

Consistent Estimator in Partial Profile Design Choice Experiments

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Abstract

Researchers propose using a partial profile design using a subset of attributes in choice experiments (CEs) with a high number of attributes. Previous studies report estimation bias in partial profile CEs with a “no choice” option. This study considers consistent estimations for partial profile designs. The theoretical analysis shows that the estimated parameters using partial profile CEs with a “no choice” option are not consistent. This paper proposes a consistent estimator using information about the excluded attributes for a partial profile. The simulation results suggest that the proposed consistent estimator can yield unbiased parameters. Following the theoretical and simulation results, the authors discuss some implications for addressing estimation bias in partial profile CEs.

Keywords

Choice experiments, partial profile, “no choice” option, estimation bias, simulation

Choice experiments (CEs) are a popular method to estimate people's preferences for attributes of products or services in studies in areas such as marketing, transportation, health, and environmental economics (Louviere, Hensher, and Swait 2000). CEs attract much interest in various fields because the task of choosing the most preferred profile is simple and similar to the choice behavior of consumption respondents actually perform in the real market. Furthermore, CEs have the advantage that they can include a "no choice" option, which can replicate a real no choice alternative such as "I would not choose any of these," or the status-quo alternative such as "I will remain with my own product." Dhar and Simonson (2003) shows that not including a "no choice" option might cause a biased estimation.

These advantages make CEs popular in many fields; however, the choice responses of CEs are very complex tasks and have issues with experiments with a large number of attributes due to respondents' limited ability to handle so many options at once. Though Green and Srinivasan (1990) suggested approximately six as the maximum number of attributes for traditional conjoint analysis with the full profile, some CE studies use more than six attributes. For example, Tanaka et al. (2014) review 20 prior CE studies of the electric vehicle and find that they use a range of 4-13 attributes and nine studies have more than six attributes. Figure 1 provides an example of a vehicle choice task with the full profile with nine attributes. This choice task might be difficult for some respondents due to the complexity of a large number of

attributes.

Figure 1

Alternatively, Chrzan (2010) propose partial profile CEs to address issues with large numbers of attributes. The partial profile design uses a subset of attributes, typically three to five, for the choice tasks (Patterson and Chrzan 2003), generated via random draw (Sawtooth 2008) or using an efficient design (Kessels, Jones, and Goos 2011; Cuervo et al. 2016). Figure 2 shows an example partial profile choice task with three attributes. There are two types of partial profile CEs: implicit and explicit designs. For the former, researchers present respondents with only a subset of attributes and assume that the respondents evaluate the alternatives holding all attributes that are not represented as constant. For the latter, researchers present all attributes to the respondents and assume that the excluded attributes that did not belong to the subset have fixed specific levels across the alternatives. In Figure 2, I show the excluded attributes as grayed out so respondents will focus on the differences in the subset of attributes. It is important to distinguish between implicit and explicit partial profiles, since, as I show later, their consistencies differ.

Figure 2

The partial profile question should be easier for respondents to answer than the full profile question. Chrzan (2010) argues that the partial profile design lowers response error and has equal or greater predictive validity than full profile CEs do. However, other researchers show different estimations for the partial and full profile designs. Notably, the partial profile may yield lower price importance than the full profile design (Johnson, Huber, and Orme 2004). Patterson and Chrzan (2003) reports a correlation between the choice probabilities of “no choice” and the number of attributes in the partial profile. They suggest that it is not best to include a “no choice” option in partial profile CE designs. However, deleting the “no choice” option might discard the advantage of a realistic choice task in CEs, and thus cause biased estimation.

To address the problematic effect of partial profile CEs, I consider a consistent estimation of the partial profile with a “no choice” option. I provide the conceptual models of the full and partial profile CEs and analyze the consistency of the estimated parameters using these models. The results of the theoretical analysis suggest that the estimated parameters using the implicit partial profile design with a “no choice” option are inconsistent. I propose a consistent estimator using information about the excluded attributes for implicit partial profile CEs. To illustrate the proposed estimator, I consider Monte Carlo simulations of the full and partial

profile CEs, the results of which show that the choice probability of a “no choice” option in the implicit partial profile CE design is significantly higher than that in the full profile design. Furthermore, the price importance estimated using the implicit partial profile CE is lower than that using the full profile. The simulation results suggest that our proposed consistent estimator can yield unbiased parameters for the implicit partial profile CE design with a “no choice” option.

MODEL

Utility Function of the Full and Partial Profiles

Consider the following random utility model:

$$U_i^F(x_i^F) = V_i^F(x_i^F) + \varepsilon_i = \sum_{k \in F} \beta_k x_{ki}^F + \varepsilon_i, \quad (1)$$

where U_i^F is the utility function of the full profile model of alternative i , $x_i^F = (x_{1i}^F, \dots, x_{Ki}^F)$ is the vector of K attributes, V_i^F is the observable component of the utility function, ε_i is the random component, $F = \{1, 2, \dots, K\}$ is the full set of the K attributes, x_{ki}^F is the k th attribute of alternative i , and β_k is the parameter.

Suppose that the individual chooses alternative i from the choice set $C = \{1, 2, \dots, J\}$.

Let $P(i|x^F, \beta)$ be the choice probability given the full profile attributes (x^F) and parameter vector (β). For the full profile model, the choice probability of alternative i is

$$P^F(i|x^F, \beta) = \Pr[U_i^F > U_j^F, \forall j \neq i] = \Pr[V_i^F - V_j^F + \varepsilon_i > \varepsilon_j, \forall j \neq i]. \quad (2)$$

Note that the choice probability is related to the utility differences ($V_i^F - V_j^F$).

For the partial profile model, the individual faces alternatives with a subset of attributes.

Let S be the subset of attributes included in the partial profile. I decompose the observable utility component into the included and excluded components for the partial profile:

$$U_i^F(x_i^F) = V_i^S(x_i^S) + V_i^E(x_i^E) + \varepsilon_i = \sum_{h \in S} \beta_h x_{hi}^S + \sum_{m \notin S} \beta_m x_{mi}^E + \varepsilon_i, \quad (3)$$

where V_i^S is the included component in the partial profile, V_i^E is the excluded component from the partial profile, x_{hi}^S is the included h^{th} attribute of alternative i , and x_{mi}^E is the excluded m^{th} attribute of alternative i .

Respondents do not see the excluded attributes x_{mi}^E in the implicit partial profile design.

Ignoring the excluded component from the partial profile, I can write the utility function of the implicit partial profile as

$$U_i^S(x_i^S) = V_i^S(x_i^S) + \varepsilon_i = \sum_{h \in S} \beta_h x_{hi}^S + \varepsilon_i. \quad (4)$$

The choice probability using the implicit partial profile is

$$P^S(i|x^S, \beta) = \Pr[U_i^S > U_j^S, \forall j \neq i] = \Pr[V_i^S - V_j^S + \varepsilon_i > \varepsilon_j, \forall j \neq i]. \quad (5)$$

In general, the choice probability using the implicit partial profile is not equivalent to one using the full profile, unless $V_i^E = V_j^E$ for all i and j .

For the explicit partial profile design, researchers explicitly present the respondents with the excluded attributes, which have fixed specific levels across the alternatives. Assume that the excluded attributes do not differ across the alternatives, $x_{mi}^E = \bar{x}_m^E$ for all i . Then, I can construct the utility function of the explicit partial profile as

$$U_i^Q(x_i^S, \bar{x}^E) = V_i^S(x_i^S) + V^E(\bar{x}^E) + \varepsilon_i = \sum_{h \in S} \beta_h x_{hi}^S + \sum_{m \notin S} \beta_m \bar{x}_m^E + \varepsilon_i. \quad (6)$$

To clarify, U_i^Q is the utility function with the “quasi” full profile because it has all attributes; however, I assume that the excluded attributes are the same across alternatives. The choice

probability using the explicit partial profile is equal to that using the partial profile, which ignores the excluded attributes.

$$\begin{aligned}
P^Q(i|x^S, \bar{x}^E, \beta) &= \Pr[U_i^Q > U_j^Q, \forall j \neq i] \\
&= \Pr[V_i^S + V^E - V_j^S - V^E + \varepsilon_i > \varepsilon_j, \forall j \neq i] = P^S(i|x^S, \beta).
\end{aligned} \tag{7}$$

As I show later, when the alternatives include a “no choice” option, it is difficult to assume that the excluded attributes have same values across all alternatives. If the excluded attributes have different values for some alternatives, say \tilde{x}_{mi}^E , the choice probability using the explicit partial profile design is not equal to that using the implicit partial profile.

Estimation Consistency Using the Partial Profile

Consider the log likelihood function of the full profile:

$$L_n^F(\beta) = \frac{1}{N} \sum_{n=1}^N \ln P^F(i_n|x_n^F, \beta), \tag{8}$$

conditional on observed choice i_n and the full set of attributes x_n^F for the full profile, and

where n is the index of the observation. By the strong law of large numbers, as $N \rightarrow \infty$, the probability limit is

$$L^F(\beta) = \sum_{i \in C} \sum_{x^F \subset X} P^F(i|x^F, \beta^*) f(x^F) \ln P^F(i|x^F, \beta), \quad (9)$$

where β^* is the true parameter, C is the choice set, X is the profile set, $P^F(i|x^F, \beta^*)$ is the choice probability of the full profile with a true parameter, and $f(x^F)$ is the probability such that the respondent sees profile x^F . Assume that I draw the profile randomly from the profile set X ; thus $f(x^F)$ is independent of choice i . Then, the maximum log likelihood estimator of the full profile model is consistent because the derivative of the log likelihood is equal to zero at the true parameter.

$$\begin{aligned} \frac{\partial L^F(\beta^*)}{\partial \beta} &= \sum_{i \in C} \sum_{x^F \subset X} \frac{P(i|x^F, \beta^*) \cdot f(x^F)}{P(i|x^F, \beta^*)} \frac{\partial P^F(i|x^F, \beta^*)}{\partial \beta} \\ &= \sum_{x^F \subset X} f(x^F) \frac{\partial \sum_{i \in C} P^F(i|x^F, \beta^*)}{\partial \beta} = 0. \end{aligned} \quad (10)$$

Note that the sum of the choice probability over all alternatives is always a fixed value,

$$\sum_{i \in C} P^F(i|x^S, \beta) = 1.$$

For explicit partial profile CEs, the analyst knows the values of the excluded attribute; therefore, I can construct the utility function of the quasi-full profile using the included attributes x_n^S and excluded attributes \tilde{x}_n^E . The log likelihood function of the quasi full profile is then:

$$L_n^Q(\beta) = \frac{1}{N} \sum_{n=1}^N \ln P^Q(i_n | x_n^S, \tilde{x}_n^E, \beta). \quad (11)$$

The probability limit of the log likelihood function is

$$L^Q(\beta) = \sum_{i \in \mathcal{C}} \sum_{x^F \subset X} \sum_{x^S \subset x^F} P^Q(i | x^S, \tilde{x}^E, \beta^*) \pi(x^S | x^F) f(x^F) \ln P^Q(i | x^S, \tilde{x}^E, \beta), \quad (12)$$

where $\pi(x^S | x^F)$ is the probability such that the attributes x^S of the partial profile are drawn from the full set of attributes x^F . Assume that I draw the full attribute set x^F randomly from the profile set X and the partial attributes x^S from the full attribute set x^F . Then, $f(x^F)$ and $\pi(x^S | x^F)$ are independent of choice i . For the explicit partial profile design, the analyst knows the values of the excluded attributes. Since I can construct the utility function of the quasi-full profile accurately for the explicit partial profile design, the maximum log likelihood estimator of the explicit partial profile CEs is consistent.

$$\begin{aligned}
\frac{\partial L^Q(\beta^*)}{\partial \beta} &= \sum_{i \in C} \sum_{x^F \subset X} \sum_{x^S \subset x^F} \frac{P^Q(i|x^S, \tilde{x}^E, \beta^*)}{P^Q(i|x^S, \tilde{x}^E, \beta^*)} \pi(x^S|x^F) f(x^F) \frac{\partial P^Q(i|x^S, \tilde{x}^E, \beta^*)}{\partial \beta} \\
&= \sum_{x^F \subset X} \sum_{x^S \subset x^F} \pi(x^S|x^F) f(x^F) \frac{\partial \sum_{i \in C} P^Q(i|x^S, \tilde{x}^E, \beta^*)}{\partial \beta} = 0.
\end{aligned} \tag{13}$$

For the implicit partial profile design, however, the analysis does not know the values of excluded attributes that respondents do not see. If I ignore the excluded attributes \tilde{x}^E , the probability limit of the log likelihood function for the implicit partial profile is

$$L^S(\beta) = \sum_{i \in C} \sum_{x^F \subset X} \sum_{x^S \subset x^F} P^Q(i|x^S, \tilde{x}^E, \beta^*) \pi(x^S|x^F) f(x^F) \ln P^S(i|x^S, \beta). \tag{14}$$

The maximum likelihood estimator $\hat{\beta}$ is the solution to the following equation:

$$\frac{\partial L^S(\hat{\beta})}{\partial \beta} = \sum_{i \in C} \sum_{x^F \subset X} \sum_{x^S \subset x^F} \frac{P^Q(i|x^S, \tilde{x}^E, \beta^*)}{P^S(i|x^S, \hat{\beta})} \pi(x^S|x^F) f(x^F) \frac{\partial P^S(i|x^S, \hat{\beta})}{\partial \beta} = 0. \tag{15}$$

In general, the maximum log likelihood estimator may not be consistent ($\hat{\beta} \neq \beta^*$) because the derivative of the log likelihood is not always equal to zero at the true parameter. If the ratio of the

choice probability using the quasi-full profile and the partial profile ($R^{QS}(i) = P^Q(i|x^S, \tilde{x}^E, \beta)/P^S(i|x^S, \beta)$) is independent of chosen alternative i at the true parameter (β^*), then the log likelihood function has a maximum at $\beta = \beta^*$. If the ratio $R^{QS}(i)$ is independent of i , then I can write the derivative of the log likelihood as

$$\begin{aligned} \frac{\partial L^S(\beta^*)}{\partial \beta} &= \sum_{x^F \subset X} \sum_{x^S \subset x^F} \frac{P^Q(i|x^S, \tilde{x}^E, \beta^*)}{P^S(i|x^S, \beta^*)} \pi(x^S|x^F) f(x^F) \frac{\partial \sum_{i \in \mathcal{C}} P^S(i|x^S, \beta^*)}{\partial \beta} \\ &= 0. \end{aligned} \tag{16}$$

Even if the choice probabilities differ between the quasi-full and the partial profiles, $P^Q(i|x^S, \tilde{x}^E, \beta^*)/P^S(i|x^S, \beta^*) \neq 1$, the estimated parameters using the partial profile could be consistent when the ratio is independent of the chosen alternative at the true parameters. I next consider some specific cases.

Case 1: Excluded Attributes Have Zero Values for all Alternatives

Consider the choice experiment task with four attributes and three alternatives (Figure 3). x_1 is the price attribute and x_2 , x_3 , and x_4 are other attributes of each alternative. Alternative 3 is the “no choice” option, which is the fixed profile for all choice tasks. For the partial profile, I

draw three attributes randomly from four attributes. For example, I include x_1 , x_2 , and x_3 in the partial profile, while I exclude x_4 . Alternative 3 is the “Do not buy” option such that all attributes are zero values.

Figure 3

Assume that the excluded attributes have zero values for all alternatives. Namely, $x_{mi}^E = 0$ for all $i \in C$ and $m \notin S$. Then, the excluded component of the observed utility is equal to all alternatives, $V_i^E = 0$ for all $i \in C$. Then, the choice probabilities of the quasi-full and partial profiles are equivalent:

$$P^Q(i|x^S, \tilde{x}^E, \beta) = \Pr[V_i^S - V_j^S + \varepsilon_i > \varepsilon_j, \forall j \neq i] = P^S(i|x^S, \beta). \quad (17)$$

The ratio of two choice probabilities is equal to one, $P^Q(i|x^S, \tilde{x}^E, \beta)/P^S(i|x^S, \beta) = 1$, which is independent of i . Thus, the maximum log likelihood estimation using the implicit partial profile without excluded attributes, including the conditional logit and mixed logit models, yields consistent parameters.

Nevertheless, it may not be realistic to assume zero values for some excluded attributes.

If I exclude the price attribute, I assume the price of alternatives 1 and 2 are \$0, though the respondent may consider some specific prices for alternatives 1 and 2, which may lead to biased parameter estimations.

Case 2: Excluded Attributes Have the Same Values for all Alternatives

Consider a choice experiment task with the status quo option, such as “I will keep my own product” (Figure 4). x_1 is the price and x_2 , x_3 , and x_4 are attributes of each alternative. Alternative 3 is the “status quo” option such that the price is \$0 and the other attributes are the current state (100%). Assume that the excluded attribute has the same values for all alternatives. Namely, $\tilde{x}_{mi}^E = \bar{x}_m^E$ for all $i \in C$ and $m \notin S$. Then, the excluded component of the observed utility is equal to all alternatives, $V_i^E = V^E$ for all $i \in C$. Similar to case 1, the choice probability of the quasi-full profile with all attributes is equal to that of the implicit partial profile without the excluded attributes. Thus, the maximum log likelihood estimator is consistent.

However, this assumption may be also unrealistic. When I exclude the price attribute, I assume that the price has the same values, say \$100, for all alternatives; however, this status quo is not realistic. When I exclude the price attribute, the respondent may consider \$0 for alternative 3, which may lead to a biased estimation.

Figure 4

Case 3: Excluded Attributes Have the Same Values for all Alternatives Except the “No Choice” Option

Here, alternative 3 is the “no choice” option that has a no attribute for all choice tasks (Fig. 5). Assume that the excluded attributes are equal to all alternatives except the “no choice” alternative. Namely, $\tilde{x}_{mi}^E = \bar{x}_m^E$ for all $i \neq J$ and $\tilde{x}_{mJ}^E = 0$, $m \notin S$. For example, I exclude x_1 and x_4 , and include x_2 and x_3 in the partial profile.

Figure 5

Assume that the “no choice” alternative has only one parameter of an alternative specific constant ($V_J = \alpha_J$). For the conditional logit model, the choice probabilities of the quasi-full profile and the partial profile are different unless $\bar{x}_m^E = 0$ for all $m \notin S$.

$$\begin{aligned}
 P^Q(i|x^S, \tilde{x}^E, \beta) &= \frac{\exp(\sum_{h \in S} \beta_h x_{hi} + \sum_{m \notin S} \beta_m \tilde{x}_m^E)}{\sum_{j=1}^{J-1} [\exp(\sum_{h \in S} \beta_h x_{hj} + \sum_{m \notin S} \beta_m \tilde{x}_m^E)] + \exp(\alpha_J)}, \\
 P^S(i|x^S, \beta) &= \frac{\exp(\sum_{h \in S} \beta_h x_{hi})}{\sum_{j=1}^{J-1} [\exp(\sum_{h \in S} \beta_h x_{hj})] + \exp(\alpha_J)}.
 \end{aligned} \tag{18}$$

The ratio of the choice probabilities of the full and partial profiles $R^{QS}(i)$ are independent of the chosen alternative for $i \neq J$:

$$\begin{aligned}
 R^{QS}(i) &= \frac{P^Q(i|x^S, \tilde{x}^E, \beta)}{P^S(i|x^S, \beta)} \\
 &= \frac{(\sum_{j=1}^{J-1} [\exp(\sum_{h \in S} \beta_h x_{hj})] + \exp(\alpha_J)) \cdot \exp(\sum_{m \notin S} \beta_m \bar{x}_m^E)}{\sum_{j=1}^{J-1} [\exp(\sum_{h \in S} \beta_h x_{hj} + \sum_{m \notin S} \beta_m \bar{x}_m^E)] + \exp(\alpha_J)}. \tag{19}
 \end{aligned}$$

Note that the ratio $R^{QS}(i)$ does not have x_{hi} . However, for the “no choice” alternative J , the ratio $R^{QS}(J)$ has a value different from $R^{QS}(i)$ unless $\sum_{m \notin S} \beta_m \bar{x}_m^E = 0$. The ratio $R^{QS}(i)$ is not independent of the chosen alternative. Therefore, the estimated parameters of the conditional logit using the partial profile may be biased unless there is no observation for a selection of the “no choice” option:

$$\begin{aligned}
 R^{QS}(J) &= \frac{P^Q(J|x^S, \tilde{x}^E, \beta)}{P^S(J|x^S, \beta)} = \frac{\sum_{j=1}^{J-1} [\exp(\sum_{h \in S} \beta_h x_{hj})] + \exp(\alpha_J)}{\sum_{j=1}^{J-1} [\exp(\sum_{h \in S} \beta_h x_{hj} + \sum_{m \notin S} \beta_m \bar{x}_m^E)] + \exp(\alpha_J)} \\
 &= \frac{P^Q(i|x^S, \tilde{x}^E, \beta)}{P^S(i|x^S, \beta)} \frac{1}{\exp(\sum_{m \notin S} \beta_m \bar{x}_m^E)} \neq R^{QS}(i). \tag{20}
 \end{aligned}$$

If the analyst knows the values of the excluded attributes, I can adjust the choice probability of

the partial profile as follows:

$$\check{P}^S(i|x^S, \beta) = \frac{\exp(\sum_{h \in S} \beta_h x_{hi})}{\sum_{j=1}^{J-1} [\exp(\sum_{h \in S} \beta_h x_{hj})] + \exp(\alpha_J - \sum_{m \notin S} \beta_m \bar{x}_m^E)}. \quad (21)$$

Then, the ratio of the choice probabilities $R^{QS}(i) = P^Q(i|x^S, \tilde{x}^E, \beta) / \check{P}^S(i|x^S, \beta) = 1$ is independent of the chosen alternative. Therefore, the estimated parameter of the conditional logit using the adjusted estimator for the implicit partial profile CEs can be consistent.

For the mixed logit model, ratio of the choice probabilities is

$$\begin{aligned} R^{QS}(i) &= \frac{P^Q(i|x^S, \tilde{x}^E, \beta)}{P^S(i|x^S, \beta)} \\ &= \frac{\int \frac{\exp(\sum_{h \in S} \beta_h x_{hi} + \sum_{m \notin S} \beta_m \bar{x}_m^E)}{\sum_{j=1}^{J-1} [\exp(\sum_{h \in S} \beta_h x_{hj} + \sum_{m \notin S} \beta_m \bar{x}_m^E)] + \exp(\alpha_J)} g(\beta)}{\int \frac{\exp(\sum_{h \in S} \beta_h x_{hi})}{\sum_{j=1}^{J-1} [\exp(\sum_{h \in S} \beta_h x_{hj})] + \exp(\alpha_J)} g(\beta)}, \end{aligned} \quad (22)$$

where $g(\beta)$ is the density function of β . Note that the ratio has x_{hi} , suggesting that the ratio is not independent of chosen alternative i . Thus, the estimated parameters using the mixed logit model might not be consistent, unless $\sum_{m \notin S} \beta_m \bar{x}_m = 0$. Additionally, I can adjust the choice probability of the mixed logit using the partial profile:

$$\begin{aligned}
\check{P}^S(i|x^S, \beta) &= \int \frac{\exp(\sum_{h \in S} \beta_h x_{hi})}{\sum_{j=1}^{J-1} [\exp(\sum_{h \in S} \beta_h x_{hj})] + \exp(\alpha_J - \sum_{m \notin S} \beta_m x_m)} g(\beta) \\
&= P^Q(i|x^S, \tilde{x}^E, \beta).
\end{aligned} \tag{23}$$

MONTE CARLO EXPERIMENT

To illustrate the estimation using the partial profile, I provide a Monte Carlo simulation of the choice experiment using full and partial profiles. I generate the data and estimation as follows:

- (a) Defining attributes: The simulated data of the full profile have nine attributes: price (x_1) and other attributes (x_2, \dots, x_9).
- (b) Generating data for the full profile: I generate the attributes using the uniform random distribution of $x \in \{.5, .6, \dots, 1.5\}$. I have three alternatives with a “no choice” option, 500 respondents, and five choice tasks for each respondent.
- (c) Generating data for the partial profile: The partial profile has three included attributes that I draw randomly from the nine attributes of the full profile. I consider several models for the excluded attributes, as I describe later.
- (d) Generating choice data using the included and excluded attributes: I generate random draws ε_j from a Gumbel distribution and μ from a standard normal distribution for each respondent (Train 2009). I then calculate the utility function $V_j = (b + s\mu)x_j + \varepsilon_j$, where b

is the mean parameter and s is the standard deviation parameter, which I assume to be $s = 0$ for the conditional logit model and $s = 1$ for the mixed logit model. I keep the choice data for each choice task such that the chosen alternative has the highest utility.

- (e) Estimating the parameters using the included attributes: I apply the conditional logit or mixed logit models to the generated data for the implicit partial profile without the excluded attributes.
- (f) Repeat (c) – (e) for 100 iterations.

I consider six models to analyze the effect of partial profile. The Appendix provides a sample of the generated profiles for the first and second choice tasks for the first respondent for each model.

Model 1 is the full profile with all attributes. I generate all attributes for the profile data and estimate all attributes. The “no choice” option has zero values for all attributes. I expect unbiased estimated parameters for this model.

Model 2 is the partial profile with zero values for all excluded attributes and a “no choice” option. This model corresponds to case 1; thus, I expect unbiased estimated parameters for this model.

Model 3 is the partial profile with the same values for all excluded attributes except

price in the “no choice” option. For this model, the excluded attributes except price are equivalent over alternatives, $x_{mi}^E = 1$, for all i . The excluded price (x_{1i}^E) has same values for alternatives 1 and 2, while it has zero value for alternative 3; namely, $x_{1i}^E = 1$ for $i \neq J$ and $x_{1J}^E = 0$. The “no choice” option is the status-quo alternative and therefore has zero price. If the excluded price has same values for the all alternatives ($x_{1i}^E = 1, \forall i$), the model corresponds to case 2, and the estimated parameters could be unbiased. However, a non-zero price for the status-quo alternative is not realistic and a zero price for alternative 3 may cause a biased estimation.

Model 4 is a partial profile that includes price. All excluded attributes have same values for all alternatives, $x_{mi}^E = 1$, for all i . The choice tasks always includes price. The price of the “no choice” option has zero value. This model corresponds to case 2, and I expect unbiased estimated parameters.

Model 5 is the partial profile with the same values for all excluded attributes except for the “no choice” option, which are themselves equivalent over alternatives, $x_{mi}^E = 1, \forall i \neq J$. All attributes in the “no choice” option have zero values. This model corresponds to case 3, and I expect biased estimated parameters.

Model 6 has adjusted estimators of the partial profile with the same values for all excluded attributes except the “no choice” option. I use generated data equivalent to that in

Model 5. I estimate the parameters using the adjusted estimator for the conditional logit model (21) or the mixed logit model (23), which we propose in this paper. I expect the estimated parameters using the adjusted estimator to be equivalent to the assumed values.

Table 1

Table 1 provides the estimation results using the conditional logit model. I generate the choice data using the conditional logit model based on the assumed values in the table. The ASC is the alternative specific constant of alternative 3, the “no choice” option. For the full profile with all attributes (Model 1), no estimated parameters are significantly different from the assumed values. For the partial profile, I estimate the parameters without the excluded attributes. When I assume that all excluded attributes are zero values (Model 2), the estimated parameters using the partial profile are equal to the assumed values, as expected. When I assume that all excluded attributes are constant except price (Model 3), the price and the ASC are significantly different from the assumed values. The estimated price parameter is $-.572$, while the assumed value is -1.6 . Namely, the implicit partial profile may produce lower price importance than the full profile. When I always include the price and hold all excluded attributes constant (Model 4), the estimated parameters using the partial profile are not significantly different from the assumed

values. When the excluded attributes are constant except the “no choice” option (Model 5), the estimated values of most attributes are significantly different from the assumed values. In this model, price is also less important than in the full model. If I apply the adjusted estimator to the partial profile (Model 6), all parameters are equal to the assumed values. Therefore, the implicit partial profile requires an adjusted estimator because it is difficult to assume that the excluded attributes are constant across all alternatives.

Table 2

Table 2 reports the choice probabilities of each model. While the choice probability of the “no choice” option is .408 for the full profile (Model 1), some models using the partial profile have significantly lower choice probabilities for alternative 3. For example, the choice probability of the “no choice” of the Model 2 is .160, while the estimated parameters of Model 2 are not significantly different from the assumed values. Therefore, the difference in the choice probabilities of the full and partial profiles does not indicate a biased estimate for the partial profile.

Table 3

Table 3 shows the estimation results using the mixed logit model with 200 Halton draws.¹ While some standard deviation parameters are significantly different from the assumed values, the mean parameters of the mixed logit model have a similar tendency as the estimated parameters of the conditional logit model. Namely, the mean parameters of Models 3 and 5 are biased, while the other models have unbiased parameters. Table 4 provides the choice probabilities of the mixed logit models, which are similar to the results for the conditional logit model.

Table 4

DISCUSSION

This paper considers a consistent estimator for the partial profile with a “no choice” option. The theoretical analysis shows that the estimated parameters using the full and explicit partial profile CE designs are consistent, while the estimation of the implicit partial profile is not consistent, unless the ratio of the choice probabilities of the quasi-full profile and the partial profile is independent of the chosen alternative. If the excluded attributes have equivalent values across all

¹ Bhat (2001) finds that 100 Halton draws provide more precise results than 1000 random draws.

alternatives, the implicit profile could be consistent. Analysts usually assume that the respondents evaluate the alternatives and hold all excluded attributes as constant. However, this assumption may be violated for the “no choice” option; therefore, the estimated parameters are not consistent for the implicit partial profile with the “no choice” option. To address this problem, I propose an adjusted estimator, which is consistent for the implicit partial profile design using information about the excluded attributes.

To illustrate the proposed estimator, I analyze Monte Carlo simulations of the full and partial profile CEs. The simulation results show that the choice probability of the “no choice” option in the implicit partial profile can be significantly higher than that in the full profile design. However, when the partial profile has zero values for all excluded attributes (Model 2) or the partial profile always includes price (Model 4), the estimated parameters using the implicit partial profile are not significantly different from the assumed values, even if the choice probabilities of the “no choice” option for the full and partial profiles are different. This suggests that the difference in the choice probabilities of the “no choice” option of the full and partial profiles does not indicate a biased estimation. Furthermore, the simulation results show that the price importance estimated using the implicit partial profile CE is lower than that using the full profile CE when I do not always include the price attributes (Models 3 and 5). I can fix the biased estimation when I always show the price attribute to respondents (Model 4) or apply the

adjusted estimator (Model 6).

The theoretical and simulation results suggest some implications in addressing estimation bias in the partial profile CE design. The first approach is to delete the “no choice” option from the implicit partial profile CE tasks, though I would lose the advantage of a realistic choice task in CEs. The second approach uses an implicit partial profile that always includes the price attributes. It is difficult for respondents to assume that the price attribute has the same values across all alternatives; therefore, excluding the price attribute may cause an estimation bias. Providing the price for all choice tasks is the simple solution to the problem of estimation bias in implicit partial profile CEs. However, this approach does not apply if some attributes besides price may also have different values across all alternatives. The third approach is to use an explicit partial profile design, for which the estimation parameters with the “no choice” option are consistent. However, providing all excluded attributes may create information or cognitive overload among respondents, though I gray out the excluded attributes to ensure respondents focus on the included attributes. The fourth approach is to apply the adjusted estimator, which I propose here, to implicit partial profile CEs with the “no choice” option. The adjusted estimator requires information about the values of the excluded attributes. The analyst can ask respondents for the values of all attributes for their own product before the choice tasks. When asking the choice question in the implicit partial profile CEs, the analyst can include a message such as

“please assume that all features not shown are the same as your own product.” When estimating the parameters, I can apply the adjusted estimator using information about the respondents’ own product for the excluded attributes. The proposed adjusted estimator might be attractive because it can apply to implicit partial profile CEs, which are easier to answer than the full profile or the explicit partial profile CEs.

Finally, I suggest two additional paths of research into partial profile CEs. First, studies should test the adjusted estimator using field data. While the theoretical and simulation analysis shows that the adjusted estimator is consistent, we need to confirm the consistency using survey data. Second, researchers should analyze the cognitive errors in partial profile CEs. This study investigates estimation bias for rational respondents without cognitive errors. Though the simulation results are consistent with previous studies, including the higher choice probability of “no choice” and the lower price importance for the partial profile design, the cognitive errors due to the heuristics of consumer behavior might also cause bias in partial profile CEs. Identifying the effect of the cognitive errors in partial profile CEs is an important topic for future research.

APPENDIX

This appendix provides an example of the profile data used in the simulation section. Table A1

shows the profile data for the first and second tasks for each model.

Table A1

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Table 1 Estimation Results for the Conditional Logit Model

Attributes	Assumed values	Model 1		Model 2		Model 3	
		Estimation	Difference	Estimation	Difference	Estimation	Difference
x1	-1.6	-1.621 *** (-12.27)	-0.021 (-0.16)	-1.595 *** (-13.56)	0.005 (0.04)	-0.572 *** (-5.49)	1.028 *** (9.88)
x2	1.5	1.515 *** (11.81)	0.015 (0.12)	1.535 *** (10.00)	0.035 (0.23)	1.448 *** (7.26)	-0.052 (-0.26)
x3	0.6	0.611 *** (4.52)	0.011 (0.08)	0.578 *** (4.32)	-0.022 (-0.17)	0.634 *** (3.88)	0.034 (0.21)
x4	-0.5	-0.498 *** (-4.23)	0.002 (0.02)	-0.511 *** (-4.45)	-0.011 (-0.10)	-0.472 ** (-2.49)	0.028 (0.15)
x5	1.0	1.015 *** (7.55)	0.015 (0.11)	0.975 *** (7.26)	-0.025 (-0.18)	0.991 *** (4.67)	-0.009 (-0.04)
x6	-1.5	-1.514 *** (-12.73)	-0.014 (-0.12)	-1.505 *** (-12.44)	-0.005 (-0.04)	-1.478 *** (-7.65)	0.022 (0.11)
x7	-1.8	-1.810 *** (-13.63)	-0.010 (-0.08)	-1.790 *** (-12.82)	0.010 (0.07)	-1.697 *** (-8.78)	0.103 (0.53)
x8	0.7	0.707 *** (6.35)	0.007 (0.06)	0.679 *** (5.99)	-0.021 (-0.19)	0.683 *** (3.72)	-0.017 (-0.09)
x9	-1.9	-1.915 *** (-15.59)	-0.015 (-0.12)	-1.906 *** (-16.32)	-0.006 (-0.05)	-1.843 *** (-9.61)	0.057 (0.30)
ASC	-3.0	-3.004 *** (-7.22)	-0.004 (-0.01)	-3.008 *** (-14.64)	-0.008 (-0.04)	-1.629 *** (-21.92)	1.371 *** (18.44)

Attributes	Assumed values	Model 4		Model 5		Model 6	
		Estimation	Difference	Estimation	Difference	Estimation	Difference
x1	-1.6	-1.620 *** (-14.95)	-0.020 (-0.18)	-0.548 *** (-6.00)	1.052 *** (11.50)	-1.598 *** (-7.82)	0.002 (0.01)
x2	1.5	1.521 *** (9.36)	0.021 (0.13)	-0.079 (-0.87)	-1.579 *** (-17.51)	1.506 *** (7.41)	0.006 (0.03)
x3	0.6	0.588 *** (3.01)	-0.012 (-0.06)	-0.236 ** (-2.50)	-0.836 *** (-8.87)	0.594 *** (2.87)	-0.006 (-0.03)
x4	-0.5	-0.509 *** (-2.64)	-0.009 (-0.04)	-0.400 *** (-4.03)	0.100 (1.00)	-0.505 ** (-2.42)	-0.005 (-0.02)
x5	1.0	1.026 *** (5.20)	0.026 (0.13)	-0.161 (-1.61)	-1.161 *** (-11.60)	1.029 *** (5.46)	0.029 (0.15)
x6	-1.5	-1.496 *** (-7.87)	0.004 (0.02)	-0.534 *** (-6.04)	0.966 *** (10.94)	-1.500 *** (-6.76)	0.000 (-0.00)
x7	-1.8	-1.771 *** (-8.56)	0.029 (0.14)	-0.545 *** (-6.14)	1.255 *** (14.14)	-1.766 *** (-9.72)	0.034 (0.19)
x8	0.7	0.709 *** (3.74)	0.009 (0.05)	-0.210 ** (-2.33)	-0.910 *** (-10.08)	0.723 *** (3.28)	0.023 (0.10)
x9	-1.9	-1.911 *** (-9.46)	-0.011 (-0.06)	-0.562 *** (-5.48)	1.338 *** (13.02)	-1.940 *** (-9.05)	-0.040 (-0.19)
ASC	-3.0	-3.014 *** (-23.09)	-0.014 (-0.11)	-0.684 *** (-3.77)	2.316 *** (12.78)	-2.951 *** (-5.43)	0.049 (0.09)

Note: The values in parentheses are t statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2 Choice Probabilities for the Conditional Logit Model

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Alt1	0.297	***	0.418	***	0.443	***	0.451	***	0.286	***	0.285	***
	(36.59)		(39.28)		(40.77)		(41.98)		(32.04)		(39.16)	
Alt2	0.295	***	0.422	***	0.449	***	0.439	***	0.287	***	0.285	***
	(36.96)		(44.79)		(45.29)		(42.27)		(29.96)		(29.16)	
Alt3	0.408	***	0.160	***	0.109	***	0.110	***	0.428	***	0.430	***
	(43.26)		(21.94)		(17.54)		(18.83)		(41.79)		(46.29)	

Note: The values in parentheses are t statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 3 Estimation Results for the Mixed Logit Model

Attributes mean	Assumed values	Model 1		Model 2		Model 3	
		Estimation	Difference	Estimation	Difference	Estimation	Difference
x1	-1.6	-1.515 *** (-8.05)	0.085 (0.45)	-1.542 *** (-8.60)	0.058 (0.32)	-0.463 *** (-3.59)	1.137 *** (8.83)
x2	1.5	1.544 *** (7.56)	0.044 (0.22)	1.447 *** (6.85)	-0.053 (-0.25)	1.448 *** (6.07)	-0.052 (-0.22)
x3	0.6	0.583 *** (3.10)	-0.017 (-0.09)	0.611 *** (3.21)	0.011 (0.06)	0.579 ** (2.15)	-0.021 (-0.08)
x4	-0.5	-0.562 *** (-2.89)	-0.062 (-0.32)	-0.492 *** (-2.98)	0.008 (0.05)	-0.475 * (-1.84)	0.025 (0.10)
x5	1.0	0.989 *** (5.07)	-0.011 (-0.06)	0.955 *** (5.13)	-0.045 (-0.24)	0.990 *** (4.77)	-0.010 (-0.05)
x6	-1.5	-1.541 *** (-8.07)	-0.041 (-0.21)	-1.430 *** (-8.19)	0.070 (0.40)	-1.445 *** (-6.12)	0.055 (0.23)
x7	-1.8	-1.825 *** (-9.29)	-0.025 (-0.13)	-1.705 *** (-9.20)	0.095 (0.51)	-1.769 *** (-6.42)	0.031 (0.11)
x8	0.7	0.661 *** (3.73)	-0.039 (-0.22)	0.668 *** (3.79)	-0.032 (-0.18)	0.699 *** (3.02)	-0.001 (-0.01)
x9	-1.9	-1.915 *** (-9.78)	-0.015 (-0.08)	-1.817 *** (-10.99)	0.083 (0.50)	-1.820 *** (-7.64)	0.080 (0.34)
ASC	-3.0	-3.049 *** (-7.42)	-0.049 (-0.12)	-2.810 *** (-8.97)	0.190 (0.61)	-1.563 *** (-11.88)	1.437 *** (10.92)

Attributes mean	Assumed values	Model 4		Model 5		Model 6	
		Estimation	Difference	Estimation	Difference	Estimation	Difference
x1	-1.6	-1.540 *** (-10.40)	0.060 (0.41)	-0.649 *** (-3.96)	0.951 *** (5.81)	-1.444 *** (-5.86)	0.156 (0.64)
x2	1.5	1.426 *** (5.52)	-0.074 (-0.28)	0.066 (0.31)	-1.434 *** (-6.84)	1.547 *** (6.07)	0.047 (0.18)
x3	0.6	0.602 *** (2.60)	0.002 (0.01)	-0.201 (-1.12)	-0.801 *** (-4.46)	0.595 ** (2.38)	-0.005 (-0.02)
x4	-0.5	-0.508 ** (-2.24)	-0.008 (-0.03)	-0.430 ** (-2.39)	0.070 (0.39)	-0.513 (-1.64)	-0.013 (-0.04)
x5	1.0	1.024 *** (4.17)	0.024 (0.10)	-0.102 (-0.53)	-1.102 *** (-5.69)	1.004 *** (2.99)	0.004 (0.01)
x6	-1.5	-1.448 *** (-6.61)	0.052 (0.24)	-0.621 *** (-3.63)	0.879 *** (5.13)	-1.539 *** (-5.64)	-0.039 (-0.14)
x7	-1.8	-1.785 *** (-7.53)	0.015 (0.06)	-0.696 *** (-4.56)	1.104 *** (7.23)	-1.858 *** (-6.27)	-0.058 (-0.20)
x8	0.7	0.743 *** (3.13)	0.043 (0.18)	-0.133 (-0.86)	-0.833 *** (-5.40)	0.682 ** (2.27)	-0.018 (-0.06)
x9	-1.9	-1.880 *** (-7.70)	0.020 (0.08)	-0.725 *** (-4.16)	1.175 *** (6.73)	-1.903 *** (-5.88)	-0.003 (-0.01)
ASC	-3.0	-2.950 *** (-14.70)	0.050 (0.25)	-0.849 ** (-2.45)	2.151 *** (6.22)	-2.924 *** (-6.97)	0.076 (0.18)

Note: The values in parentheses are t statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Parameter estimates generated with 200 Halton draws.

Table 3 Estimation Results for the Mixed Logit Model (Continued)

Attributes s.d.	Assumed values	Model 1		Model 2		Model 3	
		Estimation	Difference	Estimation	Difference	Estimation	Difference
x1	1.0	0.383 (1.39)	-0.617 ** (-2.23)	0.344 (1.47)	-0.656 *** (-2.81)	0.195 (1.45)	-0.805 *** (-5.99)
x2	1.0	1.013 ** (2.19)	0.013 (0.03)	0.672 (1.50)	-0.328 (-0.74)	0.366 (1.32)	-0.634 ** (-2.28)
x3	1.0	1.096 *** (3.07)	0.096 (0.27)	0.900 ** (2.37)	-0.100 (-0.26)	0.996 ** (2.56)	-0.004 (-0.01)
x4	1.0	1.029 ** (2.58)	0.029 (0.07)	0.925 ** (2.57)	-0.075 (-0.21)	0.999 ** (2.55)	-0.001 (-0.00)
x5	1.0	1.025 *** (2.84)	0.025 (0.07)	0.911 ** (2.42)	-0.089 (-0.24)	1.016 *** (2.95)	0.016 (0.05)
x6	1.0	1.056 *** (3.15)	0.056 (0.17)	0.907 *** (2.75)	-0.093 (-0.28)	1.000 *** (2.96)	0.000 (0.00)
x7	1.0	1.023 *** (2.78)	0.023 (0.06)	0.902 *** (2.79)	-0.098 (-0.30)	0.996 *** (2.77)	-0.004 (-0.01)
x8	1.0	1.110 *** (3.63)	0.110 (0.36)	0.875 *** (2.58)	-0.125 (-0.37)	0.999 ** (2.41)	-0.001 (-0.00)
x9	1.0	0.947 *** (2.72)	-0.053 (-0.15)	0.847 *** (2.80)	-0.153 (-0.51)	0.906 ** (2.49)	-0.094 (-0.26)
asc	1.0	0.803 * (1.86)	-0.197 (-0.46)	0.821 ** (2.32)	-0.179 (-0.50)	1.424 *** (10.09)	0.424 *** (3.01)

Attributes s.d.	Assumed values	Model 4		Model 5		Model 6	
		Estimation	Difference	Estimation	Difference	Estimation	Difference
x1	1.0	0.312 (1.48)	-0.688 *** (-3.26)	0.266 (1.31)	-0.734 *** (-3.60)	0.378 (1.26)	-0.622 ** (-2.07)
x2	1.0	0.458 (1.26)	-0.542 (-1.50)	1.167 *** (2.82)	0.167 (0.40)	1.124 *** (2.82)	0.124 (0.31)
x3	1.0	1.053 ** (2.10)	0.053 (0.11)	0.831 ** (2.00)	-0.169 (-0.41)	0.990 ** (2.30)	-0.010 (-0.02)
x4	1.0	0.966 ** (2.45)	-0.034 (-0.09)	0.597 * (1.80)	-0.403 (-1.21)	1.100 ** (2.46)	0.100 (0.22)
x5	1.0	0.969 ** (2.16)	-0.031 (-0.07)	0.957 ** (2.24)	-0.043 (-0.10)	1.047 ** (2.10)	0.047 (0.09)
x6	1.0	0.981 ** (2.24)	-0.019 (-0.04)	0.379 (1.39)	-0.621 ** (-2.28)	0.956 ** (2.09)	-0.044 (-0.10)
x7	1.0	0.909 ** (2.10)	-0.091 (-0.21)	0.354 (1.24)	-0.646 ** (-2.27)	1.093 ** (2.54)	0.093 (0.22)
x8	1.0	0.998 ** (2.22)	-0.002 (-0.00)	0.836 ** (2.38)	-0.164 (-0.47)	1.086 ** (2.46)	0.086 (0.19)
x9	1.0	0.874 ** (2.01)	-0.126 (-0.29)	0.277 (1.16)	-0.723 *** (-3.03)	0.977 ** (2.14)	-0.023 (-0.05)
asc	1.0	1.252 *** (4.46)	0.252 (0.90)	3.140 *** (10.51)	2.140 *** (7.17)	0.818 ** (2.12)	-0.182 (-0.47)

Note: The values in parentheses are t statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Parameter estimates generated with 200 Halton draws.

Table 4 Choice Probabilities of the Mixed Logit Model

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Alt1	0.284	***	0.396	***	0.420	***	0.417	***	0.277	***	0.276	***
	(22.55)		(37.71)		(31.76)		(30.31)		(19.03)		(22.65)	
Alt2	0.287	***	0.401	***	0.417	***	0.423	***	0.278	***	0.279	***
	(22.54)		(33.84)		(34.46)		(34.39)		(20.35)		(19.27)	
Alt3	0.429	***	0.203	***	0.162	***	0.160	***	0.446	***	0.445	***
	(25.38)		(20.70)		(19.41)		(14.54)		(24.31)		(25.40)	

Note: The values in parentheses are t statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Parameter estimates generated with 200 Halton draws.

Table A1 Example Profile Data for the First and Second Tasks

Model 1	Task1			Task2		
	Alt1	Alt2	Alt3	Alt1	Alt2	Alt3
x1 (price)	1.1	1.3	0.0	0.6	0.8	0.0
x2	1.4	1.0	0.0	1.4	1.3	0.0
x3	0.9	0.7	0.0	1.0	1.0	0.0
x4	0.9	1.2	0.0	1.0	1.5	0.0
x5	0.9	0.9	0.0	0.6	1.3	0.0
x6	0.5	1.0	0.0	1.1	0.9	0.0
x7	1.3	0.7	0.0	1.0	1.2	0.0
x8	0.9	1.0	0.0	1.4	1.1	0.0
x9	1.0	1.5	0.0	0.7	1.1	0.0

Model 2	Task1			Task2		
	Alt1	Alt2	Alt3	Alt1	Alt2	Alt3
x1 (price)	0.8	1.2	0.0	0.0	0.0	0.0
x2	1.0	1.1	0.0	0.0	0.0	0.0
x3	1.5	0.7	0.0	0.0	0.0	0.0
x4	0.0	0.0	0.0	1.4	1.2	0.0
x5	0.0	0.0	0.0	1.1	1.3	0.0
x6	0.0	0.0	0.0	0.0	0.0	0.0
x7	0.0	0.0	0.0	0.0	0.0	0.0
x8	0.0	0.0	0.0	0.5	0.6	0.0
x9	0.0	0.0	0.0	0.0	0.0	0.0

Model 3	Task1			Task2		
	Alt1	Alt2	Alt3	Alt1	Alt2	Alt3
x1 (price)	1.0	1.0	0.0	1.0	1.0	0.0
x2	1.3	1.4	1.0	1.0	0.6	1.0
x3	1.0	1.0	1.0	1.0	1.0	1.0
x4	1.0	1.0	1.0	1.0	1.0	1.0
x5	0.7	0.6	1.0	1.0	1.0	1.0
x6	1.0	1.0	1.0	1.4	1.0	1.0
x7	1.0	1.0	1.0	1.0	1.0	1.0
x8	1.0	1.0	1.0	1.0	1.0	1.0
x9	1.2	1.5	1.0	0.6	0.7	1.0

Model 4	Task1			Task2		
	Alt1	Alt2	Alt3	Alt1	Alt2	Alt3
x1 (price)	0.7	0.5	0.0	1.3	0.8	0.0
x2	1.0	1.0	1.0	1.0	1.0	1.0
x3	1.0	1.0	1.0	1.0	1.0	1.0
x4	1.5	0.6	1.0	1.4	0.7	1.0
x5	1.0	1.0	1.0	1.0	1.0	1.0
x6	1.0	1.1	1.0	0.8	1.2	1.0
x7	1.0	1.0	1.0	0.9	1.5	1.0
x8	1.0	1.0	1.0	1.0	1.0	1.0
x9	0.7	0.9	1.0	1.0	1.0	1.0

Model 5	Task1			Task2		
	Alt1	Alt2	Alt3	Alt1	Alt2	Alt3
x1 (price)	1.4	0.8	0.0	1.0	1.0	0.0
x2	1.0	1.0	0.0	0.7	1.3	0.0
x3	1.0	1.0	0.0	1.0	1.0	0.0
x4	1.0	1.0	0.0	1.0	1.0	0.0
x5	1.0	1.0	0.0	1.0	1.0	0.0
x6	1.0	1.0	0.0	1.1	0.7	0.0
x7	1.0	1.0	0.0	1.5	1.0	0.0
x8	1.0	1.0	0.0	1.0	1.0	0.0
x9	0.9	1.2	0.0	1.0	1.0	0.0

Model 6	Task1			Task2		
	Alt1	Alt2	Alt3	Alt1	Alt2	Alt3
x1 (price)	1.0	1.0	0.0	0.9	1.4	0.0
x2	1.0	1.0	0.0	1.0	1.0	0.0
x3	1.1	0.6	0.0	1.0	1.0	0.0
x4	1.0	1.0	0.0	1.0	1.0	0.0
x5	1.0	1.0	0.0	1.0	1.0	0.0
x6	1.0	0.9	0.0	0.8	1.2	0.0
x7	1.0	1.0	0.0	1.0	1.0	0.0
x8	1.0	1.0	0.0	1.0	0.6	0.0
x9	1.3	1.3	0.0	1.0	1.0	0.0

Figure 1. Example Full Profile Choice Experiment

	Option 1	Option 2	Option 3
Vehicle type	Compact car	SUV	
Fuel type	Gasoline	HEV	
Age of vehicle	New	3 years	
Annual fuel cost	\$1,300	\$1,000	I wouldn't choose any of these
Annual maintenance cost	\$300	\$500	
Acceleration (0-60mph)	10 seconds	12 seconds	
Driving range	400 miles	700 miles	
Emission reduction	10%	30%	
price	\$20,000	\$35,000	

Figure 2. Example Partial Profile Choice Experiment

(a) Implicit Partial Profile

	Option 1	Option 2	Option 3
Fuel type	Gasoline	HEV	I wouldn't choose any of these
Acceleration (0-60mph)	10 seconds	12 seconds	
price	\$20,000	\$35,000	

(b) Explicit Partial Profile

	Option 1	Option 2	Option 3
Vehicle type	Compact car	Compact car	I wouldn't choose any of these
Fuel type	Gasoline	HEV	
Age of vehicle	New	New	
Annual fuel cost	\$1,300	\$1,300	
Annual maintenance cost	\$300	\$300	
Acceleration (0-60mph)	10 seconds	12 seconds	
Driving range	400 mile	400 mile	
Emission reduction	10%	10%	
price	\$20,000	\$35,000	

Figure 3. Excluded Attributes Have Zero Values for all Alternatives

	Alternative 1	Alternative 2	Alternative 3 (Don't Buy)
x_1 (price)	\$100	\$50	\$0
x_2	125%	125%	0%
x_3	+150%	75%	0%
x_4 (Excluded)	0%	0%	0%

Figure 4. Excluded Attributes Have the Same Values for all Alternatives

	Alternative 1	Alternative 2	Alternative 3 (Status quo)
x_1 (price)	\$100	\$50	\$0
x_2	125%	125%	100%
x_3	+150%	75%	100%
x_4 (Excluded)	100%	100%	100%

Figure 5. Excluded Attributes are Equal to All Alternatives Except “No Choice”

	Alternative 1	Alternative 2	Alternative 3
x_1 (price, Excluded)	\$100	\$100	Don't buy /
x_2	125%	125%	Keep my own
x_3	+150%	75%	product /
x_4 (Excluded)	100%	100%	Not sure