Spatial Differences in Price Elasticity of Demand for Ethanol

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Increased public environmental awareness, concern for national energy security, and high transportation fuel prices have all served to heighten interest in alternative fuels. A fundamental issue influencing 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 studying this problem by estimating geographically varying price elasticity of demand for E85 ethanol fuel across the study area. This is a departure from previous studies of ethanol demand, in which price elasticity of demand is spatially identical. Considering spatial heterogeneity in household composition and demand preferences, using stationary estimates to explain price-demand relationships over a large geographic area may lead to biased results and inference. Resulting price elasticity estimates for ethanol demand revealed significant geographic variation (ranging from 0.5 to 5.0), suggesting that use of spatially disaggregated data provides more detailed empirical results and, therefore, a more thorough understanding by policymakers.

INTRODUCTION AND BACKGROUND

Alternative fuel policies are designed to increase U.S. energy independence and to reduce harmful environmental emissions from transportation fuels. According to Renewable Fuel Standards (RFS), biofuels production and use in the U.S. will reach 36 billion gallons by 2022 (Sissine 2007). To meet the RFS target, the U.S. Department of Energy (DOE) promotes use of higher blends of ethanol (e.g., E85—85% ethanol and 15% gasoline) by targeting specific regions and cities to establish high concentrations of flexible fuel vehicles (FFVs). 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. Under requirements of the Government Performance Results Act, the Office of Energy Efficiency and Renewable Energy (EERE) estimates benefits of biofuel promotion programs. Based on these estimates, EERE evaluates the cost effectiveness of its programs and uses the findings in allocating program budgets (Bernstein and Griffin 2006). One of the key parameters used in estimating the benefits of those programs is the extent to which biofuel demand is sensitive to price changes (i.e., price elasticity of demand). Therefore, understanding consumers' demand responsiveness to ethanol and gasoline price changes at a county level is critical to implementing state level renewable fuel policies in a more cost effective manner.

The main purpose of this paper is to investigate consumers' demand responsiveness to fuel price changes across geographical space. In particular, spatial variations for own price and cross price elasticity (gasoline price elasticity) of demand for E85 ethanol fuel in Minnesota were estimated. The model includes explanatory variables, such as disposable income, the number of fueling stations within close proximity, vehicle stock, and distances from ethanol fueling stations to major highways, and blending terminals used to explain variations in E85 ethanol monthly sales (dependent variable). In previous studies of ethanol demand, price elasticity of demand for fuels was assumed to be constant across the study area (Anderson 2010; Hughes et al. 2008; Schmalensee and Stoker 1999; Yatchew and No 2001). In this paper, we start by estimating own price and cross price elasticity of ethanol demand using monthly price observations ($/gallon) and sales volumes (in gallons) of individual E85 service stations in Minnesota. The base model was extended and improved by an alternative specification that accounts for spatial heterogeneity in data structure and provides a set of estimates that were visualized on a map. Henceforth, the terms "ethanol" and

"E85" are used interchangeably. Also, nearly all gasoline sold in Minnesota is required to contain 10% ethanol (E10). Thus, gasoline in this paper refers to E10 fuel.

The models were estimated using data collected from ethanol service stations in Minnesota, a nationwide leader in production and use of ethanol as an additive to gasoline for the last two decades. Prior to 1990, Minnesota provided a tax credit for blending ethanol into gasoline. However, the tax credit was found to negatively influence funding for transportation. The credit was classified as ineffective in increasing ethanol production and was phased out in the mid-1990s. Another state financial support program, started in 1987, provided 20 cents per gallon to in-state ethanol processors for the first 15 million gallons of annual production. Minnesota also 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 stations participated in a monthly survey conducted by the Minnesota Department of Commerce and the American Lung Association of Minnesota. By August 2013, the requirement for ethanol blend will be increased to 20% (E20) from the current 10% (E10) blend, conditional on the increase in the current up to 10% ethanol blend restrictions established by the federal government. The combination of these state financial incentives and consumption mandates aims to achieve a broader goal of securing 25% of Minnesota's energy demand from renewable sources by 2025 (Yunker 2009).

RELEVANT LITERATURE

Due to the relatively short period of ethanol availability in the marketplace and consequent data limitations, the literature on ethanol demand estimation is minimal. Anderson (2010) shows that household demand for ethanol as a close substitute for gasoline is sensitive to gasoline/ethanol relative prices. The gasoline price (cross price) elasticity of ethanol demand was estimated to be in the 2.5–3.0 range. The results were applied to study ethanol content standard related policies. A relatively recent study by Bromiley et al. (2008) analyzed factors that influence consumers' use of E85 in Minnesota. The authors concluded that estimating household demand for ethanol for the purposes of understanding their sensitivity to price changes is an important component for economic viability of the emerging ethanol industry.

In contrast, a great deal of attention has been paid to estimating price elasticity of demand for gasoline. Hughes et al. (2008) analyzed U.S. gasoline demand in two time periods—1975 to 1980 and 2001 to 2006. The short-run elasticity 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 and Glaister 2002), which report 0.27 and 0.23 for the short-term and 0.71 for the long-term price elasticity of demand. 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 elasticity.

However, none of these studies explicitly considers spatial attributes and/or provides a county-level geographic comparison for price elasticity, which has important policy implications relating to local governmental regulations for low level versus higher blends of ethanol or distributional impacts from tax policy. For example, subsidizing E85 fueling stations in Minnesota will have different impacts at the sub-state level if the price elasticity is spatially variable. The same can be said about the distributional impacts of tax policies on ethanol. Bernstein and Griffin (2006) use a dynamic demand model to investigate geographic differences in price-demand relationships at regional, state and sub-state levels. Their results showed that there are regional and state differences in 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 to analyze data that have spatial characteristics (Case 1991), including hedonic house price spatio-temporal autoregressive models (Pace et al. 1998)

and transportation spatial demand models (Henrickson and Wilson 2005). Henrickson and Wilson used a moving-window regression to estimate barge transportation demand elasticity. This approach is conceptually relevant to the geographically weighted regression (GWR) approach as it produces spatially varying parameter estimates. However, the moving-window regression introduces so-called edge effects because data points within each local grid are given a weight equal to one (thus, they are included in the regression), while those outside of grid are given a weight of a zero, which imposes limitations on capturing spatial variation between the two (Fotheringham et al. 2002).

One of the specifications considered in the non-spatial model by Anderson (2010) restricted the data to two relationships by including urban and 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 a 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 that eliminates the local spatial variations among different locations (for which data are available) in a study area.

Theoretical support for the GWR approach can be found in Schmalensee and Stoker (1999), who 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 household demand for transportation fuel. Regardless of the importance of demographic changes in preference formation, there is a lack of research investigating the influence of household composition, demographic characteristics, and location on transportation fuel demand (Dahl and Sterner 1991). Additionally, consumers' environmental perceptions regarding biofuels and their attitudes about price and performance relative to imported petroleum-based fuels may vary depending on where they live and purchase fuel—urban versus rural setting (Bromiley et al. 2008).

However, the GWR methodology is not without criticism. Although some previous findings showed that, in some cases, spatial error dependence can be considerably mitigated with the use of GWR (McMillen 2004), it does not explicitly account for spatial dependence in regression residuals (see, for example, Fotheringham et al. [2002], Paez et al. [2002], as cited in Cho et al. [2010]). Cho et al. attempted to address GWR shortcomings by calibrating a weighting scheme bandwidth to minimize spatial dependence in regression residuals. Another study investigated the issue of using time series data in GWR (Crespo et al. 2007). These authors proposed a new spatiotemporal weighting scheme using timedecay and inversevariance bandwidths, which allow interpolating local parameters not only spatially, but also throughout time.

The review of relevant literature shows that there are regional, state or sub-state differences in demand responsiveness to price changes, which exist due to spatially heterogeneous household composition, demographic characteristics and preferences, to name only a few. Meanwhile, to the best of our knowledge, there are no studies that investigate the variability of the price-demand relationship for transportation fuels at a sub-state level. In what follows, we develop a model of ethanol fuel demand, which accounts for spatial heterogeneity in price-demand relationships.

MODEL DESCRIPTION

Basic Model of Consumer Demand for Ethanol

We start with a basic demand model that draws from the works of Anderson (2010), Hughes et al. (2008), and Rask (1998). In particular, the demand for ethanol fuel is modeled as a function of own and gasoline prices (e.g., Hughes et al. 2008, Yatchew and No 2001), income and geographic location (e.g., Schmalensee and Stoker 1999), and the number of vehicles and fueling stations in a county (e.g., Anderson 2010). Given our purpose of extending the basic model of ethanol demand

into a spatial model, we also included distance variables. Distances from each fueling station to the closest of five major ethanol blending terminals in the state (e.g., consumers may choose to support the local ethanol terminal), and distances to major highways where there are higher concentrations of vehicles and thus higher demand for ethanol fuels. The logarithmic form presented in equation (1) is used for easy derivation and interpretation of elasticity estimates. Following the model in Anderson (2010)[1], the econometric model for estimating the ethanol demand basic model described above can be specified by the following equation:

$$(1)\quad \begin{aligned} lnE_{it} = \beta_0 + \beta_1 \ln(PE_{it}) + \beta_2 \ln(PG_{it}) + \beta_3 \ln(INC_{it}) + \beta_4 \ln(VEH_{it}) + \\ + \beta_5 \ln(NSTAT_{it}) + \theta_1 \ln(DISTB_i) + \theta_2 \ln(DISTH_i) + \gamma(TC_t) + \\ + \psi_1(M1) + \cdots + \psi_{11}(M11) + \varepsilon_{it} \end{aligned}$$

where E_{it} is the monthly ethanol sales for the ith E85 station throughout the period studied, PE_{it} is retail ethanol price, PG_{it} is retail gasoline price, INC_{it} is per-capita income, VEH_{it} is the number of vehicles in each county. $NSTAT_{it}$ is the number of E85 stations in each county in each period (i.e., service stations having E85 dispensers/pumps); $DISTB_i$ represents time-invariant distances from each E85 station to the nearest ethanol blending terminal; $DISTH_i$ is time-invariant distance-to-highway variable representing the distance from each E85 station to the nearest major highway node in the state; TC_t is a regional dummy variable controlling for regional effects for the Twin Cities area; and finally $M1$ through $M11$ are controls for time effects, and ε_{it} is random error term. The estimation of equation (1) allows interpreting the coefficient of ethanol price variable as own price elasticity and the coefficient of gasoline price variable as cross price elasticity of ethanol demand.

Estimating demand functions that include price among the explanatory variables is often subject to endogeneity issues. In this model, the parameter estimates will be biased if the fuel prices are correlated with unobserved characteristics embedded in the error term. As argued in Anderson (2010), many ethanol retail stations in Minnesota price ethanol at a fixed discount relative to gasoline. The fixed discounted price, which sometimes remains over lengthy periods, translates into weak or no correlation between ethanol prices and local and short-term ethanol demand shifts. To empirically test for this, the distances to major highways variable was used to instrument ethanol prices. However, using two-stage least squares (2SLS) estimation did not result in statistically significant estimates. The first-stage statistics had the following results: F(1, 6842)=3.10 p-value=0.078. Tests for endogeneity returned Durbin score $\chi(1)=31.26$, p-value=0.00 and Wu-Hausman score F(1, 6841)=31.32, p-value=0.00. Unfortunately, due to data limitations, it is not possible to examine this issue further. Anderson (2010) used interactions of logged wholesale ethanol and gasoline prices with station brand dummies, the logarithm of distance to ethanol refinery, and the logarithm of the numbers of ethanol and gasoline stations in the same county. While the first-stage summary statistics had favorable results, the overidentification test statistics were not statistically significant. Therefore, it was not possible to rule out the possibility of the instruments being jointly correlated with the error term.

Spatial Non-Stationarity

The existence of spatial non-stationarity in data violates the Gauss-Markov assumption that there is a single linear relationship with constant variance across a sample of data observations (Lesage and Pace 2009). Spatial non-stationarity is typical of any data that include geographic information (e.g., fueling station locations). Schmalensee and Stoker (1999) argued that 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 a strong effect on gasoline demand. In addition to geographically varying household composition, the existence of spatial patterns in demand can be motivated by consumers' interdependent preferences. Yang and Allenby (2003) introduced 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. The approach described in equation (1) above does not incorporate considerations of spatial patterns in household demand into the model. In what follows, the model of ethanol demand is specified such that it captures the influence of local factors.

Spatially Explicit Model of Consumer Demand for Ethanol

In this section, equation (1) is extended to a spatially weighted regression model. The GWR model accounts for spatial non-stationarity in data and allows estimating geographically varying coefficients (Fotheringham et al. 2002). It includes a spatial weighting matrix that assigns higher weights to regressors in the near locations and gradually decreases the weights as the distance from the regression point increases. The GWR model for this study can be represented in the following form (Brundson et al. 1998):

$$(2)\quad y_{it} = \beta_{0t}(\upsilon_i, v_i) + \Sigma_m \beta_{mt}(\upsilon_i, v_i) X_{it} + \Sigma_k \theta_k(\upsilon_i\ v_i) Z_i + \varepsilon_{it},$$

where y_{it} is the dependent variable (monthly ethanol sales volume) for the ith fueling station. The matrix X_{it} includes time and location-specific explanatory variables as in equation (1) (e.g., prices for ethanol and gasoline, disposable income, vehicle stock, number of stations in each county), Z_i represents the time-invariant variables (distances to major highways and blending terminals), and ε_i is the error term. The coefficients β and θ are to be estimated for each of the fueling stations at (υ_i, v_i) projected coordinates (i.e., converted from geographic coordinates). The expressions for $\beta(\upsilon_i, v_i)$ and $\theta(\upsilon_i, v_i)$ indicate that the price elasticity of demand of ethanol and the other estimates are location-specific. The estimator for this model has the following form:

$$(3)\quad \hat{\beta}(\upsilon_i, v_i) = (X' W(\upsilon_i, v_i) X)^{-1} X' W(\upsilon_i, v_i)\, y,$$

where $W(\upsilon_i, v_i)$ is a distance-based weighting matrix for expressing potential interaction among spatial units (e.g., fueling stations). One possible way to assign weights to the elements in the weighting matrix is to use a kernel that has a Gaussian shape, as shown below:

$$(4)\quad w_i = \exp[-1/2(d(\upsilon_i, v_i)/h)]^2.$$

In this weighting scheme, the $d_i(\upsilon_i, v_i)$ is of Euclidean distance, as described above, and is bandwidth. The bandwidth parameter for our distance-based weighting matrix is selected using the following cross-validation (CV) procedure:

$$(5)\quad CV = \sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(h)]^2,$$

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). In the CV equation, omitting the ith observation is necessary, otherwise the score will be minimized when h is zero, i.e., as h tends to zero, $\hat{y}_i(h)$tends to y_i, so the CV score is minimized when h is zero. A value of h that minimizes the CV score is then used as the distance-weighting bandwidth. If the ith observation and the location (υ_i, v_i) in the weighting scheme given by equation (4) coincide, i.e., if the data were observed at the location (υ_i, v_i), the weight for that point will be one. Then the weights of other locations around it will decrease according to a Gaussian curve as the distance between the two increases.

Taking the natural logarithm of both sides of equation (2), we specify the demand for ethanol at each location as follows:

$$
\begin{aligned}
lnE_{it} &= \beta_0(\upsilon_i, v_i) + \beta_1(\upsilon_i, v_i)\ln(PE_{it}) + \beta_2(\upsilon_i, v_i)\ln(PG_{it}) + \\
&+ \beta_3(\upsilon_i, v_i)\ln(INC_{it}) + \beta_4(\upsilon_i, v_i)\ln(VEH_{it}) + \beta_5(\upsilon_i, v_i)\ln(NSTAT_{it}) + \\
&+ \theta_1(\upsilon_i, v_i)\ln(DISTB_{it}) + \theta_2(\upsilon_i, v_i)\ln(DISTH_{it}) + \varepsilon_{it},
\end{aligned} \tag{6}
$$

where the variables are interpreted as in equation (1). In contrast, however, the coefficients are geographically referenced, and the model provides a "surface" of parameter estimates across the study area (e.g., the coefficient estimates are derived for each location). To estimate the model, we use the GWR tool provided under ArcMap Spatial Statistics Toolbox. The estimates then were visualized on a map using Geographic Information Systems (GIS) software.

DATA SOURCES

Ethanol price information was obtained from a survey conducted by the Minnesota Department of Commerce and the American Lung Association of Minnesota. Initial data included monthly price observations and sale volumes of individual E85 service stations in Minnesota from 1997–2009. Starting with only 10 stations in 1997, the number of E85 service stations steadily increased up to more than 330 by mid-2009. As of mid-2010, with more than 350 stations, Minnesota had the highest number of E85 stations in the nation. This makes up more than 18% of the total number of E85 stations in the U.S. (U.S. DOE Alternative Fuels and Advanced Vehicles Data Center 2009). The distribution of all E85 service stations in the United States is provided in Table 1.

Table 1: 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*

Figure 1: Geographic Distribution of E85 Service Stations in Minnesota

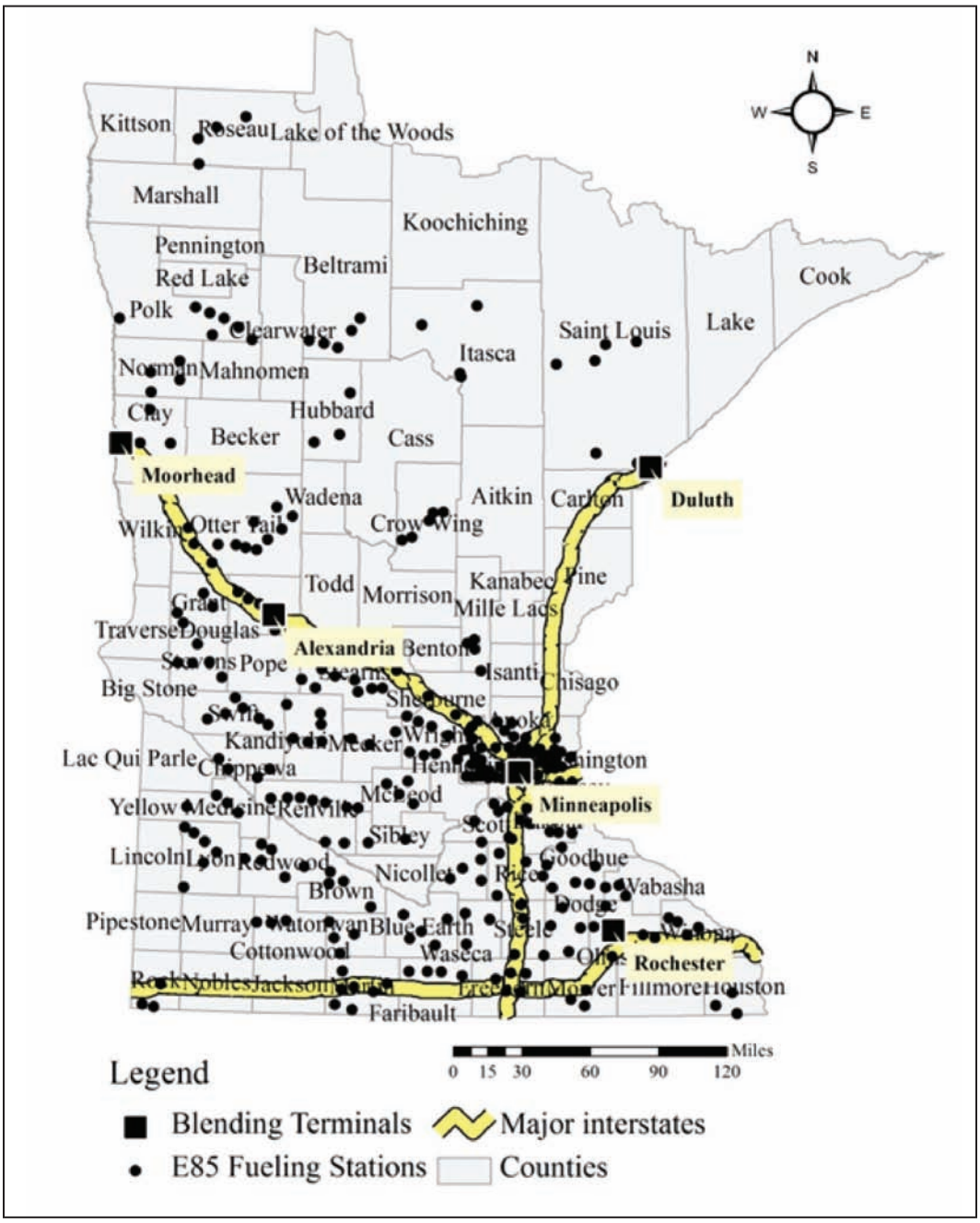


Figure 1 depicts the study area and the spatial distribution of E85 service stations. The number of E85 fueling stations in each county for each period was derived from the E85 sales dataset. Monthly observations for retail gasoline prices were averaged from the Minnesota Weekly Gasoline Retail Price Reports provided by the Energy Information Administration (Energy Information Administration 2009). In contrast to service station-level ethanol sales data, gasoline prices were only available at county-level, and only for 2000–2009. As a result, the number of observations decreased from 13,339 to 8,542.

Per-capita income information was obtained from the Federal Reserve Economic Data (FRED) state/county-level database (Federal Reserve Economic Data 2009). Vehicle stock information per county was obtained from the U.S. Census Bureau (U.S. Census 2000). A small portion of observations were dropped due to missing or not reported prices and sales volumes. The inclusion of income and vehicle stock variables available only for the 2003–2008 period restricted the number of usable observations further. As a result, the number of observations was decreased from 8,542 to 6,860, and data used in this paper are for the 2003-2008 period. Using a historical consumer price index from the Department of Labor, all fuel prices and income were converted into real 2009 prices.

GIS ArcMap software was also utilized to identify E85 fueling stations. The Minnesota road network shapefile (Minnesota Department of Transportation 2009) was overlaid with a station locations map available from the American Lung Association and Clean Air Choice organization (American Lung Association and Clean Air Choice 2008). According to data confidentiality requirements by the American Lung Association and Clean Air Choice, counties containing fewer than three service stations were excluded from the analysis. ArcMap software was used to derive distances between ethanol fueling stations and major highways in the state as well as to five ethanol blending terminals in Minnesota (Minneapolis, Alexandria, Moorhead, Rochester, and Duluth). Fuel blending terminal location information was obtained from the Oil Price Information Service (OPIS) Rack Cities guide (OPIS 2009). Table 2 provides descriptive statistics for the data used in this paper.

Table 2: Descriptive Statistics

Variables	Mean	St.Dev.	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
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

RESULTS

Basic Model Results

Table 3 provides a summary of OLS estimates from the model described above. The model was first estimated by using data for the period after the passage of the Energy Independence and Security Act of 2007 (EISA). For the entire period (2003–2008), the own price elasticity of demand was found to be 3.27, indicating a 10% increase in the price of ethanol leads to a 32.7% decrease in the quantity of ethanol demanded.

Table 3: Basic Model Estimation Results

	All Data		*Prior EISA 2007 Data*		*Post EISA 2007 Data*	
ln(PE)	-3.27	***	-2.52	***	-4.07	***
	(0.12)		(0.16)		(0.18)	
ln(PG)	4.41	***	4.73	***	4.35	***
	(0.12)		(0.17)		(0.18)	
ln(INC)	0.11	***	0.12	***	0.006	
	(0.02)		(0.03)		(0.02)	
ln(VEH)	0.29	***	0.23	***	0.43	***
	(0.01)		(0.02)		(0.02)	
ln(NSTAT)	-0.25	***	-0.21	***	-0.46	***
	(0.02)		(0.02)		(0.03)	
ln(DISTB)	0.02	**	-0.003		0.04	***
	(0.01)		(0.01)		(0.01)	
ln(DISTH)	0.01	**	0.06	***	-0.01	
	(0.01)		(0.01)		(0.01)	
Twin Cities Area	2.51	***	2.20	***	2.87	***
	(0.05)		(0.07)		(0.09)	
Greater MN	2.11	***	1.81	***	2.45	***
	(0.06)		(0.08)		(0.09)	
Month Indicators	Yes		Yes		Yes	
N	6860		3164		3696	
Adj. R-squared	0.98		0.98		0.98	

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

One of the reasons that the change in quantity of ethanol demanded is proportionately larger than the change in price (i.e., demand is elastic) is that consumers have quick access to close substitute fuel—gasoline—at almost zero search cost. In other words, every station that offers E85 also offers gasoline. Imperfect information about the environmental and economic benefits of ethanol fuels is another reason for high demand sensitivity to price increases. 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 either decreasing their consumption of ethanol fuel or by switching to gasoline.

For the post EISA period (2007–2008), elasticity was estimated to be -4.07, much higher in absolute value compared to that of the period prior to EISA (2003-2006), which was found to be -2.52. The results of two-sample t-test, (t = 46.3, p < .00), showed that there is a statistically significant difference between the two samples. One possible reason for increased demand sensitivity after the EISA was passed is that consumers became more aware about the environmental impacts from the production and use of ethanol. Provided that every ethanol station also offers gasoline, the consumers may switch to gasoline at zero search cost. The economic recession, which started in

2008, may be another plausible explanation for overall increased sensitivity to price changes for transportation fuels.

However, the demand responsiveness to gasoline price changes did not vary to the same extent (4.73 for prior, and 4.35 for post-EISA period). For the whole period (2003-2008), the estimate was 4.41, indicating that a 10% increase in the price of gasoline leads to a 44.1% increase in the quantity of ethanol demanded. The estimates for pre- and post-EISA periods (4.73 and 4.35, respectively), suggest relatively stable, sensitive ethanol demand responsiveness to gasoline price changes throughout the study period.

Income elasticity of demand for ethanol was found to be 0.11 for 2003–2008. This estimate is relatively higher than those reported in a recent study by Bromiley et al. (2008). These authors found that the influence of income levels on E85 monthly sales is minimal in magnitude and statistically insignificant. Although not directly comparable, our income elasticity estimates are lower than the estimates for gasoline, ranging from 0.47 to 0.54, as reported by Hughes et al. (2008).

The estimate for the vehicle stock variable (0.29) for 2003–2008 suggests that every 10% increase in vehicle stock will lead to only a 2.9% increase in ethanol sales. However, due to data limitations, the vehicle stock variable is a proxy for flexible fuel vehicle (FFV) stock in this analysis. Therefore, this coefficient may not fully reveal the relationship between increasing FFV stock and E85 sales levels. The estimates for pre- and post-EISA were found to be 0.23 and 0.43, respectively. According to the Minnesota Department of Public Safety registration records, the total number of passenger vehicles in Minnesota reached 3.34 million in 2006, then increased slightly to 3.4 million in 2008. Considering 125,000 FFVs in 2006 in Minnesota, as reported in Bromiley et al. (2008), the proportion of FFVs is less than 5%. Overall, the estimate is in accordance with the expectation of a positive relationship between stock of vehicles and fuel sales.

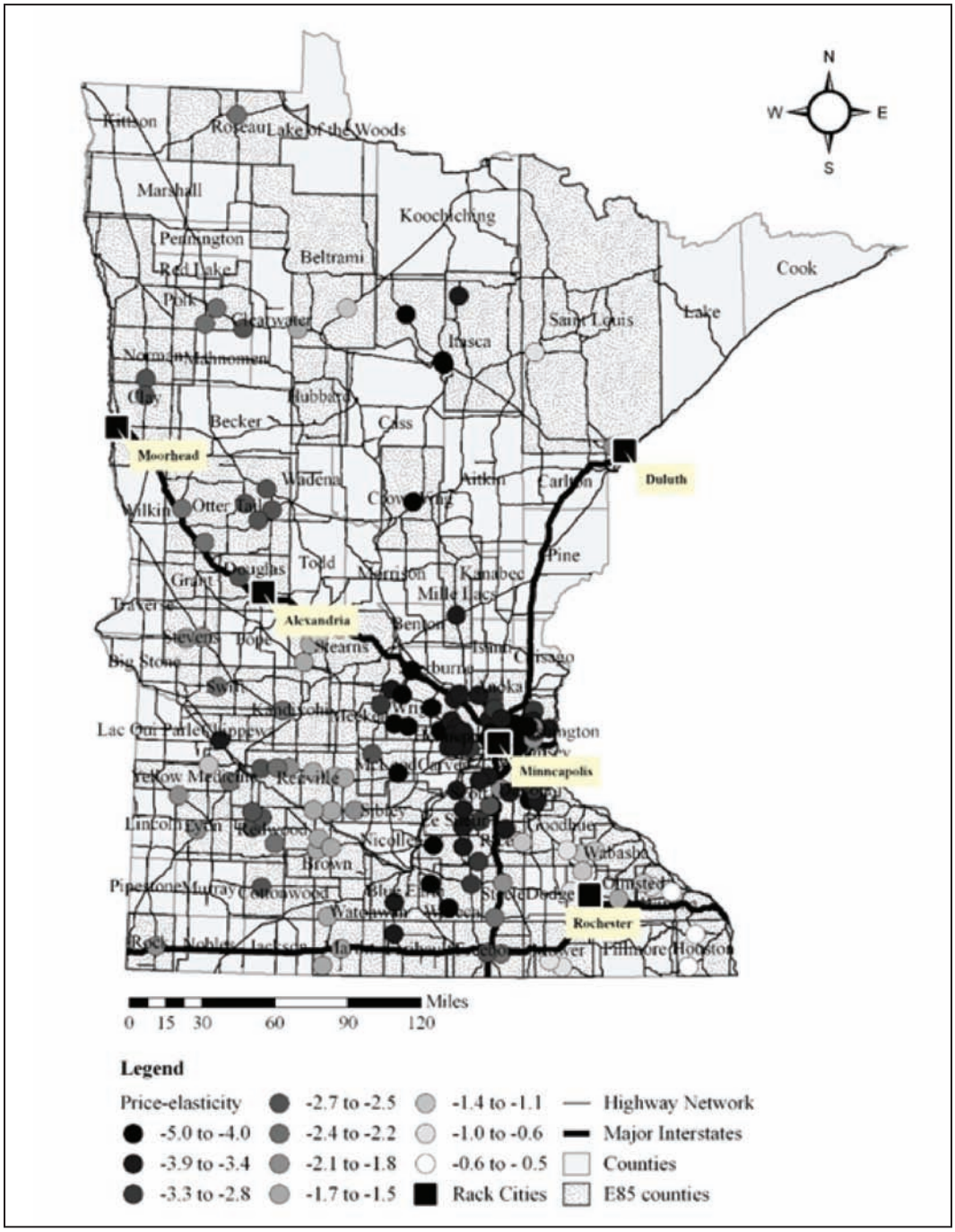
The estimates for the number of ethanol stations per county variable was in -0.25 for 2003–2008, and -0.21 and -0.46 for the pre- and post-EISA periods. The negative sign suggests that a percentage increase in the number of ethanol stations in a county will reduce ethanol sales at an individual station by 0.25% (0.21% and 0.46% for the pre- and the post-EISA periods, respectively). These results have the same negative sign, but not the same statistical significance as the estimates found in Anderson (2010).

The distance to major highways variable showed relatively weak influence on the E85 sales volume. The estimate for 2003–2008 is 0.01, and 0.06 for the pre-EISA period. The influence of distances to blending terminals in Minnesota on E85 monthly sales volume was also found to be weak (0.02 for 2003–2008 , 0.04 for post EISA period). Consumer choice behavior is mainly influenced by fuel prices, which partly reflect distance-related cost increments. This can partially explain the weak relationship of distance-related variables. Influenced by a higher concentration of fuel stations, the estimate for the Twin Cities area dummy variable is positively correlated with ethanol sales. Lastly, monthly dummy estimates (not reported here) reflect expected seasonal variation in transportation fuel demand, indicating relatively increased levels of ethanol sales during summer months.

GWR Model Results

Figure 2 illustrates spatial changes in the magnitude of price elasticity of demand for ethanol. As shown, the relationship between price and quantity demanded varies geographically. (The map includes only statistically significant coefficients.) The distribution of the estimates shows relatively higher price-sensitivity for E85 quantity demanded around the Twin Cities area as well as Itasca, Crow Wing, Nicollet, LeSueur, Blue Earth, Waseca and Faribault counties (-2.2 to -5.0). Most of the estimates in the rural areas vary from -0.5 to -2.7.

Figure 2: Spatial Distribution of Own Price Elasticity for E85 Fuel Demand in Minnesota



Overall, the estimated high elasticity ranges are consistent with our expectations, and are explained by the availability of close substitute, gasoline, at almost zero search cost (since every service station where E85 is available also offers gasoline). However, the main distinction from the first model is that the elasticity is not constant across the study area. The variation in estimates also supports motivation for the existence of spatial heterogeneity in the data structure.

The estimates in the OLS model showed that consumers are generally sensitive to both ethanol and gasoline price changes. However, the findings from the GWR model indicate that consumers' demand sensitivity to price changes varies geographically. In addition to visualizing elasticity estimates on a map, Table 4 provides a summary of estimates for comparing GWR and OLS results side by side, and shows that the OLS cross price elasticity estimate (4.35) is between the upper quartile and maximum values of the GWR results. The own price elasticity estimate from the OLS model (-3.21) falls between the minimum and lower quartile values of the GWR estimates. Spatial distribution of the own price and gasoline price elasticity estimates from the GWR model reveals that the OLS results represent only a portion of the geographic variation in price-demand relationships.

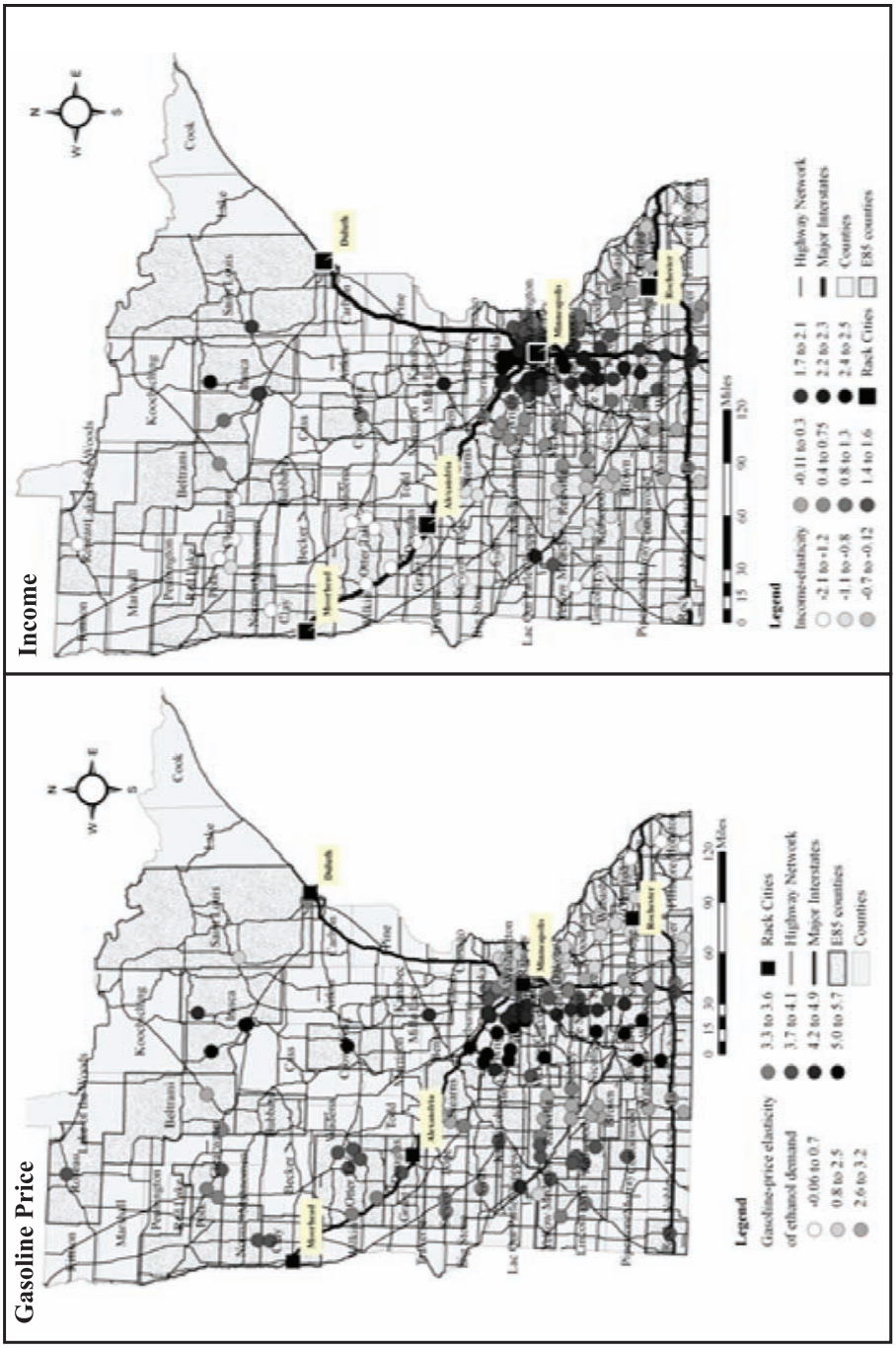
Table 4: GWR Parameter Summary and Comparison With the OLS Model Coefficients

Variables	Min	Lower quartile (25th percentile)	Median quartile (50th percentile	Upper quartile (75th percentile	Max	OLS (2003–2008)	Standard errors–OLS (2003–2008)	GWR coefficients variability statistic ($\sqrt{\rho i}$)
ln(PE)	–5.00	–2.70	–2.08	–1.40	–0.50	–3.21	0.05	1.06
ln(PG)	–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(DISTB)	–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

The statistical significance of the variation in the GWR coefficients was tested based on the following hypothesis: $H_0{:}\beta(\upsilon_i, v_i) = \beta_{OLS}$, where i indexes the fueling station locations, against $H_1{:}\beta(\upsilon_i, v_i) \neq \beta_{OLS}$. To test this hypothesis, Brundson et al. (1998) suggest measuring the variability in the GWR coefficients using the following statistics: $\rho_i = \sum_i(\beta(\upsilon_i, v_i) - \beta_{i\cdot}^2 / N$, where a dot in the subscript of the second β coefficient denotes averaging GWR coefficients over locations. The $\sqrt{\rho_i}$ for all variables in the model (the last column of Table 4) is then compared with the standard errors from the OLS model. As shown, all of the variability statistics are greater than the standard errors from the OLS model. Thus, the null hypothesis is rejected in support of the GWR model.

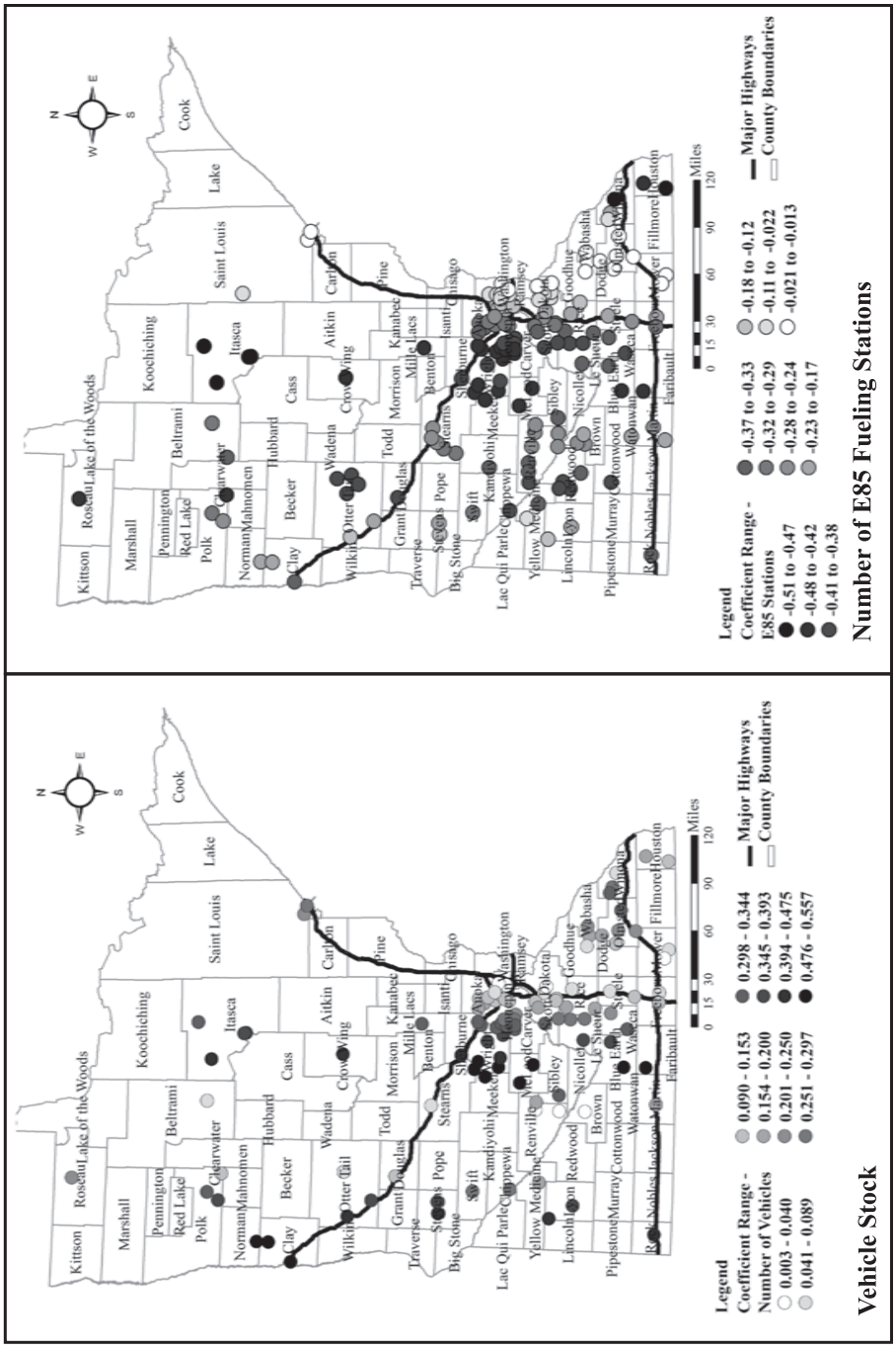
The first part of Figure 3 shows gasoline price (cross) elasticity ranges. The estimates vary from -0.06 to 5.7 across the study area. The areas that revealed high sensitivity to gasoline price changes with respect to quantity demanded for ethanol fuel are similar to those found in Figure 2. Income elasticity estimates for the Twin Cities area were found to be in the 1.4 to 2.5 range, indicating a positive relationship between income levels and ethanol consumption in the urban area. The signs of the estimates for the rest of the regions change from negative to positive, ranging from -2.1 to 1.3. According to the comparison in Table 4, the OLS estimate (0.41) for income elasticity falls between the lower and median quartiles of the GWR estimates.

Figure 3: Spatial Distribution of Gasoline (Cross Price) and Income Elasticity Estimates



The distribution of the elasticity estimates with respect to vehicle stock and the number of neighboring E85 stations is shown in Figure 4. The coefficients for vehicle stock are statistically significant and positive, thus meeting our expectations of a positive influence of vehicle availability in the close proximity to fueling stations on fuel sales. Given a small fraction of E85 compatible vehicles, the negative sign for the number of E85 fueling stations provides the size of local competition among fueling stations.

Figure 4: Spatial Distribution of Vehicle Stock and Number of E85 Fueling Station Estimates



CONCLUSIONS

Minnesota is one of the nation's leaders in per capita use of environmentally cleaner fuel alternatives, such as E85 ethanol, and understanding consumers' demand responsiveness to price changes reveals important policy implications. From the general relationship found in the first model, it was concluded that increasing the price of E85 ethanol by 10% will lead to a 32% decrease in the quantity of E85 demanded. Likewise, increasing the price of gasoline by 10% will increase the quantity of E85 demanded by 43%. These results show fundamental differences between price-demand relationships for ethanol and gasoline. The demand for gasoline is known to be inelastic. However, due to the availability of a substitute fuel in the form of gasoline, consumers are highly sensitive to ethanol price changes and can switch to the alternative at zero search cost. In addition to this general relationship, the resulting price elasticity estimates from the spatial regression model showed significant spatial variation across the study area. The demand for ethanol was found to be elastic, with estimates varying from -5.0 to -2.2 within the Twin Cities area.

Although high elasticity levels were found in a few more areas, the Twin Cities area represents the largest cluster of consumers, whose demand is responsive to price changes. With the exception of the counties described in the results section, most demand elasticities for the rural areas of the state vary from -0.5 to -2.7. Although the OLS model's static estimates showed that consumer demand for E85 is highly sensitive to prices changes, their comparison with the GWR estimates showed that the OLS model results are specific to certain geographic areas and that the coefficients vary geographically. One possible reason for this variation is that the demand function itself does not have a constant elasticity shape and follows the geographic variation in consumer preferences.

In addition to joining several regional biofuel initiative programs (e.g., the Energy Security and Climate Stewardship Platform Plan), several local private-public partnerships in Minnesota (e.g., "E85 Everywhere" campaign) propose to considerably increase E85 availability at retail fueling stations in the state. Understanding consumer demand sensitivity to price changes reveals important insights about the potential impacts of policy decisions. For example, the distributional impacts from a tax or subsidy policy depend on the price elasticity of demand, and knowing the geographic patterns of price-demand relationships indicates that some areas may be more (or less) influenced by statewide policies. The results show that the impacts of E85 tax policy will be stronger in counties with relatively higher price elasticities. Additionally, the results showed that some areas in the state are relatively more sensitive to increasing the number of service stations. This is also relevant to the consideration that the E85 grants and subsidies should vary across the state. The evaluation of these impacts is imperative as the Office of Energy Efficiency and Renewable Energy (under requirements of the Government Performance Results Act) estimates the benefits of the state's portfolio of biofuel promotion programs. The spatially variable estimates may also be useful for alternative fuel policy simulation analysis that requires consideration of a range of price-elasticities to be used in calibration. The outcome of the GWR model allows obtaining more detailed estimates, which can be used in these policy simulations with more certainty. Non-spatial econometric models emphasize similarities or regularities of data being analyzed. In contrast, a spatially disaggregated estimation approach helps to reveal differences across the study area. With this distinction, this approach may be useful for investigating regional differences in the way consumers react to price variations.

Several limitations of this study are worth mentioning. Although this 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 included in these data. Additionally, a portion of E85 sales can be attributed to households not residing in Minnesota since many E85 stations are close to major interstate highways connecting the state with the neighboring states.

Endnotes

1. Following Anderson (2010), the household's utility function in terms of transportation fuels and other goods can be represented as $U = f(Q_e + rQ_g) + X$, where Q_e and Q_g are consumption levels of close substitutes (ethanol and gasoline), r specifies the rate at which the consumer converts gallons of gasoline into ethanol-equivalent gallons, and X represents the composite good. Since gasoline and ethanol are close substitutes, the household demand is 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. Therefore, ethanol is purchased when its price is less than ethanol-equivalent fuel price, which is p_g/r. 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 ethanol-equivalent price (Anderson 2010). Relative prices influence households' decisions in choosing between gasoline and ethanol. However, the quantity demanded still depends on the absolute levels. For the consumer who owns a flexible fuel vehicle (FFV that uses both gasoline and ethanol), this approach allows the quantity of ethanol demanded to be expressed as $d(p_e)$. The household demand for ethanol can be aggregated by assuming that out of households that own vehicles, ϕ fraction own FFVs. It is also assumed that each household owns a single vehicle. Further, it is assumed that the 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 fuel-switching ratio is less than the relative price, the portion of households that chooses ethanol is the function evaluated at $H(p_g/p_e)$. Given these assumptions, the aggregate demand for ethanol, as represented in Anderson (2010), takes the following form $E(p_e, p_g) = N\phi \int_0^{p_g/p_e} d(p_e)dH(r) = N\phi H\left(\frac{p_g}{p_e}\right) d(p_e)$, where the total number of households, N, is multiplied by the fraction that own FFVs (ϕ), multiplied by the fraction of those FFV owners who choose ethanol (which, as shown in the equation above, 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 (Anderson 2010). Further, the following logarithmic aggregate demand model can be used to derive the price elasticity of demand for ethanol, and gasoline price elasticity (cross price) of demand for ethanol $lnE(p_e, p_g) = lnN\phi + lnH\left(\frac{p_g}{p_e}\right) + lnd(p_e)$.

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