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Assessing Public Preferences for Forest Biomass Based Energy in the Southern United States

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Abstract This article investigated public preferences for forest biomass based liquid biofuels, particularly ethanol blends of 10% (*E10*) and 85% (*E85*). We conducted a choice experiment study in three southern states in the United States: Arkansas, Florida, and Virginia. Reducing atmospheric CO_2, decreasing risk of wildfires and pest outbreaks, and enhancing biodiversity were presented to respondents as attributes of using biofuels. Results indicated that individuals had a positive extra willingness to pay (WTP) for both ethanol blends. The extra WTP was greater for higher blends that offered larger environment benefits. The WTPs for *E10* were \$0.56 gallon^{-1}, \$0.58 gallon^{-1}, and \$0.48 gallon^{-1}, and for *E85* they were \$0.82 gallon^{-1}, \$1.17 gallon^{-1}, and \$1.06 gallon^{-1} in Arkansas, Florida, and Virginia, respectively. Although differences in WTP for *E10* were statistically insignificant among the three states, significant differences were found in the WTP for *E85* between AR and FL and between AR and VA. Preferences for the environmental attributes appeared to be heterogeneous, as respondents' were willing to pay a premium for *E10* in all three states to facilitate the reduction of CO_2 and the improvement of biodiversity but were not willing to pay more for *E85* in order to enhance biodiversity.

Keywords Biofuels · Choice experiment · Willingness to pay

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Introduction

Currently, around 26% of the total energy used in the United States (U.S.) is imported, and 84% of the imports are represented by crude oil and petroleum products (EIA 2009). Further, 46% of the petroleum imports come from the Organization of the Petroleum Exporting Countries (OPEC) (EIA 2009). The transportation sector was the largest consuming sector of petroleum in 2008, at 13.7 million barrels day^{-1} (70% of all petroleum used), and motor gasoline was the single largest petroleum product consumed (64% of all petroleum consumption) (EIA 2009). This strong dependency on foreign markets, particularly from volatile Middle East countries, together with concerns about the effects of greenhouse gas (GHG) emissions, have prompted policy makers to find alternative renewable energy sources. Although 53% of renewable energy consumption comes from biomass—wood, waste and biofuels—biofuels—transportation fuels such as ethanol and biodiesel—represent only 19% of the total consumption of renewable energy and only 7% of the total U.S. energy consumption (EIA 2009). Nevertheless, Perlack and others (2005) estimates that the U.S has the potential to displace 30% of current petroleum consumption with biofuels by 2030, providing a sustainable supply of biomass of more than 1 million dry tons.

Blends of 10% (*E10*) and 85% (*E85*) ethanol with petroleum are the most widely used liquid biofuels in the

U.S. transportation fuels, accounting for 95% of total U.S. biofuel consumption (EIA 2009). *E10* can be run in any vehicle, while *E85* is restricted to Flexible Fuel Vehicles. The main disadvantage are low energy content; *E10* and *E85* have 3.3 and 24.7% less energy content per gallon, respectively, than gasoline. This implies that around 1.03 gallons of *E10* and 1.33 gallons of *E85* are required for a vehicle to cover the same distance that it would cover with 1 gallon of gasoline (EIA 2007). Greenhouse gas emissions per mile traveled, however, are reduced by around 2 and 25% for corn based *E10* and *E85* and 10 and 65–90% for cellulosic based *E10* and *E85*, respectively (Wang and others 1999; Wang 2005).

The purpose of this article is to explore public preferences for biofuels created from forest biomass. Forest based biofuels potentially provide a number of environmental and social benefits including the following: reduction of GHG emissions; reduced soil acidification, improved nitrogen balance, and reduced nutrient leaching (Borjesson 2000); opportunities for forest stand site rehabilitation (Manley and Richardson 1995); improved forest sustainability; increased rural employment; and improved financial returns to landowners (Domac and others 2005; Gan and Smith 2007). Despite the recent policy incentives for producing cellulosic biofuels, questions remain concerning the demand for biofuels and whether the public is willing to pay a premium for forest based biofuels and their associated environmental and social benefits.

A variety of stated preference techniques have been applied to gauge the willingness to pay for renewable energy. A number of studies have focused on the generation of green electricity (Menegaki 2008). For example, Roe and others (2001) projected a median willingness to pay ranging between \$0.38 and \$5.66 year^{-1} for green electricity that would decrease GHG emissions by 1% in the U.S. In Scotland, Bergmann and others (2006) reported that respondents would be willing to pay an additional £14.03 year^{-1} household^{-1} for renewable energy projects that do not increase air pollution. Solomon and Johnson (2009) used contingent valuation and fair share methods to assess the public's willingness to pay for cellulosic ethanol to mitigate global climate change in the upper Midwestern U.S. They estimated a mean total willingness to pay between \$252–\$556 per capita year^{-1} and a fair share between \$192–\$472 per capita year^{-1}.

We employed an online choice experiment (CE) to assess preferences for ethanol blends of 10% (*E10*) and 85% (*E85*) in the southern U.S. Web based surveys emerged during the last decade (Champ 2003) due to their low cost, speed, and accuracy in stated preferences studies (Berrens and others 2004; Banzhaf and others 2006; Marta-Pedroso and others 2007). Although web based surveys provide similar welfare estimates compared to traditional mail surveys (Fleming and Bowden 2007), they have been criticized for problems with sample frame selection and non response bias (Manfreda 2001).

In addition to reducing GHG emissions and improving soil chemistry, we also examined the public's preferences for biodiversity benefits resulting from a reduction of wildfires and pest outbreaks associated with forest based biofuel production. Although fire is a natural component of some forest ecosystems, changes in the dynamic of wildfires and its effects have been considered a major threat to forest biodiversity (Secretariat of the Convention on Biological Diversity 2001). Repeated wildfire can reduce soil fertility, damage the soil structure, and increase soil erosion resulting in declines in water quality (Cochrane and Schulze 1999; Dawson and others 2001). Wildfires can destroy habitats, food trees, and standing cavity tress reducing the carrying capacity of the forest and associated species (Secretariat of the Convention on Biological Diversity 2001). Pest outbreaks can also decrease some forms of biodiversity (Simberloff 1999). For example, southern pine beetle kills pines where red-cockaded woodpeckers nest (Coulson and Stephen 2006). Many argue that conservation, preservation, and fire suppression policies have distorted the effect of natural processes such as wildfires and pest outbreaks in reducing forest biomass. Removal of the resulting excessive forest biomass may enhance forest sustainability and biodiversity and reduce wildfire risk (Richardson 2006). In fact, silvicultural practices such as stand thinnings are commonly used to extract small diameter wood and reduce excessive amounts of forest biomass to improve forest productivity and reduce the risk of wildfire and pest outbreaks (Belanger and others 1993; Speight 1997; Neary and Zieroth 2007).

This article is organized into sixth sections. First, we present a review of the U.S. bioenergy policy. Second, we contrast corn ethanol with cellulosic ethanol production. Then we outline the CE questionnaire and describe the attributes and socioeconomic variables. The fourth section contains descriptions of the econometric model and the welfare estimates. In the fifth section, we report the results and discussion. Lastly, we summarize the main findings.

Bioenergy Policy

Incentives for liquid biofuels were first instituted in the late 1970s to enhance U.S. energy security. The Energy Tax Act of 1978 provided a \$0.40 gallon^{-1} exemption from the federal gasoline excise tax for blends with at least 10% ethanol, which increased to \$0.60 gallon^{-1} when the Tax Reform Act of 1984 was enacted and then reduced to \$0.51 gallon^{-1} by the 1998 Transportation Equity Act of the 21st Century. The American Jobs Creation Act of 2004 replaced the excise tax exemption with a volumetric ethanol excise tax credit of \$0.51 $gallon^{-1}$ until 2010. Further, a tariff of \$0.54 $gallon^{-1}$ was imposed on imported ethanol under the purview of the Omnibus Reconciliation Act of 1980 to stimulate domestic industry.

Several other federal policies have been adopted to address environmental concerns about the use of fossil fuels. For example, the Clean Air Act amendment of 1990 established an oxygenated gasoline program to create a new, balanced strategy to address the problems of urban smog and carbon monoxide. The Energy Policy Act of 1992 extended the tax exemption to include blends of 7.7 and 5.7% ethanol. The Energy Policy Act of 2005 introduced the concept of a Renewable Fuel Standard (RFS) requiring a minimum amount of renewable fuel production, starting with 4 billion gallons in 2006 and achieving 7.5 billion gallons by 2012. After 2012, renewable fuel and gasoline production would grow at the same rate. The Energy Independence and Security Act of 2007 established higher RFSs of 15.5 billion gallons in 2012 and 36 billion gallons by 2022, of which 21 billion gallons must be cellulosic biofuel. Title IX of the 2002 and 2008 Farm Bills established new programs and grants for the procurement of biobased products to support development of biorefineries and assistance to farmers and ranchers in purchasing renewable energy systems.

A number of federal policies, such as the 2002 Farm Bill, 2005 Energy Policy Act, and the 2007 Energy Independence Security Act have specifically encouraged the production of cellulosic ethanol. The Biomass Research and Development Act of 2000 attempted to replace 30% of petroleum consumption with biofuels produced from agricultural and forest resources. The Healthy Forests Restoration Act of 2003 (p 198) encouraged communities to use more wood and other plant materials removed through forest health projects as energy feedstocks. The Food, Conservation, and Energy Act of 2008 expanded the renewable energy programs authorized by the 2002 Farm Bill. In its Title IX, it authorized mandatory funding of \$1.1 billion for the period 2008–2012, providing grants and loans to promote alternative feedstock resources such as switchgrass and woody biomass.

Ethanol Production: Corn Versus Cellulosic Biomass

The U.S. emerged as the world's leading producer of ethanol (95% from corn) in 2006 (Hettinga and others 2009, Solomon and others 2007). Corn based ethanol production has been criticized, however, for reducing food security and consequently, increasing prices of related products such as milk, meat, and eggs (Pimentel and Patzek 2005). Several environmental impacts and low (even negative) net energy balance ratios have also been associated with corn based ethanol (Pimentel and Patzek 2005; Hill and others 2005; Solomon and others 2007). Although some predict that food prices will remain high along with higher energy prices (Renewable Fuels Association (RFA 2008), Evans (1998) predicts that as ethanol production expands and new feedstocks materialize, any increase in food prices may be offset by lower energy prices Furthermore, Urbanchuk (2007) argues that the increase in food prices due to higher corn price will only produce half the impact on the Consumer Price Index (CPI) for food as the same percentage increase in energy prices.

Cellulosic biomass for ethanol production, on the other hand, has a higher net energy balance ratio, provides more environmental benefits in terms of GHG reduction, and is potentially cost competitive compared to food-based biofuels (Hill and others 2005). In addition, the use of forest biomass for cellulosic ethanol production could establish markets for currently non commercial harvest residues reducing flammable materials on the forest floor and the risk of wildfires and pest outbreaks while improving the profitability of forest landowners (Neary and Zieroth 2007; Susaeta and others 2009). However, careful consideration must be given to managing forests intensively for bioenergy purposes. Without appropriate planning, optimal harvest systems, and maintaining the connectivity of habitat networks, the production of bioenergy could lead to a loss of biodiversity (Cook and others 1991).

Study Design and Data Collection

CE Questionnaire

We employed a survey based choice experiment (CE), to elicit the public's preferences for transportation biofuels. Our web based survey of households in Arkansas (AR), Florida (FL), and Virginia (VA) was administered and hosted by Knowledge Networks (KN). KN was founded in 1998 seeking to develop online research methodologies, and established the first online research panel—KnowledgePanel—based on probability sampling covering online and offline populations in the U.S. Since households, selected with random digit dialing (RDD), were provided access to the internet and hardware if needed, our sample was not limited to web users or computer owners. Once a person decided to join the panel, she/he was sent a survey by email. KN sample design is an equal probability sample design that is self weighting. To correct for potential oversampling of minorities or households with access to the internet and subsampling of telephone numbers without an address, adjustments to the geographic frame—to areas with larger concentrations of African Americans and

Hispanics to increase their panel membership—and language were incorporated into the base weights.

To minimize non response bias, subjects were encouraged to participate through incentives, newsletters, and other techniques (e.g., a toll free helpline for providing assistance with survey questions). In addition, non respondents were re-contacted several times. Lastly, the final data set was post-stratified using current demographic distributions from the Current Population Survey (CPS) as benchmarks to adjust for non response bias and non coverage (Huggins and others 2002). A random sample of 630 households drawn from the KN online research panel that met the criteria of being in the general population and over 18 years old received the questionnaire in March and April 2008.

The questionnaire contained two parts, the CE section and a section eliciting information about the respondents' socioeconomic conditions. In the CE section, respondents were asked to choose between two alternative plans, Plan A, purchasing biofuels to reduce GHG emissions and improve biodiversity and Plan B, no change in current fuel consumption. The first part of the CE questionnaire informed respondents about the benefits producing ethanol from forest biomass, i.e., reduced GHG emissions, reduced loss of biodiversity due to reduced risk of wildfires and pest outbreaks. Biodiversity was informally explained in terms of species variety—particularly trees and animals—and their abundance. A "cheap talk script" was incorporated in the design to avoid a common problem of stated preference experiments (i.e., the difference between stated and actual behavior) (Cummings and Taylor 1999; List 2001; Menges and others 2005; Carlsson and others 2005). The attributes and their respective levels were explained to respondents, and an example was provided to facilitate comprehension. Respondents were then asked to provide their views about bioenergy and outline their stated preferences.

Respondents were presented only one questionnaire, regarding the use of either *E85* or *E10*. The attributes were: (1) reduced CO_2 emission per mile traveled, (2) reduced probability of biodiversity loss by decreasing wildfires and pest outbreaks, and (3) increased price of fuel at the pump. A brief description of the attributes and their levels is given in Table 1. The three attributes and their respective levels provided 36 possible combinations ($3^2 \times 4^1$) for Plan A, achieving a 100% A-efficiency. A-Efficiency refers to a measure of the goodness of the experimental design and is a function of the arithmetic mean of the variances given by trace of $(X'X)^{-1}/p$, where X is the coded design and p is the number of columns of the inverse of the information matrix $X'X$ (Kuhfeld 2005). Because it is not practical to ask a respondent to answer 36 different CE questions, we applied an orthogonal full factorial experiment design to produce six different versions of the questionnaire, each having six pair wise alternative plans. Thus, each respondent received one questionnaire with six sets of CE questions, each consisting of two plans, Plan A and Plan B, representing six different observations. Six CE questions is in accordance with previous CE studies, which have found that a range of 4–12 alternative plans avoid violating the assumption of stability of preferences (Hanemann 1984; Carlsson and others 2003; Shresta and Alavalapati, 2004; Mogas and others 2006). The SAS 9.1%MKTRuns and %MktEx macros were used to determine the number of alternative plan sets and the linear design (Kuhfeld 2005).

Table 2 presents an example of the alternative plan presented to respondents. The valuation question in this example is:

> Are you willing to pay an extra \$0.60 per gallon at the pump for reducing the CO_2 emissions between 61–70% (medium reduction) and improving the biodiversity between 1–25% (low improvement) (Plan A) or not to pay a premium at all without having any changes in CO_2 emissions and biodiversity improvement (Plan B).

The attributes were based on a literature review regarding forest based bioenergy (Farnsworth and others 2003; Gan 2007; Polagye and others 2007) and discussions with stakeholders and experts from academia, industry, and nongovernmental organizations specializing in forest biomass research. Two focus groups of 12 people each—

Table 1 Description of the attributes and levels

Attribute	Description	Level	
		E10	*E85*
Reco2	Percentage reduction of CO_2 emissions (per mile traveled)	1–3% (low)	1–60% (low)
		4–7% (medium)	61–70% (medium)
		8–10% (high)	71–90% (high)
Biomp	Percentage improvement of biodiversity by reducing wildfire risk and improving forest health	1–20% (low)	1–25% (low)
		21–40% (medium)	26–50% (medium)
		41–60% (high)	51–75% (high)
Prem	Increase of the price of fuel at the pump per gallon	\$0.2, \$0.5, \$0.75, \$1	\$0.3, \$0.6, \$1, \$1.5

Table 2 Description of the choice situation

Please choose	Plan A	Plan B
Reco2	Reduction of CO_2 between 61–70% per mile traveled	No reduction (0%)
Biomp	Improvement of biodiversity between 1–25%	No improvement (0%)
Prem	Additional payment of \$0.60 per gallon at the pump	No extra payment (\$0)

randomly selected and contacted by phone—followed by a pilot survey were used to develop the final list of attributes and their levels. Although Plan A is described in terms of attributes and their levels in our study, we focus on the WTP for improving environmental quality rather than valuing individual attributes. Plan B allowed respondents to choose the status quo.

The levels of percentage reduction of CO_2 depend on the energy and chemical usage intensity of biomass farming, ethanol yield per dry ton of biomass, and electricity credits in cellulosic ethanol plants (Wang and others 1999; Wang 2005). To facilitate respondent understanding of the attribute levels, we linked each level of reduction of CO_2 emission to a non numerical category: low, medium or high. Catastrophic disturbance rates in forests are generally around 1% annually, ranging from 0.5 to 2% (Runkle 1985). The levels of reduction of pest outbreaks and wildfires were based on existing literature (Agee and others 2000; Fettig and others 2006; Susaeta and others 2009). Again, each level of reduction was linked to a non numerical category: low, medium, or high. We assumed a higher price premium for *E85* based on higher environmental benefits and lower energy content per gallon. Since the decision to pay a premium for biofuels is influenced by current market fuel prices (Aguilar and Vlosky 2007), a reference price of gasoline was provided to respondents decision. For AR, FL, and VA the average gasoline prices were \$3.45 gallon^{-1}, \$3.63 gallon^{-1} and \$3.69 gallon^{-1}, respectively (http://e85prices.com/archive.php). Socioeconomic variables elicited in the second section are described in Table 3. Non automobile owners, expected to be few in number, were included in the survey because they might also be interested in purchasing biofuels.

Econometric Model

The theoretical framework to analyze the CE method is based on random utility theory in which the indirect utility of an individual is the sum of a deterministic part and a stochastic element McFadden (1974). Formally:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{1}$$

where U_{ij} is the utility for each respondent i to choose among different j alternatives, V_{ij} is the deterministic part of the utility, and ε_{ij} reflects unobservable influences on respondent choice. With two alternatives, the individual chooses alternative j, which reflects an improved state, over alternative k (status quo) if the utility associated with alternative j exceeds the utility of alternative k. The probability that individual i will choose alternative j over k is:

Table 3 Socioeconomic variables

Variable	Description
Member	Membership in an environmental organization: 1 if respondent is a member and 0 otherwise
Knowledge	Knowledge of other natural resources based energy: 1 if respondent knows and 0 otherwise
Ownership	Ownership of an automobile: 1 if respondent owns and 0 otherwise
Age	Years
Miles week	Distance driven weekly (miles)
Education	*Less high*: 1 if respondent has exclusively less than high school level and 0 otherwise
	High: 1 if respondent has exclusively high school level and 0 otherwise
	Some college: 1 if respondent has exclusively some college level and 0 otherwise
	Bachelor: 1 if respondent has exclusively bachelor degree or higher level and 0 otherwise
Income	*Lincome*: 1 if household Annual Income is less than \$24,9999 and 0 otherwise
	Mincome: 1 if household Annual Income is between \$25,000–\$74,999 and 0 otherwise
	Hincome: 1 if Household Annual Income is greater than \$75,000 and 0 otherwise
Size	Number of people in the household
Work	1 if respondent is working and 0 otherwise
Gender	1 if respondent is male and 0 otherwise
Head	1 if respondent is the household head and 0 otherwise

$$P_{ij} = P(V_{ij} + \varepsilon_{ij}) > P(V_{jk} + \varepsilon_{ik}), \quad j \neq k \tag{2}$$

Following Haab and McConnell (2002) hereafter, we assumed a linear utility function in income and covariates. Although not conclusive, linear utility functions are a reasonable assumption for decision making processes (Dijkstra and others 1990). The deterministic part of the indirect utility function for an individual i can be written as:

$$V_{ij}(y_i) = \alpha_j z_i + \beta_j y_i \tag{3}$$

where y_i is the income of individual i and z_i is the matrix of attributes and socioeconomic characteristics of individual i, and α_j and β_j are the multidimensional vector and the marginal utility of income of alternative j, respectively.

Our dichotomous choice experiment requires each individual to choose between alternative j paying an amount t_j and the status quo. Thus, the deterministic parts of the utility function for alternatives j and k are:

$$V_{ij}(y_i - t_j) = \alpha_j z_i + \beta_j (y_i - t_j) \tag{4}$$

$$V_{ik}(y_i) = \alpha_k z_i + \beta_k (y_i) \tag{5}$$

Replacing (4) and (5) into (2) and rearranging, we obtain the following expressions:

$$P(yes_i) = P(\alpha_j z_i + \beta_j (y_i - t_j) + \varepsilon_{ij}) > P(\alpha_k z_i + \beta_k (y_i) + \varepsilon_{ik}) \tag{6}$$

$$P(yes_i) = P(\alpha_k - \alpha_j) z_i + \beta_j (y_i - t_j) - \beta_k (y_i) + \varepsilon_{ij} - \varepsilon_{jk}) > 0 \tag{7}$$

Assuming that the marginal utility of income is constant and denoting $\propto = \alpha_k - \alpha_j$ and $\varepsilon_i = \varepsilon_{ij} - \varepsilon_{ik}$, the probability of a yes response is:

$$P(yes_i) = P(\alpha z_i + \beta t_j + \varepsilon_i) > 0 \tag{8}$$

Assuming that $\varepsilon_i \sim N(0, \sigma^2)$ and converting the errors to a standard normal, we obtain the probit model:

$$P(yes_i) = \varphi\left({}^{\alpha z_i}/_{\sigma} - {}^{\beta t_j}/_{\sigma}\right) \tag{9}$$

Estimates for the parameters $\propto/\sigma$, β/σ, are obtained by maximizing the likelihood function. In the case of a probit model, the log likelihood function takes the following form:

$$\ln L\left(\frac{\alpha}{\sigma}, \frac{\beta}{\sigma} | y, z_i, t_j\right) = \sum_{i=1}^{T} I_i \ln\left[\left(\varphi\left({}^{\alpha z_i}/_{\sigma} - {}^{\beta t_j}/_{\sigma}\right)\right)\right] + (1 - I_i) \ln\left[1 - \varphi\left({}^{\alpha z_i}/_{\sigma} - {}^{\beta t_j}/_{\sigma}\right)\right] \tag{10}$$

where T is the sample size and $I_i = 1$ if individual i answers yes.

We assumed that the attributes and the socioeconomic variables of this discrete choice model were exogenous, i.e., determined outside of the model. However, distance driven per week may be correlated with the error term (endogenously determined). If endogeneity arises for this particular case, the estimated coefficient of weekly mileage will be upwardly or downwardly biased depending on the direction of the correlation with the error terms. Potential solutions to correct for endogeneity are the use of instrumental variables or the determination of the endogenous variable by an equilibrium model (Besanko and others 1998). However, correction for endogeneity bias is beyond the purview of this article.

Welfare Estimates

Two measures of central tendency were developed by Hanemann (1984), the expected WTP [E(WTP)] and the median WTP [Md(WTP)], which are equal under the assumption of a linear utility function. Thus,

$$E(WTP) = Md(WTP) = {}^{\alpha \bar{z}}/_{\beta} \tag{11}$$

where $\bar{z}$ is the mean of attributes and socioeconomic characteristics.

Results and Discussion

A total of 408 questionnaires were completely answered (65% response rate), 201 questionnaires regarding *E10* (56 in AR, 76 in FL, and 69 in VA) and 207 questionnaires for *E85* (53 in AR, 79 in FL, and 74 in VA). We used STATA 9.0 to estimate separate probit models for *E10* and *E85*. Tables 4 and 5 present the descriptive statistics for the socioeconomic variables of the *E10* and *E85* samples, respectively. Generally, respondents were not part of any environmental organization, had achieved one of the two highest levels of education, and owned an automobile. Further, respondents belonged mainly to the middle income category, with the exception of *E10* respondents in VA.

Consistent with expectations, respondents were less likely to accept the premium as the price increased (Figs. 1, 2). Regardless of the premium level, the average relative decrease for a yes response was around 10% in each state for *E10*. In the case of *E85*, the average relative decrease amounted to 15.1, 9, and 8.6% for AR, FL, and VA, respectively. The majority of the respondents were willing to pay a premium for both blends in FL and for only *E85* in AR. In VA, the majority of the respondents were not willing to pay a premium for either *E10* or *E85*.

Table 4 Descriptive statistics for socioeconomic variables, *E10*

Variable	AR				FL				VA			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Member	0.05	0.23	0	1	0.11	0.31	0	1	0.12	0.32	0	1
Knowledge	0.46	0.50	0	1	0.54	0.50	0	1	0.49	0.50	0	1
Ownership	0.98	0.13	0	1	0.89	0.31	0	1	0.90	0.30	0	1
Miles week	169.3	142.7	0	750	121	102.4	0	420	168.4	179.7	0	1,100
Age	51.9	12.8	22	76	52.3	17	18	81	46.7	15.4	20	89
Less high	0	0	0	1	0.08	0.27	0	1	0.06	0.23	0	1
High	0.21	0.41	0	1	0.26	0.44	0	1	0.30	0.46	0	1
College	0.34	0.47	0	1	0.34	0.47	0	1	0.32	0.47	0	1
Bachelor	0.45	0.50	0	1	0.32	0.47	0	1	0.32	0.47	0	1
Gender	0.41	0.49	0	1	0.45	0.50	0	1	0.46	0.50	0	1
Head	0.93	0.26	0	1	0.92	0.27	0	1	0.87	0.34	0	1
Lincome	0.14	0.35	0	1	0.21	0.41	0	1	0.17	0.38	0	1
Mincome	0.63	0.48	0	1	0.51	0.50	0	1	0.35	0.48	0	1
Hincome	0.23	0.42	0	1	0.28	0.45	0	1	0.48	0.50	0	1
Size	2.39	1.31	1	6	2.30	1.40	1	9	2.65	1.26	1	6
Work	0.64	0.48	0	1	0.43	0.50	0	1	0.67	0.47	0	1
Number of observations	330					456			414			

Table 5 Descriptive statistics for socioeconomic variables, *E85* sample

Variable	AR				FL				VA			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Member	0.04	0.19	0	1	0.06	0.24	0	1	0.07	0.25	0	1
Knowledge	0.43	0.50	0	1	0.43	0.50	0	1	0.39	0.49	0	1
Ownership	0.96	0.19	0	1	0.92	0.27	0	1	0.99	0.12	0	1
Miles week	128.8	127.3	0	580	132.3	126.4	0	500	158.5	146.4	0	750
Age	53.1	14.6	21	87	51.1	18.9	19	89	45.4	15.1	18	81
Less high	0.02	0.14	0	1	0.10	0.30	0	1	0.07	0.25	0	1
High	0.13	0.34	0	1	0.24	0.43	0	1	0.31	0.46	0	1
College	0.42	0.49	0	1	0.37	0.48	0	1	0.26	0.44	0	1
Bachelor	0.43	0.50	0	1	0.29	0.45	0	1	0.36	0.48	0	1
Gender	0.36	0.48	0	1	0.82	0.38	0	1	0.45	0.50	0	1
Head	0.94	0.23	0	1	0.47	0.50	0	1	0.92	0.27	0	1
Lincome	0.21	0.41	0	1	0.27	0.44	0	1	0.12	0.33	0	1
Mincome	0.53	0.50	0	1	0.43	0.50	0	1	0.53	0.50	0	1
Hincome	0.26	0.44	0	1	0.30	0.46	0	1	0.35	0.48	0	1
Size	2.30	1.19	1	5	2.30	1.37	1	6	2.43	1.30	1	7
Work	0.53	0.50	0	1	0.55	0.50	0	1	0.68	0.47	0	1
Number of observations	306				474				444			

Attributes

Tables 6 and 7 show the coefficients, P values, and standard deviations of the estimated probit models in AR, FL, and VA for *E10* and *E85*, respectively. The log likelihood ratios ($P < 0.001$) suggested that the overall models for both blends were statistically significant in all three states.

STATA routines dropped variables that perfectly predicted success or failure in the dependent variable. For *E10*, all respondents owned a car in AR; thus, this dummy

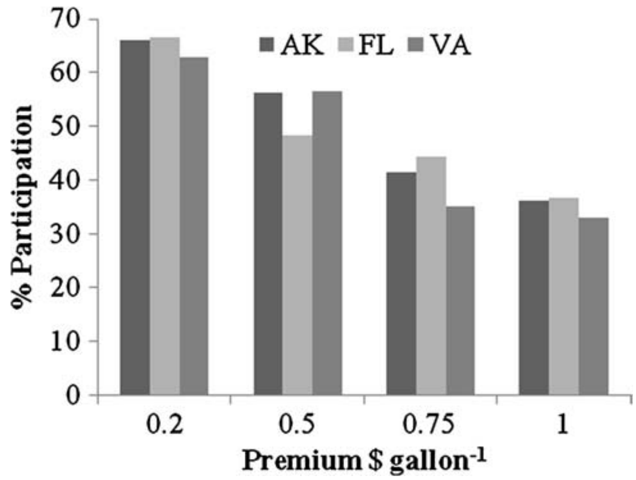

Fig. 1 Percentage of yes responses for *E10*

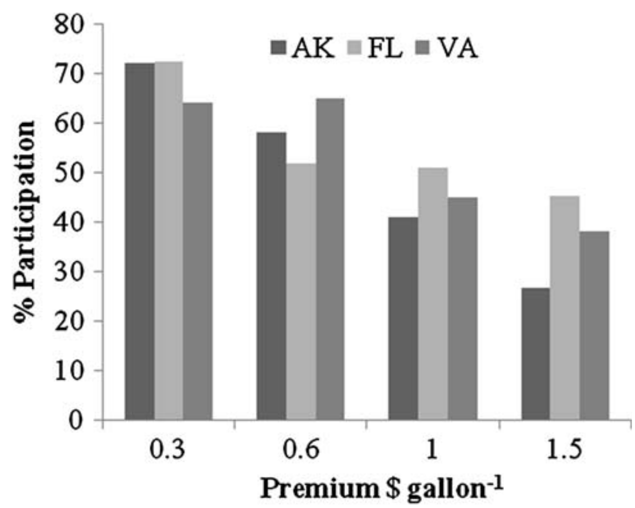

Fig. 2 Percentage of yes responses for *E85*

variable only took the value of 1, showing no variation across the sample. In the case of educational variables, *Less high* was not included in the model to avoid the dummy variable trap. However, this variable only took the value of 0 in AR, as all respondents had some high school level. Thus, *College* was dropped to avoid collinearity. For E85 *Member* in AR and *Ownership* in VA were dropped. Almost none of the respondents were members of an environmental organization, and almost all owned an automobile.

Consistent with economic theory under the assumption of a negative price elasticity of demand—a percent change in the quantity demanded given a percent change in price—the utility of individuals decreased as the premium increased for either blend and was statistically significant in all three states. In response to questions concerning *E10*, the coefficient of the attribute "Percentage reduction of CO_2 emissions" (*Reco2*) was positive in all three states but only statistically significant in FL and VA. Likewise, "Percentage improvement of Biodiversity" (*Biomp*) was positive in AR and FL but was not statistically significant. This indicates that the probability of paying a premium increased as the reduction of CO_2 increased and biodiversity conditions improved. Results differed when the choice concerned *E85*. Respondents from AR and VA were less likely to use *E85*, and *Reco2*, which was significant only in AR, had negative coefficients in AR and VA, while the variable *Biomp*—although statistically insignificant in all states—had negative coefficients in all three states.

The probability of paying a premium for *E10* increased in all three states as reductions in CO_2 increased or biodiversity improved. These results were consistent with previous studies which found that when environmental quality improved, the utility of respondents increased, and therefore they were willing to pay more for green electricity (Roe and others 2001; Bergmann and others 2006). However, the same trend was not observed in the *E85* scenario, as respondents declined to pay a premium for reducing CO_2 in AR or improving biodiversity in all states at higher rates. Nevertheless, except for the variable *Reco2* in VA, the results for *E85* fuel were consistent with the probabilities of the model for the environmental attributes (Table 8).

Socioeconomic Variables

Member, Knowledge, Ownership, and Miles Week

Neither the condition of being a "Member of an environmental organization" (*Member*) nor having "Knowledge of other natural resources based energy" (*Knowledge*) were statistically significant in any of the states for *E10*. For *E85*, however, *Member* was significant only in AR, and *Knowledge* was significant only in VA. Further, the likelihood of switching to biofuels increased if respondents were members of an environmental organization in AR and VA for *E10* and in VA for *E85*. Similar behavior was observed for *E85* respondents in AR who were aware of other options for green energy. In the case of the variable "Ownership of an automobile" (*Ownership*), this probability increased only for *E85* and was significant in AR and FL. However, preferences of automobile owners and non automobile owners differed. The percentage of non automobile owners who chose to use *E10* was 100% in AR, 50% in FL, and 64% in VA. These percentages were lower for *E85* in AR and FL (17 and 25%, respectively), while in VA 100% of non automobile owners chose to use biofuels. The variable "Distance driven weekly" (*Miles week*) was significant when deciding whether to switch to biofuels. For *E10*, the probability of switching to biofuels increased in FL and decreased in VA. However, *Miles week* was not significant in any of the states for *E85*.

Table 6 Probit model results for *E10* sample

Variable	AR		FL		VA	
	Coefficients	Std	Coefficients	Std	Coefficients	Std
Reco2	0.020	0.102	0.261***	0.092	0.262***	0.095
Biomp	0.159	0.107	0.020	0.093	−0.009	0.01
Prem	−0.973***	0.322	−0.883***	0.267	−0.962***	0.310
Member	0.465	0.430	−0.180	0.266	0.409	0.277
Knowledge	−0.238	0.211	−0.191	0.142	−0.223	0.179
Ownership	n.a	n.a	−1.146***	0.315	−0.320	0.305
Miles week	−0.0002	0.001	0.002***	0.001	−0.002***	0.000
Age	−0.017***	0.009	0.000	0.006	0.010	0.007
High	0.718***	0.239	1.267***	0.445	−0.341	0.315
College	n.a	n.a	1.705***	0.391	0.570	0.377
Bachelor	−0.050	0.269	2.095***	0.427	−0.134	0.396
Gender	0.528**	0.207	−0.572***	0.151	−0.355*	0.210
Head	0.302	0.351	1.767***	0.344	−0.423	0.267
Mincome	−0.093	0.278	0.409*	0.230	−0.214	0.241
Hincome	−0.763**	0.368	0.660***	0.239	0.188	0.282
Size	−0.205**	0.083	0.118	0.074	−0.236***	0.074
Work	−0.140	0.209	0.001	0.189	0.029	0.252
Intercept	1.393*	0.829	−2.848***	0.774	1.352*	0.775
Number of observations	330		456		414	
Log likelihood	−186.7		−227.3		−237.84	
Log likelihood ratio	67.34		129.9		86.47	
P value	0.00		0.00		0.00	
Pseudo R^2	0.178		0.278		0.172	

*,**,*** Denote significant at 10, 5 and 1%, respectively

Education

Effects of educational background differed in the three states. The variable "Respondent with exclusively high school level" (*High*) was statistically significant and positive, "Respondent with exclusively bachelor degree or higher" (*Bachelor*) was not statistically significant, and "Respondent with some college level" (*College*) was significant for *E10* in AR. However, in AR and FL, the likelihood of choosing *E85* and *E10* increased for individuals who had higher education levels, respectively. In VA, no education variables were statistically significant for *E10*. Individuals with some high school or bachelor's degrees were less likely to pay a premium, but individuals with some college education were more likely to use the *E10* blend. Individuals with high school in FL and some college education in VA showed no intention of using *E85*.

Income

Income was another variable that showed heterogeneity in individuals' perceptions about biofuels. In AR, only the variable "Households with high income" (*Hincome*) was statistically significant for both biofuels. Contrary to expectations, the probability of paying a premium decreased as an individual had greater earnings. Although this is inconsistent with economic theory, respondents might have considered exogenous factors such as the unfavorable economic situation prevailing in the country during the time the survey was conducted.

In FL, the variables "Households with middle income" (*Mincome*) and *Hincome* were both statistically significant as compared to the lowest income level for *E10*. Although this situation was not observed for *E85*, the utility of choosing any of the biofuel blends appeared to increase with increasing income. In VA, no income variables were statistically significant for *E10*. However, for *E85*, the middle income category showed significant differences compared to low income individuals.

Age, Gender, and Work

Age was significant only in AR for *E10* and *E85*. Further, as AR respondents aged they would only be likely to choose *E10*. On the other hand, *Gender* was statistically significant in all three states for *E10*, and in FL and in VA for *E85*. The probability that females would choose either blend was lower compared to males in FL. The variable

Table 7 Probit model results for *E85* sample

Variable	AR		FL		VA	
	Coefficients	Std	Coefficients	Std	Coefficients	Std
Reco2	−0.441***	0.156	0.073	0.087	−0.005	0.082
Biomp	−0.017	0.161	−0.053	0.090	−0.012	0.082
Prem	−1.431***	0.227	−0.508***	0.163	−0.803***	0.153
Member	n.a	n.a	−0.521	0.335	0.293	0.295
Knowledge	0.310	0.194	−0.004	0.170	−0.316*	0.167
Ownership	2.936***	0.738	1.532***	0.309	n.a	n.a
Miles week	−4.14E−06	0.0008	0.0003	0.0006	−3.2E−05	0.0005
Age	0.055***	0.010	0.007	0.005	−0.006	0.006
High	3.281***	0.636	−0.037	0.287173	−0.181	0.289
High	1.614***	0.493	0.179	0.289	−0.056	0.290
Bachelor	1.870***	0.516	0.404	0.285	0.0148	0.304
Gender	0.320	0.213	−0.465***	0.155	0.287**	0.143
Head	−1.501***	0.414	−0.733***	0.206	0.400	0.315
Mincome	−0.187	0.309	0.258	0.193	−0.463*	0.245
Hincome	−0.702*	0.386	0.266	0.211	−0.285	0.252
Size	0.349***	0.099	−0.081	0.059	0.073	0.058
Work	0.569**	0.257	−0.139	0.167	−0.07	0.190
Intercept	−5.234***	1.141	−0.559	0.540	1.055**	0.512
Number of observations	306		474		438	
Log likelihood	−144.1		−275.8		−272.8	
Log likelihood ratio	114.4		88.8		43.36	
P value	0.00		0.00		0.00	
Pseudo R^2	0.316		0.16		0.09	

*,**,*** Denote significant at 10, 5 and 1%, respectively

Table 8 Probabilities of using biofuels for level of environmental attributes at state level

Attribute	*E10*				*E85*			
Reco2	Level	AR	FL	VA	Level	AR	FL	VA
	1–3%	0.476	0.382	0.367	1–60%	0.667	0.534	0.573
	4–7%	0.491	0.484	0.468	61–70%	0.520	0.563	0.577
	8–10%	0.506	0.588	0.573	71–90%	0.370	0.592	0.580
Biomp	1–20%	0.429	0.481	0.453	1–25%	0.530	0.585	0.583
	21–40%	0.490	0.489	0.449	26–50%	0.520	0.564	0.577
	41–60%	0.551	0.497	0.445	51–75%	0.510	0.543	0.570

"Respondent was working" (*Work*) was insignificant in all three states for *E10* and significant only in AR for *E85*. Furthermore, individuals would continue using cheaper fuel if they were unemployed in AR for *E10* and FL and VA for *E85*.

Size, Head, and Intercept

The "Size of the household" (*Size*) was statistically significant in AR and VA for *E10*. Consistent with expectations, as the number of people in the household increased, individuals were less likely to use biofuel blends. For *E85*, *Size* was statistically significant only in AR, where the results showed that an increase in number of people in the household would decrease the utility of individuals. Being the "head of the household" (*Head*) was significant in FL for *E10* and AR and FL for *E85*. Heads of household were not likely to choose *E85* in AR and FL or *E10* in VA. Finally, the effect of unobservable influences was statistically significant in all three states for *E10* and in VA and AR for *E85*. Further, respondents were not likely to pay a premium for *E85* in AR and in FL for *E10*.

Willingness to Pay (WTP)

The estimates of WTP a price premium for biofuels are shown in Table 9. The greatest WTP for *E10* was in FL (\$0.58 gallon^{-1}), followed closely by AR (\$0.56 gallon^{-1}),

Table 9 WTP ($ gallon^{-1}) for biofuels at state level

Blend	AR	FL	VA
E10	0.56	0.58	0.50
E85	0.82	1.17	1.06

and VA ($0.50 gallon^{-1}). Similar findings were obtained by Bhattacharjee and others (2008), who calculated a mean WTP of $0.49 gallon^{-1} for *E10* in a U.S. nationwide study. We found that the mean WTP for *E85* was 1.46, 2.00 and 2.1 times greater than for *E10* in AR, FL and VA, respectively. Three multiple comparison tests (Bonferroni, Scheffe and Sidak tests) were performed to detect differences in WTP among the three states for both blends. For *E10* there were no significant differences in WTP among the three states. For *E85* there were significant differences in the WTP between AR and FL and between AR and VA. However, there were no significant differences in the WTP between FL and VA.

The average prices of *E85* when the questionnaire was administered were $2.52 gallon^{-1}, $3.00 gallon^{-1}, and $3.07 gallon^{-1} in AR, FL, and VA, respectively (E85 Price Archives 2009). As noted earlier, average gasoline prices were $3.13 gallon^{-1}, $3.21 gallon^{-1}, and $3.69 gallon^{-1} for the same states. Thus, the ratios of WTP to actual *E85* price were 1.57, 1.46, and 1.54 in AR, FL, and VA, respectively, averaging 1.52. On the other hand, assuming the current price of gasoline as a proxy for *E10*, the ratios were much lower: 1.18, 1.18, and 1.13 in AR, FL, and VA, respectively, averaging 1.16. The ratios for both blends might be higher in the future, as market prices for gasoline and *E85* are expected to increase. Gasoline is predicted to have an annual price increase of 1.4% reaching $4 gallon^{-1} (2007 dollars) in 2030, while the annual price increase of *E85* will be 0.5% over the same period, reaching less than $3 gallon^{-1} (EIA 2008a).

Respondents were willing to pay more for biofuels if the proposed change offered better conditions for the environment. In VA, the state with the lowest WTP, respondents appeared to believe that the environmental improvements would not compensate for the premium for *E10*. VA's respondents, however, had the second greatest WTP ($1.06 gallon^{-1}) for *E85*. Although the percentage of respondents rejecting the premiums were almost the same for both blends in VA (Figs. 1, 2), a larger percentage rejected the higher premiums. For example, for premiums of $0.75 gallon^{-1} and $1 gallon^{-1}, 65 and 67% respondents rejected the purchase of *E10*, whereas in the case of *E85*, 55 and 62% rejected premiums of $1 gallon^{-1} and $1.5 gallon^{-1}, respectively. Further, the ratios of no versus yes responses to the premiums were 1.86 and 2.03 for *E10* and 1.22 and 1.63 for *E85*.

The WTP for price premiums for ethanol was converted into total future expenditures per year (TE_e) by multiplying the total WTP by the quantity of gallons of ethanol (Q_e) consumed as a proportion of total fuel consumption in the next period compared to the previous one (Solomon and Johnson 2009). This proportion is equal to the price elasticity of demand for biofuels (Ed_e). The average per capita motor gasoline expenditures in 2006 (EIA 2008b) were used to calculate the quantity of gallons of ethanol. The real motor gasoline expenditures (2007 = 100) accounted for $1,295, $1,200, and $1,373 per capita in AR, FL, and AK, respectively. The total WTP can be separated into an average price of gasoline (P_g) and the mean WTP for ethanol in each state (WTP_e). Formally:

$$TE_e = \left(P_g + WTP_e\right)Q_e * Ed_e \tag{12}$$

The mean total expenditures for *E10* were $585.20, $485.90, and $596.20 per capita year^{-1} in AR, FL, and VA, respectively. For *E85* the total expenditures were $919.60, $330.80, and $532.60 per capita year^{-1}. With the exception of E85 in AR, the results are similar to those found by Solomon and Johnson (2009). They reported a mean total future expenditure between $252–$556 per capita year^{-1} in Michigan, Minnesota, and Wisconsin. The ratios of total expenditures of *E85* to *E10* were 1.57, 0.68, and 0.93 in AR, FL, and VA, respectively. The price elasticity of the demand was relatively inelastic ($-1 < Ed_e < 0$) for both blends in the three states. The values for Ed_e for *E10* were −0.38, −0.34, and −0.38 in AR, FL, and VA, respectively, while those for *E85* were −0.56, −0.2, and −0.31. In general, the Ed_e for *E85* was less elastic for *E85* than E10, with the exception of AR, where the total expenditures for Arkansans were higher.

Conclusions

This article reported the findings of a choice experiment designed to elicit WTP and public preferences for *E10* and *E85* in AR, FL, and VA. We found that individuals had a positive WTP for price premiums for both blends. WTP was higher for biofuels that led to environmental improvements. No significant differences were found in the WTP among the three states for *E10*. For *E85*, significant differences were found between AR and FL and between AR and VA. The WTP ratios of *E85* to *E10* were 1.46, 2.00, and 2.12 for AR, FL, and VA, respectively. Thus, consumers in the U.S. south appeared to value the environmental benefits obtained from a modified transportation fuel. Converting WTP into future total expenditures produced ratios of total expenditures on *E85* to *E10* of 1.57, 0.68, and 0.93 in AR, FL, and VA, respectively. With the exception of AR, total future expenditures were higher for

E10 because of a more elastic price elasticity of the demand.

Our study also suggested that preferences for environmental attributes were heterogeneous. Respondents indicated to be willing to pay a premium for *E10* in order to achieve CO_2 reduction in all three states and for biodiversity improvement in AR and FL. However, in all three states, results were opposite for improved biodiversity associated with *E85*. This heterogeneity was also observed in some socioeconomic variables. For example, only individuals with higher levels of education indicated willingness to purchase *E10* in FL and *E85* in AR. The high oil prices at the time of the survey and the higher premium proposed for *E85* might explain why individuals from middle and high income households in AR and VA were reluctant to pay more for that biofuel.

Understanding present and future individual preferences for bioenergy is an important tool for policymakers. Our results support the initiation of a consistency policy instrument such as the Renewable Fuel Standard (RFS), aiming to produce 15.2 billion gallons of renewable fuels by 2012. However, it also underscores the need for federal or state governments to continuously reinforce in consumers the environmental benefits associated with biofuels. Although we find that individuals are willing to pay a premium for biofuels, periodic revisions of these studies are needed to ensure policies reflect changing public perceptions and preferences. The research could be extended in several ways. For example, different approaches might be used to allow welfare measures to be adjusted for different policy contexts. Meta analysis could also be used to validate and explore the systematic and identifiable variation of WTP to determine its appropriateness for benefits transfer. Finally, we assumed that people's preferences were homogeneous within each state. However, if people's choices are influenced by different geographical locations or other variables a more specific level of aggregation or an incorporation of spatial variation could be a plausible extension of this study.

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