dynamics model, which uses the information from feebate formula and fund balance components to search for the optimal rate that guarantees revenue-neutrality. Figure 14 shows the system dynamics representation of rate search algorithm. The dotted converters titled “fees collected” and “rebates paid” are internally linked to the balance fund component, and are used to calculate the annual balance for a given rate. The rate is considered as a stock and is increased over time if the balance in fund for that particular year is above zero.

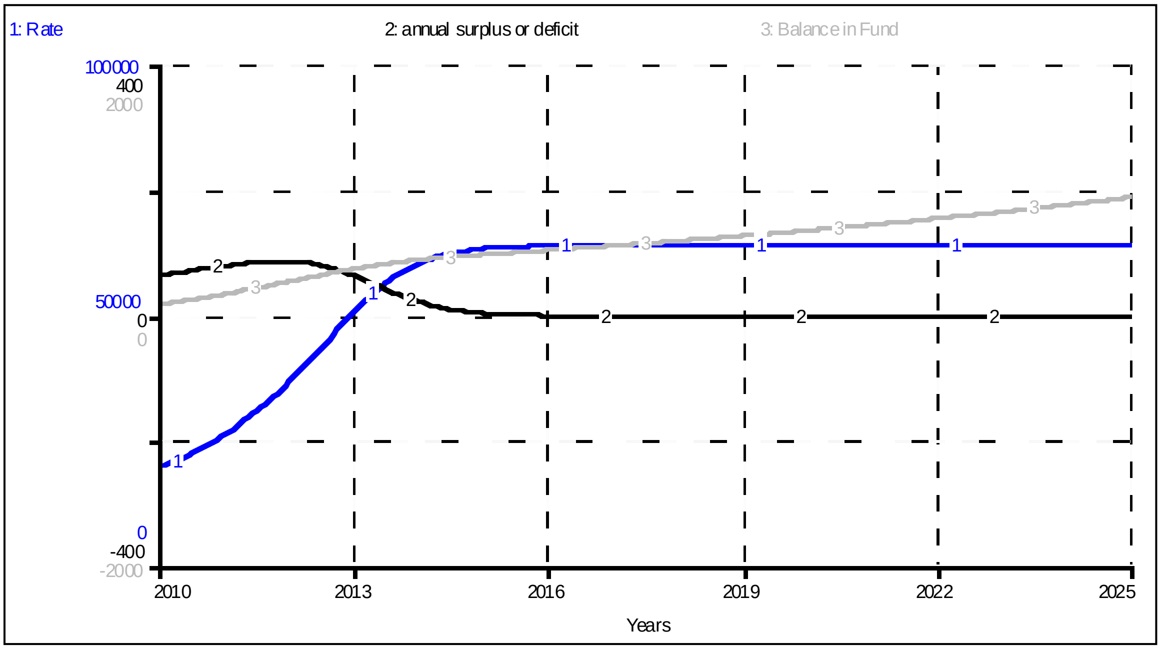
Figure 14: Optimal Rate for Feebates Model



Alternatively, the amount of the rate is reduced if the balance in fund declines below zero. The iteration is repeated until the trajectory converges to zero fund balance. The rate search model is simulated with the initial values started below and above the rate that provided zero balance in the simulations above. In the first case, as shown in Figure 15 a, the initial value is set to $200 per 0.01 GPM. The rate converges to $642 per 0.01 GPM at the end of the sixth year of the simulation. Note that this value is close to the rate $662 per 0.01 GPM reached above (Table 11).

Figure 15: Search for the Optimal Rate (start low)

a) The simulation starts at $200 per 0.01 GPM



b) The simulation starts at $500 per 0.01 GPM Start Value

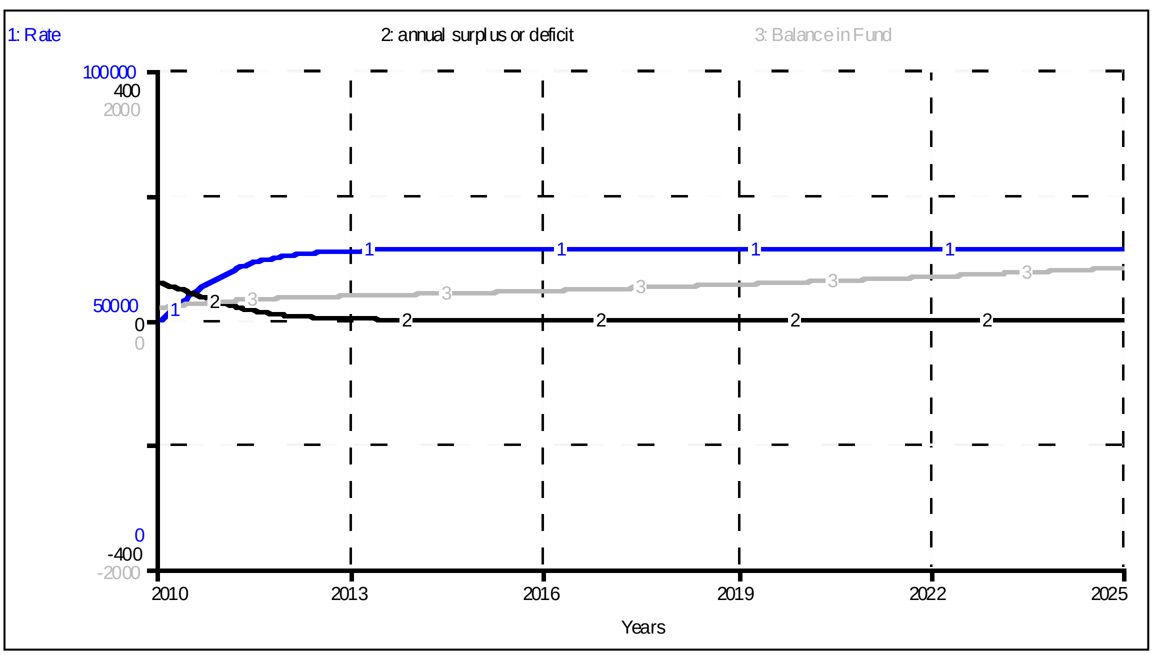
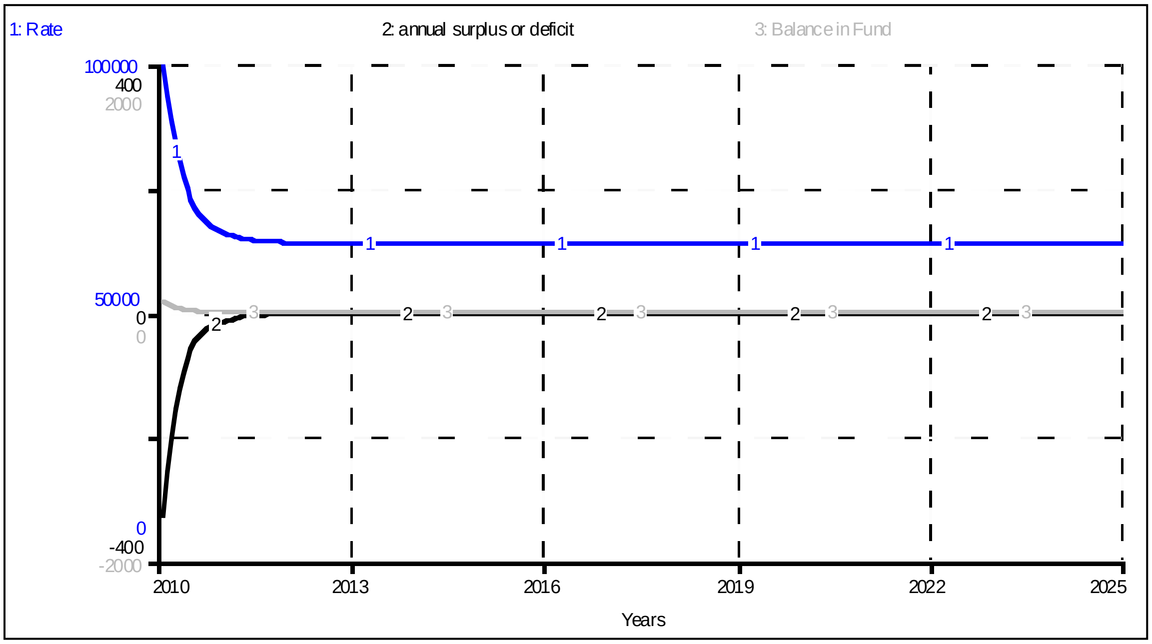
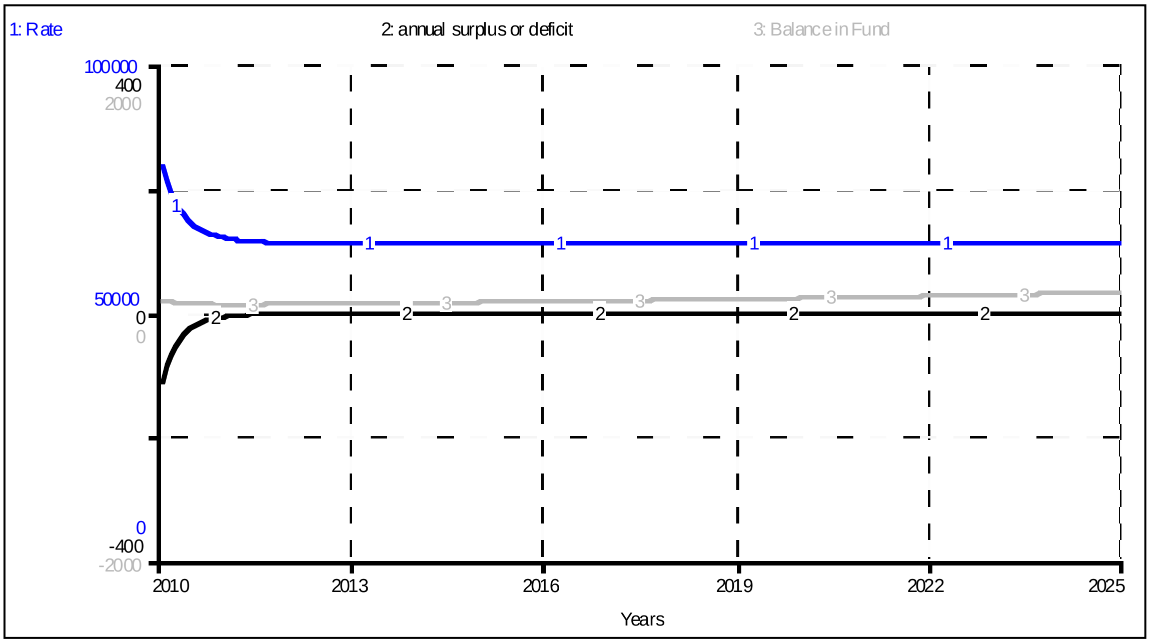


Figure 16: Search for the Optimal Rate (start high)

b) The simulation starts at $1000 per 0.01 GPM



b) The simulation starts at $800 per 0.01 GPM



The second graph, Figure 15 b, shows the convergence with a start rate of $500 per 0.01GPM. The behavior of the rate curves depicted in these simulations (Figure 15) shows that the closer the initial "guess" is, the faster the optimal rate that provides revenue-neutrality will be achieved. In contrast, simulations with initial rate starting above the optimal rate (found in initial simulations, Table 11) converge within the first two-three years regardless the accuracy of the initial "guess." The first simulation depicted in Figure 16 a, started with an initial value of $1000 per 0.01 GPM. The curve converges to $642 per 0.01 GPM as early as during the second year of the simulation. Alternatively, the simulation shown in Figure 16 b started with an initial value of $800 per 0.01 GPM, but converged to the same rate level in the same time.

Revenue-neutrality Sensitivity to Fuel Price Volatility

This section investigates the influence of gasoline price volatility on the revenue-neutrality of the feebates model simulated above. Recently, gasoline prices have shown increased volatility. In the summer of 2008, gasoline prices stroke the highest price in the past three decades – over $4.00 per gallon for unleaded regular grade gasoline. A month later, the prices plummeted to about $1.70 per gallon (U.S. Energy Information Administration 2009). Previous studies have linked the gasoline price volatility to consumer demand-responsiveness. Lin & Prince (2009) found that gasoline price volatility has no impact on the consumer gasoline demand-responsiveness in the very short run. However, the study has found that in the intermediate and long run, the price volatility decreases consumers' demand-responsiveness (less elastic demand for gasoline).

Fuel cost is one of the attributes in the market shares component of the feebates model. It is expected that the introduction of fuel price volatility will influence vehicle market shares. Accordingly, we expect alteration in the revenue-neutrality of the feebate programs simulated above.

Figure 17: Sensitivity of Revenue-neutrality in Fund Balance to Gasoline Price Fluctuations

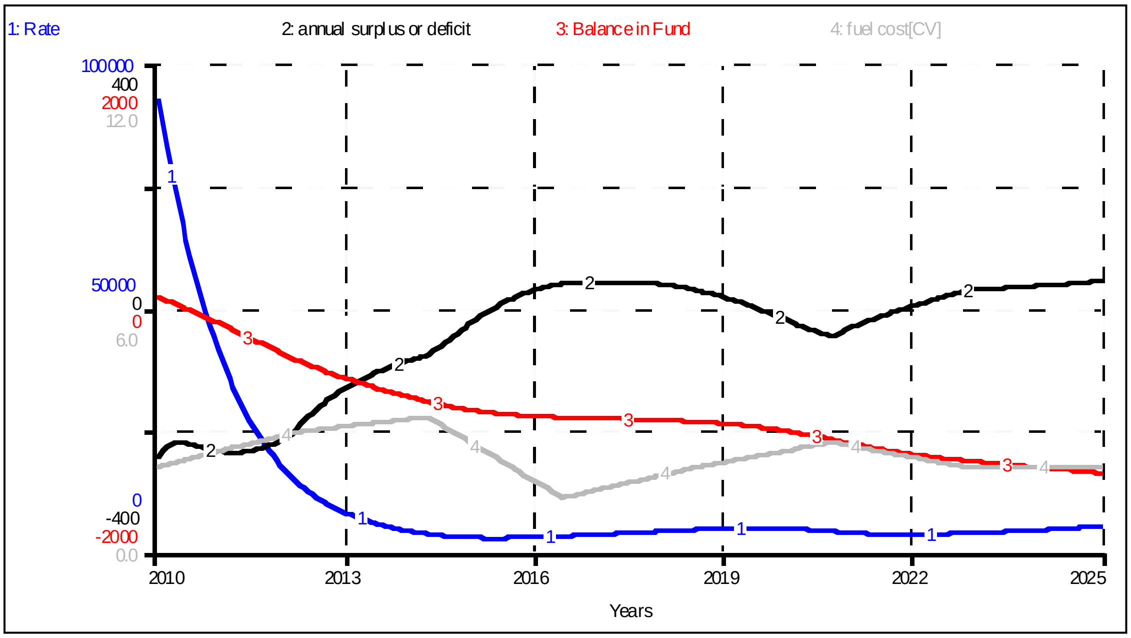


Figure 17 shows the results of the simulation, which included gasoline price volatility. The prices were allowed to vary in the range of –36% to 59% over the simulation period 2010 – 2025. As shown in the graph, the volatility in prices resulted in declining fund balance over time, such that the program is not self-financing anymore.

Concluding Remarks

While public acceptance for feebates program is positive (Peters et al. 2008), the long-term implementation issues remain less investigated. The system dynamics model of feebates program developed in this paper demonstrated the complexity of maintaining revenue-neutrality in the feebates program. The model allowed annual adjustment of the feebate rates in the initial simulations, which helped to approximate the rate level for maintaining zero balance in the fund. Assuming $250, $750, and $662 per 0.01 GPM feebate rates, a hypothetical scenario of 10,000 vehicle sales illustrates three extreme conditions in the fund balance at the end of the simulation period – surplus, deficit, and zero balance.

Additionally, a stock-and-flow model was constructed and simulated for finding the rate that will ensure revenue-neutrality in the program. Regardless of the starting value, the rate curve that ensures revenue-neutrality converged at around $640 per 0.01 GPM. However, the revenue-neutrality was not maintained when the simulation included fuel price volatility. The volatility ranging from –36 to 59% influenced the vehicles' market mix, which resulted in significant declines in the fund balance over time. In the next steps, we plan to use the model developed in this paper to investigate the influence of feebates program on annual emissions from the vehicle types under consideration. Additionally, modifications in the optimal rate search model have to be made to account for fuel cost volatility.

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Appendix (Ch. 2)

Data

Table 12: Full Sample Summary Statistics **(**Number of respondents = 300)

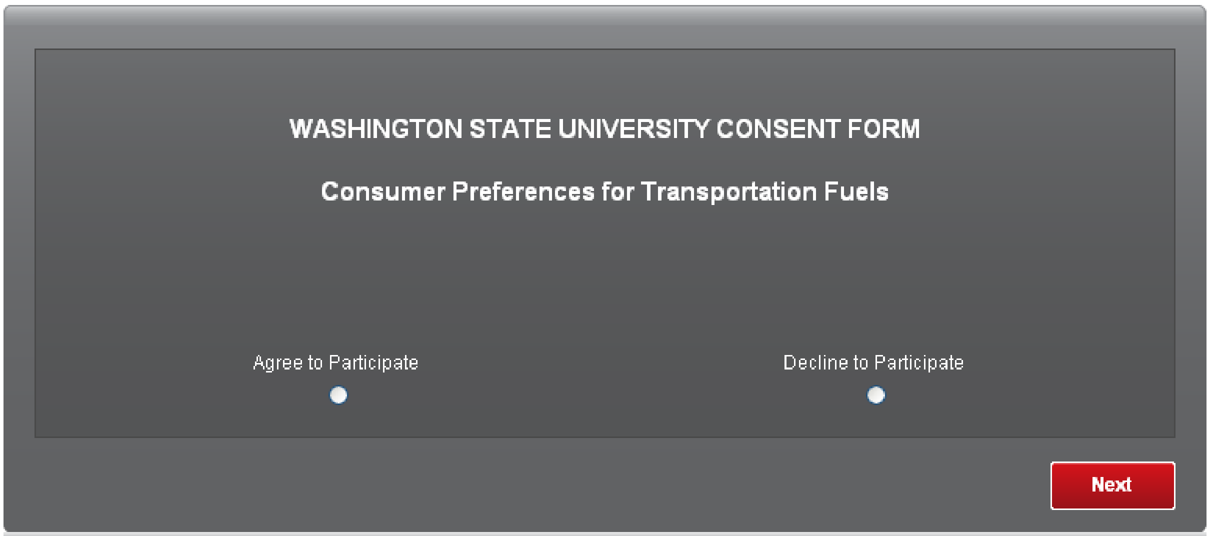
Variable Notation	Variable Description	Mean	Std.Dev.	Min	Max
VALUES	**Values (Likert-scale, 0-6)**				
Vego	Egoistic orientation	3.2	0.8	2	6
Valt	Altruistic orientation	4.9	0.8	2	6
Vbio	Biospheric orientation	4.8	1.0	1	6
EC	**Environmental Concern (Likert-scale, 0-6)**				
ECego	Egoistic orientation	4.6	1.0	1	6
ECalt	Altruistic orientation	5.0	0.9	1	6
ECbio	Biospheric orientation	4.9	1.0	1	6
AC	**Awareness of Consequences (Likert-scale, 1-7)**				
ACego	Egoistic orientation	4.9	1.8	1	7
ACalt	Altruistic orientation	5.1	1.7	1	7
Acbio	Biospheric orientation	5.2	1.7	1	7
NORMS	**Proenvironmental Personal Norms (Litert-scale, 1-7)**				
Bpers	Egoistic orientation	4.2	1.7	1	7
Bgov	Altruistic orientation	5.2	1.6	1	7
Bgus	Biospheric orientation	5.5	1.7	1	7
CFC	**Consideration of Future Consequences**				
CFC-i	Immediate	3.6	1.3	1	6
CFC-f	Future	4.6	0.9	1	6
PERC1	**Perceptions about Prices (Likert-scale, 1-7)**				
gcornp	Gas vs. Corn-based ethanol	3.6	1.6	1	7
gcellp	Gas vs. Cellulose-based ethanol	3.5	1.5	1	7
ccellp	Corn- vs. Cellulose-based ethanol	3.8	1.2	1	7
PERC2	**Perceptions about Emissions (Likert-scale, 1-7)**				
gcorne	Gas vs. Corn-based ethanol	5.3	1.5	1	7
gcelle	Gas vs. Cellulose-based ethanol	5.1	1.4	1	7
ccelle	Corn- vs. Cellulose-based ethanol	4.0	1.2	1	7
PERC3	**Perceptions about Service (Likert-scale, 1-7)**				
gcells	Gas vs. Cellulose-based ethanol	2.8	1.5	1	7
gcons	Gas vs. Corn-based ethanol	2.9	1.6	1	7
ccells	Corn- vs. Cellulose-based ethanol	3.5	1.2	1	7
	Car Ownership Characteristics				
cars	Number of cars in the household	1.9	0.9	1	7

carsy	Year of the vehicle most driven	10.0	5.4	1986	2010
carsd	Equals 1if vehicle year > 2002, 0 otherwise	0.5	0.5	-	-
	Ethanol Knowledge Characteristics				
used	Equals 1 if used ethanol	0.3	0.5	-	-
kncell	Knowledge about cellulose-based fuel (Likert-scale, 1-7)	2.2	1.5	1	7
kncorn	Knowledge about corn-based fuel (Likert-scale, 1-7)	3.1	1.6	1	7
	Likelihood of FFV purchase				
Ffv	Likert-scale, 1-7, likelihood of purchasing FFV	4.1	1.8	1	7
DRIV	**Driving Habits**				
drwork	Equals 1 if drives to work, 0 otherwise	0.5	0.5	-	-
drsch	Equals 1 if drives to school, 0 otherwise	0.1	0.2	-	-
drerr	Equals 1 if drives for daily errands, 0 otherwise	0.9	0.3	-	-
OCCUP	**Occupation**				
fullt	Full-time employed, 1= yes, 0 = no	0.35	0.48	-	-
partt	Part-time employed, 1= yes, 0 = no	0.12	0.33	-	-
selfemp	Self-employed, 1= yes, 0 = no	0.09	0.29	-	-
unemp	Unemployed, 1= yes, 0 = no	0.18	0.39	-	-
stud	Student, 1= yes, 0 = no	0.02	0.15	-	-
retd	Retired, 1= yes, 0 = no	0.20	0.40	-	-
Oth	Other occupation, 1= yes, 0 = no	0.03	0.17	-	-
EDUC	**Education**				
lesshs	Education: less then high school , 1= yes, 0 = no	0.01	0.10	-	-
HS	Education: high school, 1= yes, 0 = no	0.16	0.36	-	-
scollg	Education: some college, 1= yes, 0 = no	0.30	0.46	-	-
2collg	Education: 2-year college, 1= yes, 0 = no	0.14	0.35	-	-
4collg	Education: 4-year college, 1= yes, 0 = no	0.26	0.44	-	-
MA	Education: Master's degree, 1= yes, 0 = no	0.11	0.32	-	-
PhD	Education: PhD, 1= yes, 0 = no	0.01	0.10	-	-
Pro	Education: Professional degree, 1= yes, 0 = no	0.01	0.08	-	-
	Age				
Age	Age	50	13	19	78
	Gender				
Gender	Equals 1 if male, 0 otherwise	0.50	0.50	-	-
MARIT	**Marital Status**				
mchld	Equals 1 if married with child, 0 otherwise	0.48	0.50	-	-
mnochld	Equals 1 if married with no child, 0 otherwise	0.15	0.35	-	-
div	Equals 1 if divorced, 0 otherwise	0.15	0.36	-	-
sing	Equals 1 if single, 0 otherwise	0.18	0.39	-	-
wid	Equals 1 if widowed, 0 otherwise	0.04	0.20	-	-
	Race				

white	Equals 1 if race is white, 0 otherwise	0.91	0.29	0	1
	Annual Income				
Inc	Annual income per respondent	4.44	2.59	< $20k	≥ $90k
	Political Orientation				
Polit	1= Liberal, 7 = Conservative	4.31	1.65	1	7
GEOG	**Geographic Distribution of respondents**				
West	Responses from West, 1= yes, 0 = no	0.23	0.42	-	-
East	Responses from East, 1= yes, 0 = no	0.32	0.47	-	-
Midwest	Responses from Midwest, 1= yes, 0 = no	0.22	0.41	-	-
Northeast	Responses from Northeast, 1= yes, 0 = no	0.23	0.42	-	-

Online Survey Template

Webpage 1



Note: This page of the online survey included Washington State University Consent Form.

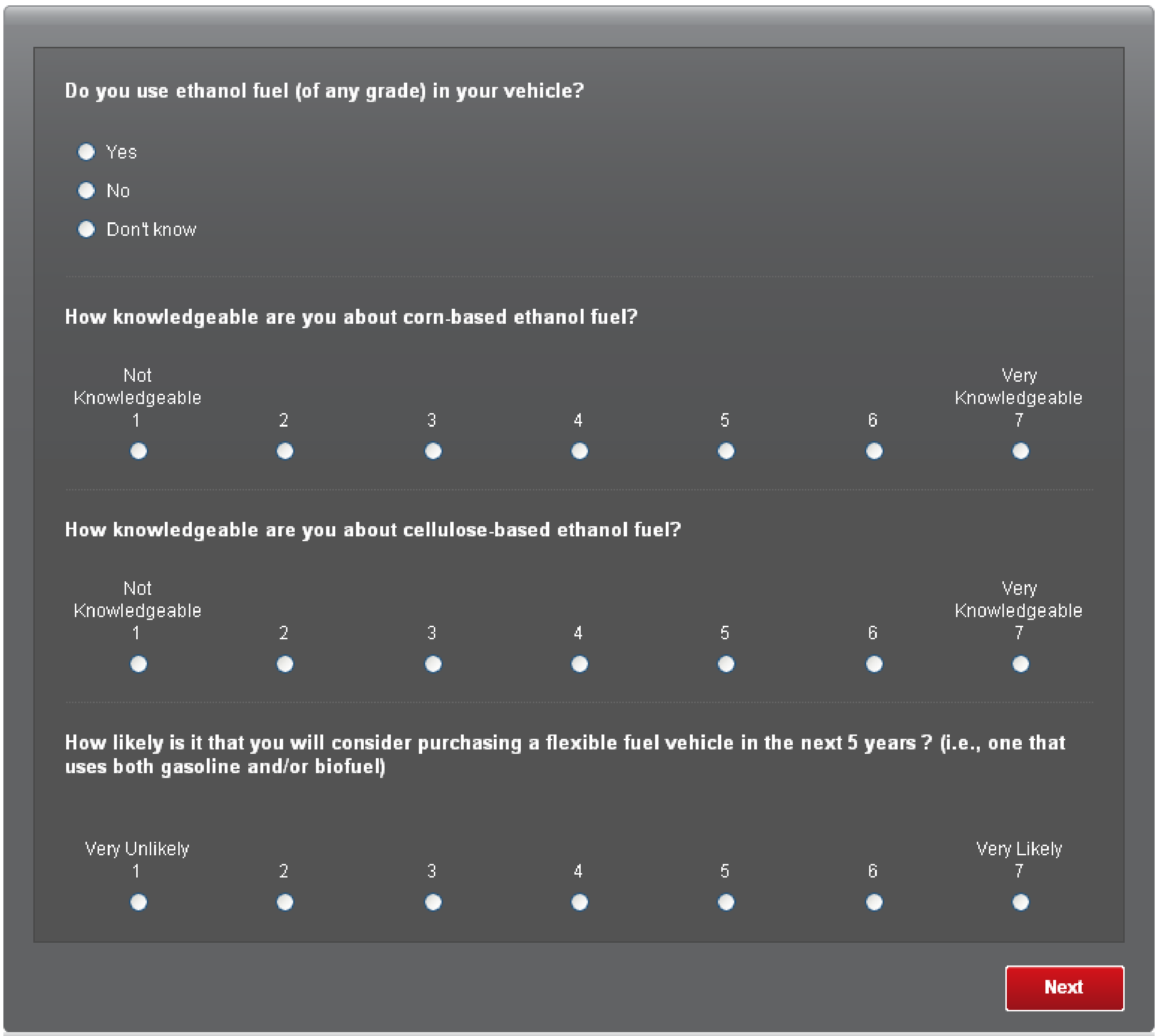
Webpage 2
Introduction


Do you currently own a vehicle?

- Yes
- No

Next

Webpage 3


Do you use ethanol fuel (of any grade) in your vehicle?

- Yes
- No
- Don't know

How knowledgeable are you about corn-based ethanol fuel?

Not Knowledgeable 1	2	3	4	5	6	Very Knowledgeable 7
○	○	○	○	○	○	○

How knowledgeable are you about cellulose-based ethanol fuel?

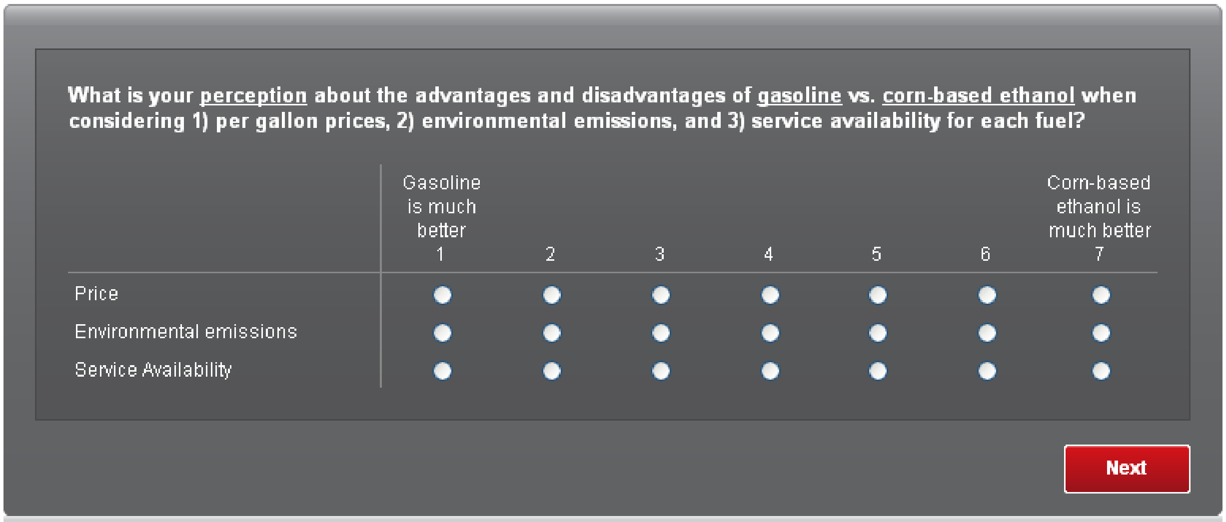
Not Knowledgeable 1	2	3	4	5	6	Very Knowledgeable 7
○	○	○	○	○	○	○

How likely is it that you will consider purchasing a flexible fuel vehicle in the next 5 years ? (i.e., one that uses both gasoline and/or biofuel)

Very Unlikely 1	2	3	4	5	6	Very Likely 7
○	○	○	○	○	○	○

Next

Webpage 4

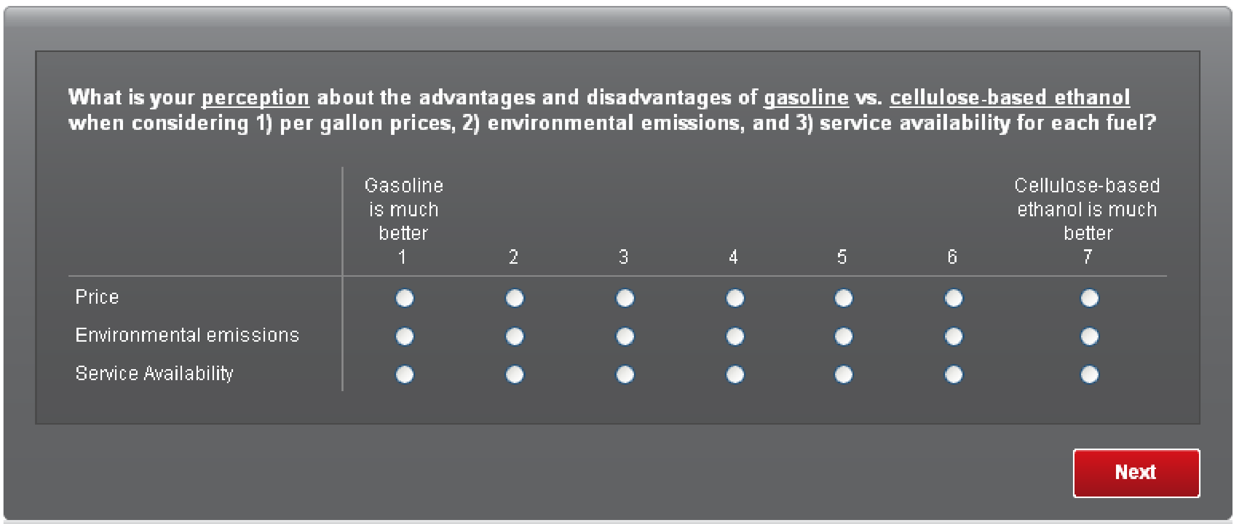


What is your perception about the advantages and disadvantages of gasoline vs. corn-based ethanol when considering 1) per gallon prices, 2) environmental emissions, and 3) service availability for each fuel?

	Gasoline is much better 1	2	3	4	5	6	Corn-based ethanol is much better 7
Price	○	○	○	○	○	○	○
Environmental emissions	○	○	○	○	○	○	○
Service Availability	○	○	○	○	○	○	○

Next

Webpage 5



What is your perception about the advantages and disadvantages of gasoline vs. cellulose-based ethanol when considering 1) per gallon prices, 2) environmental emissions, and 3) service availability for each fuel?

	Gasoline is much better 1	2	3	4	5	6	Cellulose-based ethanol is much better 7
Price	○	○	○	○	○	○	○
Environmental emissions	○	○	○	○	○	○	○
Service Availability	○	○	○	○	○	○	○

Next

Webpage 6

What is your <u>perception</u> about the advantages and disadvantages of <u>corn-based ethanol</u> vs. <u>cellulose-based ethanol</u> when considering 1) per gallon prices, 2) environmental emissions, and 3) service availability for each fuel?

	Corn-based ethanol is much better 1	2	3	4	5	6	Cellulose-based ethanol is much better 7
Price	○	○	○	○	○	○	○
Environmental emissions	○	○	○	○	○	○	○
Service Availability	○	○	○	○	○	○	○

Next

Webpage 7

Introduction to fuel choice scenarios

On the next several slides, we will be asking you about your preference for three different forms of transportation fuels (gas, cellulose-based ethanol, and corn-based ethanol). Some of these fuels are widely available today, while others are less available or still under development.

In today's study, we will be asking you to imagine eight *future* "fuel-choice scenarios" and indicate your preference for the three types of fuels in these scenarios. Before presenting the scenarios, we would like to provide some background information on the two ethanol-based fuels. Please read this information carefully before moving on.

<u>Cellulose-based ethanol</u> is processed from cellulose, which is extracted from such sources as forest biomass, wood chips, agricultural crop residue, animal manure, or municipal solid waste.

<u>Corn-based ethanol</u> is processed from corn.

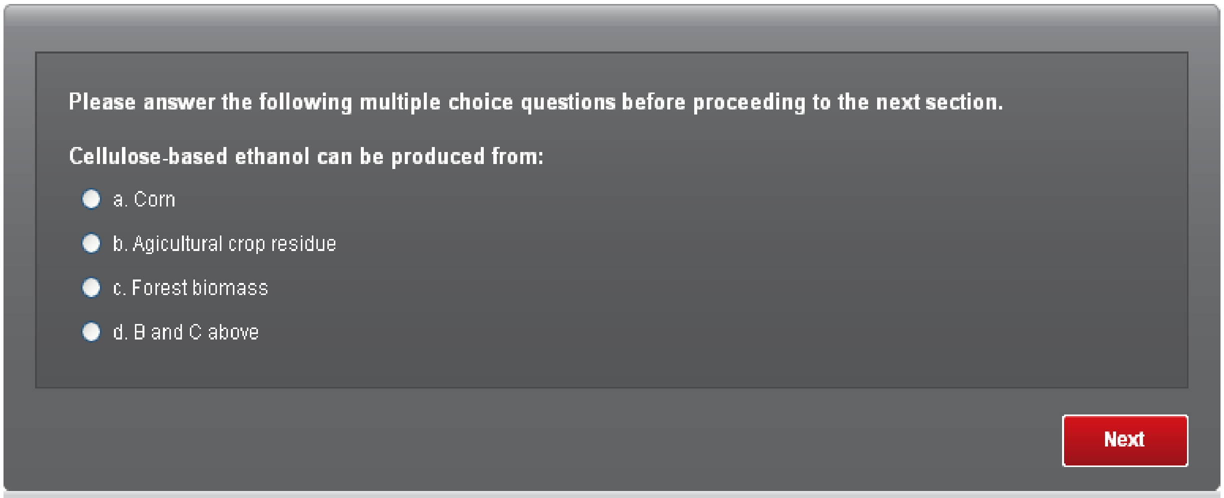
After production, the pure ethanol is blended with gasoline to create different grades of motor fuels. <u>In this study, both cellulose-based and corn-based ethanol fuels refer to E85 grade (a blend of 85% ethanol and 15% gasoline).</u>

Both cellulose-based and corn-based biofuels contribute to U.S. oil independence.

Next

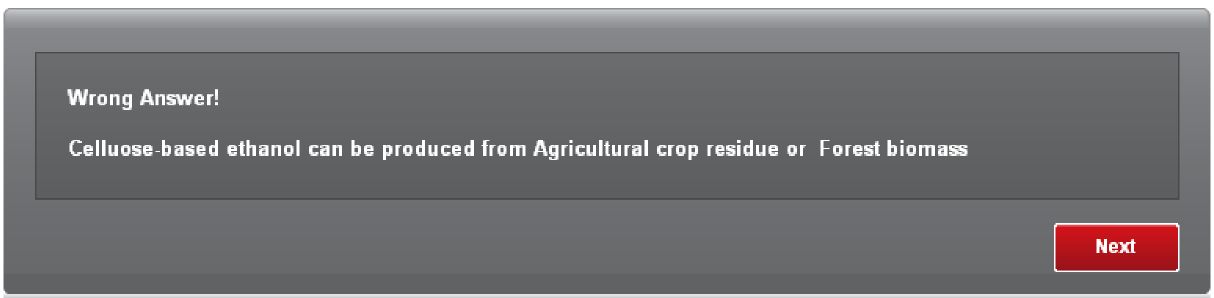
Webpage 8

<u>Quiz questions</u>

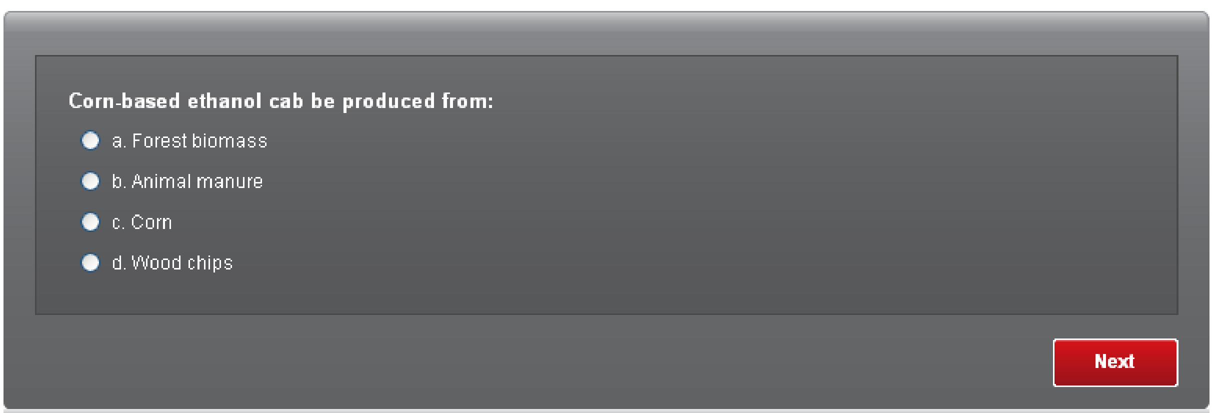


Webpage 9

(Pop-up message for wrong answers to the previous question)

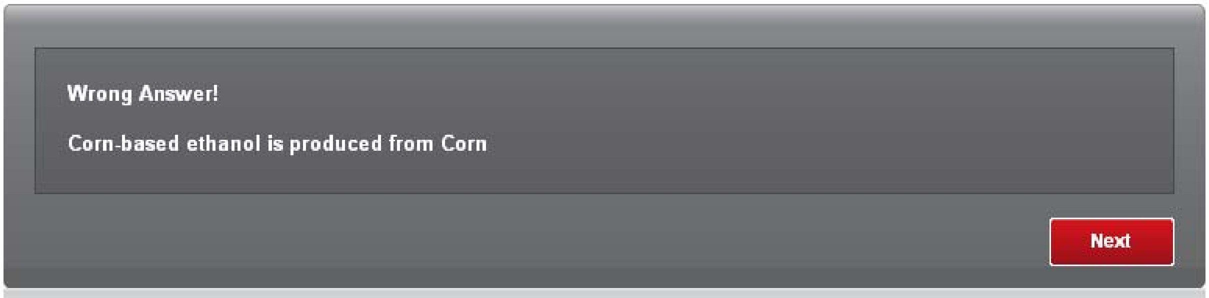


Webpage 10

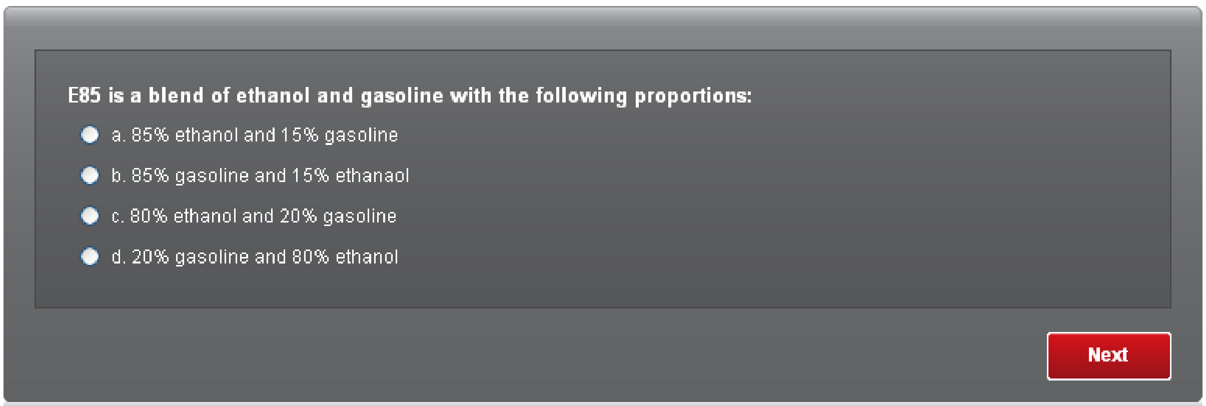


Webpage 11

(Pop-up message for wrong answers to the previous question)



Webpage 12



Webpage 13

(Pop-up message for wrong answers to the previous question)

Webpage 14

Choice Sets

Instructions

In this part of the survey, we would like you to imagine that you are at a service station and you have a choice between the three types of fuels shown below.

1. Gasoline
2. Cellulose-based ethanol
3. Corn-based ethanol

On each of the following eight pages, we will present a fuel-choice scenario. In each scenario, you will find a table listing the price, environmental emissions and service availability for each type of fuel.

Each table contains a different combination of price, emissions and service availability for cellulose-based and corn-based ethanol fuels. The emissions and service availability for gasoline are the same in every table.

Please read each table carefully before selecting your preferred fuel type.

Next

Webpage 15

Here is an example. In this fuel-choice scenario, we would like you to imagine:

- Gas costs $2.75/gallon, while cellulose-based and corn-based ethanol cost $2.50/gallon.
- Gas has an emissions rating of 20 (lbs. per gallon)[a], while cellulose-based ethanol has an emissions rating of 16, and corn-based ethanol has an emissions-rating of 14.
- Gas is available at every fueling station; cellulose-based and corn-based ethanol are available at every third fueling station.

This is an example. On the following eight pages, we would like you to select your preferred fueling option after carefully reviewing the information provided in the table on that page. *Please note that the information in each table will change from page to page*.

	GASOLINE	CELLULOSE-BASED ETHANOL	CORN-BASED ETHANOL
PRICE/GALLON	2.75	2.50	2.50
EMISSIONS (IN LBS/GALLON)	20[a]	16	14
SERVICE AVAILABILITY	every fueling station	every 3rd fueling station	every 3rd fueling station

[a]One gallon of gasoline weights only 6.3 pounds. However, according to U.S. Department of Energy calculations, 1 gallon of gasoline can produce 20 pounds of carbon dioxide (most of the weight of the CO2 doesn't come from the gasoline itself, but the from the oxygen in the air). This occurs because burned gasoline produces carbon and hydrogen, which after interacting with the oxygen in the air, increases its weight to 20 pounds of carbon dioxide (CO2) per gallon.

Next

Webpage 16

A. Please select your preferred fuel option.

SCENARIO 1

	GASOLINE	CELLULOSE-BASED ETHANOL	CORN-BASED ETHANOL
PRICE/GALLON	2.75	3.00	2.50
EMISSIONS (IN LBS/GALLON)	20	16	16
SERVICE AVAILABILITY	every fueling station	every 3rd fueling station	every 3rd fueling station

	Gasoline	Cellulose-based Ethanol	Corn-based Ethanol
	○	○	○

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Webpage 17

A. Please select your preferred fuel option.

SCENARIO 2

	GASOLINE	CELLULOSE-BASED ETHANOL	CORN-BASED ETHANOL
PRICE/GALLON	2.75	2.50	3.00
EMISSIONS (IN LBS/GALLON)	20	16	16
SERVICE AVAILABILITY	every fueling station	every fueling station	every fueling station

	Gasoline	Cellulose-based Ethanol	Corn-based Ethanol
	○	○	○

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Webpage 18

A. Please select your preferred fuel option.

SCENARIO 3

	GASOLINE	CELLULOSE-BASED ETHANOL	CORN-BASED ETHANOL
PRICE/GALLON	2.75	3.00	2.50
EMISSIONS (IN LBS/GALLON)	20	16	14
SERVICE AVAILABILITY	every fueling station	every fueling station	every fueling station

	Gasoline	Cellulose-based Ethanol	Corn-based Ethanol
	○	○	○

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A. Please select your preferred fuel option.

SCENARIO 4

	GASOLINE	CELLULOSE-BASED ETHANOL	CORN-BASED ETHANOL
PRICE/GALLON	2.75	3.00	3.00
EMISSIONS (IN LBS/GALLON)	20	14	16
SERVICE AVAILABILITY	every fueling station	every 3rd fueling station	every fueling station

	Gasoline	Cellulose-based Ethanol	Corn-based Ethanol
	○	○	○

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A. Please select your preferred fuel option.

SCENARIO 5

	GASOLINE	CELLULOSE-BASED ETHANOL	CORN-BASED ETHANOL
PRICE/GALLON	2.75	2.50	3.00
EMISSIONS (IN LBS/GALLON)	20	16	14
SERVICE AVAILABILITY	every fueling station	every 3rd fueling station	every 3rd fueling station

	Gasoline	Cellulose-based Ethanol	Corn-based Ethanol
	○	○	○

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A. Please select your preferred fuel option.

SCENARIO 6

	GASOLINE	CELLULOSE-BASED ETHANOL	CORN-BASED ETHANOL
PRICE/GALLON	2.75	3.00	3.00
EMISSIONS (IN LBS/GALLON)	20	14	14
SERVICE AVAILABILITY	every fueling station	every fueling station	every 3rd fueling station

	Gasoline	Cellulose-based Ethanol	Corn-based Ethanol
	○	○	○

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A. Please select your preferred fuel option.

SCENARIO 7

	GASOLINE	CELLULOSE-BASED ETHANOL	CORN-BASED ETHANOL
PRICE/GALLON	2.75	2.50	2.50
EMISSIONS (IN LBS/GALLON)	20	14	14
SERVICE AVAILABILITY	every fueling station	every 3rd fueling station	every fueling station

	Gasoline	Cellulose-based Ethanol	Corn-based Ethanol
	○	○	○

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Webpage 23

A. Please select your preferred fuel option.

SCENARIO 8

	GASOLINE	CELLULOSE-BASED ETHANOL	CORN-BASED ETHANOL
PRICE/GALLON	2.75	2.50	3.00
EMISSIONS (IN LBS/GALLON)	20	14	16
SERVICE AVAILABILITY	every fueling station	every fueling station	every 3rd fueling station

	Gasoline	Cellulose-based Ethanol	Corn-based Ethanol
	○	○	○

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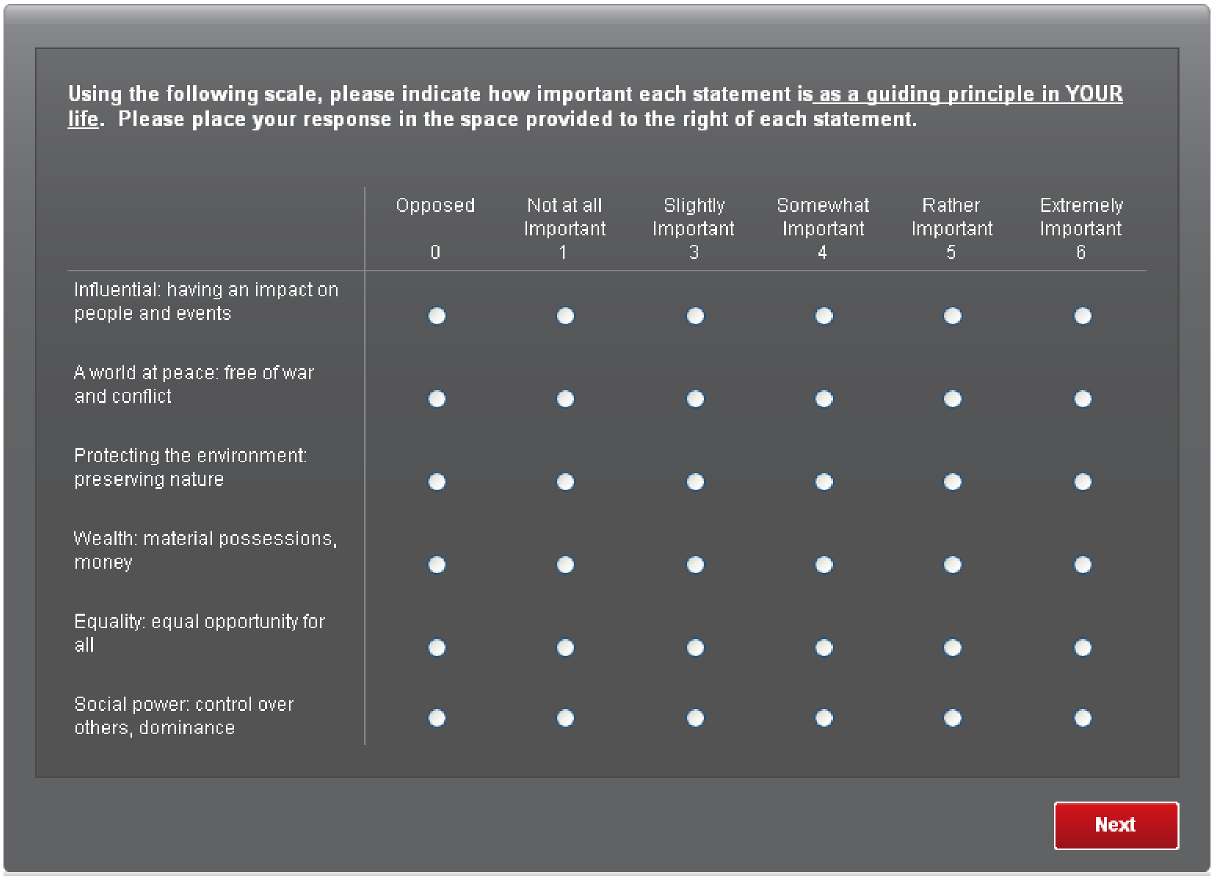
<u>Value Orientations</u>



Using the following scale, please indicate how important each statement is <u>as a guiding principle in YOUR life</u>. Please place your response in the space provided to the right of each statement.

	Opposed 0	Not at all Important 1	Slightly Important 3	Somewhat Important 4	Rather Important 5	Extremely Important 6
Influential: having an impact on people and events	○	○	○	○	○	○
A world at peace: free of war and conflict	○	○	○	○	○	○
Protecting the environment: preserving nature	○	○	○	○	○	○
Wealth: material possessions, money	○	○	○	○	○	○
Equality: equal opportunity for all	○	○	○	○	○	○
Social power: control over others, dominance	○	○	○	○	○	○

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Using the following scale, please indicate how important each statement is <u>as a guiding principle in YOUR life</u>. Please place your response in the space provided to the right of each statement.

	Opposed 0	Not at all Important 1	Slightly Important 3	Somewhat Important 4	Rather Important 5	Extremely Important 6
Preventing pollution: protecting natural resources						
Respecting the earth: harmony with other species						
Authority: the right to lead or command						
Helpful: working for the welfare of others						
Social justice: correcting injustice, care for the weak						
Unity with nature: fitting into nature						

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Webpage 26
Environmental Concerns

People around the world are generally concerned about environmental problems because of the consequences that result from harming nature. However, people differ in the consequences that concern them the most. Please rate each of the following items from 1 (not important) to 7 (very important) in response to the question:

I am concerned about environmental problems because of the consequences for _____

	Opposed 0	Not at all Important 1	Slightly Important 3	Somewhat Important 4	Rather Important 5	Extremely Important 6
My lifestyle	○	○	○	○	○	○
Children	○	○	○	○	○	○
Animals	○	○	○	○	○	○
My health	○	○	○	○	○	○
People in my community	○	○	○	○	○	○
Plants	○	○	○	○	○	○
Me	○	○	○	○	○	○
All people	○	○	○	○	○	○
Marine life	○	○	○	○	○	○
Future generations	○	○	○	○	○	○
Birds	○	○	○	○	○	○
My future	○	○	○	○	○	○

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<u>Awareness of Consequences</u>

Shown below are several statements. Please use the scale provided to the right to indicate the extent to which you disagree or agree with each statement.

	Strongly Disagree 1	Disagree 2	Slightly Disagree 3	Neutral 4	Slightly Agree 5	Agree 6	Strongly Agree 7
Climate change will be a very serious problem for me and my family in the next 30 years.	○	○	○	○	○	○	○
Climate change will be a very serious problem for the country as a whole in the next 30 years.	○	○	○	○	○	○	○
Climate change will be a very serious problem for other species of plants and animals in the next 30 years.	○	○	○	○	○	○	○
Toxic substances in the air due to automobile emissions will be a very serious problem for me and my family in the next 30 years.	○	○	○	○	○	○	○
Toxic substances in the air due to automobile emissions will be a very serious problem for the country as a whole in the next 30 years.	○	○	○	○	○	○	○
Toxic substances in the air due to automobile emissions will be a very serious problem for other species of plants and animals in the next 30 years.	○	○	○	○	○	○	○
To ensure that you are reading the statements, please choose stongly agree as your answer to this statement.	○	○	○	○	○	○	○

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Proenvironmental Norms/Beliefs (personal, for government and for businesses)

Please use the scale below to provide the extent to which you agree with the following statements.

	Strongly Disagree 1	Disagree 2	Slightly Disagree 3	Neutral 4	Slightly Agree 5	Agree 6	Strongly Agree 7
I feel a personal obligation to purchase ethanol instead of gasoline to prevent climate change.	○	○	○	○	○	○	○
I feel a sense of personal obligation to take action to stop oil drilling that causes harmful environmental consequences.	○	○	○	○	○	○	○
The U.S. government should take stronger action to encourage public use of biofuels, such as ethanol, to reduce environmental emissions and prevent global climate change.	○	○	○	○	○	○	○
The U.S. government should increase tariffs on Brazilian ethanol imports in order to exert pressure on Brazil to prevent deforestation of Amazon rainforests (which are used for ethanol production).	○	○	○	○	○	○	○
The U.S. Department of Transportation should encourage the use of biofuels for industrial heavy truck fleets and buses to reduce harmful environmental emissions.	○	○	○	○	○	○	○
Business and industry should reduce their environmental emissions to help prevent climate change.	○	○	○	○	○	○	○

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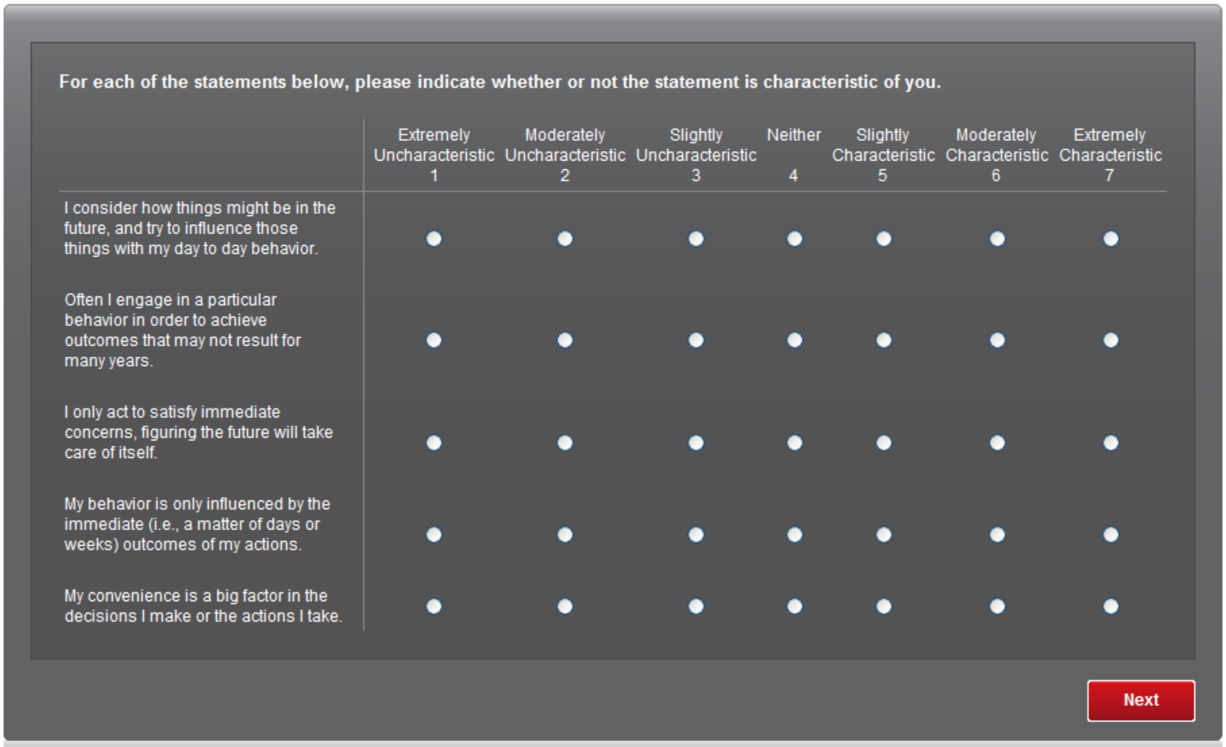
Consideration of Future Consequences



For each of the statements below, please indicate whether or not the statement is characteristic of you.

	Extremely Uncharacteristic 1	Moderately Uncharacteristic 2	Slightly Uncharacteristic 3	Neither 4	Slightly Characteristic 5	Moderately Characteristic 6	Extremely Characteristic 7
I consider how things might be in the future, and try to influence those things with my day to day behavior.							
Often I engage in a particular behavior in order to achieve outcomes that may not result for many years.							
I only act to satisfy immediate concerns, figuring the future will take care of itself.							
My behavior is only influenced by the immediate (i.e., a matter of days or weeks) outcomes of my actions.							
My convenience is a big factor in the decisions I make or the actions I take.							

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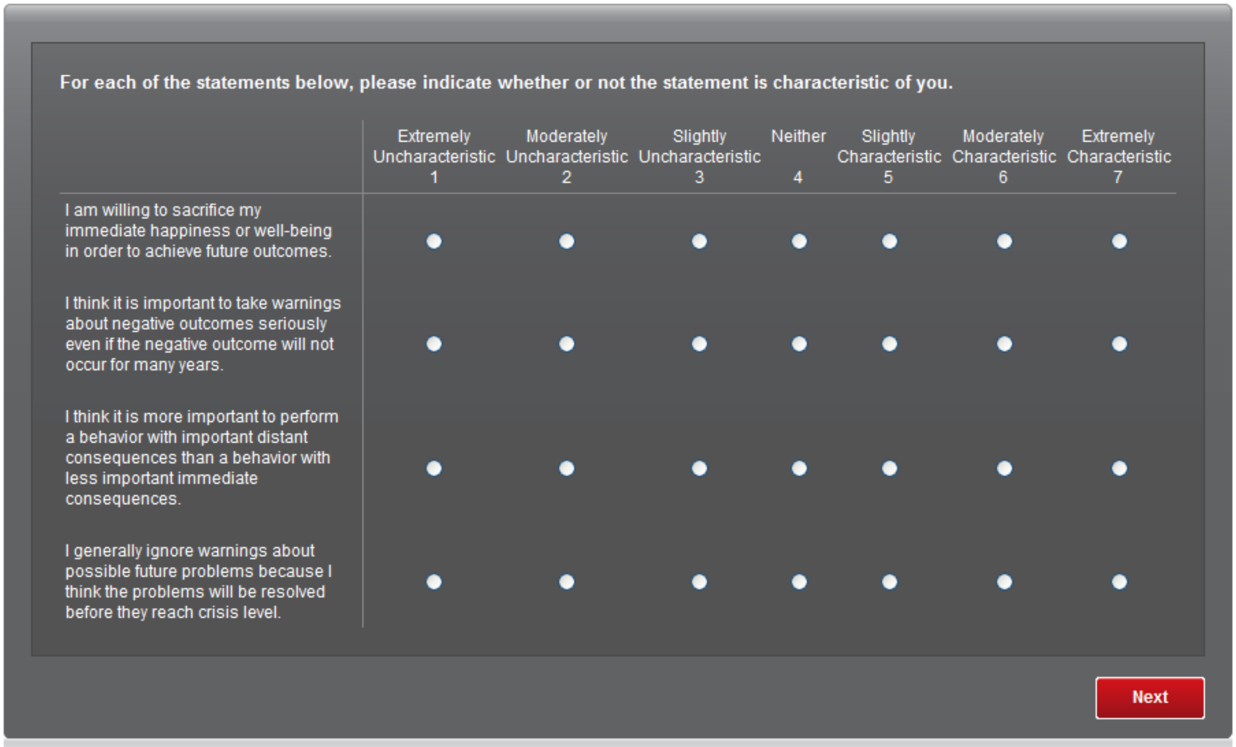

For each of the statements below, please indicate whether or not the statement is characteristic of you.

	Extremely Uncharacteristic 1	Moderately Uncharacteristic 2	Slightly Uncharacteristic 3	Neither 4	Slightly Characteristic 5	Moderately Characteristic 6	Extremely Characteristic 7
I am willing to sacrifice my immediate happiness or well-being in order to achieve future outcomes.							
I think it is important to take warnings about negative outcomes seriously even if the negative outcome will not occur for many years.							
I think it is more important to perform a behavior with important distant consequences than a behavior with less important immediate consequences.							
I generally ignore warnings about possible future problems because I think the problems will be resolved before they reach crisis level.							

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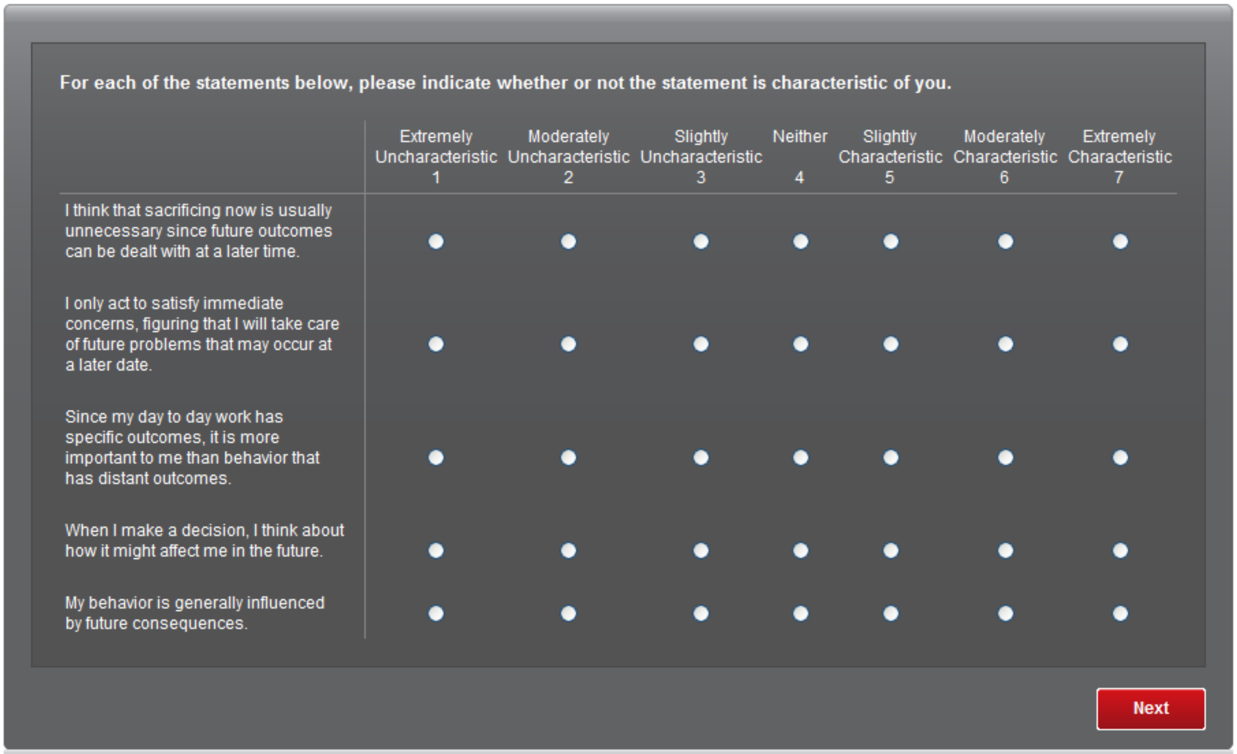

For each of the statements below, please indicate whether or not the statement is characteristic of you.

	Extremely Uncharacteristic 1	Moderately Uncharacteristic 2	Slightly Uncharacteristic 3	Neither 4	Slightly Characteristic 5	Moderately Characteristic 6	Extremely Characteristic 7
I think that sacrificing now is usually unnecessary since future outcomes can be dealt with at a later time.	●	●	●	●	●	●	●
I only act to satisfy immediate concerns, figuring that I will take care of future problems that may occur at a later date.	●	●	●	●	●	●	●
Since my day to day work has specific outcomes, it is more important to me than behavior that has distant outcomes.	●	●	●	●	●	●	●
When I make a decision, I think about how it might affect me in the future.	●	●	●	●	●	●	●
My behavior is generally influenced by future consequences.	●	●	●	●	●	●	●

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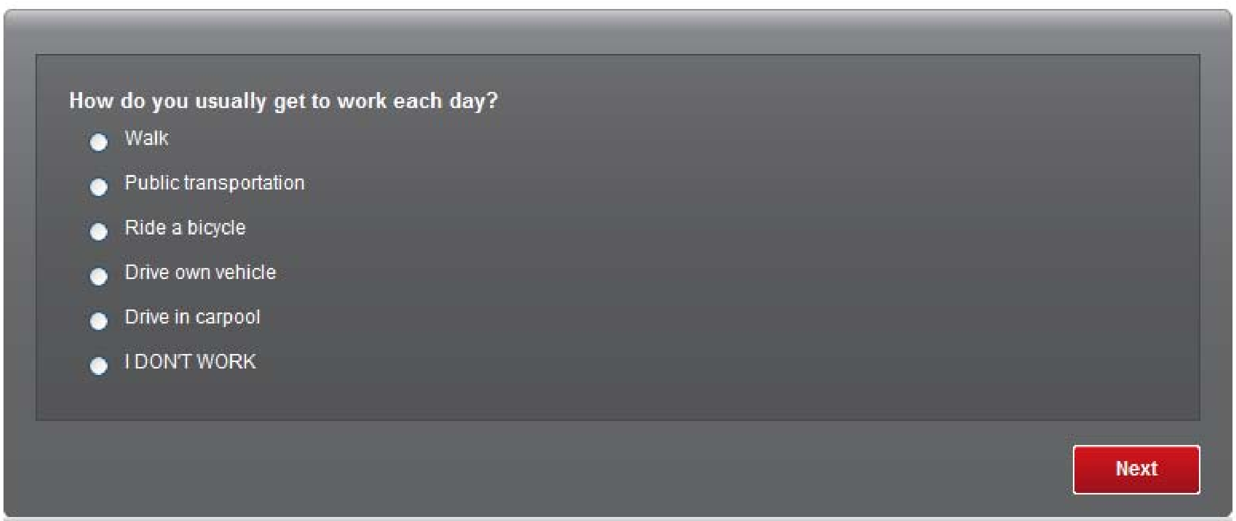
<u>Modal Choice</u>



How do you usually get to work each day?

- Walk
- Public transportation
- Ride a bicycle
- Drive own vehicle
- Drive in carpool
- I DON'T WORK

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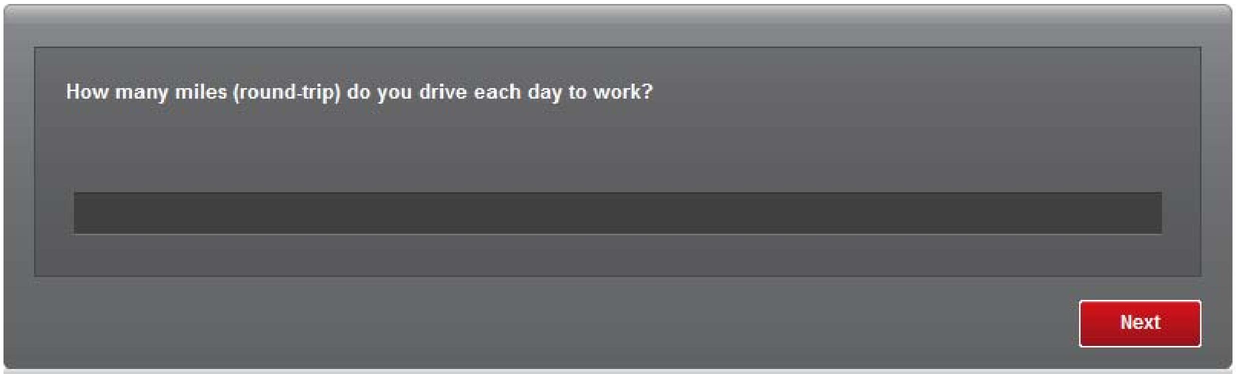
(If the respondents selected drive own vehicle or drive in carpool options above)



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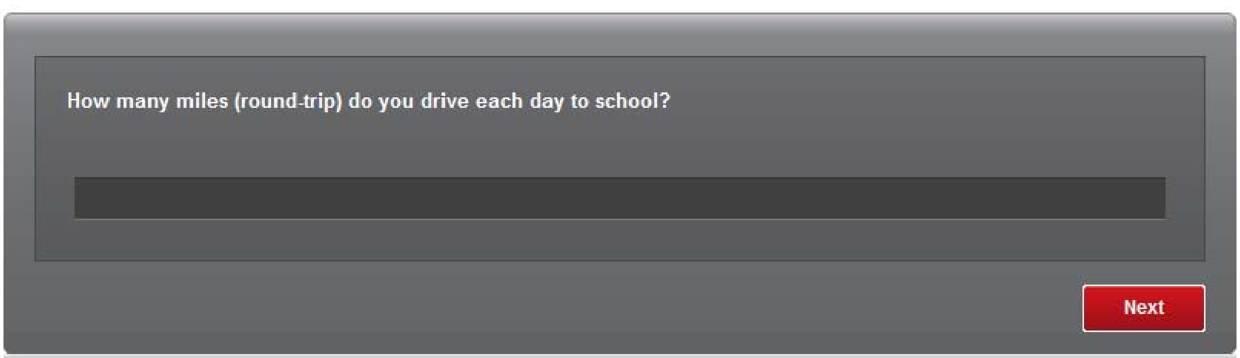
Webpage 35

(If the respondents selected drive own vehicle or drive in carpool options above)



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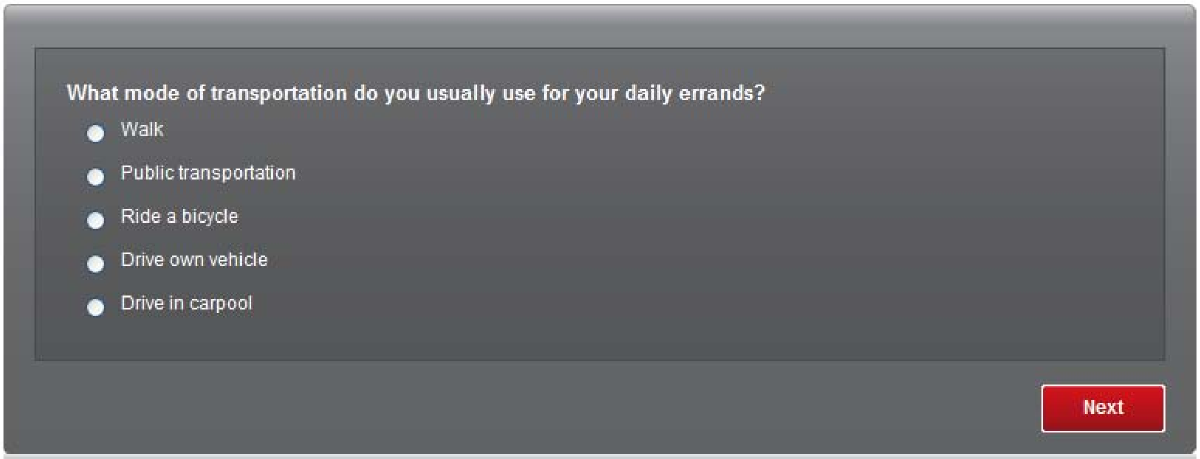

What mode of transportation do you usually use for your daily errands?

- Walk
- Public transportation
- Ride a bicycle
- Drive own vehicle
- Drive in carpool

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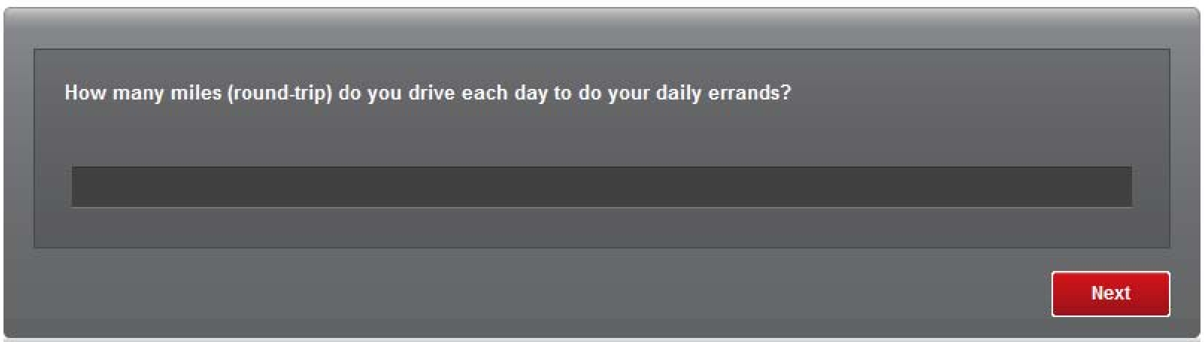
(If the respondents selected drive own vehicle or drive in carpool options above)



How many miles (round-trip) do you drive each day to do your daily errands?

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How many cars does your household own?

Next

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What is the year of the car that you drive most?

(IF YOUR HOUSEHOLD OWNS ONE VEHICLE, JUST SELECT THE YEAR)

Click to select the year

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Socio-Demographics

Which of the following best describes you?

- Full-time employed
- Part-time employed
- Self employed
- Unemployed
- Student
- Retired
- Other

What is the highest level of education you have completed?

- Less than High School
- High School / GED
- Some College
- 2-year College Degree
- 4-year College Degree
- Master's Degree
- Doctoral Degree
- Professional Degree (JD, MD)

Please indicate your age.

Please indicate your gender.

- Male
- Female

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Please indicate your current marital status.

- Married with children
- Married without children
- Divorced
- Single
- Widowed

Please indicate your race.

- African American
- Asian American
- Caucasian
- Hispanic
- Pacific Islander
- Other

Please indicate yourannual income range.

- Below $20,000
- $20,00 - $29,999
- $30,000 - $39,999
- $40,000 - $49,999
- $50,000 - $59,999
- $60,000 - $69,999
- $70,000 - $79,000
- $80,000 - $89,999
- $90,000 or more

Please indicate your political orientation.

Liberal						Conservative
1	2	3	4	5	6	7

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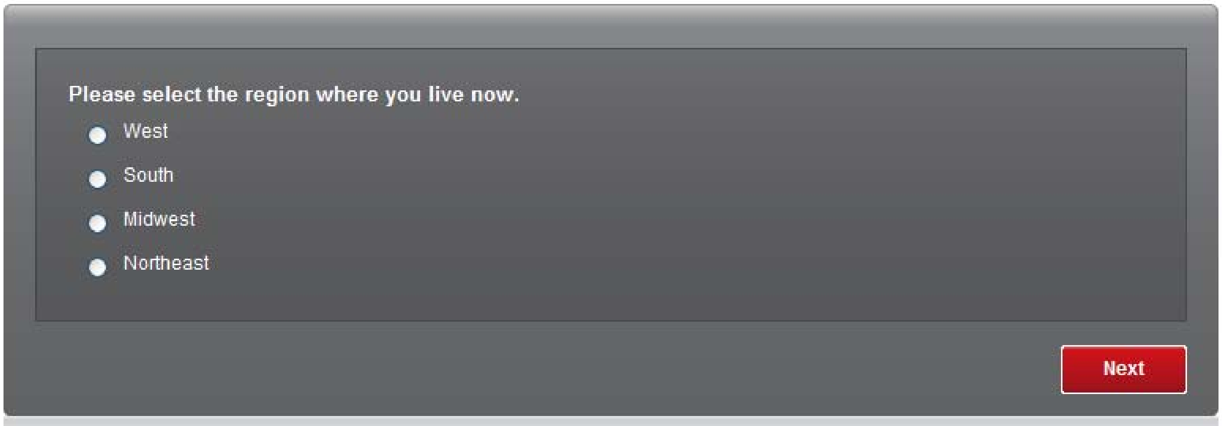

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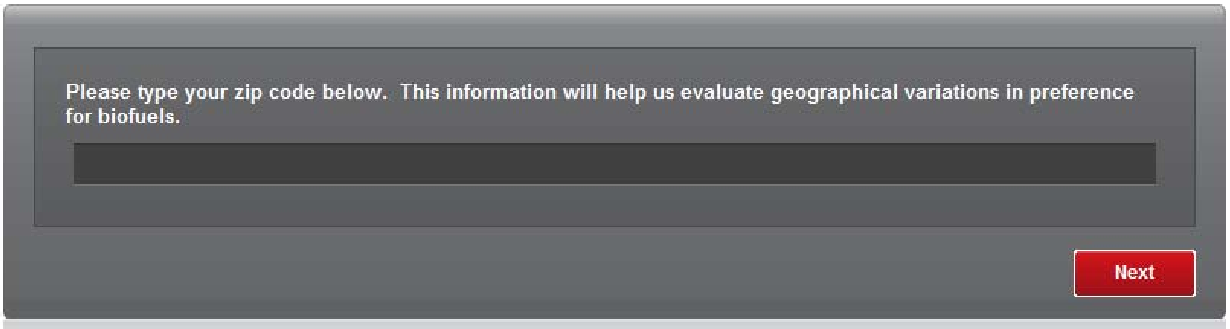

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<u>End-of-Survey Message</u>