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LETTER

Choice at the pump: measuring preferences for lower-carbon combustion fuels

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Supplementary material for this article is available online

Abstract

A decarbonized future will require a transition to lower carbon fuels for personal transportation. We study consumer preferences for combustion fuels including gasoline, diesel, natural gas, and E85 (85% ethanol and 15% gasoline) using consumer choice survey data from two settings: online ($n = 331$) and in-person at refueling stations ($n = 127$). Light-duty vehicle owners were asked in a series of choice tasks to choose among fuels that varied in type, price, CO_2 emissions, and location of origin for a hypothetical vehicle that could accept all fuels. We find that the majority of gasoline and E85 users are willing to substitute towards other fuels at today's prices and attributes, while diesel users have a strong preference for diesel fuel. We also find that respondents are willing to pay on average \$150/ton CO_2 avoided from fuel consumption—more than most estimates of the social cost of carbon. Thus, communicating the climate benefits from alternative fuels may be an important strategy for decarbonizing the transportation sector.

1. Introduction

The transportation sector is now the largest contributor to anthropogenic greenhouse gas emissions in the US—60% of which are from light-duty vehicles [1]. If the ambitious decarbonization goals such as those set by the Paris Agreement are to be realized, the transportation sector—and in particular light-duty vehicles—must transition away from carbon-intensive fuels such as gasoline and diesel. Fortunately, emerging vehicle powertrains are beginning to expand the fuel choices consumers have at the pump. Ethanol, natural gas, electricity, and hydrogen are all becoming part of the energy mix of light-duty vehicles in the US (see figure 1).

Nonetheless, since most consumers have historically never had a choice beyond oil-based fuels at the pump, less is known about how consumers perceive other alternative vehicle fuels. Existing research on consumer preferences for alternative fuels spans literatures on how consumers value (1) alternative vehicle *fuels*, (2) alternative fuel *vehicles* (AFVs), (3) alternative fuel *attributes* in non-automotive applications, such as the energy sector.

Much of the work examining consumer preferences for alternative vehicle fuels examines different blends of ethanol with gasoline, with origins dating back to the introduction of ethanol blends in the US in the 1970s. Results are often presented in terms of

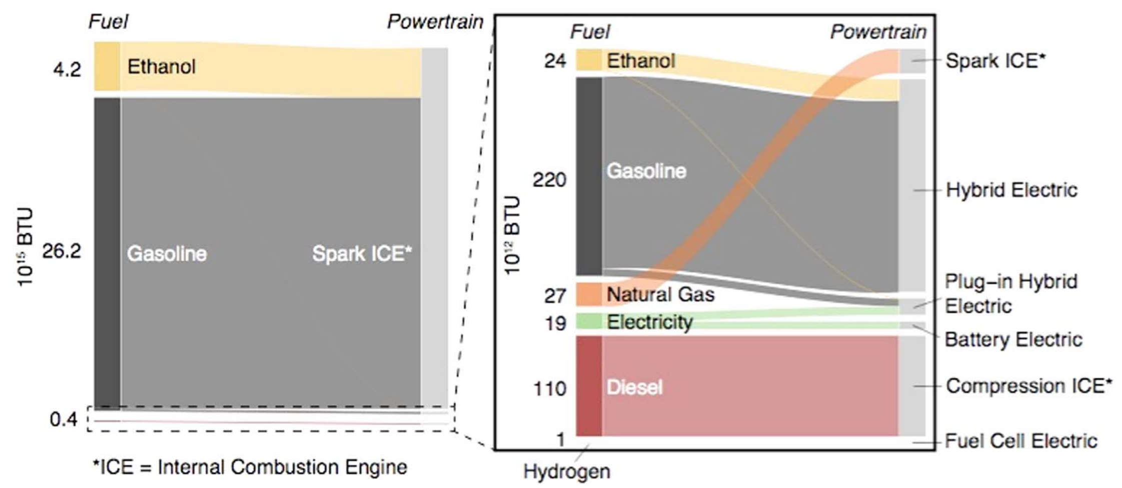

Figure 1. Energy consumption by fuel and powertrain for all light-duty vehicles in the US in 2016. Figure developed by the authors using data from table 38 in [2]. Detailed assumptions are included in section 3 of the supplementary information is available online at stacks.iop.org/ERL/14/084035/mmedia.

'willingness-to-pay' (WTP) for a specific feature, holding all other features constant. Previous studies have found that, on average, survey respondents stated a positive WTP for higher percentages of ethanol-blended over regular gasoline [3, 4] and that respondents perceived ethanol-blended gasoline as having a positive influence on the environment, the economy, and national security [4, 5]. Other studies have estimated high own-price elasticities for E85, suggesting consumers may not view gasoline and E85 that differently beyond price [6]. Consumers also may value ethanol differently depending on how it is sourced [4, 7–9]; in particular, there is concern that corn-sourced E85 (a blend of 85% ethanol and 15% gasoline) may compete with food sources, and some studies find that consumers are willing to pay more for E85 sourced from alternatives to corn, such as cellulosic sources [7–9]. In this study, we examine differences in WTP for ethanol derived from corn and natural gas, another potential ethanol source for which there has been recent interest [10].

The literature on consumer preferences for different AFVs has found that US consumers prefer some vehicle technologies over others, such as plug-in hybrid over battery electric vehicles [11, 12], and these preferences can be influenced by government incentives [13–15]. Research has also found that preferences for different vehicle types can be influenced by a number of attributes unrelated to specific vehicle technologies, such as the behavior of neighbors [16, 17] as well as consumer characteristics such as personality, lifestyle, travel attitude, and environmental awareness [18, 19]. A related study on car sharing suggests that the associated emissions of AFVs are also important to consumers, with car sharing users stating a slightly higher WTP for vehicles with lower emissions [20].

Finally, research in the energy industry (where diverse fuel sources are common) has shown that consumers are willing to pay premiums for different fuel sources if they lead to reduced air emissions [21–23] or if they are perceived as more environmentally friendly than other sources [24]. Similar to the AFV preference literature, consumer WTP for these attributes can vary by demographic variables [25] as well as the information shown to respondents, such as annual cost [26] or emissions reductions [22]. These studies suggest that consumers are sensitive to specific attributes of different fuels, such as their origin and environmental impacts. In this study, we use a controlled experiment to quantify and disaggregate preferences for different vehicle fuels from their associated attributes.

2. Methods

Given the challenges of eliciting preferences for technologies or products that might not yet be available in the market, a common method applied across related prior literature is to model preferences by estimating discrete choice models on survey data collected through controlled experiments. In this study, we apply this approach by fielding choice-based conjoint surveys that ask respondents to choose from a set of different combustion fuels: gasoline, diesel, compressed natural gas (CNG), and E85. We chose to focus on combustion fuels in order to avoid conflating fuel choice with important vehicle attributes associated with fuel choice, such as the limited range or slow refueling time of electric vehicles. The fuels we selected can all be used in variants of internal combustion engines, and most of the vehicle attributes can be reasonably held constant across each fuel (an exception is cargo space, which may be reduced for CNG and E85 given the larger tank required to drive similar ranges as the other fuels). This makes the fuel choice task more consistent with the survey respondents' prior refueling experiences and also facilitates our research interest in studying fuel preferences separate from powertrain preferences. While we considered including other combustion fuels, such as biodiesel, our experimental design limited the number of fuels that could be included as additional alternatives require more data to achieve a given level of statistical significance in model parameters.

Several preliminary steps were taken prior to designing and fielding the final survey. We first considered the results of an online survey conducted by *Civic Science*, a Pittsburgh-based firm, that asked 1129 respondents in the greater Pittsburgh area about converting or buying natural gas-powered vehicles. The insights into drivers' considerations and concerns about alternative vehicle fuels were used to design and field a pilot conjoint survey distributed on Amazon Mechanical Turk (MTurk) in December 2015, obtaining 100 responses. The results suggested that participants understood the choice tasks with no particular areas of confusion, and coefficients from a multinomial logit (MNL) model on these pilot data showed reasonable results (see table 6 in section 1 of the supplementary information). We based our final survey design on this pilot survey with only minor aesthetic changes.

The final survey included 13 choice tasks of three choice options each, including one fixed question with an obviously dominant choice (i.e. lowest price, lowest emissions, and no difference in other attributes) used for checking attention. We used a randomized design of experiment where each choice set was randomly chosen (without replacement for each respondent) from the full factorial design to ensure that interaction effects could be captured. Participants were provided with initial instructions that explained each fuel attribute and described the choice task as choosing between gasoline, diesel, CNG, and E85 for a hypothetical vehicle that can run on any of these fuels. The attributes included in the choice tasks were *origin* (local, national or from abroad), *emissions* (grams of CO_2 per mile), *price* (\$/tank of fuel), and *fuelType* (gasoline, diesel, E85, or CNG).

To mitigate selection bias, we provided respondents with incentives, and respondents accepted or rejected the invitation to participate in the survey before knowing that the survey would ask about alternative fuels. Additionally, it is known that hypothetical consumer choices in a survey context may not be consistent with purchase choices in a market context [27, 28]. To try and mitigate this potential source of bias, we designed the aesthetics of the choice questions to mimic an actual fuel pump and used labeling that is consistent with typical consumer refueling experiences. For example, we adopted the way that emissions are displayed in EPA vehicle fuel economy labels in order to retain familiarity to consumers and provide the respondent with the same reference to scale. Figure 2 shows an example choice task, and a full copy of the survey is included in section 6 of the supplementary information.

For *origin*, we chose 'Home State', 'United States', and 'Rest of World', where 'Home State' was dynamically replaced with the respondent's stated home state. Levels for the *emissions* and *price* attributes were chosen to reflect the variation in historical values of fuel prices and fuel economy, as summarized in table 7 in section 2 of the supplementary information. We collected the fuel economy for all 2015 model vehicles from fueleconomy.gov, and we collected historical fuel prices from afdc.energy.gov, with the mean price taken from the most recent six months prior to the survey fielding and the upper and lower bounds taken from 2009 to 2015. We chose three levels for *emissions* (170, 355, and 530 g CO_2/mile) which spanned the full range of best and worst values from the Environmental Protection Agency (EPA) ratings of light-duty vehicles, with the average rate for model year 2015 vehicles being 358 g CO_2/mile [29]. These emissions values reflect tailpipe emissions, which exclude upstream emissions from fuel production and distribution (life-cycle emissions are considered in a sensitivity analysis). We presented *price* in terms of the cost to fill a tank that can propel the vehicle 300 miles. Because the fuels considered are measured in different units, have different energy densities, and are associated with vehicle powertrains that differ in efficiency, fixing the driving range allows the tank size and fuel efficiency to vary without creating alternatives that are inconsistent with the true energy densities of each fuel. Given the limits of today's technology, some vehicle attributes, such as trunk space, may be compromised to accommodate the fuel tank required to drive 300 miles, and these vehicle attributes may have additional value to consumers that we do not measure in our study. Nonetheless, we instructed respondents to consider only the different fuel attributes presented holding all else equal. The levels for *price* (\$25, \$30, \$35, \$40, \$45, \$50, \$55, \$60) were chosen by examining the mean cost to fill a tank that can propel a vehicle 300 miles using the mean fuel prices and mean vehicle fuel economy values from each fuel type, which ranged from \$26 for diesel fuel to \$63 for E85. Finally, for *fuelType* we included gasoline, diesel, E85, and CNG.

Since previous studies found differences in consumer preferences for ethanol depending on the source [7–9], we randomized participants so that half are informed that the ethanol is derived from corn while the other half are informed that the ethanol is derived from natural gas. Although ethanol is not currently produced from natural gas in the US, there has been interest in understanding the potential for this process [10].

Our target population was light-duty passenger vehicle drivers who regularly refuel their vehicle. Surveys were fielded using two samples: (1) online using MTurk in January, 2016 ($n = 331$), and (2) in-person at refueling stations in San José and Fullerton, California in April and May, 2016 ($n = 127$). The two-sample approach was used to balance trade-offs

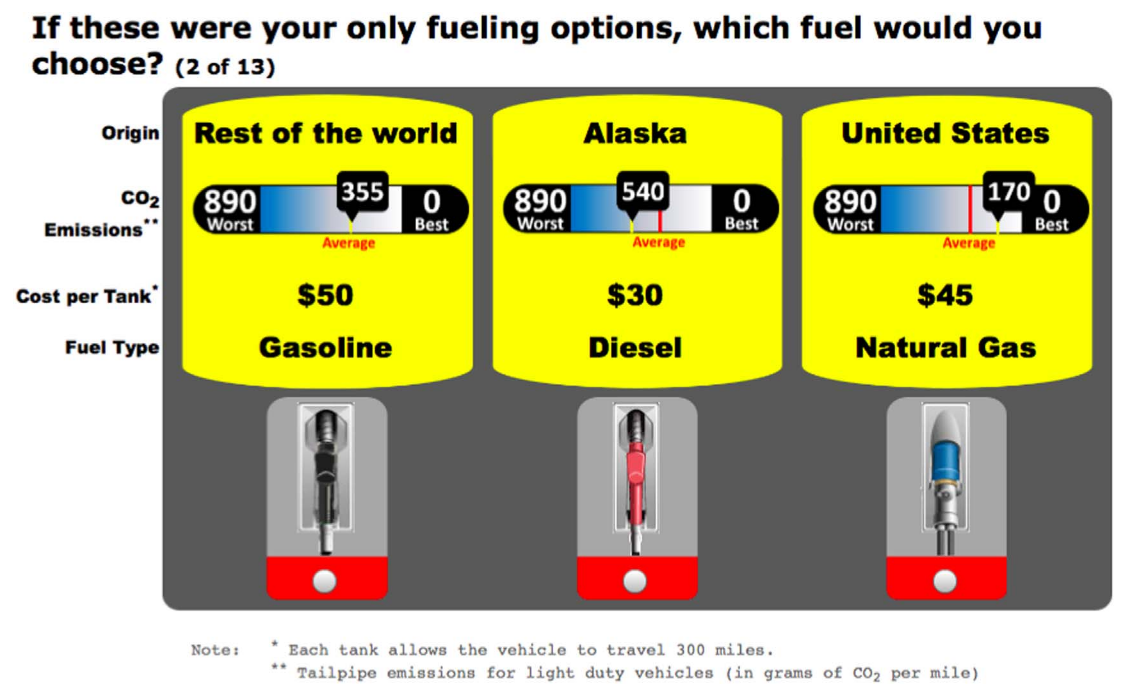

Figure 2. Example survey choice question.

between obtaining a larger and more diverse sample size at lower cost (online) with collecting responses in the same context where fuel purchase decisions are made (in-person at refueling stations). We chose California to field the in-person surveys due to the availability of refueling stations with multiple fuels, partnering with Propel Fuels—the largest E85 retailer in California. In an effort to attract a diverse group of consumers and mitigate selection bias, in-person participants were given \$20 Amazon gift cards for completing the survey. Online respondents were paid \$0.50 for completing the survey on MTurk (a rate of \$3 to \$6/h if completed in 5–10 min). The mean completion times were 8.7 min in-person and 8.4 min online. Sawtooth Software was used to design and field the surveys online, and in-person respondents took the surveys using web-connected tablet devices [30]. Compared to the in-person sample, the online survey respondents had lower incomes, similar levels of education, a more even balance between male and female respondents, more liberal political views, and fewer E85 or diesel users. Details about the survey fielding process and sample are provided in section 5 of the supplementary information.

We estimate different MNL and mixed logit (MIXL) models on the choice data using a random utility model specified in the willingness-to-pay (WTP) space [31]:

$$u_j = \lambda(\boldsymbol{\beta}'\mathbf{x}_j - p_j) + \varepsilon_j, \qquad (1)$$

where the model parameters $\boldsymbol{\beta}$ are the WTP for marginal changes in non-price attributes $\mathbf{x}$ and λ is the scale of the deterministic portion of utility relative to the standardized scale of the error term. Price is p, and the error term, ε, is an IID random variable with a Gumbel extreme value distribution of mean zero and fixed variance of $\pi^2/6$. This specification enables us to directly estimate WTP for marginal changes in non-price attributes and also facilitates the direct comparison of model coefficients across different model specifications [32].

We first estimate a MNL model (model 1) with all main WTP effects as described in table 1. We then estimate a MIXL model (model 2) to capture patterns of heterogeneity and relax the Independence of Irrelevant Alternative property of the MNL model [33]. We assume each main WTP effect has an independent normal distribution and the scale parameter has a log-normal distribution in order to impose positivity. Model fit is conducted via maximum likelihood using simulation for MIXL models [34]. To explore the heterogeneity in WTP for different fuel attributes, we also estimate multiple MNL models interacting main effect variables with different socio-demographic variables, including with the current primary fuel respondents use (model 3a), self-described political views (model 3b), and self-described concern for the environment (model 3c). All data input, output, formatting, calculations, figures, and tables were handled using the *R* programming language, and all models were estimated via maximum likelihood estimation in *R* using the *logitr* package [35].

In addition to estimates of WTP for fuel attributes, we use the estimated model coefficients to simulate respondent choices for different fuels given today's fuel attributes. While WTP coefficients must be interpreted holding all other attributes equal, the simulations approximate the same choice scenario posed in

Table 1. Description of model variables.

Effect	Variable	Description	Units/Values
Price	*Price*	Price of one tank of fuel (300 miles driving range)	Price in $USD
Emissions	*Emissions*	Per-mile CO_2 emissions	100 g of CO_2/mi
Fuel Type (base = gasoline)	*Diesel*	Dummy for diesel fuel type	1 = Diesel; 0 = Not diesel
	cng	Dummy for natural gas fuel type	1 = CNG; 0 = Not CNG
	e85	Dummy for E85 fuel type	1 = Ethanol; 0 = Not ethanol
Origin (base = home state)	*National*	Dummy for nationally-sourced fuel	1 = US; 0 = Not US
	Imported	Dummy for imported fuel	1 = Imported; 0 = Not imported
Socio-Demographic	*DieselUser*	Dummy for current diesel user	1 = Diesel user; 0 = Not diesel user
	e85User	Dummy for current E85 user	1 = E85 User; 0 = Not E85 user
	Conservative	Dummy for self-described political view as 'conservative' or 'very conservative'	1 = Conservative; 0 = Not conservative
	Liberal	Dummy for self-described political view as 'liberal' or 'very liberal'	1 = Liberal; 0 = Not liberal
	EnviroConcern	Dummy for self-described environmental concern	1 = More Concerned; 0 = Less Concerned
Sample	*Online*	Dummy for whether respondent was from online (MTurk) sample.	1 = Online; 0 = In-person

our survey and account for differences in all other attributes. To examine the robustness of our baseline results, we conduct several sensitivity case simulations using different assumptions for the fuel attributes.

3. Results

3.1. Consumer WTP for fuels and fuel attributes

We assess consumer WTP for fuel attributes by estimating five models shown in table 2. We present the results in terms of WTP for a 300 mile tank of fuel; as a reference point, a 300 mile tank of gasoline at $3/gallon for a 25 mpg car would cost $36. Each model is estimated using the full dataset of choice observations from all respondents (i.e. online and in person at refueling stations) except some omissions for missing socio-demographic information in models 3a—3c. Since each of the 458 respondents answered 12 choice questions, our final data set includes 5496 choice observations. Section 1 of the supplementary information includes results from additional models that were not statistically significant at the 0.01 level, including models testing for differences between the online and in-person samples, interactions between the main effects, differences in WTP for E85 depending on the ethanol fuel source (corn versus natural gas), and differences in WTP depending on income levels, education levels, and vehicle ownership. We find that the key conclusions of the paper do not differ when looking at these different groups.

Results suggest that respondents are sensitive to different fuel types and origins. Model 1 suggests that, on average, respondents are willing to pay: (1) $3.12 to switch from a tank of diesel to a tank of gasoline (and no statistically significant difference between gasoline and CNG or E85) when all other attributes are equal; (2) $1.26 to switch from nationally-sourced to locally-sourced; and (3) $3.39 to switch from an imported to locally-sourced, *ceteris paribus*. Consumers are also willing to pay $4.63 more to reduce CO_2 emissions of a 300 mile tank by 100 g mi^{-1} (30 kg total), which is about $150 per ton. In Model 2, WTP coefficients are modeled as normally distributed across the sample population, and the magnitude and significance of the standard deviation coefficients suggests considerable heterogeneity exists. In this model, the WTP to reduce emissions has a mean of $4.52 and a standard deviation of $2.62, suggesting that approximately 96% of the survey population would be willing to pay a premium to reduce emissions. In contrast, the mean and standard deviation of the fuel type and fuel origin coefficients vary widely. Models 3a–3c explore this heterogeneity by examining variation in preferences for different sub-groups in the sample.

Results from Model 3a suggest that preferences for fuel type vary widely depending on the primary type of fuel the respondents use, which includes gasoline, diesel, and E85. Holding cost, emissions, and origin constant, gasoline users are willing to pay $3.66 per 300 mile tank to avoid diesel but have no significant WTP for CNG or E85 over gasoline. Diesel users hold strong preferences for diesel fuel, with large, negative WTP values for all alternatives: -$14.06 for gasoline, -$29.66 for CNG, and -$20.68 for E85. Finally, E85 users are willing to pay $7.11 more for a 300 mile tank of ethanol than for a 300 mile tank of gasoline, all else equal. Figure 3 illustrates these differences. Note that because E85 is less energy dense, more is required to produce a 300 mile tank, so WTP per 300 mile tank (a value of service metric) does not translate linearly to WTP per gallon (a value of commodity metric). For example, consider a flex-fuel vehicle with a 25 mpg efficiency when running on gasoline and an 18 mpg efficiency when running on E85 and gasoline at $3/gal. In this case, a willingness to pay of $7.11 *more*

Table 2. Parameter estimates for MNL and MIXL models. Coefficients represent average WTP ($USD) for a 300 mile tank of fuel.

Model #:		1	2	3a	3b	3c
Model type:		MNL	MIXL	MNL	MNL	MNL
Description:		Main effects	Random coeff.	Fuel users	Political views	Enviro. views
	Lambda	0.096 (0.002)***	0.035 (0.001)***	0.1 (0.002)***	0.1 (0.002)***	0.098 (0.002)***
100 g CO_2/mile	Emissions	−4.633 (0.134)***	−4.516 (0.227)***	−4.684 (0.137)***	−4.804 (0.215)***	−3.4 (0.163)***
Fuel type (baseline = gasoline)	Diesel	−3.115 (0.567)***	−3.299 (0.836)***	−3.644 (0.586)***	−1.706 (0.97).	−3.543 (0.753)***
	cng	−0.089 (0.549)	−0.362 (1.557)	−0.115 (0.563)	0.459 (0.945)	−0.681 (0.727)
	e85	0.598 (0.545)	0.393 (0.652)	−0.172 (0.564)	2.246 (0.928)*	−0.584 (0.727)
Fuel origin (baseline = home state)	National	−1.255 (0.444)**	−1.479 (0.52)**	−1.427 (0.458)**	−2.047 (0.768)**	−1.083 (0.589)
	Imported	−3.386 (0.459)***	−4.148 (0.534)***	−3.361 (0.472)***	−2.615 (0.775)***	−2.856 (0.607)***
Random heterogeneity effects	sd.lambda		0.016 (0.001)***			
	sd.emissions		2.623 (0.19)***			
	sd.diesel		7.336 (0.717)***			
	sd.cng		6.576 (0.219)***			
	sd.e85		5.95 (1.897)**			
	sd.national		4.754 (0.8)***			
	sd.imported		9.085 (0.569)***			
Interaction effects: dieselUser	Emissions			−1.453 (0.894)		
	Diesel			17.689 (3.262)***		
	cng			−15.493 (4.433)***		
	e85			−6.448 (3.851)		
	National			−1.029 (3.083)		
	Imported			0.43 (3.089)		
Interaction effects: flexUser	Emissions			2.968 (0.531)***		
	Diesel			0.384 (2.668)		
	cng			3.196 (2.513)		
	e85			7.269 (2.469)**		
	National			1.696 (2.023)		
	Imported			−0.62 (2.131)		
Interaction effects: conservative	Emissions				1.401 (0.308)***	
	Diesel				−2.737 (1.453)	
	cng				−1.154 (1.409)	
	e85				−3.123 (1.396)*	
	National				1.123 (1.136)	
	Imported				−1.567 (1.174)	
Interaction effects: liberal	Emissions				−0.42 (0.287)	

Table 2. (Continued.)

Model #:		1	2	3a	3b	3c
Model type:		MNL	MIXL	MNL	MNL	MNL
Description:		Main effects	Random coeff.	Fuel users	Political views	Enviro. views
	Diesel				−0.778 (1.334)	
	cng				−0.012 (1.301)	
	e85				−1.991 (1.291)	
	National				0.887 (1.053)	
	Imported				−0.859 (1.074)	
Interaction effects: enviroConcern	Emissions					−2.701 (0.245)***
	Diesel					1.008 (1.128)
	cng					1.206 (1.1)
	e85					2.136 (1.091)
	National					−0.3 (0.885)
	Imported					−1.133 (0.915)
Log-likelihood:		−3926.331	−3848.525	−3623.482	−3609.563	−3798.598
Number Obs.:		5496	5496	5244	5172	5436

Significance codes: ***=0.001, **=0.01, *=0.05.

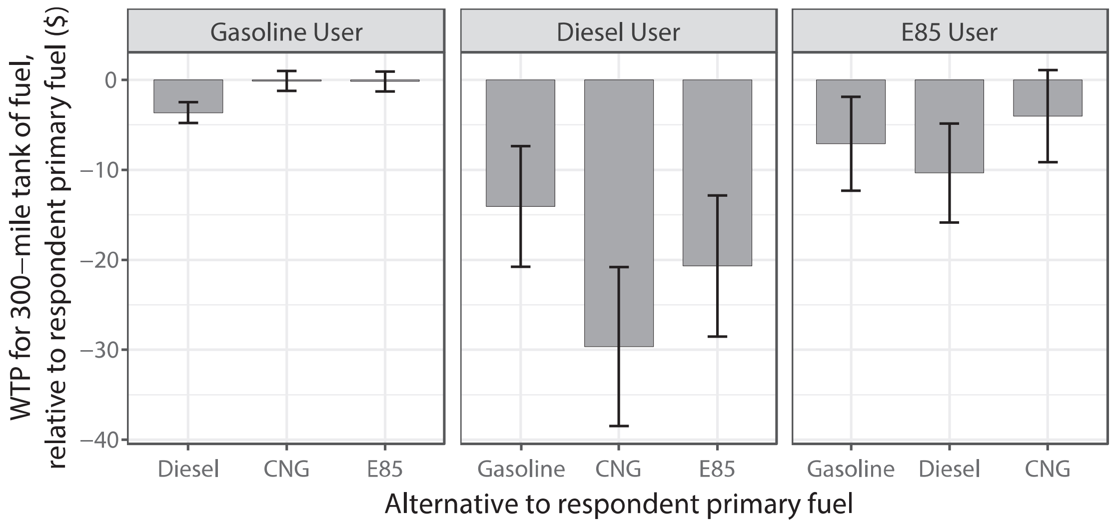

Figure 3. Respondent average WTP per 300 mile tank for alternative fuels relative to respondent primary fuel. Values are computed from the parameter estimates in model 3a ($n = 5244$). Negative values imply a preference for the respondent's primary fuel. Error bars reflect at 95% confidence interval computed using simulation (detailed calculations are included in section 3 of the supplementary information).

for a 300 mile tank of E85 over gasoline translates to a WTP of $0.41 *less* per gallon for ethanol compared to gasoline (see section 3 of the supplementary information for details). To examine the robustness of these results, we also re-estimated Models 1 and 3a after removing respondents who always chose their current primary fuel when it was in the choice set (see table 5 in section 1 of the supplementary information). In both models, removing these individuals has little effect on the model parameters.

Results also suggest that, on average, respondents are willing to pay $4.63 (Model 1) or $4.52 (Model 2) more to reduce CO_2 emissions by 100 g mi^{-1}, *ceteris paribus*. These coefficients can be converted into $/ton CO_2 avoided by dividing by 30 kg CO_2 (100 g mi^{-1} of CO_2 over 300 miles) and multiplying by 1000 (kg to ton), resulting in an average WTP of approximately $150/ton CO_2 avoided. This is three to fifteen times higher than the estimated social cost of CO_2 used by US government agencies, which ranged from $10 to $50 in 2015 depending on the discount rate [36].

Models 3a–3c reveal substantial heterogeneity in the WTP to reduce CO_2 emissions according to a variety of socio-demographic variables. We present this heterogeneity in units of $/ton CO_2 avoided. Respondents that stated having more conservative political views are willing to pay approximately $110/ton CO_2 avoided whereas moderate and liberal respondents have a higher WTP of $160/ton CO_2 avoided. Respondents that stated a greater concern for the environment are willing to pay $200/ton CO_2 avoided compared to a WTP of $110/ton CO_2 avoided for those who did not indicate concern for the environment. Results also suggested that E85 users had a lower average WTP to reduce CO_2 emissions of $60/ton CO_2 compared to diesel users ($200/ton) and gasoline users ($160/ton). Figure 4 illustrates these differences.

3.2. Simulating consumer fuel choices

While the estimated model coefficients help explain WTP for fuel attributes, direct interpretation only explains preferences for each attribute while holding all others fixed. To understand how the combination of multiple attributes affects consumer response to alternative fuels, we use the estimated model coefficients to simulate respondent choices for different fuels. We use historical values for fuel prices and fuel efficiencies for each fuel to compute the associated cost and per-mile CO_2 emissions of a 300 mile tank (see table 8 in section 2 of the supplementary information). In our baseline case, we use the mean fuel price for the year prior to when the survey was fielded (May 2014–May 2015) and we hold origin constant. For CO_2 emissions, we use 2015 EPA tailpipe emissions factors (g CO_2 per gallon). In addition to this case, we conduct five sensitivity cases: (1) we hold fuel efficiency constant across the different fuels, (2–3) we compute fuel price means from five- and ten-year periods prior to fielding the survey, (4) we use life-cycle emissions factors, which includes upstream emissions from fuel production and distribution, and (5) we assume gasoline and diesel are imported, CNG has a national origin, and E85 has a local (home state) origin. The simulations were conducted by taking draws of estimated parameters from Models 1 and 2.

Figure 5 shows the resulting choice shares from each simulation case. Error bars represent a 95% confidence interval reflecting uncertainty in the model parameters while holding the fuel attribute values constant. Across each simulation case, CNG was the most preferred alternative due to its lower per-mile CO_2

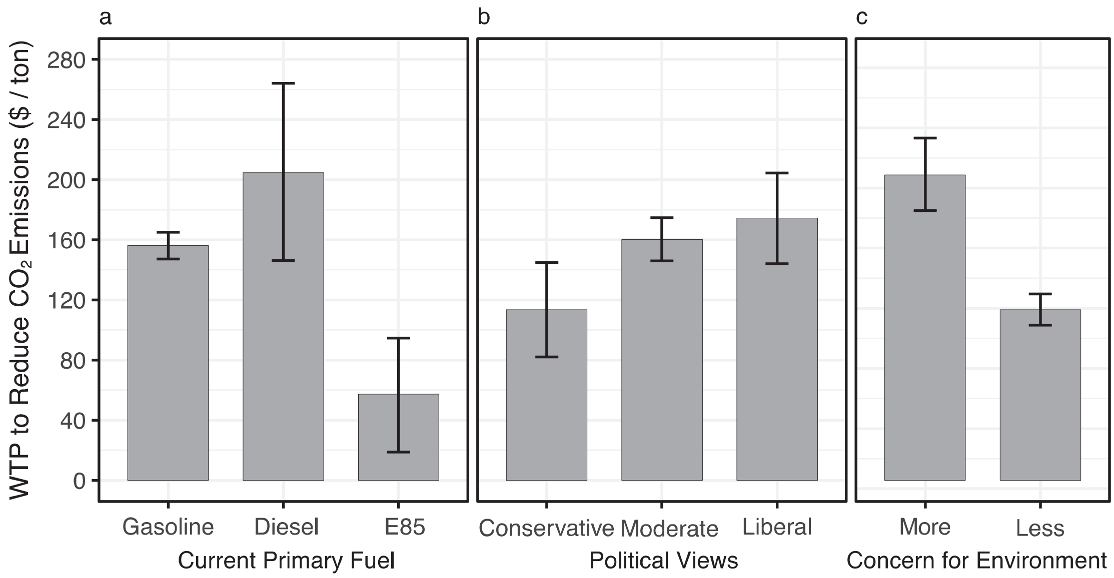

Figure 4. Respondent average WTP to reduce CO_2 emissions based on demographic variables. (a) WTP based on current primary fuel, from Model 3a ($n = 5244$). (b) WTP based on stated political views, from Model 3b ($n = 5172$). (c) WTP based on stated concern for the environment, from Model 3c ($n = 5436$). Error bars reflect at 95% confidence interval computed using simulation (detailed calculations are included in section 3 of the supplementary information).

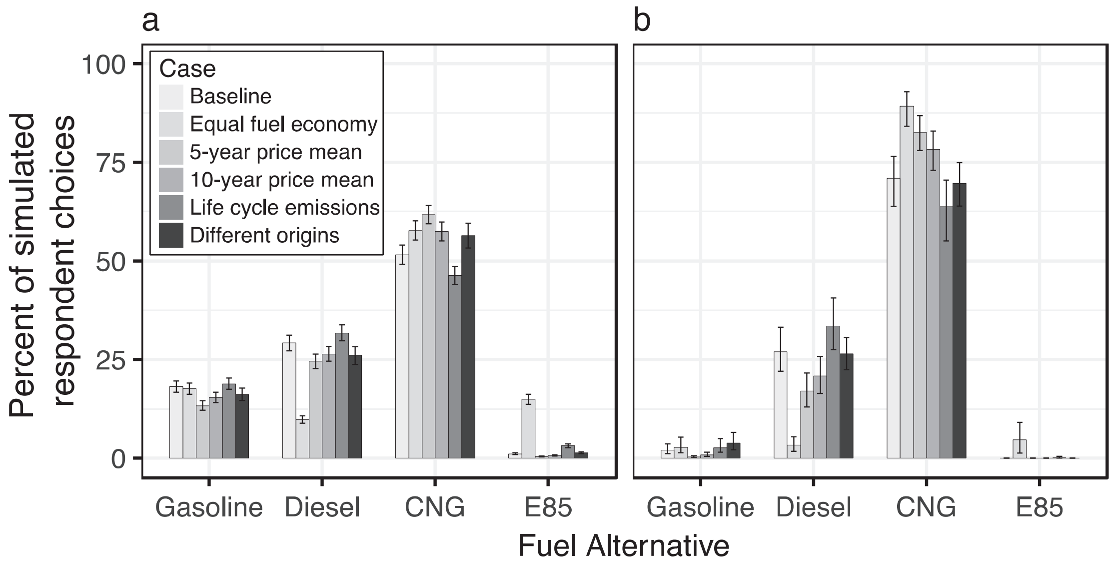

Figure 5. Simulated choice shares for different fuel attribute assumptions. Values are computed from estimated model parameters. (a) Model 1 (MNL, $n = 5496$). (b) Model 2 (MIXL, $n = 5496$). Error bars represent a 95% confidence interval reflecting uncertainty in the model parameters while holding the fuel attribute values constant, computed using simulation (details are provided in section 3 of the supplementary information).

emissions and competitive price for a 300 mile tank. Even when using life-cycle emissions (where the per-mile emissions are similar to those of diesel), the expected average choice share was 46% using Model 1 and 64% using Model 2. Diesel fuel is the second most preferred alternative in every case except for when the fuel economy is assumed equal across all fuels. This is because diesel's higher fuel economy leads to lower prices for a 300 mile range tank and lower per-mile CO_2 emissions; when that advantage is assumed away (i.e. the equal fuel economy case), the lower-emitting E85 captures some of the diesel share. The low expected share of E85 (0%–4% in most cases) is due to its higher per-gallon price and lower fuel economy, which both lead to a higher tank price.

Since the WTP for each fuel type varied significantly depending on the respondent's current primary fuel, we also run a simulation separating out choices by the respondent's current fuel, using the baseline case assumptions for fuel attributes and the estimated coefficients in Model 3a. As shown in figure 6, gasoline and E85 users have a similar market response as the full population baseline simulation where the top-two alternatives are CNG and diesel,

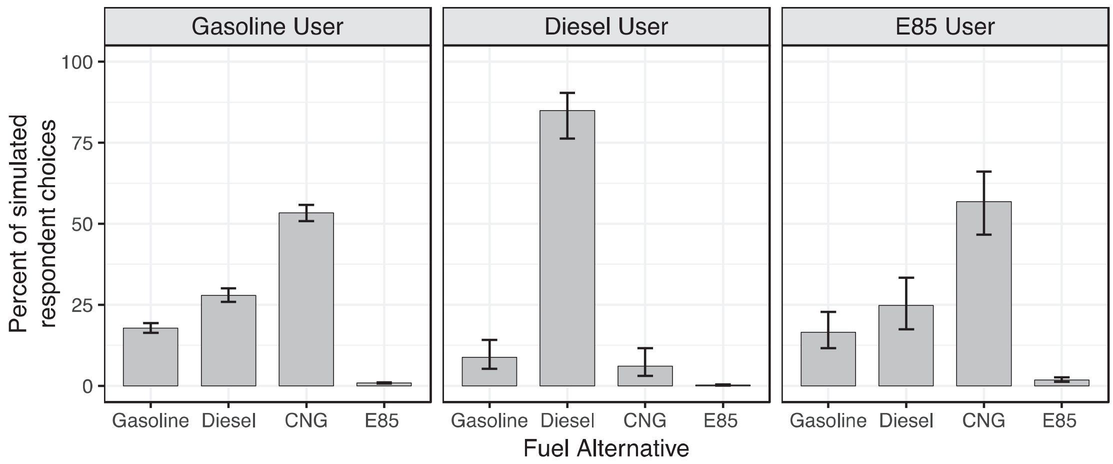

Figure 6. Simulated choice shares for different fuels based on respondents' current primary fuel. Values are computed from the parameter estimates in model 3a ($n = 5244$). Error bars represent a 95% confidence interval reflecting uncertainty in the model parameters while holding the fuel attribute values constant, computed using simulation (details are provided in section 3 of the supplementary information).

but diesel users' strong preference for diesel fuel results in diesel obtaining an overwhelming majority for diesel users. In addition, although gasoline users on average have a negative WTP for diesel (all else equal), these results suggest more gasoline users would choose diesel over gasoline. This is a result of the higher fuel efficiency for diesel in our baseline simulation assumptions, which results in diesel having a lower tank price and lower per-mile emissions than gasoline. In this case, the tank price and emissions attributes overcome the negative WTP for the diesel fuel type. While diesel users have the highest WTP to reduce emissions, lower emissions from alternatives do not overcome the large WTP for the diesel fuel type. These simulations suggest that there is considerable heterogeneity in the ability of lower CO_2 emissions and lower prices of some fuels to overcome some consumers' preference for their current primary fuel.

Although our simulation results are robust to the fuel attribute assumptions across the six different cases, it is important to note that they assume the same vehicle could take any of the fuels and thus do not account for the real-world differences in vehicle prices or other vehicle attributes, such as storage space, for each fuel.

4. Discussion and conclusions

We measure and model consumer preferences for different vehicle fuels by estimating discrete choice models on data from choice-based conjoint surveys fielded online and in-person at refueling stations in 2016. Our results suggest that consumers are, on average, willing to pay premiums for gasoline over diesel, for more locally-sourced fuels, and to reduce the CO_2 emissions associated with driving, all else being equal.

On average, consumers were willing to pay \$3.12/tank for gasoline over diesel, and there was no statistically significant difference between gasoline and CNG or E85, *ceteris paribus*. These preferences vary depending on the primary type of fuel the respondents use (gasoline, diesel, or E85). While diesel users showed a particularly strong preference for diesel fuel over all alternatives in our survey, gasoline and E85 users alike were willing to pay premiums to avoid diesel and had no preference for or aversion to CNG or E85. It is important to note that diesel fuel accounted for just 0.37% of all energy consumption by light-duty vehicles in 2016, as opposed to the much larger contributions by gasoline (94.6%) and E85 (4.92%) [2]. Thus, gasoline and E85 users' aversion to diesel may outweigh diesel users' preference for diesel in terms of changes to the relative proportions of fuels consumed for light-duty vehicles.

On average, respondents' stated WTP to reduce per-mile CO_2 emissions from fuel consumption is equivalent to \$150/ton CO_2 avoided, which is three to five times higher than the estimated social cost of CO_2 used by US government agencies [36]. To put this into context, the average car in the US has a fuel economy of 26 mpg (9.05 l/100 km) and a 12 gallon (45.4 l) tank; to release 1 ton of CO_2, the car would have to drive 2960 miles (4,764 km), consuming 9.5 tanks of gasoline. A WTP of \$150 to avoid these emissions is the equivalent of increasing the fuel cost to drive those miles by 45% at an average price of \$2.92/gallon. Interaction models revealed substantial heterogeneity in the average WTP to avoid one ton of CO_2, with politically moderate and liberal respondents having a higher WTP compared to conservatives, and respondents with a greater stated concern for the environment having a higher WTP compared to those who did not indicate concern for the environment. In addition, despite their aversion to alternatives to diesel fuel, diesel users were willing to pay just over three times as much as E85 users ($200 compared to $60) to avoid one ton of CO_2 emissions.

The magnitude of these estimates may be affected by the increased salience of the CO_2 emissions attribute in our survey—information that is not provided at most refueling stations [37, 38]. Nonetheless, the result does suggest the potential for consumers to value CO_2 emissions reductions if the relevant information is available and salient when decisions are made. More informative fuel labels at refueling stations (such as the emissions impact of different fuels) may be effective in steering some consumers towards choosing fuels with lower greenhouse gas emissions. Also, if respondents judged the different emissions levels categorically (i.e. 'more polluting' or 'less polluting') regardless of the actual amount displayed, then it is possible these estimates are on the upper bound of true WTP since the levels shown spanned a wide range of emissions levels.

Our choice simulations suggest that the majority of gasoline and E85 users in our sample would be willing to substitute towards CNG due to its lower CO_2 emissions and lower prices. However, the benefits of this substitution in terms of reducing greenhouse gas emissions may be limited. The life-cycle emissions assumptions in our simulations implies a savings of just 8 kg CO_2 over 300 miles by substituting from gasoline to CNG, and prior research suggests that per-mile life-cycle CO_2 emissions from CNG may actually be higher than those of gasoline [36, 39]. Unfortunately, although E85 can have far lower life-cycle emissions (depending on the production process [40]), the higher prices and lower fuel economy associated with E85 reduces its attractiveness against other, higher-emitting alternatives. It is important to note that our simulations only consider the fuel attributes shown in our survey and do not account for the different costs of the vehicles that accept each fuel. In addition, these simulations omit other alternative fuels, such as hydrogen or electricity, that may produce even lower per-mile CO_2 emissions.

We find no statistically significant difference in WTP for corn-derived versus natural gas-derived ethanol. Prior literature has found mixed results on whether consumers value ethanol differently by feedstock, with some finding significant differences [8] and others not [9]. Respondents did prefer more locally-sourced fuel to imported fuel, and this effect size is similar to the average difference in WTP for different fuel types. For example, in our baseline model, the WTP to switch from diesel to gasoline is $3.12/tank whereas the WTP to switch from imported fuel to locally-sourced fuel is $3.39/tank, *ceteris paribus*. This result agrees with Ulmer *et al* (2004) [5], which found that reducing dependence on foreign oil was an important factor in consumers' decision to choose ethanol-blended gasoline over regular gasoline.

As with all stated preference experiments, our results are limited by the hypothetical nature of the choice task on the survey. In particular, we frame our survey by asking consumers to consider refueling a hypothetical vehicle that could take any of the different fuels included in the survey. Since no such vehicle currently exists, it is possible that respondents might have not fully believed or understood the choice task, although an examination of the choice counts suggest many users were willing to choose an alternative to their primary fuel when it was in the choice set (see section 5 of the supplementary information). Other fuel attributes that we did not include in our survey (and thus did not observe) but which respondents may have inferred about certain fuels may have influenced their choices. In addition, the sample of in-person respondents is from two refueling stations in California, and the online sample is from a random sampling across the entire US; as a result, the sample is not representative of all US drivers, and the heterogeneity in preferences for different fuels and fuel attributes that was revealed in our results suggests that substantial heterogeneity may exist in a more representative sample.

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