

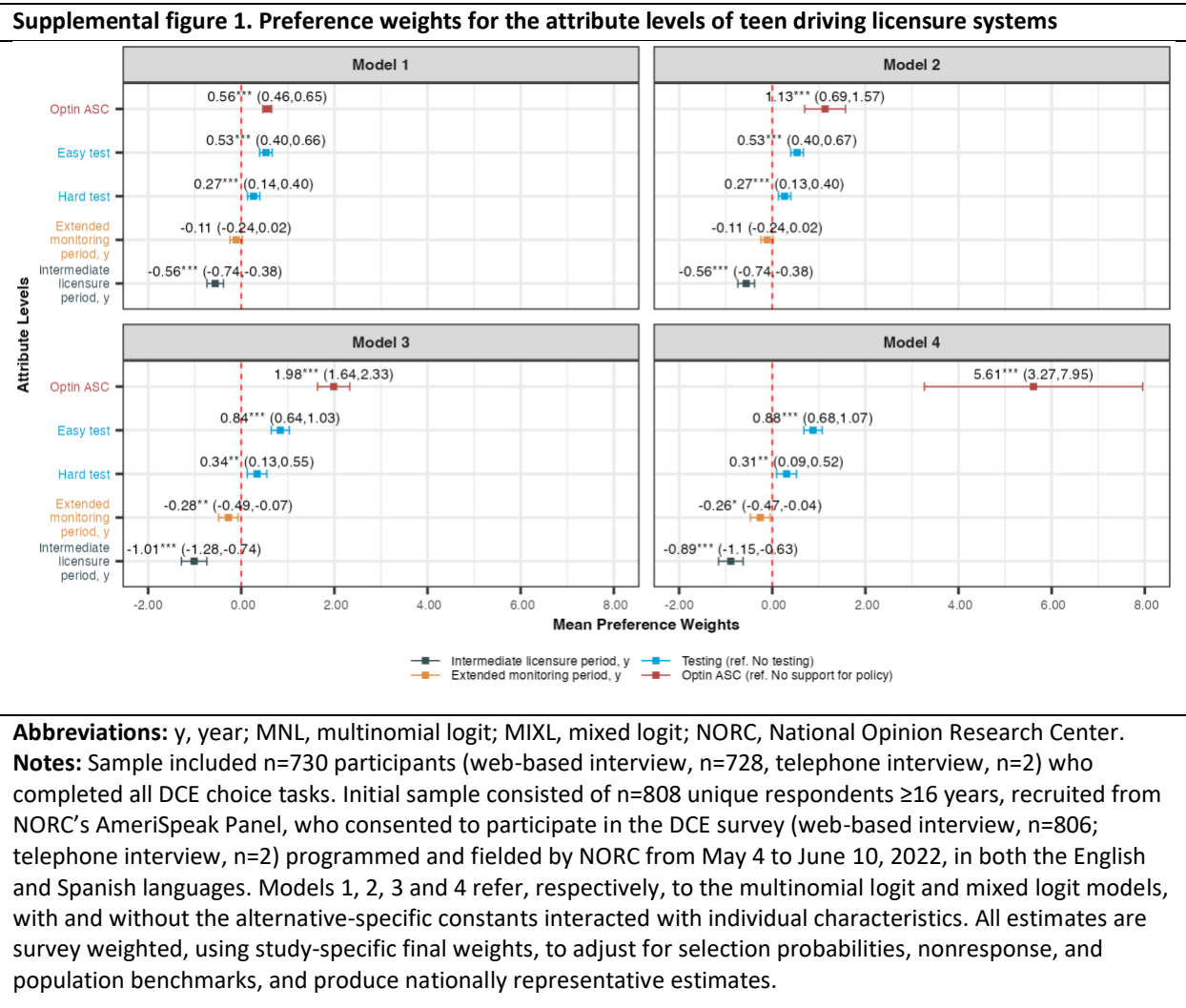
Supplemental Material — Assessing the American Public’s Preferences for Reforms to Teen Driving Licensure Systems: A Discrete Choice Experiment

Emmanuel F Drabo, MPhil, PhD,¹ Jeffrey P Michael, EdD^{1,2}, Johnathon P Ehsani, PhD,^{1,2}

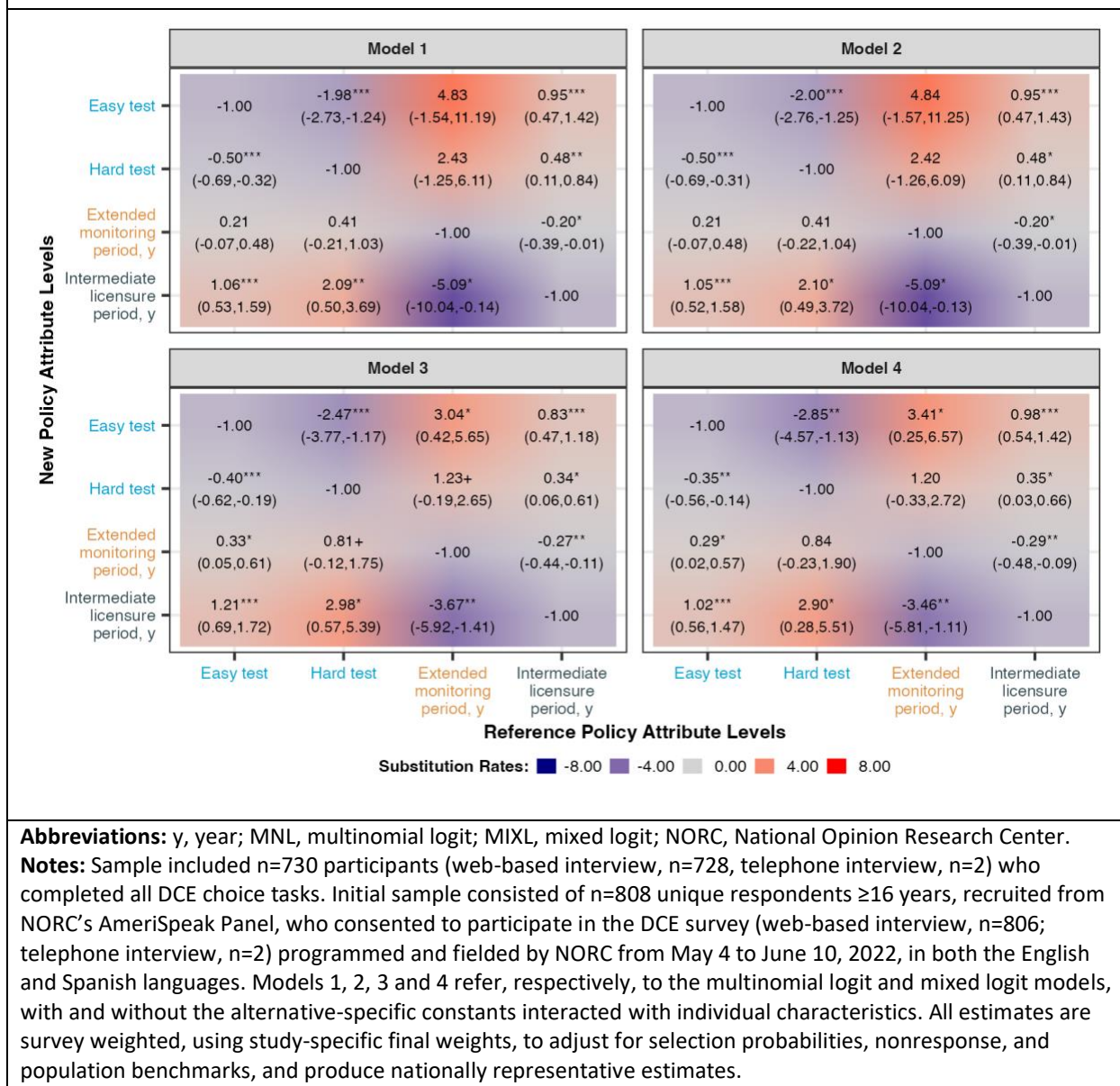
¹ Department of Health Policy and Management, Johns Hopkins University Bloomberg School of Public Health, Baltimore, MD

² Johns Hopkins University Center for Injury Prevention

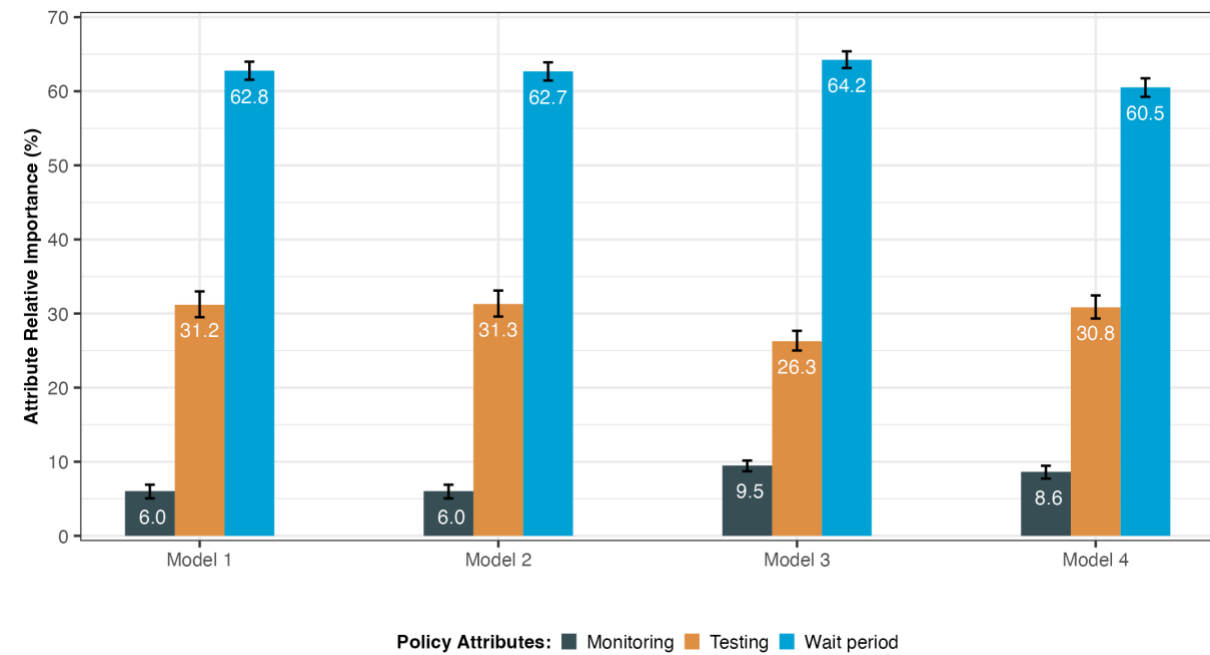
A. Appendix A: Additional Results



Supplemental figure 2. Marginal rates of substitution between the attribute levels of teen driving licensure systems



Supplemental figure 3. Relative importance of attributes of teen driving licensure systems



Abbreviations: MNL, multinomial logit; MIXL, mixed logit; NORC, National Opinion Research Center.

Notes: The relative importance of each attribute i (ARI_i) was calculated as $ARI_i = 100 \times (\bar{U}_i - \underline{U}_i) / \sum_{j=1}^J (\bar{U}_j - \underline{U}_j)$, where $\bar{U}_i$ and $\underline{U}_i$ denote, respectively, the largest and smallest utility level of attribute i . Bars represent the bootstrap means with $N=50$ sampled values and $R=500$ replications; error bars around the bars denote the 95% bootstrap confidence interval around the bootstrapped means. Values for the coefficients were sampled from a multivariate normal distribution, using the mean and variance-covariance matrices from the choice models (MNL and MIXL). Sample included $n=730$ participants (web-based interview, $n=728$, telephone interview, $n=2$) who completed all DCE choice tasks. Initial sample consisted of $n=808$ unique respondents ≥ 16 years, recruited from NORC's AmeriSpeak Panel, who consented to participate in the DCE survey (web-based interview, $n=806$; telephone interview, $n=2$) programmed and fielded by NORC from May 4 to June 10, 2022, in both the English and Spanish languages. Models 1, 2, 3 and 4 refer, respectively, to the multinomial logit and mixed logit models, with and without the alternative-specific constants interacted with individual characteristics. All estimates are survey weighted, using study-specific final weights, to adjust for selection probabilities, nonresponse, and population benchmarks, and produce nationally representative estimates.

B. Appendix B: Theoretical Framework

We first estimated multinomial logit (MNL) models to calculate mean preference weights. The MNL model assumes homogeneous preferences among respondents and is subject to the assumption of independence of irrelevant alternatives (IIA). Thus, we also estimated mixed logit (MIXL) [1-3] – also known as random parameter logit (RPL) models – to determine potential individual-level heterogeneity in preferences for different attribute levels, as they are more flexible and not subject to the IIA assumption. In addition to relaxing the IIA assumption, the MIXL model takes preference heterogeneity into account and uses random coefficients and slopes to model the correlation of choices across alternatives, while assuming each response to be independent.

Although these models have important differences described above, they are all grounded in random utility theory (RUT), which assumes that the perceived utility (U) of an individual n in choice situation j can be estimated as the sum of the systematic utility component (V), that is the mean utility of the target population, and a random error term, ϵ , representing the deviation of the utility of each individual, n , from the mean utility.

$$U_{nj} = V_{nj} + \epsilon_{nj} \quad (1)$$

where $V_{nj} = V(X_{nj}, Z_n)$ denotes the systematic component of the utility and is defined to be a function of observable attributes X_{nj} of the alternatives, and the characteristics Z_n of the individual. V_{nj} is usually assumed to be linear of the form:

$$V_{nj} = X'_{nj}\beta + Z'_n\gamma_j \quad (2)$$

where β and γ_j denote, respectively, the contributions of the attributes and those of the individual characteristics to the overall utility from choosing the alternative. Further, the probability that an individual n will choose alternative j is given by:

$$P_{nj} = P(\epsilon_{nk} - \epsilon_{nj} < V_{nj} - V_{nk}), \forall j \neq k \quad (3)$$

Under the assumption that the error terms are independent and identically distributed (IID) type I extreme value, the choice probability takes the form, corresponding to the MNL model:

$$P_{nj}(\beta) = \frac{e^{X'_{nj}\beta + Z'_n\gamma_j}}{\sum_{j=1}^J e^{X'_{nj}\beta + Z'_n\gamma_j}} \quad (4)$$

For the RPL model, the probability that individual n chooses alternative j , conditional on the random parameter β_n is:

$$P_{nj}(\beta) = \frac{e^{X'_{nj}\beta_n + W'_{nj}\alpha + Z'_n\gamma_j}}{\sum_{j=1}^J e^{X'_{nj}\beta_n + W'_{nj}\alpha + Z'_n\gamma_j}} \quad (5)$$

The unconditional choice probability, P_{nj} , is derived by integrating over the mixing distribution $f(\beta)$, as follows:

$$P_{nj} = \int P_{nj}(\beta)f(\beta)d\beta \quad (6)$$

C. Appendix C: Statistical Analyses

We will apply a linear and additive parameters utility function in our models and dummy code the levels of the attributes. We will use the following utility function in the MNL and MIXL models:

$$\begin{aligned}
U(Y_{n,i,t}) = & \beta_{n,Opt-in} + \beta_{n,HardTest}HardTest_{n,i,t} + \beta_{n,EasyTest}EasyTest_{n,i,t} + \\
& \beta_{n,LicensurePeriod}LicensurePeriod_{n,i,t} + \\
& \beta_{n,MonitoringPeriod}MonitoringPeriod_{n,i,t} + \gamma_n Z_{n,i,t} + \epsilon_{n,i,t},
\end{aligned} \tag{7}$$

where $\epsilon_{n,i,t}$ is assumed to be independently and identically distributed (iid) extreme value, type I (a.k.a., Gumbel) for the MNL model, and can assume any distribution for the MIXL. In this application, we assumed $\epsilon_{n,i,t}$ to have a multivariate normal distribution. The coefficients represent the estimated effects of the levels of the policy attributes and individual characteristics on the probability of choosing the policy.

C.1. Marginal Rates of Substitution Between Attribute Levels

To estimate the tradeoffs between different attribute levels of a given policy, we calculated the public's average marginal rate of substitution (MRS) between different attribute levels. The MRS represents how much of one attribute or attribute level the public is willing to give up for an additional unit of another attribute or attribute level. It is calculated as the ratio of the mean preference weights of the pair of attributes being compared, as follows:

$$E(WTP_{kr}) = -E(\beta_k)/E(\beta_r) \tag{8}$$

where β_r denotes the coefficient of the fatalities attribute.

C.2. Relative Importance of Attributes

We also calculated the relative importance given on average by respondents to the different attributes when deciding whether to support a particular policy. We compute the importance of an attribute as the ratio of the part-worth utility range for each attribute to the sum of all ranges, multiplied by 100, as follows:

$$ARI_i = 100 \times \frac{(\overline{U}_i - \underline{U}_i)}{\sum_{j=1}^J (\overline{U}_j - \underline{U}_j)} \tag{9}$$

where $\overline{U}_i = \max\{\beta_{i,k}Z_{i,k}, \forall k \in K_i\}$ and $\underline{U}_i = \min\{\beta_{i,k}Z_{i,k}, \forall k \in K_i\}$ denote, respectively, the largest and smallest utility level of attribute i where $Z_{i,k}$ is the k^{th} attribute level ($k \in K_i$, where K_i denotes the number of attribute levels of attribute i) of the i -th attribute, $\beta_{i,k}$ is the coefficient of the attribute level $Z_{i,k}$, and $\min\{\beta_{i,k}Z_{i,k}, \forall k \in K_i\} = 0$ when an attribute is continuous rather than discrete, and $\beta_{i,k} = 1$ when $Z_{i,k}$ is the reference level. [4-7] Results are summarized in main document table 4 and in supplemental figure 3.

D. Appendix D: Design of the Discrete Choice Experiments (DCEs)

D.1. D-Efficient Fractional Factorial Design

We used an efficient fractional factorial design which maximized D-efficiency. D-efficiency measures the goodness of a design relative to a hypothetical orthogonal design and is function of the number of points in the design, independent variables in the model, and the maximum standard error prediction over the design points. With this chosen efficient design, we could estimate all main effects and some two-way interactions between attributes.

D.2. DCE Questionnaire Prompts and Examples of Choice Profiles

Supplemental figure 4. Example of choice scenarios included in DCEs

Suppose that you are in charge of changing the driver licensing system for teenagers.

Before teenagers can drive on their own, they need to pass a driving test. Currently, almost all states use an easy test where almost everybody passes on their first try. You could require a harder test that new drivers have to practice a lot to pass, and many would fail on their first try.

After passing the driving test teenagers are now allowed to drive on their own. Most states now have 1 year of nighttime restrictions (for example, no driving after 9 PM) and passenger restrictions (for example, no carrying any passengers except members of your family). You could require that states extend this to 2 years of nighttime and passenger restrictions.

Although no state now does this, you could also require an additional restriction that would only allow them to drive if they used a driver monitoring system. The monitoring system would detect speeding and distracted driving, and report violations to the licensing agency. As part of the Graduated Driver Licensing system, they would be required to drive for a period of time without serious violations before getting their full license. Driver monitoring could go for 1 year or 2 years.

Suppose that two options (option A and option B) are being considered for a new driver licensing system, and that the decision depended only on you. If you had to choose between option A and option B on the following screen, which would you select?

Q1.

Option A: Easy test, 2 years of driver monitoring, and 1 year of nighttime and passenger restrictions.

Option B: Easy test, no years of driver monitoring, and 2 years of nighttime and passenger restrictions.

RESPONSE OPTIONS:

1. I would prefer Option A
 2. I would prefer Option B
 3. I would prefer neither of these options
-

Q2.

Option A: Easy test, 2 years of driver monitoring, and 1 year of nighttime and passenger restrictions.

Option B: No test, no years of driver monitoring, and 2 years of nighttime and passenger restrictions.

RESPONSE OPTIONS:

1. I would prefer Option A
2. I would prefer Option B
3. I would prefer neither of these options

Q3.

Option A: No test, 1 year of driver monitoring, and 2 years of nighttime and passenger restrictions.

Option B: Hard test, 1 year of driver monitoring, and 1 year of nighttime and passenger restrictions.

RESPONSE OPTIONS:

1. I would prefer Option A
 2. I would prefer Option B
 3. I would prefer neither of these options
-

Q4.

Option A: Hard test, no years of driver monitoring, and 1.5 years of nighttime and passenger restrictions.

Option B: No test, 2 years of driver monitoring, and 1.5 years of nighttime and passenger restrictions.

RESPONSE OPTIONS:

1. I would prefer Option A
 2. I would prefer Option B
 3. I would prefer neither of these options
-

Q5.

Option A: Easy test, no years of driver monitoring, and 2 years of nighttime and passenger restrictions.

Option B: Hard test, 2 years of driver monitoring, and 1.5 years of nighttime and passenger restrictions.

RESPONSE OPTIONS:

1. I would prefer Option A
 2. I would prefer Option B
 3. I would prefer neither of these options
-

Q6.

Option A: Hard test, 1 year of driver monitoring, and 1 year of nighttime and passenger restrictions.

Option B: No test, no years of driver monitoring, and 1.5 years of nighttime and passenger restrictions.

RESPONSE OPTIONS:

1. I would prefer Option A
 2. I would prefer Option B
 3. I would prefer neither of these options
-

Q7.

Option A: No test, 1 year of driver monitoring, and 2 years of nighttime and passenger restrictions.

Option B: Hard test, 2 years of driver monitoring, and 1 year of nighttime and passenger restrictions.

RESPONSE OPTIONS:

1. I would prefer Option A
2. I would prefer Option B
3. I would prefer neither of these options

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