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Greenhouse gas emission reductions as a motivator of e85 purchases across market segments

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Abstract

Background: Climate change has become a concern of both policy makers and consumers. Transportation constitutes a key source of greenhouse gas (GHG) emissions; hence, alternative transportation fuels with reduced GHG emissions are of increasing interest as a potential strategy for decreasing emissions. However, consumer views on achieving emission reductions through the use of alternative fuels have not been widely studied. Understanding consumer preferences related to alternative fuels is relevant as new fuel options become available.

Methods: This study uses a two-step cluster analysis of opinion variables to segment consumers into four market segments (*Potential activists, Environmentals, Neutrals*, and *National interests*). Cluster profiles are examined based on demographics and opinion variables related to concerns about national security, food versus fuel, perceived effects of personal actions, perceived effects of other's actions, and environmental issues. Willingness to pay (WTP) for reductions in GHG emissions through purchases of ethanol blends is estimated via conjoint analysis from a national survey.

Results: Estimates reveal that WTP varies in significance and magnitude across the four segments. In particular, the *Environmentals* market cluster is the only cluster consistently willing to pay a premium for emission reductions.

Conclusions: Market opinion clusters play a significant role in WTP for emission reductions through purchases of E85. Results suggest the existence of a potential niche market consisting of consumers with strong environmental concerns who are willing to pay a premium for renewable fuels in order to reduce GHG emissions.

Keywords: Market opinion clusters, Willingness to pay, Emission reductions

Background

The US Environmental Protection Agency estimated that the transportation sector was the largest contributor to US greenhouse gas (GHG) emissions in 2010, contributing about 30.4% of US CO_2 emissions [1]. In 2009, the USA was responsible for nearly 18% of the world's CO_2 emissions [2]. Consumers have become increasingly aware of their role in contributing to GHG emissions, as evidenced by the 73% of surveyed consumers who were aware of the term carbon footprint in 2010 [3]. Public opinion polls have indicated concerns about GHG and the environment, but have provided mixed opinions on the most effective means to reduce GHG emissions. A June 2010 Pew Research Center Poll revealed that about two-thirds of the respondents favored limits on CO_2 and other greenhouse gas emissions [4]. Furthermore, while 37% favored keeping energy prices low as the most important priority, about 56% favored protecting the environment as the most important priority. However, an earlier poll by Stanford University and Resources for the Future found that US consumers tended to favor policies directed at the electricity sector rather than at transportation, with transportation emission taxes receiving little support [5]. In addition, a 2007 Gallup poll showed that 55% did not favor a policy that would ban vehicles averaging less than 12.75-km/l fuel efficiency [6].

Accumulating evidence of the link between GHG emissions and climate change has prompted the adoption of an array of policies designed to reduce GHG

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emissions. In the USA, many of these policies have focused on the transportation sector, given its importance to GHG emissions [7]. Some of these policies have been designed to reduce GHG emissions by improving automotive fuel efficiency. For example, the Energy Independence and Security Act of 2007 [8] raised the Corporate Average Fuel Economy standards for passenger cars and light trucks for the first time since 1975. Other policies are designed to promote the production and consumption of alternatives to petroleum-based gasoline.

Several US renewable fuel policies have focused on promoting production and consumption of ethyl alcohol (ethanol). Ethanol is a renewable fuel made from various plant materials, which are collectively referred to as 'biomass'. Most of the gasoline sold in the USA is blended with ethanol to oxygenate the fuel and reduce air pollution [9]. In general, the ethanol content is limited to 10% (E10) or less. However, flexible fuel vehicles (FFVs) can safely operate on a blend of up to 85% ethanol (E85). As a renewable fuel made from biomass, ethanol has the potential to reduce net GHG emissions associated with transportation. Ethanol production and consumption is subsidized in the USA through a tax credit equal to \$0.12/l of pure ethanol blended into gasoline. Also, a 2005 federal law created a Renewable Fuels Standard (RFS) requiring 2.84×10^{10} l of renewable fuel to be blended into the transportation fuel on an annual basis by 2012. The RFS was amended in 2007 to increase the requirement to 1.36×10^{11} l by 2022. Production of ethanol in the USA has increased significantly over time with production rising from 6.62×10^{8} l in 1980 to 5.26×10^{11} l in 2011 [10].

Despite these preferential policies, ethanol will ultimately have to compete for its share of the transportation fuel market. In particular, for consumers to purchase E85 and E85-compatible vehicles, they will need to perceive benefits from consuming this fuel compared with either regular gasoline (E0) or other lower-level ethanol blends such as E10. One attribute that may influence consumer decision making in selecting a fuel, whether an ethanol blend or conventional gasoline, is the level of emissions generated when using the fuel.

The objectives of this study are to estimate willingness to pay (WTP) for GHG emission reductions through the use of E85 and analyze how WTP is influenced by demographics and attitudes toward renewable energy, fuel security, and the environment. Data on consumer preferences are collected with a conjoint analysis exercise that asks respondents to choose among fuel varieties that are differentiated along the dimensions of price (*Price*), ethanol blend (*E85*, *E10*, and *E0*), percent imported (*Imports*), availability (*Inconvenience*), and reductions in GHG emissions (*Reduce*). WTP for GHG emission reductions through the use of E85 are estimated using the random parameters logit (RPL) model to analyze the data from the conjoint exercise. The effects of consumer demographics and attitudes toward the environment and fuel security on WTP for emissions reductions are incorporated in the analysis through interactions with the emission reduction attribute.

One might argue that two of the primary 'benefits' of ethanol consumption relative to gasoline, improved environmental performance and increased domestic production, are externalities that primarily accrue to a broader set of individuals than the set of ethanol consumers. As a result, in the absence of any price advantage, the market for ethanol might be expected to be a niche market, driven largely by consumer attitudes toward issues such as the environment, fuel security, and food security. To explore these attitudes, a cluster analysis is used to group respondents on the basis of their responses to a variety of attitudinal questions. The resulting clusters are used to analyze how differences in attitudes may impact WTP for GHG emission reductions.

Market segmentation

Smith's pioneering article [11] emphasized the role of the consumer in the market and discussed the strategy of market segmentation over 5 decades ago. In the years since, market segmentation has become a commonly utilized marketing tool to identify the preferences and needs of distinct market segments for new products and to address these needs with specific marketing strategies [12,13]. Classification of consumers into groups or market segments is often used in order to gain a better understanding of consumer needs and motivations in order to facilitate the marketing of a product [11,14]. A common way of segmenting markets is through clustering. Clustering is a basic investigative technique that involves grouping similar objects together based on a set of characteristics [15]. It is the art of finding groups in data and relies on the meaningful interpretation of the researcher or classifier [16]. Simply stated, clustering involves gathering similar objects (data) into distinct clusters that are internally homogeneous and externally heterogeneous.

A popular approach to finding clusters in a data set is to employ a hierarchical method followed by a non-hierarchical method [17-19]. Van de Velde et al. [20] used such a two-step process to cluster consumers based on their perceptions of the importance of fuel characteristics and beliefs about biofuels. The first step involved a hierarchical cluster method that was used to create an agglomeration schedule and dendrogram from which a four-cluster solution was determined to be optimal. The second step used the cluster centers from the hierarchical method to refine the solution using a *k*-means cluster analysis. Clusters were identified as performance-oriented, society-oriented, environment-oriented, and convenience-oriented consumers.

WTP for GHG emission reductions and ethanol blends

Several studies have focused on attitudes toward and WTP for GHG emission reductions. Jeanty and Hitzhusen [21] used a contingent valuation exercise to estimate WTP for air pollution reduction from the use of biodiesel in diesel engines. More specifically, they valued the benefits of reducing CO_2 emissions by 75%, fine particulates by 47%, sulfur emissions by 100%, and volatile organic compounds by 56%. They reported premiums of \$0.02/l, \$0.05/l, \$0.08/l depending on the statistical model used. Achtnicht [22] used a stated preference exercise to estimate WTP for the abatement of CO_2 emissions among German car buyers and to examine whether CO_2 emissions per kilometer is a relevant attribute when choosing a vehicle. The results revealed that CO_2 emissions were a significant attribute related to vehicle choice and that women, younger respondents, and those who possessed a Higher Education Entrance Qualification were willing to pay more for CO_2 reductions. MacKerron et al. [23] examined airline passengers' WTP for emission offsets for their airline flights. They estimated that passengers were willing to pay about \$39.10 per flight to offset associated emissions. While they found females were more likely to buy the offsets than males, neither income nor having children had a significant effect.

O'Connor et al. [24] reported the results of a mail survey of 623 residents of Central Pennsylvania on support for policies to reduce GHG emissions. Ordinary least squares analysis revealed that respondents who could correctly identify the causes of climate change and who expected negative consequences from climate change were likely to support both government initiatives that were focused on replacing fossil fuels and voluntary actions to do the same. Economic circumstances and concerns were not found to be significant predictors of support for such policies. The belief that environmental protection efforts do not threaten jobs, limit personal freedoms, or hurt the economy was a strong predictor for support of the GHG mitigation policies. Overall, respondents wanted to reduce emissions if they understood the causes of climate change, perceived climate change to be a significant risk, or felt that climate change mitigation policies would not reduce employment opportunities.

Roe et al. [25] examined consumer WTP for emission reductions from electricity production when there is no change in fuel source and when the fuel source is renewable. Their results suggest that many population segments are willing to pay for decreases in air emissions. They also found that several groups were willing to pay significantly more when the emission reductions were generated by increased use of renewable fuels. Significant differences in WTP were found across regions and income levels.

Dietz et al. [26] examined social influences on the support for climate change policies and found political orientation, income, race, gender, and age to be influential. Similarly, Berrens et al. [27] estimated WTP for various climate change policies and found that political ideology had a significant influence.

Several studies have focused specifically on consumer preferences for ethanol blends [28-31]. Petrolia et al. [28] used a contingent valuation exercise to examine WTP for E10 and E85 among US consumers. They found that demand for E85 is more price inelastic than E10, with much stronger preferences for E85 than E10. Their results suggested that more educated people are more likely to be accepting of E10, but less likely to pay a premium. However, politically 'liberal' respondents were more likely to pay a premium for both E10 and E85.

Solomon and Johnson [29] conducted a study of Michigan, Wisconsin, and Minnesota residents to determine how these residents valued climate protection through the potential purchase and consumption of cellulosic ethanol. Using a multi-part, split-sample contingent valuation method, the authors found that 83.8% of the respondents were willing to pay higher fuel prices for cellulosic ethanol. Variables that were significant determinants of WTP were household income, political views, gender, climate change concerns and beliefs, and whether the premium would go towards reducing climate change.

Aguilar and Thompson [30] examined attitudes toward ethanol use and WTP for ethanol blends among Missouri consumers. They found widespread agreement with statements suggesting that ethanol could benefit farmers, reduce dependence on fossil fuels, and improve the environment (i.e., 'The use of ethanol as a motor vehicle fuel benefits U.S. farmers', 'The use of ethanol as a motor vehicle fuel helps reduce U.S. dependence on fossil fuels', and 'The use of ethanol as a motor vehicle fuel has a positive impact on the environment'). However, their estimated WTP for ethanol blends of 20% (E20) was lower but statistically indistinguishable from WTP for E0 or E10. They examined the fuel attributes of price, octane rating, feedstock source, and blend but did not include emission reductions as an attribute in their modeling.

Finally, Jensen et al. [31] examined WTP for E85 from corn, switchgrass, and wood residues compared with E10, using some of the same survey data used in this analysis. Results from their study suggest consumers are willing to pay a premium for E85 with switchgrass as the ethanol feedstock as opposed to E10 with corn as the ethanol feedstock. They also found that consumer concerns about land use for fuel instead of food production had a negative impact on WTP for E85 from corn grain, while greater concerns about fuel security relative to the environment had a positive impact. They also estimated WTP for emission reductions from E85 compared with E10 from corn to be about 0.0043 cents/km for each percent in emission reductions (0.036 cents/l for a vehicle with a fuel efficiency of 8.50 km/l) However, their study neither examined the effects of attitudes or demographics on WTP for emission reductions nor did it consider consumer preferences for E0.

While several studies ([21-26]) have examined WTP for emission reductions or for ethanol blends ([28-31]), these studies have not examined WTP for emission reductions as an attribute of E85 within the context of conjoint analysis. This study will extend the literature by estimating how WTP for emission reductions through E85 purchases vary across market segments using cluster analysis to identify the market segments, conjoint analysis to estimate WTP, and data from a nationwide US survey.

Methods

Economic model of willingness to pay

Consumers are assumed to maximize utility and that when presented with a set of alternatives, they will select the alternative that provides the greatest amount of utility relative to the other alternatives. It is also assumed that the utility received from any alternative is related to a set of observable attributes associated with that alternative. Thus, the utility that individual n receives from the jth alternative (U_{nj}) can be expressed as $U_{nj} = \theta' Z_j + \varepsilon_{nj}$, where Z_j is a vector of observed attributes of the jth alternative, θ is a vector of unobserved parameters to be estimated, and ε_{nj} is an error term. Under certain conditions, a conditional logit model [32] can be used to estimate this model, in which case the probability of selecting alternative j can be expressed as:

$$\Pi_{nj} = \frac{exp\left(\theta' Z_j\right)}{\sum_i exp\left(\theta' Z_j\right)} \tag{1}$$

Mean WTP for attribute l is calculated using:

$$WTP_l = -\frac{\hat{\theta}_l}{\hat{\theta}_P} \tag{2}$$

where $\hat{\theta}_l$ is the estimated coefficient for l, a non-price attribute, and $\hat{\theta}_p$ is the estimated coefficient for price.

However, the conditional logit is limited in that it assumes homogeneity of individuals, implying that there is homogeneity of preferences across the sample. Heterogeneity of preferences across consumers can be incorporated into the model using a random parameter model [33]. Individual utility within this framework can be expressed as:

$$U_{nj} = \left(\bar{\theta} + \sigma_n\right)' Z_j + \varepsilon_{nj=} = \theta' Z_j + \sigma_n{}' Z_j + \varepsilon_{nj}, \tag{3}$$

where $\bar{\theta}$ is a vector of the mean parameters to be estimated across the n individuals, and σ_n is the vector of individual deviations from the population mean $\bar{\theta}$. Mean WTP can be estimated using [34]:

$$WTP_l = -\frac{\bar{\theta}_l}{\bar{\theta} p} \tag{4}$$

The attribute for price is assumed to be constant across respondents to avoid problems associated with individual coefficient estimates that are the same sign as $\bar{\theta}_l$ [35] or are near zero [36].

Heterogeneity of preferences can also be incorporated into the model by including demographic and attitudinal variables in a 'mixed' model [37]. When the fixed parameter model is modified to include these demographic and attitudinal variables, utility can be expressed as:

$$\begin{aligned} U_{nj} &= (\theta + \varphi Y_n)' Z_j + \varepsilon_{nj=} \\ &= \varphi Y_n Z_j + \theta' Z_j + \varepsilon_{nj}, \end{aligned} \tag{5}$$

where Y_n are individual characteristics or taste indicators, and φ are their associated parameters. The individual characteristics enter the model as interactions with the product attributes. Mean WTP for attribute l, calculated at the sample mean, becomes:

$$WTP_l = -\frac{\hat{\theta}_l + \varphi_l \bar{Y}_n}{\hat{\theta}_P} \tag{6}$$

This mixed model is modified by Lavin and Hanemann [38] to enable the incorporation of the taste indicators of the consumers into the random parameters model. Utility in this model can be expressed as:

$$\begin{aligned} U_{nj} &= \left(\bar{\theta} + \varphi Y_n + \sigma_n\right)' Z_j + \varepsilon_{nj=} \\ &= \varphi Y_n Z_j + \bar{\theta}' Z_j + \sigma_n{}' Z_j + \varepsilon_{nj}, \end{aligned} \tag{7}$$

where Y_n are taste indicators and φ are their associated parameters. Again, $\bar{\theta}$ is a vector of the mean parameters, and σ is the vector of individual deviations from the mean. This model becomes the RPL with individual characteristics or taste indicators interacted with the product attributes.

If the demographic and attitudinal variables are interacted with non-price variables, then the individual-level estimate for WTP for attribute l becomes:

$$WTP_{nl} = -\frac{\hat{\theta}_{nl} + \varphi_l Y_n}{\hat{\theta}_P}. \tag{8}$$

The individual-level WTP is calculated according to Equation 8 using the individual-level parameters for the non-price attributes, respondent characteristics, and the fixed parameters on these characteristics, along with the fixed parameter on price. Mean WTP can be calculated at the means of the random parameters and the demographic and attitudinal variables using [39]:

$$WTP_l = -\frac{\hat{\bar{\theta}}_l + \varphi_l \bar{Y}}{\hat{\theta}_P}. \tag{9}$$

In this analysis, the attitudinal variables and individual characteristics are interacted with the emission reduction attribute (*Reduce*). The parameters on the fuel attributes other than fuel price are randomized, while the parameters on price and on the interactions of the emission reduction variable (*Reduce*) with the demographic and attitudinal variables are held fixed. The coefficient on emission reductions (*Reduce*) is hypothesized to be positive [21]. The coefficients on percentage of imported fuel (*Import*), on fuel that is less widely available (*Inconvenience*), and on fuel price (*Price*) are expected to be negative.

The RPL is estimated with simulated maximum likelihood and, in this case, using Halton draws with 1,000 replications. The randomized parameters are assumed to follow a normal distribution.

Survey

The data were obtained through an online survey conducted in January and February of 2009. The survey sample and online services were provided by Knowledge Networks® (KN). The sample was drawn from an online research panel maintained by KN and designed to be representative of the US population. More information on the online research panel and recruitment methodology can be found in KN [40].

The sample was a simple random sample of panel members 18 years of age or older. The survey was fielded to 2,851 panel members, and 1,909 responses were received before the survey was closed to further responses. The survey instrument began with two screening questions. If the household did not currently own or lease at least one automobile or the household automobile the respondent drove the most often did not have a gasoline or gasoline/electric engine, the respondent was screened out of the survey. Out of the 1,909 respondents, 1,727 passed the screening and provided useable responses to the survey. Out of these 1,727 responses, 1,668 were used for the cluster analysis based on the completeness of responses to the clustering questions.

A survey weight designed to compensate for non-response to the survey was calculated by comparing respondent demographics with benchmark demographics (i.e., gender, age, race/ethnicity, education, Census Region, metropolitan area, and internet access) from the Current Population Survey. The weight was calculated with an iterative proportional fitting procedure [38]. The distribution of the calculated weights was examined to identify and, if needed, trim outliers at the extreme upper and lower tails of the weight distribution. The post-stratified and trimmed weights were then scaled to the sum of the total sample size. All results presented in this paper have been weighed with the resulting weights.

In addition to the screening questions, the survey instrument provided respondents with some basic information on ethanol blends and feedstocks. This information was provided on eight different 'information screens'. The information screens were interspersed with questions covering such issues as vehicle ownership, driving patterns, and familiarity and experience with ethanol and FFVs. Following the information screens was a conjoint analysis exercise where respondents were asked to choose between three different varieties of E85 and, depending on the survey version, either E0 or E10 produced with corn grain ethanol. Participants were asked to assume that their automobile was compatible with E85 when responding to the conjoint analysis questions. Following the conjoint analysis exercise, respondents were asked a number of attitudinal and behavioral questions on a variety of topics related to ethanol production and consumption, including fuel security, fuel consumption behavior, the food vs. fuel debate, climate change, and the environment. Finally, responses to the survey questions were supplemented with demographic information from the panel member profile maintained by KN.

The conjoint analysis exercise consisted of 14 different choice tasks, although three of these were fixed or holdout tasks that were constant across all respondents.[a] Each choice task had four alternative combinations of fuel attributes, and respondents were asked to select their most preferred alternative from these four. Three of the alternatives were an E85 blend with differing levels of attributes while the remaining alternative was either E0 or E10 from corn, depending on the survey version. The levels of the attributes for the three E85 blends differed from one alternative to another and from one choice task to another, while the levels of the attributes for the E0 or E10 alternative were constant across all choice tasks. [b]See Figure 1 for an example of the choice task presented to respondents.

	E85	E85	E85	Gasoline
Product Attributes	70% of MPG of Gasoline	70% of MPG of Gasoline	70% of MPG of Gasoline	100% of MPG of Gasoline
Price	$1.56	$1.48	$1.40	$2.00
Price per mile*	7.8 ¢	7.4 ¢	7 ¢	7 ¢
Ethanol made from	Switchgrass	Switchgrass	Corn	No Ethanol
% imported from foreign countries	10%	33%	50%	67%
Greenhouse Gas (GHG) Emissions	10% less than gasoline	10% less than gasoline	50% less than gasoline	0% less than gasoline
Available at:	Gas station located 5 minutes out of your way	Gas station located 2 minutes out of your way	Gas station located on your way	Gas station located 2 minutes out of your way
Which option do you prefer?	●	●	●	●

* The price per mile is calculated for an example automobile that gets 20 miles per gallon.

Figure 1 Example of choice task.[a] Price levels offered in this example are 7.8, 7.4, and 7 cents/mile driven. These prices convert to 4.8, 4.6, and 4.4 cents/km. Assuming 8.5 km/l, the prices per liter are $0.41/l, $0.39, and $0.37 for E85 and $.53 for gasoline.

The attributes included in the choice task were fuel price (stated both in dollars per gallon and dollars per mile or $/l and $/km), feedstock for the ethanol, percent of fuel from imported sources, level of GHG emission reductions relative to either E0 or E10 (depending on survey version), and availability of the fuel. For the analysis presented in this study, the ethanol feedstock types are aggregated to E85 from a biomass feedstock to focus on willingness to pay for emission reductions. Price per kilometer was calculated using an example vehicle that gets 8.5 km/l with E85. For the E0 survey, the price levels used for the E85 alternatives were 3.9, 4.1, 4.3, 4.6, and 4.8 cents/km driven, while the E0 alternative was priced at 4.4 cents/km. These prices per kilometer convert to $0.33, $0.35, $0.37, $0.39, and $0.41/l for E85 and $.53/l for E0. For the E10 survey, the price levels used for the E85 alternatives were 4.2, 4.4, 4.7,4.9, and 5.2 cents/km driven, with the E10 alternative priced at 4.7 cents/km. These prices per mile convert to $0.35, $0.38, $0.40, $0.42, and $0.44/l for E85 and $.53/l for E10 on an energy equivalent basis.

The levels of emission reductions for the E85 alternatives were 10%, 50%, and 73% compared with E0 or E10 (the percent reduction for E0 or E10 was obviously zero). The percentages of E85 fuel imported were 10%, 33%, and 50%, with the E0 alternative listed as being 67% imported and the E10 alternative listed as being 60% imported. Availability of the E85 alternative was stated as being located at a fuel station that was 'on your way' or either 2 or 5 min 'out of your way'. The E0 and E10 alternatives were presented as being 2 min out of the way.

The resulting fuel attribute variable definitions are provided in Table 1. These fuel attributes include price (*Price*), blend (*E85*), minutes out of the consumer's way that he or she must travel to purchase the fuel (*Inconvenience*), percent of GHG emission reductions from E10 or E0 (*Reduce*), and percent of fuel from imported sources (*Import*).

The experimental design used to determine how the levels of the attributes of the E85 alternatives varied across alternatives and choice tasks were generated using Sawtooth Software's CBC/Web software (UT, USA). The design was a randomized design created using the Balanced Overlap design strategy. The Balanced Overlap strategy prohibits duplicate alternatives within the same choice task but does not strictly minimize the number of times a particular attribute level is shown in a single task. Allowing some overlap of attribute levels within a choice task improves the researcher's ability to analyze interactions between the attributes [41] and may outperform strategies that minimize level overlap [42]. Although the software can produce a unique design for each respondent, the need to import the design into KN's web architecture rendered such a large number of alternative designs infeasible. Instead, 20 different

Table 1 Names, definitions, and hypothesized signs of variables used in the models

Variable name	Definition	Hypothesized sign
Dependent variable		
Chosen	1 if the alternative is chosen, 0 otherwise	
Explanatory product attribute variables		
Price ($, cents/km)	3.9, 4.1, 4.3, 4.6, and 4.8 (E0) or	-
	4.2, 4.4, 4.7,4.9, and 5.2 (E10)	
Import (%)	10, 33, 50, and 60 imported	-
Inconvenience (min.)	0, 2, or 5 out of the way	-
E85	1 if blend is E85, 0 otherwise	+
Reduce (%)	0, 10, 50, and 73 GHG emission reductions compared with either E10 or E0	-
Variables interacted with reduce		
Potential activist	1 if in the *Potential activist* cluster, 0 otherwise	+
Environmental	1 if in the *Environmental* cluster, 0 otherwise	+
National interest	1 if in the *National interest* cluster, 0 otherwise	-
Neutral	1 if in the *Neutral* cluster, 0 otherwise (omitted category)	

designs were created, and each respondent was randomly assigned to one of the 20 designs.

Cluster analysis

Market segments were identified using a cluster analysis of responses to the series of 15 attitudinal and behavioral questions that followed the conjoint analysis exercise. These questions were actually statements where the respondents were asked to list their level of agreement with the statement using a five-point Likert scale ranging from 'strongly disagree' (1) to 'strongly agree' (5). These statements pertained to attitudes and behaviors related to fuel security, the food vs. fuel debate, environmental concern, perceived consumer effectiveness (PCE)[c], and faith in the efficacy of others (FIO)[d]. A complete list of variables used in the cluster analysis can be found in Table 2. Several of the variables in Table 2 were based upon [26]. A popular two-stage cluster method in which a hierarchical cluster method is followed by a non-hierarchical method was chosen for this analysis [17-20]. Ward's minimum variance method was the hierarchical method used to determine the optimal number of clusters. This method minimizes the within-cluster sum of squares [43]. At each stage of the analysis, joining of every possible pair of clusters is considered, and the two clusters whose union results in the minimum increase in 'information loss' are combined [15]. The number of clusters was determined based on inspection of the dendrograms and interpretation of the relevance of three, four, and five cluster solutions. The number of clusters was also ascertained using the Duda-Hart Je(2)/Je(1) index for which larger values indicate more distinct clustering [44].[e] Based on these observations, a four-cluster solution emerged as optimal. Cluster centroids were saved from the Ward's analysis to be used as starting seeds for the *k*-means analysis. It is widely recognized in the literature that the performance of the *k*-means method depends largely on the initial seeds used to begin the clustering process [19,44,45]. Steinley [46] cautions about the starting seeds used in the *k*-means procedure and notes that researchers have often chosen to use starting seeds from a hierarchical method like Ward's minimum variance to obtain the starting seeds for the *k*-means method [47,48]. The results from the Ward's method analysis were refined

Table 2 Names and descriptions of variables used in cluster analysis

Variable name	Description (1 = strongly disagree, . . ., 5 = strongly agree)
FVFlanduse	US farmland should be devoted to producing food and not fuel.
FVFfoodprice	Increasing ethanol production from corn will lead to higher food prices.
Natsecurity	Reducing our dependence on foreign oil is important to improving our national security.
SecVsEnviron	Reducing our dependence on foreign oil is more important than protecting the environment.
Drill	More land in the USA should be opened up for oil drilling.
Climate	Global climate change is occurring.
Health	Climate change will lead to environmental and health problems in many parts of the world.
Urgent	There is no urgent need to take measures to prevent climate change.
Forest	I am extremely worried about loss of the world's forests.
Future	I am extremely worried about the state of the world's environment and what it will mean for my future.
LackKnow	I don't have enough knowledge to make well-informed decisions on environmental issues.
NoEffect	My personal actions don't have any significant effect on the quality of the environment.
Science	Science and technology will come up with ways to solve environmental damage and pollution.
Sacrifice	Most people are not willing to make sacrifices to protect the environment.
Responsible	We have a responsibility to future generations to protect the environment.

Table 3 Multinomial logit of market opinion clusters on demographic variables[a,b]

Demographic variables	Estimated coefficient	Standard error	z
Potential activists			
Intercept	−1.7833	0.4987	−3.58[a]
Female	−0.0112	0.1295	−0.09
Education	0.1568	0.0749	2.09[b]
Income	0.0168	0.0176	0.96
Age	0.0199	0.0040	4.95[a]
West	−0.2042	0.2176	−0.94
South	0.2422	0.1973	1.23
Midwest	0.2164	0.2122	1.02
Political views	0.0319	0.0346	0.92
White	0.3643	0.2851	1.28
Black	−0.6958	0.3469	−2.01[b]
Hispanic	0.6340	0.3327	1.91[c]
Environmentals			
Intercept	−3.4788	0.5427	−6.41[a]
Female	−0.1657	0.1444	−1.15
Education	0.6551	0.0852	7.69[a]
Income	0.0071	0.0195	0.36
Age	0.0095	0.0045	2.10[b]
West	−0.2446	0.2261	−1.08
South	−0.1753	0.2117	−0.83
Midwest	−0.3044	0.2308	−1.32
Political views	0.3173	0.0400	7.93[a]
White	−0.0299	0.2800	−0.11
Black	−1.5249	0.3710	−4.11[a]
Hispanic	0.4219	0.3406	1.24
National interest			
Intercept	−3.4829	0.7874	−4.42[a]
Female	−0.6325	0.1883	−3.36[a]
Education	0.3263	0.1116	2.92[a]
Income	0.0730	0.0266	2.75[a]
Age	0.0393	0.0059	6.68[a]
West	0.5051	0.3250	1.55
South	0.6310	0.2989	2.11[b]
Midwest	0.6212	0.3250	1.91[c]
Political views	−0.5056	0.0588	−8.60[a]
White	0.6011	0.4615	1.30
Black	−0.2921	0.6352	−0.46
Hispanic	−0.7650	0.6452	−1.19
Number of observations	1,668		
LLR test against intercept only	544.47[a]		

[a,b,c]Significance levels of 0.01, 0.05, and 0.10, respectively. The demographic variables are defined as follows: *Female* = 1 if female, 0 otherwise; *Education* = 1: less than high school, 2: high school, 3: some college, 4; bachelor's degree or higher; *Income* = 1: less than \$5,000, 2: \$7,500 to \$9,999. . .19: \$175,000 or more; *Age* = age in years. *West*, *South*, *Midwest* = 1 if reside in region, 0 otherwise; *Political views* = 1: strong Republican, 2: not a strong Republican, 3: leans Republican, 4: independent or undecided, 5: leans Democrat, 6: not a strong Democrat, 7: strong Democrat; and *White*, *Black*, *Hispanic* = 1 if race/ethnicity, 0 otherwise.

using the *k*-means non-hierarchical method. The *k*-means method is a simple, non-parametric clustering method that minimizes within-cluster variability and maximizes between cluster variability.

To investigate associations between clusters and demographics and other survey questions, analyses of variance were conducted to determine differences in mean opinion ratings across the four clusters for each of the opinion variables. The analyses of variance were calculated based on an approach suggested by Kennedy [49]. In this case, dummy variables are created for three of the four clusters. The variable of interest is then regressed on the three cluster dummy variables. In this method, the coefficients for the dummy variables are the means for the variable for each cluster. The analysis of variance *F*-test is the same as testing whether or not the dummy variable coefficients (means) are significantly different from each other [49]. It was necessary to use this method so that the post-stratification weight could be applied to the data. Mean comparison tests (*t* tests) were conducted by omitting one cluster dummy variable at a time and evaluating the significance of the coefficients on the other dummy variables by examining the *t*-statistics associated with each estimated coefficient. Names for the four clusters (*Potential Activist*, *Environmental*, *Neutral*, and *National Interest*) were based on inspection and interpretation of the mean responses to the clustering variables.

The effects of demographic characteristics on market opinions were examined using a multinomial logit with the *Neutral* cluster as a base. The demographics examined included gender, age, education level, income, region of residence, political views, and race/ethnicity. The definitions of these variables are shown at the bottom of Table 3.

Conjoint analysis

WTP for emission reductions is estimated using responses to the conjoint analysis tasks. Conjoint analysis has been used extensively in consumer research as a means of predicting consumer preferences among multi-attribute alternatives since the early 1970s [50]. The type of conjoint analysis used in this study is also referred to as contingent choice. With contingent choice, respondents choose a preferred product defined along a set bundle of product attributes from among two or more product choices. The set of attributes for all products is the same, but the attribute levels differ among the product varieties. This method was chosen because of its similarity to the actual purchase decisions faced by consumers. The inclusion of price as a product attribute in this survey allows WTP to be estimated for changes in levels of non-price attributes such as GHG emission reductions.

Results and discussion

Market opinion clusters

As stated earlier, the cluster analysis revealed four clusters: the *Potential activist*, *Environmental*, *Neutral*, and *National interest* clusters. Table 4 displays the overall *F*-tests for differences in the mean opinion ratings among these four clusters. In each case, statistically significant differences among the mean ratings across clusters were observed. Further examination of the *t* tests revealed that significant differences existed among most of the means across the clusters. A description of each cluster is provided below.

Potential activist cluster

The *Potential activist* cluster is the largest of the four and contains 560 respondents. As can be seen in Table 4, while the members of the *Potential activist* cluster feel strongly about several of the clustering questions, they tend not to have either the highest or lowest mean responses. Issues surrounding climate change are of greater importance to this cluster than the *National interest* and *Neutral* clusters, but not greater than the *Environmental* cluster. The *Potential activists* are also second behind the *Environmentals* when it comes to environmental concerns both now and in the future; however, the *Potential activists* led all clusters in agreement with the statement that they do not have enough information to make well-informed decisions about environmental issues. The *Potential activists* have varying opinions about consumer effectiveness – they tend to disagree that personal actions do not have any significant effect on the environment, but they are also the most likely out of the four clusters to agree that most people are not willing to make sacrifices to protect the environment. Finally, the *Potential activists* are the second most likely behind the *National interests* to agree that science and technology will solve environmental problems.

Environmental cluster

The *Environmental* cluster is the second largest cluster with 459 respondents and its members are the most likely to agree that climate change is occurring and that it will lead to environmental and health problems around the world. As shown in Table 4, this cluster strongly disagrees that there is no urgent need to take

Table 4 Mean market opinion ratings across clusters[a,b]

Market opinion variable	Cluster (mean: 1 = strongly disagree, . . ., 5 = strongly agree)				*F* value (*N* = 1,668)
	Potential activist	Environmental	Neutral	National interest	
FVFlanduse	3.22 a	3.32 a	2.73	3.94	52.12[f]
FVFfoodprice	3.75 b	3.88 b	2.96	4.27	82.32[f]
Natsecurity	4.41	4.21	3.24	4.57	119.71[f]
SecVsEnviron	3.07	2.00	2.84	4.16	196.32[f]
Drill	3.93	2.37	3.20	4.75	239.86[f]
Climate	4.11	4.75	3.16	2.36	417.96[f]
Health	3.97	4.66	3.09	2.15	421.45[f]
Urgent	2.48	1.39	2.85	3.99	352.76[f]
Forest	3.76	4.49	3.00	2.50	277.39[f]
Future	3.73	4.50	2.94	2.01	427.24[f]
LackKnow	3.44	2.30	3.04	2.06	101.25[f]
NoEffect	2.54	1.67	2.75	3.13	109.67[f]
Science	3.37 c	3.11 d	3.00 d	3.49 c	17.80[f]
Sacrifice	3.75 e	3.73 e	3.15	3.54	32.93[f]
Responsible	4.40	4.79	3.38	3.71	234.33[f]

Like letters beside the individual means indicate no significant difference between the means at the 0.05 significance level. [f]Significant differences among the means at α = .01.

measures to prevent climate change. The *Environmentals* are the second most likely behind the *National interests* cluster to agree that US farmland should be used to produce food and not fuel and that increased corn ethanol production will lead to higher food prices. This cluster believes that the USA should reduce its dependence on foreign oil, but does not believe that it is more important than protecting the environment. The *Environmentals* are the least likely to support opening up more US lands for oil drilling. Concerns for the loss of the world's forests are highest in this cluster as well as concern for the state of the environment both present and in the future. Members of the *Environmental* cluster disagree, more than any other cluster, with the statement that their personal actions do not have an effect on the quality of the environment; however, like *Potential activists*, they are likely to agree that most people are not willing to make sacrifices to protect the environment. They are second behind the *National interest* cluster in disagreeing with the statement that they do not have enough information to make well-informed decisions on environmental issues. Not surprisingly, the *Environmentals* feel a greater responsibility to protect the environment for future generations than the other clusters.

Neutral cluster

The *Neutral* cluster is the third largest with 410 respondents. The *Neutral* cluster is so named because its means are clustered around the value of three, which represents neutral in the Likert scale range used. As a result, the *Neutral* cluster lags the other clusters in agreeing with a number of the statements (i.e., farmland should be devoted to food and not fuel, increasing ethanol production from corn will lead to higher food prices, reducing dependence on foreign oil more important than improving national security, science and technology will come up with ways to solve environmental damage and pollution, most people not willing to make sacrifices to protect the environment, and that we have responsibility to protect environment for future generations). Their level of agreement with six of the other statements is below two of the three other clusters. There is no variable for which the *Neutral* cluster has the highest mean level of agreement of the four clusters, although they have the second highest mean level of agreement for three of the statements (i.e., there is no urgent need to take measures to prevent climate change, do not have enough knowledge to make well-informed decisions on environmental issues, and personal actions do not have any significant effect on the environment).

National interest cluster

The *National interest* cluster is the smallest of the four with 239 respondents. This cluster agrees more strongly than any other cluster that US farmland should be used for food not fuel, and that increasing corn ethanol production will lead to higher food prices (Table 4). National security is of utmost importance to this cluster as they are most likely to agree that reducing our dependence on foreign oil is important and that it is more important than protecting the environment. Hence, they also feel most strongly about opening more US lands for oil drilling. In terms of climate change, this cluster is the least likely of all the clusters to agree that climate change is occurring and that it will lead to health and environmental problems around the world. The *National interest* cluster is also the most likely to disagree that there is an urgent need to take measures to prevent climate change, that they are concerned for the loss of the world's forests, and that they are concerned for the state of the environment both now and in the future. This cluster feels most strongly about their ability to make well-informed decisions on environmental issues, but they are also most likely to agree that personal actions do not have any significant effect on the quality of the environment. The *National interest* cluster is the most likely to agree that science and technology will develop solutions for environmental and pollution problems. They are the least likely out of the four clusters to agree that there is a responsibility to protect the environment for future generations.

The effects of cluster membership on WTP for emission reductions through use of E85 can be hypothesized based upon observed differences in the attitudes of the four clusters. Using membership in the *Neutral* cluster as the base case, membership in the *Environmental* cluster is expected to have a positive influence on WTP for emission reductions, as members of the *Environmental* cluster tend to have strong views about the importance of protecting the environment. Membership in the *National interest* cluster is expected to have a negative influence on WTP as these individuals are more concerned about national security and less concerned about the environment. WTP by the *Potential activist* cluster relative to that by the *Neutral* cluster is difficult to hypothesize, a priori, as the members of the *Potential activist* cluster are concerned about the environment, but feel that their personal actions have little effect while also believing that science and technology will solve environmental problems.

Estimated multinomial model of opinion clusters on demographics

As can be seen in Table 3, the coefficient on the *Female* variable for the *National interest* cluster in the multinomial logit model was negative and significant, implying that females were less likely to be members of the *National interest* cluster than of the *Neutral* cluster.

Female was not significant for either of the other two clusters. The coefficient on *Education* was positive and significant for the each of the clusters. Thus, greater educational attainment increased the likelihood that the respondent would fall into an opinion cluster other than the *Neutral* cluster. *Income* was positively correlated with membership in the *National interest* cluster relative to the *Neutral* cluster. The coefficient on *Age* was positive and significant for all three clusters, suggesting that older respondents were more likely to have non-neutral opinions about the issues. The coefficient on the regional variables indicates that respondents residing in the South and the Midwest were more likely to fall in the *National interest* cluster. Respondents who leaned more toward being a Democrat were more likely to be a member of the *Environmental* cluster, but less likely to be a member of the *National interest* cluster. Relative to other races, respondents who were *Black* were less likely to fall into the *Potential activists* and the *Environmental* clusters. *Hispanic* respondents were more likely to be a member of the *Potential activists* cluster. A Hausman test revealed that the Independence of Irrelevant Alternatives assumption holds for the multinomial logit in this case.

Estimated models of WTP

Three different econometric analyses were performed on both the E0 and E10 survey versions to measure the effects of membership in the different clusters on WTP for emission reductions. These three analyses were a conditional logit and a RPL, in which the *Potential activist*, *Environmental*, and *National interest* cluster variables were interacted with the emissions reduction (*Reduce*) product attribute, and a RPL on the product attributes only. The base or omitted cluster for the analyses with interaction terms was the *Neutral* cluster. In order to identify whether conditional logits were sufficient or RPL needed to be employed, both the RPL models with E0 and E10 as bases were compared with their conditional logit counterparts. In both cases, the log-likelihood ratio test indicated that the RPL model was preferred (E0: LLR = 4559.17, 4df; E10: LLR = 3164.47, 4 df) at the 95% confidence level.[f] To measure whether the clusters as a group contributed to the model, log-likelihood ratio tests were also conducted using the RPL with fuel attributes only and the RPL with fuel attributes and the cluster interactions with *Reduce*. In both cases (E0 and E10), the tests indicated that the cluster interactions contributed significantly to the models (E0 79.449, 3 df; E10 81.6058, 3 df).

The results of the RPLs with the interaction terms for both the E0 and E10 cases are shown in Table 5. Both the E0 and E10 models were significant overall, as indicated by the LLR tests against an intercept only model. All of the coefficients on the non-emission characteristics were significantly different from zero and were of

Table 5 Estimated random parameters logits for E85, with E0 and E10 as the base fuels[a]

	E0 base			E10 base		
Variable	**Estimated coefficient**	**Standard error**	***z***	**Estimated coefficient**	**Standard. error**	***z***
Mean						
Price	−1.9492	0.1057	−18.44[a]	−1.9241	0.1019	−18.88[a]
Import	−0.0229	0.0022	−10.36[a]	−0.0332	0.0025	−13.36[a]
Inconvenience	−0.2085	0.0173	−12.06[a]	−0.2076	0.0158	−13.13[a]
E85	3.1436	0.4331	7.26[a]	3.9106	0.4251	9.20[a]
Reduce	0.0073	0.0067	4.29[a]	0.0019	0.0018	1.04
*Potential activist*Reduce*	0.0021	0.0024	0.86	0.0059	0.0026	2.31[b]
*Environmental*Reduce*	0.0163	0.0030	5.36[a]	0.0174	0.0028	6.29[a]
*National interest*Reduce*	−0.0060	0.0027	−2.19[b]	0.0001	0.0024	0.03
Standard deviation						
Import	0.0393	0.0026	15.05[a]	0.0428	0.0027	15.85[a]
Inconvenience	−0.2287	0.0217	−10.55[a]	0.2403	0.0189	12.77[a]
E85	5.1851	0.7015	7.39[a]	3.864	0.4097	9.43[a]
Reduce	−0.0143	0.0015	−9.31[a]	−0.0136	0.0015	−9.14[a]
Number of observations	34,996			38,656		
LLR Test Against Intercept Only	709.49[a]			748.86[a]		

[a] and [b] represent significance levels of 0.05 and 0.01, respectively.

the expected sign. The coefficient on *Reduce* was significant in the E0 model, but not in the E10 model. The pattern of significance for the interaction of the cluster variables with emission reductions differed across the two models. The coefficient on *Environmental*Reduce* was positive and significant in both models, suggesting that WTP was higher among members of the *Environmental* cluster than among those in the *Neutral* cluster regardless of whether E0 or E10 was the base fuel. The patterns for the *Potential activist* and *National interest* interactions were mixed. The coefficient on *Potential activist*Reduce* was positive and significant in the E10 model, but insignificant in the E0 model, perhaps suggesting that *Potential activists* were more receptive to emission reductions when choosing between E85 and E10 than when choosing between E85 and E0. The coefficient on *National interest*Reduce* was negative and significant in the E0 model, but insignificant in the E10 model. This result could suggest that *National interest* respondents are less receptive to emission reductions when choosing between E85 and E0 than when choosing between E85 and E10. These two results together may reflect the reticence of certain market segments about moving away from existing gasoline technologies.

As can be seen in Table 6, for the E0 and E10 respondents, the estimated WTP for each of the non-emissions attributes was significantly different from zero and of the anticipated sign. The estimated WTP for emission reductions by the *Environmentals* cluster is positive and significantly different from zero in both the E0 and E10 models. The *Neutrals*' WTP for emission reductions is positive and significant in the E0 model, but not significantly different from zero in the E10 model. The WTP estimates for the *National Interests* and *Potential Activists* clusters are insignificantly different from zero for both E0 and E10. Among the *Environmentals*, the estimate of WTP for each percentage point reduction in emissions is about 0.07 cents/km or about 0.63 cents/l given a 8.5 km/l vehicle for the E0 base and 0.08 cents/km or about 0.67 cents/l given a 8.5 km/l vehicle for the E10 base.

Conclusions

This study segmented survey respondents into four distinct market clusters. The *Potential activists* are those who have environmental concerns, but who are also the least likely to feel that they have enough information to make well-informed decisions about environmental issues and tend not to believe that others will make sacrifices to protect the environment. The *Environmentals* have strong concerns about the environment and feel that we all have a responsibility to preserve the environment for future generations. Those in the *Environmental* cluster tend to be more educated and have more liberal political views. The members of the *National interest* cluster are more concerned about national security, placing a higher importance on it than the environment and believe most strongly in opening up additional lands for oil drilling. Members of this cluster are the greatest climate skeptics, being the least likely to agree that climate change is occurring. They also are the most likely to agree that land should be used for food and not fuel. Those in the *National interest* cluster tended to be more conservative in their political leanings, be males, and to have higher incomes. The *Neutral* cluster is generally neutral about environmental and national security issues, but were the least likely to believe that we should protect the environment for future generations.

These market opinion clusters play a significant role in estimates of WTP for emission reductions through purchases of E85. In particular, *Environmentals* is the only cluster which is consistently in willing to pay a premium for emission reductions. The *Environmentals* are willing to pay around 0.63 to 0.67 cents/l per percentage point of emission reduction. This result suggests that those who feel strongly about environmental issues may be the only consumers who are willing to pay a premium for

Table 6 Estimated willingness to pay for fuel emission reductions and other fuel attributes[a,b,c]

	E0 base			E10 base		
Variable	**WTP[a]**	**Standard error**	***z***	**WTP[a]**	**Standard error**	***z***
Import	−0.0117	0.0025	−4.6547[c]	−0.0173	0.0030	−5.6765[c]
Inconvenience	−0.1069	0.0195	−5.4796[c]	−0.1077	0.0186	−5.7882[c]
E85	1.6091	0.4886	3.2929[c]	2.0298	0.4860	4.1762[c]
Reduce[b]						
Neutrals	0.0037	0.0018	2.0886[c]	0.0010	0.0019	0.5219
Potential activist	0.0164	0.0276	0.5949	0.0349	0.0280	1.2461
Environmental	0.0740	0.0253	2.9287[c]	0.0786	0.0244	3.2253[c]
National interest	−0.0085	0.0101	−0.8354	0.0012	0.0094	0.1259

[a]WTP is in cents/km. For a vehicle with a fuel efficiency of 8.5 km/l, the cost per liter can be obtained by multiplying the WTP estimate by 8.5. [b]WTP for each of the *Reduce* cluster interactions is calculated at the sample means of the cluster and *Reduce* variable interaction. [c]Significance level of 0.01.

E85 due to its potential to reduce GHG emission reductions. The *Environmentals* constituted just under 28% of the respondents to a national survey that was weighted to better represent the US population.

The results suggest that there is a potential niche market of consumers with strong environmental concerns who are willing to pay a premium for renewable fuels in order to reduce GHG emissions. While other consumers may not, in general, be willing to pay a premium for E85 in order to achieve emission reductions, they may be interested in other attributes of ethanol blends, such as the share that is produced domestically or availability of the fuel. Future research should focus on how the market opinion segments may impact WTP for these attributes. Policy makers may find this information useful as they seek to market E85 and facilitate the development of markets for alternative fuels more generally.

Endnotes

[a]Holdout tasks are used as a means of assessing the validity of econometric models used to analyze responses to the choice tasks [51]. [b]Structured this way, the E0 or E10 alternative acts similar to the 'none' option that is commonly included in contingent choice tasks. [c]Perceived consumer effectiveness measures the extent to which an individual feels that his or her behavior has an impact on a given situation [52]. Berger and Corbin's study suggests that PCE is extremely influential as a representative of the environmental attitude/consumer behavior relationship [52]. [d]Faith in others represents a circumstance in which, rather than changing a personal action, an individual could choose to support policies, research, or groups to solve a particular problem. Bergin and Corbin's study suggests that an individual's level of FIO will influence the extent to which the individual supports others' actions in pursuing a solution to a problem [52]. [e]$J_e(1) = \sum_{i=1}^{N} (x_i - \bar{x})^2$, while $J_e(2) = \sum_{j=1}^{2} \sum_{i=1}^{Nj} (x_i - \bar{x}_j)^2$. [f]The log-likelihood ratio test is calculated as −2 (log likelihood restricted – log likelihood unrestricted).

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

AM performed the analysis and was responsible for writing the manuscript. KJ, CC, BE, and DT all contributed by proofreading and editing the manuscripts as well as giving guidance and technical advice throughout the analytical and writing processes. All authors read and approved the final manuscript.

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