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To Buy an Electric Vehicle or Not? A Bayesian Analysis of Consumer Intent in the United States

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To Buy an Electric Vehicle or Not? A Bayesian Analysis of Consumer Intent in the United States

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Abstract

The adoption of electric vehicles (EVs) is considered critical to achieving climate goals, yet it hinges on consumer interest. This study explores how public intent to purchase EVs relates to four unexamined factors (exposure to EV information, perceptions of EVs' environmental benefits, views on government climate policy, and confidence in future EV infrastructure) while controlling for prior EV ownership, political affiliation, and demographic characteristics (age, gender, education, and geographic location). We use data from three nationally representative opinion polls by the Pew Research Center 2021–2023 and Bayesian techniques to estimate the ordinal probit and ordinal quantile models. Results from ordinal probit show that respondents who are well informed about EVs, perceive them as environmentally beneficial, or are confident in development of charging stations are more likely to express strong purchase interest, with covariate effects (CEs)−a metric rarely reported in EV research−of 10.2, 15.5, and 19.1 percentage points, respectively. In contrast, those skeptical of government climate initiatives are more likely to express no interest, by more than 10 percentage points. Prior EV ownership exhibits the highest CE (19.0–23.1 percentage points), and the impact of most demographic variables is consistent with the literature. The ordinal quantile models demonstrate significant variation in CEs across the distribution of purchase intent, offering insights beyond the ordinal probit model. We are the first to use quantile modeling to reveal how CEs differ significantly throughout the spectrum of purchase intent.

Keywords: Decarbonization, electric vehicle, ordinal probit, Pew Research, quantile regression, technology adoption.

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1. Introduction

Transportation is the largest source of greenhouse gas emissions in the United States, representing 28 percent of the total emissions in 2022, with light-duty vehicles responsible for more than half (Environmental Protection Agency, 2024). Electric vehicles (EVs) are widely regarded as a key solution for reducing emissions and meeting climate targets, given their zero tailpipe emissions. To accelerate EV adoption, governments worldwide, including the United States, have implemented a range of policies and incentives. Key US measures include nationwide greenhouse gas standards to reduce emissions from new vehicles; up to $7,500 federal tax credits for EV buyers; investments in charging infrastructure; and state-level mandates, such as California's Zero-Emission Vehicle (ZEV) program, which requires automakers to sell an increasing share of EVs.[1]

Despite these efforts, US sales remain relatively low, accounting for only about 10 percent of global new EV sales in 2023, trailing behind China (60 percent) and Europe (25 percent) (International Energy Agency, 2024). The trajectory of US adoption is also increasingly uncertain. In 2024, several automakers, including GM and Ford, scaled back ambitious EV targets, citing weak consumer demand (Colias and Otts, 2024). Successive administrations have taken sharply different approaches, creating uncertainty around long-term incentives and regulations. The Biden administration promoted EV adoption through subsidies, infrastructure investments, and emissions regulations as part of its broader climate agenda, but the Trump administration signaled a deregulatory shift with plans to weaken both incentives and regulations.[2] These changing political priorities may reflect broader tensions between environmental regulations, industry interests, and fiscal considerations. Although EVs reduce emissions—particularly in regions with cleaner electricity grids—subsidies and incentives, along with declining gas tax revenue, pose budgetary challenges (Banta et al., 2024). The Trump administration has also cited concerns that stringent emissions and fuel economy regulations increase compliance costs for automakers and restrict consumer choice.

Ultimately, the future of the EV market depends on consumer interest, which is likely to be shaped by multiple factors, including cost, convenience, perception of environmental benefits, and awareness of these trade-offs. Although EVs often have higher up-front costs due to the battery technology, they can offer long-term savings through lower operational and maintenance expenses, as electric motors require less maintenance. However, the overall cost of ownership can vary significantly, depending on factors such as local gasoline and electricity prices, climate, purchase incentives, home charging access, and annual mileage (Woody et al., 2024). Access to reliable charging infrastructure also remains an important consideration. Limited availability in some regions can exacerbate range anxiety and inconvenience, particularly for long-distance travel. Environmental

[1] For more details, see the EPA's greenhouse gas regulations, the IRS EV tax credit guidelines, National Electric Vehicle Infrastructure (NEVI) Program and California's ZEV Program.

[2] President Trump's executive order on January 20, 2025 outlined plans to halt $7.5 billion in charging infrastructure funding, weaken vehicle emissions standards that drive EV production, eliminate EV tax credits, and revoke California's EV mandate waiver, which would limit state-level regulations. See `https://www.whitehouse.gov/presidential-actions/2025/01/unleashing-american-energy/`

concerns also affect consumer attitudes, but perceptions may vary, given the regional heterogeneity in short-term benefits (Holland et al., 2016) and perception about critical minerals mining (Lakshman, 2024).

Recognizing the importance of public interest in shaping the future of this market, we examine how public opinion on purchasing EVs is associated with factors such as exposure to EV information, perceptions about the environmental impact of EVs (compared to gas-powered vehicles) and government action to mitigate climate change, confidence in related infrastructure development, prior ownership, and demographic characteristics such as age, gender, education, political affiliation, and geographical location of the respondents.

Our paper makes three key contributions. First, we explore the role of novel factors that have been largely overlooked in the EV adoption literature. Studies have examined how a combination of factors, including range anxiety, performance concerns, charging infrastructure, environmental attitudes, government policies, peer effects, and demographic characteristics, influences purchase intent (Carley et al., 2013; Tiwari et al., 2020; Zhao et al., 2022; Mamkhezri, 2025) or the impact of specific factors, such as providing information about total cost of ownership (Dumortier et al., 2015), media coverage (Scherrer, 2023), reputation (Buhmann and Criado, 2023), and consumer incentives (Xue et al., 2023; Stekelberg and Vance, 2024). Related research examines factors driving actual EV sales rather than purchase intent, including tax credits and rebates (DeShazo et al., 2017; Jenn et al., 2018; Clinton and Steinberg, 2019; Sheldon et al., 2023), charging infrastructure (Li et al., 2017), and automakers' responses to environmental policies (Aghion, Philippe and Antoine Dechezlepretre and David Hemous and Ralf Martin and John Van Reenen, 2016; Gillingham, 2022; Lohawala, 2023). We contribute to this literature by examining how EV purchase intent is influenced by factors such as confidence in future charging infrastructure development, perceptions of government climate efforts, exposure to EV-related information, and perceptions of EVs' environmental benefits.

Our second contribution is using large and nationally representative datasets. Research on the trends and determinants of public opinion and EV purchase intent has predominantly relied on small-scale surveys. For example, Tiwari et al. (2020), Lashari et al. (2021), Hu et al. (2023), and Mamkhezri (2025) analyzed 1,800 responses from UK residents, 1,500 responses from South Korea, 807 responses from China, and 1,500 responses from the United States, respectively.[3] Singh et al. (2020) provide a meta-analysis of 211 peer-reviewed research articles 2009–2019, identifying key factors influencing public opinion of EVs. Notably, most such studies are based on a single survey for a particular year, not nationally representative, or constrained by sample size, which diminishes their generalizability. We overcome these limitations by drawing on three nationally representative opinion polls conducted by the Pew Research Center with a significantly larger sample size than other studies. Specifically, we use data from 2021, 2022, and 2023, with 11,052, 7,173, and 7,201 observations, respectively.

[3]Although some recent studies (e.g., Pani et al. (2023) and Ruan and Lv (2022)) use large-scale online sentiment analysis to track the evolution of public perceptions of EVs, they do not examine individual-level predictors of it.

Our third contribution lies in applying advanced modeling and estimation techniques to study EV purchase intent. Research has used various methods to analyze it, such as linear regression to assess the effects of personal beliefs and preferences (Carley et al., 2013; Krause et al., 2013) and positive media coverage (Scherrer, 2023); binary probit and logit to explore motivational factors, such as reputation in shaping EV preferences (Buhmann and Criado, 2023); mixed logit models to explore attitudes toward various EV policy incentives, employment changes, and electricity costs (Mamkhezri, 2025); structural equation modeling to examine the role of adoption barriers, such as range anxiety and charging infrastructure reliability (Tiwari et al., 2020), peer effects (Zhao et al., 2022), and policy incentives (Hu et al., 2023); and topic modeling and sentiment analysis to track shifts in online sentiment toward EVs over time (Ruan and Lv, 2022). These papers rely on classical (frequentist) methods, which provide point estimates and confidence intervals but fail to capture uncertainty in model parameters. This can lead to biased estimates of covariate effects (CEs), particularly in nonlinear models, such as probit or logit, where parameters do not directly translate to changes in outcome probabilities (Jeliazkov and Vossmeyer, 2018).

In contrast, we adopt a Bayesian modeling framework that provides a posterior distribution over the parameters, systematically incorporates uncertainty in parameters (and observations) when computing covariate effects, and enables us to make direct probability statements about the parameters—rather than relying on the notion of "confidence" as in the classical framework. Our empirical analysis consists of two stages. First, we estimate an ordinal probit model using Markov chain Monte Carlo (MCMC) methods to assess how different factors are associated with consumer interest in EV adoption. We present the CEs on the average probabilities of outcomes, an aspect rarely explored in the EV literature. Next, we extend the analysis using ordinal quantile models at the 20th, 50th, and 80th percentiles of purchase intent to examine how different factors shape the decisions of consumers who are more inclined to adopt EVs compared to those who are less inclined. We are the first to apply ordinal quantile analysis to EV purchase intent. As no classical estimation methods exist for ordinal quantile models, Bayesian estimation is essential. The results reveal considerable heterogeneity in CEs across the distribution of EV purchase intent, which would be missed by ordinal probit models.

The remainder of the article is structured as follows. Section 2 introduces the ordinal probit and ordinal quantile models, along with their MCMC algorithms for estimation. Section 3 outlines the data and provides a preliminary investigation. In Sections 4, we present the results from our models and discuss their implications. Finally, Section 5 offers concluding remarks.

2. The Modeling Framework

We briefly describe the ordinal probit and ordinal quantile models. For both, we outline the Bayesian estimation algorithm using MCMC methods and explain the computation of CEs.

2.1. The Ordinal Probit Model

Ordinal data models (Johnson and Albert, 2000), also known as "ordered choice models," allow fitting a regression model to an ordinal dependent (outcome or response) variable, typically denoted by y, as a function of the covariates. These models are grounded in the random utility framework from economics and explained, among others, in Jeliazkov and Rahman (2012) and Batham et al. (2023). In a typical setting, y has several categories, and each one is assigned a score (value or number) that is inherently ordered or ranked. However, these scores only carry ordinal meaning and lack cardinal interpretation—although the categories are ranked, the differences between them cannot be compared directly. For example, in our study, responses to the question about purchasing an EV are coded as follows: 1 for not at all likely, 2 for not too likely, 3 for somewhat likely, and 4 for very likely. A score of 2 compared to 1 implies more purchase intent, but we cannot interpret it as twice the intent. Similarly, the difference in intent between 2 and 1 is not the same as that between 4 and 3.

The ordinal regression model, following Albert and Chib (1993), can be written in terms of a continuous latent variable z_i as follows:

$$z_i = x_i'\beta + \varepsilon_i, \qquad \forall\, i = 1, \cdots, n, \tag{1}$$

where x_i is a $k \times 1$ covariate vector including a column of ones, β is a $k \times 1$ parameter vector, and n is the number of observations. We assume the error ε is *independent and identically distributed* (*iid*) as a standard normal distribution (i.e., $\varepsilon_i \sim N(0,1)$ for $i = 1, 2, \ldots, n$), which gives rise to the *ordinal probit* model.

In our study, the unobserved variable z_i represents intent to purchase EV and is associated with the observed discrete response y_i to the question about purchasing an EV, as follows:

$$\gamma_{j-1} < z_i \leq \gamma_j \iff y_i = j, \qquad \forall\, i = 1, \cdots, n;\ j = 1, \cdots, J, \tag{2}$$

where $-\infty = \gamma_0 < \gamma_1 \cdots < \gamma_{J-1} < \gamma_J = \infty$ are the cutpoints (or thresholds), and J denotes the number of categories or outcomes of y. This relationship between the latent z (intent to purchase an EV) and observed y (response to the question about purchasing an EV) is shown in Figure 1. $P(y_i = 1)$ is the area under $f(z_i)$ to the left of γ_1, $P(y_i = 2)$ is the area under $f(z_i)$ between γ_1 and γ_2, and so on. We set $\gamma_1 = 0$ and $var(\varepsilon) = 1$ to anchor the location and scale of the distribution, respectively. These restrictions are required for parameter identification and further explained in (Jeliazkov et al., 2008) and Jeliazkov and Rahman (2012).

Given the data $y = (y_1, \cdots, y_n)'$ and the covariates, the likelihood function for ordinal probit model can be written as follows:

$$f(y|\beta,\gamma) = \prod_{i=1}^{n}\prod_{j=1}^{J} \Pr(y_i = j|\beta,\gamma)^{I(y_i=j)} = \prod_{i=1}^{n}\prod_{j=1}^{J} \Big[\Phi(\gamma_j - x_i'\beta) - \Phi(\gamma_{j-1} - x_i'\beta)\Big]^{I(y_i=j)}, \tag{3}$$

where $\Phi(\cdot)$ is the cumulative distribution function (*cdf*) of a standard normal distribution and

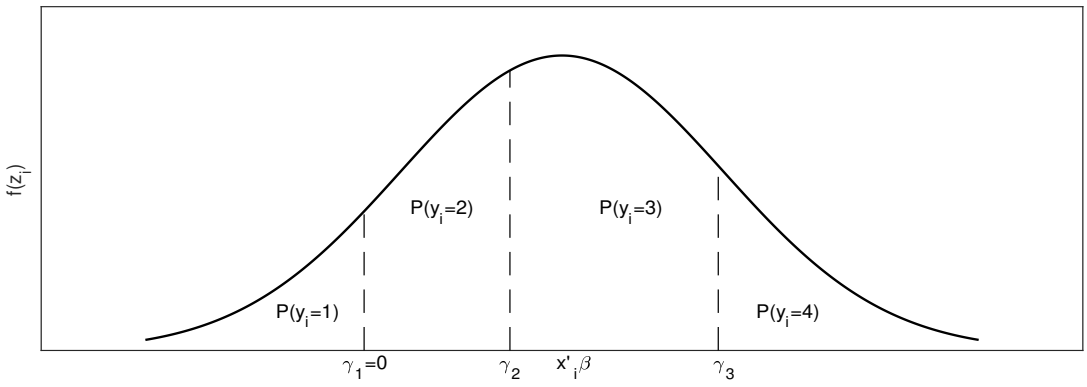


Figure 1: The distribution of the latent variable z. The four probabilities $\mathrm{P}(y_i = 1)$, $\mathrm{P}(y_i = 2)$, $\mathrm{P}(y_i = 3)$, and $\mathrm{P}(y_i = 4)$ correspond to the responses regarding the intention to purchase an electric vehicle (z_i) for individual i with mean $x_i'\beta$: not at all likely, not too likely, somewhat likely, and very likely.

$I(y_i = j)$ is an indicator function, which equals 1 if the condition within parenthesis is true and 0 otherwise. But the ordering constraint $\gamma_1 = 0 < \gamma_2 < ... < \gamma_{J-1}$ is difficult to satisfy during the MCMC sampling. So, we apply the transformation of Albert and Chib (2001): $\delta_j = \ln(\gamma_j - \gamma_{j-1})$, for $2 \leq j \leq J-1$, and rewrite the likelihood as a function of β and $\delta = (\delta_2, \ldots, \delta_{J-1})'$, which allows us to make inferences from $f(y|\beta, \delta)$.

To complete the Bayesian framework, we use the Bayes theorem to combine the augmented likelihood $f(y, z|\beta, \delta)$ with the prior distributions: $\beta \sim N(\beta_0, B_0)$ and $\delta \sim N(d_0, D_0)$. The resulting augmented posterior distribution can be written as

$$\pi(\beta, \delta, z|y) \propto f(y|\beta, \delta, z)\, f(z|\beta)\pi(\beta)\pi(\delta) = \left\{ \prod_{i=1}^{n} f(y_i|\delta, z_i) \right\} f(z|\beta)\pi(\beta)\pi(\delta), \tag{4}$$

where $f(y_i|\delta, z_i) = 1\{\gamma_{j-1} < z_i \leq \gamma_j\}$, the correspondence between γ and δ is determined by the one-to-one mapping, and the cutpoint index j is determined by the observed value of y_i. Additionally, $f(z|\beta) = f_N(z|X\beta, I_n)$ and the priors $\pi(\beta)$ and $\pi(\delta)$ are *pdf*s of normal distribution. Based on the augmented joint posterior (4), the conditional posteriors can be derived and the model estimated using MCMC sampling, as outlined in Algorithm 1.

After estimation, an important construct is to compute the CEs (or marginal effects) on the outcome probabilities, as, unlike linear regression, the coefficients do not give the CE of a variable. Assume that the l-th covariate, $x_{i,l}$, is set to two distinct values, a and b, denoted as $x_{i,l}^a$ and $x_{i,l}^b$, respectively. We partition the covariate and parameter vectors as follows: $x_i^a = (x_{i,l}^a, x_{i,-l})$, $x_i^b = (x_{i,l}^b, x_{i,-l})$, and $\beta = (\beta_l, \beta_{-l})$, where $-l$ denotes all covariates (and parameters) except for the l-th. Our goal is to examine the distribution of the difference $\Pr(y_i = j|x_{i,l}^b) - \Pr(y_i = j|x_{i,l}^a)$ for $1 \leq j \leq J$, by marginalizing over $x_{i,-l}$ and (β, δ), which enables us to incorporate the uncertainty associated with data and model parameters and avoid nontrivial biases in estimating CEs (Jeliazkov and Vossmeyer, 2018).

Algorithm 1: MCMC algorithm for estimating ordinal probit model.

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1. Sample $\delta, z|y, \beta$ in one block as follows:

   (a) Sample $\delta|y, \beta$ marginally of z by generating δ' from a random-walk chain $\delta' = \delta + s$, where $s \sim N(0_{J-2}, \iota^2 \hat{D})$, ι is a tuning parameter, $\hat{D} = -\left[\frac{\partial^2 \ln f(y|\beta,\delta)}{\partial\delta\partial\delta^T}\right]^{-1}\Big|_{\delta=\hat{\delta}}$, and $\hat{\delta} = \arg\max_\delta \ln f(y|\beta, \delta)$. Accept the proposed value δ' with probability

$$\alpha_{MH}(\delta, \delta') = \min\left\{1, \frac{f(y|\beta, \delta')\pi(\delta')}{f(y|\beta, \delta)\pi(\delta)}\right\},$$

   otherwise repeat the current value δ.

   (b) Sample $z_i|y, \beta, \delta \sim TN_{(\gamma_{j-1},\gamma_j)}(x_i'\beta, 1)$ for $i = 1, \ldots, n$, where $TN_{(\gamma_{j-1},\gamma_j)}$ denotes a truncated normal distribution constrained between γ_{j-1} and γ_j; and γ is derived from the one-to-one mapping relating γ and δ.

2. Sample $\beta|z \sim N(\hat{\beta}, \hat{B})$ where $\hat{B}^{-1} = (B_0^{-1} + X'X)$, and $\hat{\beta} = \hat{B}(B_0^{-1}\beta_0 + X'z)$.

To obtain draws from the distribution $\Pr(y_i = j|x_{i,l}^b) - \Pr(y_i = j|x_{i,l}^a)$, we use the method of composition (Chib and Jeliazkov, 2006). This involves selecting an individual, extracting the corresponding covariate values, drawing (β, δ) from their posterior distributions, and evaluating the difference $\Pr(y_i = j|x_{i,l}^b, x_{i,-l}, \beta, \delta) - \Pr(y_i = j|x_{i,l}^a, x_{i,-l}, \beta, \delta)$, where $\Pr(y_i = j|x_i^q, \beta, \delta) = \Phi(\gamma_j - x_{i,l}^q\beta_l - x_{i,-l}'\beta_{-l}) - \Phi(\gamma_{j-1} - x_{i,l}^q\beta_l - x_{i,-l}'\beta_{-l})$, for $q = b, a$, and $1 \leq j \leq J$. The process is repeated for all individuals and MCMC draws. The average CE (ACE) for outcome j is then computed as the mean of pointwise probability differences:

$$ACE_{y=j} \approx \frac{1}{M}\frac{1}{n}\sum_{m=1}^{M}\sum_{i=1}^{n}\Big[\Pr(y_i = j|x_{i,l}^b, x_{i,-l}, \beta^{(m)}, \delta^{(m)}) - \Pr(y_i = j|x_{i,l}^a, x_{i,-l}, \beta^{(m)}, \delta^{(m)})\Big], \quad (5)$$

where $(\beta^{(m)}, \delta^{(m)})$ denotes the MCMC draws, and M is the number of after-burn-in MCMC draws.

2.2. The Ordinal Quantile Model

The parameter estimates from the ordinal probit model provide information on the expected value of the latent response variable and average probabilities of outcomes conditional on the covariates. However, researchers are often more interested in examining specific quantiles of the dependent variable, particularly the lower and upper extremes, to answer policy-relevant questions. For instance, confidence that public charging infrastructure will continue to expand—one of our key covariates—may have less effect on individuals with low interest in EVs. However, among those who are moderately interested, increased confidence may strengthen intent, reassuring them that charging access will not be a barrier and moving them from "somewhat likely" to "very likely" buyers. To capture how the influence of confidence and other factors varies across levels of

purchase intent, we use ordinal quantile regression. These insights provide suggestive evidence for more targeted interventions; for example, they show that improving infrastructure visibility may be more effective when directed at consumers already considering EVs rather than those with little or no interest.

The ordinal quantile regression model, proposed by Rahman (2016), can be written in terms of a latent variable z_i as follows:

$$\begin{aligned} z_i &= x_i'\beta_p + \varepsilon_i, && \forall\ i = 1, \cdots, n, \\ \gamma_{p,j-1} < z_i \leq \gamma_{p,j} &\iff y_i = j, && \forall\ i = 1, \cdots, n;\ j = 1, \cdots, J, \end{aligned} \tag{6}$$

where the regression coefficient β_p and cutpoint vector γ_p are quantile dependent as indicated by the subscript p, and $\varepsilon_i \overset{iid}{\sim} AL(0, 1, p)$ for $i = 1, 2, \ldots, n$; where AL denotes an asymmetric Laplace distribution (Yu and Zhang, 2005). The AL distribution is essential to create a working likelihood function and yields the following expression,

$$\begin{aligned} f(y|\beta_p, \gamma_p) &= \prod_{i=1}^{n}\prod_{j=1}^{J} P(y_i = j|\beta_p, \gamma_p)^{I(y_i=j)} \\ &= \prod_{i=1}^{n}\prod_{j=1}^{J} \Big[F_{AL}(\gamma_{p,j} - x_i'\beta_p) - F_{AL}(\gamma_{p,j-1} - x_i'\beta_p)\Big]^{I(y_i=j)}, \end{aligned} \tag{7}$$

where $F_{AL}(\cdot)$ denotes the *cdf* of an AL distribution and $I(y_i = j)$ is an indicator function.

At this stage, three key issues need attention. First, the ordering constraint of cutpoints during sampling is addressed using the transformation, $\delta_{p,j} = \ln(\gamma_{p,j} - \gamma_{p,j-1})$ for $2 \leq j \leq J - 1$, where note that δ_p is quantile dependent. Second, we set $\gamma_{p,1} = 0$ to anchor the location and fix variance for any quantile to meet the scale restriction. Third, the AL distribution is not convenient for MCMC sampling, as it does not yield tractable conditional posteriors. So, following Kozumi and Kobayashi (2011), we use the normal-exponential mixture formulation: $\varepsilon_i = \theta w_i + \tau\sqrt{w_i}\, u_i$, where $\theta = (1-2p)/(p(1-p))$ and $\tau = \sqrt{2/(p(1-p))}$. The variable w_i follows an exponential distribution, $w_i \sim \mathcal{E}(1)$, and is independent of u_i, which follows a normal distribution, $u_i \sim N(0, 1)$. Based on this formulation, $z_i|\beta_p, w_i \sim N(x_i'\beta_p + \theta w_i, \tau^2 w_i)$ for $i = 1, \ldots, n$; enabling us to leverage the properties of normal distribution for an efficient MCMC algorithm.

By Bayes theorem, we combine the augmented likelihood $f(y, z|\beta_p, \delta_p, w)$ with the normal priors:

$\beta_p \sim N(\beta_{p0}, B_{p0})$, $\delta_p \sim N(\delta_{p0}, D_{p0})$, to arrive at the augmented joint posterior distribution,

$$\begin{aligned}
\pi(z, \beta_p, \delta_p, w|y) &\propto f(y|z, \beta_p, \delta_p, w)\ f(z|\beta_p, w)\ \pi(w)\ \pi(\beta_p)\ \pi(\delta_p), \\
&\propto \Big\{ \prod_{i=1}^{n} f(y_i|z_i, \delta_p) \Big\}\ f(z|\beta_p, w)\ \pi(w)\ \pi(\beta_p)\ \pi(\delta_p), \\
&\propto \prod_{i=1}^{n} \Big\{ \prod_{j=1}^{J} 1\{\gamma_{p,j-1} < z_i < \gamma_{p,j}\}\ N(z_i|x_i'\beta_p + \theta w_i, \tau^2 w_i)\ \mathcal{E}(w_i|1) \Big\} \\
&\quad \times\ N(\beta_p|\beta_{p0}, B_{p0})\ N(\delta_p|\delta_{p0}, D_{p0}).
\end{aligned} \tag{8}$$

In the first line, we use the factorization $f(y, z|\beta_p, \delta_p, w) = f(y|z, \beta_p, \delta_p, w) \times f(z|\beta_p, w)$ and note that z is independent of δ_p. In the second line, we exploit the independence of y_i from (β_p, w) given (z_i, δ_p), which follows from the second line of Equation (6), where y_i given (z_i, δ_p) is determined with probability 1. In the third and fourth lines, we specify the conditional distribution of the latent variable z and the prior distribution on the parameters (β_p, δ_p).

The conditional posterior distributions are derived from the augmented joint posterior distribution (Equation 8), and the parameters are sampled as per Algorithm 2. The implementation of this algorithm, available in the bqror package, is explained in Maheshwari and Rahman (2023).

Algorithm 2: MCMC algorithm for estimating ordinal quantile model.

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1. Sample $\beta_p|z, w \sim N(\tilde{\beta}_p, \tilde{B}_p)$, where,

$$\tilde{B}_p^{-1} = \Big(\sum_{i=1}^{n} \frac{x_i x_i'}{\tau^2 w_i} + B_{p0}^{-1} \Big), \quad \text{and} \quad \tilde{\beta}_p = \tilde{B}_p \Big(\sum_{i=1}^{n} \frac{x_i (z_i - \theta w_i)}{\tau^2 w_i} + B_{p0}^{-1} \beta_{p0} \Big).$$

2. Sample $w_i|\beta_p, z_i \sim GIG\,(0.5, \tilde{\lambda}_i, \tilde{\eta})$, for $i = 1, \cdots, n$, where,

$$\tilde{\lambda}_i = \Big(\frac{z_i - x_i'\beta_p}{\tau} \Big)^2, \quad \text{and} \quad \tilde{\eta} = \Big(\frac{\theta^2}{\tau^2} + 2 \Big).$$

3. Sample $\delta_p|y, \beta_p$ marginally of w (latent weight) and z (latent data), by generating δ_p' from a random-walk chain $\delta_p' = \delta_p + s$, where $s \sim N(0_{J-2}, \iota^2 \hat{D})$, ι is a tuning parameter and $\hat{D}$ denotes negative inverse Hessian, obtained by maximizing the log-likelihood with respect to δ_p. Given the current value of δ_p, accept the proposed draw δ_p' with probability,

$$\alpha_{MH}(\delta_p, \delta_p') = \min \left\{ 1, \frac{f(y|\beta_p, \delta_p')\ \pi(\beta_p, \delta_p')}{f(y|\beta_p, \delta_p)\ \pi(\beta_p, \delta_p)} \right\};$$

   otherwise repeat the value δ_p. The variance of s may be tuned for appropriate step size and acceptance rate.

4. Sample $z_i|y, \beta_p, \gamma_p, w \sim TN_{(\gamma_{p,j-1}, \gamma_{p,j})}(x_i'\beta_p + \theta w_i, \tau^2 w_i)$ for $i = 1, \cdots, n$, where TN denotes

a truncated normal distribution and γ_p is obtained via δ_p using the one-to-one mapping.

After estimating the ordinal quantile models, we compute the covariate effects using the method of composition. Studies on quantile regression that have applied it to estimate CEs include (Rahman and Vossmeyer, 2019) and Bresson et al. (2021). Assuming a setup similar to Section 2.1, our goal is to obtain draws from the distribution $\{\Pr(y_i = j|x^b_{i,l}) - \Pr(y_i = j|x^a_{i,l})\}$. We randomly select an individual, extract their covariates, draw a value (β_p, δ_p) from their posterior distributions, and evaluate $\{\Pr(y_i = j|x^b_{i,l}, x_{i,-l}, \beta_p, \delta_p) - \Pr(y_i = j|x^a_{i,l}, x_{i,-l}, \beta_p, \delta_p)\}$, where $\Pr(y_i = j|x^q_i, \beta_p, \delta_p) = F_{AL}(\gamma_{p,j} - x^q_{i,l}\,\beta_{p,l} - x'_{i,-l}\,\beta_{p,-l}) - F_{AL}(\gamma_{p,j-1} - x^q_{i,l}\,\beta_{p,l} - x'_{i,-l}\,\beta_{p,-l})$, for $q = b, a$ and $1 \leq j \leq J$. This process is repeated for all individuals and MCMC draws, and the ACE for outcome j at quantile p is calculated as the mean of difference in pointwise probabilities.

3. Data

The study draws on survey data from three opinion polls by the Pew Research Center in three years. The first survey was conducted April 20–21, 2021 on a sample of 13,749 adults, the second May 2–8, 2022 on a sample of 10,282 adults, and the third May 30–June 4, 2023 on a sample of 10,329 adults. After removing all missing observations and cleaning the data, we have a sample of 11,052, 7,173, and 7,201 observations available for analysis. Table 1 shows a descriptive summary of the independent and dependent variables. Specifically, it presents mean and standard deviation for the continuous variables and count and percentage for the categorical variables.

The survey data offer at least three distinct advantages over studies that use survey data to gauge EV purchase intent. First, they are nationally representative and span multiple years. As a result, the estimates we generate are more likely to be robust to cross-sectional heterogeneity. All survey data and additional information on the surveys are available for download from the Pew Research Center dataset portal (and the corresponding author's webpage). Second, an appealing feature of our data sets is the availability of ordinal responses to purchase likelihood. This enables us to model public preference in much greater detail compared to studies that use binary responses, such as (Buhmann and Criado, 2023). Third, the first and second surveys were during COVID-19, but the third survey was in the postpandemic phase. Therefore, if interest increased for sustainable products during the pandemic, this should be evident in the data summary, with a higher percentage of respondents expressing a preference for buying EVs during the pandemic phase.

We begin by discussing the independent variables that have a direct influence on purchasing an EV—the question of primary interest. Two such variables, `EV Info` and `Env Better`, are specific to the April 2021 survey. `EV Info` measures how much a respondent has read or heard about EVs. It is coded as 1 if the respondent has read or heard a lot about EVs and 0 otherwise. As shown in Table 1, about 38 percent of respondents have read or heard a lot about EVs. `Env Better` reflects perception about the environmental impact of EVs compared to gas-powered vehicles. It takes the value 1 if the respondent believes that EVs are better for the environment and 0 otherwise

Table 1: Descriptive summary of the variables for three Pew Research Center surveys: April 2021; May, 2022; and May–Jun, 2023. Mean (MEAN) and standard deviations (STD) are reported for variables treated as continuous; count (COUNT) and percentages (PER) are reported for categorical variables.

		April 2021		May 2022		May–June 2023	
VARIABLE		MEAN	STD	MEAN	STD	MEAN	STD
INCOME/1,0000 (USD)		7.00	3.33	8.00	3.23	8.00	3.24
		COUNT	PER	COUNT	PER	COUNT	PER
EV Info	◦ Read or heard a lot	4,170	37.73	..	..	..	..
	◦ Little or nothing at all	6,882	62.27	..	..	..	..
Env Better	◦ EVs are environmentally better than gas-powered vehicles	7,944	71.88	..	..	..	..
	◦ About the same or worse	3,108	28.12	..	..	..	..
EV Infra	◦ US will build charging stations and infrastructure: extremely or very confident	..	..	..	..	1,263	17.54
	◦ Somewhat confident, not too confident, or not at all confident	..	..	..	..	5,938	82.46
EV Owner	Owns electric or hybrid vehicle	1,039	9.40	769	10.72	812	11.28
GACC	◦ Federal government is doing "too much" to reduce the effects of climate change	1,962	17.75	1,684	23.48	1,736	24.11
	◦ About the right amount	2,203	19.93	1,636	22.81	1,582	21.97
	◦ Too little	6,887	62.31	3,853	53.72	3,883	53.92
Age < 50	Indicator for age below 50	5,124	46.36	2,687	37.46	2,596	36.05
Female	Indicator for female gender	5,848	52.91	3,819	53.24	3,815	52.98
Education	◦ Graduate and above	6,447	58.33	3,846	53.62	3,730	51.80
	◦ Some college	3,194	28.90	2,201	30.68	2,276	31.61
	◦ HS and below	1,411	12.77	1,126	15.70	1,195	16.59
Married	Married or living with a partner	..	..	5,692	79.35	5,640	78.32
Metropolitan	Lives in a metropolitan area	9,817	88.83	6,260	87.87	6,286	87.29
Region	◦ Northeast	1,784	16.14	1,100	15.34	1,084	15.05
	◦ Midwest	2,444	22.11	1,613	22.49	1,586	22.02
	◦ South	4,245	38.41	2,841	39.61	2,987	41.48
	◦ West	2,579	23.34	1,619	22.57	1,544	21.44
US Born	Indicator for born in the United States	9,664	87.44	6,150	85.74	6,188	85.93
Race	◦ White	7,801	70.58	5,335	74.38	5,083	70.59
	◦ Black	820	7.42	446	6.22	726	10.08
	◦ Other races	2,431	22.00	1,392	19.41	1,392	19.33
Party	◦ Democrat	4,201	38.01	2,258	31.48	2,268	31.50
	◦ Republican	2,667	24.13	2,453	34.20	2,341	32.51
	◦ Independent & others	4,184	37.86	2,462	34.32	2,592	36.00
Purchase EV	Very likely	2,411	21.82	1,526	21.27	1,397	19.40
	Somewhat likely	2,819	25.51	1,936	26.99	1,815	25.20
	Not too likely	3,381	30.59	1,787	24.91	1,736	24.11
	Not at all likely	2,441	22.09	1,924	26.82	2,253	31.29

(worse for the environment or about the same). According to Table 1, approximately 72 percent of respondents view EVs as environmentally superior. Another variable is `EV Infra`, which is only available in the May–June 2023 survey. It is coded as 1 if the respondent is extremely or very confident that the United States will build the necessary charging stations and infrastructure to support a large number of EVs on the roads and 0 otherwise (somewhat confident, not too confident, or not at all confident). As seen in Table 1, about 82 percent of respondents express a negative perception about this.

Two key variables of interest to our study, which are available in all the surveys, are `EV Owner` and `GACC`. `EV Owner` indicates whether the respondent owns an electric or hybrid vehicle and takes the value 1 if true and 0 otherwise. As shown in Table 1, respondents who own an electric or hybrid vehicle are 9.40, 10.72, and 11.28 percent across the three survey datasets. `GACC` reflects respondents' perceptions of government actions to mitigate global climate change. It is divided into three categories: too much, about the right amount, and too little (with the latter as the reference category). Table 1 indicates that in each sample, more than half of the respondents feel that government action is insufficient.

We also incorporate a broad set of demographic variables as covariates in our regression models. These variables (except marital status) are common across all surveys and include income, age, gender, education, marital status (not available in the April 2021 survey), metropolitan area, region of residence, birth country, racial background, and party affiliation.

Pew surveys record income as belonging to one of nine categories: 0–30k, 30k–40k, 40k–50k, 50k–60k, 60k–70k, 70k–80k, 80k–90k, 90k–100k, and $> 100k$, where k denotes a thousand dollars. To simplify, we use the midpoint of each income range and assign an imputed value of \$20,000 for the first category and \$110,000 for the last. Age is recorded in four categories (18–29, 30–49, 50–64, and ≥ 65), but for convenience, we recode it to a binary indicator taking the value 1 for below 50 and 0 otherwise. As shown in Table 1, 46.36 percent of respondents in the first dataset are under 50, with this approximately 10 percent lower in the next two datasets. Gender is represented by a binary indicator `Female`, where 1 indicates female and 0 indicates male. More than 50 percent respondents across all three datasets are female. Education is classified into three categories: `Graduate & Above`, `Some College`, and `High School (HS) and Below`; the latter is the reference category. As shown in Table 1, the majority of respondents are graduates or have higher education, followed by those with some college education. Therefore, respondents across the three samples are generally well educated.

Information on marital status is available only in the May 2022 and May−June 2023 surveys. We create an indicator variable `Married` that takes the value 1 if the respondent is married or living with a partner and 0 if they are divorced, separated, widowed, or never married. Table 1 shows that more than three-quarters of respondents are married or living with a partner. Two variables reflect residential background. `Metropolitan` is an indicator that equals 1 if the respondent lives in a metropolitan area and 0 otherwise. Across the three datasets, more than four-fifths of the respondents are in metropolitan areas. We add regional indicators for `Northeast`, `Midwest`, `South`,

and `West`, with `Northeast` as the reference category. As shown in Table 1, the largest proportion of respondents (about 40 percent) reside in the South, followed by approximately 22 percent in both the Midwest and West. The smallest fraction, about 15 percent, lives in the Northeast.

The variable `US Born` indicates whether the respondent is US born or an immigrant. According to Table 1, a predominant fraction (about 86 percent) of the sample across three datasets was US born. Our demographic variable list also includes race indicators for `White` (reference category), `Black`, and `Other Races`. As expected, the largest proportion of respondents (over 70 percent) are White, followed by about 20 percent from other races. The smallest group, about 8 percent, is Black. Finally, party affiliation is captured with indicator variables for `Democrat`, `Republican` (reference category), and `Independent & Others`. Respondents are roughly equally distributed across these three political categories.

As noted, our objective is to analyze the factors that influence individuals' decision to purchase an EV. However, a continuous measure of support or opposition is not directly observable. The data are limited to the respondent's answer to the question: "The next time you purchase a vehicle, how likely are you to seriously consider purchasing an electric vehicle?" Response to this question serves as the dependent variable in our models and has four categories: very likely, somewhat likely, not too likely, and not at all likely. The surveys also include a fifth category (I do not expect to purchase a vehicle); we exclude these responses to simplify the framework and adhere to ordinal modeling. Table 1 presents the count and percentage of each response category in the three datasets: 47.33 and 48.26 percent of the respondents in the April 2021 and May 2022 surveys are either very or somewhat likely to purchase an EV, respectively. In comparison, this is 44.60 percent in the May–June 2023 survey. Based on these percentages, we do not observe a significant decline in preference for purchasing EVs in the postpandemic phase. Overall, our data summary clearly shows that public attitude toward purchasing an EV is generally positive.

Figure 2 offers further insights into the association between the dependent variable and selected regressors from the three survey datasets. In each panel, the bars represent two opinion categories: not likely and likely. The first bar displays the percentage of responses for not at all likely (shown in dark shade) and the cumulative percentage for both not at all likely and not too likely (sum of dark and light shades). The second bar illustrates the percentage of responses for somewhat likely (in dark shade) and the cumulative percentage for somewhat likely and very likely (sum of dark and light shades).

The first two panels of Figure 2 highlight the influence of information on consumers' decisions to purchase EVs. In the first panel, among respondents who have read or heard little or nothing at all about EVs, only 46.99 percent are likely to consider purchasing one. In contrast, the second panel reveals a much higher likelihood—62.07 percent—among those who have read or heard a lot about EVs. A more striking difference emerges in perceptions of the environmental impact. As shown in the third panel, just 19.18 percent of respondents who view EVs as about the same or worse than gas-powered vehicles are likely to purchase one. However, as shown in the fourth panel, that jumps to 65.79 percent for those who believe EVs have a lower environmental impact. A similar pattern

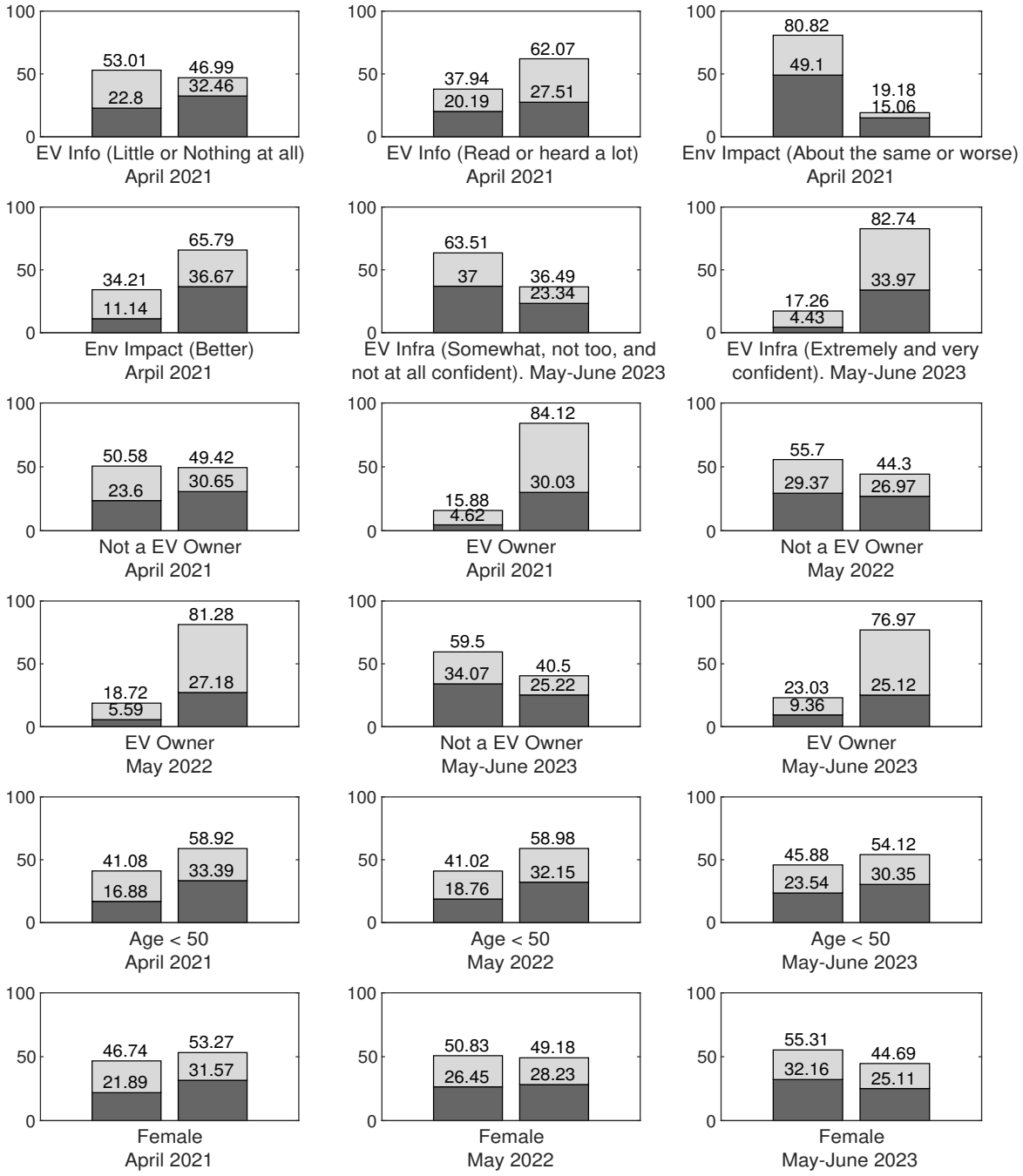


Figure 2: Stacked bars displaying the percentage of observations corresponding to the four opinion categories for a selected list of covariates. In each panel, the first stacked bar shows the percentage of observations for "not at all likely" and the cumulative percentage for "not at all likely" and "not too likely." The second stacked bar shows the percentage of observations for "somewhat likely" and the cumulative percentage for "somewhat likely" and "very likely."

is evident from Panels 5 and 6 when considering views on the development of charging stations and infrastructure to support large number of EVs on the road. Among those who lack confidence that the government will build the necessary facilities, only 36.49 percent are likely to buy an EV. In stark contrast, a much higher 82.74 percent of respondents with that confidence are likely to make a purchase. These relationships highlight how knowledge and environmental impact of EVs, and confidence in supporting infrastructure play pivotal roles in shaping consumer purchase decisions.

The remainder of panels in Figure 2 (7–18) exhibit how factors such as ownership of an EV or hybrid vehicle, age, and gender affect the purchase decision. The stacked bars from Panels 7–12 clearly show that owning an EV or hybrid vehicle (as opposed to not) increases the purchase likelihood across all survey datasets. For instance, 84.12 percent of EV or hybrid owners are likely to purchase an EV compared to only 49.42 percent of non-owners in the April 2021 survey data. For the same comparison, a difference of 36.98 percent ($81.28 - 44.3$ percent) and 36.47 percent ($76.97 - 40.5$ percent) appears in the May 2022 and May–June 2023 survey data. Age also plays a role, with a majority of respondents under 50 being likely to purchase an EV across all three datasets. With respect to gender, women's purchase likelihood is 53.27 percent in the April 2021 dataset but decreases to 49.18 and 44.69 percent in May 2022 and May–June 2023, respectively.

4. Empirical Results and Discussion

We report the results from the Bayesian estimation of ordinal probit and ordinal quantile models and the marginal likelihood that may be used for model comparison. Moreover, for each model, we compute the CEs for all or some of the significant variables and discuss our findings in the context of the literature.

4.1. Results from Ordinal Probit Models

We begin by presenting the results from ordinal probit models estimated separately for each survey. Specifically, Table 2 presents the posterior means and standard deviations of the parameters along with the logarithm of marginal likelihood (Chib and Jeliazkov, 2001). The estimates are obtained from 10,000 MCMC iterations (after a burn-in of 2,500 iterations) and use the following prior distributions: $\beta \sim N_k(0, I)$ and $\delta \sim N_{J-2}(0, 0.25 * I)$, where I denotes an identity covariance matrix. The priors are relatively diffuse to allow the data speak for themselves. The sign of coefficients indicates the direction of covariate effects for the first and last response categories. For example, in Table 2, the coefficient for `EV Info` is positive (0.43), so it increases (decreases) the probability of last (first) category "Very likely" ("Not at all likely"). However, these coefficients do not represent the CEs, nor can we state anything a priori about those effects on intermediate outcomes ("Not too likely" and "Somewhat likely"). Therefore, Table 3 provides the CEs for all variables statistically different from 0; our measure accounts for uncertainty in parameters and observations to avoid biases (Jeliazkov and Vossmeyer, 2018).

The combined results from the three surveys reveal consistent patterns in factors associated with EV purchase intent. As shown in Table 3, the CEs from the 2021 survey show that respondents

who have read or heard extensively about EVs are 10.2 (2.2) percentage point more likely to express strong interest (some interest) in purchasing EVs compared to those with limited exposure. These gains in probability comes from a reduction of 8.5 and 3.9 percentage points from the first two opinion categories. Our findings align with Zhao et al. (2022) and Scherrer (2023), who demonstrate that greater exposure to information about EVs—whether through peer effects or media—positively influences attitudes toward EVs, and with Krause et al. (2013), who underscore the crucial role of accurate information in shaping consumer perceptions.

Going forward, we discuss the CEs only on the first and last categories, as they show the largest changes in probability. For the 2021 survey, the belief that EVs are environmentally better than gas-powered vehicles is associated with a 15.5 percentage point increase in strong interest and a 19.5 percentage point decrease in no interest, underscoring the importance of environmental perceptions in shaping purchase intent. This finding aligns with Carley et al. (2013), Krause et al. (2013), Scherrer (2023), and Mamkhezri (2025) who show that environmentally sensitive respondents tend to have a more favorable opinion of EVs [4].

Confidence in charging infrastructure, assessed in the 2023 survey, is one of the strongest predictors of EV interest. Respondents who are very or extremely confident are 19.1 (18.8) percentage points more (less) likely to express strong (no) interest in purchasing EVs compared to those who report lower confidence. This finding aligns with research such as Carley et al. (2013) and Li et al. (2017). As shown in Table 1, 82 percent of respondents lack such confidence. Taken together, these results suggest that skepticism about charging infrastructure is likely to be a significant barrier to broader adoption, highlighting the importance of both improving infrastructure and clearly communicating its availability, reliability, and expansion plans to the public.

[4]Relatedly, Buhmann and Criado (2023) find that reputation-conscious consumers prefer EVs only when their prices exceed those of internal combustion engine vehicles, suggesting that reputation takes precedence over environmental concerns.

Table 2: Results from ordinal probit models: posterior mean (Mean) and standard deviation (Std) of the parameters, and logarithm of marginal likelihood, from 2021, 2022, and 2023 survey data.

	April 2021		May 2022		May–June 2023	
	Mean	Std	Mean	Std	Mean	Std
Intercept	−0.28	0.07	0.36	0.09	−0.05	0.09
EV Info	0.43	0.02	..	..	..	..
Env Better	0.79	0.03	..	..	..	..
EV Infra	..	..	..	..	0.82	0.04
EV Owner	0.79	0.04	0.86	0.05	0.82	0.04
GACC (TM)	−0.79	0.04	−1.13	0.04	−1.07	0.04
GACC (RA)	−0.52	0.03	−0.63	0.03	−0.49	0.04
Age < 50	0.16	0.02	0.17	0.03	0.15	0.03
Female	−0.02	0.02	−0.11	0.03	−0.12	0.03
Grad & Above	0.38	0.04	0.45	0.04	0.49	0.04
Some College	0.18	0.04	0.23	0.04	0.21	0.04
Married	..	..	0.06	0.03	0.02	0.04
Metropolitan	0.24	0.03	0.25	0.04	0.20	0.04
Midwest	−0.08	0.03	−0.05	0.04	−0.07	0.04
South	−0.05	0.03	−0.02	0.04	−0.07	0.04
West	0.19	0.03	0.19	0.04	0.18	0.04
US Born	−0.21	0.04	−0.33	0.04	−0.22	0.04
Black	−0.28	0.04	−0.14	0.06	−0.18	0.05
Other Races	0.05	0.03	0.01	0.04	−0.03	0.04
Democrat	0.59	0.03	0.65	0.04	0.75	0.04
Ind & Others	0.40	0.03	0.36	0.03	0.43	0.03
Income/1,0000 (USD)	0.01	0.01	0.02	0.01	0.03	0.01
δ_1	0.01	0.02	−0.10	0.02	−0.11	0.02
δ_2	0.12	0.01	−0.00	0.02	0.04	0.02
ln ML	$-12,415$		$-8,301$		$-7,914$	

Table 3: Covariate effects (CEs) from ordinal probit models. CE for variables not statistically different from 0 are marked with ×.

	April 2021				May 2022				May–June 2023			
	ΔP(y=1)	ΔP(y=2)	ΔP(y=3)	ΔP(y=4)	ΔP(y=1)	ΔP(y=2)	ΔP(y=3)	ΔP(y=4)	ΔP(y=1)	ΔP(y=2)	ΔP(y=3)	ΔP(y=4)
EV Info	−0.0851	−0.0388	0.0217	0.1022	..	..	..	..	..	..	..	..
Env Better	−0.1955	−0.0565	0.0970	0.1551	..	..	..	..	..	..	..	..
EV Infra	..	..	..	..	..	..	..	..	−0.1880	−0.0553	0.0526	0.1908
EV Owner	−0.1321	−0.0849	0.0051	0.2119	−0.1749	−0.0794	0.0231	0.2312	−0.1814	−0.0513	0.0421	0.1905
GACC (TM)	0.1971	0.0453	−0.0945	−0.1478	0.3341	0.0133	−0.1507	−0.1968	0.3170	−0.0153	−0.1395	−0.1622
GACC (RA)	0.1180	0.0391	−0.0490	−0.1082	0.1649	0.0267	−0.0639	−0.1278	0.1282	0.0079	−0.0486	−0.0875
Age < 50	−0.0326	−0.0130	0.0099	0.0356	−0.0410	−0.0090	0.0129	0.0371	−0.0371	−0.0036	0.0126	0.0282
Female	×	×	×	×	0.0268	0.0055	−0.0082	−0.0240	0.0301	0.0027	−0.0100	−0.0228
Grad & Above	−0.0815	−0.0322	0.0276	0.0860	−0.1139	−0.0240	0.0378	0.1001	−0.1264	−0.0130	0.0445	0.0949
Some College	−0.0373	−0.0152	0.0099	0.0426	−0.0541	−0.0118	0.0156	0.0503	−0.0517	−0.0052	−0.0166	0.0403
Married	..	..	..	..	−0.0154	−0.0029	0.0050	0.0134	×	×	×	×
Metropolitan	−0.0534	−0.0179	0.0191	0.0522	−0.0662	−0.0099	0.0232	0.0528	−0.0512	−0.0027	0.0183	0.0356
Midwest	0.0162	0.0061	−0.0051	−0.0172	×	×	×	×	×	×	×	×
South	×	×	×	×	×	×	×	×	×	×	×	×
West	−0.0378	−0.0164	0.0101	0.0441	−0.0457	−0.0109	0.0135	0.0431	−0.0454	−0.0053	0.0148	0.0360
US Born	0.0416	0.0186	−0.0106	−0.0497	0.0777	0.0217	−0.0214	−0.0781	0.0551	0.0071	−0.0178	−0.0444
Black	0.0614	0.0200	−0.0220	−0.0594	0.0349	0.0058	−0.0116	−0.0291	0.0460	0.0026	−0.0160	−0.0326
Other Races	×	×	×	×	×	×	×	×	×	×	×	×
Democrat	−0.1211	−0.0578	0.0403	0.1386	−0.1569	−0.0497	0.0513	0.1553	−0.1882	−0.0353	0.0677	0.1558
Ind & Others	−0.0808	−0.0310	0.0219	0.0898	−0.0890	−0.0187	0.0266	0.0811	−0.1091	−0.0093	0.0356	0.0827
ΔI= $50,000	×	×	×	×	−0.0223	−0.0051	0.0066	0.0209	−0.0363	−0.0045	0.0116	0.0291

Across all three surveys, previous EV ownership is consistently linked with a higher interest in purchasing an EV. Respondents who have owned an EV or hybrid vehicle are 19.0–23.1 percentage points more likely to report strong interest and 13.2–18.1 percentage points less likely to express no interest. Studies such as Carley et al. (2013) and Buhmann and Criado (2023) have also documented this pattern, suggesting that firsthand experience reduces uncertainty and fosters positive perceptions of EVs. However, selection effects may also be at play, as these individuals are likely early adopters with a strong pre-existing interest, making them more engaged with the EV market.

Respondents who think the government is doing too much to address climate change (GACC, TM) are 14.8–19.7 percentage points less likely to express strong interest in purchasing EVs and 19.7–33.4 percentage points more likely to report no interest. Those who believe the government is doing the right amount (GACC, RA) also express lower interest, though the effects are smaller.

Respondents under age 50 are 2.8–3.7 percentage points more likely to express strong interest and 3.3–4.1 percentage points less likely to report no interest in purchasing EVs compared to older respondents. Our finding aligns with Zhao et al. (2022), Carley et al. (2013), Krause et al. (2013), Scherrer (2023), and Mamkhezri (2025). For instance, Zhao et al. (2022) finds that EV buyers in Shanghai are predominantly younger, with most between the ages of 31 and 40.

Results from the 2022 and 2023 surveys also show that female respondents are modestly less likely to express strong interest and more likely to report no interest. The CE on strong interest decreases 2.3–2.4 percentage points, and the CE for no interest increases 2.7–3.0 percentage points. This finding is consistent with several studies, including Carley et al. (2013), Krause et al. (2013), Scherrer (2023), Buhmann and Criado (2023), and Mamkhezri (2025), which also find that men in their samples exhibit a stronger preference for EVs.

Higher education is also linked to greater EV interest. Respondents with a graduate degree are 8.6–10.0 percentage points more likely to report strong interest and 8.1–12.6 percentage points less likely to express no interest compared to those with a high school diploma or less. Similar, though smaller, effects are observed for respondents with some college education. The positive relationship between education and EV interest is similarly documented in Carley et al. (2013), Krause et al. (2013), Buhmann and Criado (2023), and Mamkhezri (2025).

Metropolitan residents are 3.6–5.3 percentage points more likely to report strong interest and 5.1–6.6 percentage points less likely to express no interest. This finding aligns with Buhmann and Criado (2023) and Mamkhezri (2025), who also report EV preference to be higher among urban residents. Moreover, respondents in the West are 3.6–4.4 percentage points more likely to report strong interest compared to those in the Northeast, though those in the Midwest and South show no significant difference from their Northeastern counterparts. This pattern likely reflects California's leadership in EV adoption, driven in part by policies such as ZEV mandates and the Clean Vehicle Rebate Program, along with a robust charging network.[5]

US-born respondents are 4.4–7.8 percentage points less likely to express strong interest and

[5]See https://www.eia.gov/todayinenergy/detail.php?id=61082

4.2–7.8 percentage points more likely to express no interest, possibly reflecting differences in cultural attitudes, driving patterns, or perceptions about the cost of ownership. Such a difference is also evident by race. Black respondents are 2.9–5.9 percentage points less likely to express strong interest and 3.5–6.1 percentage points more likely to express no interest compared to White respondents, likely reflecting structural barriers, such as limited access to charging infrastructure (Hsu and Fingerman, 2021). Other non-White respondents show similar preferences to White respondents.

Political affiliation is a consistent and significant predictor of EV purchase intent. Democrats are 13.9–18.8 percentage points more likely to report strong interest in EVs and 12.1–18.8 percentage points less likely to report no interest compared to Republicans. Similarly, Independents and others are also about 8 percentage points more likely to express strong interest relative to Republicans. These findings align with Mamkhezri (2025) and likely reflect Democrats' stronger perceptions of EVs as environmentally responsible, as documented by Sintov et al. (2020). They also reflect the starkly contrasting policy approaches of the two major political parties, particularly during the tenures of Presidents Biden and Trump. During his first term (2017–2021), Trump rolled back Obama-era fuel efficiency standards, slowing regulatory pressure on automakers to transition toward EVs. In contrast, the Biden administration adopted an aggressive pro-EV stance, prioritizing stricter fuel efficiency and emissions standards and allocating $7.5 billion through the Infrastructure Investment and Jobs Act to develop a nationwide network of 500,000 EV charging stations.

Conditional on other factors, an additional $50,000 in income is either not significantly associated with EV interest or changes the probability of strong interest (no interest) by a meager 2.1–2.9 (2.2–3.6) percentage points. Our results find support in Zhao et al. (2022) and Mamkhezri (2025), who report greater support for EVs among higher-income individuals. The small CE may reflect the growing availability of EVs across various market segments and the subsidies for low-income consumers, which reduce affordability barriers compared to earlier market years.

Overall, the results show that interest in EVs varies by environmental attitudes, experience with EVs, confidence in charging infrastructure, and demographics. Some patterns likely reflect personal preferences; others may reflect barriers, such as limited awareness or charging access.

4.2. Results from Ordinal Quantile Models

We present the results from ordinal quantile models (Rahman, 2016) that shift attention from average probabilities of outcomes to those at specific quantiles, conditional on the covariates. Table 4 presents the posterior means and standard deviations of the parameters from the ordinal quantile models along with the logarithm of marginal likelihood, estimated separately for each survey. Table 5 reports the corresponding CEs. Those at the 50th percentile align closely with those from the ordinal probit model, but across all surveys, those at the 20th and 80th quantiles are noticeably different. We find compelling evidence that the impact of covariates on purchase intent is not uniform but varies across the distribution. This highlights the value of quantile modeling for capturing these variations. Next, we emphasize the key differences across quantiles.

Although having heard or read extensively about EVs corresponds to higher purchase intent, the relationship is stronger among respondents more inclined toward adoption. In the 2021 survey and

at the 80th percentile of purchase intent, respondents who have heard or read extensively about EVs are 12.6 percentage points more likely to express strong intent compared to those who have read or heard little to nothing. At the 50th and 20th percentiles of purchase intent, the difference is 9.9 and 6.1 percentage points, respectively. The smaller CE of prior exposure to EV information at the 20th percentile suggests that simply raising awareness may not be enough to persuade consumers with low purchase interest. In contrast, for those already inclined toward adoption, providing practical, consumer-focused information—such as total cost of ownership, available incentives, and charging logistics—may influence purchase decisions.

Similarly, the relationship between confidence about building the charging infrastructure (measured in the 2023 survey) and purchase intent varies across the distribution of the latter. At the 80th percentile, confident respondents are 20.0 percentage points more likely to express strong purchase intent compared to those who are not confident. The corresponding differences are 18.1 percentage points at the median and 13.3 percentage points at the 20th percentile. Conversely, at the 80th percentile, those who are confident are 14.5 percentage points less likely to express no interest, with differences of 18.3 and 18.6 percentage points at the median and 20th percentile, respectively. These findings suggest that confidence strengthens commitment among those already inclined toward adoption and reduces outright rejection among those with lower purchase intent. Enhancing the affordability, accessibility, and reliability of charging infrastructure—and effectively communicating these efforts—can build consumer confidence and promote broader EV adoption.

Table 4: Results from quantile ordinal model: posterior mean (Mean) and standard deviation (Std) of the parameters, along with the logarithm of marginal likelihood, from 2021, 2022, and 2023 survey data.

	April 2021						May 2022						May–June 2023					
	20TH		50TH		80TH		20TH		50TH		80TH		20TH		50TH		80TH	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Intercept	−3.60	0.25	−0.58	0.17	2.60	0.25	−2.15	0.30	0.80	0.21	4.64	0.29	−2.81	0.30	−0.05	0.20	2.77	0.28
EV Info	1.28	0.08	0.98	0.06	1.64	0.08	..	..	..	..	..	..	..	..	..	..	..	..
Env Better	2.52	0.11	1.80	0.07	2.85	0.10	..	..	..	..	..	..	..	..	..	..	..	..
EV Infra	..	..	..	..	..	..	..	..	..	..	..	..	2.83	0.13	1.92	0.10	2.71	0.14
EV Owner	2.80	0.13	1.76	0.10	2.91	0.16	2.94	0.16	1.83	0.11	3.31	0.20	2.65	0.16	1.99	0.11	3.08	0.19
GACC (TM)	−2.81	0.13	−1.96	0.09	−2.49	0.13	−3.79	0.16	−2.63	0.10	−3.70	0.14	−4.00	0.17	−2.41	0.10	−3.45	0.14
GACC (RA)	−1.79	0.10	−1.24	0.07	−1.55	0.11	−1.94	0.12	−1.48	0.08	−2.03	0.12	−1.77	0.12	−1.15	0.08	−1.48	0.12
Age < 50	0.40	0.08	0.36	0.05	0.58	0.08	0.50	0.09	0.37	0.07	0.63	0.10	0.42	0.11	0.34	0.07	0.55	0.10
Female	−0.11	0.08	−0.02	0.05	−0.03	0.07	−0.36	0.10	−0.22	0.06	−0.33	0.09	−0.49	0.10	−0.31	0.07	−0.27	0.09
Grad & Above	1.42	0.14	−0.93	0.08	1.17	0.13	1.93	0.16	1.04	0.10	1.19	0.13	1.94	0.16	1.09	0.10	1.43	0.13
Some College	0.66	0.14	0.47	0.09	0.57	0.12	1.08	0.16	0.53	0.10	0.49	0.13	0.92	0.16	0.42	0.10	0.53	0.13
Married	..	..	..	..	..	..	0.22	0.13	0.12	0.08	0.19	0.12	0.02	0.13	0.08	0.08	0.12	0.11
Metropolitan	0.77	0.12	0.64	0.08	0.71	0.12	0.91	0.16	0.59	0.10	0.79	0.13	0.79	0.16	0.46	0.10	0.61	0.13
Midwest	−0.31	0.12	−0.19	0.08	−0.24	0.11	−0.09	0.15	−0.09	0.10	−0.11	0.14	−0.18	0.16	−0.15	0.10	−0.21	0.14
South	−0.21	0.10	−0.12	0.07	−0.17	0.10	0.00	0.13	−0.02	0.09	−0.06	0.13	−0.22	0.15	−0.22	0.09	−0.17	0.13
West	0.57	0.12	0.47	0.08	0.70	0.12	0.46	0.15	0.45	0.10	0.89	0.14	0.63	0.16	0.46	0.10	0.66	0.15
US Born	−0.63	0.12	−0.49	0.09	−0.80	0.14	−0.89	0.15	−0.67	0.10	−1.25	0.16	−0.91	0.16	−0.45	0.11	−0.67	0.15
Black	−1.23	0.15	−0.70	0.10	−0.56	0.14	−0.86	0.20	−0.25	0.14	−0.06	0.18	−0.94	0.16	−0.42	0.11	−0.36	0.16
Other Races	0.08	0.10	0.14	0.07	0.25	0.11	−0.19	0.14	0.07	0.10	0.22	0.13	−0.30	0.15	0.00	0.10	0.02	0.14
Democrat	2.00	0.11	1.33	0.08	1.94	0.12	2.30	0.14	1.45	0.09	1.90	0.13	2.49	0.14	1.71	0.10	2.40	0.14
Ind & Others	1.29	0.10	0.88	0.07	1.42	0.11	1.32	0.12	0.80	0.08	1.06	0.11	1.40	0.13	0.95	0.08	1.44	0.12
Income/1,0000 (USD)	0.04	0.01	0.02	0.01	0.00	0.01	0.07	0.02	0.05	0.01	0.05	0.02	0.12	0.02	0.06	0.01	0.08	0.02
δ_1	1.16	0.02	0.91	0.02	1.45	0.02	1.09	0.02	0.76	0.02	1.25	0.02	1.14	0.02	0.74	0.02	1.21	0.02
δ_2	1.53	0.02	0.95	0.02	1.35	0.02	1.46	0.02	0.84	0.02	1.16	0.02	1.52	0.02	0.93	0.02	1.19	0.02
ln ML	$-12,871$		$-12,529$		$-12,901$		$-8,563$		$-8,357$		$-8,624$		$-8,237$		$-7,981$		$-8,194$	

Table 5: Covariate effects (CE) from quantile analysis. CE for variables not statistically different from zero are marked with ×.

	April 2021 Survey											
	20th Quantile				50th Quantile				80th Quantile			
	ΔP(y=1)	ΔP(y=2)	ΔP(y=3)	ΔP(y=4)	ΔP(y=1)	ΔP(y=2)	ΔP(y=3)	ΔP(y=4)	ΔP(y=1)	ΔP(y=2)	ΔP(y=3)	ΔP(y=4)
EV Info	−0.0722	−0.0421	0.0527	0.0615	−0.0792	−0.0374	0.0172	0.0995	−0.0722	−0.0453	−0.0089	0.1265
Env Better	−0.1958	−0.0191	0.1135	0.1014	−0.1771	−0.0730	0.1122	0.1379	−0.1384	−0.1127	0.0789	0.1722
EV Owner	−0.1357	−0.0896	0.0633	0.1620	−0.1212	−0.0757	−0.0113	0.2083	−0.1053	−0.0953	−0.0265	0.2270
GACC (TM)	0.2192	0.0097	−0.1217	−0.1072	0.1974	0.0635	−0.1203	−0.1406	0.1283	0.0779	−0.0575	−0.1487
GACC (RA)	0.1216	0.0312	−0.0780	−0.0747	0.1097	0.0534	−0.0613	−0.1018	0.0763	0.0421	−0.0124	−0.1059
Age < 50	−0.0237	−0.0106	0.0156	0.0187	−0.0303	−0.0134	0.0095	0.0343	−0.0265	−0.0164	0.0003	0.0427
Metropolitan	−0.0483	−0.0174	0.0318	0.0338	−0.0565	−0.0225	0.0237	0.0553	−0.0345	−0.0185	0.0030	0.0500
Midwest	0.0185	0.0080	−0.0123	−0.0141	0.0161	0.0068	−0.0053	−0.0177	0.0114	0.0066	−0.0003	−0.0177
South	0.0124	0.0056	−0.0083	−0.0098	×	×	×	×	×	×	×	×
West	−0.0327	−0.0168	0.0220	0.0275	−0.0382	−0.0176	0.0092	0.0467	−0.0311	−0.0200	−0.0015	0.0526
Black	0.0784	0.0256	−0.0519	−0.0520	0.0613	0.0244	−0.0259	−0.0598	0.0269	0.0141	−0.0014	−0.0396
Democrat	−0.1242	−0.0523	0.0808	0.0958	−0.1081	−0.0631	0.0431	0.1280	−0.0828	−0.0676	0.0070	0.1434
	May 2022 Survey											
EV Owner	−0.1782	−0.0723	0.0880	0.1624	−0.1573	−0.0695	0.0121	0.2147	−0.1465	−0.1110	−0.0071	0.2646
GACC (TM)	0.3425	−0.0568	−0.1515	−0.1341	0.3304	0.0226	−0.1778	−0.1752	0.2471	0.0963	−0.1459	−0.1975
GACC (RA)	0.1541	0.0026	−0.0790	−0.0777	0.1527	0.0497	−0.0852	−0.1171	0.1269	0.0392	−0.0308	−0.1352
Age < 50	−0.0362	−0.0066	0.0199	0.0229	−0.0390	−0.0085	0.0130	0.0344	−0.0358	−0.0167	0.0072	0.0453
Metropolitan	−0.0684	−0.0054	0.0360	0.0378	−0.0643	−0.0109	0.0258	0.0493	−0.0483	−0.0165	0.0114	0.0535
Black	0.0642	0.0060	−0.0342	−0.0359	×	×	×	×	×	×	×	×
Democrat	−0.1719	−0.0295	0.0927	0.1087	−0.1437	−0.0574	0.0601	0.1410	−0.0996	−0.0659	0.0217	0.1438
	May–June 2023 Survey											
EV Infra	−0.1863	−0.0428	0.0956	0.1335	−0.1827	−0.0603	0.0616	0.1813	−0.1452	−0.0730	0.0187	0.1995
EV Owner	−0.1684	−0.0350	0.0727	0.1307	−0.1842	−0.0542	0.0459	0.1925	−0.1580	−0.0817	0.0183	0.2215
GACC (TM)	0.3323	−0.0635	−0.1405	−0.1283	0.3103	−0.0250	−0.1426	−0.1427	0.2512	0.0486	−0.1423	−0.1575
GACC (RA)	0.1318	−0.0065	−0.0592	−0.0661	0.1238	0.0132	−0.0570	−0.0799	0.0975	0.0183	−0.0329	−0.0830
Age < 50	−0.0296	−0.0007	0.0131	0.0173	−0.0363	−0.0034	0.0139	0.0258	−0.0349	−0.0082	0.0102	0.0329
Metropolitan	−0.0568	0.0013	0.0250	0.0304	−0.0511	−0.0026	0.0204	0.0333	−0.0408	−0.0067	0.0129	0.0345
Black	0.0665	−0.0010	−0.0296	−0.0359	0.0462	0.0029	−0.0182	−0.0309	0.0239	0.0039	−0.0069	−0.0209
Democrat	−0.1832	−0.0084	0.0851	0.1066	−0.1815	−0.0384	0.0798	0.1401	−0.1393	−0.0660	0.0491	0.1562

Beliefs about EVs' environmental benefits (measured in the 2021 survey) also show varying relationships with purchase intent across quantiles. Among respondents at the 80th percentile, those who believe EVs are better for the environment are 17.2 percentage points more likely to express strong purchase intent. The corresponding differences are 13.8 percentage points at the median and 10.1 percentage points at the 20th percentile. Conversely, such respondents are 13.8 percentage points less likely to express no interest at the 80th percentile, compared to 17.7 and 19.6 percentage points less likely at the median and 20th percentile, respectively. This finding suggests that belief in EVs' environmental benefits reinforces commitment among likely adopters and eases skepticism among consumers with lower purchase interest; this indicates that highlighting benefits, such as local air quality improvements, could broaden support for EV adoption.

The influence of prior EV ownership also varies across quantiles. At the 80th percentile, respondents with prior EV ownership are 22.7 percentage points more likely to express strong purchase intent. This difference decreases to 20.8 and 16.2 percentage points at the median and 20th percentile, respectively. A similar pattern is observed in both the 2022 and 2023 surveys. In the 2022 survey, the probability of strong interest increases by 26.5, 21.5, and 16.2 percentage points at the 80th, 50th, and 20th quantiles, respectively. For the same quantiles, the CEs for strong interest in the 2023 survey are 22.1, 19.2, and 13.1 percentage points.

When it comes to views on government action, respondents who believe the government is doing too much or enough to reduce climate change are significantly less likely to express strong purchase interest, with this becoming more pronounced at higher percentiles. In the 2021 survey, those at the 80th percentile of purchase intent who hold this belief are 14.9 percentage points less likely to report strong purchase intent. The gap is 14.1 and 10.7 percentage points at the median and 20th percentile, respectively. Likewise, at the 80th percentile, these respondents are 12.8 percentage points more likely to express no interest in EVs, with the gap widening to 19.7 and 21.9 percentage points at the median and 20th percentile, respectively. More recent surveys indicate even stronger CEs, with those who believe the government is doing too much approximately 33 and 25 percentage points more likely to express no interest in EVs at the 20th and 80th percentiles, respectively. These patterns suggest that efforts to promote adoption can be more effective if they emphasize benefits that resonate across ideological lines. Rather than positioning EVs primarily as a climate solution, emphasizing other benefits—such as long-term cost savings and air quality improvements—may be more effective in engaging a broader range of potential buyers. Moreover, endorsements from nongovernmental entities, such as automakers, dealerships, and industry groups, may be more persuasive than government-led campaigns, particularly for consumers who are wary of climate-focused policies.

Geographic and demographic factors show smaller but consistent relationships with EV purchase intent across all surveys. Younger respondents (under 50), metropolitan residents, and those living in the West are more likely to express higher purchase intent across all considered quantiles, with the strongest CEs observed at the 80th percentile.

Finally, the relationship between political party affiliation and EV purchase intent varies consid-

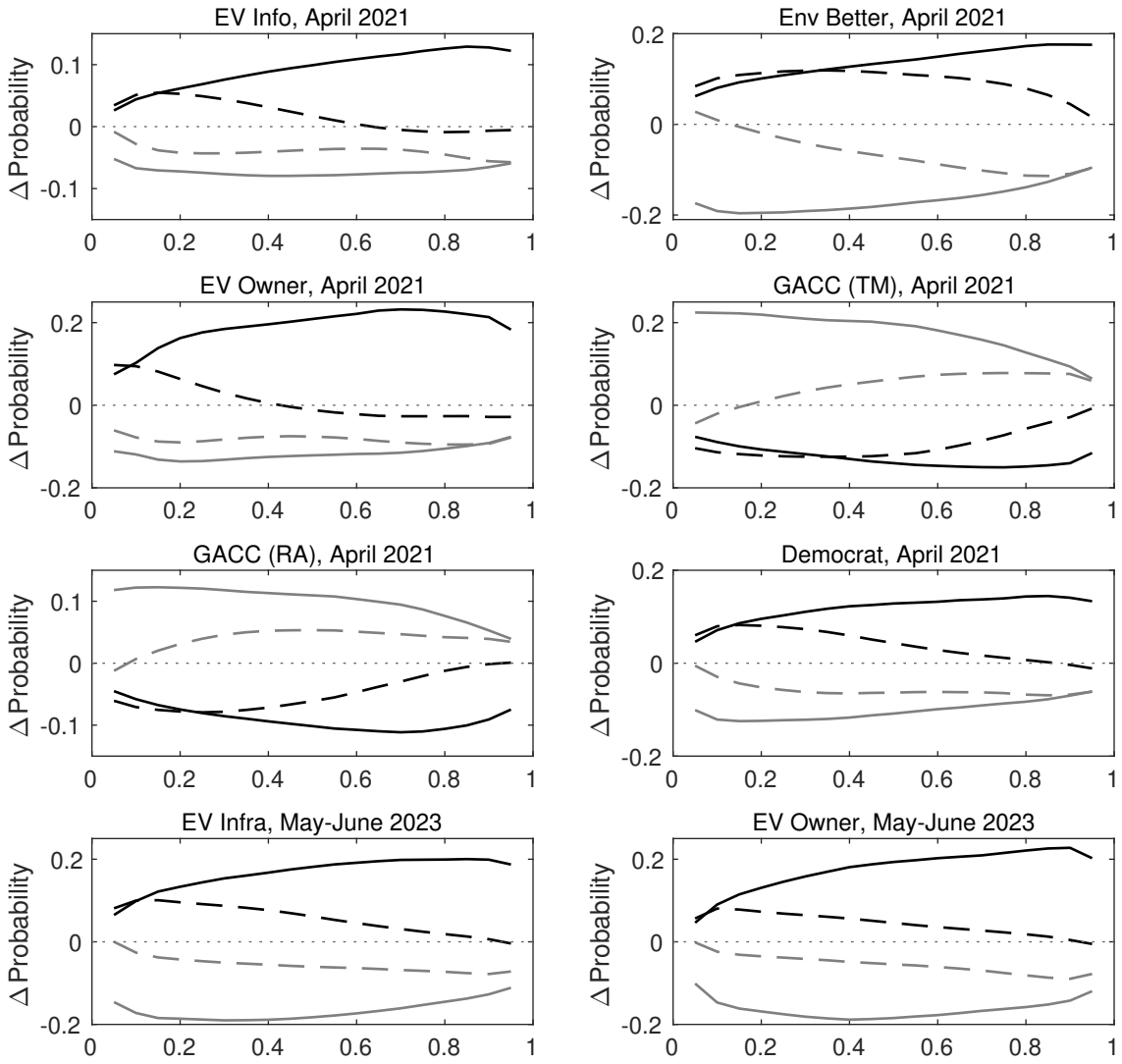


Figure 3: The figure presents the covariate effects for some selected variables from the April 2021 and May–June 2023 surveys, spanning the 5th to 95th quantiles in 5-percentile increments. Legend: Δ Pr(Not at all likely): ——; Δ Pr(Not too likely): — —; Δ Pr(Somewhat likely): – –; Δ Pr(Very likely): ——.

erably across quantiles. Results from the 2021 survey show that at the 80th percentile, Democrats are 14.3 percentage points more likely than Republicans to express strong purchase intent, with the difference narrowing to 9.6 percentage points at the 20th percentile. Similarly, at the 80th percentile, Democrats are 8.3 percentage points less likely than Republicans to express no interest in EVs, but the difference was 12.4 percentage points at the 20th percentile. These patterns remain consistent in more recent surveys. The results indicate that political identity is closely linked to EV purchase intent across the entire distribution: at higher quantiles, Democrats are significantly more likely to express strong purchase intent, and at lower quantiles, they are far less likely to reject EVs outright. Once again, emphasizing nonpartisan benefits—such as long-term cost savings

and energy independence—may help broaden EV appeal across the political spectrum.

To provide a clearer understanding of how CEs vary across quantiles, Figure 3 presents these for some selected variables from a series of ordinal quantile regression models, covering the 5th to 95th percentiles of EV purchase intent in 5-percentile increments. Each panel corresponds to a different covariate; with the solid gray, dashed gray, dashed black, and solid black lines representing the change in probability of reporting "not likely at all," "not too likely," "somewhat likely," and "very likely," respectively, for a given change in covariate across the quantiles. The figure clearly illustrates the substantial differences in CEs across the distribution.

For example, the solid black line indicates that respondents at higher quantiles who have read or heard extensively about EVs, perceive them as environmentally beneficial, have owned one, identify as Democrats, or are confident in the US ability to develop the infrastructure are much more likely to report strong purchase interest compared to those at lower quantiles. Conversely, the solid gray lines show that those who believe government action is excessive or adequate are significantly more likely to report no interest at lower quantiles and markedly less likely to report strong interest at higher quantiles.

Overall, these results highlight the need for tailored strategies to address the barriers to EV adoption for different population segments.

5. Conclusion

EVs are increasingly regarded as a cornerstone of transportation decarbonization and broader climate change mitigation efforts. However, government support has varied by administration. The Obama administration facilitated adoption by introducing federal tax credits for purchase and strengthening fuel economy and emissions standards, which incentivized automakers to develop EVs. In contrast, the first Trump administration prioritized deregulation and rolled back these standards. The Biden administration implemented stricter emissions regulations and allocated substantial funding for EV infrastructure through the Bipartisan Infrastructure Law. A second Trump administration has signaled a likely return to deregulation, though specific policies remain unclear.

As policies and regulatory standards continue to evolve with changing administrations, the future of EVs depends largely on consumer interest, which is crucial in shaping national policies. Public opinion has a well-documented influence on US policymaking (Burstein, 2003; Shapiro, 2011), yet no research has systematically analyzed EV purchase sentiment using a nationally representative sample over multiple years, quantified the impact of the covariates, or applied quantile analysis to examine how different factors influence the distribution of purchase intent.

This study addresses these gaps by examining public attitudes toward EVs using three nationally representative surveys by the Pew Research Center 2021–2023. Given the ordinal nature of the response data, we employ both ordinal probit and ordinal quantile regression to model purchase intent as a function of four novel variables (exposure to EV information, perceptions of EVs'

environmental benefits, views on government climate policy, and confidence in future EV infrastructure), along with prior EV ownership, political affiliation, and demographic characteristics such as age, gender, income, and geographic location. We adopt the Bayesian approach to modeling and estimation, as it offers the entire posterior distribution of the parameters, enables direct probability statements, and allows us to account for uncertainty in observations and parameters when evaluating the effects of covariates.

The results from ordinal probit models indicate that respondents who say they have read or heard a lot about EVs, perceive them as environmentally beneficial, have owned an EV or hybrid vehicle, and are confident in the nation developing charging infrastructure are more likely to express strong purchase interest. Other factors positively influencing purchase intention include being under 50 years old, having a higher level of education, living in metropolitan areas and the West (compared to the Northeast), identifying with the Democratic Party (rather than the Republican Party), and having a higher income. In contrast, those who believe government action is excessive or adequate, are female, live in the Midwest, were born in the United States, or are Black (as opposed to White) are less likely to express strong interest and more likely to report no interest in EVs. Results from covariate effects reveal that prior EV ownership, confidence in EV infrastructure, belief in EVs' environmental benefits, attitudes toward government climate policy, and political affiliation have the strongest influence on purchase decisions.

In addition, results from ordinal quantile analysis show that the relationship between these factors and EV purchase intent varies across the latter's conditional distribution. Respondents who are knowledgeable about EVs, believe in their environmental benefits, are confident in US charging infrastructure, have prior EV ownership, or identify as Democrats are especially likely to express strong purchase intent at higher quantiles. Similarly, those who believe EVs are environmentally beneficial, have confidence in infrastructure development, or identify as Democrats are particularly less likely to express no interest at lower quantiles. In contrast, respondents who believe the government is doing too much to address climate change are particularly more likely to express no interest at lower quantiles and less likely to express strong interest at higher quantiles. Overall, the quantile models highlight significant variation in CEs across the distribution of EV purchase intent, providing a more nuanced understanding than the ordinal probit model.

The findings demonstrate how targeted strategies may be able to accelerate EV adoption. For consumers with low purchase intent (lower quantiles), general awareness campaigns may have limited impact; instead, emphasizing practical aspects, such as long-term cost savings, availability and reliability of charging infrastructure, and financial incentives could be more effective. For more interested consumers (higher quantiles), reinforcing beliefs about environmental benefits can transform them into EV owners. Confidence in charging infrastructure plays a dual role, both strengthening commitment among likely adopters and reducing outright rejection among skeptics, highlighting the potential value of visible investments and clear public communication about infrastructure progress. The results also indicate that political identity and views on climate policy are closely related to EV purchase intent, suggesting that framing EVs in terms of widely appeal-

ing features, such as financial savings and energy independence—rather than solely as a climate solution—could resonate with a broader range of potential buyers. Moreover, for consumers wary of government climate policy, information provided by automakers, dealerships, and industry groups may be more credible than government-led campaigns. Overall, our empirical findings provide useful insights for policymakers, industry stakeholders, and advertisers seeking to bolster adoption.

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