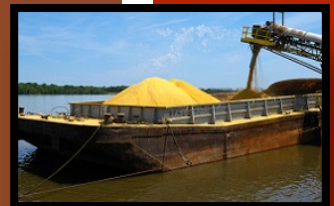# FREIGHT

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## Spatial and Temporal Differences in Price-Elasticity of Demand for Biofuels

WASHINGTON STATE UNIVERSITY

FPTI

# Spatial and Temporal Differences in Price-Elasticity of Demand for Biofuels

FPTI Research Report Number 5

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**Spatial and Temporal Differences in Price-Elasticity of Demand for Biofuels**

Abstract

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 I present an alternative approach to studying this problem by estimating geographic variations in price-elasticities of demand for ethanol across the study area, 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 global estimates to explain price-demand relationships over a large geographic area may lead to biased results. I demonstrate that a spatially weighted regression technique provides superior estimates to a global regression model. Resulting price-elasticities of demand for ethanol 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 leading change in the ethanol industry.

# 1 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),[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 use of higher blends of ethanol (e.g., E85, 85% ethanol and 15% gasoline)[2] 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 Government Performance Results Act (GPRA), the Office of Energy Efficiency and Renewable Energy (EERE) estimates benefits of their portfolio 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 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, I estimate temporal and spatial variations for own-price and cross-price elasticity (gasoline-price elasticity) of demand for ethanol in Minnesota. In previous studies of ethanol demand, price-elasticity of demand for fuels was assumed to be constant across the study area (Anderson 2008; Hughes et al. 2008; Yatchew

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[1] The Renewable Fuel Standard is a key provision of the Energy Independence and Security Act (EISA) of 2007, a government policy designed to secure roughly one-third of U.S. transportation fuel consumption.
[2] Henceforth, "E85" and "ethanol" are used interchangeably.

and No 2001; Schmalensee and 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 sales volumes of 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 show evidence for spatial autocorrelation in regression residuals from OLS and 2SLS specifications. The spatial structure of data indicates that the value of dependent variable in one spatial unit (a service station in this case) is affected by independent variables in nearby units. Thus, the assumption of normally and independently distributed error terms when employing ordinary least squares (OLS) regression is violated with the existence of spatial autocorrelation. This indicates that non-spatial methods can lead to biased and inefficient parameter estimates (Lesage and Pace 2009). 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 (i.e., OLS) regression models.

I utilize 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 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. 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 stations participated in a monthly survey conducted by Minnesota Department of Commerce and American Lung Association of Minnesota.  Nearly all 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.  The Theoretical Framework section introduces a basic model of household demand for close substitute fuels (gasoline and ethanol).  This section also incorporates spatial patterns in price-elasticity into the model.  In the section titled Empirical Model 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 subsection, including a map that shows distribution of service stations in relation to five ethanol blending terminals (racks) and major highways in Minnesota. The remaining sections report and compare basic and spatial model results. The geographically weighted regression (GWR) estimates were used to visualize variation of price-elasticity estimates across time and space in the study area.  I conclude by discussing implications of my findings on state-level ethanol policies and for continued research in this realm at the national-level in the Policy Implications and Conclusions section.

## 2 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 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 sensitivity to price changes is an important component for economic viability of the emerging ethanol industry. Schmalensee and 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 household demand for transportation fuel. 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 (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 and 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 county-level geographic comparison for price-elasticities, which has important policy implications related to local governmental regulations for low-level vs. higher blends of 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. The 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 has spatial characteristics (Case 1991), including hedonic house price spatiotemporal autoregressive models (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 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.

## 3 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 model 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 levels of close substitutes (ethanol and gasoline), and $X$ represents the composite good. Consumers' fuel choice decisions depend on the difference between gasoline and ethanol fuels. 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, and $r$ (alternatively called fuel-switching price ratio) specifies the rate at which the consumer converts gallons of gasoline into ethanol-equivalent gallons. 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 2008).

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), I allow 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 $N$ households that own vehicles, $\phi$ fraction own FFVs. 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 fuel-switching ratio

is less than the relative price, the portion of households that choose ethanol is the function

evaluated at $H(p_g/p_e)$. Given these assumptions, the aggregate demand for ethanol, as

represented in (Anderson 2008), 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 ($\phi$),

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 level of ethanol consumption by

households that choose ethanol, which is a function of absolute price of ethanol (Anderson

2008). Further, the following logged aggregate demand model then can be used to derive the

price-elasticity of demand for ethanol, and gasoline-price elasticity (cross-price) of demand for

ethanol

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

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 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 consumers' 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.

In our analysis, the model of ethanol demand can be specified such that it captures the influence of local factors. 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.

## 4 EMPIRICAL MODEL

### 4.1 Basic Model of Consumer Demand for Ethanol

The model of consumer demand for ethanol in Minnesota uses sales volume and price data reported by more than 300 service stations over 12-year period. The econometric model for estimating the ethanol demand basic model described above can be specified by the following equation

(3) $$y_{it} = \beta_0 + \sum_m \beta_m X_{it} + \theta Z_i + \gamma_i + \psi_t + \varepsilon_{it}$$

where $y_{it}$ is the monthly ethanol fuel sales volume for location $i$ (service station) and time $t$ (months), $X_{it}$ is a matrix of explanatory variables. For each of the locations, the regressors included in the $X_{it}$ capture county/station-specific characteristics, such as retail ethanol prices, retail and wholesale gasoline prices, the number of fueling stations that offer E85, per-capita disposable income, and number of vehicles. Matrix $Z_i$ represents time-invariant station-specific variables, such as service stations' distance to ethanol blending terminals (alternatively called racks) and stations' distance to the state's major highways. The $\gamma_i$ represents the regional dummy (e.g., rural vs. urban), $\psi_t$ represents unobserved demand factors that vary at the month

level, and $\varepsilon_{it}$ 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. Therefore, according to this specification, any geographic variations of the relationships between $y_{it}$ and the parameters are captured in the error term. The focus of the next section is addressing these spatial variations in the model.

### 4.2 Identification Issues and Spatial Non-Stationarity

Estimating demand functions that include price among the explanatory variables is often subject to endogeneity issues. In my model, the parameter estimates will be biased if the fuel prices are correlated with 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, 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 local ethanol demand shifts are not correlated with individual (i.e., fueling station) price variations. Conditional on the argument above, OLS estimation results will not be biased.

Another concern is possible spatial autocorrelation in my data, which conflicts with the assumption of normally and independently distributed error terms in the model. "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

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

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 spatial dependence can be related to E85 station locations (e.g., proximity to ethanol blending terminal or to major highways in the study area).

The second problem is spatial heterogeneity, which violates another Gauss-Markov assumption that a single linear relationship with constant variance exists across the sample data observations. As shown in equation (5), local relationships can be modeled for each service station in the study area

(5) $$y_i = X_i \beta_i + \varepsilon_i, \quad i = 1, \dots, n$$

where $y_i$ is the dependent variable at location $i$ (indexed as $i = 1, \dots, n$ points in space), $X_i$ is a vector of explanatory variables, $\beta_i$ is the associated set of parameters to be estimated, and $\varepsilon_i$ is a stochastic disturbance term.

I calculated the Moran's $I$ statistic (Moran 1950) for residuals from the OLS regression (11). Results represented in the Results section revealed a moderate spatial correlation in OLS residuals, with statistically significant Moran's $I$ statistic varying from 0.115 to 0.17. The GWR model, which allows spatial variation of underlying data structure, should largely eliminate the

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problem of spatial autocorrelation in the error term. To confirm validity of the GWR approach, the Moran's *I* statistic for OLS/2SLS and GWR model residuals are compared in the GWR Model Estimation section.

### 4.3 Spatially Explicit Model of Consumer Demand for Ethanol

In this section I extend the econometric model (3) 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 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, which eliminates the local spatial variations among different locations (for which data are available) in the study area.

The GWR model that I utilize to estimate spatially varying price-elasticity coefficients is a relatively recent methodology that accounts for spatial non-stationarity in data (Fotheringham et al. 2002). The GWR methodology 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. In my spatially weighted model, the regression points are service stations. 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 notation in Fotheringham et al. (2002), I specify

demand for ethanol fuel at each location from which the data were drawn as the following

$$
(6) \qquad y_{it} = \beta_{ot}(v_i, v_i) + \sum_m \beta_{mt}(v_i, v_i)X_{it} + \sum_k \theta_k(v_i, v_i) Z_i + \varepsilon_{it}
$$

where $y_{it}$ is the dependent variable (monthly ethanol sales volume) for each of the $i$th 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 $\varepsilon_i$ is the error term. Coefficients

$\beta$ and $\theta$ are to be estimated for each of the fueling station at $(v_i, v_i)$ projected coordinates (i.e.,

converted from geographic coordinates). The expressions for parameters $\beta(v_i, v_i)$ and

$\theta(v_i, v_i)$ 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

$$
(7) \qquad \hat{\beta}(v_i, v_i) = (X'W(v_i, v_i)X)^{-1}X'W(v_i, v_i)y
$$

where $W(v_i, v_i)$ is a distance-based weighting matrix for expressing potential interaction among

spatial units (e.g., fueling stations). One way to assign weights to the elements in the weighting

matrix is using the following relationship

$$
(8) \qquad w_i = \begin{cases} 1 & if \ \ d(v_i, v_i) < h \\ 0 & otherwise \end{cases}
$$

where the $d(v_i, v_i)$ is a measure of Euclidean distance between the $i$th observation and the

location $(v_i, v_i)$ (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. One possible way of calculating it is according to a kernel that has a

Gaussian shape:

(9)
$$w_i = exp[-1/2(d(v_i, v_i)/h)]^2$$

In this weighting scheme, the $d_i(v_i, v_i)$ 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

(10)
$$CV = \sum_{i=1}^{n}[y_i - \hat{y}_{\neq i}(h)]^2$$

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).[3] A value of $h$ that minimizes the *CV* score is then used as the distance-weighting bandwidth. If the $i$th observation and the location $(v_i, v_i)$ in weighting scheme (9) coincide, i.e., data were observed at location $(v_i, v_i)$, the weight for that point will be unity. Then the weights of other locations around it will decrease according to a Gaussian curve as distance between the two increases.[4] The spatial kernel represented in (9) 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).

## 5 DATA SOURCES

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 of 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 by mid 2009. As of September 2009, Minnesota had the highest

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[3] 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 $h = 0$.
[4] 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 nation (351). 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).[5]

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.

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).

**Figure 1:** Gasoline and ethanol retail prices

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[5] For the distribution of all E85 service stations in the U.S. see Table 4 in the Appendix.
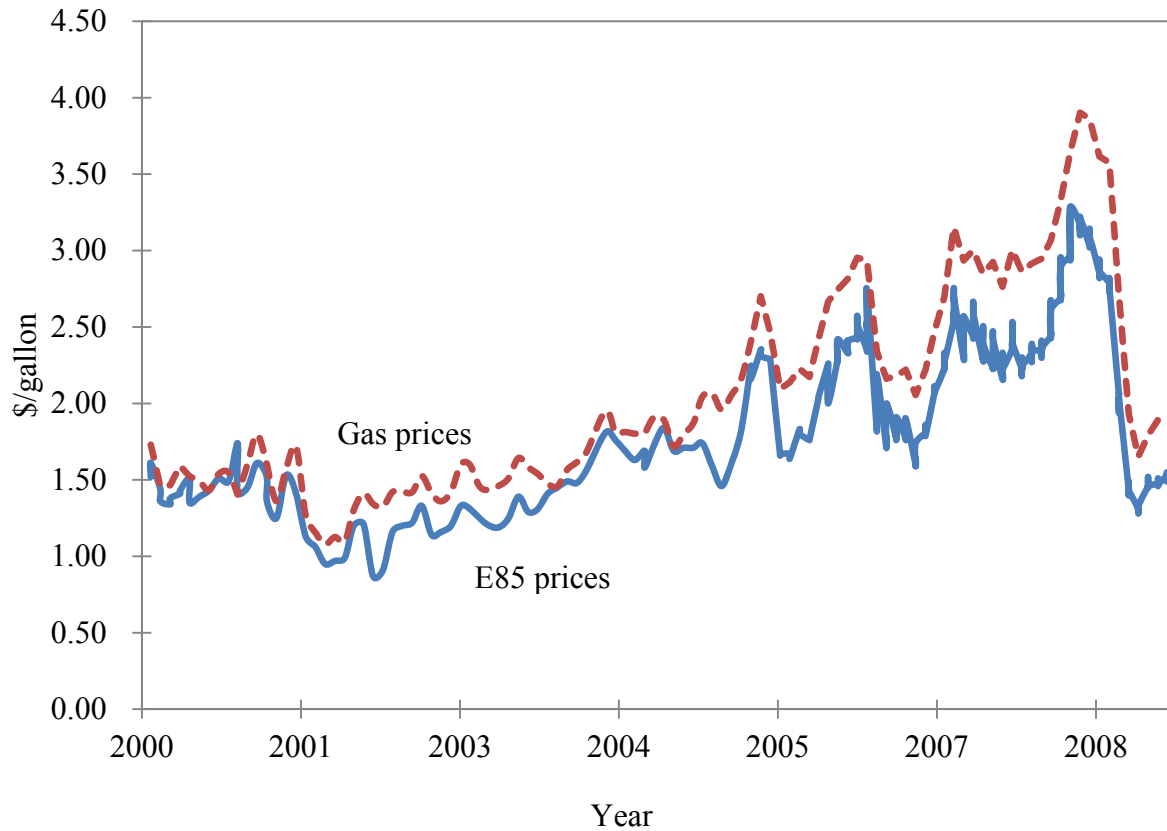
Per-capita income information (converted into 2009 dollars) was obtained from the
Federal Reserve Economic Data (FRED) state/county-level database. Time series of the number
of vehicles per county was obtained from Driver and Vehicle Services at the Minnesota
Department of Public Safety.  A small portion of observations were dropped due to missing or
not reported prices and sales volumes.  The inclusion of income and 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 spatial distribution of E85 service stations included in my analysis, in which some level
of local clustering can be observed around the Twin Cities area.

**Figure 2:** Geographic distribution of E85 service stations in Minnesota in 2009

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.

I also used Minnesota's highway network GIS shapefile[6] and station locations available from the American Lung Association and Clean Air Choice organization.[7] Table 1 provides descriptive statistics for the data used in this paper.

**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 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 |

# 6 RESULTS

## 6.1 Basic Model Results

First, I estimate the model of aggregate ethanol demand as specified in the equation (3). 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, $\gamma_i$ and $\psi_t$ represent regional and monthly dummy variables respectively. The equation (3) can be represented as the following

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

[7] 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

$$(11) \quad lnE_{it} = \beta_0 + \beta_1 \ln(PE_{it}) + \beta_2 \ln(PG_{it}) + \beta_3 \ln(INC_{it}) + \beta_4 \ln(VEH_{it}) +$$

$$+\beta_5 \ln(NSTAT_{it}) + \theta_1 \ln(DISTR_i) + \theta_2 \ln(DISTH_i) + \gamma(TC) +$$

$$+\psi_1(M1) + \cdots + \psi_{11}(M11) + \varepsilon_{it}$$

where $E_{it}$ is the monthly ethanol sales for all participating E85 stations throughout the time

period, $PE_{it}$ is the retail ethanol price (that was instrumented with wholesale gasoline prices in

the 2SLS regression), $PG_{it}$ is the retail 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 in each county in

each time period (i.e., service stations having E85 dispensers/pumps). $DISTR_i$ represents time-

invariant distances from each E85 station to the nearest ethanol blending terminal; $DISTH_i$ is

time-invariant distance-to-highway variable representing distance from each E85 station to the

nearest major highway node in the state. $TC_t$ is a regional dummy variable controlling regional

effects for the Twin Cities area. Finally, $M1$ through $M11$ are controls for time effects, and $\varepsilon_{it}$ is

the random error term.

Table 2 provides a summary of OLS/2SLS estimates from the model described above.[8] I

estimated the model for the whole time period, as well as separating data for the prior and post

Energy Independence and Security Act of 2007 periods. The own-price elasticity of demand was

found to be -3.21 for the 2003-2008 period, and -3.33 for the 2SLS model, indicating a ten

percent increase in the price of ethanol leads to 32.1 and 33.3% decrease in the quantity of

ethanol demanded respectively.

**Table 2:** Basic Model Estimation Results

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[8] 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.

| Dep. Var. = LN(ethanol monthly sales) | | | | |
|---|---|---|---|---|
| | 2003-2008 (OLS) | 2003-2006 (OLS) | 2007-2008 (OLS) | 2003-2008 (2SLS) |
| LN(PE) | -3.21*** | -2.60*** | -4.11*** | -3.33*** |
| | (0.05) | (0.09) | (0.09) | (0.06) |
| LN(PG) | 4.35*** | 4.67*** | 4.36*** | 4.22*** |
| | (0.12) | (0.17) | (0.18) | (0.12) |
| LN (INC) | 0.41*** | 0.66*** | 0.17* | 0.25*** |
| | (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 (Twin Cities area) | 2.51*** | 2.19*** | 2.88*** | 2.49*** |
| | (0.05) | (0.07) | (0.09) | (0.02) |
| Month. Dummies | y | y | y | y |
| N | 6860 | 3163 | 3697 | 6860 |
| Adj. R-squared | 0.43 | 0.47 | 0.45 | 0.43 |
| Moran's *I* Statistic | 0.165 | 0.115 | 0.112 | 0.170 |
| Z-score | 3.98 | 3.21 | 2.58 | 4.00 |
| P-value | 0.000 | 0.000 | 0.000 | 0.000 |

***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 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. 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 ethanol fuel or by switching to gasoline. The estimate for post EISA period (2007-2008) was estimated to be -4.11, much higher in absolute value compared to prior to EISA period (2003-2006) estimate of -2.60.

Gasoline-price elasticity of ethanol demand was estimated to be 4.35 for the whole period (2003- 2008); 4.67 and 4.36 for prior and post EISA periods, suggesting relatively stable, sensitive ethanol demand-responsiveness to gasoline prices changes throughout the study period. Gasoline-price elasticity derived from the 2SLS model is in a similar range (4.22), indicating a 10% increase in the price of gasoline leads to 42.2% increase in the quantity of ethanol demanded. Income-elasticity of demand for ethanol was found to be 0.41 for the 2003-2008 period. This estimate is consistent with 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 estimates found in (Hughes et al. 2008), which reports income-elasticity of gasoline demand in the 0.47 to 0.54 range.

The estimate for vehicle stock variable (0.29) for the 2003-2008 period suggests that every 10% increase in vehicle stock will lead to only 2.9% increase in ethanol sales. However, due to data limitations I am using a conventional vehicle stock variable as a proxy for FFV stock in my analysis. Therefore, this coefficient may not fully reveal the relationship between increasing FFV stock and E85 sales levels. The estimates for prior and post EISA periods was found to be 0.22 and 0.43, respectively. According to 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 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 my expectation of a positive relationship between stock of vehicles and fuel sales.

The number of ethanol stations per county estimate resulted in -0.27 for 2003-2008, and -0.22 and -0.47 for prior and post EISA periods. Consistent with previous findings (Anderson 2008), the negative sign suggests that a 10% increase in number of ethanol stations in a county will reduce existing neighbor station E85 sales by 2.7, 2.2 and 4.7% respectively.

The distance to a major highway variable showed relatively weak (0.02, 2003-2008 data; 0.07, 2003- 2006 data) influence on the E85 sales volume. Generally, retail gasoline prices are positively correlated with distance from source of supply (i.e., refineries, blending terminals, pipelines, ports, etc.) as distribution costs increase with distance. However, retail ethanol is primarily shipped to service stations from blending terminals located near large consumption areas. Also, major highways are positively correlated with local clusters of regular gasoline stations and relatively dense traffic of both conventional vehicles and FFVs. This suggests that there is more demand for regular gasoline at locations around or in close proximity to major highways. Therefore, ethanol stations that are near major highways may sell less E85 compared to those located further away.

The influence of distances to blending terminals in Minnesota on E85 monthly sales volume is slightly weaker than that of distance to highway variable described above (0.02, 2003-2008 data; 0.03, 2007-2008 data). All five blending terminals are located close to 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 distance to racks variable on E85 sales. The estimate for regional dummy variable TC (Twin Cities) is positively correlated with ethanol sales. Lastly, monthly dummy estimates (not

reported here) reflected expected seasonal variation in transportation fuel demand, indicating

relatively increased levels of ethanol sales during summer months.

### 6.2    GWR Model Results

In this section I estimate and visualize the spatial extension of the ethanol demand model

described in the Spatially Explicit Model of Consumer Demand for Ethanol.  Considering the

variable descriptions ($X_{it}$ includes ethanol and gasoline retail prices, per-capita income, number

of vehicles, and number of stations offering ethanol, $Z_i$  represents time-invariant distances to

blending terminals and to highways, $\gamma_i$ and $\psi_t$ represent regional and monthly dummy variables

respectively), the GWR model (6) can be represented as

$$(12) \quad lnE_{it} = \beta_{ot}(v_i, v_i) + \beta_1 ln(v_i, v_i)PE_{it} + \beta_2 ln(v_i, v_i)PG_{it} + \beta_3 ln(v_i, v_i)INC_{it} +$$

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

Note that the model does not include binary variables as GWR allows explanatory variable

coefficients to vary across the study area. Thus, 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 ethanol stations in Minnesota included in this study.  Figure 3

illustrates spatial changes in magnitude of price-elasticity of demand for ethanol for 2008.  The

coefficient estimates covering the full time period are included in Figure 8 of the Appendix.

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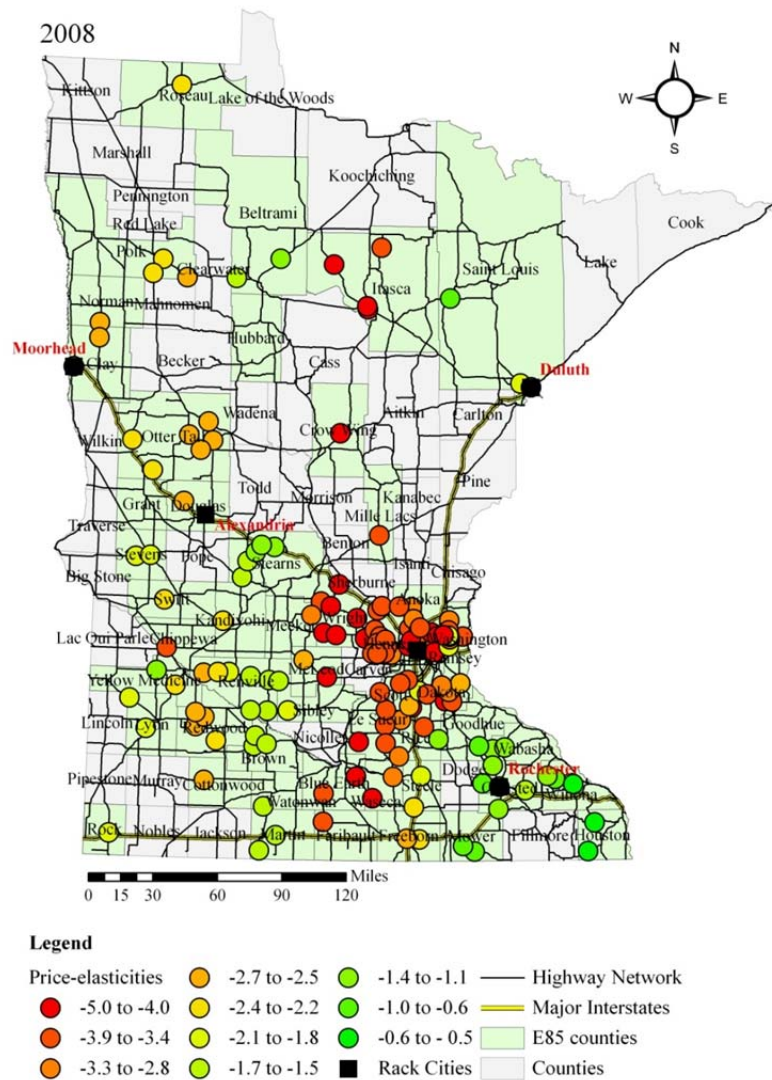


With a few outliers in Itasca County in the northern part of the state, the figure shows elastic

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 my

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

estimates also supports motivation of the existence of spatial heterogeneity in the data structure.

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 my analysis assumes only gasoline and ethanol fuels, the cross-price elasticity is comparable to elasticity of Minnesota's ethanol market share. The estimates in OLS/2SLS estimation showed that consumers are generally highly sensitive to both ethanol and gasoline price changes. However, my findings from the GWR model indicate that consumers' demand-sensitivity to price changes widely varies geographically.

In addition to visualizing own- and cross-price elasticities in a map, Table 3 provides a summary of estimates for comparing 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 (-3.21) 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.

**Figure 4:** Gasoline-price elasticities of ethanol demand
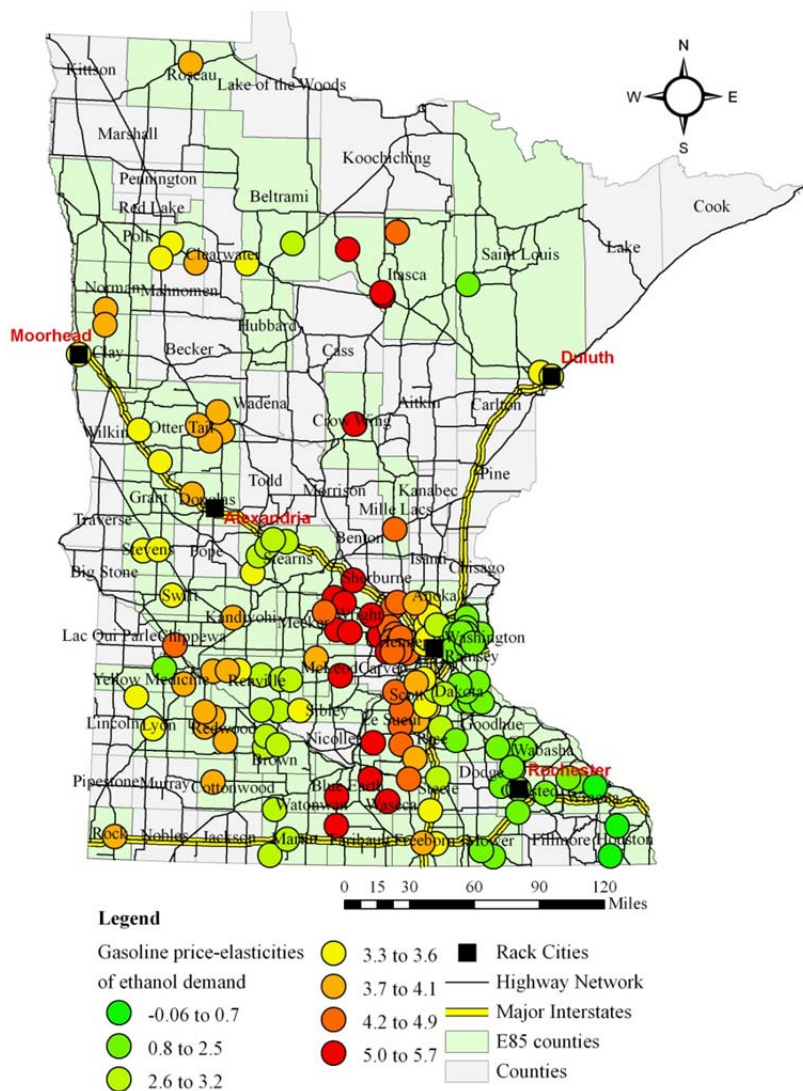


Income-elasticities for the Twin-Cities area were found in the 1.4 to 2.5 range (Figure 5), indicating a positive relationship between income levels and ethanol consumption in the urban area. The estimates for the rest of the regions change from negative to positive sign, ranging from -2.1 to 1.3. According 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 coefficients

| 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 | −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(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 OLS estimates. Comparison of estimates across all variables shows that OLS results are representative of only a segment of the entire range of elasticity estimates.

I test the following hypothesis: $H_0: \beta(v_i, v_i) = \beta_{OLS}$ where $i$ indexes the locations, against $H_1: \beta(v_i, v_i) \neq \beta_{OLS}$. To test this hypothesis, Brundson et al. (1998) suggest to measure variability of GWR coefficients (price-elasticities in this case) using the following statistics: $\rho_i = \sum_i (\beta(v_i, v_i) - \beta_{i.})^2 / N$, where a dot in the subscript of the second $\beta$ coefficient denotes averaging GWR coefficients over $N$ locations. The $\sqrt{\rho_i}$ for all 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
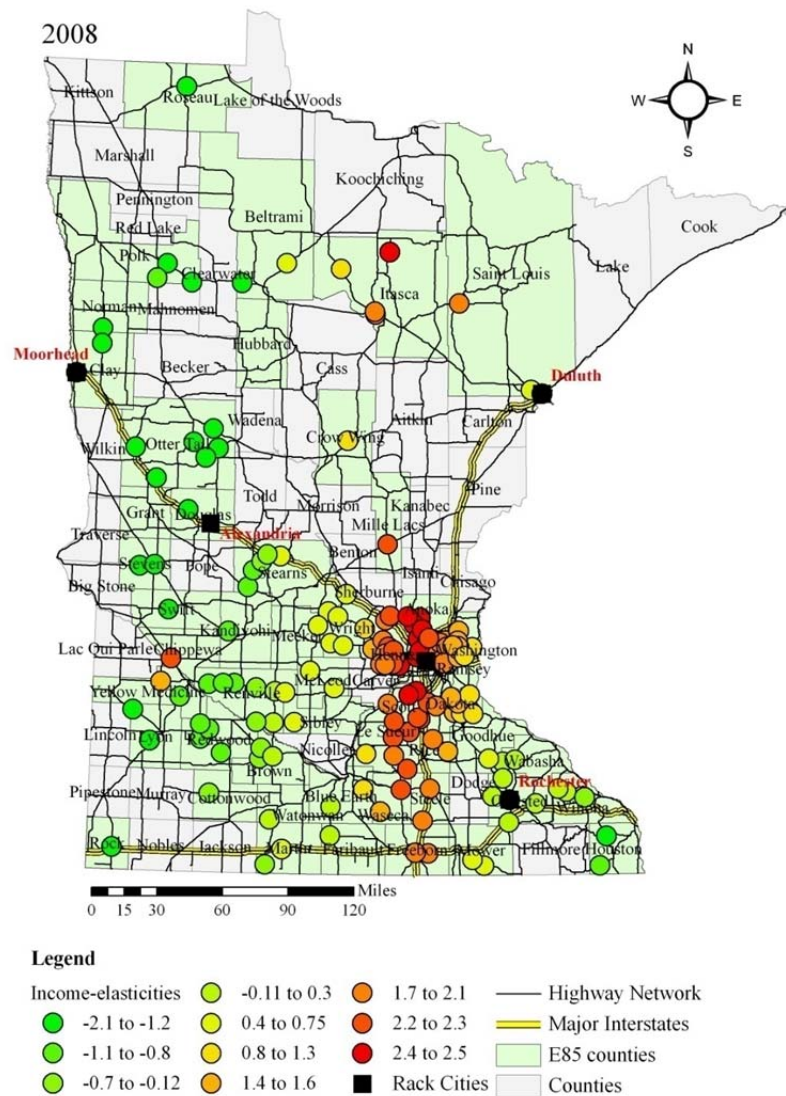


As shown in Table 3, all of the variability statistics are greater than the standard errors from OLS/2SLS models, suggesting an improvement upon the conventional estimation method. Additionally, I tested residuals from the GWR for spatial dependence. The global Moran's *I* statistic is used to check for spatial dependence in the residuals from the OLS model, and takes the following form (Moran 1950)

(13)
$$I = \frac{N \sum_i \sum_j W_{i,j}(X_i - \bar{X})(X_j - \bar{X})}{(\sum_i \sum_j W_{i,j}) \sum_i (X_i - \bar{X})^2}$$

The localized version of the same statistic for testing the residuals from the GWR model takes the following form, and is mapped in Figure 7 of the Appendix.

(14)
$$I_i = \frac{(X_i - \bar{X}) \sum_j W_{i,j}(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2 / N}$$

The Moran's *I* statistic for OLS models was found to be statistically significant, ranging between 0.165 to 0.17. The test for GWR model residuals (see Figure 7) shows that spatial dependence has almost been eliminated. This provides additional evidence for the advantage of estimating price-elasticities with the GWR specification.

## 7    POLICY IMPLICATIONS AND CONCLUSIONS

The primary objective of this study was to estimate a spatially explicit version of ethanol demand model. The resulting price-elasticity estimates from the GWR model showed significant spatial variation in 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. Most of the estimates for 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, temporal variation in price-elasticity of demand for ethanol was found to be less in magnitude. However, 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 visualized GWR elasticity estimates showed that OLS model results can be attributed to only certain geographic areas.

My findings of 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%; 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 potential sources of biomass for cellulosic ethanol and other low-carbon fuels production.

Additionally, under requirements of the Government Performance Results Act (GPRA), the Office of Energy Efficiency and Renewable Energy (EERE) estimates benefits of their portfolio of biofuel promotion programs. Those evaluations are used to assess overall cost-effectiveness and for the allocation of program budgets (Bernstein and Griffin 2006). The development of the E85 infrastructure in Minnesota is one such program. Therefore, the estimates found in this study may be useful for policy determination in the region.

As mentioned above, cellulosic biofuels development in the region is another key component for the regional biofuel promotion plan. In contrast to corn-based ethanol, cellulosic feedstocks are geographically dispersed. So, cellulosic ethanol costs (and thus retail prices) are sensitive to feedstock transportation and processed fuel (pure ethanol) distribution costs (Khachatryan et al. 2009). Because of variable geographic distribution of biomass resources, ethanol processing plant least-cost location decisions are a key consideration. Should the

processing plant be located near feedstock sources or close to end-use markets?  One component

that is necessary for solving this spatial optimization problem is to understand consumers'

location-specific demand-responsiveness to price changes.  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 (existing)

station-specific sales of 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 this 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, 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 volumes observed in this 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).

In future research, I plan to simulate ethanol policy effects on environmental emissions

reduction in Minnesota.  From a methodological perspective, for future research it will be useful

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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**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)

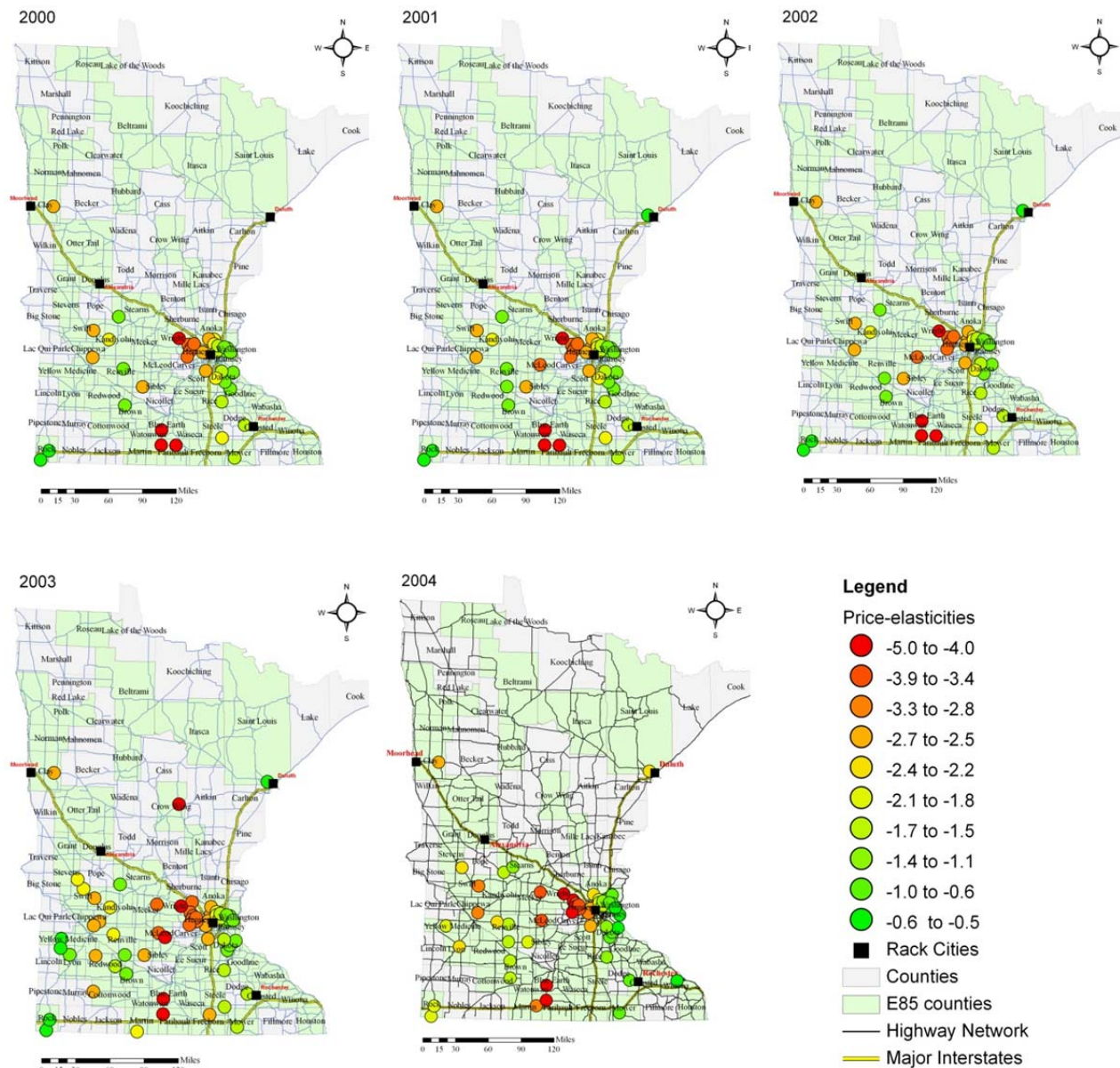**Figure 6:** Geographically Weighted Regression - Local R-squares Map
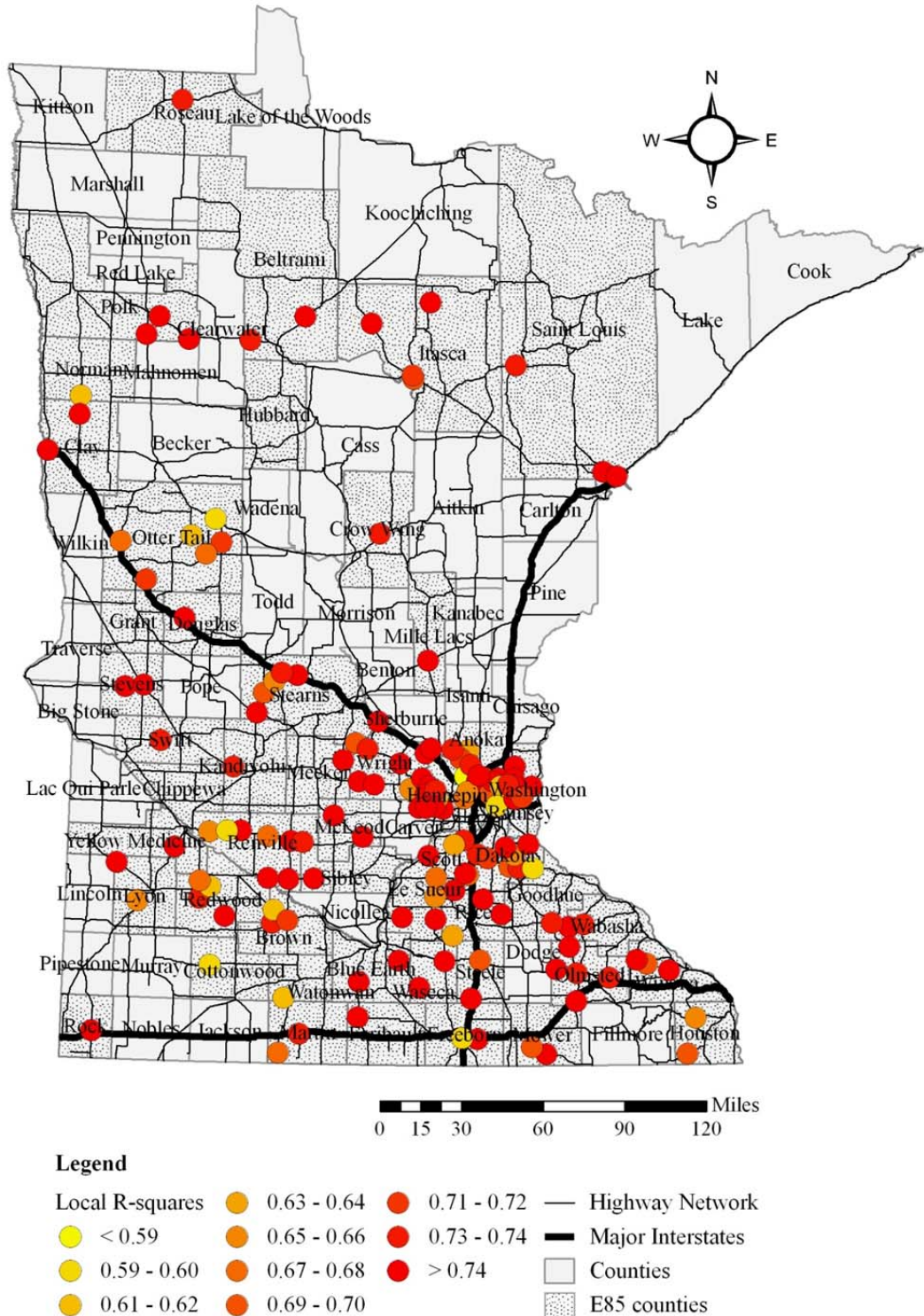
**Figure 7:** Localized Version of Moran's *I* Statistic for GWR Model
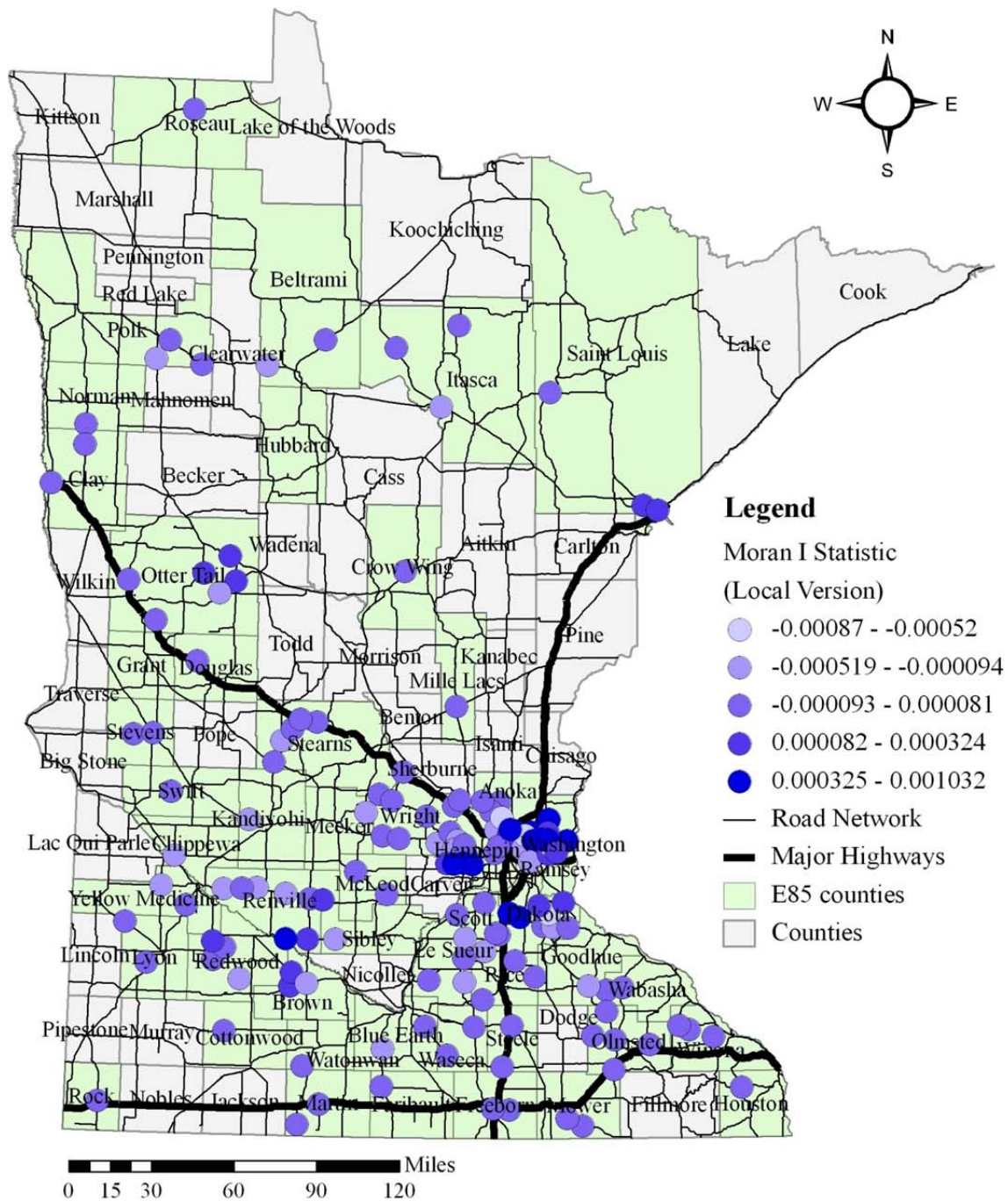
**Figure 8:** Spatial distribution of price-elasticity of demand for ethanol in Minnesota (2000-2008)

a)



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

b)