# Consumer Uptake Modeling – Multi-Modal Mobility

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# Executive Summary

This project was funded by the Graham Sustainability Institute as part of its work on promoting livable communities. The livable communities initiative seeks to research a broad array of policies, interventions, innovations and partnerships that best enable urban areas to create more livable communities. The key goals of this project are to review the relevant literature, provide a new modeling framework, and collect new data all in service of developing multi-modal mobility choice models that can inform policy decisions and provide a platform to examine the impact of different policy decisions. The present project focused on Portland, Oregon as a test site with the view that the modeling framework could scale to different cities both in the US and abroad.

The project was completed mainly in collaboration with Metro, which is the Portland metropolitan area urban planning agency (individuals included Deena Plattman, Principal Transportation Planner; Thaya Patton, Transportation Research and Modeling Services; Cindy Pederson, Principal Transportation Modeler; Bud Reiff, Principal Transportation Modeler). During the developmental phase of this project we also consulted with the Los Angeles County Metropolitan Transportation Authority, the Santa Monica, California Transportation Management Office, TriMet (Oregon), the Portland Bureau of Planning and Sustainability, the Oregon Department of Transportation's GreenSTEP Program (individuals included Brian Gregor; Tara Weidner, Integrated Transportation Analysis Engineer), and the Oregon Transportation Research and Education Consortium at Portland State University (John Macarthur, Research Associate).

Key contributions and findings:

1. Developed a choice model to enable scenario planning within a policy framework.
2. Collected stated preference data through an online survey from residents of the Portland metropolitan area including the city of Portland and the region surrounding the city, which spanned seven counties.
3. In addition to standard models, we used two models to analyze the data – a latent variable model and a hierarchical Bayes model.
4. We found evidence that two dual-mode commuting options---Car + Transit and Bike + Transit---receive some support in the sample. While the single mode Car attracted the most support (i.e., most preferred mode), the dual-mode Car + Transit emerged second in the preference rank ordering and above the single mode Transit. This indicates that an alternative with the combination of two modes can be preferred to one of its single mode options (i.e., Car + Transit preferred to Transit). We see the analogous ordering in

the case of Transit, Bike + Transit and Bike where the dual-mode Bike + Transit is preferred to the single mode Bike.

5. In addition, we observe that attitude shifts are associated with these mode share choices and infer that attitudes can play a significant role in bringing about changes in mode shares. Specifically, emphasizing the benefits of active lifestyle could be effective in increasing the choice probability of non-motorized modes such as Bike and Walk. This could lead to creative new interventions or policy frameworks for mobility use connected through wellness programs. Though, of course, the empirical findings in this project provide association patterns at best.
6. We observe that Car has the highest preference among the respondents and, according to the model estimates, very few factors of the ones studied are able to bring about a shift to other modes. One such important factor is parking cost. An increase in parking cost appears to be most effective in bringing about a shift from Cars to other modes than the other factors we studied.
7. We explored the benefit of adding more complexity to the modeling efforts by considering heterogeneity in tradeoffs through a Hierarchical Bayes model and incorporated the concept of choice inertia.
8. The modeling framework also allows us to study unintended consequences of policy changes even on attributes not relevant to an individual's current mode choice. For example, a decrease in parking cost could have the unintended consequence of moving a current Transit user to either Car or to the dual-mode Car + Transit.

We presented the findings, models and the models' scenario planning results to our constituent groups in Portland, Oregon. They found value over their current tools in the ability to include attitude information in the modeling process, explore policy implications of shifting consumer attitudes (e.g., promoting healthy living and exercise as a way to change mobility mode use), the ability to examine unintended consequences of transportation policy, our modeling of heterogeneity in user tradeoffs, and our attempts to model choice inertia.

The multi-modal travel options, which was the focus of this study, was particularly interesting to Metro. One of the central results of this study indicates that it may be easier to move commuters from car use to a multi-mode consisting of car and transit in comparison to having them use transit alone. This observation provides initial evidence in support for the viability of an integrated transportation system where multiple modes could be used for a single commute trip. Such integrated systems are of particular interest for Metro because they could address issues such as congestion, lack of parking and poor air quality within the densely populated areas of the city of Portland.

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# 1. Introduction

The goal of this project was to develop multi-modal mobility choice models and provide detailed information about existing multi-modal mobility commuting options in Portland, Oregon. The survey and choice models were developed to aid policy makers in their efforts to understand tradeoffs people make around their mobility options. The project was completed in collaboration with officials at the Metro, which is the agency responsible for urban planning for a region of about 25 cities in Oregon including the city of Portland (1).

We expanded well-known choice models to enable scenario planning within a policy framework i.e., we developed choice models from the survey data to enable evaluation of "what if" scenarios. An important outcome of this project is that it included measures of attitude and those attitude measures were included in the choice model in a novel way. This provides a way to model how policy can influence behavior (i.e., influencing attitude in order to influence behavior). That is, in addition to examining the direct attributes of choice objects (e.g., fuel price, parking fees, travel time, safe bike lanes) as in the standard modeling frameworks, we also included attitude measures that provide complementary routes for changing behavior. We found that, for this sample, attitudes about the environment and attitudes about exercise were related to adoption of different transportation modes, including multi-mode options, and that other attitudes such as safety were not related to transportation mode choice. This addition of attitudes in the choice modeling framework expands the types of "policy levers" that are available to nudge behavior in policy-consistent directions. For example, it may be better for policy makers to focus on exercise and environment over, say, safety concerns when developing policy to encourage multi-modal mobility.

A second major concern of this research was to study multi-modal mobility decisions. Most of the research on transportation choice has used single mode options (e.g., car only, bus only, etc.). In a few examples, such as McFadden's classic analysis of BART in the Bay Area, a multi-mode option was treated as merely another option. In our view, however, it is inappropriate to treat multiple modes as another choice option because relevant parameters are not estimated appropriately. We can estimate, say, the part worth of an increase in gas price by one dollar for Car, but that same part worth also plays a role in any multi-mode mobility options that includes Car as one of the modes. By treating a multi-mode option as another option in the choice set without constraining the part worth in both Car Only and Car + Another Mode options, the parameter estimates in the model could be severely biased. To our knowledge no one has developed the appropriate choice model for multi-modal mobility decisions so the present research helps to fill an important void.

To put this in different words, traditional choice models focus on selecting one option out of k options available in the choice set. Multi-modal mobility decision involves the selection of two or more options (such as Car + Bike on the same trip) out of k options in the choice set. The difference is in selecting one from (k + 1) or selecting one from 2^k, where "no choice" is possible as well. In this project we focus on multiple modes without considering order but in future work it will be important to consider order (e.g., Car + Bike versus Bike + Car). One may not feel save riding a bicycle in a congested area so may prefer to have a sequence of Bike + Car in one direction and Car + Bike in the other direction to minimize the amount of bike riding in congested areas, or maybe parking fees are expensive near the place of work so the sequence Car + Bike in one direction and Bike + Car in the other direction may be preferred. Other factors such as picking up children from day care or location of errands may impact the preference order over multiple modes. These are all important aspects to consider when evaluating the role of multi-modal policy on choice and behavior. There clearly are many research problems to solve in this field, which makes it exciting and an area ripe for important new insights.

The remainder of the report is organized as follows. We discuss the sample, the survey and data collection in Section 2. Section 3 presents analysis based on a standard logit model, which is one of the most commonly used discrete choice models in transportation literature. We further discuss two models, more advanced than the standard logit model: the integrated choice and latent variable model in Section 4 and the Hierarchical Bayes model in Section 5. Section 6 presents the choice inertia model, which we developed after examination of the survey findings. Finally in Section 7 we summarize the findings from our modeling approaches as well as the counterfactual analyses and place them in a broader transportation context, including discussing practical implications.

# 2. Data Collection

Stated preference data were collected through an online survey. Survey respondents included residents of the Portland metropolitan area including the city of Portland and the region surrounding the city center, which spanned seven counties[1]. Recruitment of the respondents for the survey was managed by the firm Research Now (2), which provided a distribution across the seven counties in the Portland area.  The focus on this particular region in Portland was motivated by discussions with municipal and NGO units in Portland.

## 2.1. Survey Design

The survey included four sections. The first three sections collected information about household demographics, current commuting arrangements and responses to a series of questions measuring specific attitudes and perceptions of the respondent. Details regarding these sections are provided in the Appendix.

The fourth section of the survey consisted of a travel mode choice conjoint study to gather information about travel mode choice behavior. Two separate conjoint studies were conducted – one related to the choice of single modes (one mode for the entire trip) and the second related to the choice of multi-mode options (use of more than one travel mode during a single trip). All participants completed the single mode version first followed by the version that included some multiple modes. The conjoint study uses a design of experiment approach to present to participants sets of different options that vary in the values of the attributes (e.g., gas price, bus fare, etc.). This permits the measurement of tradeoffs of the different attributes and the assessment of the effect on choice of changes on each attribute.  This information and modeling approach makes it possible to examine how to influence or nudge behavior by changes on those attributes (such as through policy) and minimize unintended consequences of those changes.  Thus, the survey data can be used to model behavior under different scenarios, which goes beyond typical survey instruments that can merely report current behavior.

**Conjoint Study**

Conjoint analysis is a method for simulating how consumers might react to changes in current products, goods or services or to new products, goods and services introduced into an existing competitive array. The problem the decision maker faces is how to trade off the possibility that

[1] Clackamas, Washington, Multnomah, Columbia and Yamhill – in the state of Oregon
Clark and Skamania – in the state of Washington

option X is better than option Y on attribute A while Y is better than X on attribute B, and various extensions of these conflicts (3). This is a better approach than standard stated preference surveys because it allows tradeoffs to be measured and used in subsequent modeling efforts. In conjoint experiments respondents are presented with multiple choice scenarios that vary in the levels of attributes. The selection of the attribute levels to present the participants follows traditional principles from design of experiments where attributes are varied in a factorial manner across multiple choice scenarios. Respondents are asked to choose one alternative in each choice scenario. With this approach we not only observe the product, good or service they chose but also observe the trade-offs they make when comparing attribute levels of different alternatives and can use that information in the modeling effort.

Table 1 presents a complete list of attributes used in this study and their levels. Not all attributes are relevant to all alternatives and these are called alternative-specific attributes, e.g., bus fare is an attribute related to the bus mode but not the car mode. Table 2 and Table 3 present the design of the single-mode and multi-mode conjoint choice tasks, respectively. Figure 3 and Figure 4 in the Appendix provide screenshots of single-mode and multi-mode conjoint tasks as presented to the respondent.

**Table 1: Attributes and their levels in the conjoint study**

| Attributes | Levels | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| Fuel economy (mpg) | 25 | 40 | 55 |
| Fuel price ($/gal) | 3.50 | 4.50 | 5.50 |
| Parking charge ($/month) | 0 | 100 (roughly $5/day) | 200 (roughly $10/day) |
| Tri Met fares ($/month) (Regular/Senior or Honored) | 75 / 20 (~$3.75/day / $1/day) | 100 / 26 (~$5/day / $1.30/day) | 125 / 32 (~$6.25/day / $1.60/day) |
| Free Park & Ride facilities | Available | Unavailable | |
| Bike & Ride facilities (at nominal charge) | Available | Unavailable | |
| Real-time info on transit schedule and mobile ticketing | Available | Unavailable | |
| Bike lanes on busy roads | Unmarked | Marked and separate | |
| Travel time change relative to your current travel time (%, negative means shorter) | -25% of current travel time | 0 (remains same) | +25% of current travel time |
| Availability of sidewalks | Available | Unavailable | |

**Table 2: Attributes and the modes used in the single-mode choice conjoint portion**

<table>
<tr><th>Mode</th><th>Car</th><th>Transit (+ Walk)</th><th>Walking</th><th>Bike</th></tr>
<tr><td rowspan="8">Attributes</td><td>Fuel economy</td><td></td><td></td><td></td></tr>
<tr><td>Fuel price</td><td></td><td></td><td></td></tr>
<tr><td>Parking charge</td><td></td><td></td><td></td></tr>
<tr><td></td><td>Transit Fare</td><td></td><td></td></tr>
<tr><td></td><td>Real-time schedule info and mobile ticketing for transit</td><td></td><td></td></tr>
<tr><td colspan="2">Travel time change (in percent) relative to the currently experienced travel time</td><td></td><td></td></tr>
<tr><td></td><td colspan="2">Sidewalks</td><td></td></tr>
<tr><td></td><td></td><td></td><td>Bike lanes</td></tr>
</table>

**Table 3: Attributes and the modes used in the multi-mode choice conjoint portion**

<table>
<tr><th>Mode</th><th>Car</th><th>Car + Transit</th><th>Transit (+ Walk)</th><th>Bike + Transit</th><th>Bike</th><th>Walking</th></tr>
<tr><td rowspan="10">Attributes</td><td>Fuel economy</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Fuel price</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Parking charge</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>Park and ride facility</td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td>Bike locker facility</td><td></td><td></td></tr>
<tr><td></td><td colspan="3">Transit fare</td><td></td><td></td></tr>
<tr><td></td><td colspan="3">Real-time schedule info and mobile ticketing for transit</td><td></td><td></td></tr>
<tr><td colspan="4">Travel time change (in percent) relative to the currently experienced travel time</td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td colspan="2">Bike lanes</td><td></td></tr>
<tr><td></td><td></td><td>Sidewalks</td><td></td><td></td><td>Sidewalks</td></tr>
</table>

In order to reduce the burden on study participants, each participant was given a random subset of potential combinations of attributes. We ran diagnostics within the Sawtooth software to verify that the experimental design would allow estimation of all relevant parameters with reasonable standard errors. We selected the sample size and various parameters of the conjoint design (e.g., number of modes to present within each choice) given the diagnostic checks of our experimental design.

## 2.2. Sample Data Characteristics

1208 complete responses were received. Details pertaining to the distribution of other demographic characteristics, namely age, family size, education, and gender are presented in Table 4. Most of these demographics correspond to the individuals who completed to the survey rather than their household. Therefore, these distributions may not be comparable with the corresponding values from census data as done in the case of county-wise population and household income distributions. There was representation across the seven counties as shown in Table 5. There was some under-representation among the lower income households and over-representation in the higher income groups as shown in Table 6.

The percentage share of the modes currently used for commuting as reported by the respondents is presented in Table 7. Driving a personal vehicle (termed simply as 'Car' in the rest of this report) at 81% share is the most popular mode of commuting transportation in this sample.

**Table 4: Distribution of age, family size and level of education attained**

| Age Groups | % of Respondents |
|---|---|
| 24 or under | 3% |
| 25 -34 | 16% |
| 35 - 44 | 17% |
| 45 - 54 | 19% |
| 55 - 64 | 23% |
| 65 or over | 21% |

| Family Size | % of Respondents |
|---|---|
| 1 | 20% |
| 2 | 47% |
| 3 | 16% |
| 4 | 11% |
| 5 | 4% |
| more than 5 | 3% |

| Education Level | % of Respondents |
|---|---|
| Grammar school | 0.20% |
| High school or equivalent | 23% |
| Vocational school | 14% |
| Bachelor's degree | 41% |
| Master's degree | 15% |
| Doctoral/professional degree | 7% |

| Gender | % of Respondents |
|---|---|
| Female | 62% |
| Male | 38% |

### Table 5: County-wise population representation in the survey

| County-wise Population | | |
|---|---|---|
| **County** | **Reference** (4) | **Survey** |
| Clackamas | 17% | 14% |
| Washington | 25% | 28% |
| Multnomah | 32% | 33% |
| Columbia | 2% | 1% |
| Yamhill | 4% | 3% |
| Clark | 20% | 20% |
| Skamania | 0% | 1% |

### Table 6: Total household income category representation in the survey

| Total Household Income | | |
|---|---|---|
| **Income Categories** | **Reference** (4) | **Survey** |
| Under $15,000 | 11% | 4% |
| $15,000 - $29,999 | 14% | 7% |
| $30,000 - $44,999 | 15% | 15% |
| $45,000 - $59,999 | 13% | 15% |
| $60,000 - $74,999 | 11% | 13% |
| $75,000 - $99,999 | 13% | 20% |
| $100,000 - $150,000 | 14% | 17% |
| Over $150,000 | 9% | 8% |

### Table 7: Percentage share of commute modes currently used (self-report)

| Current Travel Mode Used | |
|---|---|
| Driving a car | 81% |
| Carpooling | 1% |
| Driving + transit | 4% |
| Biking | 2% |
| Biking + transit | 1% |
| Walking only | 4% |
| Transit | 6% |
| By motorcycle | 0.3% |

## 3. Logit Model

The Logit model is one of the most commonly used discrete choice models in the transportation literature (5). Equation 1 presents the form of a standard logit model. The Utility ($U_i$) of option *i* is modeled as a linear function of the attributes of option *i* and their corresponding parameters $\beta$. The error $\varepsilon_i$ is assumed to be independent and identically (iid) distributed, and to follow a double exponential distribution for all alternatives. There are other ways to derive the logit model (e.g., the Luce framework) but we rely on McFadden's rationale in this report.

$$U_i = \boldsymbol{\beta X_i} + \varepsilon_i \qquad (1)$$

where,

$\boldsymbol{X}$ – Explanatory variables (could include mode-specific attributes)

$\boldsymbol{U}$ – Utility of the option

$\boldsymbol{\varepsilon}$ – Random error term

$\boldsymbol{\beta}$ – Unknown parameters to estimate

$i$ – Index to identify each transportation mode (aka transportation option)

The assumption regarding the error term allows us to calculate the choice probability in a simple manner. The probability $P_i$ of choosing a travel mode *i* is given by Equation 2 below. In order to make choice probability predictions, one needs to estimate the parameters $\beta$, which are estimated to maximize the likelihood of observing the choice data (e.g., the observed choice of option *i* over the other options). The choice proportions are estimated using Equation 2. In this section we base our analysis on choice data from the single-mode conjoint portion of the conjoint study because the objective is to examine how well the logit model can represent the mode share observed in the sample. Parameter estimates for this case are presented in Table 8.

$$P_i = \frac{\exp(\beta X_i)}{\sum_i \exp(\beta X_i)} \qquad (2)$$

**Table 8: Logit model estimation results for single-mode scenario**

| Parameter Category | Parameter | Estimate | Standard Error |
|---|---|---|---|
| $\beta$ | Car | 1.165 | 0.020 |
| | Transit | 0.624 | 0.022 |
| | Walk | -0.777 | 0.032 |
| | mpg level 1 | -0.094 | 0.032 |
| | mpg level 2* | 0.056 | 0.032 |
| | Gas price level 1 | 0.195 | 0.032 |
| | Gas price level 2* | -0.040 | 0.032 |
| | Parking cost level 1 | 0.490 | 0.032 |
| | Parking cost level 2* | -0.051 | 0.032 |
| | Travel time level 1 | 0.182 | 0.020 |
| | Travel time level 2 | 0.052 | 0.020 |
| | Bus fare level 1 | 0.131 | 0.034 |
| | Bus fare level 2* | -0.026 | 0.034 |
| | Real-time info level 1 (available) | 0.051 | 0.024 |
| | Sidewalk level 1 (available) | 0.232 | 0.019 |
| | Bike lane level 1 (unmarked) | -0.509 | 0.048 |

* Not significant at 95% confidence interval

The findings from this basic model suggest that all factors influence the choice proportion but for a few cases there was not sufficient difference between adjacent levels of a factor to reach statistical significance (e.g., gas price as a factor mattered in the model between two levels but not the third). Taking these parameter estimates at face value we conclude that there may be diminishing return from making particular changes to levels of factors mpg, gas price, parking cost and bus fare, at least within the ranges examined in our conjoint experiment; this is expected from the diminishing sensitivity (i.e., concavity) of standard utility functions.

## 3.1. Counterfactual Assessment Based on Logit Model

Table 9 presents a list of travel mode attributes $\boldsymbol{X_i}$ that are approximately representative of the choice set available to the respondents in the Portland area at the time the survey was conducted. We call this combination of attributes and their levels the “Base Case” scenario and use it as a baseline for comparing the nature of changes in travel mode choice share under different “what if” scenarios throughout the rest of this report.

**Table 9: Variables and their levels for base case scenario**

| | Attributes | Levels |
|---|---|---|
| Applicable to both the single-mode and the multi-mode choice cases | Fuel economy (mpg) | 25 |
| | Fuel price ($/gal) | 4.5 |
| | Parking charge ($/month) | 0 |
| | Tri Met fares ($/month) | 100 |
| | Real-time info on transit schedule and mobile ticketing | Unavailable |
| | Bike lanes on busy roads | Unmarked |
| | Travel time change relative to your current travel time | 0 (unchanged) |
| | Availability of sidewalks | Available |
| Applicable to the multi-mode choice case only | Free Park & Ride facilities | Available |
| | Bike & Ride facilities (at nominal charge) | Unavailable |

**Table 10: Logit model predicted mode choice probabilities for the base case scenario**

| Modes | Choice Probability (%) |
|---|---|
| Car | 61 |
| Transit | 29 |
| Walk | 7 |
| Bike | 3 |

Table 10 presents the mode choice probabilities for the base case scenario using the estimates from standard logit model on our data. Comparison of these values with the observed shares presented in Table 7 could be considered as an approximate measure of how well the model represents the mode shares observed in the sample. As presented previously in, the percentage share of Cars in the sample is 81% and Transit is at most 11% (combining Transit, Transit + Bike and Transit + Car). Compared to these observed values, the logit model dramatically under-predicts an individual's probability of choosing a Car (the logit model predicts 61%, see Table 10) and over-predicts the choice probability for Transit (the logit model predicts 29%). This inconsistency indicates that the standard logit model fails to account for mode choice behavior observed in this sample. Of course, this assumes that the stated preferences reported both in the questionnaire and in conjoint study are accurate reflections of consumer preferences, but this is a standard issue with all such research relying on state preference. While on these grounds one could argue for revealed preferences, the key drawback of revealed preference data is that they do not directly permit scenario planning and consideration of hypothetical "what if" scenarios, which is an important goal in the present work. The ability to model "what if" scenarios is a key aspect of the state preference approach of the conjoint method. These predicted choice probabilities provide a baseline against which the quality of predictions by the two, more sophisticated models considered in the next section can be assessed. For our purposes, the standard logit model provides a baseline against which the new models can be compared. Do the newer models make better predictions of mode choice in the Base Case than the standard logit model?

## 4. Latent Variable Choice Model

A key innovation of this project is to include respondent's unobserved attitudes and perceptions in the choice model in order to investigate their role in the choice of travel modes along with the traditional (observed) attributes of the travel modes. Unobserved variables are called latent variables and they are estimated from observed variables called indicators. The integrated choice modeling framework shown in Figure 1 consists of two components, a traditional choice model and a latent variable model, which in our application corresponds to attitudes. A simultaneous estimator is used, which results in a set of parameters that provide the best fit to both the choice and the latent variables indicators. This model has been called the Integrated Choice and Latent Variable (ICLV) model in the literature, though it has not received wide-spread attention mostly because the right kind of data are rarely collected.

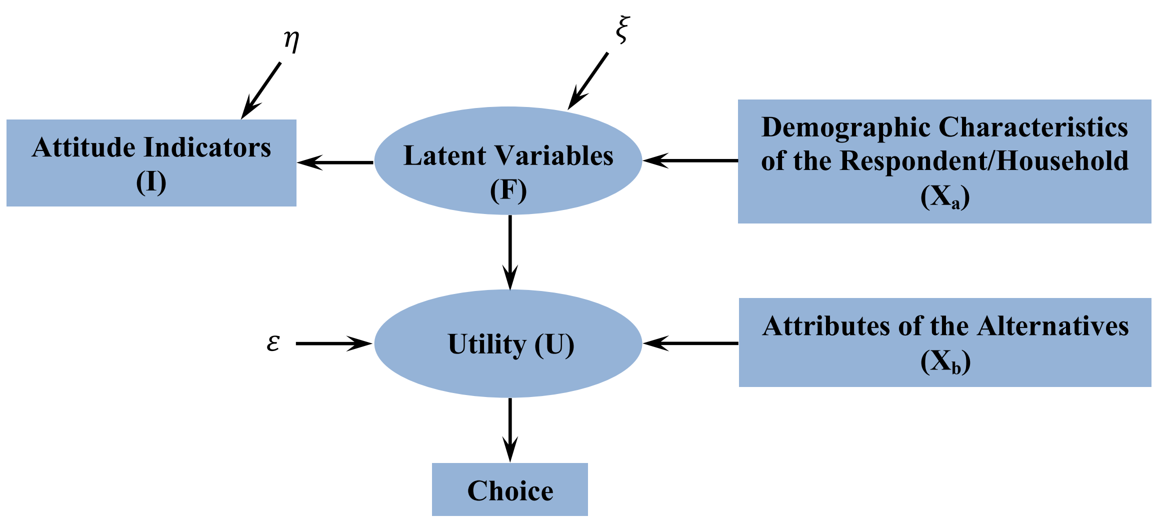


**Figure 1: Integrated choice and latent variable (ICLV) model**

Notation used in Figure 1:

- Rectangular or square box signifies an observed variable
- Ellipse signifies an unobserved or latent variable
- Greek letters signify a disturbance term (error in either measurement or relation between constructs), which are also unobserved and some conventions also assign disturbance terms circles or ellipses for consistency with other unobserved variables
- Straight arrows signify the assumption that variables at base of arrow "cause" variables at head of arrow (can be interpreted as a regression parameter); a double-headed arrow (not used in Figure 1) denotes correlation between the two variables

The key point of the ICLV model is that both attitudes and the attributes of the choice objects are included in the choice modeling and estimated simultaneously. One benefit of treating attitudes as latent variables is that noise related to individual items can be modeled; the ICLV performs a simultaneous factor analysis on the attitudes to reduce predictor dimensionality and properly model noise and modeling the parameters of choice. From a computational and modeling standpoint the simultaneous approach is more efficient and does a better job of handling the joint distribution of the parameters (relative to, say, a sequential process of first fitting a factor analysis model to the attitude data and then using the latent variables as predictors in the choice model). One benefit of modeling both latent variables and choice is that policy makers now have two possible routes to influence or incentivize behavior: the traditional choice attribute route (e.g., subsidize bus fare, increase parking costs, etc.) and the attitude route (e.g., develop PSAs around relevant attitudes, tailor campaigns within regions based on distribution of relevant attitudes, etc.). The ICLV provides better insight to underlying patterns of attitudes than using single attitude items from a survey directly in the choice model.

## 4.1. Methods

The ICLV model can be described with a set of three equations as shown below. Equations 3 and 4 correspond to the latent variable model and Equation 5 corresponds to the choice model.

$$\boldsymbol{I} = \boldsymbol{\alpha F} + \boldsymbol{\eta} \qquad (3)$$

$$\boldsymbol{F} = \boldsymbol{\gamma X_a} + \boldsymbol{\xi} \qquad (4)$$

$$\boldsymbol{U} = \boldsymbol{\beta_1 X_b} + \boldsymbol{\beta_2 F} + \boldsymbol{\varepsilon} \qquad (5)$$

where,

$\boldsymbol{I}$ – Attitude/behavior indicators

$\boldsymbol{F}$ – Latent variables (known as factors in the traditional factor analysis literature)

$\boldsymbol{X_a}$ – Observed demographic characteristics of the household

$\boldsymbol{X_b}$ – Observed attributes of the alternatives

$\boldsymbol{U}$ – Utility of alternative

$\boldsymbol{\eta}$, $\boldsymbol{\xi}$ and $\boldsymbol{\varepsilon}$ – Random error, or disturbance, terms; to be estimated from data

$\boldsymbol{\alpha}$, $\boldsymbol{\gamma}$, $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ – Unknown parameters to be estimated from the observed data.

We describe each part separately though the estimation procedure we used treats the submodels simultaneously to properly account for different sources of error and provide standard errors for each parameter that properly reflect their uncertainty given the joint distribution of the estimates.

#### 4.1.1. Latent Variable Model

Responses to attitudinal indicator questions are modeled not as a direct measure of attitudes, but they are treated as manifestations of underlying attitudes that include measurement error (6). Therefore, the responses to attitudinal questions should not be used directly in the choice model as explanatory variables but as latent variables to properly account for measurement error. There is a two-step process involved when incorporating attitudes in the choice model. The measurement model is the first step (described by Equation 3) where the responses to indicator questions $\boldsymbol{I}$ are treated as dependent variables accounted for by the latent attitude variables $\boldsymbol{F}$. $\boldsymbol{\alpha}$ is an estimated parameter that determines the effect of each latent variable on the respective indicators. $\boldsymbol{\eta}$ is a random error term that is assumed to be normally distributed with zero mean and some standard deviation (estimated along with other parameters). These are standard assumptions in the latent variable framework.

The second step of the latent variable part of the model (described by Equation 4) involves a linear regression that relates the observable variables $\boldsymbol{X_a}$ such as socio-demographic characteristics of the respondent/household to the latent variable $\boldsymbol{F}$. $\boldsymbol{\gamma}$ are the coefficients of the linear regression model, which permit modeling of differences in latent variable means, and $\boldsymbol{\xi}$ are the random disturbance term that are assumed to be normally distributed among the respondents with a zero mean and a standard deviation (estimated along with other parameters). These are standard assumptions within the latent variable framework.

#### 4.1.2. Choice Model

The choice model part (described by Equation 5) is a standard logit model except that the utility $\boldsymbol{U}$ is defined as a function of latent attitudes $\boldsymbol{F}$ derived in the previous steps along with the observed attributes $\boldsymbol{X_b}$ of the alternatives. $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ are the estimated coefficients of the utility function corresponding to the mode attributes and latent variables respectively. The error term $\boldsymbol{\varepsilon}$ is assumed to be independent and identically distributed among the alternatives and follows a double exponential functional form, which makes the choice model a Logit model.

### 4.1.3. Estimation of Parameters

Maximum likelihood techniques similar to those followed in (7) were used to estimate the unknown parameters of the ICLV model. The parameters of the latent variable and the choice models were estimated simultaneously. Therefore, the maximum likelihood estimation approach in this case follows the logic of jointly maximizing the likelihood of observing the choices and the responses to the behavior indicators questions. This means that the estimation of latent variable is informed both by the data on choices and the data on responses to attitudinal questions and vice versa as well as the influence of all the error terms in the model and their covariances.

## 4.2. Results and Discussion

### 4.2.1. Single-mode Case

Table 11 presents the estimated parameters for the ICLV model (for Equations 3 – 5) for the single-mode choice scenarios. Some of the estimates are not statistically different from 0 at the 95% confidence level, such parameters have been flagged in the table with an asterisk. This section also presents the results from the analyses of a few counterfactual scenarios using the ICLV model.

Counterfactual scenarios in this section have been developed to assess the effect attitudes or changes in attitudes might have on the mode choice probability of an individual. We present counterfactual estimates based on the responses of a single person who has a particular latent variable profile. In order to make forecasts over a population it is necessary to integrate over the latent variable distribution. We do not present population-level forecasts in this report.

The probability $P_i$ of choosing a travel mode *i* is given by Equation 6 below. $\beta_1$ and $\beta_2$ are obtained from Table 11, $X_b$ is the set of travel mode attributes for base case scenario as presented in Table 9 and *F* is a set of the values of latent variables “Exercise” and “Environment,” which varies depending on the scenario as presented in Table 12.

$$\boldsymbol{P_i = \frac{e^{\beta_1 X_{bi} + \beta_2 F}}{\sum_i e^{\beta_1 X_{bi} + \beta_2 F}}} \qquad (6)$$

**Table 11: ICLV model estimation results for the single-mode scenario**

| Parameter Category | Parameter | Estimate | Standard Error |
|---|---|---|---|
| $\xi$ | Exercise - Standard deviation | 0.345 | 0.032 |
| | Environment - Standard deviation | 0.220 | 0.053 |
| $\alpha$ | Exercise – indicator 2 | 0.707 | 0.099 |
| | Exercise – indicator 3 | 1.609 | 0.166 |
| | Exercise – indicator 4 | 1.962 | 0.196 |
| | Environment – indicator 2 | 1.202 | 0.307 |
| | Environment – indicator 3* | -0.117 | 0.200 |
| $\eta$ | Exercise – indicator 1 Standard deviation | 1.193 | 0.025 |
| | Exercise – indicator 2 Standard deviation | 0.942 | 0.020 |
| | Exercise – indicator 3 Standard deviation | 0.973 | 0.022 |
| | Exercise – indicator 4 Standard deviation | 1.014 | 0.024 |
| | Environment – indicator 1 Standard deviation | 1.154 | 0.024 |
| | Environment – indicator 2 Standard deviation | 1.309 | 0.027 |
| | Environment – indicator 3 Standard deviation | 1.093 | 0.022 |
| $\gamma$ | Exercise – Male* | 0.022 | 0.016 |
| | Environment – Female | 0.053 | 0.021 |
| | Exercise – Male* | 0.024 | 0.025 |
| | Environment – Female* | 0.018 | 0.025 |
| $\beta_1$ | Car | 3.027 | 0.144 |
| | Transit | 1.740 | 0.254 |
| | Walk | -1.550 | 0.179 |
| | mpg level 1 | -0.188 | 0.050 |
| | mpg level 2 | 0.109 | 0.050 |
| | Gas price level 1 | 0.486 | 0.051 |
| | Gas price level 2* | -0.087 | 0.050 |
| | Parking cost level 1 | 1.120 | 0.053 |
| | Parking cost level 2 | -0.102 | 0.049 |
| | Travel time level 1 | 0.378 | 0.031 |
| | Travel time level 2 | 0.102 | 0.031 |
| | Bus fare level 1 | 0.247 | 0.048 |
| | Bus fare level 2* | -0.029 | 0.048 |
| | Real-time info level 1 (available) | 0.091 | 0.034 |
| | Sidewalk level 1 (available) | 0.357 | 0.026 |
| | Bike lane level 1 (unmarked) | -0.966 | 0.075 |
| | Transit – Exercise | 6.566 | 0.694 |
| | Walk – Exercise | 12.735 | 1.281 |
| | Bike – Exercise | 12.796 | 1.351 |
| | Transit – Environment | 11.015 | 2.777 |
| | Walk – Environment | 2.585 | 1.285 |
| | Bike – Environment | -8.944 | 2.180 |

* Not significant at 95% confidence level

As presented in Table 11, the two latent variables included in the ICLV model, Exercise and Environment, are normally distributed among the respondents with zero mean and standard deviation of 0.35 and 0.22 respectively. For the purposes of this analysis we have chosen the zero (mean) and one standard deviation above and below the mean for each latent variable and then make various combinations of these values. For each combination of values for Exercise and Environment we determine the probability of an individual choosing a specific travel mode as presented in Table 12. The results indicate that change in attitudes (with all other mode related attributes kept constant) can bring about significant shifts in the travel modes chosen. Generally speaking, people who rate high on Exercise show some preference toward manual modes (Bike, Walk and Bike + Transit). People who rate high on Environment show some preference toward transit related modes (Transit, Car + Transit).

**Table 12: ICLV model counterfactuals for the single-mode scenario**

| Latent Variable | | % Mode Share | | | |
|---|---|---|---|---|---|
| **Exercise** | **Environment** | **Car** | **Transit** | **Walk** | **Bike** |
| 0 | 0 | 86% | 13% | 0% | 0% |
| 0.35 | 0 | 33% | 50% | 16% | 1% |
| -0.35 | 0 | 99% | 1% | 0% | 0% |
| 0 | 0.22 | 37% | 63% | 0% | 0% |
| 0 | -0.22 | 98% | 1% | 0% | 0% |
| 0.35 | 0.22 | 5% | 88% | 7% | 0% |
| 0.35 | -0.22 | 63% | 8% | 17% | 11% |
| -0.35 | 0.22 | 85% | 15% | 0% | 0% |
| -0.35 | -0.22 | 100% | 0% | 0% | 0% |

Another important observation can be made by comparing the choice probabilities for the Base Case scenario as predicted by the ICLV model (Table 12) with the logit model from the previous section (Table 10, logit model). The choice probabilities for the two commonly used modes, Car and Transit as predicted by the ICLV model are similar to the respective mode shares observed in the sample. For example, recall that the revealed preference estimate of the mode Car was 81% in the survey and the ICLV predicts 86% under the assumption of mean values on the two latent attitude factors and the Base Case scenario. This is better than the 61% estimate from the traditional logit model on the Base Case scenario. We conclude that including attitudes in the choice model improves the model's ability to capture mode choice behavior. The other entries in Table 12 present other combinations of values on the two latent variables and the corresponding ICLV predictions of mode share.

### 4.2.2. Multi-mode Case

In this section we present analysis similar to the previous section, but now the focus is on multi-mode choice. Table 13 presents the parameters for the ICLV model (for Equations 3 – 5) estimated using the data from multi-mode portion of the conjoint study.

As presented in Table 13, the two latent variables included in the ICLV model, Exercise and Environment, are normally distributed among the respondents with zero mean and standard deviation of 0.4 and 0.2 respectively. Counterfactual scenarios are generated in the same manner as in the previous section and for each scenario we calculate the probability of an individual choosing a specific travel mode as presented in Table 14. The results indicate that change in attitudes (with all other mode related attributes kept constant) can bring about significant shifts in modes chosen. As observed in the single-mode case, people who rate high on Exercise show some preference toward manual modes (Bike, Walk and Bike + Transit). People who rate high on Environment show some preference toward transit related modes (Transit, Car + Transit). These results will be discussed in greater detail in the conclusion.

**Table 13: ICLV model estimation results for the multi-mode scenario**

(Table 13 – Part A)

| Parameter Category | Parameter | Estimate | Standard Error |
|---|---|---|---|
| $\xi$ | Exercise - Standard deviation | 0.406 | 0.036 |
| | Environment - Standard deviation | 0.208 | 0.039 |
| $\alpha$ | Exercise – indicator 2 | 0.692 | 0.097 |
| | Exercise – indicator 3 | 1.663 | 0.165 |
| | Exercise – indicator 4 | 2.087 | 0.199 |
| | Environment – indicator 2 | 0.912 | 0.257 |
| | Environment – indicator 3* | 0.280 | 0.191 |
| $\eta$ | Exercise – indicator 1 Standard deviation | 1.202 | 0.025 |
| | Exercise – indicator 2 Standard deviation | 0.945 | 0.020 |
| | Exercise – indicator 3 Standard deviation | 0.967 | 0.021 |
| | Exercise – indicator 4 Standard deviation | 0.987 | 0.023 |
| | Environment – indicator 1 Standard deviation | 1.161 | 0.024 |
| | Environment – indicator 2 Standard deviation | 1.320 | 0.027 |
| | Environment – indicator 3 Standard deviation | 1.091 | 0.022 |
| $\gamma$ | Exercise – Male* | 0.013 | 0.008 |
| | Environment – Female | 0.021 | 0.010 |
| | Exercise – Male* | 0.000 | 0.013 |
| | Environment – Female* | 0.001 | 0.014 |

* Not significant at the 95% confidence level

(Table 13 – Part B)

| Parameter Category | Parameter | Estimate | Standard Error |
|---|---|---|---|
| $\beta_1$ | Car | 3.267 | 0.172 |
| | Car + Transit | 1.866 | 0.291 |
| | Transit | 1.171 | 0.298 |
| | Bike + Transit* | 0.100 | 0.133 |
| | Bike | -3.464 | 0.475 |
| | mpg level 1 | -0.201 | 0.053 |
| | mpg level 2* | 0.077 | 0.053 |
| | Gas price level 1 | 0.394 | 0.053 |
| | Gas price level 2 | -0.107 | 0.053 |
| | Parking cost level 1 | 1.218 | 0.057 |
| | Parking cost level 2 | -0.127 | 0.052 |
| | Park-ride level 1 (available) | 0.332 | 0.037 |
| | Bike-locker level 1 (available) | 0.144 | 0.055 |
| | Bus fare level 1 | 0.377 | 0.030 |
| | Bus fare level 2* | 0.049 | 0.030 |
| | Real-time info level 1 (available) | 0.051 | 0.022 |
| | Travel time level 1 | 0.526 | 0.026 |
| | Travel time level 2* | 0.004 | 0.026 |
| | Bike lane level 1 (unmarked) | -0.605 | 0.046 |
| | Sidewalk level 1 (available) | 0.503 | 0.032 |
| $\beta_2$ | Car + Transit – Exercise | 4.230 | 0.500 |
| | Transit – Exercise | 9.898 | 0.971 |
| | Bike + Transit – exercise | 10.151 | 1.016 |
| | Bike – Exercise | 15.956 | 1.620 |
| | Walk – Exercise | 17.835 | 1.723 |
| | Car + Transit – Environment | 13.729 | 2.587 |
| | Transit – Environment | 14.315 | 2.742 |
| | Bike + Transit – Environment | 5.185 | 1.255 |
| | Bike – Environment | -10.861 | 2.316 |
| | Walk – Environment * | -1.125 | 1.304 |

* Not significant at the 95% confidence level

### Table 14: ICLV model counterfactuals for the multi-mode scenario

| Latent Variable | | % Mode Share | | | | | |
|---|---|---|---|---|---|---|---|
| Exercise | Environment | Car | Car + Transit | Transit | Bike + Transit | Bike | Walk |
| 0 | 0 | 81 | 11 | 7 | 1 | 0 | 0 |
| 0.4 | 0 | 12 | 9 | 51 | 6 | 2 | 20 |
| -0.4 | 0 | 97 | 2 | 0 | 0 | 0 | 0 |
| 0 | 0.2 | 22 | 47 | 31 | 1 | 0 | 0 |
| 0 | -0.2 | 98 | 1 | 0 | 0 | 0 | 0 |
| 0.4 | 0.2 | 1 | 13 | 83 | 1 | 0 | 1 |
| 0.4 | -0.2 | 20 | 1 | 5 | 3 | 28 | 43 |
| -0.4 | 0.2 | 70 | 28 | 2 | 0 | 0 | 0 |
| -0.4 | -0.2 | 100 | 0 | 0 | 0 | 0 | 0 |

# 5. Hierarchical Bayes

## 5.1. Methods

Hierarchical Bayes (HB) provides an alternate method for estimating choice parameters in a conjoint choice study. Because the method for a combined HB and ICLV modeling has not been developed, we separately estimated a HB logit choice model using only the choice attributes. The benefit of HB over the model in Section 4 is that HB allows each respondent to have their own set of choice parameters, thus accounting for individual differences (aka heterogeneity) in the tradeoffs between choice attributes. For simplicity we focus on the multi-model scenario using HB modeling; results for the HB single mode case are available upon request.

## 5.2. Results and Discussion

Parameters for the same set of travel mode attributes $\boldsymbol{X_b}$ as in the ICLV model were estimated using the HB approach. Table 15 presents the HB parameters averaged across individuals for three different cases – full sample, current car users and current transit users only.

**Table 15: HB partworths averaged over all individuals**

| Parameter | Full Sample | Car Users | Transit Users |
|---|---:|---:|---:|
| Car | 5.944 | 7.537 | -1.484 |
| Car + Transit | 3.118 | 3.296 | 3.483 |
| Transit | 2.286 | 1.811 | 5.833 |
| Bike + Transit | -2.352 | -2.696 | -0.339 |
| Bike | -4.930 | -5.440 | -4.156 |
| mpg level 1 | -0.534 | -0.519 | -0.585 |
| mpg level 2 | 0.194 | 0.175 | 0.334 |
| Gas price level 1 | 0.866 | 0.709 | 1.583 |
| Gas price level 2 | -0.191 | -0.213 | -0.128 |
| Parking cost level 1 | 2.781 | 2.590 | 3.693 |
| Parking cost level 2 | -0.158 | -0.043 | -0.539 |
| Park-ride level 1 (available) | 0.885 | 0.916 | 0.764 |
| Bike-locker level 1 (available) | 0.709 | 0.770 | 0.419 |
| Bus fare level 1 | 0.962 | 0.985 | 0.852 |
| Bus fare level 2 | 0.049 | 0.037 | 0.128 |
| Real-time info level 1 (available) | 0.027 | 0.009 | 0.121 |
| Travel time level 1 | 1.093 | 1.120 | 1.081 |
| Travel time level 2 | 0.154 | 0.163 | 0.067 |
| Bike lane level 1 (unmarked) | -0.564 | -0.475 | -0.842 |
| Sidewalk level 1 (available) | 1.131 | 1.152 | 0.777 |

Counterfactual scenarios in this section have been developed to study the effect that a change in specific travel mode related attributes has on the probability of choosing a mode. As discussed in Section 3.1, attributes and their values as presented in Table 9 are considered to be the baseline scenario. For each counterfactual scenario a specific attribute is varied to obtain $\boldsymbol{X_b}$ that are then used in Equation 7 to determine the choice probabilities.

$$\boldsymbol{P_i = \frac{e^{\beta X_{bi}}}{\sum_i e^{\beta X_{bi}}}} \quad (7)$$

Variations in attributes $\boldsymbol{X_b}$ for the counterfactual scenarios can be grouped into two categories – changes in favor of car users (e.g., gas price decreases to \$3.5/gallon from \$4.5/gallon) and changes in favor of transit users (e.g., transit fare reduces to \$75/month from \$100/month). We study the effects these changes have on mode choice probability of an individual who is representative of the entire sample using parameters presented in Table 15. Further, we also investigate if changes in favor of car users will have any effects on transit users and vice versa, which can give us a handle on unintended consequences of policy. Therefore, this leads to three sets of counterfactual analyses from the point of view of three individuals –

a) Representative of the overall sample (results presented in Table 16)
   - Parameters $\boldsymbol{\beta}$ obtained by averaging HB partworths over all individuals

b) Representative of current Car users (results presented in Table 17)
   - Parameters $\boldsymbol{\beta}$ obtained by averaging HB partworths over current Car users

c) Representative of current Transit users (results presented in Table 18)
   - Parameters $\boldsymbol{\beta}$ obtained by averaging HB partworths over current Transit users

**Table 16: HB counterfactual scenarios based on partworths derived for all individuals**

| Scenario | | % Mode Share | | | | | |
|---|---|---|---|---|---|---|---|
| | | Car | Car + Transit | Transit | Bike + Transit | Bike | Walk |
| | Base Case | 97 | 2 | 1 | 0 | 0 | 0 |
| Changes in favor of transit users | Gas price increases to $5.5/gallon | 95 | 3 | 2 | 0 | 0 | 0 |
| | Parking cost increases to $200/month parking | 13 | 56 | 31 | 0 | 0 | 0 |
| | Transit fare reduces to $75/month | 93 | 4 | 2 | 0 | 0 | 0 |
| | Real-time information available for transit users | 97 | 2 | 1 | 0 | 0 | 0 |
| | Bike locker facility available | 97 | 2 | 1 | 0 | 0 | 0 |
| | Travel time reduced by 25% for transit users | 93 | 4 | 3 | 0 | 0 | 0 |
| changes in favor of car users | Transit fare increases to $125/month | 99 | 1 | 0 | 0 | 0 | 0 |
| | Gas price decreases to $3.50/gallon | 99 | 1 | 0 | 0 | 0 | 0 |
| | Car fuel economy increases to 55 mpg | 99 | 1 | 0 | 0 | 0 | 0 |
| | Travel time reduced by 25% for car users | 99 | 1 | 0 | 0 | 0 | 0 |

**Table 17: HB counterfactual scenarios based on partworths derived for current car users**

| Scenario | Car | Car + Transit | Transit | Bike + Transit | Bike | Walk |
|---|---|---|---|---|---|---|
| Base Case | 99 | 1 | 0 | 0 | 0 | 0 |
| Gas price increases to $5.5/gallon | 99 | 1 | 0 | 0 | 0 | 0 |
| Parking cost increases to $200/month | 44 | 43 | 12 | 0 | 0 | 0 |
| Transit fare reduces to $75/month | 98 | 1 | 0 | 0 | 0 | 0 |
| Real-time information available for transit users | 99 | 1 | 0 | 0 | 0 | 0 |
| Bike locker facility available | 99 | 1 | 0 | 0 | 0 | 0 |
| Travel time reduced by 25% for transit users | 98 | 1 | 0 | 0 | 0 | 0 |
| All changes occurring simultaneously | 8 | 71 | 20 | 0 | 0 | 0 |

**Table 18: HB counterfactual scenarios based on partworths derived for current transit users**

| Scenario | Car | Car + Transit | Transit | Bike + Transit | Bike | Walk |
|---|---|---|---|---|---|---|
| Base Case | 1 | 9 | 91 | 0 | 0 | 0 |
| Transit fare increases to $125/month | 2 | 8 | 90 | 0 | 0 | 0 |
| Fuel price decreases to $3.50/gallon | 3 | 8 | 89 | 0 | 0 | 0 |
| Car fuel economy increases to 55 mpg | 1 | 9 | 90 | 0 | 0 | 0 |
| Travel time reduced by 25% for car users | 1 | 8 | 90 | 0 | 0 | 0 |
| All changes occurring simultaneously | 37 | 5 | 58 | 0 | 0 | 0 |

While many researchers would anticipate that the HB model would provide "better" estimates than the traditional logit model because the former accounts for heterogeneity in the parameter estimates, our results suggest that the ICLV model outperforms the HB model at least in terms of mimicking the revealed preference results in our sample using the base case scenario. For example, the full sample HB estimates predict that 97% would use Car in the Base Case where we observe a reported 81% (and the ICLV models predicts 86%).

# 6. The Choice Inertia Model

In this section we present a basic assessment of the influence of choice inertia on mode choices. Inertia refers to the tendency that people have to stick with the same choices they have made in the past (8; 9). This model was not one of the three models we originally set out to test (which were the traditional logit, the ICLV and the HB models); the of choice inertia with respect to mode choice occurred to us well into the data analysis portion of this project.

Several reasons could motivate inertia in choice behavior. However, for the purposes of this analysis, as an indirect measure, we use the information regarding the modes currently used by the respondents and check how well does it function as a predictor of future choices. More specifically, we included dummy variables in the choice model to identify current car users and transit users. Bike and walk related modes were excluded from the analysis after verifying that their inclusion did not affect the outcome of the analysis. These two modes, bike and walk, make up about 7% of the overall mode share in our sample, which is why they do not affect the overall model performance. We use the conventional logit model (as show in Equation 1) in this analysis since the objective is only to assess the role of choice inertia. We would need to conduct additional experiments to fully measure the extent to which inertia affects future choices and its relation to both attitudes (as in the ICLV model) and heterogeneity in tradeoffs (as in the HB model).

Logit models for three different scenarios are estimated for comparison. The three scenarios differ from each other depending on the type of explanatory variables $\boldsymbol{X}$ included in the model as shown Table 19. Table 19 also presents the estimated parameters $\boldsymbol{\beta}$ in Equation 1 for the three scenarios.

After estimating the model parameters we tested the mode share predictions derived using the three different logit model specifications. The probability $\boldsymbol{P_i}$ of choosing a travel mode $\boldsymbol{i}$ is calculated in the same manner as in Equation 2 for the logit model. Where, $\boldsymbol{\beta}$ is obtained from Table 19, $\boldsymbol{X}$ is the same set of travel mode attributes for the Base Case scenario as presented in Table 9 and used in the analyses presented in earlier sections.

### Table 19: Estimated parameters for logit models for three scenarios of choice inertia

| | Scenario 1: With mode related attributes in ***X*** | | Scenario 2: With current mode dummy variables in ***X*** | | Scenario 3: With mode related attributes and current mode dummy variables in ***X*** | |
|---|---|---|---|---|---|---|
| **Parameter** | **Estimate** | **Std. Err.** | **Estimate** | **Std. Err.** | **Estimate** | **Std. Err.** |
| Car | 1.165 | 0.020 | | | -0.194 | 0.083 |
| Transit | 0.624 | 0.022 | | | 0.221 | 0.074 |
| Walk | -0.777 | 0.032 | | | -0.129* | 0.082 |
| mpg level | -0.094 | 0.032 | | | -0.109 | 0.034 |
| mpg level 2 | 0.056* | 0.032 | | | 0.065* | 0.034 |
| Gas price level 1 | 0.195 | 0.032 | | | 0.222 | 0.034 |
| Gas price level 2 | -0.040* | 0.032 | | | -0.046* | 0.034 |
| Parking cost level 1 | 0.490 | 0.032 | | | 0.563 | 0.035 |
| Parking cost level 2 | -0.051* | 0.032 | | | -0.073 | 0.034 |
| Travel time level 1 | 0.182 | 0.020 | | | 0.191 | 0.021 |
| Travel time level 2 | 0.052 | 0.020 | | | 0.063 | 0.021 |
| Bus fare level 1 | 0.131 | 0.034 | | | 0.149 | 0.036 |
| Bus fare level 2 | -0.026* | 0.034 | | | -0.023* | 0.036 |
| Real-time info level 1 (available) | 0.051 | 0.024 | | | 0.053 | 0.025 |
| Sidewalk level 1 (available) | 0.232 | 0.019 | | | 0.248 | 0.020 |
| Bike lane level 1 (unmarked) | -0.509 | 0.048 | | | -0.535 | 0.049 |
| Transit – car user | | | -0.834 | 0.028 | -1.308 | 0.132 |
| Walk – car user | | | -2.138 | 0.047 | -2.272 | 0.145 |
| Bike – car user | | | -2.447 | 0.054 | -2.889 | 0.143 |
| Transit – transit user | | | 1.530 | 0.090 | 1.210 | 0.158 |
| Walk – transit user | | | -0.858 | 0.149 | -0.911 | 0.203 |
| Bike – transit user | | | -0.906 | 0.152 | -1.246 | 0.202 |

* Not significant at 95% confidence level

Predicted mode shares for three scenarios are presented in Table 20. Since scenario 1 uses only the mode related attributes and no variables corresponding to choice inertia. We use the results from this scenario as a baseline against which results from scenario 2 and 3 are compared to determine the effect of inertia on choice. We can observe that predicted mode shares for scenario 2 match very closely with the results for scenario 1. In other words, the model informed only with the information regarding currently used mode could make predictions very close to those of a model with data on all mode related attributes. This could be an indication that people tend to stick with the transportation mode choices made in the past for reasons other than just the utility derived from the model related attributes.

Results for scenario 3 predict a higher mode share for Car in comparison to the predictions for scenario 1 and 2. This effect could be attributed to the inclusion of choice inertia indicators along with the data on all the mode related attributes. By including the choice inertia indicators we are able to capture the utility associated with Car currently being the most popular choice among the respondents better than the standard logit (but not better than the ICLV model).

**Table 20: Predicted mode shares for different choice inertia-based scenarios for the single-mode choice case**

| **Modes** | **Percentage mode share** | | |
|---|---|---|---|
| | Scenario 1: With mode related attributes in ***X*** | Scenario 2: With current mode dummy variables in ***X*** | Scenario 3: With mode related attributes and current mode dummy variables in ***X*** |
| **Car** | 60.91 | 61.02 | 69.45 |
| **Transit** | 29.00 | 26.50 | 22.52 |
| **Walk** | 7.32 | 7.19 | 6.12 |
| **Bike** | 2.76 | 5.28 | 1.90 |
| **Log likelihood** | 8779 | 8526 | 8100 |

The concept of choice inertia appears to be tractable and likely to play an important role in understanding choice behavior. Our preliminary results suggest that policy models need to consider the role of choice inertia when attempting to model which policy levers are likely to influence behavior. The interrelation among the main concepts explored in this report---latent variables, tradeoff heterogeneity, and choice inertia---is still an open research topic. Future research needs to explore the cost and benefits of different policy levers and their role in changing latent variables, tradeoffs and inertia in order to gain a better understanding of how to influence mobility behavior.

# 7. Conclusion

The present research project explored multi-model mobility options in the city of Portland. We used a survey method to collect data and a set of traditional and novel tools to estimate parameters of several models. Our goal was to go beyond traditional survey methods and provide tools that can be used to model policy implications, which was a major desire of our government and nongovernment partners in Portland.  We wanted to understand which mobility attributes (gas price, parking fee, safe bike paths, etc.) would lead to higher likelihood of multi-mode mobility behavior. But we also wanted to examine which features of choice, such as attitudes and heterogeneity across individuals in tradeoffs, could be used to mine additional ways to influence mobility behavior.  In the course of our research we identified two attitudes, exercise and environment, that appear to play a key role in choice behavior, at least in our Portland sample.  Further, we identified the important role of choice inertia that needs to be addressed when considering any policy implementation designed to change mobility behavior.

**Preferences toward multi-mode mobility options**

The project had a specific interest in multi-model mobility options. We tested two forms of dual-mobility options---Car + Transit and Bike + Transit. The order of preference for these two multi-mode options in the context of their single mode constituent parts, as evident from both ICLV and HB model estimates of partworths, is, Car followed by Car + Transit, Transit, Bike + Transit and Bike. Considering the class of Car, Car + Transit and Transit we observe a natural progression with preferences with Car being the most preferred (which is the most used option in the sample) followed by Car + Transit before moving on to Transit. This indicates that the alternative with the combination of two modes has a preference in between the two single modes. We see a similar pattern for the case of Transit, Bike + Transit and Bike.   The result that multi-mode  options are predicted to rank higher than either of their single mode constituents provides promising evidence that multi-mode mobility can play an important role in future mobility choice and policy planning. It suggests that there is an opportunity to move some Car users to Car + Transit rather than Transit alone.

This phenomenon can also be observed in the counterfactual scenario analyses. For instance, in the scenario based on the HB model where the parking cost increases from zero to $200/month, we observe a significant decrease in the choice probability for Car and a corresponding increase in Transit and Car + Transit choice probability. However, the choice probability for Car + Transit is almost twice that of Transit. In other words, we can say that car users respond to increases in parking cost by a higher preference for a mode that includes Car as a constituent rather than moving to a completely different mode (transit only).

As stated earlier, the focus of most research efforts to model mobility choice has been on single mode options and has used a theoretical choice modeling framework where choice is based on selecting one mode from several single mode options. The results of this first study on multi-mode mobility options provides evidence that multi-mode mobility options may be a fruitful direction for additional research.

**Role of attitudes**

Attitude shifts could play an important role in bringing about changes in the distribution of mode shares. As evident in the analyses based on the HB model, changes in mode related to attributes (e.g., increase in parking cost, increase in transit fare, etc.) do not produce major shifts from motorized modes to Bike or Walk modes. In other words, for the range of attribute values examined in this study, utility derived by choosing Bike or Walk almost never surpasses that for motorized modes and hence the probability of choosing Bike or Walk is almost zero. However, following the analyses based on ICLV model, having a latent attitude that is positive on Exercise increases the probability of choosing the Bike, Walk and Bike + Transit modes. Therefore, an awareness regarding the benefits of active lifestyle could be effective in increasing the choice probability of non-motorized modes more so than changes in, say, parking costs or transit fare (at least within the range of those attributes used in this study). This brings about the potential for embedding policy models about mobility in other related settings such as work-related wellness programs.

**Factors that can bring about a shift away from Cars**

It is evident from both the ICLV and HB model estimates of part worths that respondents have the strongest preference towards Car, and their survey responses (revealed preferences) shows that 81% use Car as the exclusive commuting mode. Results from the counterfactual analyses based on the HB model indicate that a few mobility-related attributes may be able to shift choice from Cars to other modes. One such important factor is the parking cost. An increase in parking cost is most effective in bringing about a shift from Cars to Transit and the multi-mode option Cars + Transit. Further, individuals are more sensitive to parking cost than other types of costs such as gas price and bus fares, at least within the ranges studied in the project. This is the traditional way to influence choice, i.e., change attributes of the choice options. This complements our finding that there are other routes to changing mobility behavior through changing relevant attitudes and influencing choice inertia.

**Sensitivity to changes in cross-mode attributes**

"Cross-mode attributes" refer to the attributes of modes excluding the mode currently used by an individual. Change in parking cost for Car observed by a current transit user would be an example of change in a cross-mode attribute. We are able to understand how individuals respond to changes in cross-mode attributes by performing HB model based counterfactual analyses separately for transit users and car users. Decreasing gas prices is one such change that is observed to have a significant effect. We observe that a decrease in gas prices could increase the probability of current transit user choosing Car. In fact, transit users are more sensitive to a reduction in gas price compared to the response of Car users to an increase in gas price. This is an important point because one needs to be sensitive to unintended consequences of various policy levers. In trying to make one mode more or less attractive one could in advertently make the more desired alternative less attractive in comparison, at least for a subset of individuals.

**The importance of collaborating with consumers of one's research**

Our research team maintained frequent contact with our government and nongovernment constituents. From the design of the study, to the wording of survey questions, to the choice in levels of each of the choice attributes, to the interpretation of the results, we benefitted from input and feedback. This made our final product relevant to our constituents. A key aspect about our project that our constituents frequently repeated is that they wanted us to go beyond traditional survey methods where we report percentages of people doing X or break down those percentages by various sociodemographic groups. They told us they have many such projects and they will continue to do them. They particularly wanted us to do something that they have not frequently undertaken, which is to collect information in such a way that we could build models to use in "what-if" scenarios (what we call counterfactuals throughout this report). This would allow our constituents to model the effects of various policy changes on behavior and be able to quantify, at least up to the limits of the current data and models, both intended and unintended consequences of various policy decisions. Such modeling efforts would offer the opportunity to play through various scenarios and better plan for the future in meeting various metrics.

At our final meeting reporting our results it was clear that our colleagues in Portland thought that the efforts in this relatively small project would have major payoffs moving forward as they studied the effects of various policy decisions. One of the central results of this study indicates that it may be easier to move commuters from car use to a multi-mode consisting of car and transit in comparison to having them use transit alone. This observation provides an initial evidence in support for an integrated transportation system where multiple modes could be used for a single commute trip. Such integrated systems are of particular interest for Metro because they could address issues such as congestion, lack of parking and poor air quality within the densely populated areas of the city of Portland.

In addition to Metro we discussed the details of the project and presented the final results to representatives from Oregon Department of Transportation (ODOT), Salem, OR and the Oregon

Transportation Research and Education Consortium at the Portland State University, Portland, OR. The team from ODOT was responsible for the development of GreenSTEP model. GreenSTEP is an acronym for Greenhouse gas Strategic Transportation Energy Planning. The GreenSTEP model was developed by ODOT to estimate and forecast the effects of policies and other influences on the amount of travel, household vehicle ownership, modes used for travel, fuel consumption and resulting greenhouse gas emissions (GHG) (10).

GreenSTEP has been used by several urban planning agencies in Oregon, including Metro, to analyze the effects of various transportation and land use policies on GHG emissions from transportation. The model is currently setup to consider only single-mode options. We looked into the possibility of adding the piece of multi-modal travel to the GreenSTEP model. However, after our discussions with the GreenSTEP team we determined that the model was not setup to work with discrete choice models and that extensive changes would have to be made in order to add this piece. Therefore, we did not pursue this possibility further but encourage the developers of GreenSTEP to consider adding multi-mode mobility options in a future version of that effort.

Finally, the research team benefited greatly from the input and feedback from our colleagues in Portland. The fidelity of our survey is due in large part to the careful attention offered by our colleagues. They also pushed us, the research team, to consider behaviors we had not anticipated when we first began the project, such as the concept of choice inertia. We added the inertia concept to our modeling framework after the data had been collected, mostly due to a rich discussion at our final presentation of results where we debated the difficulty of moving away from one's current mobility use.

This Integrated Assessment will continue into a related project to model multi-model mobility choice in China. We were invited to present the results of the Portland study to a group of Ford Motor Company executives as part of the annual Ford/UM Alliance meeting at the University of Michigan. That short presentation led to discussions with a research team at Ford that resulted in a collaborative research project to scale our research paradigm from this Integrated Assessment to study mobility in mega cities in China. We are currently collecting data in Beijing following the model developed in the Portland project.

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Ford Motor Company provided funding for an early, proof-of-concept study in Ann Arbor that we used as pilot data in the original proposal to the Graham Sustainability Institute.

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# 10. Appendix

**Frist Three Sections of the Survey**

A. **Socio-demographic information** – this section collected data related to the socio-demographic characteristics of the respondent (e.g., age, gender, education, etc.) and the household (e.g., family size, total annual household income, etc.)
B. **Current commuting arrangements** – this section collecting data regarding the current commute/travel arrangements of the household. This included information related to the approximate commute distance covered each day, travel mode most commonly used, frequency and purpose of side-trips, etc.
C. **Attitude/behavior indicator questions** – this section included questions about attitudes and behaviors. For example, the question shown in Figure 2 is an indicator of the environment friendly attitude. Several such questions were presented to the respondents to elicit responses related to the attitudes towards environment, personal safety, exercise and preferences towards privacy/crowds during travel.

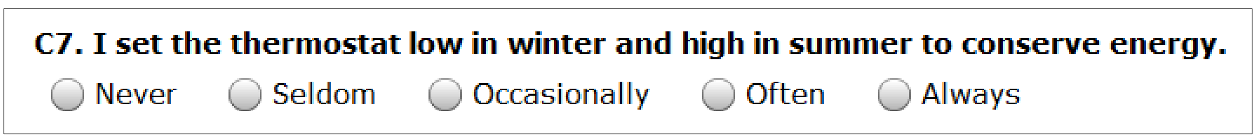


**Figure 2: Sample attitude/behavior indicator question**

| **Travel Mode ->** | **Car** | **Transit (+walk)** | **Walking** | **Bike** |
|---|---|---|---|---|
| Car fuel economy (mpg) | 55 | | | |
| Gas price ($ per gallon) | $5.50 | | | |
| Parking charge ($ per month) | $0 | | | |
| Change in travel time *relative to your present travel time* | Decreases by 25% | Remains same | | |
| Tri Met fares (Regular/Senior or Honored) ($ per month) | | $125/$32 (roughly $6.25 day / $1.60 day) | | |
| Realtime info on transit schedule and mobile ticketing | | Not available | | |
| Sidewalks | | Available | Not Available | |
| Bike lanes on busy roads | | | | Marked and separate |
| **Your choice ->** | | | | |

**Figure 3: Screenshot of single-mode conjoint task**

| **Travel Mode ->** | **Car** | **Car + Transit** | **Transit (+walk)** | **Bike + Transit** | **Bike** | **Walking** |
|---|---|---|---|---|---|---|
| Car fuel economy (mpg) | 25 | | | | | |
| Gas price ($ per gallon) | $4.50 | | | | | |
| Parking charge ($ per month) | $200 (roughly $10 day) | | | | | |
| Free park and ride facility | | Available | | | | |
| Bike locker facility (at nominal charge) | | | | Available | | |
| Tri Met fares (Regular/Senior or Honored) ($ per month) | | $125/$32 (roughly $6.25 day / $1.60 day) | $100/$26 (roughly $5 day / $1.30 day) | $75/$20 (roughly $3.75 day / $1 day) | | |
| Realtime info on transit schedule and mobile ticketing for transity | | Not available | Not available | Available | | |
| Change in travel time *relative to your present travel time* | Increases by 25% | Remains same | Decreases by 25% | Remains same | | |
| Bike lanes on busy roads | | | | Unmarked | Marked and separate | |
| Sidewalks | | | Not Available | | | Available |
| **Your choice ->** | | | | | | |

**Figure 4: Screenshot of multi-mode conjoint task**