Driving Electric Vehicle Adoption: The Role of Technology and Consumer Preferences

Connor R. Forsythe[a], Kenneth T. Gillingham[b], Jeremy J. Michalek[a,c,d], and Kate S. Whitefoot[a,c,e]

[a]Department of Mechanical Engineering, Carnegie Mellon University
[b]School of Environment, Department of Economics, School of Management, Yale University and National Bureau of Economic Research
[c]Department of Engineering and Public Policy, Carnegie Mellon University
[d]Department of Civil and Environmental Engineering, Carnegie Mellon University
[e]Heinz School of Public Policy, Carnegie Mellon University

May 2023

Abstract

Electric vehicle sales have been growing rapidly in the United States and around the world. This study explores the drivers of demand for electric vehicles, examining whether this trend is primarily a result of technology improvements or changes in consumer preferences for the technology over time. We conduct a discrete choice experiment of new vehicle consumers in the U.S., weighted to be representative of the population. Results suggest that improved technology has been the stronger force. Estimates of consumer willingness to pay for vehicle attributes show that when consumers compare a gasoline vehicle to its battery electric vehicle (BEV) counterpart, the improved operating cost, acceleration, and fast charging capabilities of today's BEVs often roughly compensate for their perceived disadvantages, particularly for longer-range BEVs. Moreover, forecasted improvements of BEV range and price show that consumer valuation of many BEVs is expected to equal or exceed their gasoline counterparts by 2030, resulting in BEVs capturing 40% to 60% of consumers choosing between gasoline and BEV powertrain options for the same vehicle. Applying the consumer choice estimates to a market-wide simulation suggests that by 2030, if every gasoline vehicle had a BEV option the majority of new car and near-majority of new sport-utility vehicle choice shares would be electric due to projected technology improvements alone.

Introduction

Technology development and consumer adoption of battery electric vehicles (BEVs) are among the greatest contributors to uncertainty in the energy efficiency and carbon intensity of future passenger transportation (NASEM, 2021). While BEVs have historically been a small percentage of the vehicle market, the pace of recent technological change in BEVs has been rapid, with battery costs alone dropping by a factor of ten from 2010 to 2021 (US DOE's VTO, 2021). The average range of BEVs has increased by 200%, while efficiency has increased by 15% (US EPA, 2021), and the number of BEV offerings has grown dramatically (US DOE, 2021). At the same time, consumer exposure to BEVs socially has likely increased as the number of these vehicles on the road has grown (U.S. Environmental Protection Agency, 2021b, Fig. 4.14), major policies have pushed electric vehicles to the forefront of political debates (Newsom, 2020; The White House, 2021), and major automakers have pledged to solely provide electric vehicles in the near future (Miller, 2021). Coffman et al. Coffman et al. (2017, p.86) provide a review of literature showing that social interactions can influence BEV adoption. The questions of how the consumer probability of choosing a BEV has changed over time, what is driving changes in consumer choices, and how much BEV market share may increase in the future have important implications for automotive technologies and policies. For example, California recently passed emission standards that effectively ban the sale of new cars that run on gasoline only (Newsom, 2020), and General Motors endorsed strengthening federal emission standards so that 50% of new vehicles are electric by 2030 (General Motors, 2022). The viability of these emissions targets and policies depends on whether technological improvements, changes in consumer preferences, or both, can generate large increases in BEV market share in the near future.

This paper examines consumer choices of plug-in electric vehicles[1], including BEVs and plug-in hybrid electric vehicles (PHEVs) relative to conventional gasoline vehicles. We focus on how consumer demand for plug-in electric vehicles has been changing over time, accounting for how the technology has improved and allowing for changing preferences. We field a discrete choice experiment where U.S. new vehicle consumers choose among potential vehicle options, mimicking the process of comparing vehicles on an automaker's website. The results of the experiment are compared to a companion discrete choice experiment that was conducted in 2012-2013 in order to examine changes in consumer vehicle choices over time Helveston et al. (2015). In both cases, the weighted respondent pool is a representative sample of new vehicle buyers in the U.S.

The results show that advances in BEV technology—in particular increases in range and reductions in the BEV price-premium—have driven substantial increases in consumer choices of BEV cars and SUVs over their conventional gasoline vehicle counterparts. Estimates of consumer willingness to pay for vehicle attributes show that any perceived disadvantages of BEVs relative to gasoline vehicles are often compensated by the BEV's improved operating cost, acceleration, and fast-charging capabilities, particularly for BEVs with longer range.

[1]The term "plug-in electric vehicle" (PEV) refers to vehicles that acquire some or all of their propulsion energy from an external electricity source (usually the power grid), including (1) battery electric vehicles (BEVs) and (2) plug-in hybrid electric vehicles (PHEVs), which use a blend of electricity and petroleum for propulsion (including extended-range electric vehicles (EREVs)). PEVs do not not include traditional hybrid electric vehicles (HEVs) (such as the Toyota Prius) that do not plug in.

This, combined with technology cost reductions that are expected to reduce the BEV price premium, implies that forecasts of technology improvements are especially important for projecting consumer demand for plug-in electric vehicles going forward. In contrast, while it is possible that consumer preferences may have changed, we do not find statistically significant changes in these preferences over the past decade.

Using the resulting estimates in consumer choice simulations, we find that for today's passenger cars that offer both gasoline and BEV powertrain options, the average premium consumers are willingness to pay for a BEV over a gasoline version of the same vehicle ranges from -$11,500 to $6,700, depending on the vehicle. We report all monetary values in year 2022 USD using the consumer price index, unless otherwise noted. Accounting for expected improvements in BEV range and price by 2030, this WTP shift to a range of -$4,400 to $8,100. For SUVs, we see a similar trend, with willingness to pay a premium for BEVs shifting from -$8,600 to -$7,900 today to a range of -$5,200 to -$2,100 by 2030.

Simulating a future scenario where every conventional gasoline vehicle has an available BEV counterpart and BEV technology improvements follow projections from the National Academies (NASEM, 2021) with supply adequate to match demand at projected prices, we estimate that BEVs would make up the majority of new car sales and near-majority of new SUVs sales by 2030.

Given the limited historical evidence available to understand mainstream consumer preferences for plug-in electric vehicles, we draw upon carefully constructed discrete choice survey experiments with randomized vehicle profiles, using a choice-based conjoint design. Specifically, the results are derived from two discrete-choice survey experiments run eight years apart and designed to be as comparable as possible, while accounting for changes in the automobile market. The surveys are of a representative sample of new vehicle buyers in the United States. The contribution of this paper is both the second survey, conducted in 2020-2021, and a comparison of this second survey to the previous survey performed in 2012-2013 Helveston et al. (2015).[2]

This work contributes to a broad literature on the consumer preferences for plug-in electric vehicles. Classic work on vehicle preferences focuses on a static equilibrium setting where the market and technology is not changing (e.g., see the studies reviewed in Dimitropoulos et al., 2013; Greene et al., 2018). Some work attempts to incorporate a time dimension in estimating consumer preferences by asking individuals to consider their own future decisions (Cirillo et al., 2017; Maness and Cirillo, 2012), but there is little empirical work on the question of how consumer preferences and demand for emerging technologies like plug-in electric vehicles might be changing over time due to technology improvements or changes in preferences.

We identify only three related studies in the peer-reviewed literature that attempt to explore trends in consumer preferences for plug-in electric vehicles. In the first notable contribution, Carley et al. (2019) examined the changes in stated intention to purchase a plug-in electric vehicle between 2011 to 2017 from potential new vehicle purchasers' in the largest 21 U.S. cities, finding that American consumers were more intent on purchasing plug-

[2]Because the second study was performed during the COVID-19 pandemic, we ask respondents how the pandemic impacted them and re-estimate results excluding respondents who were impacted in ways that may have influenced their preferences for vehicles. We do not find any statistically significant differences in results. Details are provided in the SI.

in vehicles in 2017 relative to 2011. Secondly, Jenn et al. (2020) examined changes throughout 2010 and 2017 in California plug-in electric vehicle purchasers' ratings of the importance of various incentives, such as rebates, on their decision to purchase a plug-in electric vehicle, finding that adoption of these vehicles has become more dependent on incentives over time. Finally, Kurani (2019) uses survey data up to 2017 to show that the distribution of individuals considering electric vehicles hasn't dramatically shifted. These studies lay the groundwork for understanding consumer preferences relating to plug-in electric vehicles but answer different questions in a notably different automobile market than today due to the rapidly changing technology. Furthermore, they do not explore the degree to which consumer willingness to trade off relevant vehicle attributes associated with electrification (e.g., range, operating cost, price, etc.) may have changed over time due to technology improvements or other factors and what this could imply for the sales of new vehicles in upcoming years. Our study is the first to shed light on these questions.

Scope of Study

Our data collection approach was designed to examine changes in preferences of mass-market U.S. consumers—meaning consumers representative of U.S. new vehicle purchasers. Because early-adopters' preferences differ from mass-market preferences (Eggers and Eggers, 2011; Kumar and Alok, 2020; Morton et al., 2016; Muehlegger and Rapson, 2018; Smith et al., 2017; Wang et al., 2020), revealed-preference (RP) data, such as historical sales, may not provide good estimates of mass-market consumer preferences, so we instead leverage stated-preference (SP) data. There are many pros and cons of using SP data over RP data (Louviere et al., 2000, p.21-24; Helveston et al., 2018, Table 1). In particular, the use of SP data allows us to present respondents with electric vehicles that are not yet available on the market (Louviere et al., 2000, p.22-23). For instance, a BEV passenger car with 300 miles of range could be presented with a purchase price of $17,000. Such a vehicle is not currently available in the market, although it is anticipated to be available within the next 5-10 years (NASEM, 2021). Further, we are able to account for how large changes in fuel and energy costs (beyond the variation observed in recent fuel prices) impact preferences over time. This capability of SP data allows us to analyze how future changes in technologies, as well as fuel and energy prices, may influence consumer vehicle purchases. The use of SP data also allows us to conduct a controlled experiment that would be prohibitive to conduct in the marketplace. Use of controlled experiments enables the modeler to (1) observe all of the same attributes observed by the respondent (unlike RP data, where consumers make purchases while observing attributes that are not available to the modeler); (2) observe the full choice set (unlike RP data, where the modeler does not typically know what alternatives were available at the time of purchase or which the consumer considered or was even aware of); and (3) avoid confounding (unlike RP data, where strong correlations, such as between EV technology and efficiency, can make it difficult to identify whether consumers are buying EVs because they are electric or because they are efficient). Finally, SP data avoid supply-side issues that interfere with demand-side estimates, such as reduced vehicle availability during the COVID-19 pandemic.

The key criticism of SP data is that it may not reflect the decisions consumers would make in the marketplace when they must commit large amounts of money, as is the case with purchasing a new vehicle. Aiming to mitigate this concern, we incorporate multiple features into the survey design that tend to improve the ability for survey responses to reveal comparable preferences as when making a true purchase decisions (Vossler et al., 2012). First, we use a discrete choice survey design that mimics the experience of consumers comparing vehicle specifications and prices during the purchase decision and simultaneously limits the cognitive burden on respondents to improve the reliability of responses. Second, we use the range of vehicle performance specifications and prices of vehicles available in the market so that if any anchoring effects exist in the survey (Furnham and Boo, 2011), they replicate anchoring effects that would be present in the market during the purchasing decision. Third, we explain to respondents that their responses will be used to inform automaker decisions on vehicle offerings, because it has been shown that SP survey respondents that believe that their responses will have an impact on decision-makers tend to give responses that are consistent with choices that have financial consequences (Vossler et al., 2012).

Our survey was conducted from December 2020 to September 2021. After some introductory questions and information, survey respondents chose (1) either passenger cars or SUVs, (2) vehicle size, and (3) a given aesthetic among a set of vehicle image options.[3] The image selected was held fixed for the remainder of the survey to represent the chosen vehicle to avoid the potential for respondents to conflate vehicle attributes with presumed styling or vehicle class differences. Respondents were then shown a series of fifteen choice tasks. In each choice task, respondents were asked to select their preferred option among three vehicle profiles that varied in price, powertrain type (i.e., conventional gasoline vehicle, gasoline-electric hybrid, PHEV, and BEV), operating cost, 0-60 mph acceleration time, range, whether the vehicle has fast-charging capability (if it is a BEV), and the brand country-of-origin (e.g. American, German, Japanese, Korean, Chinese). Values for these attributes were varied randomly across vehicle profiles and choice tasks to systematically and causally test the effect of varying vehicle attributes on consumer choice. The survey design is almost identical to (Helveston et al., 2015) to enable comparison, with updates made to reflect the range of attributes available in the 2020-2021 vehicle market. Additional details on the survey design are presented in SI.

In our sample, there are 734 car-buyer and 862 SUV-buyer survey responses from people who had intentions of purchasing a car within the next two years or had purchased a car within the prior year of when the survey was fielded, requirements also used in Helveston et al. (2015) so as to ensure comparability. Respondents were recruited using both Amazon's Mechanical Turk (mTurk) and Dynata. mTurk was chosen to replicate data collection from the study conducted in 2012-2013 in order to investigate changes in consumer preferences over time. Dynata was chosen because it includes older and higher-income respondents, which are under-represented by the mTurk sample and improves coverage for generating a representative sample. We weight the respondents in our analysis to ensure representativeness with the U.S. new car and new SUV buying population. Alternative data weighting results are available in the SI.

[3]Note, we only consider the car- and SUV-buyer markets, so these results cannot be extrapolated to the entire US vehicle market. However, these two vehicle classes make up a large majority of the overall American vehicle market (U.S. Environmental Protection Agency, 2021b, Fig. 3.2), making these results informative with respect to changes in the overall vehicle market.

Methodology

In our analysis, we use a random coefficients modeling framework that allows for flexible substitution patterns between vehicle offerings and thus better characterizes consumer preferences than simpler approaches. Specifically, our approach models consumer choice with a random-coefficient (mixed) logit utility over the attributes of the vehicles (Train, 2009). We estimate the model in willingness-to-pay (WTP) space (Train and Weeks, 2005), allowing us to interpret the coefficients as WTP parameters directly, while relaxing the limitations of the common independence assumption for the distribution of the coefficients (Fiebig et al., 2010).

Vehicle Choice Model

We model consumer i's utility for vehicle alternative j as follows:

$$u_{ij} = \lambda \left(\alpha_i a_j + \omega_i c_j + \beta_i b_j + \rho_i r_j + \eta_i f_j + \boldsymbol{\delta}_i^\top \mathbf{x}_j - p_j \right) + \epsilon_{ij}, \tag{1}$$

where $\alpha_i \in \mathbb{R}$ is the WTP per unit increase in vehicle acceleration time $a_j \in \mathbb{R}$ (0-60 mph time in seconds), $\omega_i \in \mathbb{R}$ is WTP per unit increase in vehicle operating costs $c_j \in \mathbb{R}$ (cents/mile), $\rho_i \in \mathbb{R}$ is WTP per unit increase in BEV range $r_j \in \mathbb{R}$ (miles), $\beta_i \in \mathbb{R}$ is WTP for a BEV powertrain $b_j \in \{0, 1\}$ relative to the baseline gasoline vehicle (with identical range), $\eta_i \in \mathbb{R}$ is WTP for BEV fast charging capability $f_j \in \{0, 1\}$, and $\boldsymbol{\delta}_i \in \mathbb{R}^n$ is a vector of WTP coefficients for the vector of remaining indicators $\mathbf{x}_j \in \{0, 1\}^n$ for gasoline-electric hybrid and PHEV powertrains as well as vehicle brand variables and fast charging indicator variables. $\lambda \in \mathbb{R}$ is a scaling factor that identifies the magnitude of the price signal relative to the normalized standard deviation of the error term. p_j is the price of the vehicle, and ϵ_j is a type I extreme value error term.

The estimated parameters are λ and the respondent population mean and standard deviation for each of the WTP random coefficients $\alpha, \omega, \beta, \rho, \eta$ and $\boldsymbol{\delta}$. For tractability, we adopt the common assumption that all WTP parameters are independent and normally-distributed across the population. Use of the WTP space avoids the conflation of taste heterogeneity and scaling effects otherwise implied by this assumption (Fiebig et al., 2010).

We use robust standard errors and account for multiple choice observations from each respondent. The model thus assumes that the error terms are independent only between individuals. In addition to the preferred random-coefficients (mixed) logit model above, we estimate alternative model specifications, which are described in the SI. Survey design and replication instructions, including selection of attributes and levels, is also detailed in the SI. Finally, we would like to note that the entire study was approved by the Carnegie Mellon University Institutional Review Board, and that all survey respondents gave informed consent to participate in this study.

Results

How are BEVs Valued Relative to Conventional Vehicles?

We begin the presentation of our results with a set of head-to-head comparisons, focusing on vehicle models that offer both a conventional and electric powertrain option.[4] These comparisons provide a clean way to illustrate relative consumer preferences without conflating unobserved attributes (styling, interior design, etc.). We look at these head-to-head comparisons using WTP values estimated from the 2021 survey data (full results are available in the SI). We also evaluate expected technology progression from (NASEM, 2021) for a hypothetical near-future vehicle. These comparisons set the stage for forward-looking simulations across the entire fleet and help identify the main drivers of our results.

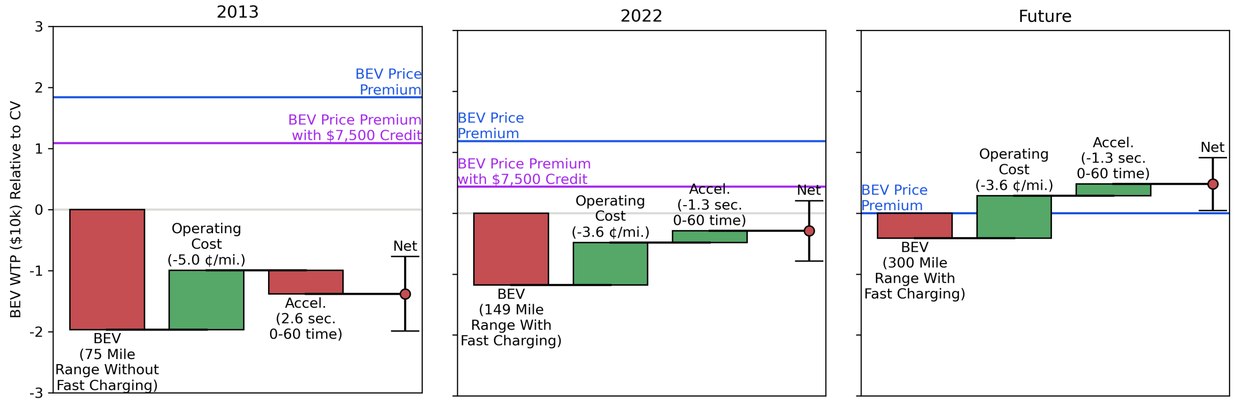
Figure 1 shows a first head-to-head comparison in a waterfall chart over time. The figure compares the Nissan Leaf to a close conventional counterpart built on the same platform, the Nissan Versa. The y-axis is the WTP for the BEV relative to the conventional vehicle. Figure 1a shows the results for the 2013 Leaf and the 2013 Versa. Figure 1b shows the 2022 Leaf and the 2022 Versa for a present-day comparison. Figure 1c shows a hypothetical Leaf with 300 miles of range and the 2022 Versa for a comparison of what might occur in the near future, based on projections from (NASEM, 2021). Lines are included in the first two panels to indicate the actual BEV price premium, both with and without a $7,500 federal tax credit.

In Fig. 1a, we observe that in 2013, relative to the Versa, the Leaf had a shorter (75 mile) range, which reduced the WTP, a lower average operating cost (see the SI for calculations), which increased WTP, and a slower acceleration, which lowered WTP. On net, the difference in the WTP for the Leaf versus the Versa, on average, is -$12,000, and the price premium was almost +$20,000 before the tax credit. This gap is consistent with the relatively low choice share of the 2013 Leaf compared to the Versa.

Figure 1b shows a distinctly different picture for model year 2022, given the same consumer preferences. The range of the Leaf is 149 miles, which produces a less negative WTP relative to the Versa. The operating cost, acceleration, and BEV fast-charging capability all increased the WTP. On net, the 2022 Leaf WTP is nearly on par with the Versa. Thus, if the two were priced the same, we should expect to see similar choice share of both. The 2022 Leaf has a $12,000 price premium over the Versa before the tax credit, and we observe lower choice share of the Leaf than the Versa, as expected. But comparing panels (a) and (b) shows a substantial change in the overall net WTP due to technology changes alone (cases including changes in preferences are available in the SI).

Figure 1c provides insight into what might happen in upcoming years with improved battery technology that allows for longer-range vehicles at a lower cost. For this scenario, we hold the operating cost, acceleration, and fast-charging capability fixed but assume a 300-mile range and no price premium for the BEV, based on projections from (NASEM, 2021, Fig. 5.37). With these changes, the net WTP for the BEV is above the zero price premium, suggesting higher share of choices for the Leaf than the Versa.

[4]Nearly all vehicle specifications were collected from Edmunds. Acceleration measures were collected from Carindigo for the most recent model year available relative to the model year listed. Press releases (found here and here) from Nissan give the MSRP for the 2013 Nissan Leaf and Versa. The base trim level is used in all comparisons unless otherwise noted.



(a) WTP for the 2013 Nissan Leaf relative to the 2013 Nissan Versa S with automatic transmission.

(b) WTP for the 2022 Nissan Leaf relative to the 2022 Nissan Versa.

(c) WTP for a hypothetical future Nissan Leaf relative to the 2022 Nissan Versa.

Figure 1: Head-to-head charts showing WTP for attributes for the Nissan Leaf BEV relative to those of the Nissan Versa gasoline vehicle, which is built on the same platform, using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the electric vehicle with and without the federal BEV tax credit applied. Error bars denote ± 2 standard errors.

We repeat the head-to-head comparison in Fig. 1 for all plug-in electic vehicles available today that offer a gasoline powertrain option, and Figure 2 summarizes the results. The first row of panels are cars and the second row shows SUVs. To simplify, we present the net WTP numbers after accounting for all attributes (range, operating cost, etc.). These net WTP estimates are presented in blue. In red, we present the BEV price premium. We include estimations using our survey data across all vehicle model years, including extrapolations out to 2030 that hold preferences constant at 2021 levels, extend the range of all BEVs to 300 miles, and assume no price premium (acceleration assumptions were informed by Woo and Magee (2020, Fig. 4), and range and price assumptions are informed by the projections in NASEM, 2021, Fig. 5.37).

The pattern in the results in Fig. 2 is consistent: for all of the 2021 comparisons, the net WTP is well below the price premium, but by 2030 the expected improved range and reduced price premium produce WTP estimates comparable to or greater than the price premium. Specifically, for the Leaf, Mini, and BMW i4, the forecasted improvements to 2030 have each BEV preferred to its gasoline counterpart, while for the Kona and XC40, the two powertrains are comparable. For the Ioniq and Niro (which are compared to an HEV counterpart) the projected WTP is still below the price premium. As before, a key finding is that changes in attributes are a clear force leading to greater WTP for BEVs, even with consumer preference parameters held constant.

Willingness to Pay Estimates

The WTP estimates represent the average value (price-equivalency) that consumers place on changes in vehicle attributes. Consistent with prior work, we find that if all vehicle attributes (range, operating cost, acceleration, brand, etc.) are identical across powertrain

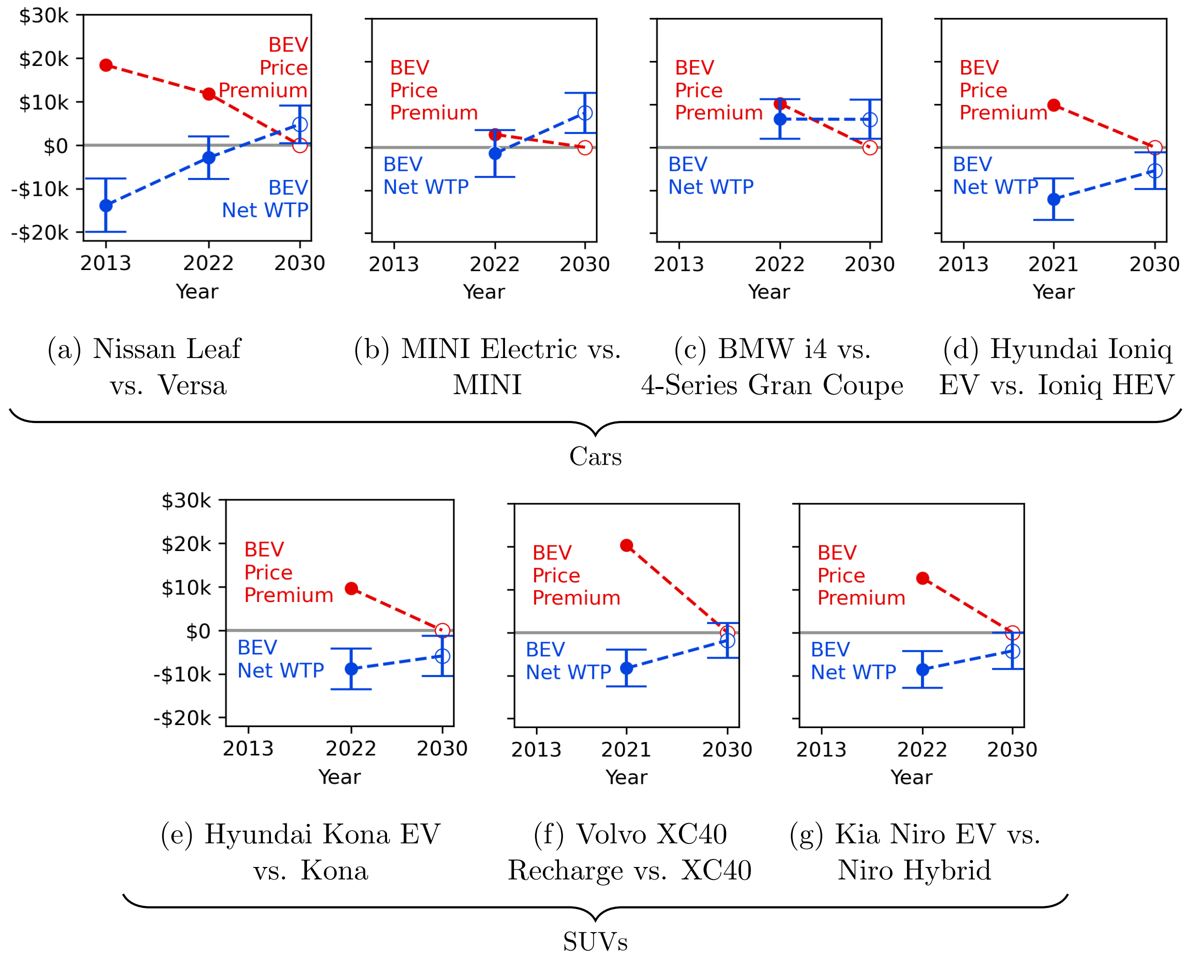


Figure 2: Car and SUV head-to-head comparisons over time. Red points denote the price premium of the BEV relative to the comparable gas-powered vehicle. Blue points denote the net willingness to pay (WTP) of the BEV relative to the comparable gas-powered vehicle. Car and SUV net WTP calculated using the 2021 study mixed logit model for car-buyers and SUV-buyers respectively. Error bars denote ± 2 standard errors. Every panel shares the same axes.

types, consumers prefer conventional gasoline vehicles over BEVs and PHEVs, on average. However, consumers significantly value improvements in attributes that plug-in electic vehicles offer, such as reduced operating cost, that have been shown to counteract the preference for gasoline vehicles. Our results estimate that car (SUV) buyers are willing to pay, on average, $4,140 ($8,620) more for a gasoline vehicle than a BEV of the same range with fast charging capability when the vehicles have identical other attributes, and they are willing to pay an additional $1,480 ($1,460) per second of reduction in 0-60 time; $1,950 ($1,490) per 1¢/mi reduction in operating cost; $5,080 ($7,040) per 100 miles of additional range; and $4,270 ($4,200) for BEV fast charging capability.

We compare WTP estimates across the new and old datasets using Wald tests for equality of means and equality of the full set of distribution parameters in the SI. We find no robust evidence to suggest that mean consumer preferences for BEVs or BEV range have shifted over time for either car or SUV buyers (additional specifications are discussed in the SI). It should be clarified that, although we cannot identify changes over time, this does not mean there hasn't been any. Rather, there isn't sufficient evidence to reject our null hypothesis that preferences have not changed. Additionally, this finding does not imply whether future changes in consumer preferences over the next decade.

It should be noted that there is an inherent limitation with the 2015 study dataset in that it has fewer observations than the 2021 study dataset. It is therefore possible that additional changes in consumer preferences have occurred during this period but were not large enough to be identified with statistical significance given the size of the 2015 sample.

Consumer Choice Implications

The head-to-head comparisons are valuable to illuminating how changes in BEV technology and cost can drive increased BEV WTP and choice shares in a concrete set of comparisons that reasonably hold factors outside the scope of our analysis constant. However, ultimately it is the overall market shares that matter. We construct future scenarios and run market-wide simulations to highlight what our estimation results might imply for the entire vehicle market if each conventional vehicle offering were to offer a BEV powertrain option. This assumption may be reasonable for 2030, given that there are dozens of planned BEV offerings by automakers (Car and Driver, 2022). We base our simulations on data from the 2022 CAFE Compliance Model (US NHTSA, 2022). It is important to emphasize that vehicle sales, and resulting market shares, result from the interaction of supply and demand, and our study assesses only demand. Specifically, our market simulations assume sufficient supply of electric vehicles at prices estimated by a recent National Academies report NASEM, 2021.

We focus on two scenarios. The first is a hypothetical current vehicle market where every conventional vehicle has a BEV counterpart, which is useful to show how more BEV offerings could change BEV share with today's technology. For each ICEV, we assume a BEV counterpart that is on par with offerings that exist today: it has a 200 mile range and a 48% price premium. The second scenario is a hypothetical future market (model year 2030) where each conventional vehicle has a BEV counterpart with 300 miles of range and a 0% price premium, representing technology projections from a recent National Academies report (NASEM, 2021). Finally, we incorporate any unobserved attributes by calibrating alternative-specific constants (ASCs) to match mean market share within the market share data U.S. National Highway Traffic Safety Administration (2022), and we assume BEV

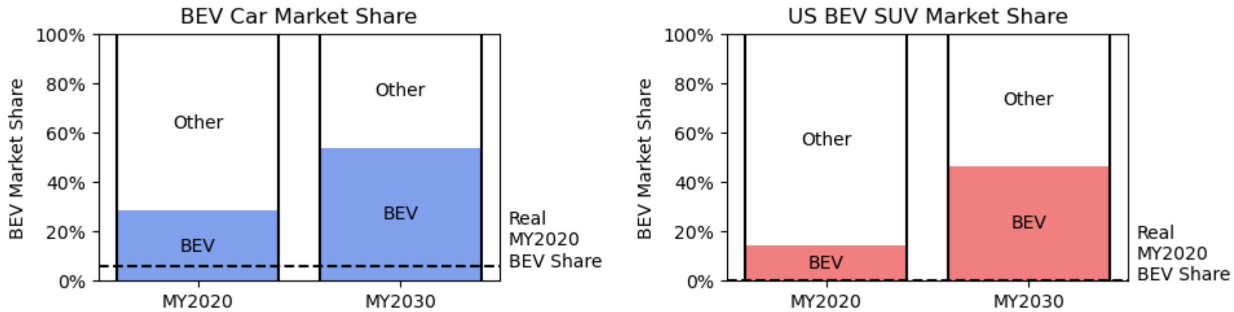


Figure 3: Hypothetical market-wide simulation for model year 2020 and 2030 where all internal combustion engine and hybrid engine vehicle models have a battery electric vehicle option associated with them.

counterparts will have identical unobserved attributes and, thus, identical ASCs. Details for the simulation can be found in the SI.

Figure 3 presents the results of this simulation. We observe that BEV offerings result in higher simulated car and SUV BEV market shares relative to today's market shares (which result from interactions of supply and demand and for which there are far fewer BEV options). Furthermore, our results suggest that the simulated BEV market share for both cars and SUVs would increase to roughly half the market by 2030, assuming widely available comparable BEV offering. These findings highlight that expected technological improvements are key to the adoption of BEVs.

Sensitivity Analysis

We perform a set of sensitivity analyses to characterize the robustness of our results. One key question stems from the weighting of our survey data to accurately represent the vehicle-buying population. The 2015 companion study Helveston et al. (2015) uses MTurk data supplemented with data from the Pittsburgh Auto Show (an event assessed to attract primarily ordinary car buyers, rather than enthusiasts), while our current survey uses data from MTurk and Dynata. To assure that these slightly different data sources do not affect our results, we re-weight and re-estimate both models using only data from Mechanical Turk respondents (see the SI). We find that the only robust, identifiable differences amongst car-buyers in these subsamples are the mean and distributional difference tests for operating costs and the American brand. For SUV buyers, there are no robust differences identified.

In a second sensitivity analysis, we examine the implications of varying WTP for operating cost to reflect estimates from the literature in place of our estimates(Busse et al., 2013; Gillingham et al., 2021; Leard et al., 2017; Sallee et al., 2016).Specifically, we apply lower and upper bounds from the literature of fixed WTP for a 1¢/mile increase in operating cost of -$232 and -$1,378 for car buyers and -$250 and -$1,438 for SUV buyers. We find that our market-wide simulation results remain fairly robust, with substantial BEV adoption at either end of the range of operating cost WTP (see SI for more details) and relatively modest changes in magnitude. Our market simulations are also similarly robust to alternative assumptions regarding fuel prices and acceleration improvements for BEVs.

Discussion and Implications for Technology and Policy

Our findings have important implications for vehicle policies as well as BEV technology development. Understanding the trajectory of consumer willingness to adopt BEVs is crucial for the effectiveness of many recent and proposed policies that aim to encourage vehicle electrification (see the wide range of policies reviewed throughout Hayashida et al. (2021) as well as Newsom (2020); US Environmental Protection Agency (2021a)). Our results imply that the likelihood of consumers purchasing BEVs has grown over time because of technological improvements that have increased range and (in many cases) reduced price premiums of particular BEVs models relative to their gasoline counterparts. This trend improves the viability and reduces the costs of regulations that encourage electrification, such as stronger greenhouse gas emission standards and zero-emission vehicle regulations.

Should technological projections hold, our results suggest that it may be possible to entirely phase out BEV purchase incentives and still have BEVs capture 50% share of choices relative to their gasoline counterparts by 2030. This is in-line with forecasts by financial and consulting companies that rely on expert predictions (McKerracher et al., 2022; Niese et al., 2022), and they suggest a need to prepare BEV-related infrastructure (e.g. charging stations, sufficient power generation and transmission, etc.) for a pending increase in adoption. These results also lend additional evidence to the optimism about transitioning the automotive industry to focus more on BEV production in the coming decade, and they suggest that technology progress projections are key for future BEV adoption projections used in policy planning and cost-benefit analyses. Importantly, we do not model supply-side factors that could affect market outcomes, and our results assume substantial BEV model availability.

Additionally, our results provide a direction for BEV technology development that can increase consumer adoption. Our consumer choice estimates underscore the potential importance of increasing BEV range. Most vehicles with a range of at least 300 miles were valued by consumers equivalently or more than their conventional gasoline vehicle counterparts. While BEVs have some disadvantages, such as longer recharging times than it takes to fill up a gasoline vehicle, our results show that these disadvantages are made up for, on average, by lower operating costs and fast-charging capability as long as range is sufficiently long. The results also suggest that further improving the efficiency of BEV powertrains to deliver faster acceleration and/or lower operating costs can help increase consumer adoption.

Interestingly, we find little evidence of major changes in underlying consumer preferences independent of vehicle technology. One might speculate that growing awareness of plug-in electric vehicles between 2013-2021 would have increased the likelihood of consumers purchasing these vehicles even if the technology remained constant over time. While our results do not rule out that some change in consumer preferences occurred, we do not find statistically significant changes in consumer valuation of plug-in electric vehicles over time once the specific technology and vehicle attributes are controlled for. This could be interpreted to imply that consumer awareness efforts are less effective than technology development or, conversely, that inadequate resources have been devoted to consumer awareness efforts in the past decade. It is possible that consumer preferences could change in the future as larger numbers of consumers gain experiences with PEVs (Roberson and Helveston, 2020).

There are some limitations to our study worth mentioning. We use a stated preference approach because historical data on plug-in electric vehicle sales is scant and largely limited to early adopters, who may differ considerably from mass-market consumers (Axsen et al., 2016). We take several precautions in our discrete choice experiment to minimize potential stated preference biases, but respondents may nevertheless make different choices in hypothetical choice scenarios than in purchase scenarios. Our sensitivity analysis suggests that our general findings are robust to variation in model parameters based in the literature. As more plug-in electric vehicles are adopted over the coming years, revealed preference work could complement our findings.

Our consumer choice results also assume that the availability of BEVs is ubiquitous and consumers can just as easily find and purchase these vehicles through automotive retailers and dealerships as conventional gasoline vehicles. This is not the case in some parts of the U.S. today, but it may be true in 2030. We also focus our study on passenger cars and SUVs for greater comparability to previous work, but further work on pickup trucks is warranted, especially given that pickup trucks are now 14% of new vehicle sales in the U.S. (U.S. Environmental Protection Agency, 2021b, p.16). We conclude by noting that there is room for much more work exploring preferences for plug-in electric vehicles, especially across geography, buyer characteristics (income, race, etc.), and in the used vehicle market.

References

Axsen, Jonn, Suzanne Goldberg, and Joseph Bailey, "How might potential future plug-in electric vehicle buyers differ from current "Pioneer" owners?," *Transportation Research Part D: Transport and Environment*, 2016, *47*, 357–370.

Barratt, Shane, Guillermo Angeris, and Stephen Boyd, "Optimal representative sample weighting," *Statistics and Computing*, feb 2021, *31* (2), 19.

Bellemare, Marc F. and Casey J. Wichman, "Elasticities and the Inverse Hyperbolic Sine Transformation," *Oxford Bulletin of Economics and Statistics*, feb 2020, *82* (1), 50–61.

Brownstone, David, "Forecasting new product penetration with flexible substitution patterns," *Journal of Econometrics*, 1999, *89*, 109–129.

_ , David S. Bunch, and Kenneth Train, "Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles," *Controlling Automobile Air Pollution*, 2018, *34*, 299–322.

_ , _ , Thomas F. Golob, and Weiping Ren, *A transactions choice model for forecasting demand for alternative-fuel vehicles*, Vol. 4, Elsevier Ltd, 1996.

Busse, Meghan R., Christopher R. Knittel, and Florian Zettelmeyer, "Are consumers myopic? Evidence from new and used car purchases," *American Economic Review*, 2013, *103* (1), 220–256.

Car and Driver, "Every Electric Vehicle That's Expected in the Next Five Years," 2022.

Carley, Sanya, Saba Siddiki, and Sean Nicholson-Crotty, "Evolution of plug-in electric vehicle demand: Assessing consumer perceptions and intent to purchase over time," *Transportation Research Part D: Transport and Environment*, 2019, *70* (April), 94–111.

Carson, Richard T. and Mikołaj Czajkowski, "A new baseline model for estimating willingness to pay from discrete choice models," *Journal of Environmental Economics and Management*, 2019, *95*, 57–61.

Cirillo, Cinzia, Yan Liu, and Michael Maness, "A time-dependent stated preference approach to measuring vehicle type preferences and market elasticity of conventional and green vehicles," *Transportation Research Part A: Policy and Practice*, 2017, *100*, 294–310.

Coffman, Makena, Paul Bernstein, and Sherilyn Wee, "Electric vehicles revisited: a review of factors that affect adoption," *Transport Reviews*, 2017, *37* (1), 79–93.

Daziano, Ricardo A., "Conditional-logit Bayes estimators for consumer valuation of electric vehicle driving range," *Resource and Energy Economics*, 2013, *35* (3), 429–450.

Dimitropoulos, Alexandros, Piet Rietveld, and Jos N. van Ommeren, "Consumer valuation of changes in driving range: A meta-analysis," *Transportation Research Part A: Policy and Practice*, 2013, *55*, 27–45.

Eggers, Felix and Fabian Eggers, "Where have all the flowers gone? Forecasting green trends in the automobile industry with a choice-based conjoint adoption model," *Technological Forecasting and Social Change*, 2011, *78* (1), 51–62.

Fiebig, Denzil G, Michael P Keane, Jordan Louviere, and Nada Wasi, "The generalized multinomial logit model: accounting for scale and coefficient heterogeneity," *Marketing science*, 2010, *29* (3), 393–421.

Furnham, Adrian and Hua Chu Boo, "A literature review of the anchoring effect," *Journal of Socio-Economics*, 2011, *40* (1), 35–42.

Ganz, Andrew, "What is MPGe ? Everything You Need to Know," 2021.

General Motors, "It's Time for American Leadership in Zero Emissions Vehicles," 2022.

Gillingham, Kenneth T., Sébastien Houde, and Arthur A. van Benthem, "Consumer Myopia in Vehicle Purchases: Evidence from a Natural Experiment," *American Economic Journal: Economic Policy*, 2021, *13* (3), 207–238.

Greene, David, Anushah Hossain, Julia Hofmann, Gloria Helfand, and Robert Beach, "Consumer willingness to pay for vehicle attributes: What do we Know?," *Transportation Research Part A: Policy and Practice*, 2018, *118*, 258–279.

Haaf, C. Grace, Jeremy J. Michalek, W. Ross Morrow, and Yimin Liu, "Sensitivity of Vehicle Market Share Predictions to Discrete Choice Model Specification," *Journal of Mechanical Design, Transactions of the ASME*, 2014, *136* (12), 1–9.

Hayashida, Sherilyn, Sumner La Croix, and Makena Coffman, "Understanding changes in electric vehicle policies in the U.S. states, 2010–2018," *Transport Policy*, 2021, *103* (December 2020), 211–223.

Helveston, John Paul, Elea Mc Donnell Feit, and Jeremy J. Michalek, "Pooling stated and revealed preference data in the presence of RP endogeneity," *Transportation Research Part B: Methodological*, 2018, *109*, 70–89.

_ , Yimin Liu, Elea Mc Donnell Feit, Erica Fuchs, Erica Klampfl, and Jeremy J. Michalek, "Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U.S. and China," *Transportation Research Part A: Policy and Practice*, 2015, *73*, 96–112.

Hess, Stephane, Kenneth E. Train, and John W. Polak, "On the use of a Modified Latin Hypercube Sampling (MLHS) method in the estimation of a Mixed Logit Model for vehicle choice," *Transportation Research Part B: Methodological*, feb 2006, *40* (2), 147–163.

_ , Mark Fowler, Thomas Adler, and Aniss Bahreinian, "A joint model for vehicle type and fuel type choice: Evidence from a cross-nested logit study," *Transportation*, 2012, *39* (3), 593–625.

Hidrue, Michael K., George R. Parsons, Willett Kempton, and Meryl P. Gardner, "Willingness to pay for electric vehicles and their attributes," *Resource and Energy*

Economics, 2011, *33* (3), 686–705.

Jenn, Alan, Jae Hyun Lee, Scott Hardman, and Gil Tal, "An in-depth examination of electric vehicle incentives: Consumer heterogeneity and changing response over time," *Transportation Research Part A: Policy and Practice*, 2020, *132* (September 2019), 97–109.

Kavalec, Chris, "Vehicle choice in an aging population: Some insights from a stated preference survey for California," *Energy Journal*, 1999, *20* (3), 123–138.

Kumar, Rajeev Ranjan and Kumar Alok, "Adoption of electric vehicle: A literature review and prospects for sustainability," *Journal of Cleaner Production*, 2020, *253*, 119911.

Kurani, Kenneth S, "The State of Electric Vehicle Markets, 2017: Growth Faces an Attention Gap," Technical Report 2019.

Leard, Benjamin, Joshua Linn, and Katalin Springel, "Pass-Through and Welfare Effects of Regulations that Affect Product Attributes," 2019.

_ , _ , and Yichen Christy Zhou, "How Much Do Consumers Value Fuel Economy and Performance? Evidence from Technology Adoption," Technical Report June, Resource for the Future 2017.

Louviere, Jordan J., David A. Hensher, Joffre D. Swait, and Wiktor Adamowicz, "Introduction to stated preference models and methods," in "Stated Choice Methods: Analysis and Applications," Cambridge University Press, 2000, chapter 2, pp. 20–33.

Maness, Michael and Cinzia Cirillo, "Measuring Future Vehicle Preferences," *Transportation Research Record: Journal of the Transportation Research Board*, jan 2012, *2285* (1), 100–109.

McFadden, Daniel and Kenneth Train, "Mixed MNL models for discrete response," *Journal of Applied Econometrics*, 2000, *15* (5), 447–470.

McKerracher, Colin, O'Donovan Aleksandra, Nikolas Soulopoulos, Andrew Grant, Siyi Mi, David Doherty, Ryan Fisher, Corey Cantor, Jinghong Lyu, Kwasi Ampofo, Andy Leach, Yayoi Sekine, Laura Malo Yague, William Edmonds, Komal Kareer, and Takehiro Kawahara, "Electric Vehicle Outlook 2022 Executive Summary," Technical Report 2022.

Miller, Caleb, "Six Major Automakers Agree to End Gas Car Sales Globally by 2040," 2021.

Morton, Craig, Jillian Anable, and John D. Nelson, "Exploring consumer preferences towards electric vehicles: The influence of consumer innovativeness," *Research in Transportation Business and Management*, 2016, *18*, 18–28.

Muehlegger, Erich and David Rapson, "Subsidizing Low- and Middle-Income Adoption of Electric Vehicles: Quasi-Experimental Evidence from California," Technical Report 1, National Bureau of Economic Research, Cambridge, MA dec 2018.

National Academies of Sciences, Engineering, and Medicine, *Assessment of Technologies for Improving Light-Duty Vehicle Fuel Economy—2025-2035*, Washington, DC: The National Academies Press, 2021.

Newsom, Gavin, "Executive Order N-79-20," 2020.

Niese, Nathan, Aakash Arora, Elizabeth Dreyer, Aykan Gökbulut, and Alex Xie, "Electric Cars Are Finding Their Next Gear," Technical Report 2022.

Nixon, Hilary and Jean-Daniel Saphores, "Understanding Household Preferences For Alternative-Fuel Vehicle Technologies," *Mineta Trasnportation Institute Publications*, 2011, pp. 1–47.

Parsons, George R., Michael K. Hidrue, Willett Kempton, and Meryl P. Gardner, "Willingness to pay for vehicle-to-grid (V2G) electric vehicles and their contract terms," *Energy Economics*, 2014, *42*, 313–324.

Roberson, Laura A. and John P. Helveston, "Electric vehicle adoption: Can short experiences lead to big change?," *Environmental Research Letters*, 2020, *15* (9).

Sallee, James M., Sarah E. West, and Wei Fan, "Do consumers recognize the value of fuel economy? Evidence from used car prices and gasoline price fluctuations," *Journal of Public Economics*, 2016, *135*, 61–73.

Segal, Robin, "Forecasting the Market for Electric Vehicles in California Using Conjoint Analysis," *The Energy Journal*, 1995, *16* (3), 89–111.

Smith, Brett, Doina Olaru, Fakhra Jabeen, and Stephen Greaves, "Electric vehicles adoption: Environmental enthusiast bias in discrete choice models," *Transportation Research Part D: Transport and Environment*, 2017, *51*, 290–303.

Tanaka, Makoto, Takanori Ida, Kayo Murakami, and Lee Friedman, "Consumers' willingness to pay for alternative fuel vehicles: A comparative discrete choice analysis between the US and Japan," *Transportation Research Part A: Policy and Practice*, 2014, *70* (2014), 194–209.

The White House, "FACT SHEET: President Biden Announces Steps to Drive American Leadership Forward on Clean Cars and Trucks," 2021.

Train, Kenneth, *Discrete Choice Methods with Simulation*, 2 ed., Cambridge University Press, 2009.

_ **and Garrett Sonnier**, "Mixed Logit with Bounded Distribution of Correlated Partworths," in Raccardo Scarpa and Anna Alberini, eds., *Applications of Simulation Methods in Environmental and Resource Economics*, Springer, 2005, chapter 7, pp. 1–16.

_ **and Melvyn Weeks**, "Discrete Choice Models in Preference Space and Willing-to-pay Space," in Raccardo Scarpa and Anna Alberini, eds., *Applications of Simulation Methods in Environmental and Resource Economics*, Springer, 2005, chapter 1, pp. 1–16.

U.S. Department of Energy, "Alternative Fuels Data Center Data Downloads: Light-duty vehicles," 2021.

U.S. Department of Energy's Vehicle Technologies Office, "FOTW # 1206 , Oct 4 , 2021 : DOE Estimates That Electric Vehicle Battery Pack Costs in 2021 Are 87 % Lower Than in 2008," 2021.

U.S. Energy Information Administration, "Table 9.4 Retail Motor Gasoline and On-Highway Diesel Fuel Prices," 2020.

_ , "Table 9.8 Average Retail Prices of Electricity," 2020.

_ , "Table 9.4 Retail Motor Gasoline and On-Highway Diesel Fuel Prices," 2022.

_ , "Table 9.8 Average Retail Prices of Electricity," 2022.

U.S. Environmental Protection Agency, "Green Vehicle Guide: Technology," 2016.

US Environmental Protection Agency, "Revised 2023 and later model year light-duty vehicle greenhouse gas emissions standards," 2021.

U.S. Environmental Protection Agency, "The 2021 EPA Automotive Trends Report: Greenhouse Gas Emissions, Fuel Economy, and Technology since 1975 (EPA-420-R-21-023)," Technical Report November 2021.

U.S. National Highway Traffic Safety Administration, "2022 Final Rule for Model Years 2024-2026 Passenger Cars and Light Trucks Central and EIS Analysis," 2022.

Vossler, Christian A, Maurice Doyon, and Daniel Rondeau, "Truth in Consequentiality: Theory and Field Evidence on Discrete Choice Experiments," *American Economic Journal: Microeconomics*, nov 2012, *4* (4), 145–171.

Walls, Margaret A, "Valuing the Characteristics of Natural Gas Vehicles: An Implicit Markets Approach," *The Review of Economics and Statistics*, 1996, *78* (2), 266–276.

Wang, Guangjun, Keita Makino, Arek Harmandayan, and Xinkai Wu, "Eco-driving behaviors of electric vehicle users: A survey study," *Transportation Research Part D: Transport and Environment*, 2020, *78* (December 2019), 102188.

Woo, Jong Roul and Christopher L. Magee, "Forecasting the value of battery electric vehicles compared to internal combustion engine vehicles: The influence of driving range and battery technology," *International Journal of Energy Research*, 2020, *44* (8), 6483–6501.

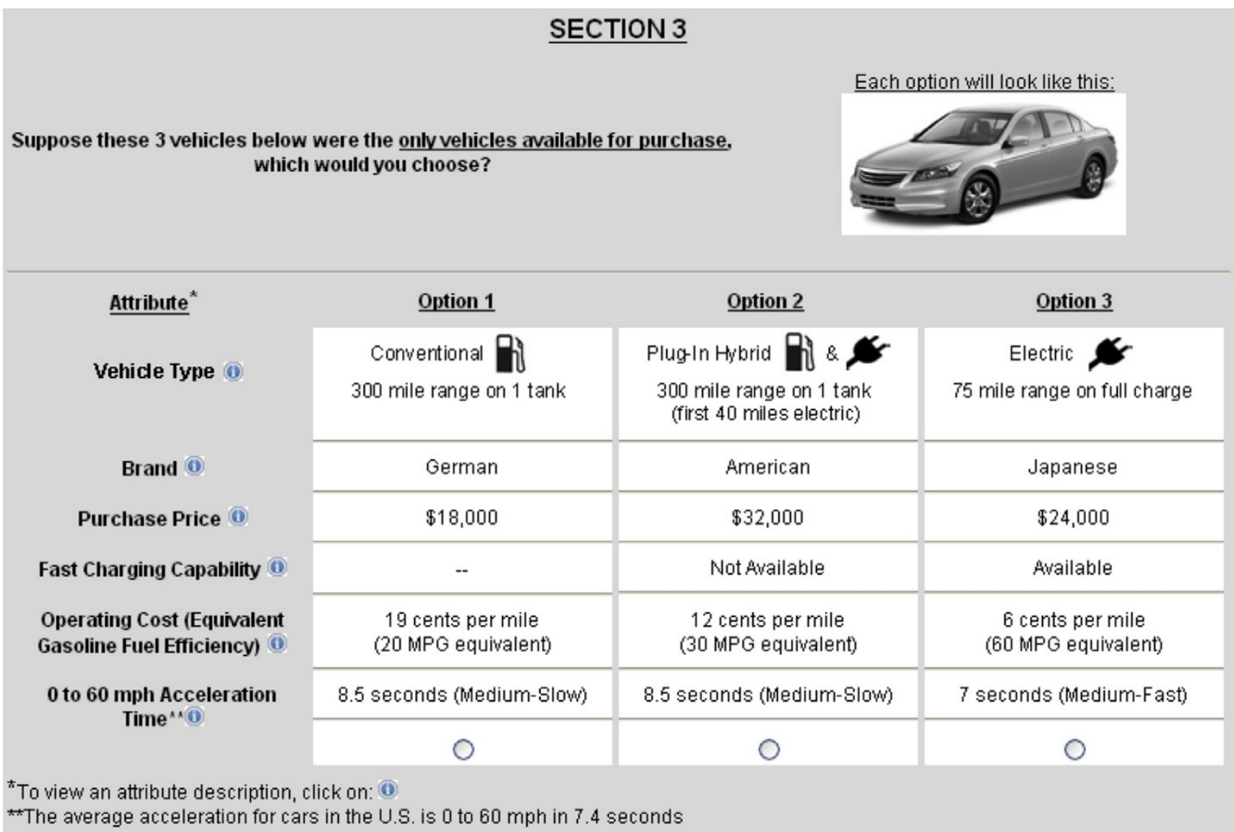
Zhang, Ting, Sonja Gensler, and Rosanna Garcia, "A study of the diffusion of alternative fuel vehicles: An agent-based modeling approach," *Journal of Product Innovation Management*, 2011, *28* (2), 152–168.

Supplementary Information

Survey and Data Cleaning Information

All de-identified data and code necessary to construct provided results are available via https://cmu.box.com/s/2zme67dl7agnstxbkhr1wcaeag0lvga1. Additionally, the full survey instruments are available at https://cmu.box.com/s/f2vp6vt8gww1pthd6yc16z79ytkubxlm.

We seek to develop a survey that is as comparable as possible to the survey utilized in Helveston et al. (2015) (see example in Fig. 4), but with appropriate updates to acknowledge the changes in the market. Examples from our MTurk and and Dynata surveys can be found in Figs. 5 and 6. The final conjoint levels used in Helveston et al. (2015) and our survey can be found in Tables 1 and 2. There were some minor formatting changes from the Helveston et al. (2015) study due to updates to the Sawtooth Lighthouse software. Additionally, the formatting is slightly different formatting between the MTurk and Dynata survey versions in order to improve legibility.



SECTION 3

Each option will look like this:

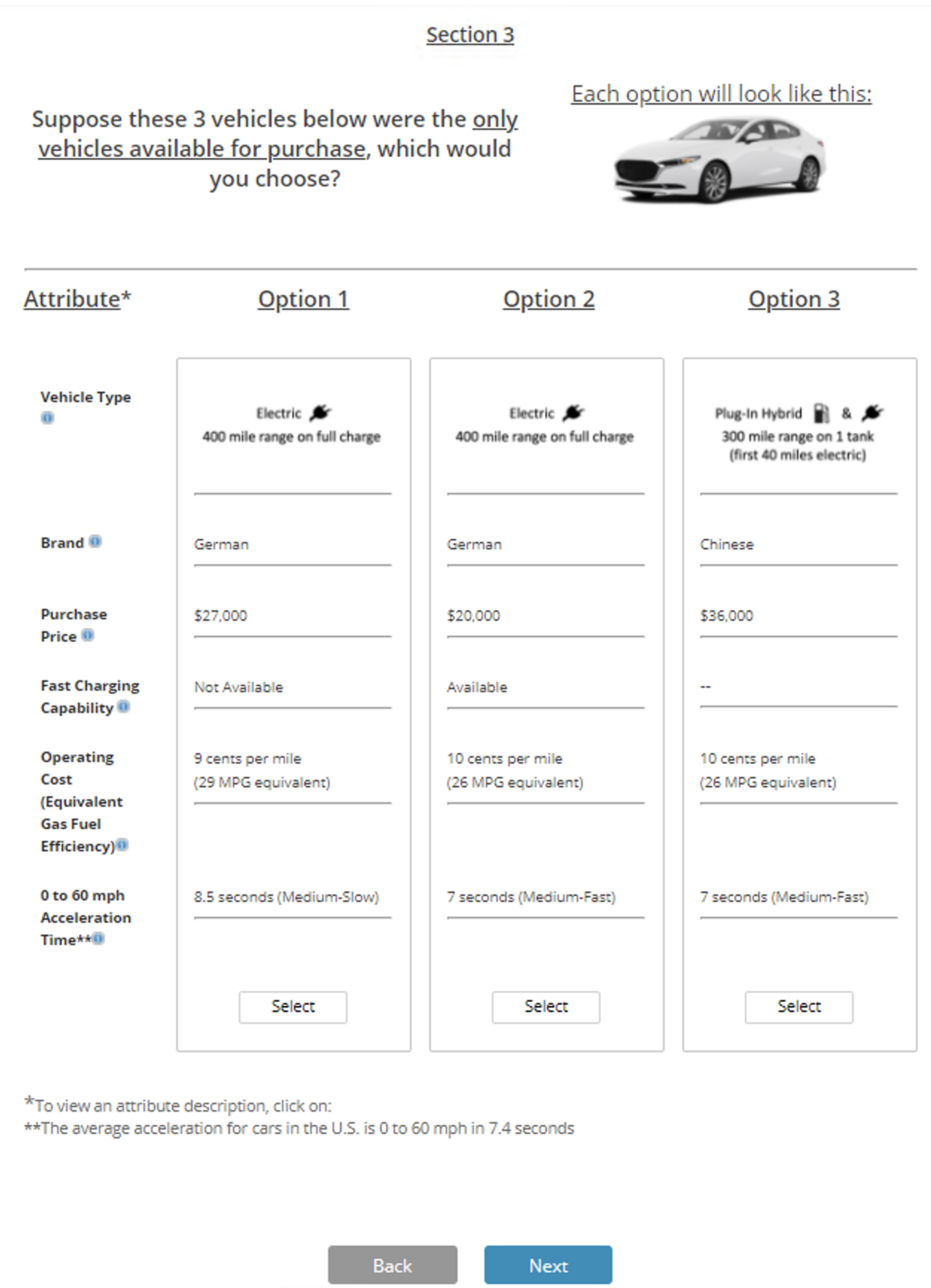
Suppose these 3 vehicles below were the only vehicles available for purchase, which would you choose?

Attribute*	Option 1	Option 2	Option 3
Vehicle Type	Conventional 300 mile range on 1 tank	Plug-In Hybrid & 300 mile range on 1 tank (first 40 miles electric)	Electric 75 mile range on full charge
Brand	German	American	Japanese
Purchase Price	$18,000	$32,000	$24,000
Fast Charging Capability	--	Not Available	Available
Operating Cost (Equivalent Gasoline Fuel Efficiency)	19 cents per mile (20 MPG equivalent)	12 cents per mile (30 MPG equivalent)	6 cents per mile (60 MPG equivalent)
0 to 60 mph Acceleration Time**	8.5 seconds (Medium-Slow)	8.5 seconds (Medium-Slow)	7 seconds (Medium-Fast)
	○	○	○

*To view an attribute description, click on:

**The average acceleration for cars in the U.S. is 0 to 60 mph in 7.4 seconds

Figure 4: Example discrete-choice question from Helveston et al. (2015) survey


Section 3

Suppose these 3 vehicles below were the only vehicles available for purchase, which would you choose?

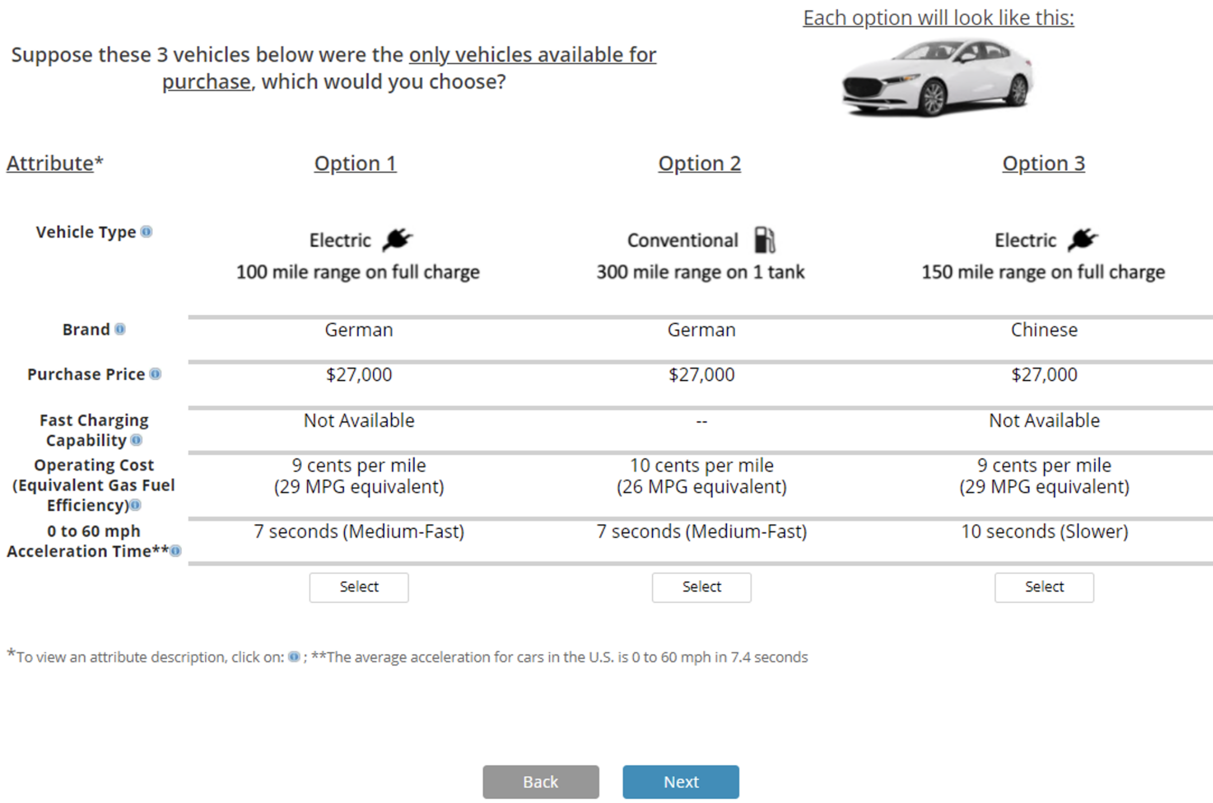
Each option will look like this:

Attribute*	Option 1	Option 2	Option 3
Vehicle Type	Electric 400 mile range on full charge	Electric 400 mile range on full charge	Plug-In Hybrid & 300 mile range on 1 tank (first 40 miles electric)
Brand	German	German	Chinese
Purchase Price	$27,000	$20,000	$36,000
Fast Charging Capability	Not Available	Available	--
Operating Cost (Equivalent Gas Fuel Efficiency)	9 cents per mile (29 MPG equivalent)	10 cents per mile (26 MPG equivalent)	10 cents per mile (26 MPG equivalent)
0 to 60 mph Acceleration Time**	8.5 seconds (Medium-Slow)	7 seconds (Medium-Fast)	7 seconds (Medium-Fast)
	Select	Select	Select

*To view an attribute description, click on:
**The average acceleration for cars in the U.S. is 0 to 60 mph in 7.4 seconds

Back Next

Figure 5: Example discrete-choice question from new MTurk survey. Each survey included 15 choice questions with attribute levels varied randomly across questions and respondents plus two choice questions designed as attention checks.



Suppose these 3 vehicles below were the only vehicles available for purchase, which would you choose?

Each option will look like this:

Attribute*	Option 1	Option 2	Option 3
Vehicle Type	Electric 100 mile range on full charge	Conventional 300 mile range on 1 tank	Electric 150 mile range on full charge
Brand	German	German	Chinese
Purchase Price	$27,000	$27,000	$27,000
Fast Charging Capability	Not Available	--	Not Available
Operating Cost (Equivalent Gas Fuel Efficiency)	9 cents per mile (29 MPG equivalent)	10 cents per mile (26 MPG equivalent)	9 cents per mile (29 MPG equivalent)
0 to 60 mph Acceleration Time**	7 seconds (Medium-Fast)	7 seconds (Medium-Fast)	10 seconds (Slower)
	Select	Select	Select

*To view an attribute description, click on: ; **The average acceleration for cars in the U.S. is 0 to 60 mph in 7.4 seconds

Back Next

Figure 6: Example discrete-choice question from new Dynata survey. Each survey included 15 choice questions with attribute levels varied randomly across questions and respondents plus two choice questions designed as attention checks.

Table 1: Conjoint levels used in Helveston et al. (2015).

	Cars	SUVs
Price ($1,000s)	15, 18, 24, 32, 50	20, 25, 30, 37, 50
Operating Cost (¢/mile)	6, 9, 12, 19	9, 13, 19, 23
Acceleration (0-60 Time Sec.)	5.5, 7, 8.5, 10	7, 8, 9, 10
BEV Range (Miles)	75, 100, 150	75, 100, 150
PHEV Range (Miles)	10, 20, 40	10, 20, 40
Brand	American, Chinese, German, Japanese, South Korean	American, Chinese, German, Japanese, South Korean

Table 2: Conjoint levels used in new study.

	Cars	SUVs
Price ($1,000s)	17, 20, 27, 36, 56	22, 28, 33, 41, 56
Operating Cost (¢/mile)	4, 8, 9, 10, 12	5, 7.5, 10, 12.5 15
Acceleration (0-60 Time Sec.)	5.5, 7, 8.5, 10	7, 8, 9, 10
BEV Range (Miles)	100, 150, 300, 400	100, 150, 300, 400
PHEV Range (Miles)	20, 40	20, 40
Brand	American, Chinese, German, Japanese, South Korean	American, Chinese, German, Japanese, South Korean

The following explains our choice-based conjoint framework. First, we utilized the latest Sawtooth Lighthouse software at the time of fielding. We vary alternative attributes randomly across alternatives, choice sets, and individuals. Each individual is shown seventeen choice sets (two serve as attention checks, one more than Helveston et al. (2015)), each with three alternatives. Each attention check shows three options that are identical other than one having 1) a lower price, 2) a lower operating cost, and in the case of BEVs 3) potentially the availability of BEV fast charging. All data from respondents who did not choose the dominant alternative in these cases were discarded because choosing a dominated alternative suggested that the respondent may have not been paying attention or may have not understood the task.

Attributes for the survey were altered to reflect modern market conditions. First, we update several of the aesthetic options available to the survey participant to reflect modern vehicle designs. Operating cost were updated to reflect modern energy efficiencies and fuel prices.[5] BEV ranges were updated to reflect modern BEV ranges available. PHEV fast charging was not included in this survey. Prices were adjusted to account for inflation. See Tables 1 and 2 for a full list of levels used in both surveys.

Individuals were screened using the following criteria: 1) they (alone or or together with a partner) are the primary decision maker when it comes to vehicle purchases and 2) they have bought a car in the last year or intend to in the next two years. Data from those who did not pass both attention check questions were omitted. These are the same criteria as applied in Helveston et al. (2015). The newly-collected data and Helveston et al. (2015) data were weighted against the nationally representative Maritz survey from 2018 and 2010, respectively.

Multinomial Logit Results

For simplicity and for comparison, we first estimate a multinomial logit model (Train, 2009) before estimating our preferred mixed logit model. Consistent with the logit assumption in the multinomial logit that preference coefficients are homogeneous, we estimate standard errors under the assumption that there is no panel relationship amongst our data (each

[5]Operating cost values are calculated based on the reported, combined MPG/MPGe rating for each vehicle. Conversion from MPGe to operating costs is based on U.S. Environmental Protection Agency (2016). See Ganz (2021) for a longer description of MPGe. Gasoline and electric costs are $2.636/gallon and $0.1304/kWh, which were used in the survey and are based on 2019 averages from U.S. Energy Information Administration (2020a,b).

observation is independent). This artifact of the model specification likely leads to over-confident estimates of parameter coefficients, but we present the results from this model only as a point of reference.

Like our preferred mixed logit specification, the logit results suggest that willingness to pay for American cars (relative to other cars) has dropped. The logit results also suggest that willingness to pay for reductions in operating cost has increased. The logit results also suggest a difference in scaling factor (the degree to which choice patterns appear systematic vs. random).

Estimation

Weighting Procedures

In order to treat data consistently, we both weight the newly-collected data and reweight data from Helveston et al. (2015) using a procedure described in the following paragraph. These data are weighted to demographic data collected from Maritz for the 2018 and 2010 year respectively - data that is nationally representative of the vehicle-buying population. Each group of vehicle buyers (passenger-car buyers, etc.) is weighted to the demographic characteristics of those who bought vehicles of that given vehicle type.

We implement an improved weighting procedure relative to that which was used in Helveston et al. (2015). We follow a weighting procedure that is outlined in Barratt et al. (2021). Essentially this involved weighting the data by minimizing the KL-divergence and subjecting the weights to constraints such that no individual can be weighted more than 25 times than any other individual. The latter set of constraints is consistent with that which was used in Helveston et al. (2015).

We collected various demographic data throughout the survey that overlaps with data provided in the Maritz surveys: age, marital status, household income, education level, gender/sex.[6] We weight on the joint distribution of decade of age (e.g. being 25 is in one's 3rd decade of age) and household income. After removing individuals who did not provide information used for the weighting procedure, we are left with 734 car buyer respondents and 862 SUV buyers respondents. Results can be seen in Tables 3 to 6.

[6] We collect information on the gender identity for respondents, Maritz collected data on their sex. Due to the discrepancy in information, we assume that the sex people responded with in the Maritz survey reflects their gender identity.

Table 3: Demographic weighting outcomes for this study's car-buyer data.

Variable	Unweighted	Weighted	Maritz 2018
Age	50.4	54.5	54.7
	(17.5)	(15.7)	(15.7)
Single	0.41	0.31	0.39
	(0.49)	(0.46)	(0.49)
Income	75.5	109.3	128.1
	(46.1)	(53.8)	(97.4)
College Grad	0.62	0.74	0.55
	(0.48)	(0.44)	(0.5)
Woman	0.51	0.48	0.46
	(0.5)	(0.5)	(0.5)
Household Size	2.44	2.6	1.99
	(1.28)	(1.3)	(1.14)

Table 4: Demographic weighting outcomes for this study's SUV-buyer data.

Variable	Unweighted	Weighted	Maritz 2018
Age	53.4	55.6	56.5
	(17.1)	(14.6)	(14.2)
Single	0.3	0.19	0.26
	(0.46)	(0.39)	(0.44)
Income	83.2	121.2	150.8
	(49.2)	(54.5)	(104.7)
College Grad	0.6	0.75	0.55
	(0.49)	(0.43)	(0.5)
Woman	0.52	0.47	0.47
	(0.5)	(0.5)	(0.5)
Household Size	2.6	2.66	2.05
	(1.29)	(1.2)	(1.18)

Table 5: Demographic weighting outcomes for car-buyer data from Helveston et al. (2015).

Variable	Unweighted	Weighted	Maritz 2010
Age	33.8	46.7	51.8
	(12.4)	(13.8)	(15.9)
Single	0.61	0.34	0.17
	(0.49)	(0.48)	(0.38)
Income	64.6	92.1	119.5
	(33.0)	(28.5)	(88.9)
College Grad	0.53	0.71	0.55
	(0.5)	(0.46)	(0.5)
Woman	0.34	0.36	0.45
	(0.48)	(0.48)	(0.5)
Household Size	2.67	2.81	2.38
	(1.27)	(1.17)	(1.15)

Table 6: Demographic weighting outcomes for SUV-buyer data from Helveston et al. (2015).

Variable	Unweighted	Weighted	Maritz 2010
Age	37.8	45.5	51.7
	(11.2)	(11.7)	(14.3)
Single	0.44	0.36	0.1
	(0.5)	(0.48)	(0.3)
Income	69.3	96.3	143.6
	(34.3)	(24.5)	(101.0)
College Grad	0.54	0.65	0.57
	(0.5)	(0.48)	(0.49)
Woman	0.49	0.44	0.47
	(0.5)	(0.5)	(0.5)
Household Size	2.96	3.02	2.55
	(1.35)	(1.27)	(1.16)

Functional Form Decisions

We estimate our preferred specifications in willingness-to-pay (WTP) space (Train and Weeks, 2005). WTP space has desirable properties for the resulting estimation uncertainty of WTP parameters (Helveston et al., 2018; Train and Weeks, 2005). Still, tradeoffs exist (including nonconcave log-likelihood functions, which we maximize using randomized multistart with gradient based algorithms) (Carson and Czajkowski, 2019; Train and Weeks, 2005). We adopt the willingness to pay space as we are most interested in characterizing the monetary tradeoffs that consumers are making with choice share prediction being of secondary interest.

Our primary specification follows that which was used in Helveston et al. (2015) except we allow for a continuous parameterization of WTP for BEV range. Past parameterizations of range in the utility function have taken many forms: linear (Brownstone, 1999; Haaf et al., 2014; Hess et al., 2006; McFadden and Train, 2000; Nixon and Saphores, 2011; Segal, 1995; Tanaka et al., 2014; Train and Sonnier, 2005; Train and Weeks, 2005),[7] quadratic (Brownstone et al., 2018, 1996), log (Daziano, 2013; Hess et al., 2012; Kavalec, 1999), partworth (Hidrue et al., 2011; Parsons et al., 2014; Zhang et al., 2011), and indirectly through its relationship to efficiency and tank size (Walls, 1996). Therefore, there isn't a clear direction for range parameterization from the literature nor in our cross-validation exercises, so we choose the functional form that was most interpretable (linear-in-range) but provide the results for a model estimated with BEV range being transformed using inverse hyperbolic sine. Inverse hyperbolic sine was chosen due to its similar behavior to the natural logarithm while still allowing for zero values (Bellemare and Wichman, 2020). All other parameterizations follow the preferred specification presented in Helveston et al. (2015).

Full Results

We present the full set of results in the following subsections.

Differences Over Time

Multinomial Logit

Table 7, we present the Wald test results for difference over time in our preferred multinomial logit specification. Most coefficients are not identifiably different at the 5% significance level with the exception of the scaling factor for both vehicle types, American cars, BEV range, and operating cost for car buyers. This is in line with previous work, which shows that individuals were not meaningfully more likely to consider electric vehicles from 2014 to 2017 (Kurani, 2019).

[7] Nixon and Saphores (2011) characterizes the range relative to gas vehicles.

Table 7: Willingness-to-Pay Equality Tests Across Studies - Multinomial Logit

Attribute	Car-Buyer Equality of Means Wald Stat	SUV-Buyer Equality of Means Wald Stat
Acceleration	3.16	1.91
Operating Cost	4.03*	0.63
Gasoline-electric hybrid	2.33	1.5
PHEV 20	0.15	0.53
PHEV 40	0.08	3.72
300-Mile Range BEV	2.85	0.0
BEV Range (100s of Miles)	5.72*	0.06
No BEV Fast Charging	0.11	2.5
American	14.6***	2.34
Chinese	1.31	2.41
Japanese	0.04	1.02
South Korean	1.67	1.73
Scaling Factor	18.16***	27.02***

* $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$

Mixed Logit

Table 8, we present the Wald test results for difference over time in our preferred mixed logit specification. Most tests are not statistically significantly different at the 5% level with the exception of the scaling factor for both vehicle types, and both the mean and full distribution for American cars among car buyers.

Table 8: Willingness-to-Pay Equality Tests Across Studies - Mixed Logit

Attribute	Car-Buyers		SUV-Buyers	
	Equality of Means Wald Stat	Equality of Distribution Wald Stat	Equality of Means Wald Stat	Equality of Distribution Wald Stat
Acceleration	0.89	7.29*	0.47	2.93
Operating Cost	1.58	4.09	0.18	3.71
HEV	1.41	1.41	0.3	0.59
PHEV 20	0.09	0.99	0.27	0.37
PHEV 40	0.03	1.6	1.76	3.84
300-Mile Range BEV	1.25	1.71	1.18	1.71
BEV Range (100s of Miles)	2.84	3.04	1.26	1.48
No BEV Fast Charging	0.0	2.42	0.48	2.89
American	11.52***	11.72**	0.77	4.69
Chinese	0.16	0.47	0.89	1.64
Japanese	0.06	0.08	0.03	0.14
South Korean	0.48	1.22	1.36	2.62
Scaling Factor	24.01***	–	11.31***	–

* $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$

Functional Form Comparison

In this section, we present the full set of results for both our preferred linear specification (presented in the main body) and an alternative specification that uses an inverse hyperbolic sine transformation of range.[8] This alternative specification (shown in Eqs. (2) and (3)) was chosen for it's log-like behavior (Bellemare and Wichman, 2020). However, as shown inTables 9, 10, 12 and 13, the linear model outperforms or performs approximately equally to the inverse hyperbolic sine model in log-likelihood in all cases.

$$\nu_{ijt} = \lambda \left(\alpha_i a_{ijt} + \omega_i o_{ijt} + \beta b_{ijt} + \rho_i \text{asinh}\left(r_{ijt}\right) + \eta_i f_{ijt} + \boldsymbol{\delta}_i^\top \mathbf{x}_{ijt} - p_{ijt}\right) + \epsilon_{ijt} \quad (2)$$

$$\nu_{ijt} = \lambda \left(\alpha a_{ijt} + \omega o_{ijt} + \beta b_{ijt} + \rho \text{asinh}\left(r_{ijt}\right) + \eta f_{ijt} + \boldsymbol{\delta}^\top \mathbf{x}_{ijt} - p_{ijt}\right) + \epsilon_{ijt} \quad (3)$$

2021 Study

Tables 9 and 10 shows the results for both the linear and inverse hyperbolic sine range parameterization for car-buyer and SUV-buyer data from the 2021 study survey data. Additionally, Table 11 shows the comparison of range formulations performance in five-fold cross validation exercise. We see that there is no clear patter as to which performs better on out-of-sample prediction, so we opt to use the linear specification as it is more interpretable. Still, both formulations are shown here.

[8] All WTP coefficients are assumed to independently and normally distributed.

Table 9: Full results for 2021 study car buyers

Attribute	Parameter	Linear-in-Range	Linear-in-Range	Arcsinh-in-Range	Arcsinh-in-Range
Price	μ	0.066*** (0.002)	0.1*** (0.003)	0.066*** (0.002)	0.093*** (0.003)
Acceleration	μ	-1.31*** (0.18)	-1.41*** (0.26)	-1.31*** (0.18)	-1.43*** (0.26)
	σ		2.42*** (0.24)		2.38*** (0.23)
Operating Cost	μ	-1.87*** (0.12)	-1.94*** (0.2)	-1.87*** (0.12)	-1.94*** (0.19)
	σ		1.82*** (0.16)		1.77*** (0.16)
HEV	μ	1.19 (1.17)	1.16 (1.17)	1.19 (1.17)	1.29 (1.19)
	σ		6.73*** (1.55)		6.28*** (1.62)
PHEV 20	μ	0.26 (1.15)	0.22 (1.09)	0.27 (1.15)	0.17 (1.12)
	σ		3.12 (2.47)		3.33 (1.97)
PHEV 40	μ	2.02 (1.17)	1.94 (1.05)	2.04 (1.17)	1.99 (1.07)
	σ		1.97 (1.61)		0.85 (1.22)
BEV (w/ equivalent range)	μ	-3.42** (1.07)	-3.91 (1.99)		
	σ		15.97*** (1.3)		
Add'l Range (100s of mi.)	μ	4.64*** (0.39)	5.05*** (0.73)		
	σ		6.69*** (0.62)		
BEV (0-mi range)	μ			-68.15*** (5.42)	-69.05*** (5.22)
	σ				12.36*** (3.17)
arcsinh(Add'l Range)	μ			10.26*** (0.87)	10.31*** (0.82)
	σ				1.69* (0.65)
No BEV Fast Charging	μ	-3.97*** (0.89)	-4.27*** (0.96)	-3.95*** (0.89)	-4.01*** (0.98)
	σ		5.37*** (1.37)		5.78*** (1.53)
American	μ	-1.72 (0.92)	-1.94 (1.15)	-1.75 (0.92)	-2.0 (1.18)
	σ		9.69*** (1.04)		9.6*** (1.02)
Chinese	μ	-18.25*** (1.14)	-21.08*** (2.41)	-18.27*** (1.14)	-20.77*** (2.41)
	σ		20.46*** (1.77)		20.08*** (1.62)
Japanese	μ	-0.88 (0.93)	-0.34 (1.14)	-0.88 (0.93)	-0.51 (1.16)
	σ		9.08*** (1.22)		9.18*** (1.27)
South Korean	μ	-5.95*** (0.94)	-5.57*** (1.08)	-6.01*** (0.94)	-5.79*** (1.12)
	σ		8.14*** (1.09)		8.59*** (1.05)
Log-likelihood		-9336.0	-8409.2	-9334.1	-8538.8
# of Individuals		734	734	734	734
# of Observations		11010	11010	11010	11010

Table 10: Full results for 2021 study SUV buyers

Attribute	Parameter	Linear-in-Range	Linear-in-Range	Arcsinh-in-Range	Arcsinh-in-Range
Price	μ	0.072*** (0.002)	0.105*** (0.004)	0.072*** (0.002)	0.098*** (0.003)
Acceleration	μ	-1.31*** (0.24)	-1.46*** (0.34)	-1.31*** (0.24)	-1.46*** (0.34)
	σ		3.3*** (0.36)		3.2*** (0.39)
Operating Cost	μ	-1.37*** (0.08)	-1.49*** (0.12)	-1.37*** (0.08)	-1.45*** (0.12)
	σ		1.13*** (0.11)		1.14*** (0.11)
HEV	μ	1.12 (0.99)	1.18 (1.02)	1.13 (0.99)	1.43 (1.04)
	σ		5.05*** (1.38)		5.06** (1.53)
PHEV 20	μ	-1.91 (1.0)	-1.44 (0.92)	-1.91 (1.0)	-1.42 (0.95)
	σ		0.09 (0.66)		0.21 (0.6)
PHEV 40	μ	-0.88 (0.99)	-0.61 (0.97)	-0.86 (0.98)	-0.39 (0.98)
	σ		4.01* (1.57)		3.27 (1.98)
BEV (w/ equivalent range)	μ	-7.86*** (0.97)	-8.91*** (1.97)		
	σ		15.7*** (1.3)		
Add'l Range (100s of mi.)	μ	6.35*** (0.38)	7.05*** (0.72)		
	σ		6.95*** (0.6)		
BEV (0-mi range)	μ			-97.24*** (5.5)	-96.27*** (5.55)
	σ				15.96*** (1.68)
arcsinh(Add'l Range)	μ			14.17*** (0.87)	13.97*** (0.84)
	σ				0.32 (1.27)
No BEV Fast Charging	μ	-3.33*** (0.84)	-4.2*** (1.01)	-3.33*** (0.85)	-3.83*** (1.02)
	σ		6.5*** (1.29)		6.56*** (1.38)
American	μ	3.72*** (0.83)	3.68** (1.21)	3.75*** (0.83)	4.08** (1.27)
	σ		11.1*** (0.97)		11.58*** (0.98)
Chinese	μ	-15.93*** (0.99)	-19.0*** (1.85)	-15.99*** (0.99)	-18.99*** (1.92)
	σ		16.56*** (1.4)		16.89*** (1.49)
Japanese	μ	0.54 (0.81)	0.34 (1.05)	0.53 (0.81)	0.48 (1.09)
	σ		8.86*** (1.2)		9.4*** (1.26)
South Korean	μ	-5.51*** (0.83)	-5.4*** (0.93)	-5.52*** (0.83)	-5.36*** (0.93)
	σ		6.58*** (1.06)		6.24*** (1.13)
Log-likelihood		-10592.0	-9521.1	-10583.2	-9676.4
# of Individuals		862	862	862	862
# of Observations		12930	12930	12930	12930

Table 11: Results from five-fold cross-validation exercise for newly-collected data.

Vehicle Type	Range Parameterization	Model Spec.	Weight Year	Mean Out-of-Sample LL	Mean In-Sample LL
Car	Asinh	MNL	2018	-1944	-7397
Car	Linear	MNL	2018	-1879	-7464
SUV	Asinh	MNL	2018	-2112	-8478
SUV	Linear	MNL	2018	-2129	-8469
Car	Asinh	MXL	2018	-1952	-6723
Car	Linear	MXL	2018	-1851	-6724
SUV	Asinh	MXL	2018	-2057	-7755
SUV	Linear	MXL	2018	-2102	-7619

2015 Study

Tables 12 and 13 shows the results for both the linear and inverse hyperbolic sine range parameterization for car-buyer and SUV-buyer data from the Helveston et al. (2015) data.

Table 12: Full results for Helveston et al. (2015) car buyers

Attribute	Parameter	Linear-in-Range	Linear-in-Range	Arcsinh-in-Range	Arcsinh-in-Range
Price	μ	0.05*** (0.003)	0.071*** (0.005)	0.05*** (0.003)	0.07*** (0.005)
Acceleration	μ	-2.13*** (0.42)	-2.17* (0.77)	-2.13*** (0.42)	-2.19* (0.78)
	σ		4.17*** (0.64)		4.12*** (0.64)
Operating Cost	μ	-1.49*** (0.15)	-1.53*** (0.26)	-1.49*** (0.15)	-1.54*** (0.25)
	σ		1.42*** (0.2)		1.45*** (0.2)
HEV	μ	-3.12 (2.58)	-2.21 (2.58)	-3.11 (2.58)	-2.35 (2.65)
	σ		6.99 (3.26)		8.13** (2.64)
PHEV 10	μ	-3.05 (2.67)	-2.23 (2.47)	-3.05 (2.67)	-2.04 (2.47)
	σ		0.42 (0.84)		0.62 (1.3)
PHEV 20	μ	1.43 (2.77)	1.03 (2.53)	1.44 (2.77)	1.18 (2.52)
	σ		0.61 (0.91)		0.03 (0.71)
PHEV 40	μ	1.22 (2.66)	1.46 (2.57)	1.23 (2.66)	1.82 (2.53)
	σ		6.61 (3.31)		5.6 (4.71)
PHEV Fast Charging	μ	4.08 (2.09)	2.99 (2.19)	4.09 (2.09)	2.93 (2.13)
	σ		8.3** (2.79)		7.4* (2.85)
BEV (w/ equivalent range)	μ	9.14 (7.36)	4.53 (7.29)		
	σ		11.96* (4.33)		
Add'l Range (100s of mi.)	μ	13.48*** (3.67)	11.7** (3.88)		
	σ		8.62*** (2.06)		
BEV (0-mi range)	μ			-94.27*** (22.01)	-75.77*** (20.55)
	σ				18.32*** (2.68)
arcsinh(Add'l Range)	μ			14.54** (4.06)	10.77* (3.78)
	σ				1.46* (0.55)
No BEV Fast Charging	μ	-4.79 (2.31)	-4.45 (2.66)	-4.79 (2.31)	-4.14 (2.57)
	σ		10.75** (3.29)		9.65* (3.38)
American	μ	6.84** (2.04)	7.56** (2.55)	6.84** (2.04)	7.29* (2.52)
	σ		12.08*** (2.41)		11.82*** (2.44)
Chinese	μ	-21.31*** (2.42)	-22.83*** (3.64)	-21.32*** (2.42)	-22.6*** (3.75)
	σ		18.89*** (2.88)		19.25*** (3.09)
Japanese	μ	-0.42 (2.04)	0.27 (2.21)	-0.42 (2.04)	0.19 (2.27)
	σ		8.67** (2.49)		9.55*** (2.28)
South Korean	μ	-9.02*** (2.18)	-7.19** (2.08)	-9.01*** (2.18)	-7.31** (2.1)
	σ		5.52 (3.54)		5.67 (3.85)
Log-likelihood		-4563.7	-4218.5	-4564.4	-4222.3
# of Individuals		358	358	358	358
# of Observations		5370	5370	5370	5370

Table 13: Full results for Helveston et al. (2015) SUV buyers

Attribute	Parameter	Linear-in-Range	Linear-in-Range	Arcsinh-in-Range	Arcsinh-in-Range
Price	μ	0.046*** (0.005)	0.074*** (0.009)	0.046*** (0.005)	0.075*** (0.009)
Acceleration	μ	-2.25** (0.64)	-2.01* (0.73)	-2.25** (0.64)	-1.94* (0.67)
	σ		2.05* (0.81)		1.74 (0.86)
Operating Cost	μ	-1.18*** (0.22)	-1.22 (0.62)	-1.18*** (0.22)	-1.19 (0.61)
	σ		2.03*** (0.47)		2.09*** (0.45)
HEV	μ	6.37 (4.17)	3.51 (4.1)	6.37 (4.17)	3.12 (4.31)
	σ		8.26 (5.23)		9.26 (4.68)
PHEV 10	μ	-0.07 (4.36)	-0.18 (3.92)	-0.09 (4.36)	0.64 (4.16)
	σ		1.78 (7.27)		6.61 (5.04)
PHEV 20	μ	1.13 (4.05)	0.54 (3.68)	1.1 (4.05)	0.47 (3.63)
	σ		0.87 (3.22)		3.95 (3.23)
PHEV 40	μ	7.56 (4.27)	5.45 (4.46)	7.54 (4.26)	5.96 (4.19)
	σ		10.49 (4.92)		7.9 (4.56)
PHEV Fast Charging	μ	-1.32 (3.29)	-0.43 (3.57)	-1.32 (3.29)	-1.04 (3.58)
	σ		8.8 (4.56)		10.74* (3.8)
BEV (w/ equivalent range)	μ	-7.42 (12.13)	4.85 (12.52)		
	σ		21.69* (7.51)		
Add'l Range (100s of mi.)	μ	7.87 (6.04)	13.7 (5.88)		
	σ		5.1 (4.37)		
BEV (0-mi range)	μ			-71.21 (36.04)	-91.07* (33.78)
	σ				13.11 (8.33)
arcsinh(Add'l Range)	μ			9.12 (6.65)	12.98 (6.22)
	σ				3.6* (1.43)
No BEV Fast Charging	μ	3.28 (4.09)	-0.43 (5.35)	3.33 (4.09)	0.38 (4.78)
	σ		14.83* (5.87)		12.35 (6.53)
American	μ	8.68* (3.13)	9.17 (6.15)	8.67* (3.13)	8.65 (5.7)
	σ		22.11*** (5.43)		21.1*** (4.76)
Chinese	μ	-22.04*** (3.81)	-25.36*** (6.47)	-22.05*** (3.81)	-23.54*** (6.11)
	σ		21.92*** (4.82)		23.0*** (4.76)
Japanese	μ	3.93 (3.25)	1.02 (3.6)	3.92 (3.25)	1.62 (3.46)
	σ		10.11** (3.28)		9.45* (3.77)
South Korean	μ	-10.4* (3.62)	-10.48* (4.26)	-10.4* (3.62)	-10.65 (4.74)
	σ		11.79 (5.57)		15.01* (5.31)
Log-likelihood		-1541.3	-1375.5	-1541.0	-1372.8
# of Individuals		116	116	116	116
# of Observations		1740	1740	1740	1740

Estimates of Those Unaffected by the COVID-19 Pandemic

We ask individuals in the survey in which of the following ways they were impacted by the COVID-19 pandemic: Permanent job loss, Temporary job loss, Salary reduction, None of the above. For those that selected "None of the above", we re-estimate our models with that subset of data. We find that results remain comparable across the samples, indicating that the COVID-19 pandemic is not a major driver of consumer preferences.

Car-Buyers

Figure 7 shows our preferred coefficients estimated with the entire 2021 study car-buyer data and only who responded as being unaffected economically by the COVID-19 pandemic. As can be seen, these coefficients overlap closely, which provides evidence that COVID-related behaviors are not driving any particular results.

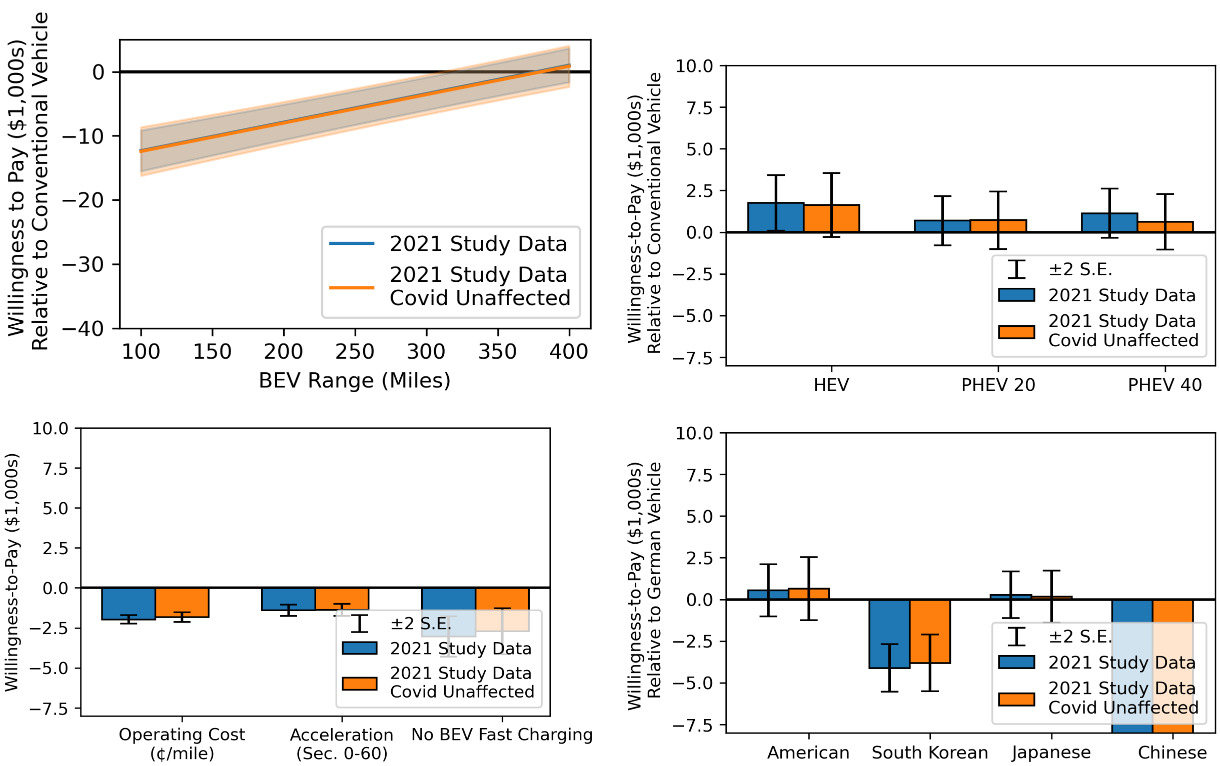


Figure 7: Mixed logit estimation with full sample and those unaffected by Covid-19. Note that the top left subfigure uses a different y-axis than the other three subfigures.

SUV-Buyers

Figure 8 shows our preferred coefficients estimated with the entire 2021 study SUV-buyer data and only who responded as being unaffected economically by the COVID-19 pandemic. As can be seen, these coefficients overlap closely, which provides evidence that COVID-related behaviors are not driving any particular results.

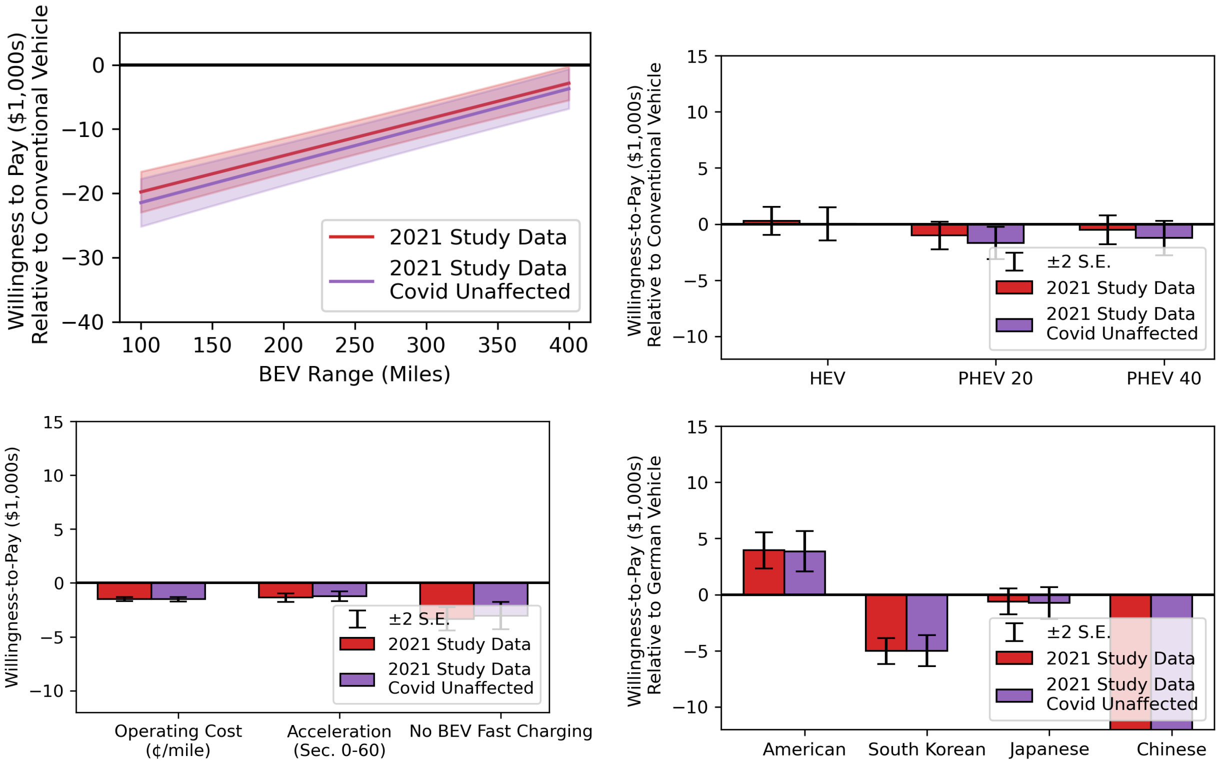


Figure 8: Mixed logit estimation with full sample and those unaffected by Covid-19.

MTurk Specific Model Comparison

In our preferred preference estimates, we compare results when using the full datasets from this study as well as Helveston et al. (2015). These data each combine two sources of data. This study collects data from mTurk and Dynata surveying populations. Helveston et al. (2015, p.102) collects data from mTurk and the Pittsburgh Auto Show. In order to identify if the change in sources of data was driving any results, we estimate our preferred specification models with both datasets using only mTurk data and compare over time.

Car-Buyers

For car buyers, the Wald test results are presented in Tables 14 and 15. The only major difference in the multinomial logit specification are increased significance levels for acceleration, operating cost, and Chinese cars. For the mixed logit specification, operating cost WTP becomes significantly different in means and distribution at the 1% and 0.1% level respectively. Additionally, there is a change in the distribution of WTP for Chinese cars.

Table 14: Comparison of 2015 study and 2021 study car buyer estimates with only MTurk-collected Data

Attribute	Equality of Means Wald Stat
Acceleration	4.38*
Operating Cost	22.48***
HEV	0.02
PHEV 20	0.05
PHEV 40	0.22
300-Mile Range BEV	0.01
BEV Range (100s of Miles)	0.05
American	17.5***
Chinese	4.78*
Japanese	2.57
South Korean	0.83
Scaling Factor	3.1

Table 15: Comparison of 2015 study and 2021 study car buyer estimates with only MTurk-collected Data

Attribute	Equality of Means Wald Stat	Equality of Distribution Wald Stat
Acceleration	1.18	2.03
Operating Cost	8.31**	19.0***
HEV	0.04	2.12
PHEV 20	0.06	0.07
PHEV 40	0.07	0.54
300-Mile Range BEV	0.07	0.68
BEV Range (100s of Miles)	0.0	0.59
American	17.22***	17.23***
Chinese	2.64	7.91*
Japanese	1.62	1.75
South Korean	0.85	1.25
Scaling Factor	1.01	–

SUV-Buyers

For car buyers, the Wald test results are presented in Tables 16 and 17.

Table 16: Comparison of 2015 study and 2021 study SUV buyer estimates with only MTurk-collected Data

Attribute	Equality of Means Wald Stat
Acceleration	3.1
Operating Cost	0.22
HEV	0.2
PHEV 20	0.42
PHEV 40	0.06
300-Mile Range BEV	3.06
BEV Range (100s of Miles)	3.58
American	1.32
Chinese	0.64
Japanese	0.07
South Korean	0.13
Scaling Factor	2.07

Table 17: Comparison of 2015 study and 2021 study SUV buyer estimates with only MTurk-collected Data

Attribute	Equality of Means Wald Stat	Equality of Distribution Wald Stat
Acceleration	4.23*	5.63
Operating Cost	0.23	0.24
HEV	0.3	3.36
PHEV 20	0.55	1.73
PHEV 40	0.05	5.35
300-Mile Range BEV	2.92	3.91
BEV Range (100s of Miles)	4.13*	4.15
American	0.76	5.62
Chinese	0.59	0.83
Japanese	0.43	0.63
South Korean	0.46	2.2
Scaling Factor	1.21	–

Mechanical Turk-Dynata Comparison

In the following tables, we present Wald test statistics between estimates based on the 2021 Mechanical Turk and 2021 Dynata weighted samples alone. As one can see, there are minimal differences for the car-buying population under a mixed logit (our preferred) specification. Across means, only the mean WTP for a 300-mile range BEV is statistically significant at the 5% level. The SUV-buying population does exhibit more differences as the mean values for electrification. Likely, these estimates differ due to differences in their demographics (see Tables 22 and 23).

Car-Buyers

Table 18: Comparison across 2021 Mechanical Turk and Dynata Car-Buyer Estimates - Mixed Logit

Attribute	Equality of Means Wald Stat	Equality of Distribution Wald Stat
Acceleration	2.05	6.21*
Operating Cost	3.65	3.65
HEV	0.21	0.41
PHEV 20	0.12	0.12
PHEV 40	0.02	0.06
300-Mile Range BEV	6.19*	6.6*
BEV Range (100s of Miles)	3.93*	3.96
American	0.96	10.08**
Chinese	3.04	3.04
Japanese	0.81	8.99*
South Korean	1.62	4.36
Scaling Factor	28.09***	–

SUV-Buyers

Table 19: Comparison across 2021 Mechanical Turk and Dynata SUV-Buyer Estimates - Mixed Logit

Attribute	Equality of Means Wald Stat	Equality of Distribution Wald Stat
Acceleration	5.56*	5.58
Operating Cost	2.32	2.38
HEV	1.73	1.81
PHEV 20	14.41***	15.21***
PHEV 40	15.28***	27.68***
300-Mile Range BEV	7.6**	10.77**
BEV Range (100s of Miles)	0.02	3.64
American	0.3	5.4
Chinese	1.41	2.18
Japanese	2.4	11.33**
South Korean	0.56	5.08
Scaling Factor	17.39***	–

Table 20: Demographic weighting outcomes for this study's Mechanical Turk car-buyer data.

Variable	Unweighted	Weighted	Maritz 2018
Age	39.2	47.4	54.7
	(11.8)	(13.6)	(15.7)
Single	0.44	0.35	0.39
	(0.5)	(0.48)	(0.49)
Income	69.3	102.3	128.1
	(42.4)	(52.8)	(97.4)
College Grad	0.62	0.72	0.55
	(0.49)	(0.45)	(0.5)
Woman	0.52	0.54	0.46
	(0.5)	(0.5)	(0.5)
Household Size	2.74	3.01	1.99
	(1.38)	(1.44)	(1.14)

Table 21: Demographic weighting outcomes for this study's Dynata car-buyer data.

Variable	Unweighted	Weighted	Maritz 2018
Age	60.4	57.0	54.7
	(15.7)	(14.8)	(15.7)
Single	0.39	0.27	0.39
	(0.49)	(0.44)	(0.49)
Income	75.9	105.9	128.1
	(45.8)	(50.3)	(97.4)
College Grad	0.63	0.76	0.55
	(0.48)	(0.43)	(0.5)
Woman	0.49	0.44	0.46
	(0.5)	(0.5)	(0.5)
Household Size	2.17	2.44	1.99
	(1.11)	(1.17)	(1.14)

Table 22: Demographic weighting outcomes for this study's Mechanical Turk SUV-buyer data.

Variable	Unweighted	Weighted	Maritz 2018
Age	39.6	48.0	56.5
	(11.1)	(12.3)	(14.2)
Single	0.26	0.18	0.26
	(0.44)	(0.39)	(0.44)
Income	77.9	114.4	150.8
	(47.5)	(56.8)	(104.7)
College Grad	0.6	0.79	0.55
	(0.49)	(0.4)	(0.5)
Woman	0.59	0.54	0.47
	(0.49)	(0.5)	(0.5)
Household Size	3.18	2.97	2.05
	(1.39)	(1.26)	(1.18)

Table 23: Demographic weighting outcomes for this study's Dynata SUV-buyer data.

Variable	Unweighted	Weighted	Maritz 2018
Age	63.5	60.0	56.5
	(13.2)	(13.3)	(14.2)
Single	0.33	0.24	0.26
	(0.47)	(0.43)	(0.44)
Income	81.8	112.3	150.8
	(47.1)	(50.9)	(104.7)
College Grad	0.6	0.73	0.55
	(0.49)	(0.45)	(0.5)
Woman	0.47	0.46	0.47
	(0.5)	(0.5)	(0.5)
Household Size	2.17	2.44	2.05
	(1.02)	(1.12)	(1.18)

Breakdown of Technology Preference Changes

It should be noted that that main body head to head figures are all based upon preferences identified with the most recently collected data. In order to identify how these changes in technology impact net WTP over time relative to underlying changes in preference, we plot the net WTP of all three technologies across two different sets of WTP estimates based on data from Helveston et al. (2015) and our newly-collected data respectively. Fig. 9 shows very clearly that both WTP estimates provide evidence of technology improvements improving BEV value. However, when comparing across outcomes based on different datasets, the overlapping uncertainty suggests that there is insufficient evidence here to suggest that underlying consumer preferences have changed over time. We examine this using statistical tests in the "Full Results" section of this document.

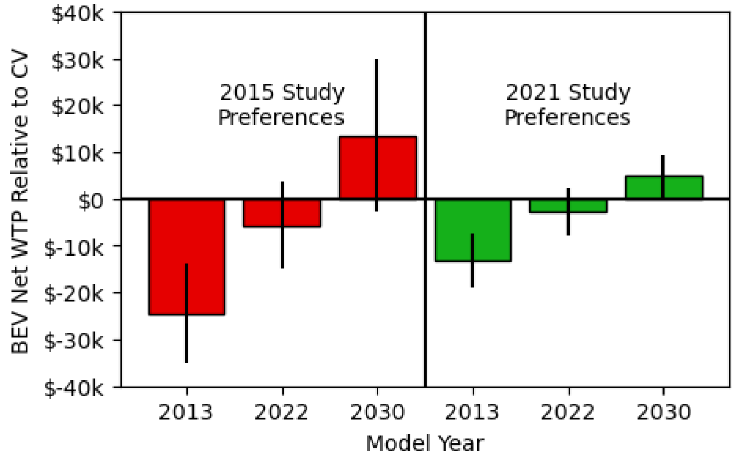


Figure 9: Comparison of net WTP across different technology offering and survey datasets for the Nissan Leaf and Versa. Error bars denote ±2 standard errors.

Market-Wide Simulation

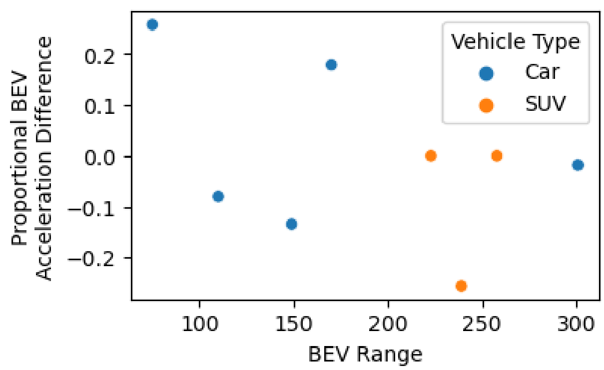
Simulation Details

In order to construct a market simulation, we begin with MY 2020 sales data from U.S. National Highway Traffic Safety Administration (2022). With these data, alternative-specific constants, conditional on the vehicles' estimated acceleration[9], operating cost, and price were calibrated to replicate market share for both cars and SUVs.

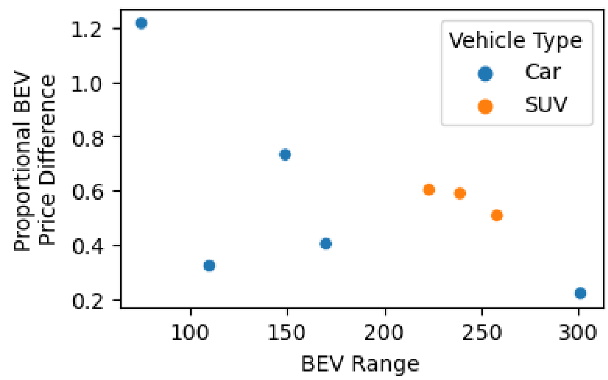
The future of acceleration for BEVs is not particularly clear because automakers may choose to forgoe acceleration improvements for other attributes due to the excellent acceleration already in many BEVs (Woo and Magee, 2020). Further, in our sample of collected head-to-head comparisons, we find inconsistent relative performance of BEVs (see Fig. 10a). Therefore, our base case assumptions in the main body assume that there will be no improvement in acceleration.

Additionally, we see wide ranges of price premiums (see Fig. 10b). In order to inform our MY2020 simulation, we use the mean proportional difference in prices to calculate the price premium for all hypothetical 2020 BEV offerings.

[9]We use the same acceleration estimation equation as Greene et al. (2018, Eq. 9).



(a) Proportional differences in 0-60 times amongst BEV-CV head-to-head comparison. Points represent specific vehicle models.

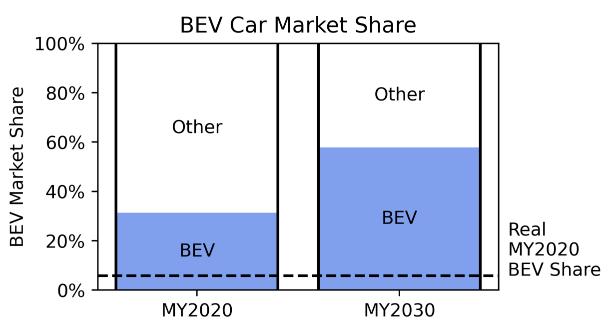


(b) Proportional differences in prices amongst BEV-CV head-to-head comparison. Points represent specific vehicle models.

Alternative Acceleration Assumptions

We run an alternative case where we assume a more optimistic case for the acceleration benefits of BEV offerings. Specifically, we reduce 0-60 acceleration time by roughly 25%, which is the most optimistic value we saw amongst our head-to-head comparisons in Fig. 10a.

As can be seen, in Fig. 11, we see no qualitative differences in adoption, which provides evidence that our simulation is not sensitive to acceleration performance assumptions.



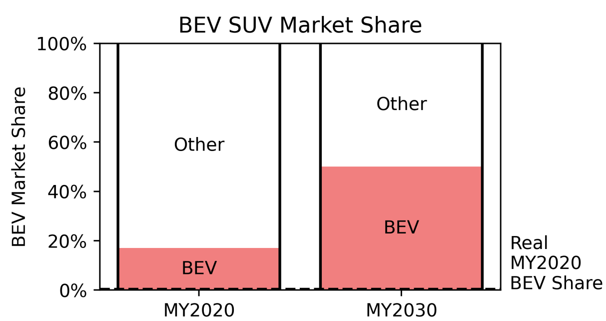


Figure 11: Hypothetical market-wide BEV simulation with alternative BEV acceleration assumptions

Alternative Fuel Cost Assumptions

In order to identify how sensitive our results are to fuel price levels, we ran an alternative simulation with fuel prices that come from more recent data. Specifically, we assume \$4.271/gallon of gasoline and \$0.1383/kWh (U.S. Energy Information Administration, 2022a,b).

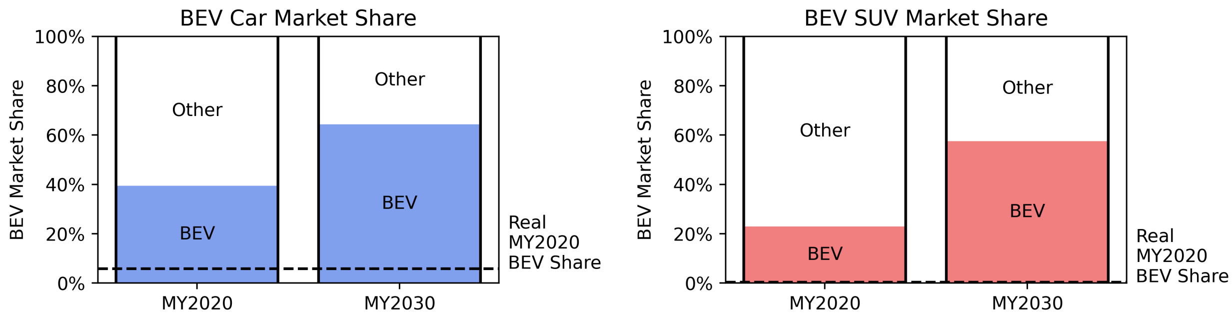


Figure 12: Hypothetical market-wide BEV simulation with alternative fuel cost assumptions

Alternative Operating Cost WTP Assumptions

Our final alternative assumption tests the sensitivity of our results to the relatively high WTP for operating cost that we measure within our sample. To test this, we plug in a fixed, alternative, operating cost WTP value, re-calibrate our ASCs, and then re-simulate our scenarios.

The alternative values used are based on extreme, exact valuation parameters presented in Gillingham et al. (2021, Table 8): 0.17 and 1.01. We take the discount rate associated with these values, the lifetime and mileage estimates from U.S. National Highway Traffic Safety Administration (2022), and the formula from Leard et al. (2019, p.64), to calculate the net present value of a 1¢ reduction in operating cost throughout the lifetime of a passenger car and SUV. We then multiply this value by the respective valuation parameters. These final values are then used in our simulations.

The results are shown in Figs. 13 and 14. The results show that our results are not particularly sensitive to our estimate WTP value, BEV adoption is still expected to grow dramatically given the simulated scenario.

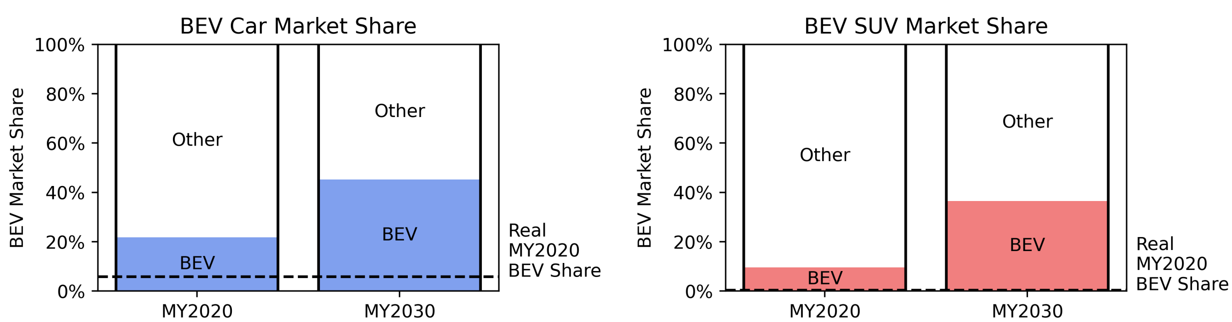


Figure 13: Hypothetical market-wide BEV simulation under an lower-bound alternative operating cost WTP assumption

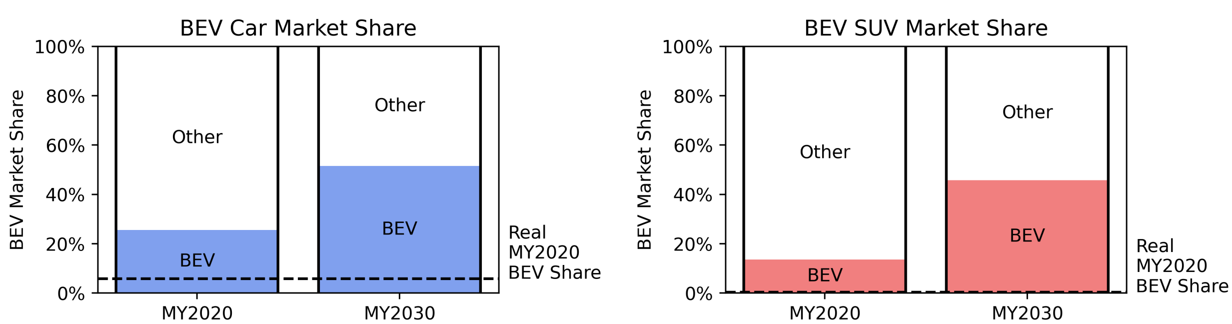


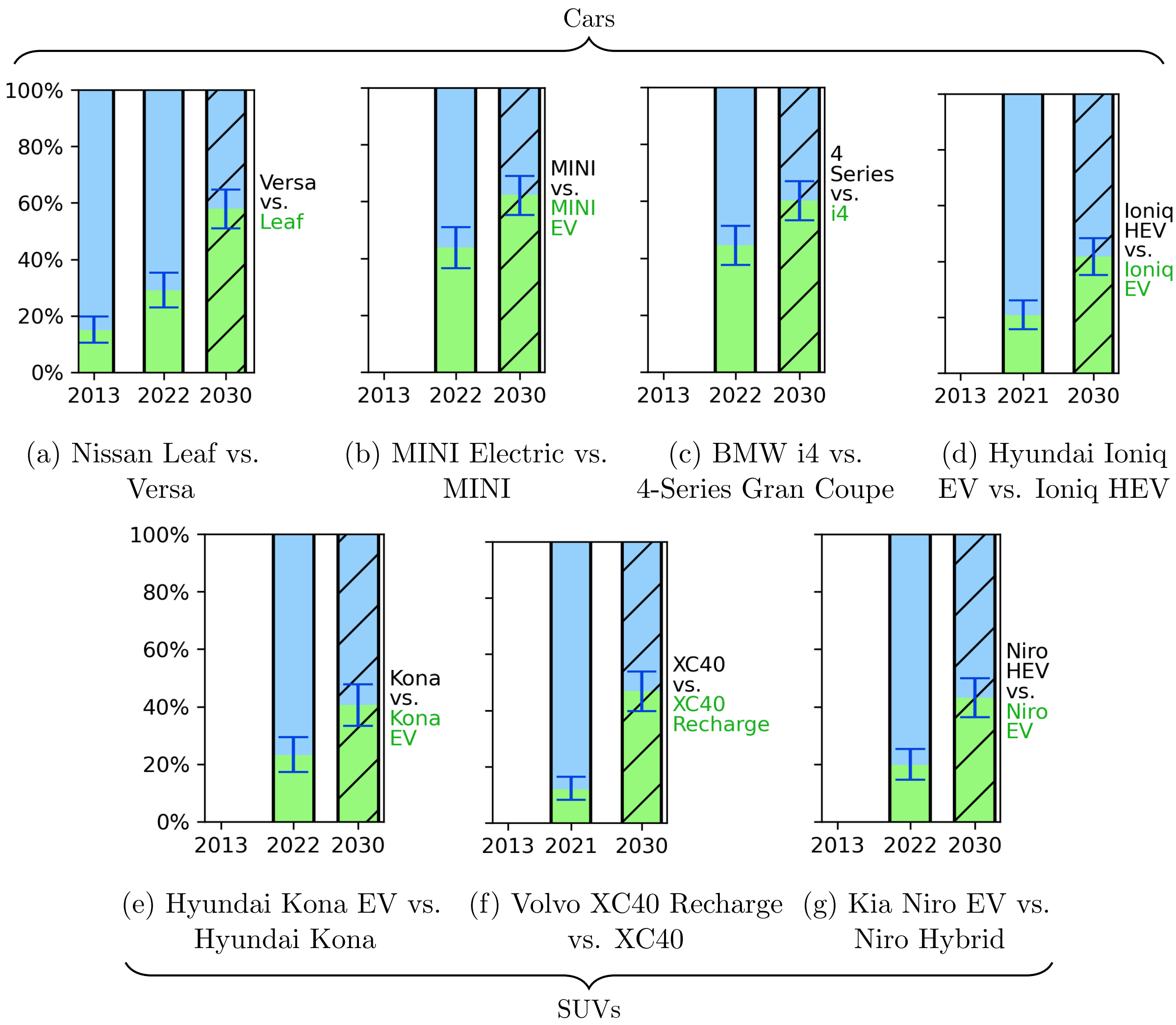
Figure 14: Hypothetical market-wide BEV simulation under an upper-bound alternative operating cost WTP assumption

Full Head-to-Head Results

BEV Comparison

Simulated Choice Shares

Figure 15 takes the same seven head-to-head comparisons from the main body of the paper and simulates the probability that a randomly selected individual will choose the BEV over the conventional vehicle. The same assumptions are made about the evolution of BEV technologies and costs as were made in the main body.



(a) Nissan Leaf vs. Versa

(b) MINI Electric vs. MINI

(c) BMW i4 vs. 4-Series Gran Coupe

(d) Hyundai Ioniq EV vs. Ioniq HEV

(e) Hyundai Kona EV vs. Hyundai Kona

(f) Volvo XC40 Recharge vs. XC40

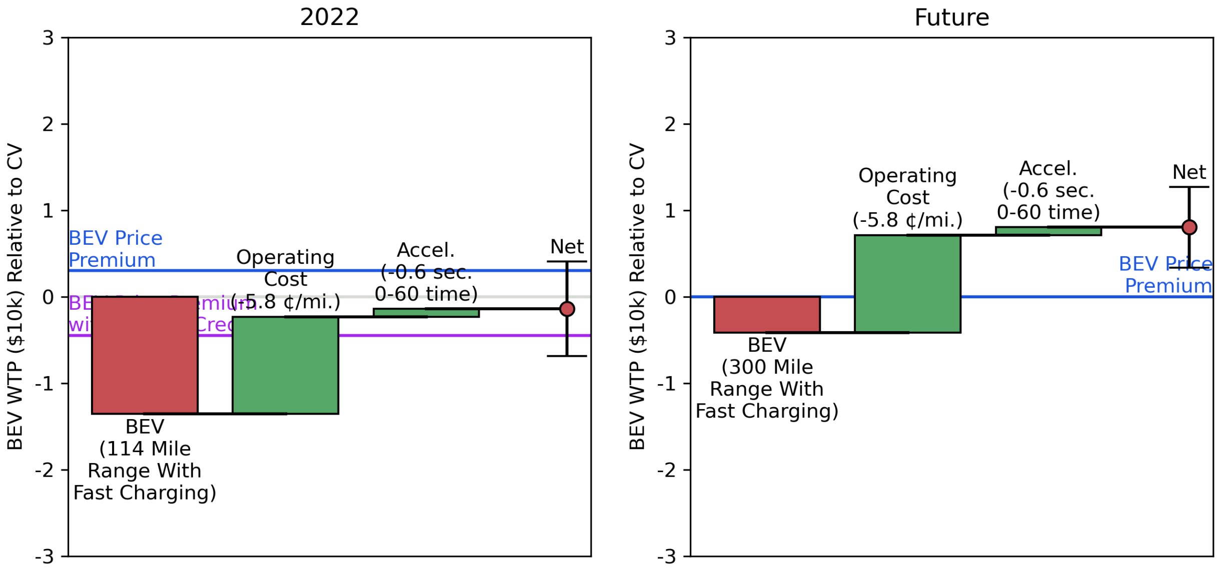
(g) Kia Niro EV vs. Niro Hybrid

Figure 15: BEV Car and SUV head-to-head choice share comparisons over time. Net WTP calculated using the 2021 study mixed logit model for car- and SUV-buyers respectively. Error bars denote 2.5 and 97.5 percentiles.

The results show a clear pattern of increasing probabilities of BEV choice over time. This is especially notable for the Leaf, Mini, and i4, all of which are estimated to take a majority share of choices by 2030 in these head-to-head scenarios under our assumptions of BEV cost and technology improvements. The Ioniq and the three SUVs are just behind, with roughly 40% shares by 2030.

Head-to-Head Comparison Plots

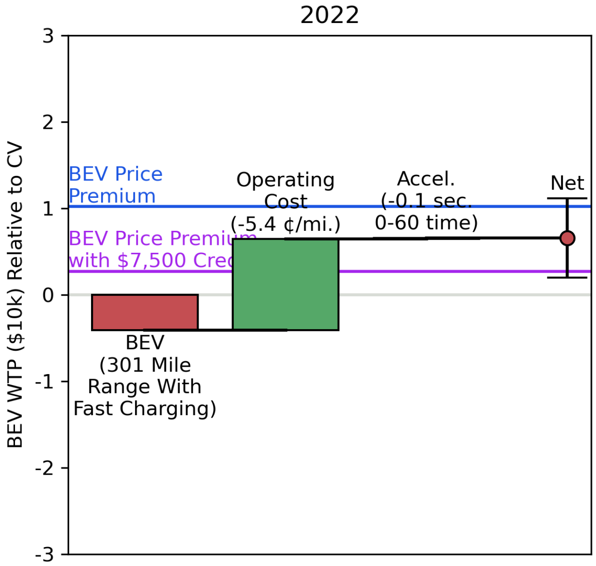
The follows sets of figures show all of the individual head-to-head comparisons that are made in the previous subsection. The y axis always refers to the WTP value or price for the BEV option relative to the conventional vehicle option. On the x axis, we show the successive relative difference between the two vehicles.



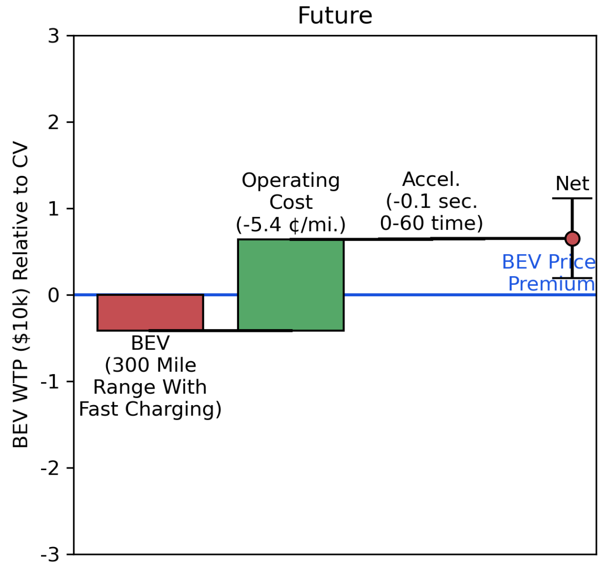
(a) WTP for the 2022 MINI Electric relative to the 2022 MINI.

(b) WTP for a hypothetical future MINI Electric relative to the 2022 MINI.

Figure 16: Head-to-head charts showing WTP for attributes for the MINI Electric BEV relative to those of the MINI gasoline vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the electric vehicle with and without the federal BEV tax credit applied. Error bars denote ±2 standard errors.

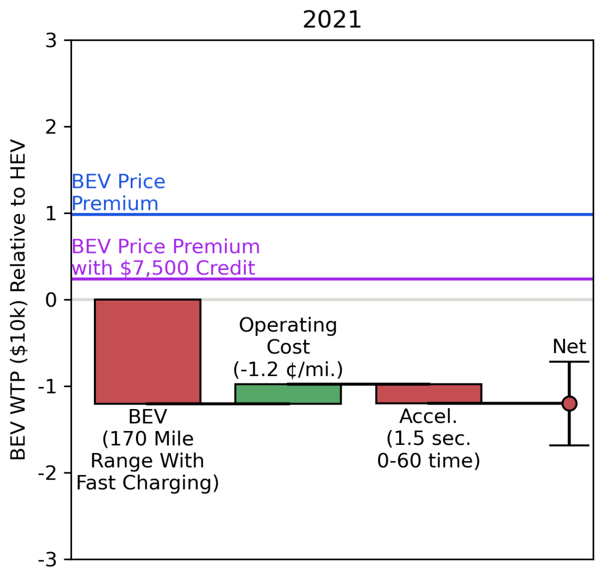


(a) WTP for the BMW i4 eDrive40 relative to the 4-series 430i.

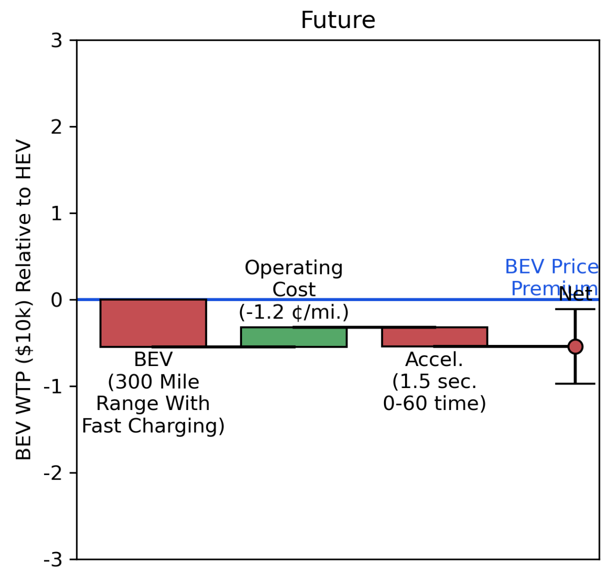


(b) WTP for a hypothetical future BMW i4 eDrive40 relative to the 4-series 430i.

Figure 17: Head-to-head charts showing WTP for attributes for the BMW i4 BEV relative to those of the 4-series vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the electric vehicle with and without the federal BEV tax credit applied. Error bars denote ±2 standard errors.

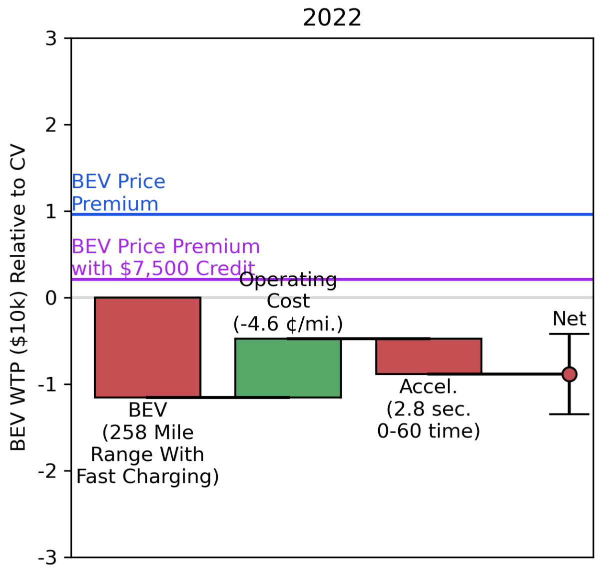


(a) WTP for the Hyundai Ioniq EV SE relative to the Ioniq Hybrid SE.

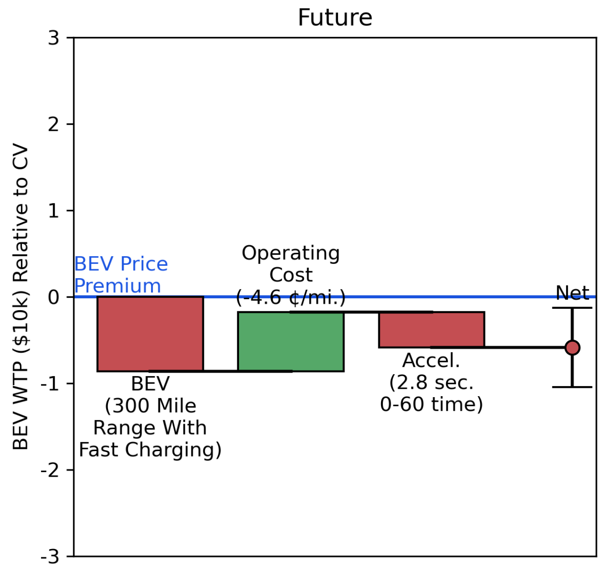


(b) WTP for a hypothetical future Ioniq EV SE relative to the Ioniq Hybrid SE.

Figure 18: Head-to-head charts showing WTP for attributes for the Hyundai Ioniq EV relative to those of the Ioniq Hybrid vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the electric vehicle with and without the federal BEV tax credit applied. Error bars denote ±2 standard errors.

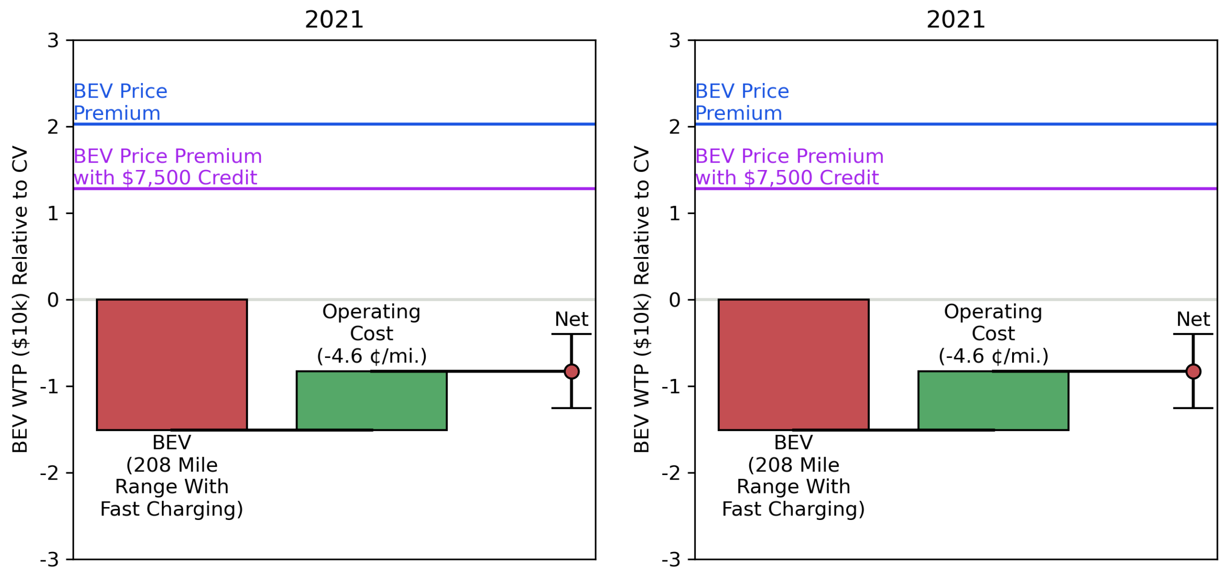


(a) WTP for the 2022 Hyundai Kona EV SEL relative to the Hyundai Kona Hybrid SEL.



(b) WTP for a hypothetical future Hyundai Kona EV SEL relative to the Hyundai Kona Hybrid SEL.

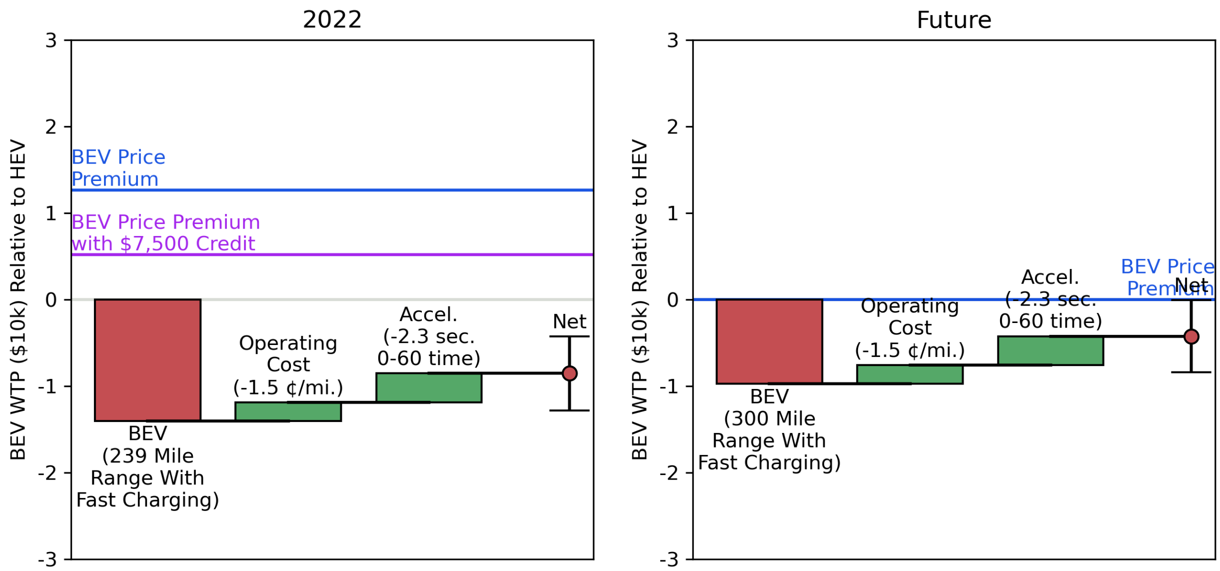
Figure 19: Head-to-head charts showing WTP for attributes for the Hyundai Kona EV relative to those of the Hyundai Kona Hybrid vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the electric vehicle with and without the federal BEV tax credit applied. Error bars denote ± 2 standard errors.



(a) WTP for the 2022 Volvo XC40 Recharge Pure Electric P8 relative to the XC40 T4 Momentum.

(b) WTP for a hypothetical future Volvo XC40 Recharge Pure Electric P8 relative to the XC40 T4 Momentum.

Figure 20: Head-to-head charts showing WTP for attributes for the Volvo XC40 Recharge BEV relative to those of the XC40 vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the electric vehicle with and without the federal BEV tax credit applied. Error bars denote ± 2 standard errors.



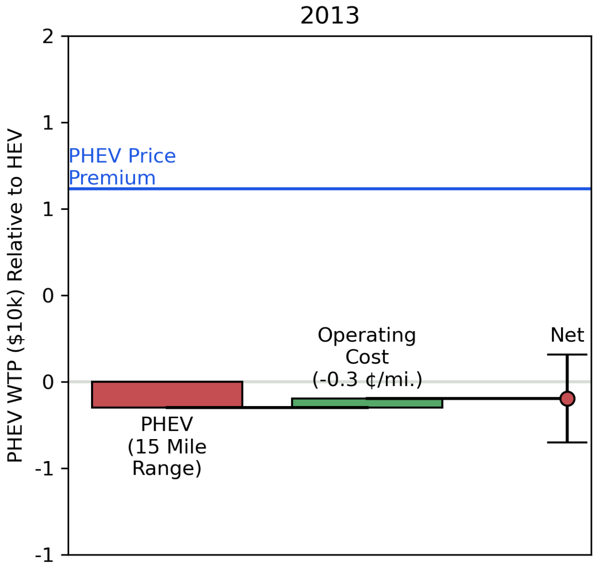
(a) WTP for the 2022 Kia Niro EV EX Premium relative to the Niro EX Premium.

(b) WTP for a hypothetical future Kia Niro EV EX Premium relative to the Niro EX Premium.

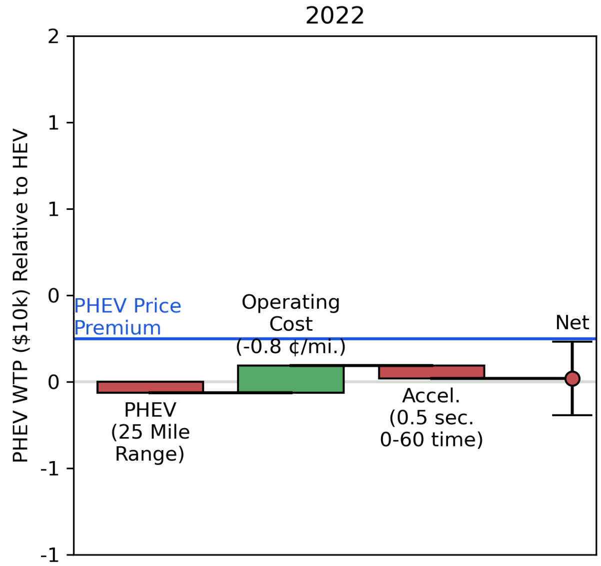
Figure 21: Head-to-head charts showing WTP for attributes for the Kia Niro EV relative to those of the Niro vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the electric vehicle with and without the federal BEV tax credit applied. Error bars denote ±2 standard errors.

PHEV Comparison

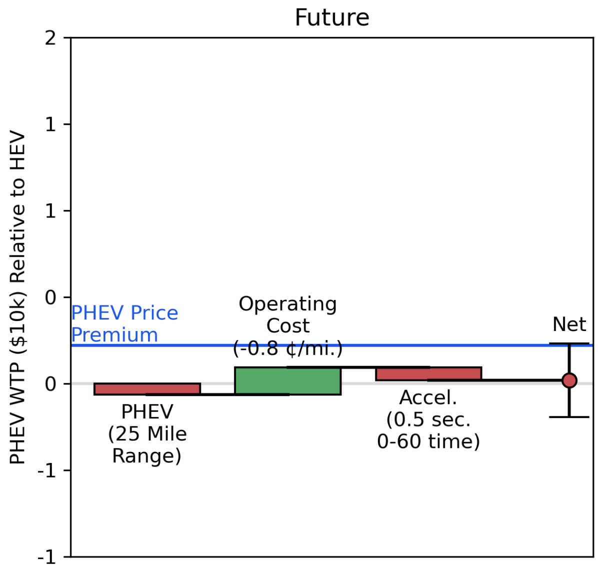
Head to Head Comparison Plots



(a) WTP for the 2013 Toyota Prius Plug-In Base relative to the Prius One.

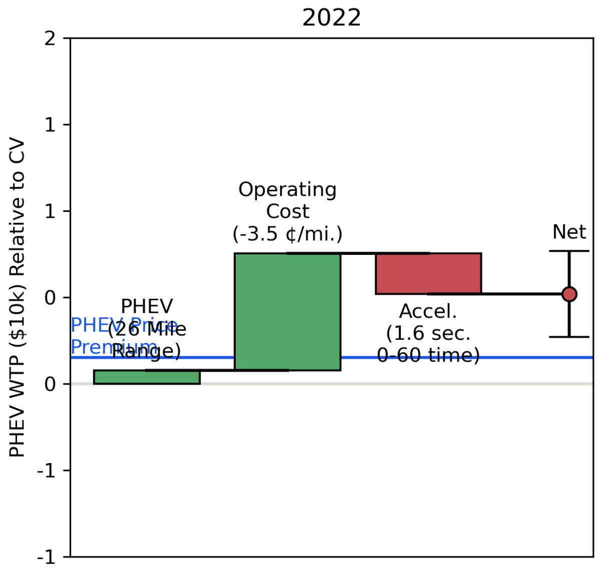


(b) WTP for the 2022 Toyota Prius Prime LE relative to the Prius LE.

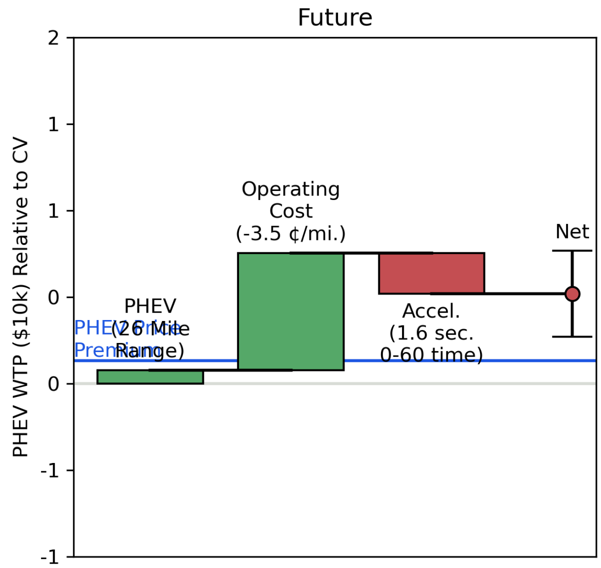


(c) WTP for a hypothetical future Toyota Prius Prime LE relative to the Prius LE.

Figure 22: Head-to-head charts showing WTP for attributes for the Toyota Prius Prime relative to those of the Prius vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.

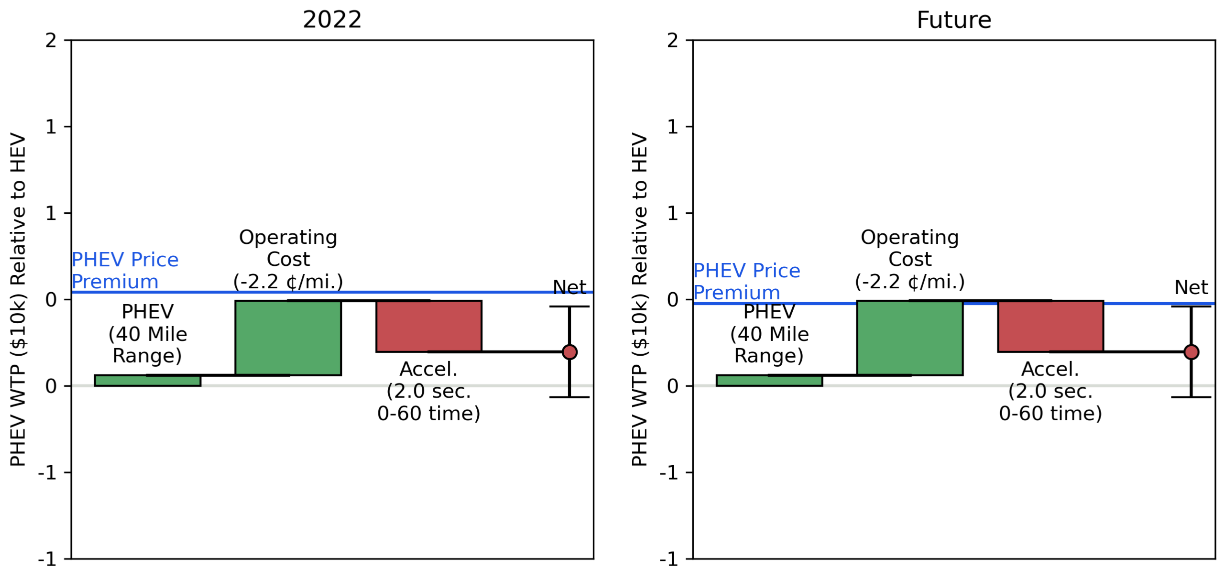


(a) WTP for the 2022 Audi A7 Recharge Premium Plus relative to the A7 Premium Plus.



(b) WTP for a hypothetical future Audi A7 Recharge Premium Plus relative to the A7 Premium Plus.

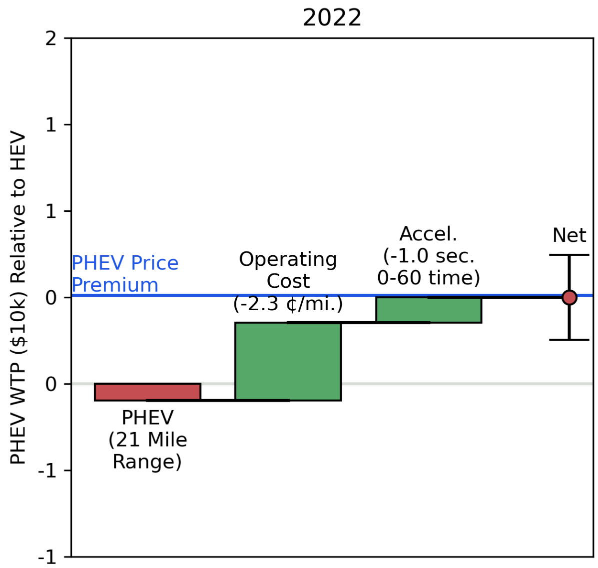
Figure 23: Head-to-head charts showing WTP for attributes for the Audi A7 Recharge relative to those of the A7 vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.



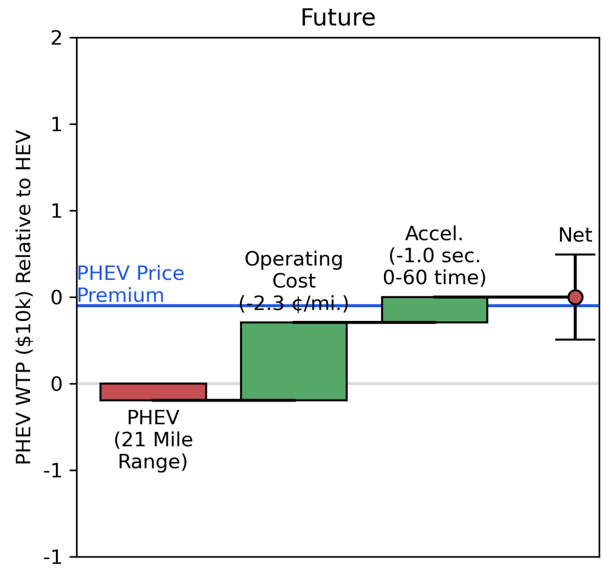
(a) WTP for the 2022 Volvo S60 Recharge T8 R-design relative to the S60 B5 R-design.

(b) WTP for a hypothetical future S60 Recharge T8 R-design relative to the S60 B5 R-design.

Figure 24: Head-to-head charts showing WTP for attributes for the Volvo S60 Recharge BEV relative to those of the S60 vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.

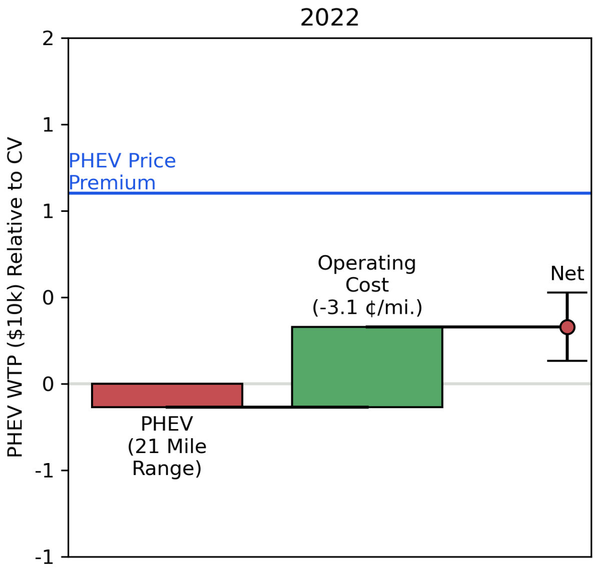


(a) WTP for the 2022 Volvo S90 Recharge T8 Inscryption relative to the S90 B6 Inscryption.

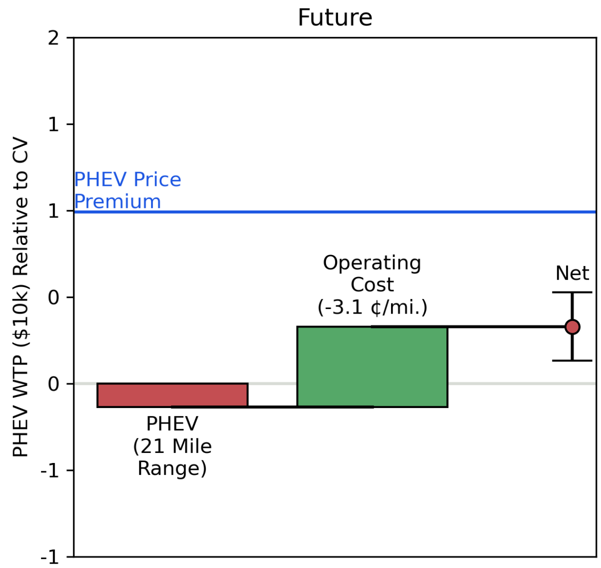


(b) WTP for a hypothetical future Volvo S90 Recharge T8 Inscryption relative to the S90 B6 Inscryption.

Figure 25: Head-to-head charts showing WTP for attributes for the Volvo S90 Recharge BEV relative to those of the S90 vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.

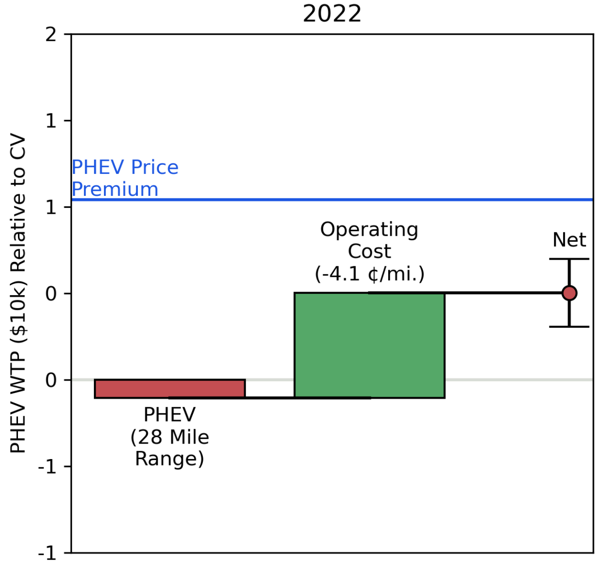


(a) WTP for the 2022 Lincoln Aviator Grand Touring relative to the Lincoln Aviator Reserve.

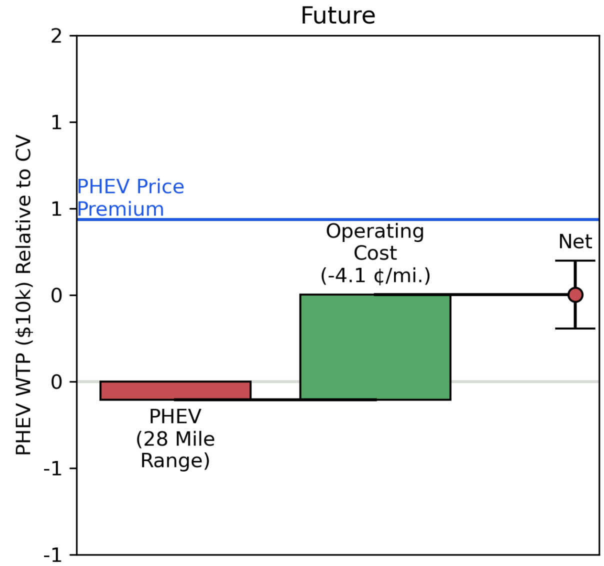


(b) WTP for a hypothetical future Lincoln Aviator Grand Touring relative to the Lincoln Aviator Reserve.

Figure 26: Head-to-head charts showing WTP for attributes for the Lincoln Aviator PHEV relative to those of the Aviator vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.

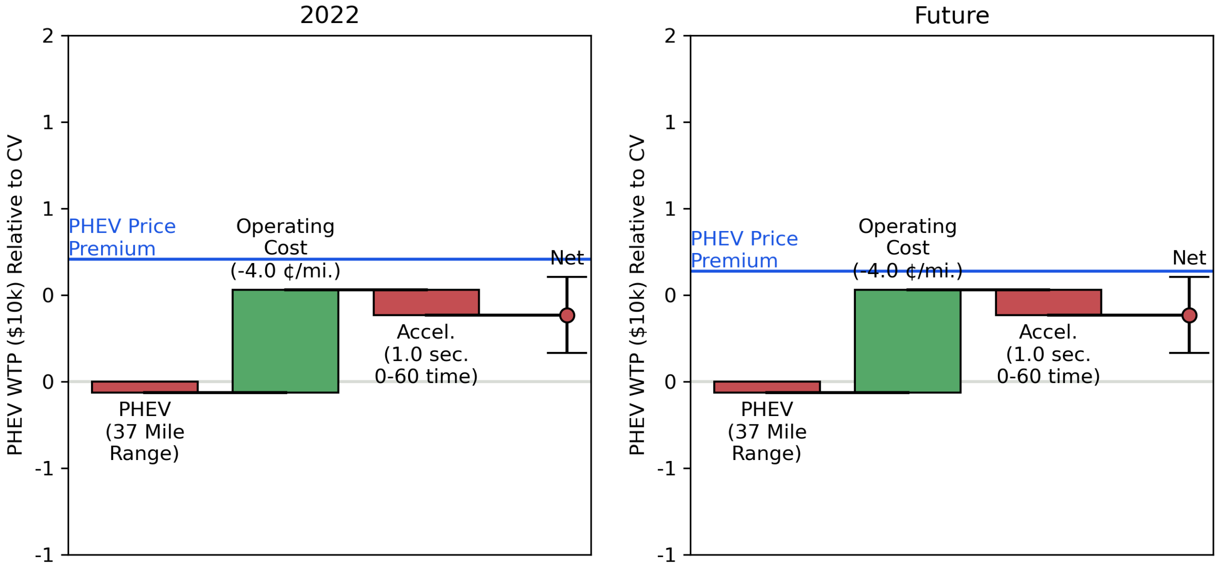


(a) WTP for the 2022 Lincoln Corsair PHEV Grand Touring relative to the Corsair Reserve.



(b) WTP for a hypothetical future Lincoln Corsair PHEV Grand Touring relative to the Corsair Reserve.

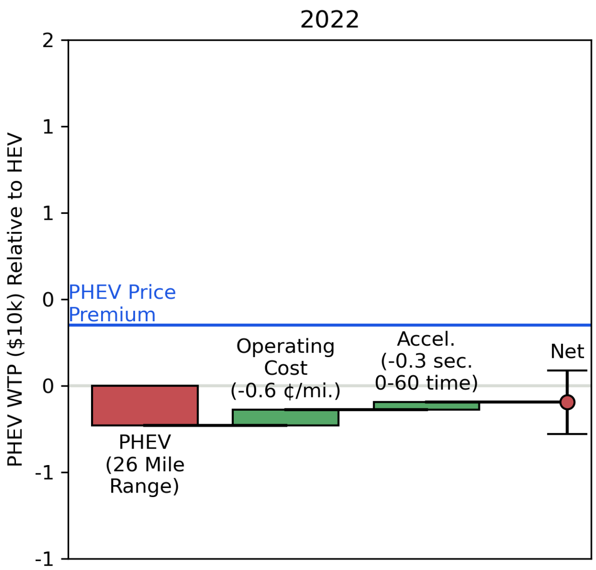
Figure 27: Head-to-head charts showing WTP for attributes for the Lincoln Corsair PHEV relative to those of the Corsair vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.



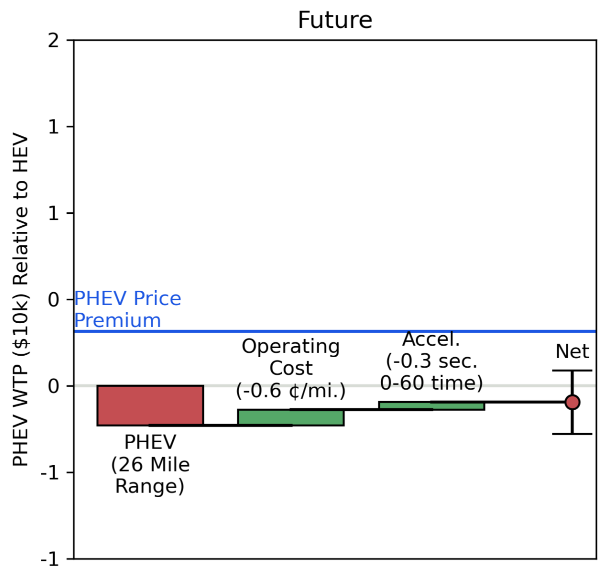
(a) WTP for the 2022 Ford Escape PHEV SE relative to the Escape SE.

(b) WTP for a hypothetical future Ford Escape PHEV SE relative to the Escape SE.

Figure 28: Head-to-head charts showing WTP for attributes for the Ford Escape PHEV relative to those of the Escape vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.

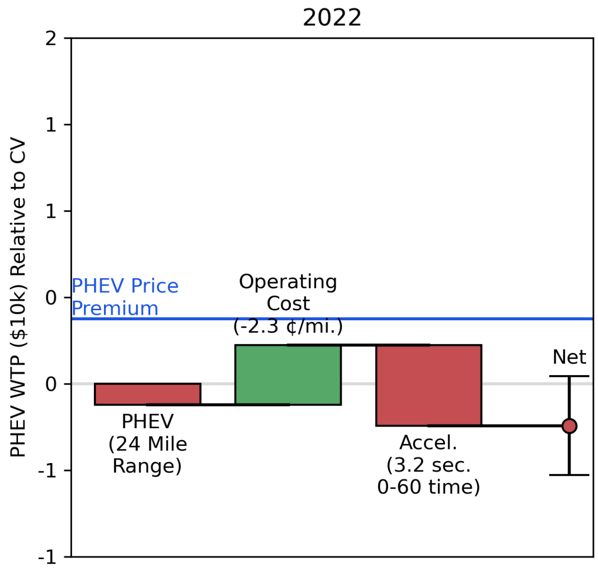


(a) WTP for the 2022 Kia Niro PHEV LXS relative to the Niro LXS.

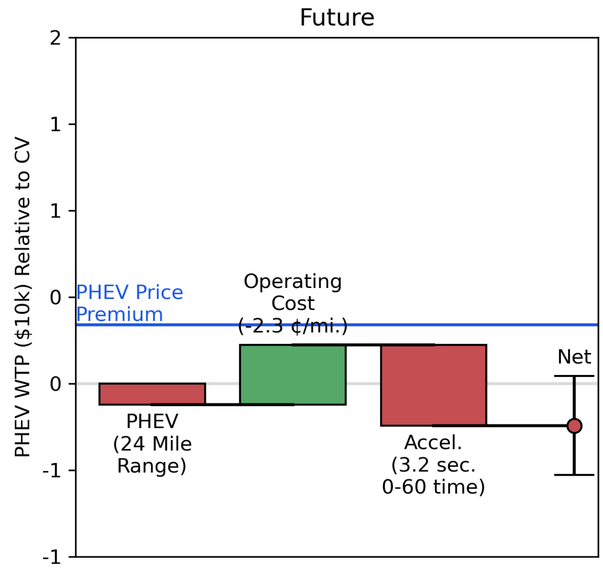


(b) WTP for a hypothetical future Kia Niro PHEV LXS relative to the Niro LXS.

Figure 29: Head-to-head charts showing WTP for attributes for the Kia Niro PHEV relative to those of the Kia Niro vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.

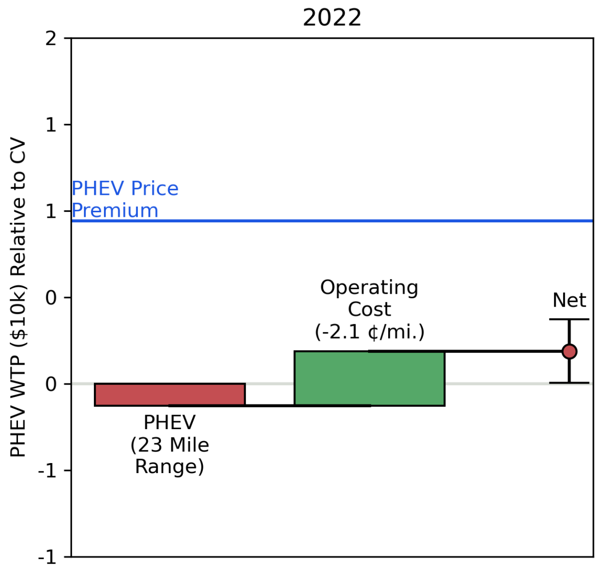


(a) WTP for the 2022 Mitsubishi Outlander PHEV SEL relative to the Outlander SEL.

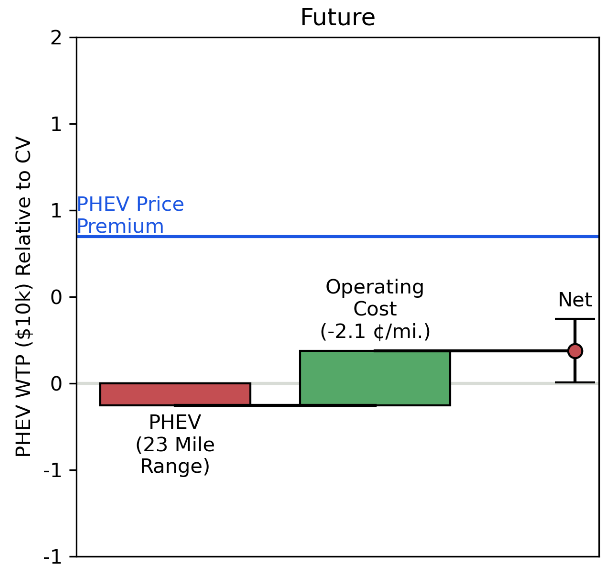


(b) WTP for a hypothetical future Mitsubishi Outlander PHEV SEL relative to the Outlander SEL.

Figure 30: Head-to-head charts showing WTP for attributes for the Mitsubishi Outlander PHEV relative to those of the Outlander vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.

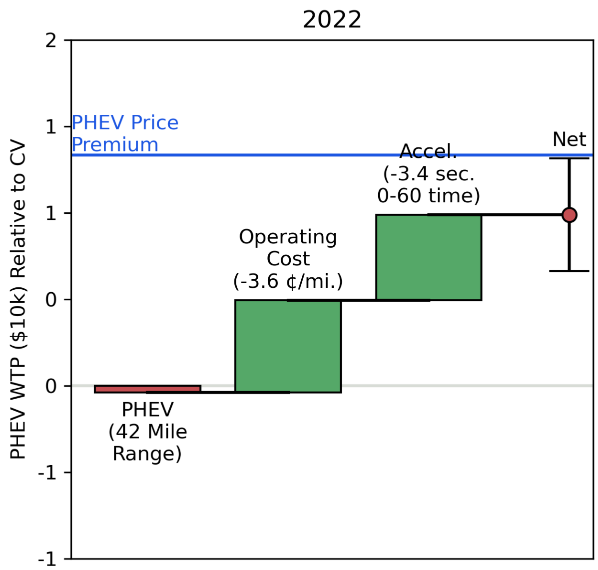


(a) WTP for the 2022 Audi Q5 PHEV Premium S Line relative to the Q5 Premium S Line.

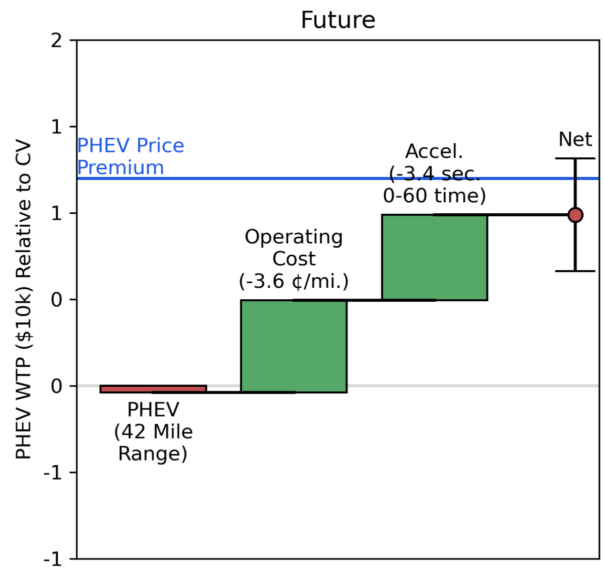


(b) WTP for a hypothetical future Audi Q5 PHEV Premium S Line relative to the Q5 Premium S Line.

Figure 31: Head-to-head charts showing WTP for attributes for the Audi Q5 PHEV relative to those of the Audi Q5 vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.

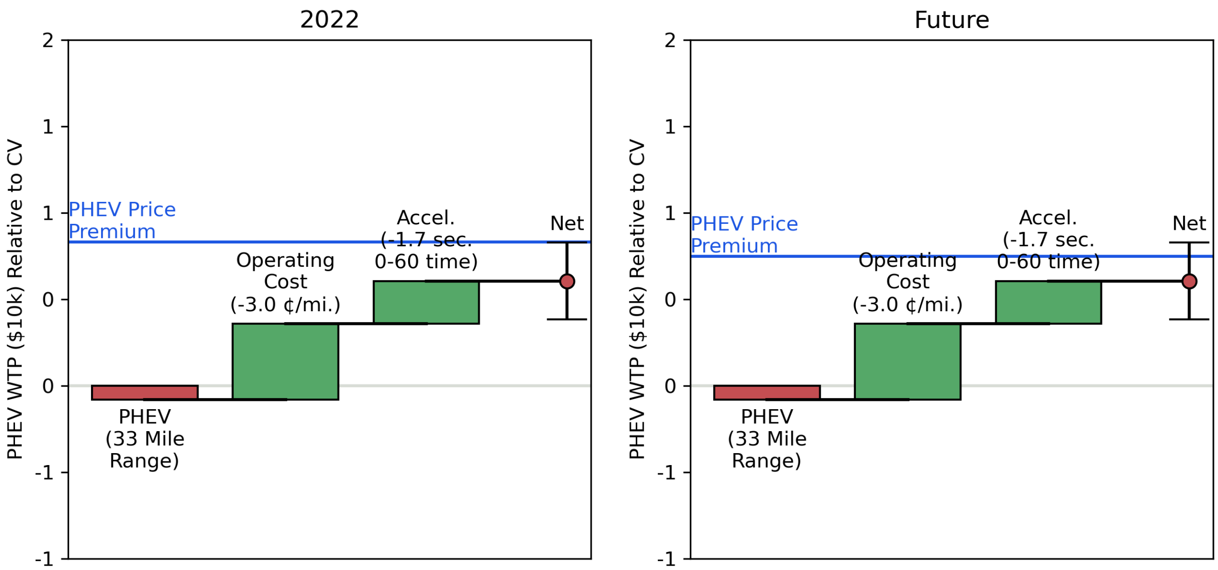


(a) WTP for the 2022 Toyota RAV4 Prime SE relative to the RAV4 SE.



(b) WTP for a hypothetical future Toyota RAV4 Prime SE relative to the RAV4 SE.

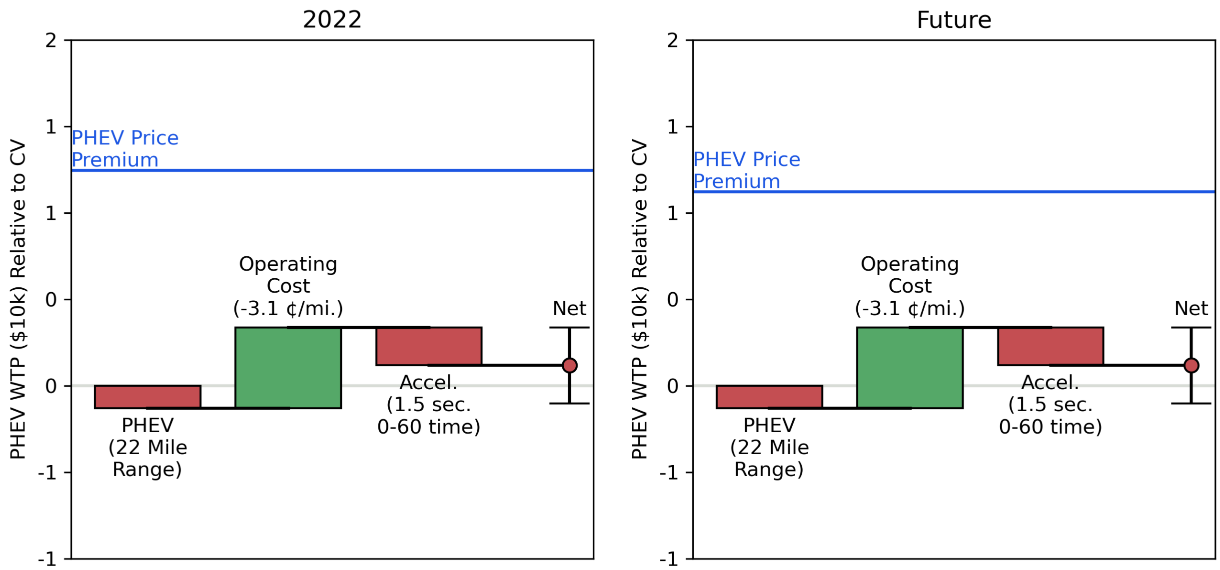
Figure 32: Head-to-head charts showing WTP for attributes for the Toyota RAV4 Prime PHEV relative to those of the RAV4 vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.



(a) WTP for the 2022 Hyundai Tucson PHEV SEL relative to the Tucson SEL.

(b) WTP for a hypothetical future Hyundai Tucson PHEV SEL relative to the Tucson SEL.

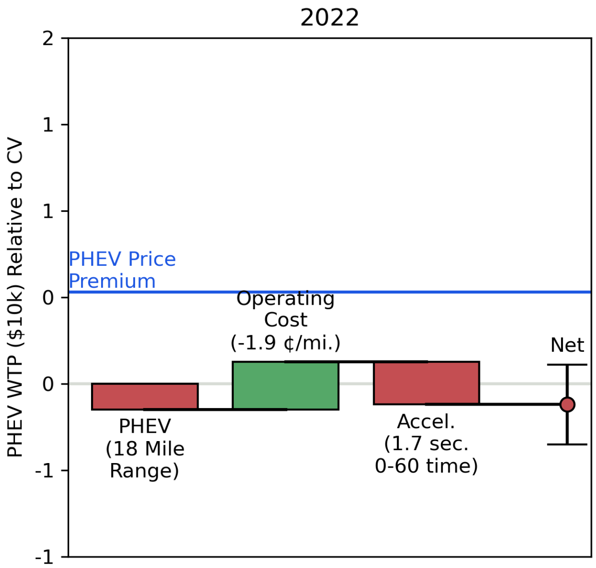
Figure 33: Head-to-head charts showing WTP for attributes for the Hyundai Tucson PHEV relative to those of the Tucson vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.



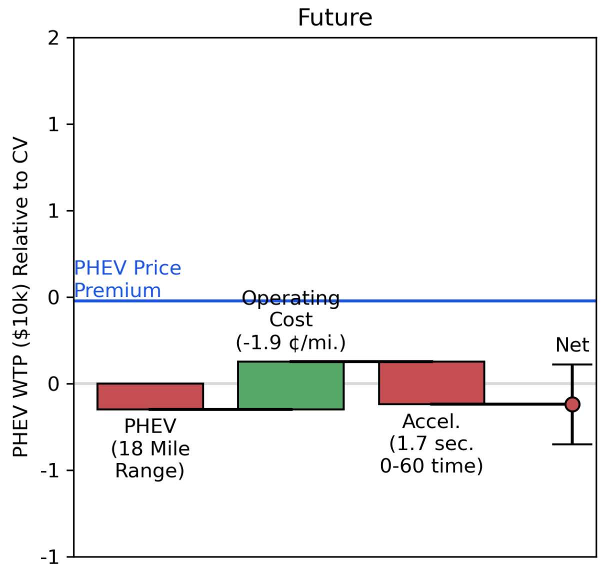
(a) WTP for the 2022 Jeep Wrangler 4xe Unlimited Sierra relative to the Wrangler Unlimited Sierra.

(b) WTP for a hypothetical future Jeep Wrangler 4xe Unlimited Sierra relative to the Wrangler Unlimited Sierra.

Figure 34: Head-to-head charts showing WTP for attributes for the Jeep Wrangler 4xe PHEV relative to those of the Wrangler vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.

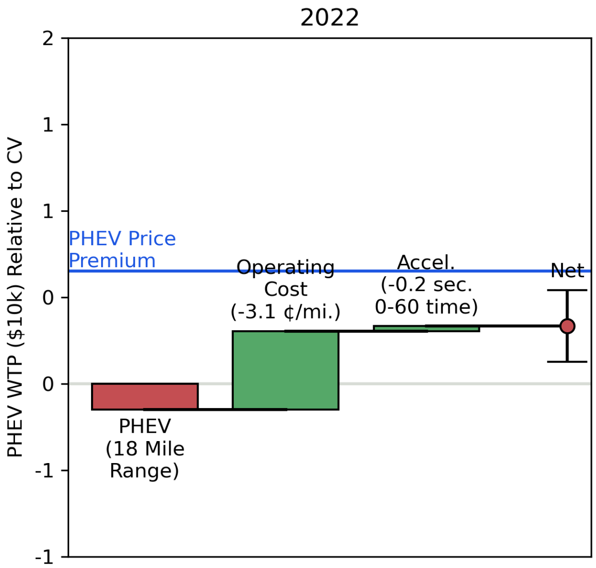


(a) WTP for the 2022 Volvo XC60 Recharge T8 Inscryption relative to the XC60 T6 Inscryption.

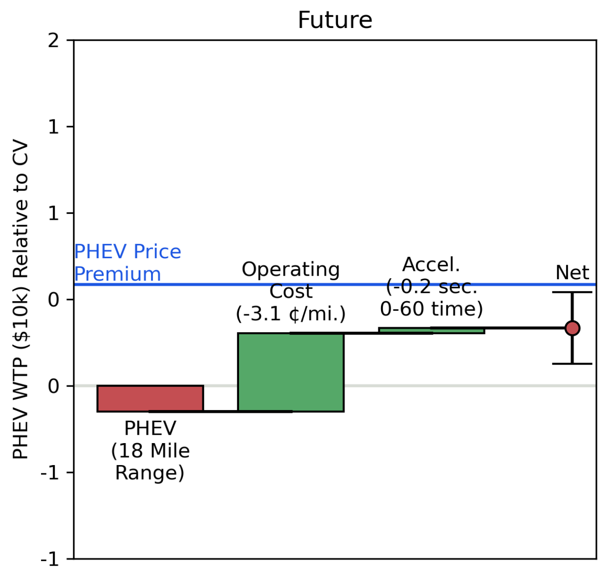


(b) WTP for a hypothetical future Volvo XC60 Recharge T8 Inscryption relative to the XC60 T6 Inscryption.

Figure 35: Head-to-head charts showing WTP for attributes for the Volvo XC60 PHEV relative to those of the XC60 vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.



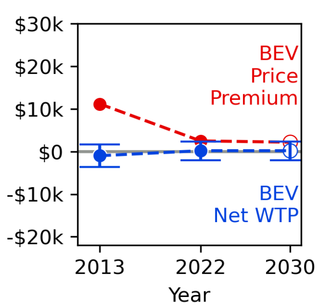
(a) WTP for the 2022 Volvo XC90 Recharge T8 Inscryption relative to the XC90 B6 Inscryption.



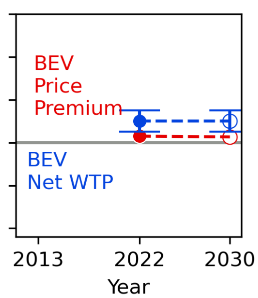
(b) WTP for a hypothetical future Volvo XC90 Recharge T8 Inscryption relative to the XC90 B6 Inscryption.

Figure 36: Head-to-head charts showing WTP for attributes for the XC90 Recharge PHEV relative to those of the XC90 vehicle built on the same platform using consumer preference data from the 2021 survey. Horizontal lines show the price premiums associated with the PHEV.

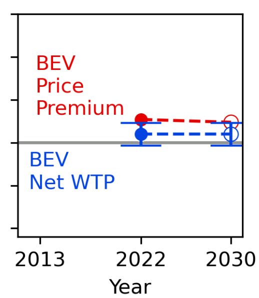
Net WTP vs. Model Year



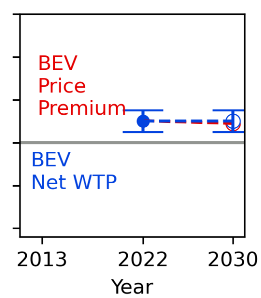
(a) Toyota Prius Prime vs. Prius



(b) Audi A7 PHEV vs. A7

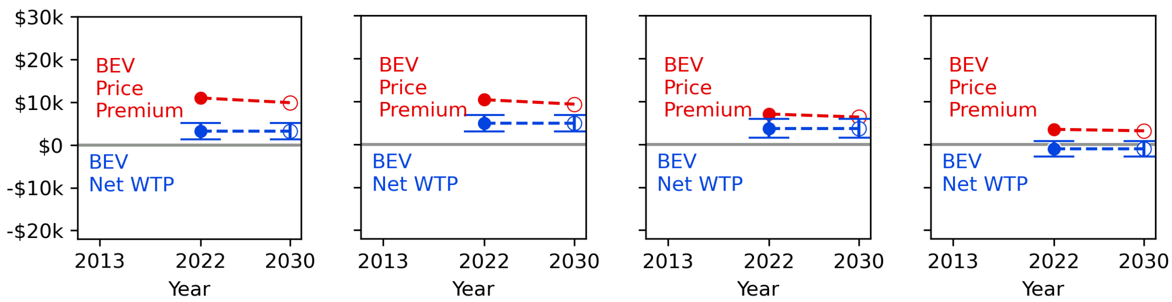


(c) Volvo S60 Recharge vs. S60



(d) Volvo S90 Recharge vs. S90

Figure 37: Car head-to-head comparisons over time. Red points denote the price premium of the PHEV relative to the comparable gas-powered vehicle. Blue points denote the net willingness to pay (WTP) of the PHEV relative to the comparable gas-powered vehicle. Car net WTP calculated using the 2021 study mixed logit model for car-buyers. Error bars denote ±2 standard errors.

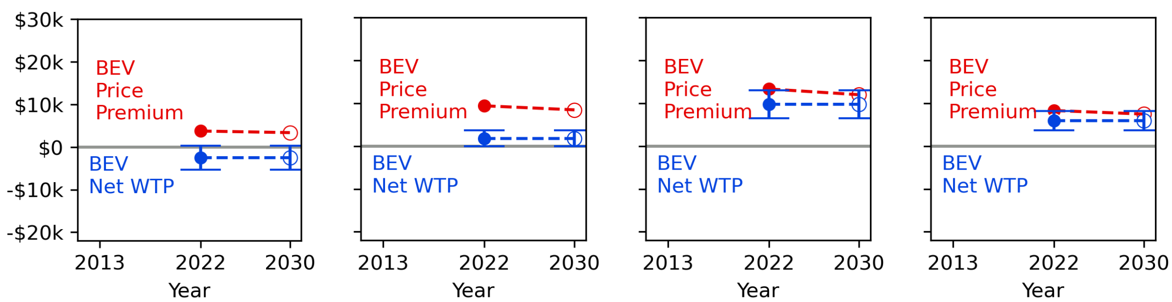


(a) Lincoln Aviator PHEV vs. Aviator

(b) Lincoln Corsair PHEV vs. Corsair

(c) Ford Escape PHEV vs. Escape

(d) Kia Niro PHEV vs. Niro

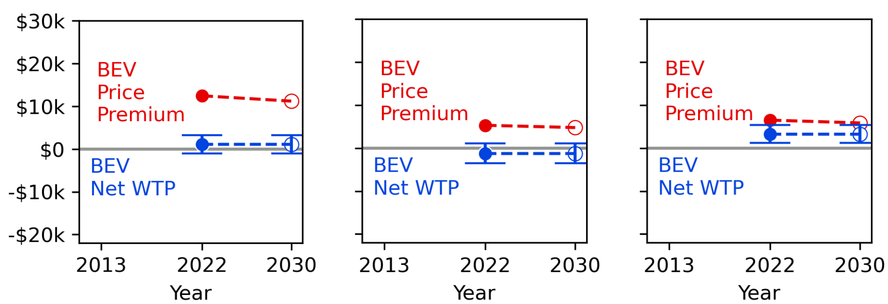


(e) Mitsubishi Outlander PHEV vs. Outlander

(f) Audi Q5 PHEV vs. Q5

(g) Toyota RAV4 Prime vs. RAV4

(h) Hyundai Tuscon PHEV vs. Tucson



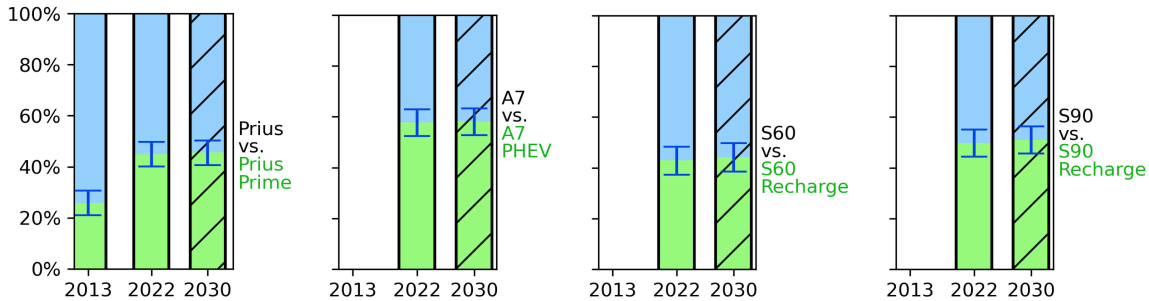
(i) Jeep Wrangler 4xe vs. Wrangler

(j) Volvo XC60 Recharge vs. XC60

(k) Volvo XC90 Recharge vs. XC90

Figure 38: SUV head-to-head comparisons over time. Red points denote the price premium of the PHEV relative to the comparable gas-powered vehicle. Blue points denote the net willingness to pay (WTP) of the PHEV relative to the comparable gas-powered vehicle. SUV net WTP calculated using the 2021 study mixed logit model for car-buyers. Error bars denote ± 2 standard errors.

Head to Head Choice Share vs. Model Year



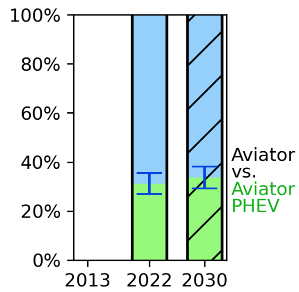
(a) Toyota Prius Prime vs. Prius

(b) Audi A7 PHEV vs. A7

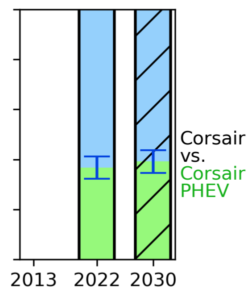
(c) Volvo S60 Recharge vs. S60

(d) Volvo S90 Recharge vs. S90

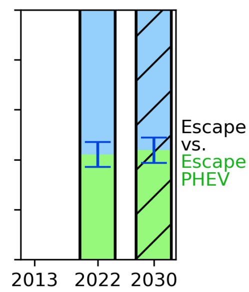
Figure 39: PHEV Car head-to-head choice share comparisons over time. Net WTP calculated using the 2021 study mixed logit model for car buyers. Error bars denote 2.5 and 97.5 percentiles.



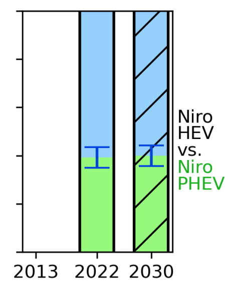
(a) Lincoln Aviator PHEV vs. Aviator



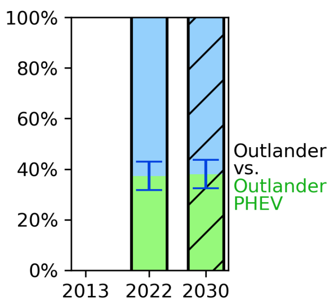
(b) Lincoln Corsair PHEV vs. Corsair



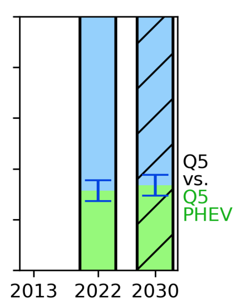
(c) Ford Escape PHEV vs. Escape



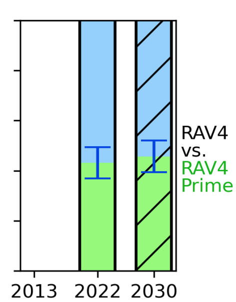
(d) Kia Niro PHEV vs. Niro



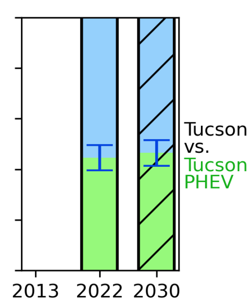
(e) Mitsubishi Outlander PHEV vs. Outlander



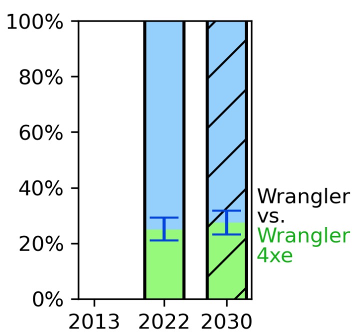
(f) Audi Q5 PHEV vs. Q5



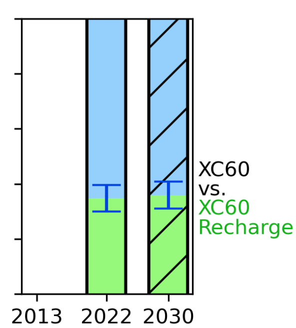
(g) Toyota RAV4 Prime vs. RAV4



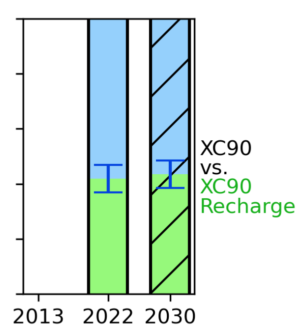
(h) Hyundai Tuscon PHEV vs. Tucson



(i) Jeep Wrangler 4xe vs. Wrangler



(j) Volvo XC60 Recharge vs. XC60



(k) Volvo XC90 Recharge vs. XC90

Figure 40: SUV head-to-head choice share comparisons over time. Net WTP calculated using the 2021 study mixed logit model for SUV buyers. Error bars denote 2.5 and 97.5 percentiles.