Consumer Preferences for Electric Vehicles: The Roles of Political Identity and Price*

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Abstract

We investigate the effects of political identity and vehicle attributes on consumer preferences for electric vehicles (EVs) in the United States. We analyze data from an online experimental survey of a hypothetical vehicle purchasing scenario and find significant negative political identity effects. Conservative Republican males, liberal Democratic females, and liberal Independent males, all without real-world exposure to EVs, are significantly less likely to purchase an EV when the EV is framed as a common choice among the 'other' political identity. Political identity labeling of EVs also induced participants to respond differently to the operating cost savings of EVs.

Keywords:
consumer behavior, polarization, political ideology, vehicle adoption, randomized experiments

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INTRODUCTION

The transportation sector in the United States is the largest contributor to greenhouse gas emissions, accounting for 29 percent of all GHG emissions in 2021 (U.S. Environmental Protection Agency, 2023). Within the US transportation sector, light-duty vehicles (passenger vehicles weighing less than 8,500 lbs) generate the vast majority of these emissions, approximately 58 percent. Furthermore, the transportation sector significantly contributes to NO_x and PM2.5 emissions, leading to serious health effects (U.S. Environmental Protection Agency, 2024). The EPA aimed for two-thirds of new passenger cars and a quarter of heavy trucks sold in the US to be all-electric by 2032 but revised these goals in March 2024 to be "technology neutral".

Understanding the heterogeneous demand for electric vehicles (EVs) is crucial for reaching the various targets for EV adoption and the light-duty fleet emissions standards for model-year 2032. However, the uptake of EVs has faced significant challenges, especially in deploying the necessary charging infrastructure to support increased demand and the prevailing consumer preferences for gasoline vehicles (Archsmith, Muehlegger, and Rapson 2022; Hardman et al. 2018). Moreover, as of summer 2023, EVs are more expensive than their gasoline counterparts, with average prices of $\$53,469$ and $\$48,334$, respectively (Kelly Blue Book 2023). Evidence suggests that intrinsic EV demand growth, which varies significantly by geography and consumer characteristics, is pivotal in increasing their market share (Archsmith, Muehlegger, and Rapson 2022).

One hypothesized challenge to the widespread adoption of EVs centers on the polarization of environmental attitudes and EVs in the US. For instance, Sintov, Abou-Ghalioum, and White (2020) examined the significance of political affiliation in predicting EV adoption intentions in central Ohio, revealing that Republicans are less inclined to adopt EVs than Democrats. Likewise, a recent working paper by Davis, Li, and Springel (2023) indicates that between 2012 and 2022, half of all EV registrations were concentrated in the top 10 percent of the most Democratic counties and noted little evidence suggesting any decrease in this correlation over time.

To understand the varied patterns of EV adoption, we contribute a novel study assessing how the political identity labeling of EVs can influence the hypothetical purchase decisions of 2500 online survey participants from Prolific's politically representative sampling feature. Specifically, we presented respondents with a vehicle purchasing scenario featuring both a generic EV and a gasoline model with randomized attributes (sale price, range, and five-year fuel plus maintenance costs), and randomly assigned them to one of three experimental groups: a group presented with a liberal political statement, a group presented with a conservative political statement, and a control group receiving no statement. The liberal statement said "keep in mind that electric vehicles are often chosen by people with liberal views" and the conservative statement read "keep in mind that lately, electric vehicles have been chosen by people with conservative views." All three groups received the same hypothetical scenario in which they "are shopping for a new everyday vehicle."

We find consistent evidence among several modeling choices that conservatives exposed to the liberal statement were significantly less likely than conservatives in the control group to hypothetically purchase the EV. The point estimates range from 9-13 percentage points, or a considerable 25-35 percent reduction relative to the mean. In a linear probability model, the average price difference between EVs and gasoline alternatives would need to drop by $\$2,000$ to $\$23,000$ to overcome these identity effects.

Further investigation into the heterogeneity of average treatment effects using machine learning (Athey, Tibshirani, and Wager 2018) revealed important nuances. First, the negative effect of the liberal statement among conservatives is concentrated among one subpopulation: conservative Republican males without some form of exposure to EVs. This subpopulation of conservatives was 26 percentage points less likely to purchase the EV, or about a 100 percent reduction relative to the mean. Additionally, liberal Democratic females and liberal Independent males, also *without any real-world exposure to EVs*, were significantly less likely to purchase the EV when receiving the statement aligning EVs with conservative consumers. Thus, some portions of the liberal and conservative populations respond to politically labeling EVs as popular among the 'other' group, and understanding the heterogeneity in the treatment effects is important for understanding consumption behavior. The significant heterogeneous treatment effects concentrated among subpopulations with no exposure to EVs suggest increasing consumers' exposure to EVs through peer effects and test driving as operators/passengers may help combat any identity effects in the marketplace. However, this should be explored in future work.

We also find significant effects of the price and range differences on determining the selection of EVs. Each \$1000 difference in sale price decreased the likelihood of selecting the EV by 1.6 percentage points. Consequently, reducing the EV sale price by \$7500, equal to the maximum Federal subsidy, would increase the purchase probability by 23 percent. Interestingly, conservatives responded differently to the price difference than non-conservatives, requiring larger price differences between EV and gasoline models to increase their probability of purchasing EVs. The driving range differences between the EV and gasoline models were also significant: increasing the mean EV driving range to match the average gasoline range (by 170 miles) would lead to a 20 percent increase in the probability of selecting the EV. Overall, lowering sale prices and increasing the driving ranges of EVs will likely increase demand for EVs and make them more competitive with gasoline models.

Linear specifications of the operating cost differences between the two vehicles failed to yield a significant marginal effect on EV uptake. However, local-linear machine learning models demonstrated the nuances of how participants responded to operating costs: the marginal effects of operating cost differences varied by treatment status. Liberal participants in the control group demonstrated a significant nonlinear response, but liberal participants who received the liberal statement ignored EV operating cost savings. The nonlinear shape demonstrated that liberal and moderate participants in the control group were the most responsive to the EV operating cost savings when these savings marginally overcame the EV price premium. On the other hand, conservative participants in the control group ignored EV operating cost savings while conservatives who received the conservative statement responded to these savings. These results have several implications. First, the politicization of EVs may induce behavioral biases that punish certain EV characteristics during motor vehicle purchases. Second, aligning EVs with conservative consumers may induce conservatives to pay attention to the operating cost savings and consider the net present value of EVs, potentially correcting this population's inattention to certain EV characteristics. Finally, the heterogeneity in the results and dependence on different modeling assumptions demonstrate the importance of strategies beyond linear models, how politically labeling EVs may have a nuanced effect on consumption decisions, and raises questions regarding the welfare effects of politicizing EVs.

The online experimental setting of our study provides some advantages and necessary limitations. One significant advantage is the capability to generate random identifying variation for the parameters of interest and provide summary statistics of stated preferences of a hypothetical scenario. About 50 percent of the participants purchased the EV under our hypothetical scenario. This implies that the uptake of EVs could be rather high if the real-world conditions are sufficiently similar to our experimental conditions (e.g. EV models exist that are considered full substitutes for their respective gasoline models). We also purchased Prolific's capability to generate a politically representative sample of the US population, providing some merit to the argument that these results may be representative of the political population. However, until the market availability of EV models expands and the operating cost savings of EVs are more salient, it is unlikely that the point estimates extrapolate to the current marketplace. Nonetheless, the results demonstrate the importance of considering political identity, polarization, and vehicle attributes for understanding the demand for EVs.

This paper expands on previous work in several different literatures. The concept of identity playing a role in consumption decisions has been extensively studied in the marketing literature (see Jung and Mittal (2020) for a review). This work also expands the growing literature regarding the role of political identity and energy efficiency, sustainability, and other "green" consumption behaviors. For example, Feinberg and Willer (2013) investigate why Americans' attitudes toward the environment are highly polarized, something observed in the literature (McCright and Dunlap 2003; Feygina, Jost, and Goldsmith 2010; Dunlap, Xiao, and McCright 2001). In similar research, Kidwell, Farmer, and Hardesty (2013) find that conservatives are more likely to participate in a recycling program when framed as "evoking duty", "patriotism", "we", or "fight". Gromet, Kunreuther, and Larrick (2013) used a randomized field experiment and found that conservatives were less likely to purchase an energy-efficient light bulb when the efficient bulb was more expensive than the alternative and came with a "Protect the environment" sticker. Davis and Metcalf (2016) found that Republicans were more likely to choose energy-inefficient air conditioners, with lower purchase prices but higher annual operating costs. Kahn (2007) points out that driving an energy-efficient vehicle or owning an energy-efficient building may be viewed as a status symbol, finding that a community's share of Green Party registered voters is associated with more public transit use and less gasoline consumption. The current paper is the first to explore how political group identity may impact consumer preferences for EVs and considers heterogeneous effects.

We also expand the relatively small literature on the adoption and attitudes of electric vehicles (Salari 2022; Parent 2023; Viola 2021; Lashari, Ko, and Jang 2021; Anfinsen, Lagesen, and Ryghaug 2019; Barth, Jugert, and Fritsche 2016; Chen, Eccarius, and Su 2021; Filippini, Kumar, and Srinivasan 2021; Brückmann and Bernauer 2023; Archsmith, Muehlegger, and Rapson 2022; Rapson and Muehlegger 2023; Holland, Mansur, and Yates 2021).

This work also expands the broader behavioral economics literature to EVs, focusing on reduced-form techniques that don't necessarily posit the precise psychologies explaining the observed behavior as outlined by Mullainathan, Schwartzstein, and Congdon (2012). The results surrounding the consumer responses to the operating cost savings of EVs is adjacent to the behavioral economics literature on energy use and efficiency (Allcott and Greenstone 2012; Allcott and Rogers 2014; Allcott and Taubinsky 2015; Allcott 2016; Allcott and Kessler 2019; Allcott et al. 2024; Sallee 2014, 2011; Kallbekken, Sælen, and Hermansen 2013; Jessoe and Rapson 2014)

MODEL OF VEHICLE CHOICE

The purchase of a new vehicle is a consumption decision, where consumers' individual utilities may vary based on measures of political identity, income, and other demographics. Conditional on these consumer characteristics, individuals will choose the vehicle that maximizes their utility. It is conceivable that purchasing an EV when that vehicle is seen as part of the 'other group' could generate disutility. We attempt to understand how framing the purchase decision in ways that appeal to the liberal and conservative identity affects stated purchase decisions. With such a goal in mind, we randomly draw the purchase price, fuel costs, and driving range from a joint normal distribution for each vehicle option separately. Specifically, the EV distribution is given by $N([\mu_{p,ev}, \mu_{op,ev}, \mu_{r,ev}], \Sigma_{ev})$, and ICE distribution given by $N([\mu_{p,ice}, \mu_{op,ice}, \mu_{r,ice}], \Sigma_{ice})$. We set the means for the price, fuel cost, and range random variables to represent what is currently available on the market and defined the covariance matrices to include a positive correlation between the different attributes (e.g. vehicles with higher ranges will have higher sticker prices).

Individuals are assumed to derive utility from the attributes of each vehicle under a discrete choice, random utility model. Our experiment included purchase price, operating costs, and the driving range. Furthermore, we assume consumer preferences are heterogeneous and depend on individual characteristics (including political identity) and treatment status. The utility from purchasing a vehicle j for individual i is given by:

$$u_{i,j} = \alpha_1 R_{i,j} - \alpha_2 P_{i,j} - \alpha_3 OC_{i,j} + \varepsilon_{i,j} \tag{1}$$

where $R_{i,j}$ is the driving range (in miles), $P_{i,j}$ is the purchase price, $OC_{i,j}$ are the yearly operating costs, and $\varepsilon_{i,j}$ is the random error. To capture consumer heterogeneity we estimate separate models for each experimental group by political identity, relying on a flexible function to estimate vehicle choice using individual characteristics and then constructing residuals to estimate the structural parameters. This is discussed in more detail below.

In the context of choosing between an electric and gasoline vehicle, consumers will choose the electric vehicle if the utility of the electric vehicle is strictly greater than the utility of the gasoline vehicle:

$$\alpha_{1i} R_{i,e} - \alpha_{2i} PP_{i,e} - \alpha_{3i} OC_{i,e} + \varepsilon_{i,e} > \alpha_{1i} R_{i,g} - \alpha_{2i} PP_{i,g} - \alpha_{3i} OC_{i,g} + \varepsilon_{i,g} \tag{2}$$

$$\Rightarrow \quad \alpha_{1i} \tilde{R}_{i,eg} - \alpha_{2i} \tilde{PP}_{i,eg} - \alpha_{3i} \tilde{OC}_{i,eg} + \tilde{\varepsilon}_{i,eg} > 0 \tag{3}$$

where tilde denotes differences (e.g. $\tilde{PP}_{i,eg} = PP_{i,e} - PP_{i,g}$). Note that in Equation 1, α_2 and α_3 denote the marginal utilities on the purchase price and yearly operating costs, respectively. Thus, the ratio of these two parameters gives the utility trade-off between the purchase price and operating costs. If we assume a vehicle lifetime of T years, then the ratio of α_2 and α_3 can be used to recover estimates of individual discount rates. Estimating the discount rates under each of our experimental conditions, by subgroup, will give us an idea of how politicizing EVs impacts consumption decisions through one potential economic mechanism: altering the discount rates on EV operating cost savings.

DATA AND EXPERIMENTAL DESIGN

Data

This study utilized survey results from approximately 2,500 respondents within the Prolific survey platform. Specifically, we employed Prolific's new US politically representative sample feature, with a maximum sample size of 2,500. This feature allocates survey spots stratified by sex, age, and political affiliation to mirror US census data. The survey was conducted from January 10 to January 16, 2024, during which 99 percent of the data was collected. Notably, 16 spots for one age-political affiliation stratum (58 or older, Independent) remained unfilled, prompting us to open this quota to any age among Independents to complete the remaining 16 spots. A total of 2,557 respondents initiated the survey and 2,512 reached the final page (Debrief page). Fifty-eight participants withdrew their consent after initiating the survey and were consequently excluded, resulting in a final study population of 2,517 participants. Among these, 3 exited the survey before the vehicle choice experiment, and 2 exited after it. While the 58 withdrawals constitute about 2 percent of all individuals who began the survey, the high completion rate mitigates concerns of sample attrition impacting empirical results.

Table 1 presents summary statistics of participant demographics across the three treatment assignments. The politically representative sample yielded approximately 49 percent Male/Female split, with about 1.6 percent responding as non-binary. Age stratification resulted in quartiles of 31 years, 45 years, and 59 years old, with a maximum age of 90. Political affiliation reported within Prolific was distributed as 32 percent Democrat, 43 percent Independent, and 26 percent Republican. This data, collected by Prolific, generally aligns with the political affiliation question included in the survey, with slight discrepancies among Democrats and Independents. It's worth noting that the inclusion of an "Other" political affiliation category contributes to some of these discrepancies. However, mismatches between survey results and the Prolific measure of political affiliation have negligible impact on the regression results. We rely on self-reported political affiliation within our survey as the most recent measure of a respondent's political leanings.

The experimental design is intended to evaluate the effect of randomized vehicle attributes and randomly assigned "political identity" statements on the stated choice of participants. The "political identity" statements are intended to activate the treated individuals' sense of political identity, relative to the control group that receives no statement. The control group allows for a clean baseline comparison and includes individuals' prior beliefs about electric

Table 1: Demographic Statistics by Treatment Assignment

	Control	Treatment 1	Treatment 2
Age	46.180	44.898	45.366
Income	82,035	89,297	81,886
Marital status	0.453	0.451	0.442
Kids	0.523	0.497	0.522
Household	2.657	2.655	2.633
Gender			
Female	0.487	0.509	0.477
Male	0.497	0.479	0.503
Non-Binary	0.016	0.013	0.020
Race			
African American or Black	0.104	0.116	0.104
American Indian or Alaska Native	0.011	0.014	0.006
Asian	0.051	0.087	0.077
Native Hawaiian or Other Pacific	0.001	0.002	0.003
Other	0.034	0.042	0.035
White	0.799	0.739	0.774
Education			
High School - no diploma	0.004	0.007	0.014
High School - diploma	0.118	0.111	0.132
Some college	0.299	0.300	0.321
Bachelor's	0.433	0.407	0.383
Master's or above	0.147	0.175	0.151
Political Affiliation			
Democrat	0.328	0.376	0.308
Independent	0.389	0.368	0.412
Other	0.007	0.010	0.008
Republican	0.277	0.246	0.272
Observations	857	867	789

Notes: Table reports averages across the various charactersitcs of the survey population. Each column represents the descriptive statistics by treatment assignment. Treatment 1 received the statement that 'Keep in mind that electric vehicles are often chosen by people with liberal views'. Treatment 2 received the statement that 'Keep in mind that lately, electric vehicles have been chosen by people with conservative views.'

and gasoline vehicles, conditional on the randomized vehicle attributes. The experimental groups included 857 individuals in the control group, 867 in the first treatment, and 789 in the second treatment. Note that the treatment probabilities were defined within Python as 1/3, so the different group counts are an artifact of random sampling among the desired sample size.

The EV range means and standard deviations used to define the multivariate normal vehicle distributions were taken from EV Database (2024). The sale price averages come from a 2023 Kelly Blue Book article (Kelly Blue Book 2023). We pulled EV charging costs from EnergySage (2024) and gasoline prices (as of fall 2023) from AAA (2023). We used the per-mile maintenance and repair costs from a report by the Argonne National Laboratory (Burnham et al. 2021), approximately \$.06/mile and \$.010/mile for EVs and ICEs, respectively. We assumed yearly vehicle miles traveled of 11,500 (United States Department of Transportation Federal Highway Administration 2022) and converted charging costs and gasoline costs to costs fuel costs per mile of \$.05 and \$.1396 for EVs and ICEs, respectively. This puts fuel plus maintenance costs for EVs and ICEs at \$.11 and \$.24 per mile, respectively.

Each participant received a random EV draw and random ICE draw based on separate multivariate normal distributions defined using the information collected from the various sources cited in the preceding paragraph. Table 2 shows the summary statistics of these random draws across the entire survey sample. The average EV and ICE sticker prices are about \$53,500 and \$48,400, respectively. The third quartile of EV prices is approximately \$57K, implying that 75 percent of the participants received an EV price less than \$57K. Note the price differences that resulted from the random draws. Twenty-five percent of the sample population were presented with a choice where the EV option was priced at least \$737 less than the gasoline option. On the other hand, 25 percent of the population was presented with options where the EV was more than \$10,951 more expensive than the gasoline option.

The range difference statistics between the EV and gasoline options shown in the last row of Table 2 demonstrate that on average, the EVs had a range of 169 miles less than the gasoline option. Additionally, twenty-five percent of the participants received options where the EV range was within 110 miles or less as compared to the gasoline option.

Survey Design and Statistics

We prepared the survey based on the extensive literature on political identity and consumer behavior, with a particular focus on consumer behavior with environmental implications. We collected respondents' socio-economic and household characteristics. We built the survey using Python within the oTree open-source programming platform (Chen, Schonger, and

Table 2: Summary Statistics of Randomized Vehicle Attributes

	M	SD	First Quartile	Third Quartile
EV Price ($)	$53,528$	$6,031$	$49,542$	$57,608$
ICE Price ($)	$48,456$	$6,028$	$44,256$	$52,420$
EV Operating Costs ($)	$6,340$	877	$5,749$	$6,934$
ICE Operating Costs ($)	$13,774$	$1,275$	$12,927$	$14,677$
EV Driving Range (miles)	234	71	185	282
ICE Driving Range (miles)	403	53	368	440
Price Diff (EV - ICE)	$5,072$	$8,466$	-737	$10,951$
Operating Diff (EV - ICE)	$-7,433$	$1,536$	$-8,465$	$-6,410$
Range Diff (EV - ICE)	-169	89	-231	-110

Notes: Table reports the mean, standard deviation, first and third quartile summary statistics of the randomized vehicle attributes from the experimental portion of the survey. Note that 'operating cost' refers to the fuel plus maintenance costs over 5 years and the difference rows represent subtracting the ICE values from the EV values for each of the respective attributes.

Wickens 2016). We structured the survey to include the treatments and vehicle choice at the beginning of the survey, after the baseline demographic questions, so as not to potentially bias the political identity responses or possibly allow the political identity questions to activate their political identity before the vehicle choice experiment. The participants were randomized into two "political identity" treatments and one control group. Every participant received a random electric and gasoline vehicle drawn from their respective multivariate distributions. See the Web Appendix for a detailed account of the survey used.

The experiment was designed as follows. The participants were given a hypothetical scenario in which they are looking for a vehicle for everyday use and are considering buying a new vehicle. They were given a choice between two vehicles, one that uses gasoline and another that uses electricity as the fuel type, with the random attributes of price, maintenance plus fuel costs over 5 years, and the range (in miles) displayed below each choice. Here are the three different experimental conditions:

1. Control Group: "Imagine this scenario: You're shopping for a new everyday vehicle and have decided which make and model you would like to purchase. Before completing the purchase, the salesperson presents the two following options for your choice, one with a gasoline engine and another with an electric engine. Please note the different attributes that are available for each option: sale price, fuel plus maintenance costs over 5 years, and the range in miles for a full charge or full tank of gasoline. Now,

choose your final vehicle from the options below."

2. Treatment 1: "Imagine this scenario: You're shopping for a new everyday vehicle and have decided which make and model you would like to purchase. Before completing the purchase, the salesperson presents the two following options for your choice, one with a gasoline engine and another with an electric engine. Please note the different attributes that are available for each option: sale price, fuel plus maintenance costs over 5 years, and the range in miles for a full charge or full tank of gasoline. Now, choose your final vehicle from the options below. **Keep in mind that electric vehicles are often chosen by people with liberal views**."

3. Treatment 2: "Imagine this scenario: You're shopping for a new everyday vehicle and have decided which make and model you would like to purchase. Before completing the purchase, the salesperson presents the two following options for your choice, one with a gasoline engine and another with an electric engine. Please note the different attributes that are available for each option: sale price, fuel plus maintenance costs over 5 years, and the range in miles for a full charge or full tank of gasoline. Now, choose your final vehicle from the options below. **Keep in mind that lately, electric vehicles have been chosen by people with conservative views.**"

After the experimental portion of the survey was completed we asked a series of questions regarding motor vehicles (shown in Table 3) and political identity. One potential concern with a hypothetical stated preference decision is that prior beliefs regarding the current electric and gasoline vehicles available on the market may heavily influence the choice. For example, if conservatives heavily dislike the aesthetic appearance of most current EVs on the market or there is a serious lack of public charging infrastructure where conservatives are more likely to live, then this population may heavily favor the gasoline model regardless of the randomized price, range, and operating costs. Although the identity statements are randomized across the population so that a simple comparison of means would produce an unbiased estimate of the average treatment effect (ATE), controlling for important prior beliefs may increase the precision of the estimates.

Table 3 shows summary statistics from the survey responses across the three populations of interest: conservatives, moderates, and liberals. These populations were defined by their self-reported measures of political stance on social issues, where participants chose from 'Very Conservative' to 'Very Liberal' on the question "what best describes your political stance on social issues". The rows under 'Purchase Importance' represent different vehicle attributes that participants were asked to prioritize their importance on a scale of 'Very Unimportant' to 'Very Important' when making a purchase decision under the following description: 'When

Table 3: Survey Resoponses - Vehicle Questions

	Conservatives	Moderates	Liberals
Purchase Importance			
Brand	3.26 (1.3)	3.13 (1.2)	3.05 (1.27)
Charging Availability	4.13 (1.32)	4.25 (1.12)	4.37 (0.94)
Charging Time	4.07 (1.3)	4.16 (1.12)	4.1 (1.05)
Vehicle Pollution	2.63 (1.34)	3.21 (1.29)	3.8 (1.17)
Vehicle Reputation	2.48 (1.42)	2.67 (1.41)	2.45 (1.34)
Aethstetics	3.54 (1.25)	3.49 (1.21)	3.4 (1.2)
Current Market Availability	3.72 (1.35)	3.96 (1.09)	4.25 (0.97)
Vehicle Ownership	1.83 (1.25)	1.84 (1.4)	1.65 (1.08)
Commute Distance	14.14 (28.88)	12.35 (19.92)	12.12 (25.07)
Currently Own EV	0.07 (0.26)	0.07 (0.26)	0.09 (0.29)
Know an EV Owner	0.21 (0.41)	0.25 (0.43)	0.3 (0.46)
Driven in an EV	0.35 (0.48)	0.37 (0.48)	0.49 (0.5)
Work Transportation			
Bicycle/Foot	0.05 (0.21)	0.06 (0.23)	0.09 (0.29)
Car	0.63 (0.48)	0.63 (0.48)	0.65 (0.48)
Motorcycle	0 (0.05)	0 (0.06)	0 (0.06)
Public Transit	0.04 (0.19)	0.06 (0.23)	0.09 (0.29)
SUV	0.19 (0.39)	0.18 (0.39)	0.14 (0.34)
Truck	0.09 (0.29)	0.06 (0.25)	0.03 (0.17)
Observations	685	585	1239

Notes: Table reports summary statstics of the survey responses to questions related to motor vehicle ownership and purchasing. The 'Purchase Importance' questions asked the participants to rank the importance on a scale from Very Unimportant to Very Important (coded as 1 to 5) of each of the factors when deciding to purchase a new vehicle. The 'Current Market Availability' asked participants to agree with the extent that the current market for EVs contains models that they would seriously consider purchasing. Each column represents self-reported measures on 'social issues in general' from a scale of Very Conservative Very Liberal.

deciding to purchase a vehicle in a real-life situation where both gasoline and electric models are available, and considering that they may not be the same make or model, how would you prioritize the importance of the following attributes or characteristics of the decision.' These questions were intended to capture the participants' prior beliefs regarding the importance of vehicle attributes not part of the experimental design of the vehicle choice question.

There aren't many obvious substantial differences in the means of the responses (each question was coded to a Likert 5-point scale) other than the importance of vehicle pollution. On the other hand, looking at the distribution of the choices among the three groups provides some interesting insights. For example, conservatives have ranked the importance of charging time on average less than moderates and liberals. However, 55 percent of conservatives and 52 percent of moderates ranked charging time as 'very important' compared to only 44 percent of liberals. The importance of considering vehicle pollution when making a purchasing decision also varies significantly across these three groups. A total of 48 percent of conservatives, 28 percent of moderates, and 16 percent of liberals ranked vehicle pollution as 'very unimportant' or 'unimportant'. When asked if the current market includes electric vehicles that they would consider purchasing, 36 percent of conservatives, 35 percent of moderates, and 51 percent of liberals responded as 'strongly agree'. The brand is also more important among conservatives: 51 percent of conservatives ranked the brand as 'important' or 'very important' compared to 42 and 40 percent among moderates and liberals, respectively. It is clear that the importance of vehicle attributes that are not captured in the randomized vehicle attributes vary significantly across these populations and provide some useful insight as to which attributes drive the stated preferences for motor vehicles.

We also asked simple questions regarding participants' current motor vehicle ownership, commute, and EV experience, also shown in Table 3. Vehicle ownership, commute distance, and the percentage who drive an SUV or Truck are all higher among conservatives and moderates as compared to liberals. On the other hand, liberals are more likely to report cycling/walking or using public transit to commute to work and are also more likely to currently own an EV, know an EV driver among their family/friends, or have driven in an EV as a passenger. Perhaps surprisingly, conservatives and moderates report a share of EV ownership that is about equal to the current market share of EVs on the road overall, implying that these consumers are currently participating in the market for EVs.

Finally, Table 4 shows the distribution of the number of participants that were assigned to the different experimental conditions, stratified by self-reported measures of their political stance on social issues.

Table 4: Experimental Group Participants by Political Identity

	Conservatives	Liberals	Moderates
Control	237	422	197
Liberal Statement	232	440	195
Conservative Statement	216	377	193

Notes: Table reports the number of participants in each experimental condition, separated by self-reported measures of political stances on social issues in general from a scale of 'Very Conservative' to 'Very Liberal'.

IDENTITY TREATMENT EFFECTS

Comparison of Means

We begin by presenting a comparison of means on the stated preferences of the participants. Table 5 gives the proportions of participants who chose to purchase the EV, separated by each experimental group and by their self-reported measure of social political identity. Liberal participants chose to purchase the EV approximately 66 percent. Moderates chose to purchase the EV about 50 percent of the time and Conservatives less than 40 percent of the time. Comparing these proportions across the experimental groups provides an estimate of the average treatment effects among these subpopulations.

The standard errors on the treatment effects are large with the majority of the effects statistically indistinguishable from zero. However, there is some preliminary evidence of a significant negative effect of including the liberal statement among conservatives. Specifically, conservatives in the liberal treatment group were 9.5 percentage points less likely to choose the EV than conservatives in the control group. Interpreting the significance of this result will depend on whether one adjusts for conventional levels of significance for testing multiple hypotheses.[1] At conventional levels of significance, the $-.095$ result is significant at the 5 percent level. When adjusting the p-values using the Bonferroni or Sidak corrections, then this result is no longer significant at the 5 percent level. Overall, this provides us with some preliminary evidence that the liberal statement may have a large, negative effect on the probability of purchasing an EV among conservatives.

[1]We test two hypotheses using the same control group, one for the liberal statement and one for the conservative statement.

Table 5: Proportion Choosing EV by Treatment Assignment and Political Identity

	Conservatives	Liberals	Moderates
Control	0.388	0.668	0.472
Liberal Statement	0.293	0.682	0.477
Conservative Statement	0.366	0.621	0.43
Average Treatment Effects			
Liberal - Control	-0.095 (0.044)	0.014 (0.032)	0.005 (0.05)
Conservative - Control	-0.022 (0.046)	-0.048 (0.034)	-0.042 (0.05)

Notes: Table reports the proportion of participants who chose to purchase the EV by treatment assignment and self-reported measures of political stances on social issues in general from a scale of 'Very Conservative' to 'Very Liberal'. The two bottom rows report the difference in the proportions between each treatment group and the control group separately for Conservatives, Moderates, and Liberals. Standard errors of these differences are given in paranthesis.

Regression Results

Given the theoretical utility model in Equation 3, the baseline estimating regression equation reflects binary choice:

$$
\begin{aligned}
P(Y_i = 1|\boldsymbol{Z}_i, T_i) = \beta_0 + \sum_{j=1}^{2} \beta_j 1\{T_{ij} = 1\} + \delta(p_{i,ev} - p_{i,ice}) + \\
\alpha(f_{i,ev} - f_{i,ice}) + \lambda(r_{i,ev} - r_{i,ice}) + X_i' \Pi + \omega_i
\end{aligned}
\tag{4}
$$

where $\boldsymbol{Z}_i$ represents a vector of all covariates, T_{ij} denotes the treatment for an individual among the $j = \{1, 2\}$ treatments, p_i, op_i, and r_i are the price, operating costs, and range for EV and ICE options. X_i' is a vector of individual characteristics and ω_i the random error. Thus, $Y_i = 1$ if an individual chooses the electric vehicle, and 0 if they choose the gasoline vehicle. Our main results rely on the LPM of Equation 4 using ordinary least squares. Note that we also run estimates under logistic maximum likelihood, which produce results that are qualitatively similar and as such are presented in the Appendix.

Baseline OLS regression results using Equation 4 under a linear probability model (LPM)[2] are shown in Table 6. These regressions incorporate the randomized identity treatments and differenced vehicle characteristics, with specifications incorporating covariates and ranked

[2]The linear probability model produces coefficients that can be interpreted directly as marginal effects.

vehicle attributes. It's important to note that the liberal indicator variable was defined based on individuals scoring 'very liberal' or 'liberal', while the conservative indicator was based on those scoring 'very conservative' or 'conservative' in response to the survey question regarding their political stance on social issues. Individuals who selected 'moderate' constituted the remaining and omitted category.

Column (1) includes the differenced vehicle attributes, treatment dummies, and interaction terms between the treatment dummy and liberal/conservative indicator variables. Column (2) introduces an interaction between the conservative indicator and the price difference[3]. Column (3) incorporates socioeconomic covariates, such as political affiliation, EV ownership, family/friends EV ownership, age, income, education, gender, participation in volunteer survey questions, commute distance to work, employment status, marital status, presence of children, household size, race, ethnicity, charity participation, and urbanization. Column (4) further adds tp the preceding column by including responses to ranked vehicle attribute questions in the survey, encompassing market availability, pollution, charging availability, charging time, reputation, aesthetics, and brand.

The average treatment effects of the liberal and conservative statements are negligible across all specifications, shown by the parameter estimates in the first two rows of Table 6. However, since these treatments were randomized across all participants, this result is not surprising. Both the price (in 1000s of dollars) and range differences (in 10s of miles) are statistically significant at the .1 percent level and exhibit economic relevance. Notably, the point estimates remain consistent across all specifications. The coefficient for the sale price difference, defined as the EV sale price minus the ICE sale price, suggests that each $1000 difference decreases the probability of selecting the EV by 1.6 percentage points. Consequently, reducing the sale price of electric vehicles by $7500 would increase the probability of EV selection by 12 percentage points, or a 22.7 percent increase relative to the mean[4].

The coefficient for the range difference implies that a 10-mile increase in EV range enhances the probability of EV selection by .6 percentage points. While this effect may seem modest, expanding the EV range by 170 miles to match the mean ICE range would result in a 10.2 percent increase in the probability of EV selection, representing a 19 percent increase relative to the mean. These substantial effects could significantly augment the market share of EVs in the US if translated into consumer behavior in the marketplace.

Another noteworthy result is the absence of statistical significance regarding fuel plus

[3]Other forms of interactions between the price difference and liberal indicators were initially included but were found to be statistically insignificant and thus omitted from the main results. These results are available upon request from the corresponding author.

[4]The mean price difference is positive since EVs are generally more expensive than ICEs on average. Hence, the price difference will be negative when EVs are cheaper

Table 6: Baseline OLS Regression Results

	Probability of choosing the EV			
	(1)	(2)	(3)	(4)
Liberal Treatment	0.003	0.002	−0.010	0.035
	(0.047)	(0.047)	(0.047)	(0.042)
Conservative Treatment	−0.030	−0.029	−0.026	0.005
	(0.047)	(0.047)	(0.047)	(0.042)
Price Diff	−0.016***	−0.018***	−0.017***	−0.016***
	(0.002)	(0.002)	(0.002)	(0.001)
Operating Cost Diff	−0.008	−0.009	−0.010	−0.009
	(0.006)	(0.006)	(0.006)	(0.005)
Range Diff	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Liberal	0.204***	0.204***	0.155***	0.108**
	(0.040)	(0.040)	(0.042)	(0.037)
Conservative	−0.085	−0.112*	−0.075	−0.002
	(0.045)	(0.047)	(0.048)	(0.043)
Liberal Treat. × Liberal	0.011	0.013	0.018	−0.042
	(0.057)	(0.057)	(0.056)	(0.050)
Conservative Treat. × Liberal	−0.021	−0.021	−0.027	−0.066
	(0.058)	(0.058)	(0.057)	(0.051)
Liberal Treat. × Conservative	−0.082	−0.085	−0.074	−0.129*
	(0.064)	(0.064)	(0.063)	(0.056)
Conservative Treat. × Conservative	0.011	0.009	−0.012	−0.043
	(0.065)	(0.065)	(0.064)	(0.057)
Price Diff × Conservative		0.006*	0.005	0.006**
		(0.002)	(0.002)	(0.002)
Mean Dependent Variable	0.527	0.527	0.527	0.527
Socioeconomic Controls	No	No	Yes	Yes
Ranked Vehicle Attributes	No	No	No	Yes
Observations	2,509	2,509	2,492	2,492
Adjusted R^2	0.121	0.123	0.165	0.350

Notes: Table reports OLS results based on Equation 4. Column (1) includes includes the differences in the randomized vehicle attributes and indicator variables defining 'liberal' and 'conservative' participants using their responses to a political stance on social issues in general. Conservatives are defined as scoring 'very conservative' or 'conservative' and liberals as 'very liberal' or 'liberal'. Note that the omitted category are those who scored as 'moderate'. All columns allow the randomized political identity treatments to vary by these different groups. Column (2) allows for the price difference coefficient to vary if individuals identify as conservative. Column (3) adds socioeconomic covariates and Column (4) includes both socioeconomic covariates and ranked vehicle attributes. The socioeconomic controls include political affiliation, EV ownership, family/friends EV ownership, age, income, education, gender, if they volunteered, commute distance to work, employment status, marital status, if they have children, household size, race, ethnicity, charity participation, and urbanization. The ranked vehicle attributes include market availability, pollution, charging availability, charging time, reputation, aesthetics, and brand. Significance levels 0.05, 0.01, and 0.001 are denoted by *, **, and ***, respectively.

maintenance costs over five years. This suggests that on average, respondents did not factor in these "operating cost" discrepancies when making their vehicle choices. This finding is somewhat unexpected, particularly given the significant disparities in fuel and maintenance costs between EVs and ICEs. However, as we explore in the Responses to Rand Vehicle Attributes section below, there are heterogeneous responses to operating cost differences that are not captured in a pooled linear model. Nonetheless, future work should investigate how consumers discount operating costs when purchasing motor vehicles and explore how presenting this information in different ways may result in different behaviors.

The most interesting identity treatment effects are represented by the coefficient on the interaction between the Liberal Treatment and Conservative indicator variable. The other treatment effect interaction terms are in the neighborhood of 0, with somewhat large standard errors. The liberal treatment effect among conservatives ranges from a 7.4 to a 12.9 percentage point reduction, consistent with the comparison of means above and also somewhat imprecisely estimated in Columns (1) - (3), but significant at the 5 percent level in Column (4)[5], which controls for beliefs about the importance of vehicle attributes. Importantly, including these covariates increases the precision of the treatment effect estimates and increases the adjusted R-squared to .35, suggesting that including individuals' perceptions of vehicle attributes drastically increases the accuracy of the model[6].

Column (4)'s point estimate of $-.129$ implies that conservatives who received the liberal statement were 12.9 percentage points less likely to choose the EV, or a 36 percent reduction relative to the mean. The comparison of means and linear probability models both provide evidence of a significant negative treatment effect and reinforce the notion that consumers may respond to identity signals when choosing which vehicles to purchase. These effects could potentially impact marketplace dynamics among conservatives through various channels. One plausible mechanism could involve consumers' initial behaviors upon embarking on the search for a new vehicle. It's highly conceivable that conservatives exposed to real-world identity statements may overlook EVs as a viable option during the research or information-gathering stage when seeking a new vehicle to purchase.

Another noteworthy finding is the economically and statistically significant heterogeneity observed in the price difference coefficient among conservatives. This implies that the marginal effect of the price difference is less negative and equal to approximately $-.01$ for every \$1000 difference. This is significantly different than the overall coefficient of $\$-.016$

[5]It is important to note that the estimation of these marginal effects using the logistic assumption produces point estimates that are significant at the 1 percent level for the same interaction term.

[6]These ranked vehicle attributes were scored from 'Very Unimportant' to 'Very Important' by each participant and are included as categorical (dummy) variables in the regressions with the omitted category being the neutral category, category 3.

implies that in cases where EVs are cheaper than ICEs, each additional \$1000 difference increases the probability that conservatives choose the EV less than the non-conservative population.

In the LPM we can use the price difference coefficient and the liberal treatment effect among conservatives to get an idea of the "cost" of receiving identity signals If receiving the liberal statement among conservatives reduces the probability of choosing the EV by 12.9 percentage points, then reducing the price of the EV option by $\$12,900$ would increase the probability of choosing the EV by 12.9 percentage points, overcoming the liberal identity effect. In other words, the "cost" of the liberal identity among conservatives is nearly $\$13,000$ or nearly twice the current maximum federal tax credit of \$7500.[7]

This is a relatively large cost but it is important to consider the uncertainty of these estimates and the experimental setting of an online survey. Using the 95 percent confidence intervals on the liberal treatment effect among conservatives produces a lower bound of about \$2000 and an upper bound of approximately $\$23,000$. It follows that the "cost" of the liberal identity among conservatives in terms of the sale price of a vehicle has a wide range so it may be difficult to use these results to inform precise policy, but there is strong evidence that the cost is nonzero and in the thousands of dollars. Future research should further refine these estimates to understand how the price differences between EVs and ICEs may affect the market purchasing decisions of conservatives in the current polarized EV climate.

Heterogeneous Treatment Effects

Since the OLS and logit models assume a linear relationship between the outcome and parameters, we also estimate nonparametric versions of Equation 4 using Honest Causal Forests Athey, Tibshirani, and Wager (2018) to allow for more complex relationships between the covariates and observed hypothetical choices. Causal forests are local nonparametric estimators of the conditional probability of choosing the EV and ICE alternatives that recursively partition the covariate space in a way that maximizes the difference in treatment effect between the two child nodes.[8] Thus, given the random variation in prices, fuel plus maintenance costs, driving range, and identity treatments, the causal forests provide estimates of heterogeneous treatment effects that aren't limited by the distributional assumptions of the parametric approach. Furthermore, the local estimation nature of honest forests provides a more sophisticated estimation technique for counterfactual probabilities of the stated hypothetical preferences.

We are interested in estimating the conditional mean functions under the various treat-

[7]The same exercise within the logit, nonlinear, or nonparametric model may produce different results.

[8]See Athey, Tibshirani, and Wager (2018) for a complete discussion on causal forest splitting and prediction.

ments using causal forests:

$$E[Y_i|X_i = x, w_i = w, D_i = d] = m(x,w)_d \tag{5}$$

where X_i represents the vector of explanatory variables excluding w_i, which is the randomized vehicle difference of interest (e.g. price), and D_i is a indicator for each experimental group that takes values from $\{0, 1, 2\}$. We can use honest causal random forests to obtain estimates of the individual treatment effects as a function of $m(x,w)_0$, $m(x,w)_1$, and $m(x,w)_2$, for the control, liberal statement, and conservative statement, respectively:

$$\begin{aligned} \tau(w)_j = E[Y_i|X_i = x, w_i = w, D_i = j] - \\ E[Y_i|X_i = x, w_i = w, D_i = 0] \\ = m(x,w)_j - m(x,w)_0 \end{aligned} \tag{6}$$

for $j \in \{1, 2\}$.

Furthermore, since we are using a machine learning method to estimate the conditional mean functions, a more accurate estimation of 6 can be obtained by using a doubly-robust estimator that leverages the additional information generated by debiasing weights. Chernozhukov et al. (2018) proved that such estimators achieve semiparametric efficient estimates and others have found useful properties of using inverse propensity weighting even in randomized treatment settings (for example, see Williamson, Forbes, and White (2014) and Shen, Li, and Li (2014)). GRF provides a direct estimation of doubly-robust treatment effects, that in practice estimate a form of the following augmented inverse propensity score weighted estimator from Li and Li (2019) for multiple treatments:

$$\begin{aligned} \tau(w)_j^{aug} = \frac{\sum_i^N ipw_j(x) D_{ij}[Y_i - m(x,w)_j]}{\sum_i^N ipw_j(x) D_i} + \frac{\sum_i^N m(x,w)_j}{N} \\ - \frac{\sum_i^N ipw_0(x) D_{i0}[Y_i - m(x,w)_0]}{\sum_i^N ipw_0(x) D_{i0}} - \frac{\sum_i^N m(x,w)_0}{N} \end{aligned} \tag{7}$$

Since we obtained numerous socioeconomic characteristics of each participant, we decided to investigate the heterogeneous treatment effects among the most likely subgroups, informed by the literature. Sintov, Abou-Ghalioum, and White (2020) find that having experience driving an EV is an important predictor of choosing and EV. Recent work by Generation180 (2023) demonstrated the importance of peer effects. Additionally, Parent (2023) finds a link between masculinity and a less favorable attitude towards EVs, suggesting another potential dimension with heterogeneity. Following these findings, we investigated the heterogeneous treatment effects for males and females, with and without exposure to EVs, stratified by political affiliation and political ideology. Note that we denote 'EV Exposure' as participants who know anyone in their friends or family that drives an EV, has ridden in an EV, or currently owns an EV. Table 7 reports the results.

Panel A of Table 7 presents the causal forest doubly-robust treatment effect for conservative participants in the overall sample. The point estimate is $-.0968$ and is statistically significant at the 5 percent level (Sidak-adjusted), implying that conservatives who received the liberal treatment statement were about 9.6 percentage points less likely to choose the EV than conservatives in the control group. This estimate is extremely similar to the above estimates from the comparison of means and LPM, providing consistent evidence of a significant negative reaction. Overall, many of the results in Table 7 have large standard errors with large point estimates, with few estimated precisely enough to identify statistically significant effects under multiple hypothesis testing. Thus, we rely on the Sidak-adjusted p-values to determine if a particular treatment effect is significantly different than zero, using an adjustment of two, since the same subpopulation in the control group is being used twice to estimate the treatment effect.[9]

Panels B and C of Table 7 show the treatment effects among conservative republicans and conservative independents, respectively. The overall pattern of these results implies that the main source of the negative treatment effect overall comes from a large and highly significant effect among conservative, republican, males, with no exposure to EVs. This population was 27 percentage points less likely to choose the EV, which represents about a 100 percent reduction relative to the mean. This is a large negative response, and combined with a lack of evidence of a strong negative effect among the other subgroups in Panels B and C, suggests some interesting conclusions. First, conservative females overall did not respond to either identity treatment, implying that the polarization of EVs may not be as big of a concern among this population. Second, and perhaps more informative from a policy perspective, is that the negative treatment effect only appears among males with *no* exposure to EVs. This implies that a potential solution to the polarization of EVs is through peer effects and inducing conservatives to test EVs as passengers or drivers.

Panels D and E provide two more interesting results. Liberal Democratic females with no EV exposure experienced a large negative effect when treated with the conservative statement (recall that the conservative statement implied that conservatives buy EVs). There is no evidence that this same group except among those with EV exposure experienced any

[9]For example, the conservative, Republican, males, with no EV exposure consist of one control group and two treatment groups. This one control group is being used twice to estimate the treatment effects within this subpopulation.

Table 7: Heterogeneous Treatment Effects

Population	Liberal ATE	Conservative ATE
Panel A: Overall		
Conservative	-0.0968* (0.0384)	-0.0406 (0.0375)
Panel B: Conservative Republicans		
Male, No EV Exposure	-0.2626** (0.0848)	-0.1523 (0.0838)
Male, EV Exposure	-0.0386 (0.1003)	-0.0887 (0.0977)
Female, No EV Exposure	0.0592 (0.0774)	0.0439 (0.0797)
Female, EV Exposure	0.0809 (0.1081)	0.122 (0.0918)
Panel C: Conservative Independents		
Male, No EV Exposure	-0.231 (0.1329)	-0.233 (0.1253)
Male, EV Exposure	-0.2989 (0.1446)	-0.1574 (0.1694)
Female, No EV Exposure	-0.137 (0.1278)	-0.0504 (0.1195)
Female, EV Exposure	-0.3698 (0.1918)	-0.0142 (0.2307)
Panel D: Liberal Democrats		
Male, No EV Exposure	0.0056 (0.0914)	0.1708 (0.0853)
Male, EV Exposure	0.0031 (0.0698)	-0.0391 (0.0702)
Female, No EV Exposure	-0.0197 (0.0743)	-0.2157** (0.0733)
Female, EV Exposure	0.1414 (0.0687)	0.0425 (0.0684)
Panel E: Liberal Independents		
Male, No EV Exposure	-0.2257 (0.117)	-0.3977** (0.126)
Male, EV Exposure	-0.0159 (0.0832)	-0.0842 (0.1)
Female, No EV Exposure	-0.0163 (0.1042)	-0.0944 (0.1088)
Female, EV Exposure	-0.0095 (0.0973)	0.0255 (0.0954)

Notes: Table reports doubly-robust average treatment effects for each subgroup using causal forests. Note that 'Liberal ATE' and 'Conservative ATE' represents the average treatment effect of receiving the liberal and conservative statement, relative receving no statement (the control group). 'EV Exposure' is defined as having either ridden in an EV or knowing someone among family and/or friends that owns and EV. Standard errors are given in parenthesis and Sidak-adjusted statistical significance levels 0.05, 0.01, and 0.001 are given by *, **, and ***, respectively.

significant treatment effect. Specifically, the point estimate of $-.21$ implies that liberal Democratic females, with no EV exposure, were 21 percentage points less likely than the control group, or a 35 percent reduction relative to the mean. Similarly, liberal, independent, males with no EV exposure were about -40 percentage points less likely to choose the EV when receiving the conservative statement, or a 73 percent reduction relative to the mean. Overall, these are large effects and imply that any strategy to label EVs as a popular choice among conservatives may reduce the likelihood that these two subpopulations among liberal consumers will show interest in purchasing an EV.

STRUCTURAL ESTIMATES

Since the randomized vehicle attributes and experimental groups provide identifying variation, there are additional results that may be of interest from economic and policy perspectives. Similar to the discussion above regarding the estimation of the conditional mean functions, we can estimate separate functions for each experimental group, yielding estimates of the probabilities of choosing the EV as a function of the random vehicle attributes and demographic controls. These counterfactual probabilities are particularly informative when the conditional mean functions are nonlinear: the parameter estimates in the linear probability model represent the marginal effects averaged over the distribution of X. However, the parameters may be nonlinear and estimating the effects away from the averaged distribution of X may be informative. For example, the lack of statistical significance on the operating costs may reflect a true null effect or misspecification of an underlying nonlinear relationship.[10]

Note that since the outcome is a Bernoulli random variable, the conditional expectation provides a direct estimate of the conditional probability. Within this framework, we can estimate these counterfactual conditional probabilities to see how different attributes affect the probability of choosing the EV. Notice, however, that random forests recursively partition the sample space using the observed values. There are few vehicle comparisons for which the EV and ICE are similarly priced, with similar ranges, and similar operating costs because of the positive covariance matrix defining their multivariate normal distributions and the relatively small sample sizes. Thus, it is difficult to use random forests to estimate extrapolated counterfactual results that deviate from the observed combinations of variables. For example, suppose we are interested in seeing how the operating costs affect the probability of choosing the EV. Random forests can estimate these probabilities as a function of different operating costs but are limited in that these will depend on *observed* price and

[10] One could "bin" operating costs but the researcher would have to specify the correct bins to capture the underlying structure in a way that generates significant results.

range differences. We are more interested in how the operating costs affect the probability of choosing the EV when prices and ranges are held constant at some fixed value (e.g. the sample mean).

With this in mind, we rely on local linear random forests (Athey, Tibshirani, and Wager (2018)), which utilize local linear projections that can overcome this extrapolation problem and estimate Equation 5. Specifically, generate nine separate models of the conditional mean functions, one for each experimental-identity group.[11] For each sample, we randomly selected 80% to train a random forest and predicted the remaining 20% using local linear corrections.[12] We repeated this 100 times to generate bootstrapped results of the local linear function. Next, to generate results for each of the randomized attribute differences, we predicted these bootstrapped functions over a grid of values while simultaneously setting the other two variables to the sample means. For example, for the operating cost function, we set each out-of-sample (the 20% sample) participant's price and range differences to $\$5,080$ and -168, respectively, and then predicted the probability of choosing the EV for each value of operating cost from $-12,500$ to $-1,776$, in increments of about 400. Using a threshold of .5 or greater to categorize each prediction as the EV, the cross-validated out-of-sample accurate percentages are in the mid-seventies. Such high out-of-sample predictive accuracy suggests that these models have accurately captured the data-generating process and provide reliable estimates of the counterfactual choices.

Figure 2 shows the average probability of choosing the EV as a function of the difference in operating costs, averaged over the subpopulation of interest. Each panel depicts a different subpopulation: the leftmost panel denotes liberal participants, the middle panel for moderates, and the rightmost panel for conservatives. The different line types represent each conditional mean function: the control group function is solid, the conservative statement function is dotted, and the liberal statement function is dot-dashed.

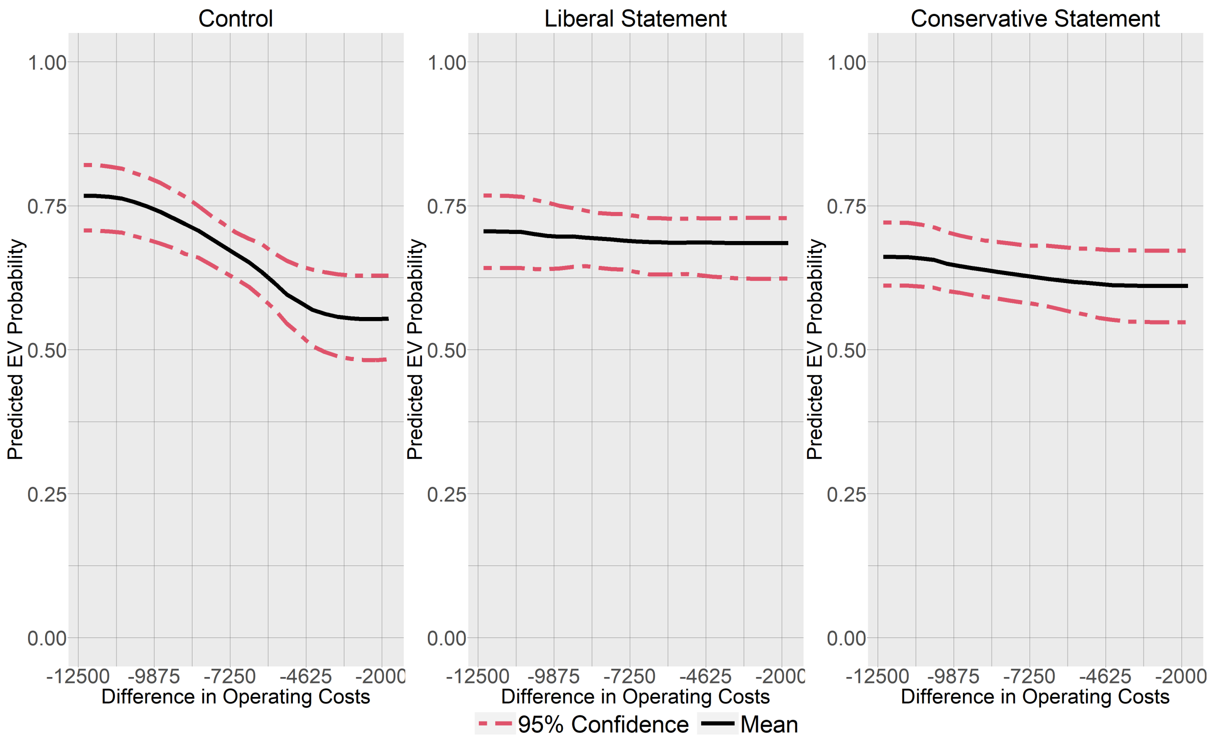
The control group functions have a clear negative and nonlinear slope[13] among liberal and moderate participants. Note that the control group function's slope among conservatives is statistically indistinguishable from zero. The significant negative slopes among the liberal and moderate subpopulations within the control group show that they respond to the difference in operating costs when making their hypothetical purchase, consistent with a rational economic agent. The nonlinear nature of the liberal and moderate control curves

[11] Each experimental group has three subgroups, resulting in nine total.

[12] The local linear correction variables included the price, range, and operating cost differences, marital status, ethnicity, if they own an EV, if they know someone who owns an EV, if they have driven in an EV, gender, Asian race, pollution and energy security policy support, work transportation mode, job status, urbanization, education, and the ranked vehicle attributes.

[13] We tested a linear projection of the grid of values on the outcome and found significant negative slopes using the bootstrapped results. These results are available upon request.

Figure 1: EV Probability by Operating Costs - Liberal Participants

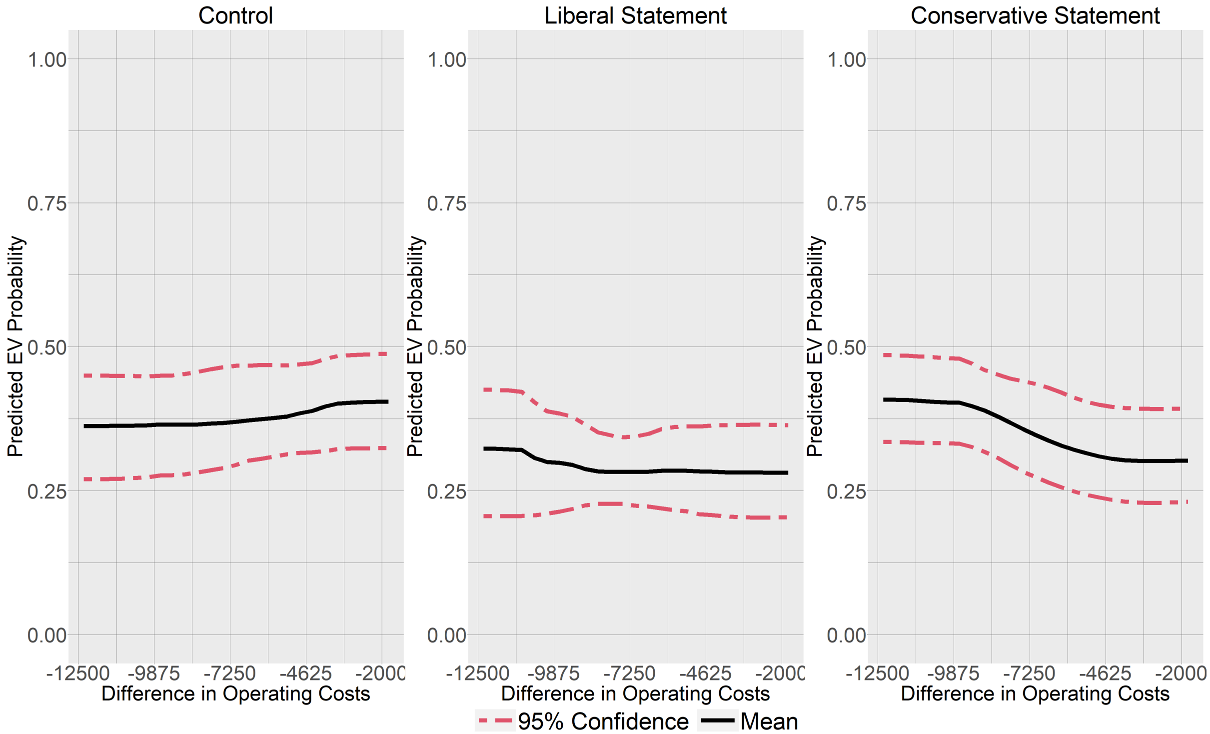


with steeper slopes between -5000 and -7000 provide additional information: since the sale price difference has been set to about 5000, this increase in slope implies a relatively sharp increase in the probability of choosing the EV when the operating cost savings outweigh the EV price premium. Overall, these patterns suggest that in a controlled setting in which consumers make hypothetical consumption decisions, the operating costs of vehicles are important.

The liberal statement functions present slopes statistically indistinguishable from zero for all three subgroups. This implies that liberal, moderate, and conservative participants who received the liberal statement ignored the operating cost differences. Relative to the control group functions with negative slopes and nonlinear shapes, this suggests that the liberal statement caused participants to act irrationally in an economic sense, suggesting there may be interventions that help any biased consumers consider the operating cost advantages of EVs.

Finally, the conservative statement function displays some interesting relationships. First, liberal consumers receiving the conservative statement ignored the operating cost savings from EVs (the slope is indistinguishable from zero). Second, the conservative populations who received the conservative statement paid significant attention to the operating cost differences (slopes are statistically different from zero). Thus, it is possible that targeting

Figure 2: EV Probability by Operating Costs - Conservative Participants



the conservative statement to conservatives could trigger these consumers to pay attention to the operating cost savings of EVs, potentially correcting any bias/limited information these consumers currently face when making new vehicle purchases.

Figures ?? and ?? of the Appendix present similar figures for the range and sale price differences, respectively. The results in these figures are much more homogeneous, with results similar to the baseline LPM and some evidence of slightly nonlinear relationships. In Figure ??, the average slope for conservatives is less steep than the moderate and liberal populations, reinforcing the results from the baseline LPM that found a heterogeneous price difference effect among conservatives. Furthermore, conservatives who received the liberal statement were less responsive to the driving range differences. Finally, moderate participants in Figure ?? were more responsive to the difference in sale prices when exposed to either identity treatment, suggesting that politicizing EVs changed how moderates reacted to the sale price differences.

Overall, the heterogeneous responses to the operating cost, range, and sale price differences by treatment group imply that the political labeling of electric vehicles may induce some subpopulations to act differently than they would in the absence of such labeling. It is plausible that political labeling has a nuanced effect on how consumers respond and use relevant information in the marketplace. For example, some consumers considering an EV as a viable alternative may fully discount the potential operating cost savings associated with EVs while others pay more attention to these differences.

Discount Rates

Recall the random utility model of vehicle choice. Individuals will be indifferent between the EV and gasoline model when the utilities are equal:

$$\tilde{\varepsilon}_{i,eg} = \alpha_1 \tilde{R}_{i,eg} - \alpha_2 \tilde{PP}_{i,eg} - \alpha_3 \tilde{OC}_{i,eg}. \tag{8}$$

Our estimation approach includes two stages. In the first stage, we model the probability of choosing the EV as a flexible function of all individual characteristics using honest random forests:

$$Y_i = m(\boldsymbol{x}_i) + e_i \tag{9}$$

where Y_i is an indicator for choosing the EV option, $\boldsymbol{x}$ is a vector of all individual explanatory variables (demographics, ranked vehicle attributes, etc.), crucially not including the three random differenced vehicle attributes, and e_i is the error. Since the range, purchase price, and operating costs are omitted from the $\boldsymbol{x}$ vector, we also assume that e_i is composed of the structural and an idiosyncratic error

$$e_i = \tilde{\varepsilon}_i + u_i \tag{10}$$

and estimate the linear projection in the second stage

$$E[e_i|\tilde{R}_i, \tilde{PP}_i, \tilde{OC}_i] = \alpha_1 \tilde{R}_{i,eg} - \alpha_2 \tilde{PP}_{i,eg} - \alpha_3 \tilde{OC}_{i,eg} + E[u_i|\tilde{R}_i, \tilde{PP}_i, \tilde{OC}_i] \tag{11}$$

with the assumption

$$E[u_i|\tilde{R}_i, \tilde{PP}_i, \tilde{OC}_i] = 0. \tag{12}$$

Since the range, purchase price, and operating costs were randomly assigned, the assumption of Equation 12 is likely to hold. Thus, the α's are identified through the linear projection of $\hat{e}_i$ on the range, purchase price, and operating cost differences. Since this approach does not allow for any interactions between the individual characteristics, treatment status, and structural parameters, we estimate separate models for each experimental-political identity group of interest.[14] We bootstrap sample each subpopulation, train an honest random forest,

[14]Specifically, we present results from separate models for control conservatives, liberal treatment conservatives, conservative treatment conservatives, control liberals, liberal treatment liberals, and conservative treatment liberals. We do not further separate the data by political affiliation but rather include political affiliation in the $\boldsymbol{x}$ vector so not to further diminish statistical power.

generate out-of-sample error estimates, and estimate the linear projection. We repeat this process 1000 times to generate the mean and uncertainty of the discount rate estimates, while within each iteration requiring the nonlinear root-solver to search for roots between 0 and 3.[15]

Table 8 shows the estimated discount rates for liberal and conservative participants by treatment assignment.

Table 8: Discount Rates by Treatment Assignment

	Liberals	Conservatives
Control	0.087 (0.016, 0.232)	0.145 (0.008, 0.571)
Liberal Statement	0.114 (0.031, 0.302)	0.176 (0.003, 0.88)
Conservative Statement	0.097 (0.018, 0.26)	0.067 (0.003, 0.207)
Discount Rate		
Treatment Differences		
Liberal - Control	0.026 (0.003)	0.03 (0.013)
Conservative - Control	0.01 (0.003)	-0.078 (0.006)

Notes: The top panel reports the estimated mean discount rates for liberal and conservative participants under each experimental condition using the structural parameter estimates from Equation 11 and assuming a lifetime ownership of 12 years. Bootstrapped confidence intervals are given in parenthesis. The bottom panel reports the t-test results of equality of means between the control and two treatment groups with standard errors of the difference in means in parenthesis.

CONCLUSIONS AND DISCUSSION

This study conducts a novel online experiment to understand how political identity and vehicle attributes affect the stated preferences for electric vehicles among the US population. We provided 2500 participants with a hypothetical motor vehicle purchase scenario of electric and gasoline choices with randomized prices, driving ranges, and operating costs. We find consistent evidence that conservatives exposed to a statement identifying electric vehicles as a common choice among liberals were significantly less likely than conservatives in the control group to purchase the electric vehicle. Specifically, the size of this effect is statistically significant and in the neighborhood of 9-13 percentage points, depending on the model specification. This represents a considerable 25-35 percent reduction relative to the mean,

[15] The relationship between the ratio of the structural parameters and the discount rate takes the form $\alpha_3/\alpha_2 = \sum_t^T \frac{1}{(1+\rho)^t}$, requiring numerical approximation to solve for the discount rate (ρ) for a given T, α_2, and α_3.

implying that average, conservatives respond negatively to the liberal labeling of EVs. Thus, the uptake of EVs in areas where conservative consumers are exposed to the liberal labeling of EVs may be difficult to overcome. In a linear probability model, the current sale price of EVs would need to drop by $\$2,000$ to $\$23,000$ on average to overcome these identity effects.

However, investigating the heterogeneity of the identity treatment effects reveals some important nuances. First, the overall negative effect of the liberal statement among conservatives was concentrated among Republican males with no EV exposure and a substantial negative reaction of 26 percentage points, or about a 100 percent reduction relative to the mean. The other subpopulations (females, conservative independents, etc.) within the conservative population failed to produce statistical effects, although the point estimates range in absolute value with large standard errors. Nonetheless, the evidence suggests that the conservative, Republican, male, with no EV exposure is one subpopulation likely to respond to the liberal identity labeling of the EV in the marketplace. Furthermore, two subpopulations within the liberal participants reacted negatively to associating the EV with the conservative population: Liberal Democratic females and liberal Independent males, both with no EV exposure have large, precisely estimated, negative treatment effects. Thus, both liberal and conservative consumers are potentially at risk of responding to the identity signaling of EVs.

The heterogeneity in the treatment effects and pattern of results provide some interesting conclusions and highlight the importance of understanding any variability of these effects across the population. Three specific subpopulations reacted negatively when the EVs were associated with the 'other' political group. However, these responses were only significant among participants with *no* exposure to EVs. It follows that one potential mechanism to combat any ideological labeling of EVs in the marketplace is to expose these populations to EVs through peer effects or passengers, which is likely to happen as the market share of EVs increases.

We find that the price and range differences between EVs and their gasoline counterparts are highly significant and economically meaningful in determining stated preferences, while the operating cost differences had a negligible impact in a linear model. However, using machine learning to model the relationship between the difference in operating costs and EV choice probability revealed a more nuanced relationship. Specifically, the effects of the operating cost differences depended on which experimental group one was assigned. Liberal participants in the control group had a nonlinear relationship between the operating cost differences and EV choices but liberal participants who received the liberal statement fully discounted the operating cost savings of EVs. Conservative participants in the control group fully discounted the operating cost savings but were responsive to these savings if they received the conservative statement. Thus, the political labeling of EVs may have a more nuanced effect and change how consumers use relevant information when making a purchasing decision.

Furthermore, including self-reported measures of the importance of different vehicle attributes when making a purchasing decision in the marketplace drastically increases the precision of the predictions, increasing the R-squared by a factor of two in the linear model and contributing to out-of-sample prediction accuracy of over 70 percent using machine learning. Other research that wants to understand how individuals make purchasing decisions should consider including questions that attempt to capture individuals' underlying preferences for attributes not considered in the experimental design.

We also find that how one defines conservative, moderate, and liberal consumers potentially plays a critical role in identifying any significant treatment effects. When defining consumers based on their political stance on economic issues in general, we failed to find any significant evidence of a political identity treatment effect, although it is important to note that these estimates produce large standard errors. Our main results use self-reported measures of 'very conservative' to 'very liberal' on *social issues*. Future research should seriously consider how to capture and define conservative, moderate, and liberal consumers.

The summary statistics regarding the selection probabilities of the EV option are interesting. Overall, about 50 percent of the total population chose to purchase the EV under our vehicle choice scenario. Specifically, the scenario was framed in a way such that the vehicle choices were the same with the only difference being the motor or fuel type (electric vs. gasoline). Thus, another important observation is that in a hypothetical market scenario in which many EV models may be seen as substitutes for the existing gasoline models, the uptake of EVs is likely to be rather high under the current limitations of EVs (driving range, sale price). It follows that consumers aren't opposed to purchasing an EV when their preferred model is available in both electric and gasoline. If the driving ranges increase and sale prices decrease for EVs, the results suggest that EVs will become even stronger competitors for current gasoline vehicles.

Finally, our study relies on stated hypothetical choices of individuals who participate in taking surveys hosted on the Prolific survey website. We used the current market conditions to define the distributions of the randomized price, range, and operating costs of the vehicle choices presented to each participant. We also purchased Prolific's capability to generate a politically representative sample of the US population. Nonetheless, it is important to acknowledge that real-world motor vehicle choices are not made the same way and there may be some uncertainty when attempting to extrapolate the results to the marketplace. Notwithstanding, the results within this study imply that political identity likely affects individual purchase decisions of electric vehicles in the US, and overcoming any negative identity effects likely requires nuanced, heterogeneous, and targeted interventions.

APPENDIX

Logistic Results

Table 9: Logit Regression Marginal Effects Estimates

	Probability of choosing the EV			
	(1)	(2)	(3)	(4)
Liberal Treatment	0.002	0.001	−0.014	0.053
	(0.052)	(0.052)	(0.055)	(0.063)
Conservative Treatment	−0.033	−0.033	−0.029	0.023
	(0.052)	(0.053)	(0.055)	(0.064)
Price Diff	−0.018***	−0.020***	−0.021***	−0.026***
	(0.002)	(0.002)	(0.002)	(0.003)
Operating Cost Diff	−0.010	−0.010	−0.013	−0.015
	(0.007)	(0.007)	(0.007)	(0.009)
Range Diff	0.007***	0.007***	0.007***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
Liberal	0.218***	0.221***	0.177***	0.158**
	(0.043)	(0.043)	(0.048)	(0.057)
Conservative	−0.092	−0.119*	−0.080	0.006
	(0.050)	(0.051)	(0.056)	(0.066)
Liberal Treat. × Liberal	0.016	0.018	0.030	−0.058
	(0.064)	(0.064)	(0.066)	(0.078)
Conservative Treat. × Liberal	−0.026	−0.026	−0.033	−0.110
	(0.065)	(0.065)	(0.068)	(0.079)
Liberal Treat. × Conservative	−0.096	−0.097	−0.088	−0.215**
	(0.072)	(0.072)	(0.075)	(0.082)
Conservative Treat. × Conservative	0.011	0.010	−0.017	−0.091
	(0.072)	(0.072)	(0.075)	(0.088)
Price Diff × Conservative		0.007*	0.006	0.011**
		(0.003)	(0.003)	(0.003)
Observations	2,508	2,508	2,491	2,491
Mean Dependent Variable	0.527	0.527	0.527	0.527
Socioeconomic Controls	No	No	Yes	Yes
Ranked Vehicle Attributes	No	No	No	Yes

Notes: Table reports estimates of the marginal effects under a logit specification of Equation 4. Column (1) includes the differences in the randomized vehicle attributes and indicator variables for 'liberal' and 'conservative' participants. Note that the omitted category are those who scored as 'moderate'. Column (2) allows for the price difference coefficient to vary if individuals identify as conservative. Column (3) adds socioeconomic covariates and Column (4) includes both socioeconomic covariates and ranked vehicle attributes. Significance levels 0.05, 0.01, and 0.001 are denoted by *, **, and ***, respectively.

Additional Figures

Figure 3: EV Probability by Purchase Price - Liberal Participants

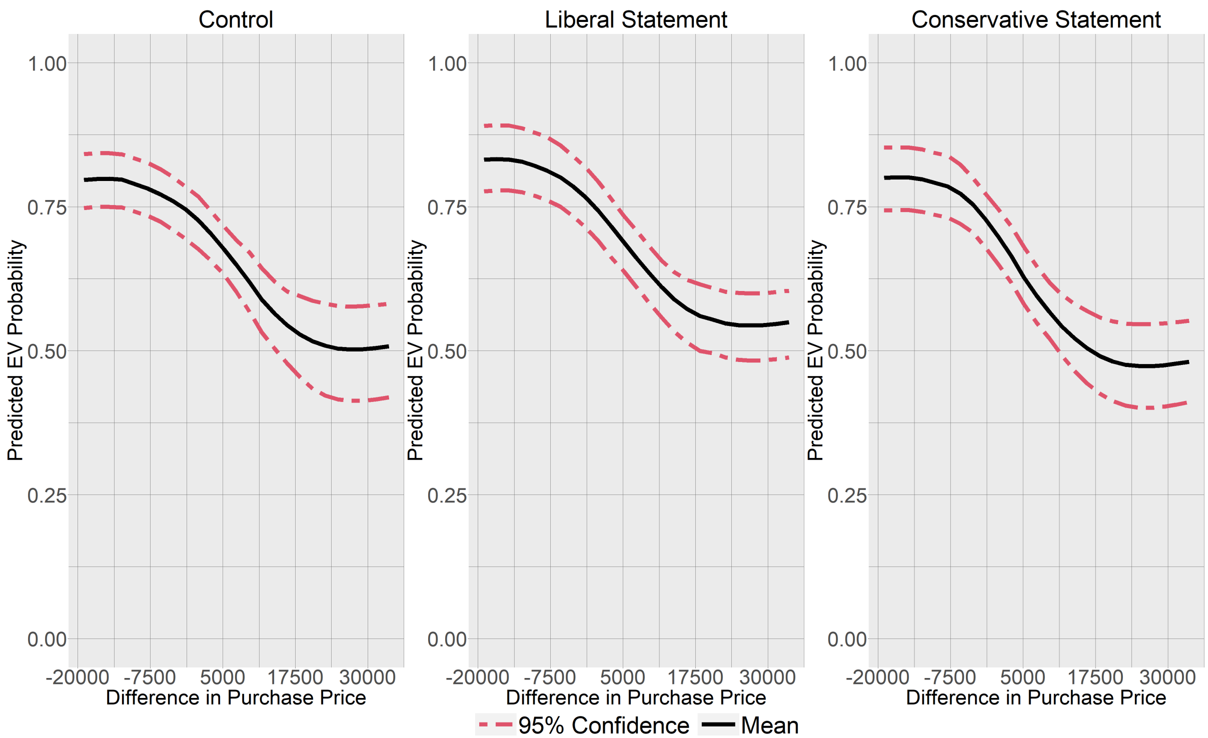


Figure 4: EV Probability by Purchase Price - Conservative Participants

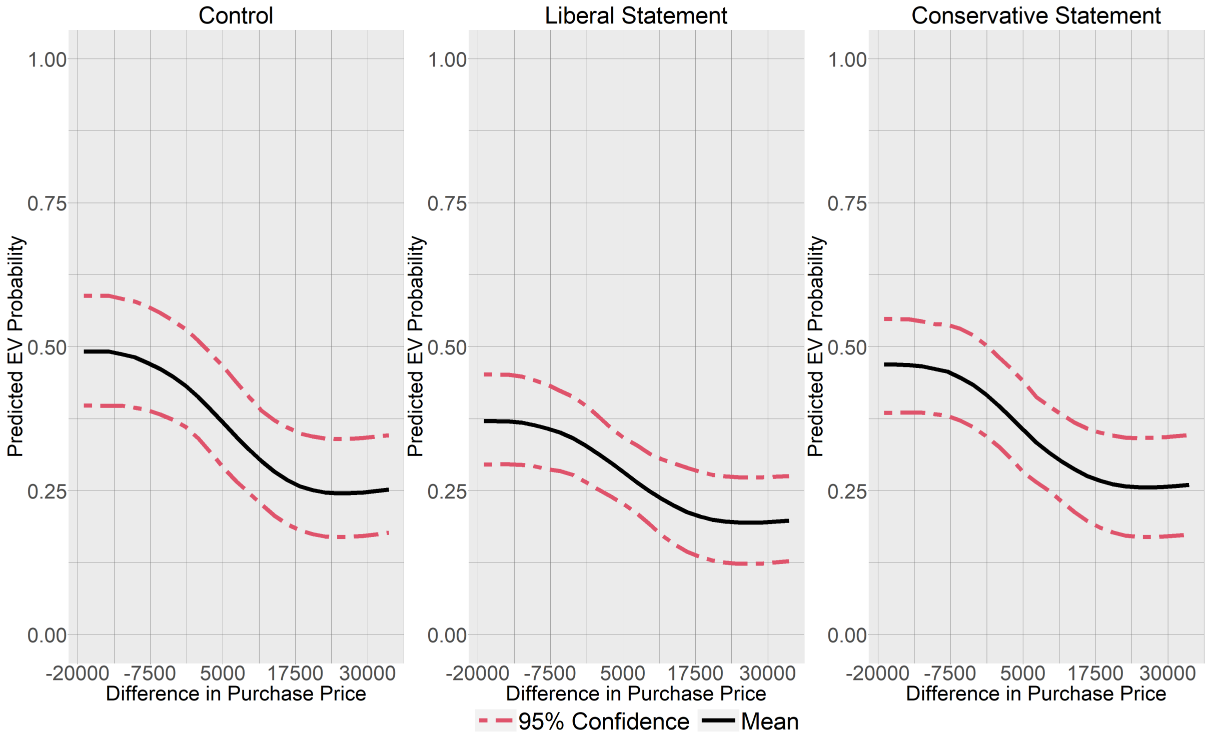


Figure 5: EV Probability by Range - Liberal Participants

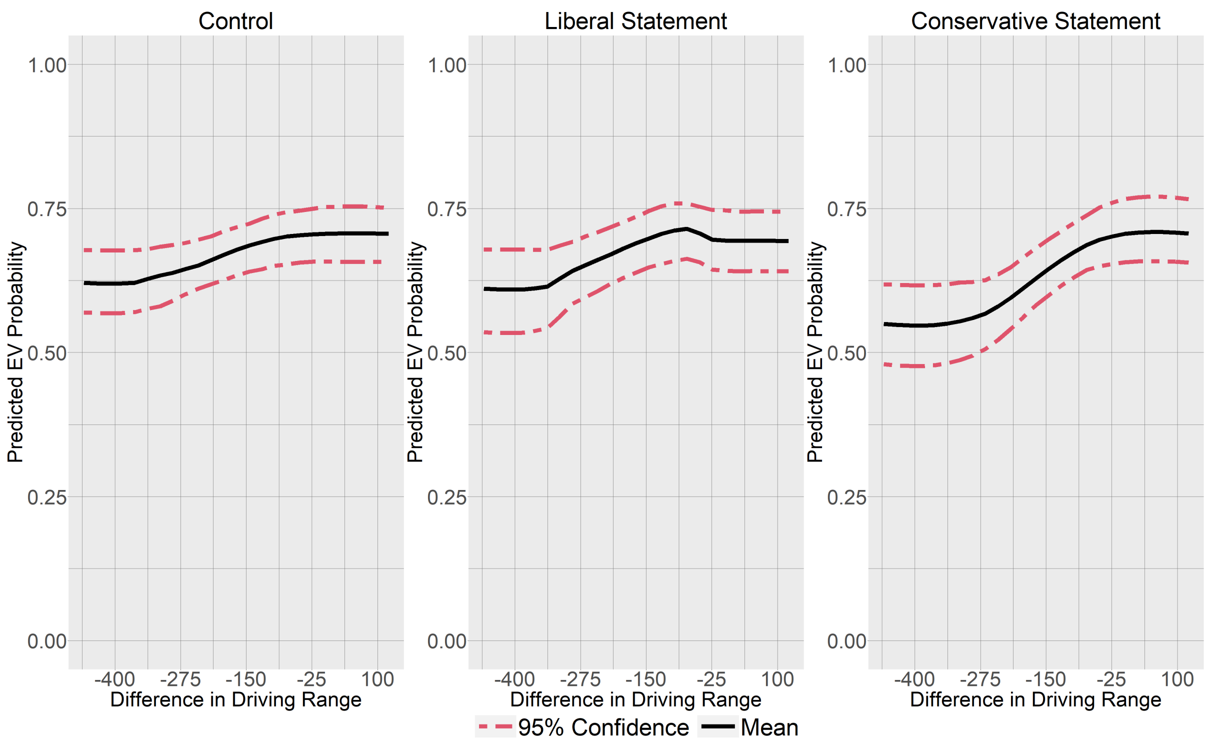
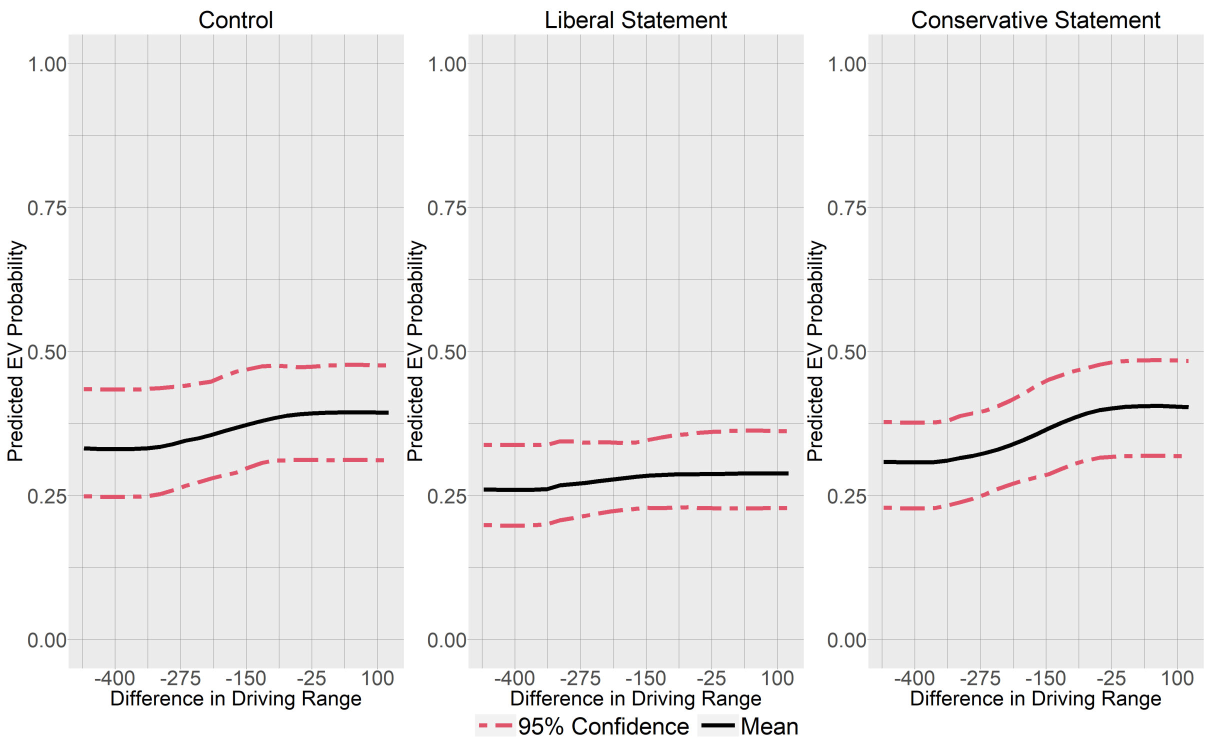


Figure 6: EV Probability by Range - Conservative Participants



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