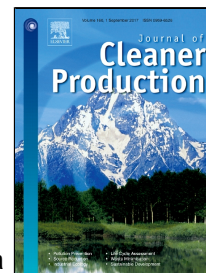


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Increasing the Influence of CO₂ Emissions Information on Car Purchase

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1 **ABSTRACT**

2 In response to concerns related to climate change, and an attempt to encourage more sustainable
3 behavior, individuals are often provided with information on greenhouse gas emissions (GHGs)
4 of consumer items, such as personal vehicles. Currently in the US, information on vehicle
5 efficiency is provided as grams of carbon dioxide (CO₂) per mile. Previous research presenting
6 CO₂ as a mass and testing willingness-to-pay through Discrete Choice Experiment has found that
7 such information can influence vehicle choice. However, other research has questioned whether
8 *how* this information is presented might affect choice. That research argues that CO₂ emission
9 information generally lacks contextualization that allows for interpretation. As well, it argues that
10 the type of contextualization may affect choices. That research though did not test willingness-to-
11 pay and the strength of its influence is not clear. In addition, research exists that argues that using
12 pro-social, as opposed to financial, contextualization might be more influential on people's
13 choices. Thus, the purpose of this paper is to build on these previous findings on how CO₂
14 emissions are presented to determine whether changing *how* that information impacts vehicle
15 choice with a Discrete Choice Experiment of vehicle choice analyzed using latent class modeling.
16 No previous study has so robustly studied the influence that different framings might have on
17 vehicle purchase. Five different methods of presenting CO₂ information are tested in this
18 experiment: CO₂ emissions as grams per mile (current method), CO₂ emissions as pounds per year
19 (consistent imperial units), CO₂ emissions as tons per year (yearly contextualization), an annual
20 tax on CO₂ (yearly financial contextualization), and CO₂ as a percentage of the 2025 US EPA
21 reduction target of 26% from 2005 levels (social goal contextualization). Results demonstrate that
22 the current method results in lowest willingness to pay for CO₂ emission reductions, while the
23 social goal contextualization results in the highest.
24

1 1. INTRODUCTION

2 In response to climate change concerns, as well as attempts to encourage more sustainable
3 behavior, individuals are often provided with information on greenhouse gas emissions (GHGs)
4 of things they buy, such as personal vehicles. Currently in the United States (US), such information
5 is provided through the US Environmental Protection Agency's (EPA) information sheet for new
6 vehicles. On these sheets, CO₂ emissions are expressed as grams of carbon dioxide (CO₂) per mile.
7 Previous research has found such information can influence vehicle choice, but it has also found
8 that it might depend on the type of person with some individuals being highly influence, while
9 others not at all. Further, other research has also questioned whether *how* this information is
10 presented might affect choice. That research found that how the information is presented
11 influences whether people who are not motivated by climate change concerns would be influenced.
12 Thus, there is a suggestion that providing CO₂ information as a mass (as the US EPA does) would
13 only influence people who are highly motivated by environmental concerns, while another set of
14 research suggests that is likely a problem of how the emissions information is presented. The
15 purpose of this paper is to build on these previous findings to determine whether changing *how*
16 CO₂ information impacts vehicle choice and Willingness-to-Pay (WTP) for CO₂ emission
17 reductions. One key contribution would be whether it is possible to influence those less concerned
18 by climate climate change. The use of Discrete Choice Experiments allows us to create controlled
19 treatments of how information about emissions is presented. Analyzing the results through latent
20 class discrete choice models allows for a segmentation of the population by their response
21 strengths. This allows us to test whether the information is influencing all groups, or just the more
22 environmentally motivated ones. One specific contribution in the application of the discrete choice
23 models is the explicit consideration of discounting not only future costs but also future emission
24 production. The next section provides background relevant to the study and is followed by a section
25 describing the methodology adopted to answer the question. Results are then presented and
26 discussed and the paper finished with some concluding remarks.

27

28 1.1 Background

29 One reason to provide information to people is so they can make more informed choices. As well,
30 businesses provide information on their products, whether rational or emotional, in order to
31 persuade consumers to choose their products. The government, on the other hand, may take a soft
32 paternalism approach where information is given so that an individual makes choices that are in
33 the individual's (or society's) best interest. For example, the provision of information about health
34 risks from smoking is often provided directly on tobacco products.

35 Another frequent approach to influencing choice is through economic means by raising the
36 price of products through taxes or other measures. This method does not require that people be
37 concerned about the problem, since the impact is on their personal budget. However, the impact
38 of such methods depends on an individual's income (the impact will be relative) and is only as
39 effective as the amount of the tax. In many cases, it is politically difficult to implement taxes of
40 any kind, let alone one those explicitly intended to coax certain types of behavior.

41 People are accustomed to understanding product attributes such as cost. However, it is
42 difficult for people to judge the meaning of CO₂ emissions. Providing only grams of CO₂ per mile
43 might be likened to providing the amount of salt in a product, but with no additional information
44 such as the percentage of recommended daily consumption to avoid health problems. A heavy
45 burden of knowledge is placed on the consumer to know what the limits are, what average

1 consumption of the product might be, and then to undertake the calculations to estimate whether
2 the amount exceeds that threshold. In such a situation, one might first question whether providing
3 CO₂ emission information has any impact on choice at all.

4 Previous stated-choice research related to vehicle purchase and use has found that
5 providing CO₂ information will affect choices. In a series of experiments, Gaker et al. (2010, 2011,
6 2013) demonstrated that for populations of students (Gaker et al., 2011; Gaker et al., 2010) and a
7 sample of San Francisco residents (Gaker and Walker, 2013), providing CO₂ information as tons
8 per year (car purchase) or grams per mile (route choice) has a measurable impact. In Germany
9 (Achtnicht, 2012; Daziano and Achtnicht, 2014) studies have also found that providing CO₂
10 information (grams per kilometer) would have an influence on car purchase choice. Thus, there is
11 evidence that such information could influence choice, but other research has questioned whether
12 this format (CO₂ as a mass) is an effective means of communicating emissions.

13 Research into how CO₂ information is provided to the general public has generally found
14 that it leaves many people uncertain. Research examining online GHG calculators (a tool where
15 individuals estimate their GHG emissions) has highlighted that presenting CO₂ as a mass (e.g.
16 grams, pounds, tons) leaves people uncertain about whether the amount is acceptable or not
17 (Chatterton et al., 2009; Coulter et al., 2007). The problem may be related to context (Avineri and
18 Waygood, 2010; Waygood and Avineri, 2010a, b; Waygood and Avineri, 2011, 2013; Waygood
19 and Avineri, 2014, 2016a; Waygood and Avineri, 2016b). As argued by Waygood and Avineri
20 (2011), people lack a budget or other means of interpreting the GHG information, thus their
21 perception of the amount is highly influenced by contextual information, such as the other choices
22 provided, the standard by which the amount is measured (Waygood and Avineri, 2011, 2013;
23 Waygood and Avineri, 2016b), or even the wording (Avineri and Waygood, 2013).

24 Whether providing people with only CO₂ mass information would influence their choices
25 may relate to how environmentally motivated they are. Waygood and Avineri (2011, 2016b) found
26 that people who were further along the climate change “stage of change process” (i.e. they accepted
27 that climate change was a problem and had made or were considering making changes to reduce
28 their impacts) were more likely to feel that they understood information on CO₂ mass. In Gaker et
29 al.’s research using latent class models (2013), they found that a group of environmentalists (with
30 “big hearts”) were influenced by the CO₂ grams per mile, whereas the non-environmentalists were
31 not; the problem being that most individuals were classified as the latter group. Thus, the problem
32 may be that providing simply CO₂ mass may require an individual to be environmentally motivated
33 (Avineri and Waygood, 2010; Gaker and Walker, 2013; Waygood and Avineri, 2011; Waygood
34 and Avineri, 2016b) in order for it to influence their behavior. In such a way, the effect of the
35 information on CO₂ emissions is moderated by environmental concerns, and if those do not exist
36 or have little value to the individual, the information is not taken into account.

37 One source of difficulty in interpreting CO₂ information in grams per mile might be related
38 to how CO₂ is discussed in the general media. Although vehicle advertisements may use grams
39 per mile or km, reports on climate change from governments and organizations are likely to use
40 tons (or ton) per year (e.g. <http://data.worldbank.org/indicator/EN.ATM.CO2E.PC> or
41 http://unstats.un.org/unsd/environment/air_co2_emissions.htm). It may be that simply
42 contextualizing the information to an estimated yearly impact would increase the effectiveness of
43 such information on vehicle choice. The EPA currently does this with fuel efficiency by estimating
44 yearly savings. This would reduce the mental burden on the individual. With a yearly
45 contextualization, the individual does not have to conduct the mental math to go from grams per

1 mile (metric unit of mass and imperial units of distance) to tons per year (imperial unit of mass
2 and unit of time).

3 The current car label system from the Environmental Protection Agency contextualizes
4 vehicles on a sliding scale from 1 to 10 (10 being best). However, this contextualization is with
5 respect to other vehicles, not with respect to total emissions. Without a clear understanding of the
6 impact of those different levels, one could not make an informed decision. It would be analogous
7 to making a decision on how much to spend each month without knowing what your financial
8 budget was.

9 Considering several different methods of presenting the same information, contextualizing
10 the information with respect to a cap or threshold may be the most effective in terms of respondents
11 being confident in ranking information or by the likelihood of a behavioral response (e.g. would
12 they consider changing their travel behavior) (Waygood and Avineri, 2011, 2013, 2014, 2016b).
13 Such contextualization provides an interpretation of the amount with respect to an authority's
14 evaluation of what is acceptable or not. This could be a respected non-governmental environmental
15 group, or a government objective for diminishing such emissions. In either case, such a method of
16 presenting the information could be considered an injunctive norm (e.g. Cialdini, 2007), as it
17 would communicate to an individual whether the choice is acceptable or approved by society. As
18 such, this method would not necessarily rely on how environmentally motivated an individual was,
19 but simply whether they value "doing the right thing" in terms of society's goals.

20 Another argument related to contextualizing information is to let the market influence
21 decisions by monetizing negative externalities. A value is determined related to the negative
22 impact of a choice (here, the negative impact of GHGs), and this is included in the cost. In Canada,
23 the province of British Columbia (BC) has since 2008 used a carbon tax as a means to contextualize
24 and give feedback to individuals related to their consumer choices. The policy has been judged to
25 be successful in reducing GHGs (Prosperity, 2012; Rivers and Schaufele, 2015). In fact, Rivers
26 and Schaufele (2015) demonstrated that the behavioral response to the BC carbon tax was 7.1
27 times larger than what would be expected from an equivalent change in the carbon tax-exclusive
28 gasoline price. In the US, the EPA provides information on how much a ton of CO₂ should be
29 valued. With such information, an individual's personal economic considerations would be
30 triggered. Thus, this is one potential way of influencing choices.

31 Arguments exist that people's behavior is not always stronger when given economic
32 signals. Monetary rewards are found to depend on the magnitude of compensation, whereas social
33 market signals are not (Heyman and Ariely, 2004). Avineri (2012) argues that people are often
34 motivated to "do the right thing," meaning that they wish to behave in a way that society approves.
35 This relates to theories such as the norm-activation theory (Schwartz, 1977) where people would
36 be made aware of their moral obligation to conduct behavior where the benefit is not, or not solely,
37 individual. Further, considering that climate change is a societal as opposed to an individual
38 problem (i.e. the impacts are on all of society irrespective of individual behavior), it may be that
39 information contextualized at a societal level may be more effective than information that is ego-
40 centric (i.e. an individual impact). This would relate to a moral responsibility to behave in a certain
41 way, which is found to be effective in explaining ecological behavior (Kaiser and Shimoda, 1999),
42 including predicting an intention to reduce car use in response to a proposed environmental
43 transportation policy (De Groot et al., 2008).

44 Thus, previous research suggests that CO₂ information can influence choice, but that its
45 influence depends on individual environmental attitudes and how it is presented. Previous research
46 on willingness to pay (Achtnicht, 2012; Daziano and Achtnicht, 2014; Gaker et al., 2011; Gaker

1 and Walker, 2013; Gaker et al., 2010) has only used grams of CO₂ per distance, whereas previous
 2 research on how the CO₂ information is presented (Avineri and Waygood, 2013; Waygood and
 3 Avineri, 2011, 2013; Waygood and Avineri, 2014, 2016a) used ranking exercises and behavioral
 4 responses (e.g. changes in travel behavior) with relatively small samples (<300) to demonstrate
 5 how different presentation modes of CO₂ can affect people's stated responses. Thus, it remains to
 6 be seen whether in Discrete Choice Experiments, such differences can be observed, to what extent
 7 they differ, and how much of an influence a respondent's environmental attitudes may have on the
 8 outcomes.

9 This research will therefore test two hypotheses:

- 10 1) Presenting CO₂ emissions information as grams/mile will result in the lowest willingness to
 11 pay;
- 12 2) Controlling for environmental attitudes, how CO₂ emissions information is provided will not
 13 affect willingness to pay.

14 15 **2. METHODOLOGY**

16 In order to evaluate the effect of presentational form of CO₂ information and environmental
 17 attitudes on WTP, a survey containing two distinct parts was used. The survey was administered
 18 as an online survey to a panel of 1,580 car owners living in Philadelphia and Boston metropolitan
 19 areas between 15 December 2015 and 15 March 2016. The Discrete Choice Experiment on vehicle
 20 choice is explained in detail below. The other part of the survey focused on the socio-demographics
 21 and environmental attitudes of respondents.

22 23 **2.1 Sociodemographics and Environmental Attitudes of Respondents**

24 General socio-demographic information along with some questions related to tax policy
 25 preferences in the context of climate change are shown in Table 1. Whereas questions related to
 26 car ownership were asked before the discrete choice experiment, questions related to the
 27 environment were asked after so as not to influence the individual's choices in the choice tasks by
 28 priming respondent environmental awareness or identity. Questions on environmental attitudes
 29 and tax policy preferences in the context of climate change included:

- 30 • 50 questions that were a version of the General Ecological Behavior (GEB) scale (Kaiser
 31 and Wilson, 2004);
- 32 • 15 questions on pro-ecological worldview of the New Ecological Paradigm (NEP) scale
 33 (Dunlap et al., 2000);
- 34 • Four questions of tax policy preferences to GHGs (Leiserowitz, 2006): (see Table 2 for
 35 complete questions).

36
 37 TABLE 1 Selected results for respondent characteristics

38
 39 TABLE 2 Responses to questions addressing climate change.

40
 41 Lachapelle et al. (2012) report that support for a cap-and-trade system for carbon emissions is
 42 opposed by 49% of Americans, and this opposition rises to 74% when the amount is \$50/tonne¹.
 43 For a carbon tax, 62% oppose the concept and this rises to 63% for \$15/tonne and 80% for
 44 \$50/tonne. Our sample also mostly opposes general increases such as question 2 (66% oppose)

¹ One metric tonne (long ton) is roughly equal to 1.1 "short" tons.

1 and 4 (61% oppose) in Table 2. A large number do not want to pay for emitting (question 1, 45%),
2 and of those willing to pay, nearly half are only willing to pay \$5/ton. At \$50/tonne (roughly
3 \$55/ton) 94% of our sample are not willing-to-pay.

4 A number of national (USA) poles exist with respect to climate change and public opinion.
5 The questions asked are not an exact match to the questions used in this study, however the
6 information is comparable. The Gallup Poll question “How much do you personally worry about
7 Global Warming?” resulted in (2014): A great deal, 34%; fair amount, 22%, only a little/not at all,
8 43%. If one considers question 5 in Table 2, those who are sufficiently concerned to want to reduce,
9 or have reduced, their emissions, this represents 56% of the population which coincides with the
10 56% of the national population who personally worry a great deal or a fair amount.

11 To account for *general ecological behavior*, questions from the GEB scale were included.
12 This scale is based on a theory of goal-directed behavior (Kaiser and Wilson, 2004), the framework
13 that describes a person’s general attitude in terms of the likelihoods of engaging in various specific
14 environmentally-friendly behaviors. The GEB questions (50 in total) relate to conservation
15 behaviors in six domains: energy conservation (11), mobility and transportation (12), waste
16 avoidance (5), consumerism (9), recycling (4), and vicarious social behaviors (9). The
17 transportation questions were separated out so that general environmental behavior and transport-
18 specific conservation behavior factors could be estimated. A principal component analysis (PCA)
19 was conducted on the participants’ responses to those 38 questions (i.e. the 50 GEB questions
20 minus the 12 mobility and transportation questions). The initial PCA found that a large number of
21 those 38 variables did not have a large explanatory role (shown as communalities less than 0.3) in
22 differentiating individuals. Thus 15 variables were retained and used in a second round of principal
23 component analysis. A two-factor solution (Table 2) was identified using Oblimin rotation and
24 Kaiser normalization that accounted for 41.3% of the variation. Those two factors were named:
25 “actively environmental,” and “not interested in solar panels.”

26
27 TABLE 3 High loading variables for each principal component of the factor analysis on general
28 ecological behavior and tax policy preferences variables.

29
30 For *transportation behavior*, the 11 variables from the GEB scale were used along with
31 questions on household car ownership, average mileage, and how often they commute by car. One
32 question from the GEB scale was adjusted from their *mobility and transportation* domain, “In
33 nearby areas (around 30 km; around 20 miles), I use public transportation or ride a bike” was
34 changed to two separate questions: “In nearby areas (around 5 miles), I ride a bike;” and “For
35 distances up to 20 miles, I use public transportation.” Of the 15 available variables (11 + 1 from
36 GEB, and the three general transportation questions), fourteen were retained for the principal
37 component analysis. A four-factor solution was found using Oblimin rotation and Kaiser
38 normalization that explained 52.4% of the variation. Those factors were named: multi-modal,
39 drives everywhere, idles, and rules (e.g. speed limit) over economics (e.g. drive to conserve fuel).

40 To account for *personal ecological values and beliefs*, the NEP scale was used. It
41 represents a more evaluative conception of attitudes assuming one’s moral values to be the core
42 concept of environmental attitudes (Dunlap et al., 2000). As well, four additional questions on tax
43 policy preferences in the context of climate change were included (36), as the NEP scale does not
44 directly target climate change. From a potential of 19 questions on attitudes towards the
45 environment (15 from NEP and 4 directly related to transportation and climate change), 18 were
46 used in a principal component analysis with Oblimin rotation and Kaiser normalization. Two

1 factors were identified which accounted for 50.4% of the variation. Those factors were named:
2 “against taxes to reduce emissions”; and “nature will not sort out environmental problems”.

3 4 **2.2 Discrete Choice Experiment**

5 The survey involved a Discrete Choice Experiment prior to the questions on ecological behavior
6 and environmental attitudes. Discrete Choice Experiments (DCE) are specialized surveys that
7 present respondents with hypothetical choice situations (or tasks). The characteristics (or
8 attributes) of the alternatives are determined through an experimental design. Respondents are
9 asked to choose their preferred alternative. The statistical analysis of these responses allows an
10 estimation of the impact of the different attributes on a person’s choice.

11 For this study, a very simple DCE was used whose focus was to enable the estimation of
12 WTP for CO₂ reductions. In order to be consistent with previous DCE research on WTP for CO₂
13 reductions, we adapted vehicle choice surveys first done by Gaker et al. (2010, 2011). The choice
14 tasks in the surveys had two alternative vehicles characterized by two to three attributes. The
15 attributes included were purchase cost, fuel costs per year and CO₂ emissions. The vehicle choice
16 experiment was designed according to a D-efficient design with Bayesian priors. The design was
17 produced using Ngene. For the priors, estimates from the literature were used for the pilot of the
18 experiment. The design was then updated with the estimates of the first 150 observations. The
19 attributes and the levels used in the experiments are summarized in Table 4. Purchase price was
20 customized to the respondent’s stated willingness to spend for their next vehicle. This was done to
21 eliminate the problem of unrealistic choices being presented to respondents, or choices being
22 dominated by price.

23 In order to test the influence of the different presentational forms, the participants were
24 randomly assigned to one of five treatments: CO₂ emissions as grams per mile, CO₂ emissions as
25 pounds per year, CO₂ emissions as tons per year, an annual tax (\$37/ton) on CO₂, and CO₂ as a
26 percentage of the 2025 US EPA reduction target of 27% from 2005 levels. 27% was used as the
27 average between 26% and 28% given as the government targets.² Following the current car-label
28 standard, for all treatments, 15,000 miles/year was used to calculate annual amounts.

29 To explain further the last treatment (target reduction), the amount used was based on 5.15
30 ton as the average per-capita road transport emissions in 2005. That number is based on per-capita
31 CO₂ road emissions (ITF data) in 2005, and is thus a conservative amount as it includes more than
32 just private light duty vehicles. Thus, a 27% reduction results in 3.75 ton/year in 2025³.

² www.whitehouse.gov/the-press-office/2014/11/11/us-china-joint-announcement-climate-change

³ For information, the US Department of Energy estimates that the per capita fuel consumption in 2005 was 461 gallons which is the equivalent of 4.1 tons (using the EPA guidelines of 8,886 g CO₂/gallon).³ Using that amount would have resulted in a target of 3 ton/year in 2025, thus increasing the percentages presented, which one assumes would have increased the strength of responses. These results would have been different had we used vehicles as opposed to the population in the calculation of average annual CO₂ production, since in the US there were 811 vehicles per 1,000 people (in 2005). This would have increased the starting amount to 6.34 ton. However, if one uses the fuel consumed by LDV only, then one arrives at 5.06 ton, which is roughly the original 5.15 ton. Next, using vehicles as opposed to the population would imply that those who buy vehicles are allowed to pollute more than those who don’t, which is not an equitable approach. Finally, if one were to take population growth into account, the reduction

TABLE 4 Experiment attributes and levels

Table 4 shows the attributes and their levels used in the experiment. Whereas these attribute levels reflect realistic values of actual vehicle characteristics, real-world correlation between fuel cost and emissions was not considered in order to ensure orthogonality of the experimental design. In addition, emission information treatments (those listed above) were constructed using relevant equivalencies depending on the treatment. The design resulted in 12 choice tasks per individual. The order of the choice situations was randomized in the online survey, as was the CO₂ presentation treatment that a respondent received. The exact wording of the choice questions is shown in Figure 1.

Figure 1. Example of choice experiment question.

2.3 Structural model

To analyze choices made by individuals in response to the vehicle choice experiment, we assume that respondents acted as utility maximizers and that utility is a function of the present value of the monetary and monetized vehicle attributes. Since personal vehicles are durable goods that are owned and used over a time horizon, utility of individual i , when choosing alternative j is specified as follows:

$$U_{ij} = \alpha [P_{ij} + PVFC_{ij} + PVFE_{ij}] + \varepsilon_{ij}, \quad (1)$$

where PVFC is the present value of the future (operating costs) over the holding horizon, PVFE is the present value of the (monetized) future emissions, and $-\alpha$ is the parameter that represents the marginal utility of income. We note that previous work (Achtnicht, 2012; Daziano and Achtnicht, 2014; Gaker et al., 2011; Gaker and Walker, 2013; Gaker et al., 2010) has not introduced discounting, failing to recognize emission production and costs over the ownership horizon.

If both emissions and operating costs are measured on a *per-month* basis, then:

$$PVFC_{ij} = \sum_{t=1}^{L_{ij}} \frac{1}{(1+r_i)^t} \mathbb{E}(C_{ijt}), \quad PVFE_{ij} = \omega_{E,i} \sum_{t=1}^{L_{ij}} \frac{1}{(1+r_i)^t} \mathbb{E}(E_{ijt}), \quad (3,4)$$

target amount should be further reduced. Thus, overall we suggest that the simple approach taken to estimate the starting per capita average CO₂ emissions is conservative and follows an equitable approach.

1
2 where r_i is the monthly subjective discount rate (reflecting time preferences of the individual), L_{ij}
3 is the total number of months of ownership, $\mathbb{E}(C_{ijt})$ is the expected value of operating costs in
4 month t , $\mathbb{E}(E_{ijt})$ is the expected value of the emissions per period, and ω_E is the marginal
5 willingness to pay for reducing emissions (over the whole ownership horizon, i.e. willingness to
6 pay for reducing one unit of emissions over the whole period in which the car is owned). If oc_i is
7 the monthly uniform equivalent of future operating costs, and emissions $_i$ is the monthly uniform
8 equivalent of the future emissions, and if the number of months of ownership is large, then:
9

$$PVFC_{ij} = \frac{C_{ij}}{r_i}, \quad PVFE_{ij} = \omega_{E,i} \frac{E_{ij}}{r_i}, \quad (5,6)$$

10
11
12
13
14 meaning that, using the capitalized cost approximation, it is possible to rewrite the choice model
15 as:
16

$$U_{ij} = \alpha \left[P_{ij} + \frac{C_{ij}}{r_i} + \frac{\omega_{E,i}}{r_i} E_{ij} \right] + \varepsilon_{ij}, \quad (7)$$

17
18
19
20 where r_i becomes an additional parameter to estimate.

21 Two different discrete choice model formulations were used: a base Multinomial Logit,
22 and a Latent Class Logit. The two discrete choice model formulations are tested to ensure that
23 differences in WTP are not the result of not having allowed for the relaxation of the strong
24 assumptions of the Multinomial Logit Model.

25 Each model was constructed to test the hypothesis that the way in which emission
26 information is presented has an impact on estimates of willingness to pay to reduce emissions.
27 Since the structural model requires a monthly basis, all time-dependent attributes were transformed
28 to units per month. In addition, tons per month was considered as the reference (because dollars
29 per ton is a relatively standard unit for emission abatement). In the case of grams per mile, the
30 stated mileage by the respondent was used to calculate the tons per month equivalent.
31

32 The base model was then specified with the use of an indicator variable for how the emission
33 information was presented, using tons (T_i) as baseline :
34

$$U_{ij} = \alpha P_{ij} + \frac{\alpha}{r} [C_{ij} + \tau_{ij} D_{tax} + (\omega_{tons} + \delta_{gpm} D_{gpm} + \delta_{ppm} D_{ppm} + \delta_{obj} D_{obj}) T_i] + \varepsilon_{ij}, \quad (8)$$

35
36
37

1 The D variables are a series of binary variables indicating the treatment used to convey the
 2 emission information. D_{tax} is thus an indicator variable that equals 1 when the information was
 3 presented as a tax, D_{gpm} indicates that the information was presented in grams per mile, D_{ppm} in
 4 pounds per month, and D_{obj} as a target objective. An additional parameter for the tax t_{ij} was
 5 considered to see if there were any additional impact of their simply being a tax ($\tau_{ij}D_{tax} + \delta_{tax}\tau_{ij}$
 6 D_{tax}), but the additional parameter (δ_{tax}) was not statistically different from zero in all
 7 specifications. Note that all parameters in the base model are assumed fixed.

9 3. RESULTS

10 Based on the structural model above, the following section presents estimates of subjective
 11 discount rates and willingness to pay for CO₂ emission reductions for each of the presentational
 12 formats, as described above. The Multinomial Logit results are presented first, followed by those
 13 of the Latent Class Logit.

14 Before presenting the WTP results, we first mention that the results for the carbon tax
 15 treatment (not presented here) demonstrated that our respondents performed logically according
 16 to financial influences. That is, respondents were willing to pay one dollar to save one dollar. Thus,
 17 using a tax to influence choice depends solely on the size of the tax. The social cost of carbon
 18 used in this study was \$37/ton, which was based on the EPA's "Fact Sheet: Social Cost of Carbon"
 19 (EPA, 2013). Thus, we found that charging individuals \$37/ton of CO₂ resulted in a WTP of
 20 roughly \$37/ton.

22 3.1 WTP Estimates with the MNL Formulation

23 The subjective discount rates and WTP for CO₂ emission reductions, both estimated with
 24 the base Multinomial Logit Model, can be found in Table 5. Subjective discount rates are presented
 25 by month and by year. The models were estimated simply as a function of price and operating cost.
 26 Two MNL specifications were formulated, MNL-1 with only one subjective discount rate and
 27 MNL-2 with a different discount rate for the treatment without emission information. The
 28 hypothesis for MNL-2 is that individuals value operating cost differently when emission
 29 information is omitted.

31 TABLE 5 Estimated WTP with Multinomial Logit Specification

33 The subjective discount rate estimated with the MNL-1 specification was 1.02% on a
 34 monthly basis, and 13.00% on an annual basis. Compared with typical automotive market interest
 35 rates (that reflect cost of capital) (Allcott and Wozny, 2014), the subjective discount estimate of
 36 13% is high. At the same time, it is well within the bounds of estimates that have been found in
 37 many different discrete choice studies of vehicle choice (Wang and Daziano, 2015). In fact,
 38 estimates were found ranging from 9.6% to 47% derived from 20 studies between 1980 and 2012.
 39 For the MNL-2 specification, the annual discount rate for the individuals who received emission
 40 information is slightly higher at 13.90%, whereas that for the group that didn't receive emission
 41 information was estimated at 10.52%. When emissions are omitted, individuals may be more
 42 attentive to operating costs and act in a more forward-looking manner (while still exhibiting
 43 somewhat myopic behavior as the discount rate still is higher than market interest rates.) In terms
 44 of the Bayesian Information Criterion (BIC), MNL-2 is preferred to MNL-1.

1 With respect to MNL-2 estimates of WTP for CO₂ reductions, Table 5 can be interpreted
 2 this way: ω_{tons} is the WTP of the base case (tons per year framing) and the δ parameters refer to
 3 the differences from the base case. The statistical significance of ω_{tons} means that its influence is
 4 statistically significantly different from zero (0). The combined results of ω_{tons} and the δ parameters
 5 may result in a non-significant result. The meaning of such a result is that the total influence is not
 6 statistically different from zero (0).

7 When CO₂ information (CO₂EI) was presented as tons per year (the base case), respondents
 8 were willing to pay \$277.25 (€13.86) to reduce CO₂ emissions by one ton. To interpret the other
 9 estimates, it is necessary to recognize they are incremental with respect to the base WTP of tons
 10 per year (ω_{tons}). This specification allows us to test directly whether variation in the willingness
 11 to pay under the different presentational modes is significant or not (statistical significance for the
 12 WTP variants are based on the δ parameters).

13 When CO₂EI was presented to respondents as pounds per month, the result of \$243.22
 14 (€12.16) per ton (pound) was found, which is statistically different from zero. However, the
 15 difference (δ) is not statistically different from the base case (ω_{tons}). Thus, there appears to be some
 16 advantage to presenting the information on a yearly as opposed to monthly amount, though this
 17 difference is not statistically significant.

18 Providing CO₂EI in the form of a societal objective was the most influential. The WTP
 19 estimate was much larger, and statistically significantly different (δ), with a value of \$371.31
 20 (€18.57) per ton (pound).

21 Presenting CO₂EI as grams per mile was not statistically different from zero at \$28.63/ton,
 22 though it was statistically different from the base case ($\delta_{gpm} = -248.62$). Thus, the first hypothesis
 23 is confirmed: presenting CO₂EI as grams per mile is the least influential framing.
 24

25 **3.2 WTP Estimates with the Latent Class Formulation**

26 The multinomial logit model, has some important limitations. Although it can capture preferences
 27 that vary systematically with respect to observed characteristics of decision makers (e.g. gender),
 28 it is not capable of capturing preferences that vary with unobserved characteristics. As a result, it
 29 is increasingly common to use “Latent Class” models (Greene and Hensher, 2003). When such
 30 models are estimated, latent classes (or categories) of respondents are identified with a “class
 31 membership” model and different logit models are estimated for the members of each of the
 32 classes. In order to ensure that the results in our logit model were not caused by aggregating all
 33 respondents into one class, a Latent Class model was estimated, which is presented in Table 6. The
 34 model was estimated with the package *gmm* in R (Sarrias and Daziano, 2016). After testing
 35 specifications with different numbers of classes, the best model (in terms of goodness of fit,
 36 statistical significance of variables, parameter magnitude, and BIC) was one with two classes. The
 37 class membership model included eight different variables resulting from the preceding factor
 38 analysis on environmental attitudes, general environmental behavior, and travel behavior
 39 indicators. As in the MNL case, two specifications were formulated. Whereas LC-1 assumes the
 40 same evaluation of costs for all treatments, LC-2 introduces a differing valuation for those
 41 individuals under the treatment without emission information. LC-2 is preferred to LC-1 in terms
 42 of BIC. McFadden’s ρ^2 index of fit is 0.29 for model LC-2.
 43

44 TABLE 6 Estimated WTP with 2 Latent Classes and Attitudinal Factors for Class Assignment
 45

1 The results of the LCL-2 model can be interpreted in the same manner as the MNL model above
 2 in that the base case (ω_{tons}) was the tons per year framing, the δ parameters refer to (statistical)
 3 differences from the base case, and the combined WTP of ω_{tons} and δ are interpreted with respect
 4 to zero.

5 Before discussing the WTP results, the two classes are described. The latent class model
 6 (Table 6) indicates a discrete distribution in which some people (class 1) are more influenced by
 7 CO₂ emissions information. Note that in terms of subjective discounting, individuals in class 1
 8 (49.98% of the sample population) use market interest rates (6.29%) for moving future costs and
 9 benefits to the present (and are forward looking when no emission information is provided, with a
 10 discount rate of 2.49%). Class 2 (50.02% of the sample population), with the lower overall
 11 willingness to pay for reducing emissions, aggregates individuals that exhibit myopic behavior in
 12 terms of discounting the future (with a 21.99% discount rate when emission information is
 13 provided; when CO₂ information is omitted, the discount rate is 9.94%, which still is somewhat
 14 higher than market interest rates).

15 As per assignment to the classes, the evidence suggests that several types of environmental
 16 attitudes and current behavior impact stated WTP to reduce car use emissions. Assignment to Class
 17 2, which negatively affects WTP for all types of CO₂ emissions information, is consistent with
 18 what one might expect. Those individuals are 1.2 times (or 20%) more likely to be against taxes
 19 to reduce emissions, 1.3 times more likely to believe that nature will sort out environmental
 20 problems, 1.3 times (or 30%) less likely to be actively environmental, 1.1 times less likely to be
 21 interested in solar panels, 1.04 times less likely to be multi-modal, and 1.2 times more likely to
 22 follow road rules as opposed to trying to drive economically.

23 Thus, the model finds that people in class 1 are more likely to: be in favor of taxes to reduce
 24 emissions, have actively environmental behavior, and think that nature will *not* sort out
 25 environmental problems. Based on the WTP results, class 1 individuals have a higher willingness
 26 to pay and are more forward looking (based on subjective discount rates).

27 In the preferred LCL-2 model, class 1 (49.98%) has a base WTP (ω_{tons}) of €15.66 per pound
 28 of CO₂, whereas class 2 (50.02%) has a base WTP of €9.69 per pound of CO₂. Both cases are
 29 statistically significantly different from zero. For both classes, the framing of pounds per month
 30 was also statistically different from zero, but not statistically different (δ_{ppm}) from the base case.

31 The results for the grams per mile framing differ. In both cases the difference (δ_{gpm}) is
 32 significant, but for class 2 individuals (less environmentally motivated), the WTP is not
 33 statistically different from zero. Thus, although statistically different from the base case (tonnes
 34 per year), presenting the CO₂ information does not statistically influence choices.

35 Finally, in both cases the largest WTP was observed for the social objective framing. Class
 36 1 individuals were found to have a WTP of \$381.70/ton while those in Class 2 had a WTP of
 37 \$236.61/ton. However, for Class 2 the difference ($\delta_{obj} = 42.74$) was not statistically different from
 38 zero. Thus, for Class 2 only the framing of grams per mile is statistically different than the base
 39 case of tons/year.

40 41 42 **4. DISCUSSION**

43 The WTP estimates found here are on the lower end of recent estimates in the same context. That
 44 is, estimating WTP for CO₂ emissions information (CO₂EI) when presented as grams per mile
 45 from discrete choice experiments of vehicle choice. First, taking the MNL-2 case (Table 5), the
 46 WTP for the case of presenting the information as grams per mile in our study, we find a value of

1 only €1.43 per pound of CO₂ which is not statistically different from zero. In contrast, Achtnicht
2 (2012) estimated a WTP of €22 per pound of CO₂ (€349 per tonne) from a survey of potential car
3 buyers in Germany, and Daziano and Achtnicht (2014) estimated €21 per pound on the same
4 dataset with different statistical analysis. We suggest a number of reasons for this large difference.
5 In the German case, beyond using grams per kilometer to present the information, the data
6 collection method was a computer-assisted personal interview, thus the individual gave an answer
7 in a public place (e.g. a car dealership) to a person. This could create a strong tendency for socially
8 desirable responses. In our experiment, the individuals were paid to complete an anonymous online
9 survey, thus the likelihood of socially desirable responses should be lower. Second, the units grams
10 and kilometers are both metric, whereas grams per mile is a mix of metric and imperial system
11 which may lead to lower comprehension. Third, 74% of Germans feel that climate change is a very
12 serious problem (Eurobarometer, 2009). In the US 26% of Americans worry a great deal about
13 climate change (Jones and Saad, 2014; Saad and Jones, 2016). Thus, there are a number of different
14 factors that might explain this large difference.

15 Except for class 1 individuals of the LCL-2 model, presenting CO₂EI as grams per mile
16 was not statistically different from zero. This result reflects previous findings such as those by
17 Gaker and Walker (Gaker and Walker, 2013) who also applied latent class modeling and found
18 that one group was willing to pay, while another was not. That study used pounds per trip in a
19 mode choice experiment. In other related research Waygood and Avineri have also found that
20 contextualizations as mass are much less influential for people who are not as concerned about
21 climate change (Waygood and Avineri, 2011; Waygood and Avineri, 2016b). In those
22 experiments, tonnes per year were used to motivate changes in driving behavior.

23 When the information was presented as tons/year, a value of €13.86 per pound of CO₂ was
24 calculated. In comparison, Gaker et al. found WTPs of €37 (2010) and €14 (2011) based on
25 samples of students from the University of California, Berkeley. Thus, the results are very similar
26 to the latter experiment (Gaker et al., 2011), though much lower than the first (Gaker et al., 2010).
27 What is striking, from a within-experiment perspective, is how much smaller our WTP estimate is
28 when CO₂ information was presented in grams per mile. It is in fact 2.4 times smaller than the
29 estimate when information is provided in tons per year (the base) for the Latent Class 1, and 5.6
30 times smaller for the Latent class 2 (Table 6). It is worth repeating that grams per mile is the
31 standard presentation of CO₂ information on EPA fuel economy and environment labels for new
32 cars. So here, the simple act of contextualizing the emissions output to a monthly or yearly amount
33 based on 15,000 miles driven per year had at least a 2.4 times increase on the influence of such
34 information on car purchase choices. As this is the current practice for information such as fuel
35 economy, it would now seem obvious that the emissions information should at least be
36 contextualized in a similar fashion.

37 Another remarkable result is how much higher WTP is when CO₂ information is presented
38 as a societal goal (3.0 times larger for class 1 and 6.9 times larger for class 2 than when using
39 grams per mile). We present two arguments why this may be. As discussed in the background
40 section, Waygood and Avineri (2011) argued that people lack a budget or other means of
41 interpreting GHG information. Thus, their perception of the amount is highly influenced by
42 contextual information, and presenting CO₂ emissions information with respect to some limit
43 might help people interpret whether an amount is appropriate or not. The second argument is that
44 people (in general) want to “do the right thing” and that presenting emissions information with
45 respect to a government objective changes the motivation from economic to social, which authors
46 such as Ariely (Ariely, 2008, 2010; Ariely et al., 2009; Heyman and Ariely, 2004) would argue

1 can have a greater influence than financial ones when the financial motivation is low. Considering
2 that the social cost of carbon estimated by the EPA ranges from \$12 to \$61 in 2015 (5% to 2.5%
3 average discount rate), but that fuel costs for an average driver in the USA would be in the
4 thousands of dollars, the relative financial influence might be too small to motivate individuals
5 towards lowering their emissions to a societally desirable level.

6 The willingness to take on personal costs for the public benefit is most apparent when not
7 contextualizing. This is demonstrated by the 73% difference for the WTP of grams per mile
8 between the two classes in the LCL-2 model. When the information is better contextualized by
9 monthly/yearly averages or by the societal goal that difference is reduced to 38% for all three
10 frames. This demonstrates that contextualizing the information can not only improve overall
11 willingness-to-pay, but also reduce the disparity in response strength between those who are more
12 environmentally motivated (class 1) and those who are not.

13 14 **5. CONCLUSION**

15 Using multinomial logit analysis, it was demonstrated that the current means of presenting CO₂
16 emissions information (in grams per mile) results in estimated WTP to reduce CO₂ that is
17 significantly lower than those with context, and not even statistically different from zero. Here, the
18 contextualizations were: tons per year (9.6x more influential than grams per mile), pounds per
19 month (8.5x), and as a percentage with respect to the government's reduction targets (13.0x). In
20 contrast to previous such studies, the experiment participants were a general American car-owning
21 population. This may explain the lower willingness to pay amounts observed with respect to grams
22 per mile. The population performed rationally when a tax was used, since they were willing to pay
23 one dollar to save one dollar (a social cost of carbon of \$37/ton was used). However, although no
24 additional cost was assigned to it, presenting the CO₂ emissions information with respect to the
25 government's reduction targets resulted in a willingness to pay \$371/ton. The clear implication for
26 this is that more effective means exist for communicating with the public about the climate change
27 emissions of their consumer choices than are currently being applied.

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41

FIGURES

Imagine that you are in a situation where you must buy a vehicle. You have decided on which vehicle you want, but you must make some final decisions on the motor type. Please make your choice from the information below.

*Annual savings are based on driving 15 000 miles/year with fuel costing \$3.70/gallon.

	Purchase Cost	Fuel Costs per year	(CO2 information; depending on treatment)
Car A			
Car B			

Given the 2 options above, which car would you buy? (Please inspect carefully all characteristics before making your choice)

Figure 1. Example of choice experiment question.

Highlights

CO₂ emissions information (CO₂EI) as grams/mile has negligible influence.

CO₂EI as a carbon tax is only as strong as the tax.

CO₂EI contextualised through use is roughly 9x as strong as g/mile.

CO₂EI contextualised with respect to reduction targets is 13x as strong as g/mile.

TABLES

TABLE 1 Selected results for respondent characteristics

<i>Variable</i>	<i>Respondents' characteristics</i>
<i>Female</i>	49.80%
<i>Education</i>	
<i>Below High School</i>	0.7%
<i>High school graduate</i>	12.2%
<i>Associate degree</i>	9.2%
<i>Some college</i>	19.8%
<i>Bachelor's degree</i>	38.6%
<i>Graduate degree</i>	19.6%
<i>Household cars</i>	
<i>1</i>	39.0%
<i>2</i>	46.7%
<i>3</i>	9.8%
<i>4 or more</i>	4.5%
<i>Mileage</i>	
<i>Less than 5,000 miles</i>	6.3%
<i>5,000 - 7,500 miles</i>	13.4%
<i>7,501 - 10,000 miles</i>	17.8%
<i>10,001 - 12,500 miles</i>	18.6%
<i>12,501 - 15,000 miles</i>	14.8%
<i>15,001 - 17,500 miles</i>	6.6%
<i>17,501 - 20,000 miles</i>	5.9%
<i>20,001 - 25,000 miles</i>	4.7%
<i>Over 25,000 miles</i>	11.9%
<i>State of residence</i>	
<i>DE</i>	5.4%
<i>MA</i>	34.2%
<i>NH</i>	6.6%
<i>NJ</i>	14.1%
<i>PA</i>	39.3%
<i>Other</i>	0.4%
<i>Household income</i>	
<i><\$30,000</i>	6.7%
<i>\$30,000-\$39,999</i>	6.6%
<i>\$40,000-\$49,999</i>	8.5%
<i>\$50,000-\$59,999</i>	10.3%
<i>\$60,000-\$74,999</i>	15.6%
<i>\$75,000-\$84,999</i>	8.4%

\$85,000-\$99,999	10.4%
\$100,000-\$124,999	11.0%
\$125,000-\$149,999	6.9%
\$150,000-\$174,999	4.2%
>\$175,000	6.5%

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TABLE 2 Responses to questions addressing climate change.

<i>Question</i>	<i>Options</i>	<i>Results</i>
<i>1. The 2025 objective of the USA federal government is a 26-28% reduction in emissions from 2005 levels. For road transportation, this would mean an average of 3.8 tons per person per year (down from 5.2 tonnes in 2005). If you were to remain at 2005 levels (and not reduce), how much would you be willing to pay per ton of additional GHG emissions?</i>		
	Nothing	45.2%
	\$5 per ton	26.9%
	\$12 per ton	15.1%
	\$39 per ton	7.2%
	\$61 per ton	2.7%
	\$116 per ton	1.8%
	\$250 per ton	0.4%
	\$500 per ton	0.6%
<i>2. How much do you support or oppose a 60-cent per gallon gasoline tax, in addition to existing gas taxes, to encourage people to drive less and thus reduce carbon dioxide emissions?</i>		
	Strongly support	5.6%
	Rather support	13.9%
	Don't know	12.6%
	Rather oppose	26.0%
	Strongly oppose	42.0%
<i>3. In order to encourage the use of more fuel-efficient vehicles, some people have proposed a 5 percent "gas guzzler" tax on cars, trucks and sport utility vehicles that get less than 25 miles per gallon. This would add \$1,000 to the price of a \$20,000 car. How much do you support or oppose this proposal?</i>		
	Strongly support	15.1%
	Rather support	30.9%
	Don't know	14.9%
	Rather oppose	18.1%
	Strongly oppose	21.1%
<i>4. To encourage industry to be more fuel efficient, some people have proposed a business energy tax. This tax would raise the average price of most things you buy, including food and clothing, by 3 percent, or approximately \$380 per person per year. How much do you support or oppose this proposal?</i>		
	Strongly support	5.3%
	Rather support	15.8%
	Don't know	17.8%
	Rather oppose	27.1%

5. Please choose the phrase that most corresponds to you for reducing greenhouse gases:

Strongly oppose	34.2%
I am not concerned	13.5%
I would like to reduce my emissions, but I don't know how	30.9%
I would like to reduce my emissions, and will do so in the future	39.7%
I have already reduced my emissions significantly	15.9%

TABLE 3 High loading variables for each principal component of the factor analysis on general ecological behavior and tax policy preferences variables.

Principal components	Variables used (high loading)
<i>General ecological behavior</i>	
Actively environmental (Responses were from Never (1) to Always (5))	I talk with friends about problems related to the environment. I read about environmental issues. I have pointed out unecological behavior to someone. I contribute financially to environmental organizations. I boycott companies with an unecological background. I buy products in refillable packages.
Not interested in solar panels (Responses were Yes =1; No = 2)	I requested an estimate on having solar power installed. I have already looked into the pros and cons of having a private source of solar power. I bought solar panels to produce energy.
<i>Transportation behavior</i>	
Multi-modal (Responses were from Never (1) to Always (5))	I take public transportation to work or school. For distances up to 20 miles, I use public transportation. In nearby areas (around 5 miles), I ride a bike. I ride a bicycle to work or school.
Drive everywhere (Responses were from Never (1) to Always (5))	I drive my car in the city. I drive my car into the city.
Idle (Responses were from Never (1) to Always (5))	I keep the engine running while waiting in front of a railroad crossing or in a traffic jam. At red traffic lights, I keep the engine running.
Rules over economics (Responses were from Never (1) to Always (5))	I drive on highways at speeds under 60 mph. I drive in such a way as to keep my fuel consumption as low as possible. (*Negative loading).
<i>Personal ecological values and beliefs</i>	
Against taxes to reduce emissions (Responses for 1, 2, and 3 were from strongly support (1) to strongly oppose (5). Responses for 4 were: Nothing (1), \$5 per ton (2), \$12 per ton (3), \$39 per ton (4), \$61 per ton (5), \$116 per ton (6), \$250 per ton (7), \$500 per ton (8).)	<ol style="list-style-type: none"> 1) How much do you support or oppose a 60-cent per gallon gasoline tax, in addition to existing gas taxes, to encourage people to drive less and thus reduce carbon dioxide emissions? 2) In order to encourage the use of more fuel-efficient vehicles, some people have proposed a 5 percent “gas guzzler” tax on cars, trucks and sport utility vehicles that get less than 25 miles per gallon. This would add \$1,000 to the price of a \$20,000 car. How much do you support or oppose this proposal? 3) To encourage industry to be more fuel efficient, some people have proposed a business energy tax. This tax would raise the average price of most things you buy, including food and clothing, by 3 percent, or approximately \$380 per person per year. How much do you support or oppose this proposal? 4) The 2025 objective of the USA federal government is a 26-28% reduction in emissions from 2005 levels. For road transportation, this would mean an average of 3.8 tons per person per year (down from 5.2 ton in 2005). If you were to remain at 2005 levels (and not reduce), how much would you be willing to pay per ton of additional GHG emissions? (Negative loading)

<p>Nature will not sort out environmental problems (Responses were from strongly agree (1) to strongly disagree (5))</p>	<p>The balance of nature is strong enough to cope with the impacts of modern industrial nations. Human destruction of the natural environment has been greatly exaggerated. Humans will eventually learn enough about how nature works to be able to control it. Humans have the right to modify the natural environment to suit their needs. Human ingenuity will insure that we do NOT make the earth unlivable. Humans were meant to rule over the rest of nature.</p>
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ACCEPTED MANUSCRIPT

TABLE 4 Experiment attributes and levels

Attribute	Levels Vehicle A	Levels Vehicle B
Purchase price	80%, 90%, 105%, 115% of stated willingness to spend	90%, 110%, 120%, 130% of stated willingness to spend
Fuel costs per year	\$1,500; \$1,900; \$2,500	\$800; \$1,200; \$1,500
Grams of CO ₂ per mile	304; 320; 336	170; 215; 260

TABLE 5 Estimated WTP with Multinomial Logit Specification

	MNL-1		MNL-2	
	Month	Year	Month	Year
Subjective discount rate: r	1.02%***	13.00%	1.09%***	13.90%
Subjective discount rate, no CO ₂ Information			0.84%***	10.52%
Presentation of CO ₂ Information	\$/ton	¢/pound	\$/ton	¢/pound
Base WTP (tons per year): ω_{tons}	245.76***	12.29	277.25***	13.86
Grams per mile: δ_{gpm}	-224.62***		-248.62***	
Pounds per month: δ_{ppm}	-33.12		-34.03	
Societal Objective: δ_{objppm}	89.09*		94.07*	
WTP Grams per mile: $\omega_{\text{tons}} + \delta_{\text{gpm}}$	21.14	1.06	28.63	1.43
WTP Pounds per month: $\omega_{\text{tons}} + \delta_{\text{ppm}}$	212.64***	10.63	243.22***	12.16
WTP Societal Objective: $\omega_{\text{tons}} + \delta_{\text{objppm}}$	334.85***	16.74	371.31***	18.57
Loglikelihood at convergence	-10655		-10632	
$\rho^2(0)$	0.190		0.192	
$\rho^2(ASC)$	0.187		0.189	
BIC	21380		21343	
AIC	21325		21281	

Significance codes: *** 0.1%, ** 1%, * 5%

TABLE 6 Estimated WTP with 2 Latent Classes and Attitudinal Factors for Class Assignment

	LCL-1		LCL-2	
Class 1 (49.98%)				
	Month	Year	Month	Year
Subjective discount rate: r	0.44%	5.39%	0.51%***	6.29%
Subjective discount rate, no CO ₂ Information			0.20%***	2.49%
Presentation of CO ₂ Information	\$/ton	¢/pound	\$/ton	¢/pound
Base WTP (tons per year): ω_{tons}	259.59***	12.98	313.13***	15.66
Grams per mile: δ_{gpm}	-157.46***		-183.94***	
Pounds per month: δ_{ppm}	47.37		50.98	
Societal Objective: δ_{objppm}	59.60*		68.57*	
WTP Grams per mile: $\omega_{\text{tons}} + \delta_{\text{gpm}}$	102.13*	5.11	129.19*	6.46
WTP Pounds per month: $\omega_{\text{tons}} + \delta_{\text{ppm}}$	306.96***	15.35	364.11***	18.21
WTP Societal Objective: $\omega_{\text{tons}} + \delta_{\text{objppm}}$	319.19***	15.96	381.70***	19.08
Class 2 (50.02%)				
	Month	Year	Month	Year
Subjective discount rate: r	1.65%***	21.77%	1.67%***	21.99%
Subjective discount rate, no CO ₂ Information			0.79%***	9.94%
Presentation of CO ₂ Information	\$/ton	¢/pound	\$/ton	¢/pound
Base WTP (tons per year): ω_{tons}	198.42***	9.92	193.87***	9.69
Grams per mile: δ_{gpm}	-165.68***		-159.45***	
Pounds per month: δ_{ppm}	27.94		30.10	
Societal Objective: δ_{objppm}	48.54		42.74	
WTP Grams per mile: $\omega_{\text{tons}} + \delta_{\text{gpm}}$	32.7	1.64	34.4	1.72
WTP Pounds per month: $\omega_{\text{tons}} + \delta_{\text{ppm}}$	226.36***	11.32	223.97***	11.20
WTP Societal Objective: $\omega_{\text{tons}} + \delta_{\text{objppm}}$	246.9***	12.35	236.61***	11.83
Assignment to Class 2				
	Estimate	Odds Ratio	Estimate	Odds Ratio
Constant	0.817***	2.264	0.892***	2.440
Against taxes to reduce emissions	0.171***	1.186	0.190***	1.209
Nature will <i>not</i> sort out environmental problems	-0.213***	0.808	-0.233***	0.792
Actively environmental	-0.256***	0.774	-0.238***	0.788
Not interested in solar panels	0.069***	1.072	0.052**	1.053
Multi-modal	-0.033	0.968	-0.04*	0.961
Drive everywhere	-0.044*	0.957	-0.027	0.973
Idle	-0.016	0.985	-0.001	0.999
Rules (e.g. speed limit) over economics (e.g. drive to conserve fuel)	-0.051**	0.951	-0.067***	1.209
Loglikelihood at convergence	-9355		-9305	
$\rho^2(0)$	0.289		0.292	
$\rho^2(ASC)$	0.287		0.290	
BIC	18917		18837	
AIC	18752		18656	
Significance codes: *** 0.1%, ** 1%, * 5%				