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

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September 25, 2024

Abstract

We investigate the impact of political identity and vehicle attributes on consumer preferences for electric vehicles (EVs). Using data from an online experimental hypothetical vehicle purchasing scenario, we find that one group of Independents and Republicans are less likely to purchase an EV when it is framed as a common choice among liberals. Socially moderate Independents are less likely to purchase an EV when it is framed as a common choice among conservatives. Our findings indicate that political identity treatments increase biases against EVs, but these biases can be mitigated by combining reduced prices and increased driving ranges. (*JEL* C83, C93, D12, D91, R40, Q21, Z13)

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

*We would like to acknowledge the financial support of the Audi Cy Pres Settlement Fund. The statements made and views expressed are solely the responsibility of the authors and declare no relevant or material financial interests related to the research in this paper. This study was approved by the Vanderbilt Institutional Review Board ID 231910 and registered at the American Economic Association's registry for randomized controlled trials ID AEARCTR-0013906.

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INTRODUCTION

The transportation sector in the United States is the largest contributor of 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 electric by 2032 but relaxed these goals in March 2024 to account for lags in automobile supply chain manufacturing.

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. 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, the purchase prices of EVs are higher 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.

We contribute a novel study assessing how the political identity labeling of EVs can influence the stated preferences for these vehicles using a randomized online experiment. 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."

First, we use a clustering algorithm to separate the distinct sets of participants. The cluster assignments are robust across different numbers of clusters and consistently separate individuals based on the interaction between political affiliation, political ideology, and work transportation. Next, our analysis consists of two complementary approaches. We begin by estimating the reduced form treatment effects of the identity statements. Our preferred specification uses four clusters to separate individuals.

The mixed Independent/Republican cluster (Cluster 2B) was 20 percent less likely to purchase the EV when the EV was framed as a common choice among liberal consumers. This is a large effect and suggests that any liberal stereotyping of EVs in the marketplace could significantly reduce the uptake of these vehicles among Independent/Republican individuals who mostly drive light trucks to work. Additionally, the socially moderate Independent cluster (Cluster 1A.1) was 23 percent less likely to purchase the EV when the EV was framed as a common choice among conservative consumers. Given that EVs are likely not currently being framed or marketed as a common choice among consumers in the marketplace, this result highlights the importance of considering the heterogeneous effects of any intervention that attempts to remove any political bias against EVs that currently exists.

We also use machine learning to explore any heterogeneous treatment effects and find that male participants are much more susceptible to the identity labeling and drive the overall negative treatment effects. On the other hand, female Republican participants who almost exclusively commute in cars were significantly more likely to purchase the EV when the EV was framed as a common choice among liberal consumers.

Taken together, the reduced form average and heterogeneous treatment effects provide evidence that some consumers punish EVs in favor of gasoline vehicles when the EV is framed as a common choice among the 'other' political identity. Overall, the political labeling of the EV choice induced strong heterogeneous effects, which may explain a portion of the low adoption rate of EVs in certain areas of the US and stresses the importance of using targeted interventions.

Our second approach uses individual characteristics and the random variation from the identity treatments and vehicle attributes to develop a structural economic model that can identify vehicle-specific utility attributes. Specifically, we identify baseline utility (which we refer to as baseline vehicle preferences) that represents the residual utility of each vehicle when all the attributes are zero. We also allow the marginal utilities on the purchase price,

yearly operating cost, and driving range to vary by vehicle type and treatment status and assume that these parameters are constant within the cluster-experimental-vehicle type. This approach allows us to identify any changes in baseline preferences (bias) induced by the identity treatments and examine how the different treatments changed the structural parameters to explain the mechanisms behind any significant average treatment effects.

The structural approach demonstrates that the driving change behind the large, negative liberal treatment effect among the mixed Independent/Republican cluster (Cluster 2B) was a large change in the baseline preferences for the EV and gasoline vehicle. Specifically, labeling the EV as a common choice among liberal consumers significantly reduced the baseline utility of purchasing the EV while simultaneously increasing the baseline utility from purchasing the gasoline vehicle. This effect was large enough to overcome the opposite effects from the operating cost and range marginal utilities that changed to favor the EV over the gasoline vehicle. The results suggest that driving range plays a crucial role in determining the utility of the EV for this subset of consumers.

On the other hand, the large, negative effect of labeling the EV as a common choice among conservative consumers among the socially moderate Independent cluster (Cluster 1A.1) can be explained through a change in the preferences for the observed vehicle attributes (purchase price, operating cost, and range). These individuals increased the disutility of the purchase price of the EV option while the disutility of the operating costs of the gasoline option when was significantly reduced. Furthermore, the marginal utility of the driving range on the EV increased relatively more than on the gasoline vehicle, but this did not overcome the operating cost effects because the EVs have significantly lower ranges. This implies that the changes in preferences for operating costs punished the EV option and contributed to the overall negative treatment effect but that increasing the driving ranges of EVs may combat some of he negative identity effects.

Finally, even though there were not significant average treatment effects among all four clusters, there are significant differences in the baseline preferences and structural marginal utilities that are worth mentioning. The structural results indicated that the price at which individuals were indifferent between the EV and gasoline option generally increased as a result of either political identity treatment. This price indifference point ranges from $\$10K$-$\$220K$ and demonstrates how the identity treatment affected the relative marginal utilities of the purchase price.

For the mixed Independent/Republican cluster (Cluster 2B), the utility of the gasoline vehicle is strictly greater than the utility of the EV for every price under \$220K. This suggests that when the range and operating costs are held fixed at the current market averages, a change in the price cannot overcome the identity bias against EVs among this population.

The results indicate that increasing the driving range of the EV option by 100 miles (while holding fixed the gasoline driving range) can overcome this identity bias.

On the other hand, the Democrat cluster (Cluster 2) strictly prefers the EV for all prices under the liberal EV treatment when the range and operating costs are held fixed at their vehicle-type means. Every other cluster-experimental group has a relatively reasonable purchase price at which they would be indifferent between the two vehicle types.

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 fully 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)

DATA AND EXPERIMENTAL DESIGN

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

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.'

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 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 gasoline vehicles, 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 gasoline vehicles, respectively. This puts fuel plus maintenance costs for EVs and gasoline vehicles at \$.11 and \$.24 per mile, respectively. Each participant received a random EV and gasoline draw based on their separate multivariate normal distributions defined using the information collected above. Table 2 shows the summary statistics of these random draws across the entire survey sample.

Table 2 shows that the average EV and gasoline purchase 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.

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 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.

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.

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 and political identity. The ranked vehicle attributes appeared immediately after the vehicle choice experiment and some of the responses were influenced by the experimental conditions and as such are viewed as additional outcomes. We asked questions on the importance of brand, EV charging availability, EV charging time, motor

vehicle pollution, vehicle reputation among friends and family, vehicle aesthetics, and if the current market includes EV models they would seriously consider. Although not the focus of the current paper, these importance rankings may provide additional insight as to how political identity treatments may influence purchase decisions and inform future research.

The final portion of the survey asked simple questions regarding participants' current motor vehicle ownership, commute vehicle and distance, and EV driving experience. The summary statistics of the responses to the survey questions are given in the Web Appendix.

One potential challenge to understanding the effects of politicizing the purchase of EVs is that the identity effects are most likely concentrated among specific subsets of participants, depending on their political ideology and other individual characteristics. Furthermore, we observe a cross-section of survey participants whose responses likely include some noise. Thus, we use a clustering algorithm to identify distinct subsets of participants. Specifically, we rely on unsupervised random forest clustering using staggered interaction data (SID) developed by Mantero and Ishwaran (2021). This process results in two data features: (i) original covariates are scaled and staggered so that the ranges are mutually exclusive (SID main features) and (ii) all pairwise interactions between the main SID features. The algorithm uses the interactive features to predict the main features using random forests and generates an $N \times N$ distance matrix. Finally, hierarchical clustering is performed on this distance matrix to separate the clusters using the complete linkage method for combining clusters.[1] See Mantero and Ishwaran (2021) for a full discussion on SID clustering.

We performed SID clustering using all individual characteristics obtained from the survey questions, excluding the experimental variables and setting the number of clusters from one to six. The descriptive statistics for two and three clusters are shown in Tables 7 and 8 in the Appendix and statistics for five and six clusters are given in Tables A1 and A2 in the Online Appendix. The results using four clusters shown below in Table 3. Note that the social and economic political ideology has been coded into three categories (from five) in these tables. Table 7 in the Appendix shows the differences between participants when separated into two clusters. Cluster 1 includes the split of Independent and Republican participants and Cluster 2 is 100 percent Democratic participants.

When expanding the number of clusters to four as shown in Table 3, Cluster 1 is split into three sub-clusters and Cluster 2 remains (the Democratic cluster). Cluster 1A.1 is the

[1]The complete linkage method combines clusters with the smallest maximum distance, where the maximum distance is defined as the largest distance between any pair of points in each cluster. Note that the complete linkage method does not guarantee that clusters obtained for k clusters will form exact subsets of clusters obtained for j, where $j < k$. This is because the method merges clusters based on minimizing the maximum distance at each step, and different decisions can be optimal at different stages of the clustering process. This can lead to different cluster structures when the number of desired clusters changes.

Independent cluster that is socially moderate and drive cars. Cluster 1A.2 is the Republican cluster that is socially and economically conservative and mostly dive cars to work. Cluster 1B is the remainder of Cluster 1 and consists of a 60/40 split of Independent and Republican participants that mostly drive light trucks (SUVs or trucks) to work.

Expanding the number of clusters to six separates Clusters 1A.1 and 2B each into two additional sub-clusters, shown in Table A2 in the Online Appendix. Cluster 1A.1.1 are Independents that are almost exclusively male and Cluster 1A.1.2 are Independents that are exclusively female. Cluster 2A are Democrats that almost exclusively drive cars to work and Cluster 2B are Democrats that mostly drive light trucks to work and are more urban.

Overall, the cluster assignments are consistent across different numbers of total clusters. Since there is no guarantee that the same participants will be clustered under different choices of k, the fact that the individuals in each cluster consistently grouped or split suggests that these groups of individuals are sufficiently similar. The clustering algorithm has successfully identified distinct subgroups of participants.[2]

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.

Individuals are assumed to derive utility from the attributes of each vehicle under a discrete choice, random utility model. Our experiment included the following vehicle attributes: purchase price, 5-year fuel plus maintenance costs (referred to as 'operating costs' throughout the paper), and driving range. 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 $\varepsilon_{i,j}$ captures all the unobserved factors affecting individual utility. To capture

[2]For each choice of k clusters, we originally labeled each cluster using generic numbering. After generating the descriptive statistics for each cluster under each different k assumption we observed the consistency of the clusters across k. We then labeled the clusters from $k = 2$ to $k = 6$ depending on the participants assigned to each cluster, creating the final cluster labels: Cluster 1A (1A.1, 1A.2, 1A.1.1, 1A.1.2), 1B, 2A, and 2B.

Table 3: Participant Characteristics with 4 Clusters

	Cluster 1A	Cluster 1B.1	Cluster 1B.2	Cluster 2
Political Party - Democrat	0	0	0	1
Political Party - Independent/Other	1.00	0.59	0.00	0.00
Political Party - Republican	0.0	0.4	1.0	0.0
Political Ideology - Social	2.29	1.86	1.32	2.86
Political Ideology - Economic	1.97	1.63	1.12	2.75
Age	44	48	45	46
Income	83593	79906	84332	87725
Gender - Female	0.49	0.47	0.48	0.50
Gender - Male	0.48	0.51	0.50	0.47
Gender - Non-Binary	0.02	0.01	0.00	0.01
Marital Status	0.41	0.49	0.49	0.41
Household	2.64	2.61	2.78	2.59
Ethnicity	0.08	0.08	0.08	0.08
Urbanization - Rural	0.18	0.27	0.21	0.11
Urbanization - Suburban	0.58	0.49	0.56	0.56
Urbanization - Urban	0.22	0.23	0.21	0.32
Race - Black	0.09	0.09	0.07	0.14
Race - Asian	0.07	0.05	0.04	0.09
Race - Other	0.06	0.04	0.02	0.05
Race - White	0.76	0.80	0.86	0.71
Education - Bachelor's	0.39	0.37	0.40	0.44
Education - High School	0.14	0.14	0.14	0.09
Education - Master's or Above	0.15	0.13	0.17	0.17
Education - Some College	0.30	0.35	0.27	0.28
Job Status - Full-Time	0.46	0.43	0.54	0.52
Job Status - Part-Time	0.12	0.08	0.12	0.09
Job Status - Other	0.17	0.17	0.15	0.15
Job Status - Retired	0.10	0.15	0.08	0.12
Job Status - Self-Employed	0.13	0.14	0.09	0.09
Number of Motor Vehicles	1.74	1.67	1.91	1.67
Work Miles Traveled	11.98	11.60	16.31	11.99
Electric Vehicle Ownership	0.08	0.05	0.06	0.10
Purchase of Durable Goods	0.92	0.93	0.93	0.92
Work Transportation - Car	0.89	0.10	0.95	0.67
Work Transportation - Light Truck	0.01	0.63	0.01	0.16
Work Transportation - Other	0.09	0.26	0.02	0.16
N	635	595	413	844

Notes: Table reports descriptive statistics when participants are separated into four clusters under SID clustering.

consumer heterogeneity implied by $\varepsilon_{i,j}$ we estimate separate models for each experimental-cluster group, 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 the Structural Estimation section 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:

$$\alpha_1 R_{i,e} + \alpha_2 PP_{i,e} + \alpha_3 OC_{i,e} + \varepsilon_{i,e} > \alpha_1 R_{i,g} + \alpha_2 PP_{i,g} + \alpha_3 OC_{i,g} + \varepsilon_{i,g} \tag{2}$$

$$\Rightarrow \quad \alpha_1 \tilde{R}_{i,eg} + \alpha_2 \tilde{PP}_{i,eg} + \alpha_3 \tilde{OC}_{i,eg} + \tilde{\varepsilon}_{i,eg} > 0 \tag{3}$$

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. We estimate discount rates for each experimental-cluster group under three and four clusters and present these results in the Structural Estimation section below.

We explicitly introduce the ideological utility associated with vehicle j for consumer i, $\lambda_{i,j}$ and allow the structural parameters to vary by cluster k and treatment status d:

$$U_{i,j} = \alpha_{1,kd} R_{i,j} + \alpha_{2,kd} P_{i,j} + \alpha_{3,kd} OC_{i,j} + \lambda_{kd,j} + \omega_{i,j} \tag{4}$$

where $\varepsilon_{i,j} = \lambda_{kd,j} + \omega_{i,j}$ and $\omega_{i,j}$ is the idiosyncratic error. The randomized nature of the vehicle attributes and political ideology statements allows us to identify the cluster-level ideological bias ($\lambda_{kd,j}$). The details of our estimation approach is discussed in more detail in Section 4.3.

RESULTS

Identity Treatment Effects

The reduced form estimating equation to identify the treatment effects and vehicle attribute marginal effects is given by:

$$\begin{aligned} P(Y_i = 1|\boldsymbol{W}_i, T_i) = \beta_0 + \sum_{k=1}^{k}\sum_{j=1}^{2}\beta_{kj}1\{T_{ij}=1\}\times 1\{K_i = k\} \\ +\beta_1(PP_{i,ev} - PP_{i,g}) + \beta_2(OP_{i,ev} - OP_{i,g}) \\ +\beta_3(R_{i,ev} - R_{i,g}) + X_i'\Pi + u_i \end{aligned} \tag{5}$$

where $\boldsymbol{W}_i$ represents a vector of all covariates, T_{ij} denotes the treatment for an individual among the $j = \{1, 2\}$ treatments, K_i is the individual cluster assignment, PP_i, OP_i, and R_i are the price, operating costs, and range for the EV and gasoline options, X_i' is a vector of individual characteristics and u_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 linear probability model (LPM) of Equation 5 using ordinary least squares.[3] 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 5 under the LPM are shown in Table 4. These regressions include the randomized identity treatments, differenced vehicle characteristics, and a polynomial of income, race, household size, marital status, EV ownership, EV driving experience, employment status, and census region.[4] Each column of Table 4 reports the results when changing the number of clusters from one to four, respectively. Note that the intercept has been omitted from these regressions so that the cluster by treatment status interaction terms can be interpreted directly as treatment effects.

Column (1) of Table 4 gives the average treatment effects (ATE) over the entire sample. Treatment 1 (the liberal EV association) and Treatment 2 (the conservative EV association) are near zero and statistically insignificant at conventional levels. Column (2) expands the number of clusters to two, where Cluster 1 is the mixed Independent/Republican cluster and Cluster 2 is the Democrat cluster. The ATEs for both identity treatments among Clusters

[3]The linear probability model produces coefficients that can be interpreted directly as marginal effects. Logistic regression results and regressions without covariates are presented in Tables A8-A10 in the Online Appendix. The conclusions are qualitatively similar.

[4]Additional regressions were run using the full set of individual covariates with many found to be statistically insignificant, with some issues of multicollinearity depending on the specification, and thus omitted from the main results. These results are available from the authors upon request.

1 and 2 remain statistically insignificant.

Table 4: Treatment Effects - OLS with Covariates

	EV Probability			
	(1)	(2)	(3)	(4)
Price Difference	-0.016 (0.002)	-0.016 (0.002)	-0.016 (0.002)	-0.016 (0.002)
Operating Difference	-0.054 (0.032)	-0.050 (0.031)	-0.050 (0.031)	-0.052 (0.031)
Range Difference	0.006 (0.001)	0.006 (0.001)	0.006 (0.001)	0.006 (0.001)
Treatment 1	-0.012 (0.023)			
Treatment 2	-0.043 (0.024)			
Cluster 1 x Treatment 1		-0.040 (0.028)		
Cluster 1A x Treatment 1			-0.002 (0.035)	
Cluster 1A.1 x Treatment 1				-0.001 (0.045)
Cluster 1B x Treatment 1			-0.105 (0.047)	-0.104 (0.047)
Cluster 2 x Treatment 1		0.015 (0.038)	0.015 (0.038)	0.015 (0.038)
Cluster 1 x Treatment 2		-0.053 (0.028)		
Cluster 1A x Treatment 2			-0.064 (0.035)	
Cluster 1A.2 x Treatment 1				-0.005 (0.056)
Cluster 1A.1 x Treatment 2				-0.123 (0.045)
Cluster 1B x Treatment 2			-0.037 (0.047)	-0.036 (0.047)
Cluster 2 x Treatment 2		-0.009 (0.041)	-0.009 (0.041)	-0.010 (0.041)
Cluster 1A.2 x Treatment 2				0.026 (0.055)
Overall Control EV Mean	0.547	0.547	0.547	0.547
Cluster 1 Control EV Mean	0.489	0.489	0.489	0.489
Cluster 2 Control EV Mean	0.667	0.667	0.667	0.667
Cluster 1A Control EV Mean	0.483	0.483	0.483	0.483
Cluster 1B Control EV Mean	0.5	0.5	0.5	0.5
Cluster 1A.1 Control EV Mean	0.539	0.539	0.539	0.539
Cluster 1A.2 Control EV Mean	0.399	0.399	0.399	0.399
Observations	2,487	2,487	2,487	2,487

Notes: Table reports OLS results based on Equation 5. Column's (1)-(4) present results when using one, two, three, and four clusters to group participants, respectively. Included covariates are a polynomial of income, race, household size, marital status, EV ownership, EV driving experience, employment status, and census region. Standard errors are given in parenthesis.

Column (3) expands the number of clusters to three and reports the results. The clusters are Cluster 1A (mixed Independent/Republican, car driving), Cluster 1B (mixed Independent/Republican, light truck driving), and Cluster 2 (Democrat cluster). The treatment 1 point estimate for Cluster 1B is statistically significant at the 5 percent level and equal to -.105, or -10.5 percentage points. This represents a 20 percent reduction relative to the Cluster 1B control group mean, a sizable effect. This implies that the Independent/Republican participants that primarily use light trucks for their work transportation were 20 percent less likely to purchase the EV when the EV was framed as a common choice among liberal consumers. This large effect, if extrapolated to the current polarized EV marketplace, may

help explain the low EV uptake in Republican counties observed by Davis, Li, and Springel (2023).

Column (4) expands the number of clusters to four, which includes Cluster 1A.1 (socially moderate Independents), Cluster 1A.2 (mostly car-driving Republicans), Cluster 1B (mixed Independent/Republican, light truck driving), and Cluster 2 (Democrats). Notice the large and statistically significant (at the 1 percent level) negative Treatment 2 effect among Cluster 1A.1 (socially moderate Independents). The point estimate implies that the socially moderate Independent cluster was 12.3 percentage points less likely to purchase the EV when the EV was framed as a common choice among conservatives, or a 23 percent reduction relative to the control group mean. The point estimate for Cluster 1B (mixed Independent/Republican, light truck driving) interacted with Treatment 1 remains a negative 10.4 percentage points and is significant at the 5 percent level. Thus, when the number of clusters is set to four, some negative treatment effects begin to be identified, reinforcing the notion that the effects of polarization are heterogeneous.

The identity effects could potentially impact marketplace dynamics through various channels. One plausible mechanism could involve consumers' initial behaviors when starting the search for a new vehicle. It's possible that Independet/Republican, light truck driving consumers 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. On the other hand, the negative treatment effect among the socially moderate Independents when the EV was framed as a common choice among conservatives is likely more theoretical since EVs are more likely to be polarized as a liberal vehicle in the current US marketplace. However, the negative effect highlights the importance of understanding how changing the framing of purchasing an EV as a conservative vehicle may negatively affect other subsets of the population and stresses the importance of targeted interventions.

The purchase price (in 1000s of dollars) and range differences (in 10s of miles) are statistically significant at the 0.1 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 gasoline 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 12.5 percentage points, or a 23 percent increase relative to the mean.

The coefficient for the range difference implies that a 10-mile increase in EV range enhances the probability of EV selection by 0.6 percentage points. While this effect may seem modest, expanding the EV range by 170 miles to match the mean gasoline range would result in a 10.2 percent increase in the probability of EV selection, representing a 19 percent in-

crease 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 of the yearly fuel plus maintenance costs. However, note that the point estimate implies that every $1000 increase in the difference in yearly operating costs reduces the EV choice probability by 5 percentage points but is noisily estimated. The imprecision of this estimate implies potential heterogeneity in how the participants responded to the operating cost differences. We further investigate the effect of yearly operating costs in the Structural Estimation section below. Future work should investigate how framing the operating cost differences between electric and gasoline vehicles impacts consumption decisions.

In the LPM, we can use the price difference coefficient and Treatment 1 (the liberal treatment) effect among Cluster 1B (mixed Independent/Republican, light truck driving) to get an idea of the purchase price "cost" of receiving identity signals. If receiving the liberal statement among this set of consumers reduces the probability of choosing the EV by 10.5 percentage points, then reducing the price of the EV option by $6500 would increase the probability of choosing the EV by 10.5 percentage points, overcoming the liberal identity effect. In other words, the purchase price "cost" of the liberal identity among the Republican cluster is nearly $6500, just about equal to the current maximum federal tax credit of $7500.[5] Using the 95 percent confidence intervals on the Republican cluster treatment effect would produce a lower bound of about $700 and an upper bound of $12,400. It follows that the "cost" of the liberal identity among Republicans in terms of the purchase price of an EV has a wide range so it may be difficult to use these results to inform precise policy, but preliminary evidence suggests that the cost may be in the thousands of dollars.

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 5 using Honest Causal Forests Athey, Tibshirani, and Wager (2019) 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 gasoline alternatives that recursively partition the covariate space in a way that maximizes the difference in treatment effect between the two child nodes.[6] Thus, given the random variation in prices, fuel plus maintenance costs, driving range, and identity treatments, the causal forests provide

[5]The same exercise within the logit, nonlinear, or nonparametric model may produce different results. It is also important to note that this assumes holding all else constant and as we explore in the Structural Estimation section it is clear that the parameters are not necessarily constant across treatment groups.

[6]See Athey, Tibshirani, and Wager (2019) for a complete discussion on causal forest splitting and prediction.

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 treatments using causal forests:

$$E[Y_i|X_i = x, w_i = w, D_i = d] = m(x, w)_d \tag{6}$$

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:

$$\begin{aligned} \tau(w)_j = E[Y_i|X_i = x, w_i = w, D_i = j] - \\ E[Y_i|X_i = x, w_i = w, D_i = 0] \\ = m(x, w)_j - m(x, w)_0 \end{aligned} \tag{7}$$

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 7 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:

$$\begin{aligned} \tau(w)_j^{aug} = \frac{\sum_i^N ipw_j(x) D_{ij}[Y_i - m(x, w)_j]}{\sum_i^N ipw_j(x) D_i} + \frac{\sum_i^N m(x, w)_j}{N} \\ - \frac{\sum_i^N ipw_0(x) D_{i0}[Y_i - m(x, w)_0]}{\sum_i^N ipw_0(x) D_{i0}} - \frac{\sum_i^N m(x, w)_0}{N} \end{aligned} \tag{8}$$

Table 5 presents the causal forest doubly-robust treatment effect for the participants. Panels A and B report heterogeneous treatment effects for each cluster under a four and

six-clustering scheme, respectively. First, notice that the liberal treatment effect among the Independent/Republican truck-driving cluster (Treatment 1 among Cluster 1B) is negative 12.7 percentage points and significant at the 1 percent level. This point estimate is about the same in magnitude but more precisely estimated than the LPM estimate, suggesting increased precision by leveraging the doubly robust nature of causal forest estimation. The negative conservative treatment effect among Cluster 1A.1 is almost identical to the OLS estimate and statistically significant.

Table 5: Causal Forest Treatment Effect Estimates

Cluster	Liberal ATE	Conservative ATE
Panel A: Four Clusters		
Cluster 1A.1	0.0264 (0.0458)	-0.1109 (0.0475)
Cluster 1A.2	0.0044 (0.0558)	0.045 (0.0589)
Cluster 1B	-0.1274 (0.047)	-0.0592 (0.0473)
Cluster 2	0.023 (0.0382)	-0.0126 (0.0387)
Panel B: Six Clusters		
Cluster 1A.1.1	0.0227 (0.0629)	-0.2365 (0.0676)
Cluster 1A.1.2	0.0105 (0.066)	-0.0059 (0.0676)
Cluster 1A.2	-0.0034 (0.0559)	0.0332 (0.058)
Cluster 1B	-0.118 (0.0475)	-0.0509 (0.0475)
Cluster 2A	0.0334 (0.046)	-0.023 (0.0473)
Cluster 2B	-0.006 (0.0679)	-0.0049 (0.0686)

Notes: Table reports doubly-robust average treatment effects for each cluster. Panel A reports heterogeneous treatment effects among four clusters. Panel B reports heterogeneous treatment effects among six clusters. Standard errors are given in parenthesis.

Panel B of Table 5 shows that additional heterogeneous treatment effects are identified when expanding the number of clusters to six. Cluster 1A.1 was split into two clusters: Cluster 1A.1.1 consists are Independents and 96 percent male and Cluster 1A.1.2 are Independents and 100 percent female. The overall negative conservative treatment effect among Cluster 1A.1 is clearly dominated by the large negative treatment effect among the males in this cluster, or Cluster 1A.1.1. Cluster 1B (mixed Independent/Republican, light truck driving) remains the same under six and four clusters, providing no additional evidence of heterogeneity in the treatment effects. However, the large effect among the males in Cluster 1A.1, combined with a recent paper by Parent (2023) that finds a link between masculinity and a less favorable attitude towards EVs, we further investigated the treatment effects by separating the four clusters by gender.

The results are shown in Table 9 in the Appendix. The general pattern is that males respond more to the politicization of EVs than females. However, it appears that some of

the zero average effects is a result of opposite effects among males and females in a particular cluster. For example, Table 9 shows that among Cluster 1A.2 (Republican car drivers), the male participants have a large negative statistically significant response to the liberal EV framing while the female participants have a large positive statistically significant response the the liberal EV framing. This suggests that tailoring different messages to male and female consumers within car-driving Republicans can be more effective in increasing the uptake of EVs.

The males in Cluster 1B (mixed Independent/Republican, light truck driving) also dominate the overall negative liberal treatment effect, although the females within Cluster 1B also display a large (albeit imprecisely estimated) negative effect. Furthermore, the males within Cluster 1B also have a large negative conservative treatment effect. This implies that males in the mixed Independent/Republican cluster punish the EV choice when the EV is politicized

Overall, there are significant heterogeneous treatment effects of associating EVs with political ideologies, highlighting the importance of considering this heterogeneity when constructing any behavioral intervention intended to overcome the polarization of EVs in the US.

Structural Estimation

Since the randomized vehicle attributes and experimental groups provide clean identifying variation we estimated additional models to demonstrate how participants behaved in the experiment. Similar to the discussion above regarding the estimation of the conditional mean functions, we can estimate separate functions for each cluster-experimental group, yielding estimates of the probabilities of choosing the EV as a function of the random vehicle attributes and demographic controls using honest random forests. These counterfactual probabilities are particularly informative if the conditional mean functions are nonlinear and allow the marginal effects of the random vehicle attributes to vary.

However, random forests recursively partition the sample space using the observed values. There are few vehicle comparisons for which the EV and gasoline vehicle 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, using random forests to estimate extrapolated counterfactual results deviating from the observed combinations of variables is difficult. 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 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 counterfactual value (e.g. the sample mean).

With this in mind, we rely on local linear random forests (Friedberg et al. 2021), which utilize local linear projections that can overcome this extrapolation problem and estimate Equation 6. Specifically, generate separate models of the conditional mean functions, one for each cluster-experimental using three and four clusters.[7] For each cluster-experimental sample, we randomly selected 80% to train an honest random forest and predict the remaining 20% using local linear corrections.[8] We repeated this 25 times to generate bootstrapped results of the local linear function. Next, we predicted these bootstrapped functions over a grid of values while simultaneously setting the other two variables to the sample means to generate results for each vehicle attribute difference. 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 the 5-year operating cost differences 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 accuracy percentages are in the mid-70s. Such high out-of-sample predictive accuracy suggests that these models have sufficiently captured the data-generating process and provide reliable estimates of the counterfactual choices.

Figure 1 shows the mean probability of choosing the EV as a function of the difference in the 5-year operating costs for each cluster-experimental group under four clusters. Bootstrapped pointwise confidence intervals are represented by the red, dot-dashed lines. Each row represents a different cluster and each column a different treatment assignment.

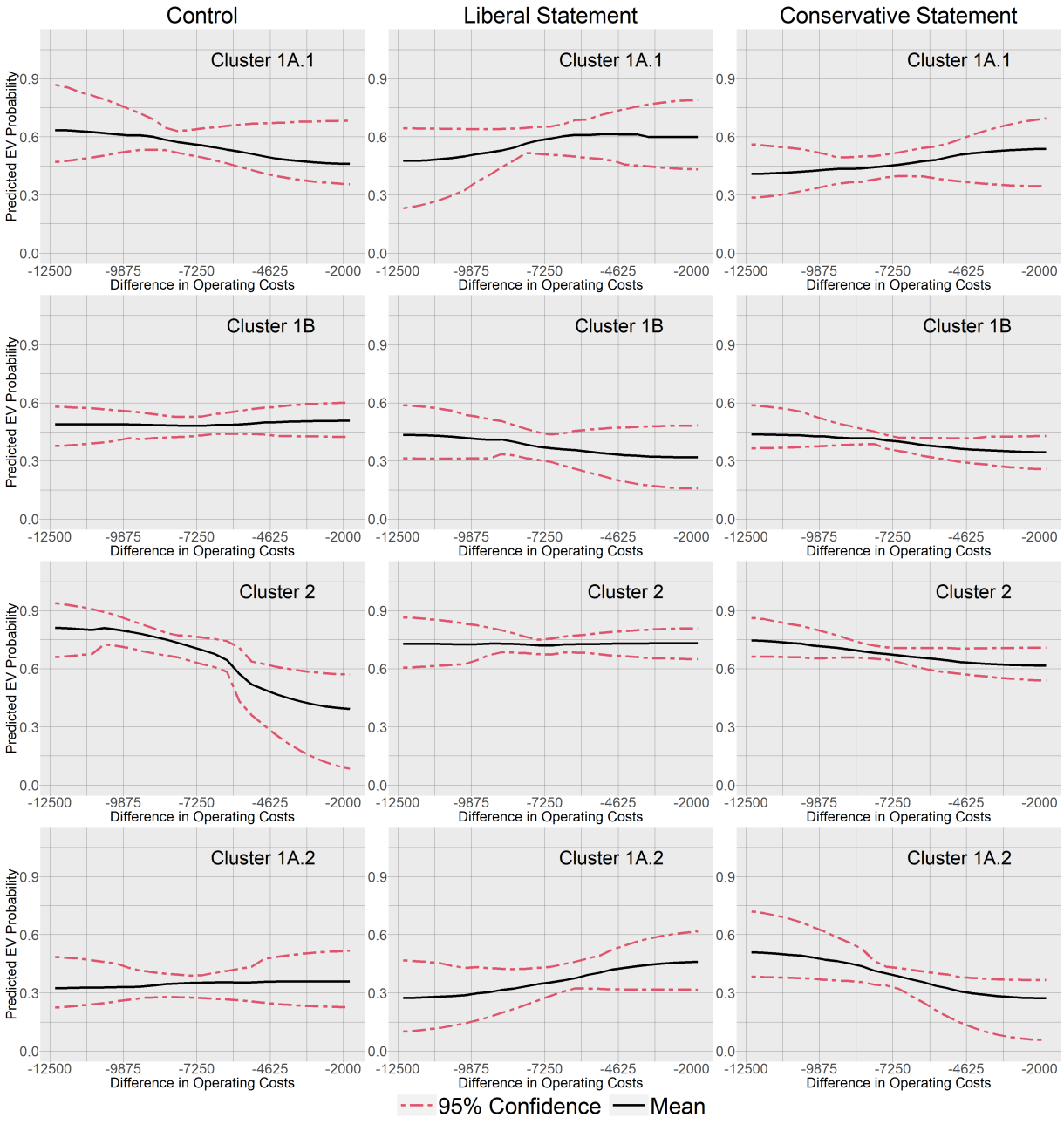
Cluster 1A.1 (socially moderate Independents) in the control group exhibited a slightly negative response to operating cost differences. Cluster 1A.2 (Republican car drivers) and Cluster 1B (mixed Independents/Republican, light truck drivers) in the control group showed no response to operating cost differences, as indicated by the flat curves in the second and fourth rows of plots. Cluster 2 (solely Democrats) displayed a negative and nonlinear response to operating cost differences, with a notably steeper slope when the 5-year operating cost difference is around \$-5000. Given the purchase price difference set at \$5,080, this increase in slope suggests a sharp rise in the probability of choosing the EV when the operating cost savings outweigh the EV price premium.

For several cluster-experimental groups, both the liberal and conservative treatments appeared to lead participants to disregard operating cost savings. Cluster 1A.1 and Cluster

[7]Expanding the number of clusters beyond four reduces statistical power significantly because each cluster is further separated by treatment assignment.

[8]We use the LASSO to cross-validate the subset of covariates used in the local linear corrections. We also use cross-validated ridge regression to select the ridge penalty parameter used in the local linear predictions.

Figure 1: EV Probability by Operating Costs



Notes: Figure presents the mean predicted probability of choosing the EV option as a function of the difference in 5-year operating costs for each of the four clusters of participants. The left panel represents the control group, the middle panel the liberal statement group, and the right panel the conservative statement group.

2 exhibited slightly positive and zero slopes, respectively, when the EV was framed as the liberal choice. Conversely, Cluster 1B (mixed Independents/Republican, light truck drivers) showed a slight negative slope when the EV was framed as either a liberal or conservative choice. This suggests that the mixed Independents/Republican cluster became somewhat

more attentive to operating cost differences under treatment. The absence of response in the control group but slight negative response under treatment implies that EVs may already be polarized among Cluster 1B consumers, with this group acting more rationally under the treatments than in the control. Overall, the graphical evidence indicates that the political framing of the EV option elicited varied reactions and potential behavioral biases across different consumer clusters, underscoring the importance of considering these heterogeneous effects to effectively increase EV adoption.

4.3.1 Structural Results

Expanding the structural random utility model of vehicle choice given in Equations 1-3 we can provide direct estimates of the structural parameters for each vehicle type, under each experimental condition. We let $\{\lambda_{jkd}, \alpha_{1,jkd}, \alpha_{2,jkd}, \alpha_{3,jkd}\}$ denote the vector of structural parameters for vehicle j in cluster k and experimental group d. Note that we allow these parameters to vary across vehicle types, clusters and experimental groups. Our estimation approach includes two stages. In the first stage, we model the probability of choosing the j vehicle as a flexible function of all individual participant characteristics using honest random forests:

$$Y_{ijkd} = m(\boldsymbol{x}_{ikd}) + e_{ijkd} \tag{9}$$

where Y_{ijkd} is an indicator for choosing the j option, $\boldsymbol{x}$ is a vector of all individual explanatory variables (demographics, ranked vehicle attributes, etc.), excluding the three random differenced vehicle attributes and treatment assignment, and e_{ijkd} is the error. Since the outcome is binary, we model the probability of choosing the EV and let the probability of choosing the gasoline option be $1 - \hat{m}(\boldsymbol{x}_i)$. The main identifying assumption is that the residual e_{ij} from predicting vehicle choice by omitting the experimental conditions can be explained by the treatment assignment and randomized vehicle attributes in the control function:

$$e_{ijkd} = \lambda_{jkd} + \alpha_{1,jkd} R_{ijkd} + \alpha_{2,jkd} PP_{ijkd} + \alpha_{3,jkd} OC_{ijkd} + \omega_{ijkd} \tag{10}$$

where $ijkd$ denotes participant i choosing vehicle j, in cluster k, in treatment group d. If we let the vector $\boldsymbol{Z}_{ijkd} = [R_{ijkd}, PP_{ijkd}, OC_{ijkd}]$, then we assume

$$E[\omega_{ijkd} | \boldsymbol{Z}_{ijkd}] = 0 \tag{11}$$

within each cluster-experimental group. Taken together, assumptions 10 and 11 allow us to identify the structural parameters within each cluster-experimental group separately for

each vehicle type.[9] We assume no additional unobserved individual characteristics exist that are correlated with range, purchase price, and yearly operating cost differences. Given the random assignment of range, purchase price, operating costs, and treatment group, this assumption is likely to hold. Consequently, the α's and λ's are identified through the linear projection of $\hat{e}_{ijkd}$ on the range, purchase price, and operating costs for each cluster-experimental group. Note that λ_{jkd} represents the intercept when the vehicle attributes are zero, indicating the residual preference for each vehicle type.

In practice, we estimate an honest random forest for the entire sample. We then bootstrap each cluster-experimental residual, range, purchase price, and yearly operating cost differences to estimate the structural parameters, treatment effects, and implied discount rates.[10] This process is repeated 500 times to generate confidence intervals for the bootstrapped statistics.[11]

We first present structural estimates of the treatment effects. Equation 9 specifies the outcome equation as $E[Y|\boldsymbol{X}, \boldsymbol{Z}] = E[Y|\boldsymbol{X}] + E[e|\boldsymbol{Z}]$ since $\boldsymbol{X} \perp \boldsymbol{Z}$. By replacing the conditional expectations with their estimates and differencing these across experimental groups (within clusters), we obtain the treatment effect estimates. Table 6 presents these results alongside the observed differences in EV shares for each comparison. The results are consistent with those from reduced-form OLS and causal forests, but allowing the structural parameters to vary by cluster and treatment status reveals additional statistical treatment effects. Cluster 1A.1 (socially moderate Independents) shows a large negative treatment effect under treatment 2 (conservative EV framing), while Cluster 1B (the Independent/Republican cluster that drives light trucks) exhibits a large negative treatment effect under treatment 1 (liberal EV framing). Additionally, Cluster 1B shows a statistically significant negative treatment effect under treatment 2, indicating that these participants were 6.2 percentage points less likely to purchase the EV when it was framed as a conservative vehicle. Thus, the Independent/Republican cluster that drives light trucks tends to penalize the EV whenever it is politicized, whether as a liberal or conservative choice.

This section provides a detailed exploration of the mechanisms underlying the average treatment effects observed in the study and examines additional treatment effects beyond changes in vehicle shares. By allowing the structural parameters to vary by vehicle type, we gain insight into how political identity treatments affect consumer preferences.

The results presented in Tables A3 and A4 in the Online Appendix reveal significant

[9] Recall that the EV and gasoline multivariate distributions are independent, so omitting the alternative vehicle attributes from the regressions will not bias the estimates.

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

[11] We report the median discount rate because the mean is sensitive to outliers.

Table 6: Structural Treatment Effects

Cluster	Comparison	Share	ATE
Cluster 1A.1	Treatment1-Control	0.008	0.009
			(-0.004,0.03)
Cluster 1A.1	Treatment2-Control	-0.103	-0.105
			(-0.148,-0.075)
Cluster 1B	Treatment1-Control	-0.126	-0.122
			(-0.152,-0.087)
Cluster 1B	Treatment2-Control	-0.062	-0.069
			(-0.103,-0.047)
Cluster 2	Treatment1-Control	0.016	0.02
			(-0.003,0.042)
Cluster 2	Treatment2-Control	-0.008	-0.007
			(-0.025,0.021)
Cluster 1A.2	Treatment1-Control	-0.029	-0.013
			(-0.049,0.017)
Cluster 1A.2	Treatment2-Control	0.030	0.029
			(-0.015,0.056)

Notes: Table reports the observed vehicle shares and estimated treatment effects using the structural approach. The corresponding bootsrapped-t 95 percent confidence intervals of these differences are given in parenthesis and can be used to determine if the differences are statistically significant.

heterogeneity in consumer preferences. However, it is challenging to determine how many of these parameters are statistically different across vehicle types and treatment groups. The key question is how these differences in parameters translate into different vehicle choices and how altering various vehicle attributes might lead to different counterfactual choices. To address this, Table 10 presents estimates of the difference in differences in structural parameters. The first difference is between the EV and gasoline structural parameters within a cluster-experimental group, and the second difference is between each treatment group and the control group for each cluster.

By combining the results from Tables 10, A3 and A4, we can better understand how changes in structural parameters drive different vehicle choices. For instance, in Cluster 1B (mixed Independent/Republican, light truck driving), the treatment 1 minus control difference in λ is -1.863, which is statistically significant. The control group in Cluster 1B shows a λ_{ev} of 0.81 and a λ_g of -0.21, while the treatment 1 group shows a λ_{ev} of 0.05 and a λ_g of 0.88. This indicates a significant decrease in baseline preference for the EV model and an increase in baseline preference for the gasoline model, suggesting that the liberal identity treatment significantly reduced the baseline preference for the EV and increased it for the gasoline vehicle, resulting in a relative increase in preference for the gasoline model.

Furthermore, the range difference-in-difference for Cluster 1B is positive and statistically

significant. In Table A4, Cluster 1B treatment 1 shows $\alpha_{r,ev}$ of 0.12 and $\alpha_{r,g}$ of -0.001, while the control group shows $\alpha_{r,ev}$ of 0.04 and $\alpha_{r,g}$ of 0.14. These estimates suggest that the marginal utility of the EV's driving range increased while the marginal utility of the gasoline vehicle's range decreased under the liberal treatment. This implies that increasing the EV's driving range could enhance the EV's value in the presence of liberal EV labeling for this cluster.

The positive and statistically significant difference-in-difference for operating costs further supports this notion. The EV's marginal disutility of operating costs becomes positive, while the gasoline vehicle's marginal utility becomes negative under the liberal treatment, indicating that the liberal labeling of the EV benefited the EV choice. However, the negative baseline preference effect (λ) appears to have outweighed the positive effects of operating cost and range, leading to an overall negative treatment effect for Cluster 1B under the liberal treatment, given the observed vehicle attributes. These results suggest that increasing the EV's range in the presence of liberal EV labeling could potentially increase EV purchases among this subpopulation.

The mechanisms driving the statistically significant effects for Cluster 1A.1 treatment 2 and Cluster 1B treatment 2 are similar. For Cluster 1B, the negative point estimates for the price and operating cost columns in Table 10 and the statistically insignificant λ difference-in-difference imply that the negative conservative treatment effect is due to the vehicle attributes rather than baseline preference differences. Similarly, for Cluster 1A.1, the statistically significant difference-in-difference estimates for vehicle attributes and the lack of a statistically significant λ difference-in-difference estimate suggest that the overall treatment effect is driven by changes in underlying parameters related to vehicle attributes, rather than differences in baseline preferences.

While clusters 1A.2 and 2 do not display significant treatment effects in the probability of purchasing the EV, there are significant treatment effects on the structural parameters induced by political labeling. For Cluster 1A.2, the baseline preferences (λ) for both vehicle types were significantly different under both political treatments. In Cluster 2 (Democrats), the difference in baseline preferences (λ) between treatment 1 and the control group is statistically significant, indicating a relative increase in preference for the EV option under the liberal treatment.

Overall, the heterogeneity in structural treatment effects highlights the complexity of how different experimental conditions influence underlying preferences for each vehicle type. The relative changes in baseline preferences and marginal utilities of vehicle attributes can have opposing effects on overall EV purchase probability. These nuanced individual responses underscore the importance of understanding heterogeneity when designing behavioral inter-

ventions aimed at overcoming political identity bias in the marketplace.

4.3.2 Counterfactual Utility

The estimated structural parameters allow us to conduct counterfactual utility estimates. By evaluating the structural function over a grid of values while holding the remaining attributes fixed, we can assess how one vehicle attribute contributes to utility. Figure 2 plots the residual purchase probability for the EV and gasoline models by purchase price, separately by cluster and experimental group.

The first row of panels in Figure 2 shows counterfactual results for Cluster 1A.1 (socially moderate Independents), which displays a negative conservative (treatment 2) effect. The price point at which these consumers are indifferent between the EV and gasoline models increases by about $18K under the conservative treatment, indicating a significant price effect. When Cluster 1A.1 participants were treated with the liberal EV framing, the utility for the EV is striclty higher than the utility of the gasoline vehicle until the price of both options reaches $78K and with negative utility.

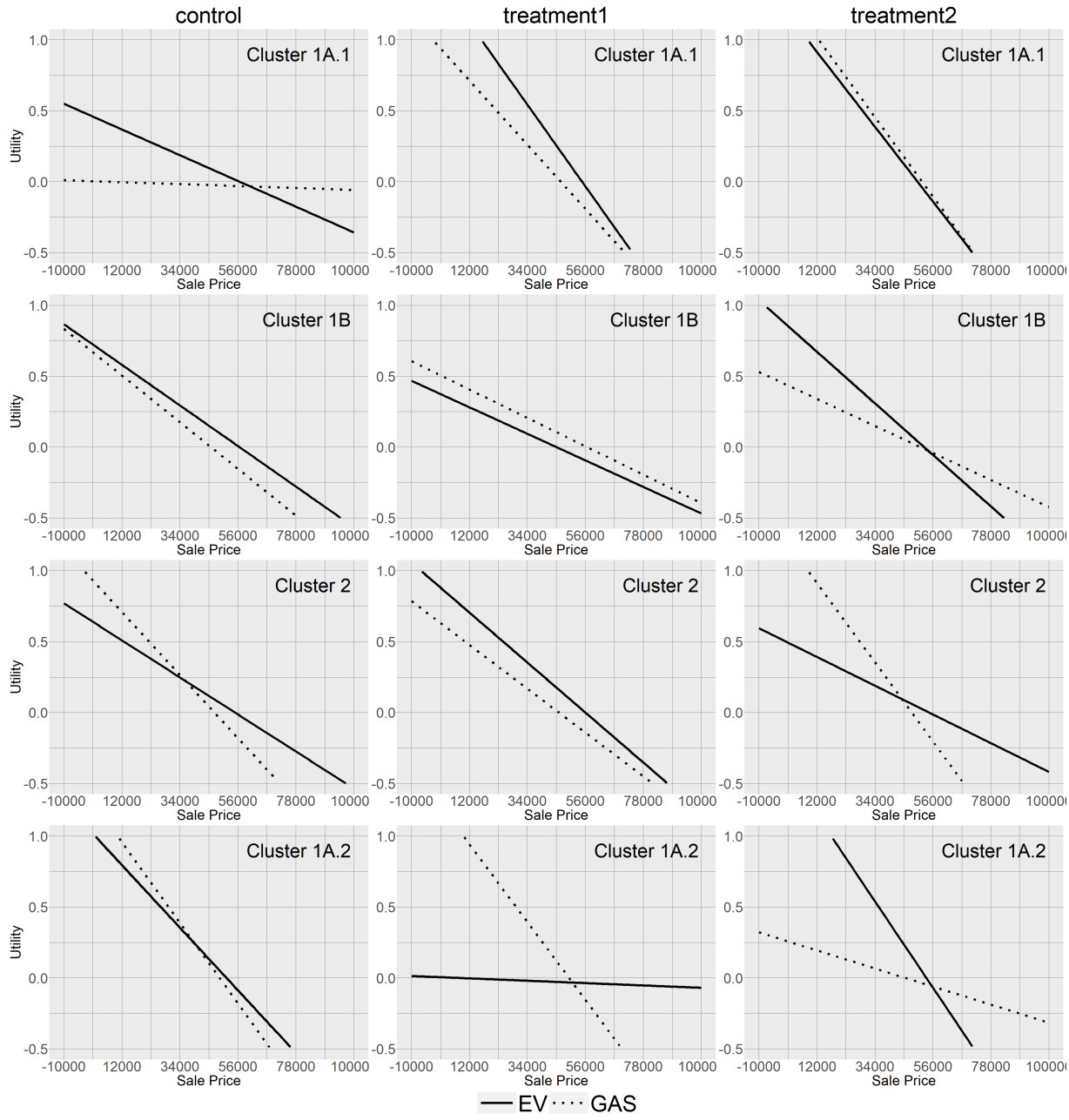
Cluster 1B shows a substantial change in slopes in the treatment 2 graph compared to the control group, with the price point at which consumers are indifferent between the two models increasing by about $70K. Notice how under treatment 1 the utility of the gasoline vehicle (dotted line) is above the utility of the EV (solid line) for every price. These two lines don't intersect until the price is over $220K (and at negative utility), implying that there is no reasonable price at which the mixed Independent/Republican cluster will prefer the EV over a gasoline vehicle under the liberal identity treatment when the range and operating costs are held fixed. However, increasing the range of the EV by 100 miles while holding the range of the gasoline vehicle will shift the EV price curve just to the point where Cluster 1B consumers are indifferent between the EV and gasoline option even at relatively low prices.[12]

Figure 2 shows that Cluster 2 (Democrats) in the control group begin preferring the EV when the sale price of the two vehicles exceeds $34K. When Cluster 2 is treated with the liberal EV association (treatment 1), the utility of the EV is strictly greater than the utility of the gasoline vehicle over the range of values presented in Figure 2. The price of both vehicles has to reach about $127K for these consumers to be indifferent between the two options (at negative residual utility). The conservative EV framing among Cluster 2 (Democrats) produces very similar results to the control group, with a slight increase to the price at which the EV is the preferred choice (around $45K).

Cluster 1A.2 (Republican car drivers) also displays significant changes across treatment groups, with the price point at which participants are indifferent between the EV and gasoline

[12]This is shown in the Web Appendix Figure A5.

Figure 2: Utility of EV and Gasoline Choices by Price



Notes: Figure presents the predicted residual choice probability over a grid of values of purchase prices for the EV and gasoline options, by cluster and treatment status. The range and operating costs have been set to their vehicle-type means. The point at which the EV and GAS lines intersect gives the price at which individuals are indifferent between the two models.

models increasing by about \$10K-\$15K under both liberal and conservative treatments.

Overall, the identity treatments tend to increase the price at which consumers are indifferent between the EV and gasoline models and can shift the relative preferences in either direction such that one vehicle is strictly preferred to the other over a wide range of purchase

prices.

Figure 3 in the Appendix presents similar results but as a function of the driving range. Cluster 1A.1 (socially moderate Independents) and Cluster 1B (Independent/Republican light-truck drivers) control groups have relatively high driving ranges (about 560 miles) at which they would be indifferent between the two vehicle types. Interestingly, under the liberal treatment this drops to about 240 miles and 340 miles, for Cluster 1A.1 and 1B, respectively. This highlights the importance of range for certain groups and suggesting that without altering range and other attributes, it may be challenging to overcome negative price identity effects.

Next, the implied discount rates estimated from the structural parameters provide further insights.[13]. Table A7 shows the mean net present value (NPV) for the EV and gasoline models by applying the implied discount rates to future operating costs. The results indicate that EVs are generally more costly over their lifetime, with a mean NPV difference of about \$6000. However, when using counterfactual NPV estimates (control group estimates), the difference drops to about \$650, suggesting that removing political identity effects could make EVs only slightly more expensive over their lifetime. It's important to note that in some control groups, the EV option may already be polarized, which could underestimate the decrease in lifetime costs from removing identity biases.

Cluster 1A.1 gasoline NPV is significantly higher than the EV option in the control group. However, under both identity treatments, the gasoline NPV drops to nearly the purchase price, making the gasoline option relatively less expensive over the lifetime. For treatment 2, this helps contribute to the overall negative treatment effect, reinforcing the observation that the changes to the structural parameters on the vehicle attributes is driving the treatment effects.

On the other hand, Cluster 1B (the mixed Independent/Republican cluster who drive light trucks) gasoline NPV is significantly higher under the liberal treatment (treatment 1). This result contradicts the negative EV treatment effect among this treatment, but reinforces the observation that the change in the baseline preferences (λ) is driving the overall negative effect. Cluster 1B treatment 2 has a negative EV treatment effect, which is consistent with the results in Table A7. Among this group, the EV NPV has increased while the gasoline NPV has stayed relatively low. Thus, the higher EV lifetime cost explains some of the overall negative treatment effect as the EV option has become relatively more expensive among this

[13]Tables A5 and A6 are presented in the Online Appendix and displays significant heterogeneity in the implicit discount rate estimates. These estimates include near infinite discount rates for many of the vehicle type cluster-experimental groups, providing evidence of hyperbolic discounting. Certain subsets of consumers display rational discount rates that are similar in magnitude to Allcott and Rogers (2014); Busse, Knittel, and Zettelmeyer (2013); Newell and Siikamäki (2015)

group.

Overall, the difference in NPV using the estimated cluster-experimental discount rates implies that EVs are more expensive over the lifetime. The mean difference in the estimated NPV between the two vehicle types is about $6000, implying that the gasoline option is the cheaper option given the set of implied discount rates. However, when using counterfactual NPV estimates by assigning each cluster their control group's discount rates, the difference in NPV drops to about $650, implying that removing the political identity effects would make the EV option just slightly more expensive to own over its lifetime. It is important to note that in some of the control groups[14], the EV option is likely already polarized, so this likely underestimates the decrease in lifetime costs of the EV option from removing any identity biases.

CONCLUSION

Understanding the demand for electric vehicles (EVs) is crucial for attaining fleet emission standards and updating and expanding the electrical grid to accommodate potentially large EV shares of the motor vehicle fleet. However, the growth of EVs has slowed recently, likely due to challenges regarding supply chain limitations, slow charging infrastructure growth, high EV purchase prices, and low resale values. Furthermore, recent evidence in Davis, Li, and Springel (2023) shows a disproportionate concentration of EVs registered in Democratic-voting counties.

We conducted a novel study investigating how framing the purchase of an EV as a choice among liberal (and conservative) consumers affects the stated preferences for EVs 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 then randomly assigned participants into a control group, a group that received a statement associating the EV choice as a common choice among liberal consumers, and a third group that received a statement associating the EV choice as a common choice among conservative consumers.

We find consistent evidence that different sets of participants responded differently to politicizing the EV option. The identity treatments induced baseline behavioral biases against (and in favor of) the EV option, depending on the characteristics of the individuals. These treatments also changed the relative underlying preferences for the observable vehicle attributes (purchase price, range, operating costs). Any intervention that intends to increase the uptake of EVs should consider the nuances in consumer responses carefully.

[14]The lack of a statistically significant negative slope on the operating costs, even in the control group, suggests some participants were already unresponsive to the EV operating cost savings.

APPENDIX

Tables

Table 7: Participant Characteristics with 2 Clusters

	Cluster 1	Cluster 2
Political Party - Democrat	0	1
Political Party - Independent/Other	0.6	0.0
Political Party - Republican	0.39	0.00
Political Ideology - Social	1.89	2.86
Political Ideology - Economic	1.63	2.75
Age	45	46
Income	82443	87725
Gender - Female	0.48	0.50
Gender - Male	0.50	0.47
Gender - Non-Binary	0.01	0.01
Marital Status	0.46	0.41
Household	2.67	2.59
Ethnicity	0.08	0.08
Urbanization - Rural	0.22	0.11
Urbanization - Suburban	0.54	0.56
Urbanization - Urban	0.22	0.32
Race - Black	0.08	0.14
Race - Asian	0.06	0.09
Race - Other	0.04	0.05
Race - White	0.80	0.71
Education - Bachelor's	0.38	0.44
Education - High School	0.14	0.09
Education - Master's or Above	0.15	0.17
Education - Some College	0.31	0.28
Job Status - Full-Time	0.47	0.52
Job Status - Part-Time	0.10	0.09
Job Status - Other	0.16	0.15
Job Status - Retired	0.11	0.12
Job Status - Self-Employed	0.13	0.09
Number of Motor Vehicles	1.76	1.67
Work Miles Traveled	12.93	11.99
Electric Vehicle Ownership	0.06	0.10
Purchase of Durable Goods	0.93	0.92
Work Transportation - Car	0.62	0.67
Work Transportation - Light Truck	0.23	0.16
Work Transportation - Other	0.13	0.16
N	1643	844

Table 8: Participant Characteristics with 3 Clusters

	Cluster 1A	Cluster 1B	Cluster 2
Political Party - Democrat	0	0	1
Political Party - Independent/Other	0.60	0.59	0.00
Political Party - Republican	0.39	0.40	0.00
Political Ideology - Social	1.91	1.86	2.86
Political Ideology - Economic	1.64	1.63	2.75
Age	44	48	46
Income	83884	79906	87725
Gender - Female	0.49	0.47	0.50
Gender - Male	0.49	0.51	0.47
Gender - Non-Binary	0.01	0.01	0.01
Marital Status	0.44	0.49	0.41
Household	2.70	2.61	2.59
Ethnicity	0.08	0.08	0.08
Urbanization - Rural	0.19	0.27	0.11
Urbanization - Suburban	0.57	0.49	0.56
Urbanization - Urban	0.22	0.23	0.32
Race - Black	0.08	0.09	0.14
Race - Asian	0.06	0.05	0.09
Race - Other	0.04	0.04	0.05
Race - White	0.80	0.80	0.71
Education - Bachelor's	0.39	0.37	0.44
Education - High School	0.14	0.14	0.09
Education - Master's or Above	0.16	0.13	0.17
Education - Some College	0.29	0.35	0.28
Job Status - Full-Time	0.49	0.43	0.52
Job Status - Part-Time	0.12	0.08	0.09
Job Status - Other	0.16	0.17	0.15
Job Status - Retired	0.09	0.15	0.12
Job Status - Self-Employed	0.12	0.14	0.09
Number of Motor Vehicles	1.81	1.67	1.67
Work Miles Traveled	13.69	11.60	11.99
Electric Vehicle Ownership	0.07	0.05	0.10
Purchase of Durable Goods	0.92	0.93	0.92
Work Transportation - Car	0.91	0.10	0.67
Work Transportation - Light Truck	0.01	0.63	0.16
Work Transportation - Other	0.06	0.26	0.16
N	1048	595	844

Table 9: Causal Forest Treatment Effect Estimates by Gender

Cluster	Liberal ATE	Conservative ATE
Panel A: Males		
Cluster 1A.1	0.0186 (0.0651)	-0.2309 (0.0681)
Cluster 1A.2	-0.1784 (0.0778)	-0.0409 (0.0862)
Cluster 1B	-0.1427 (0.0655)	-0.1609 (0.0654)
Cluster 2	-0.0072 (0.0569)	0.038 (0.0554)
Panel B: Females		
Cluster 1A.1	0.0208 (0.0663)	0.0013 (0.0666)
Cluster 1A.2	0.1887 (0.0789)	0.1328 (0.0809)
Cluster 1B	-0.104 (0.0693)	0.0354 (0.0695)
Cluster 2	0.0548 (0.0526)	-0.0492 (0.0552)

Notes: Table reports doubly-robust average treatment effects across four clusters, separated by gender. Panel A reports heterogeneous treatment effects among male participants. Standard errors are given in parenthesis.

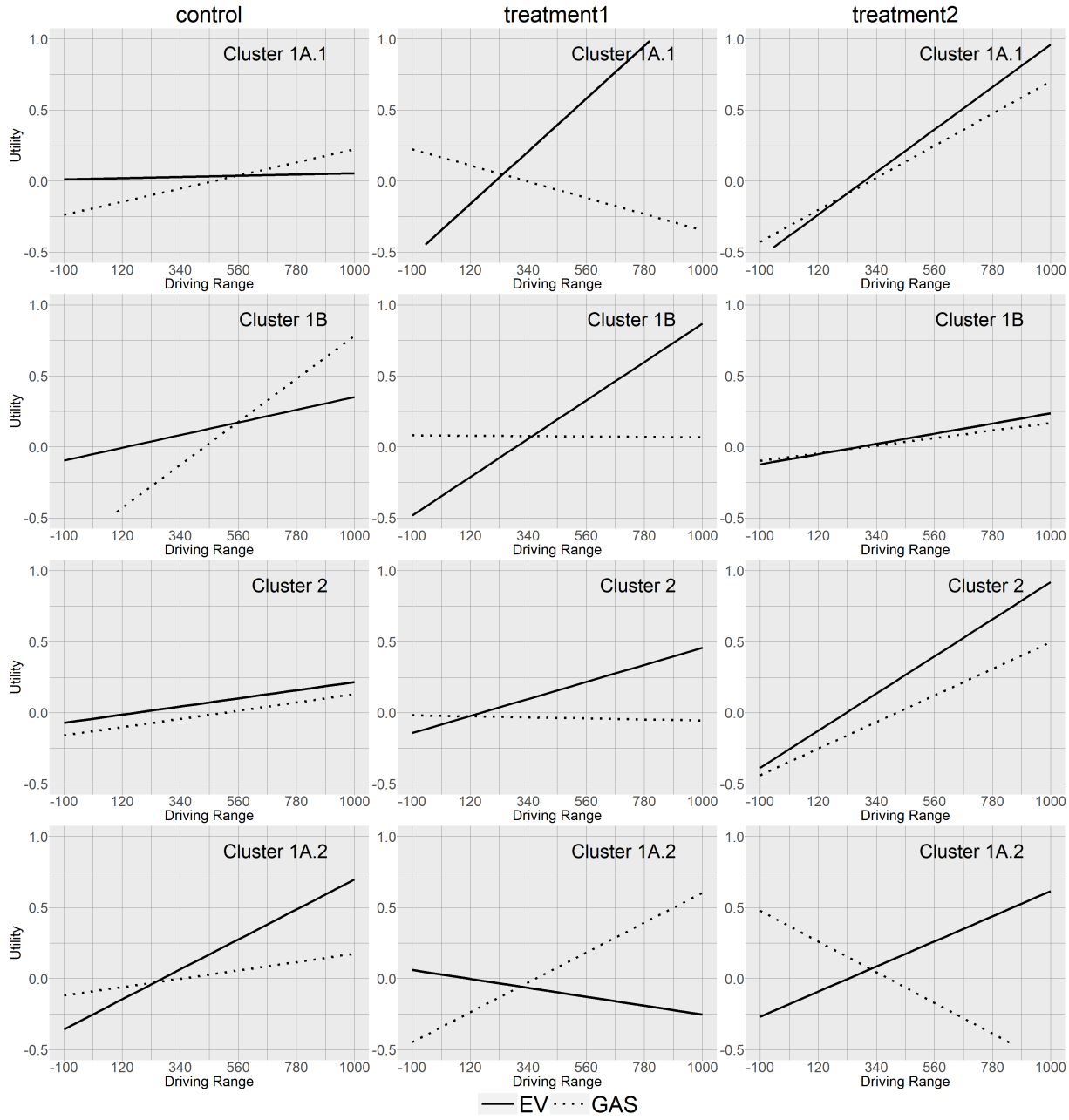
Table 10: Difference in Differences of Structural Parameters

Cluster	Comparison	Vehicle	Lambda	Price	OP	Range
Cluster 1A.1	Treatment1-Control	EV-GAS	0.93	0.002	-0.7167	0.259
			(0.557,1.304)	(-0.0037,0.0084)	(-0.9521,-0.4292)	(0.178,0.338)
Cluster 1A.1	Treatment2-Control	EV-GAS	0.483	0.0092	-0.4239	0.071
			(-0.402,1.265)	(0.0015,0.0157)	(-0.6548,-0.1744)	(0.005,0.164)
Cluster 1B	Treatment1-Control	EV-GAS	-1.863	-0.0014	0.4312	0.221
			(-2.301,-1.34)	(-0.0134,0.0067)	(0.2638,0.6054)	(0.153,0.294)
Cluster 1B	Treatment2-Control	EV-GAS	0.129	-0.0098	-0.1826	0.105
			(-0.355,0.582)	(-0.0166,-0.0043)	(-0.3946,0.0664)	(0.042,0.163)
Cluster 2	Treatment1-Control	EV-GAS	0.62	-0.0103	0.0125	0.058
			(0.369,1.1)	(-0.0154,-0.0038)	(-0.1016,0.0931)	(0.002,0.101)
Cluster 2	Treatment2-Control	EV-GAS	0.147	0.0078	-0.1842	0.034
			(-0.213,0.547)	(0.0021,0.014)	(-0.407,-0.0502)	(-0.018,0.121)
Cluster 1A.2	Treatment1-Control	EV-GAS	0.789	0.0184	-0.5548	-0.193
			(0.338,1.352)	(0.0054,0.0281)	(-0.797,-0.4515)	(-0.28,-0.09)
Cluster 1A.2	Treatment2-Control	EV-GAS	1.032	-0.0276	-0.0464	0.109
			(0.716,1.508)	(-0.035,-0.022)	(-0.2549,0.1622)	(0.009,0.193)

Notes: Table reports the difference in differences in structural parameters for a given model across experimental groups. For example, the first row gives the difference between the EV and GAS structural parameter for the Treatment 1 group minus the difference between the EV and GAS structural parameter for the Control group. The corresponding bootsrapped-t 95 percent confidence intervals of these differences are given in parenthesis and can be used to determine if the differences are statistically significant.

Figures

Figure 3: Utility of EV and Gasoline Choices by Range



Notes: Figure presents the predicted residual choice probability over a grid of values of driving ranges for the EV and gasoline options, by cluster and treatment status. The purchase price and operating costs have been set to their vehicle-type means. The point at which the EV and GAS lines intersect gives the price at which individuals are indifferent between the two models.

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