Title

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Modeling Non-ignorable Attrition and Measurement Error in Panel Surveys: An Application to Travel Demand Modeling

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Abstract
Modern panel surveys frequently suffer from high and non-ignorable attrition, and transportation surveys suffer from poor travel time estimates. The initial sampling process for most transportation surveys is also non-ignorable since rare travel modes are oversampled (and mode choice is the key dependent variable). This paper examines new multiple imputation methods for adjusting forecasts and model estimates to account for these problems in a new panel survey of 1500 commuters in San Diego, California. These data are collected to evaluate charging solo commuters to use an existing 8-mile underutilized freeway carpool lane. We illustrate the impact of attrition and measurement error on a standard conditional logit model of commuters' mode choice (solo drive in free lanes, pay to solo drive in the carpool lanes, or carpool for free in carpool lanes). Although the attrition rate between waves is 40% and non-ignorable, the quantitative impact on the results is negligible. However, measurement error in travel time does have an important impact on the key results from our model. Finally, failure to account for the measurement error process using multiple imputations yields a downward bias of at least 50% in the standard errors of the logit coefficient estimates.

1 Introduction

Modern panel surveys frequently suffer from high and likely non-ignorable attrition, and transportation surveys suffer from poor travel time estimates. This paper examines new methods for adjusting forecasts and model estimates to account for these problems. The methods we describe are illustrated using a new panel survey of 1500 commuters in San Diego, California. These data are being collected to evaluate a federally-funded 3-year "Congestion Pricing" experiment investigating the impacts of allowing solo drivers to pay to use freeway carpool lanes. The panel survey, begun in Fall 1997, collects data on travel behavior and attitudes at six-month intervals through telephone interviews. The panel sample is refreshed with new respondents at each wave to counteract the attrition between waves. Both the original and refreshment samples are stratified on commuters' mode choice (solo drive in free lanes, pay to solo drive in the carpool lanes, or carpool for free in carpool lanes) to insure sufficient sample size for estimating our models

We illustrate the impact of attrition and measurement error on a standard conditional logit model of commuters' mode choice (solo drive in free lanes, pay to solo drive in the carpool lanes, or carpool for free in carpool lanes). The basic model is documented in Kazimi *et. al.* (1999) which is summarized in Section 2 of this paper. Our model is calibrated from the third wave of the panel study which was collected in Fall, 1998. We use data from the second wave to estimate an attrition model and then use this model to predict attrition probabilities as described in Section 5. We expect non-ignorable attrition because commuters who use the carpool lanes are more interested in the survey questions. It turns out that attrition is not a problem for this application even though there is some indication that it is non-ignorable.

The selection probabilities are known for each new cross section (the initial sample plus the refreshment samples). Each sample is stratified by mode chosen for the last morning commute trip, and we have traffic counts for each mode taken at each survey date. These selection probabilities change across panel waves since the relative share of solo drivers paying to use the carpool lane increased over the panel and we tried to keep the number of observations in each mode constant over time. For panel respondents the appropriate selection probability is their initial selection probability times 1 – their attrition probability.

Our basic strategy is to use the refreshment sample to model the attrition process, and then use this attrition model to generate attrition probabilities for each panel respondent. These attrition probabilities are then used to modify the original choice-base stratification weights in our discrete-choice models. Since we are using Manski and Lerman's (1977) Weighted Exogenous Sample Maximum Likelihood estimator, we need to modify the estimator to account for the estimation error in our attrition probabilities. We use Rubin's multiple imputation (see Rubin, 1987, 1996 and Brownstone and Chu, 1997) procedure to multiply impute attrition probabilities from our attrition model. This method has the advantage of not requiring joint estimation of the attrition and mode-choice models, but it is therefore not fully efficient.

We also have potentially non-ignorable measurement error in the time saved by using the carpool lane. Carpool lane users, and especially solo drivers paying to use the carpool lanes, tend to report unrealistically high values of time savings (as described in Section 3.3). While it is certainly possible that their mode choice decisions are based on their perceptions rather than the objective time savings, any useful policy model needs to be sensitive to actual time savings. Objective measurements of time savings are available from two types of data on speeds. First, floating car observations were obtained by driving cars down the corridor at frequent intervals and recording the actual travel times. During wave 3 of the panel survey, these floating car measurements were carried out for 5 days, but the panel survey data collection involved reported travel behavior over two months. The second type of data on travel times, point speeds derived from magnetic loop detectors placed along the corridor for general traffic counting purposes, was available during the entire data collection period, but these data are subject to significant errors as described in Section 4.

We have built a model that predicts the floating car data from the loop detector data. This model fits well (R-squared of .9), and we use it to predict the actual time savings faced by each survey respondent as a function of the date and time they entered the corridor. We use multiple imputations to account for the component of error in our estimates and predictions from this imputation model.

2 The San Diego Congestion Pricing Project

The pricing demonstration project (referred to as FasTrak) allows solo drivers to pay to use an eight-mile stretch of reversible high occupancy vehicle (HOV) lanes along Interstate Route 15 (I-15). The combination of free HOV use and priced solo driver use is generally referred to as high occupancy toll (HOT) lanes. In this demonstration project, HOT lane users must travel the entire eight-mile length before exiting. The per-trip fee for solo drivers is posted on changeable message signs upstream from the entrance to the lanes, and may be adjusted every six minutes to maintain free-flowing traffic conditions in the HOT lanes. Solo drivers who subscribe to the FasTrak program are issued windshield-mounted transponders used for automatic vehicle identification. Each time they use the lanes, their accounts are automatically debited the per-trip fee. This represents a dynamic form of voluntary congestion pricing, where solo drivers can choose to pay to reduce their travel time, and the payment is generally related to the level of congestion.

2.1 The Panel Survey

The panel survey consists of three samples of approximately equal size: 1) FasTrak program subscribers and former subscribers, 2) other I-15 users, and 3) users of another freeway corridor (I-8) in the San Diego Area defined as a control group. The analysis in this paper excludes the I-8 control group. The first wave of the panel was conducted prior to per-trip pricing. The second wave of the panel was conducted in spring 1998, during the first few months of dynamic pricing. For the purposes of this analysis, we focus primarily on program subscribers and other I-15 users in the third wave of panel data, collected during the fall of 1998 (October through November). During this time period, dynamic per-trip congestion pricing was well established.

FasTrak subscribers were picked at random from a list maintained by the billing agency, and the remaining respondents were recruited using random digit dialing of residential areas along the respective corridors. In the initial wave of the panel, a partial quota sampling procedure was used to increase the number of carpoolers in non-subscriber parts of the sample. Panel attrition is about 33% per wave, and the sample is refreshed at each wave with a new random sample of FasTrak subscribers as well as I-15 and I-8 commuters recruited using the random digit dialing of residential areas along the respective corridors. The partial quota sampling procedure implies that the resulting sample is choice-based and weights are needed if the sample is being used to represent the population of regular I-15 corridor users. We estimated sampling weights from traffic counts carried out during the survey period.

Survey respondents were queried for detailed information about their most recent inbound trip along I-15 if that trip was made during the hours of operation of the HOT facility and covered the portion of I-15 corresponding to the facility. By design, trip lengths must be at least eight miles long (the length of the facility). There were 699 I-15 respondents with full information on morning trips during the peak-period that were in the inbound (southbound) direction. Table 1 presents a summary of the individual and household demographic data for the three travel modes that we investigate: 1) solo drivers in the main lanes, 2) solo drivers using FasTrak transponders to travel in the HOT facility, and 3) carpoolers who also travel in the HOT facility.

2.2 Dynamic Per-Trip Tolls

Solo drivers face tolls that are a function of arrival time at the HOT facility. The level of congestion in the HOT facility determines the toll (e.g. tolls increase to avoid exceeding preset capacity constraints).[1] While program subscribers are provided with a profile of maximum tolls that vary by time-of-day, actual tolls may be less than the maximum tolls depending upon usage of the facility. In extreme conditions, tolls may exceed the advertised maximum tolls although this is expressly advertised as a rare occurrence and has yet to occur during the demonstration period.[2]

Figure 1 shows the average toll by time of day for the months of October and November 1998 (excluding Thursday and Friday of Thanksgiving weekend). Average tolls are remarkably similar across the days of the week. (Kazimi et. al., 1999, contains data on day-to-day variation.)

Based on the estimated arrival time at the HOT lanes, each survey respondent is assigned a toll price for that specific arrival time and date of travel. For respondents who choose to drive alone in the HOT lanes, this represents actual price paid. For solo drivers in the regular lanes and those who carpool, this represents the price they would have paid had they chosen to travel with FasTrak.

Arrival time at the HOT lanes is determined using a combination of information from the panel survey and speed estimates for the upstream portion of I-15. The panel survey queried respondents for onramp used in the morning commute and arrival time at that onramp. Travel time from the onramp to the beginning of the HOT lanes is estimated using time-of-day point speeds calculated from California Department of Transportation (CALTRANS) loop detectors embedded in the roadway. These loop detector data are computed every six minutes. Speeds at loop detector locations are converted into speeds along the intervening segments (defined as the roadway between two loop detectors) using an algorithm that assumes that the loop detector point speed at the beginning of the segment applies to the first half of the segment and point speed at the end applies to the second half of the segment (van Grol, 1997). Since loop detectors are placed near onramps, the freeway is effectively broken into segments traveling from onramp to onramp.

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[1] The capacity goal is 1,300 vehicles per half-hour in the AM peak, and 1,440 vehicles per half-hour in the PM peak. This corresponds to level of service rating C (LOS C).
[2] See http://www.sandag.cog.uc/i-15fastrak/schedule.html for additional details.

Table 1. Demographic Characteristics by Mode Choice (in percentages)

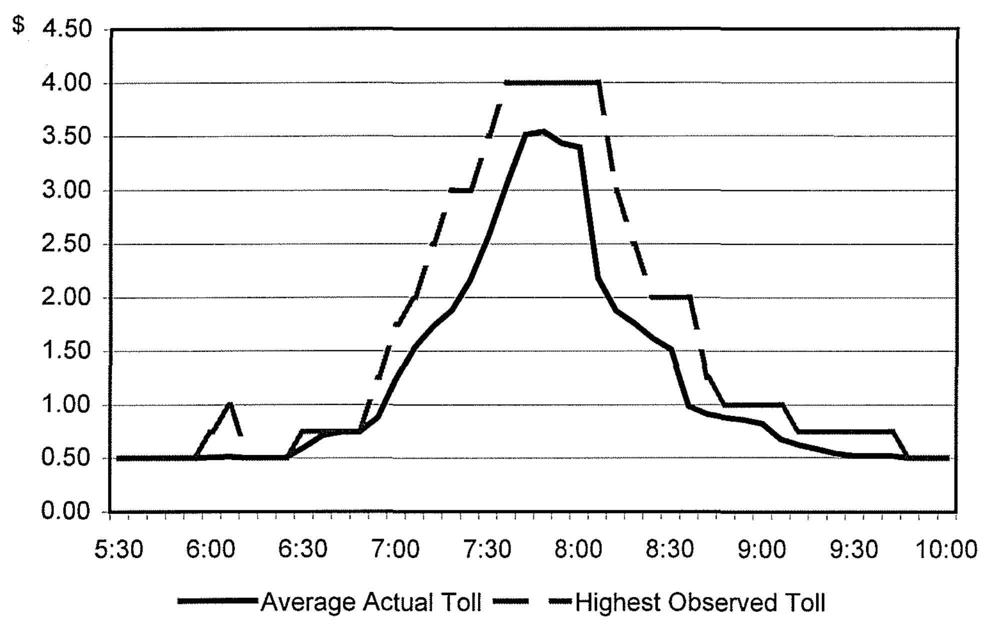
	Solo Drivers (N = 304)	FasTrak Users (N=279)	Carpool (N=116)
Age of respondent:			
18-34	20.8	8.6	15.1
35-44	34.0	46.8	39.8
45-54	33.3	33.5	32.8
54-64	9.9	10.8	10.6
65+	2.0	0.4	1.7
Education of respondent:			
High school	12.5	4.0	10.3
Some college	30.3	21.7	31.0
Bachelor's degree	33.2	36.1	37.1
Graduate work or degree	24.0	38.3	21.6
Reason for travel along I-15:			
Work or work related	94.1	98.5	79.3
School	1.3	0.7	2.6
Non-work appointments	1.6	0.4	6.8
Other social reasons	3.0	0.4	11.3
Number of workers in household: [a]			
No workers	1.3	0.4	6.9
One worker	37.8	31.5	19.5
Two workers	51.0	58.1	54.3
Three or more workers	9.9	10.0	19.0
Vehicles per worker in household: [a]			
No workers (undefined)	1.3	0.4	6.9
Less than one vehicle per worker	1.0	0.4	3.5
One vehicle per worker	67.1	70.2	67.2
More than one vehicle per worker	30.6	29.0	22.4
Household Income:			
$20,000 or less	1.3	0	2.6
$20,000 to $40,000	6.6	2.2	7.8
$40,000 to $80,000	41.8	22.6	42.2
$80,000 to $120,000	28.3	33.3	33.6
$120,000 or more	13.5	29.4	6.9
Refused to answer	8.6	12.5	6.9
Female respondent:	34.2	47.3	45.7
Household owns home:	78.6	92.1	86.2

[a] The survey only asked about those who work outside the home.

2.3 Time Savings From HOT Lane Use

For mode choice modeling, we must determine possible time saving from travel on the HOT lanes for all respondents regardless of mode choice. Time saving is defined as the difference in travel time on the HOT lanes and travel time on the parallel main lanes. Both are a function of when commuters arrive at the facility (see previous section), speeds along the HOT lanes, and speeds in the main lanes. Speed on the HOT facility is assumed to be 70 miles per hour based on several days of floating car experiments.[3] Speeds on the main lanes are estimated every six minutes during the entire survey period using loop detector point data in a similar manner as described in the previous section. These speeds were also estimated by driving along the roadway every fifteen minutes for one week in the middle of the survey period (referred to as floating car measurements). We present results using the loop detector speeds and using a combination of loop detector speeds and floating car speeds (see Section 4).

Figure 1. Tolls for October and November, 1998



The results based solely on loop detector speed measurements by time of arrival at the HOT facility are summarized in Figure 2. Median time saving peaks at about seven minutes at the same time period (7:30-8:00 AM) that average tolls peak at four dollars (Figure 2). Considerable variation occurs within each half-hour time period as indicated by the divergence between median, 90th percentile, and 10th percentile time savings. Ten percent of the time, peak time saving exceeds twelve minutes.

Those entering I-15 at one particular onramp (the Ted Williams Parkway onramp at the north end of the HOT Lanes) may also benefit from a special dedicated entrance to the HOT facility that avoids a congested main-lane onramp with a ramp-meter traffic signal. We estimated the time saving from using this dedicated onramp from floating car data

3 Speeds along the HOT lanes were measured by driving the lanes, recording start and end times, and then calculating average speed using the time differential and distance traveled. HOT lane speeds were measured every fifteen minutes of the morning peak period for five days. Speeds were generally close to 70 miles per hour with little variation across day and time.

and added the mean saving for the appropriate 15-minute time interval to the estimated time saving from use of the HOT lanes for those

Figure 2. Time Savings Associated with HOT Facility Use
(October – November, 1998)

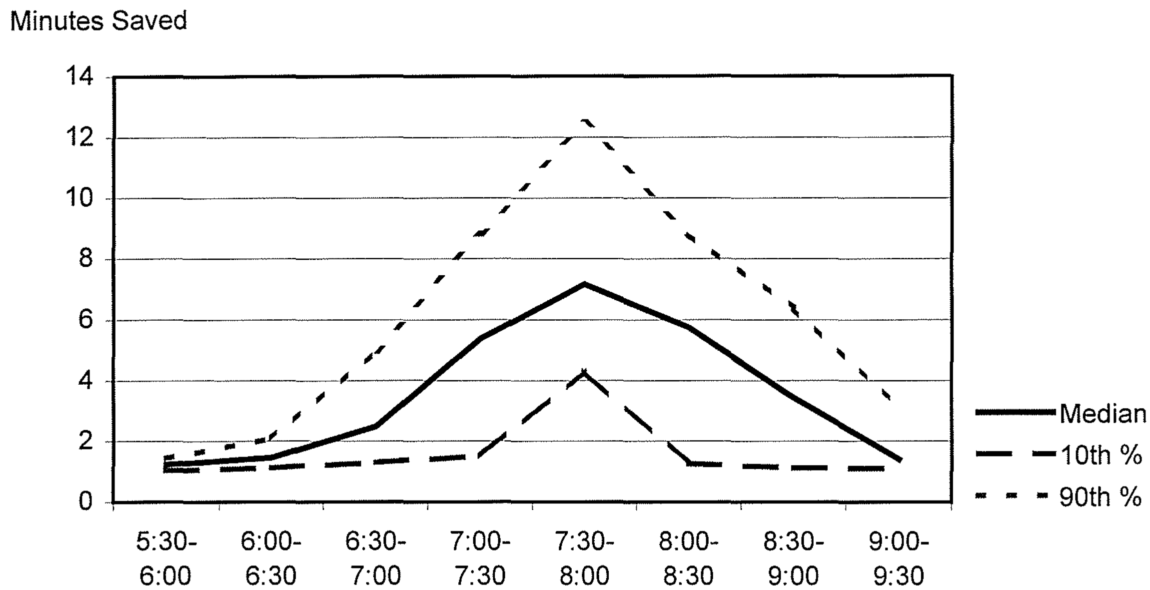
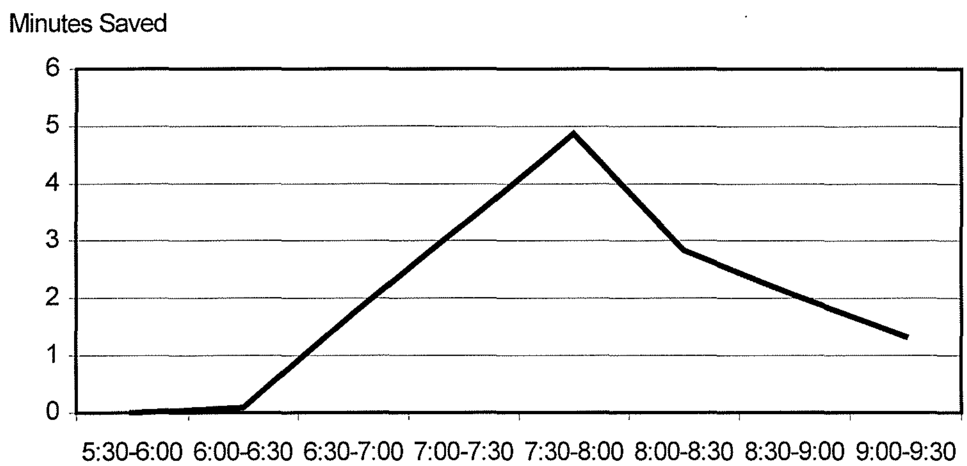


Figure 3. Mean Time Saving From Use of Ted Williams Bypass On-ramp
(October – November, 1998)



respondents entering I-15 at Ted Williams (approximately 36 percent of the sample). Figure 3 shows the mean additional savings from use of the Ted Williams onramp obtained from floating car data of the delay. Users of the dedicated HOT Lanes onramp at Ted Williams Parkway can gain up to five minutes additional time if they choose FasTrak (toll) or carpool modes.

3 Mode Choice and Value of Time

The key ingredient in evaluating projects designed to reduce travel time is commuters' willingness to pay for these reductions. If commuters value time saved from congestion reduction highly, then it may be worthwhile to make costly investments in new transportation infrastructure. This section reviews the model structure and estimation methods that transportation economists use to estimate value of time (VOT) from reducing travel delays.

3.1 Conditional Logit Mode Choice Models

Suppose that respondent n faces a choice of three modes for travel to work indexed by j. In this paper the modes are drive alone, pay to drive alone in the HOT lanes (FasTrak), or carpool in the HOT lanes. In most previous studies the modes are automobile, bus, or subway. The Conditional Logit model assumes that the probability that respondent n takes mode j conditional on observed variables x_{jn} is given by:

$$P_{jn} = \frac{\exp(\theta x_{jn})}{\sum_{i=1}^{3} \exp(\theta x_{in})}. \qquad (1)$$

The value of time is given by the increase in cost required to keep P_{jn} constant after a small decrease in travel time. If time and cost only enter as linear terms in x, then the VOT is just given by $\theta_{time}/\theta_{cost}$.

Small (1992) and Wardman (1998) provide comprehensive reviews of value-of-time studies, and Gonzalez (1997) provides a review of the theory of consumer choice and its connection to value of time and mode choice modeling. Based on his review, Small (1992) suggests that 50 percent of gross wage rate is a reasonable value of time estimate. On the higher end of previous studies, Cambridge Systematics (1977) estimate that value of time for commuters in Los Angeles is 72 per cent of gross hourly wage. These previous studies are based upon mode choice models that consider differences between transit and automobile travel, and to the extent that differences between crowded transit and private automobiles are not captured, the results will be biased. In more recent work, Calfee and Winston (1998) attempt to avoid this problem by using stated preference data that only considers the tradeoff between travel by automobile in slower, free lanes and travel by automobile in faster, priced lanes. Their results indicate that commuters place a lower value on time saving than previously estimated (roughly \$3.50 to \$5.00 per hour or 15 to 25 percent of hourly wage). Calfee and Winston rely upon stated preference data because they lack revealed preference data for the choices involved with congestion pricing. Our results are not subject to the same potential biases associated with stated preference data as we use revealed preference data.

Given a random sample of N commuters, the model in equation (1) is typically estimated by maximizing the likelihood function

$$L = \sum_{n=1}^{N} \sum_{i=1}^{3} D_{in} \log(P_{in}), \qquad (2)$$

where $D_{in}=1$ if respondent n chooses mode i and zero otherwise. This likelihood function is globally concave and therefore easy to maximize using standard algorithms. See Train (1986) for more information about this model and its application to transportation problems.

3.2 Choice-base Sampling

It is very common for one mode to have a very low market share, which makes collecting a random sample with a reasonable sample size for each mode very expensive. For example, in the I-15 corridor the FasTrak users make only 3.5 percent of the southbound morning commute trips. To reduce data collection costs most transportation surveys stratify on mode choice, which of course results in a non-ignorable sampling scheme.

Maximizing a random-sample likelihood function as in equation (2) with a choice-based sample will generally yield inconsistent parameter estimates. McFadden (see proof in Manski and Lerman, 1977) shows that for the conditional logit model with a full set of mode-specific constants only the parameters associated with these mode-specific constants are inconsistent. A relatively simple estimator which yields consistent estimates under choice-based sampling was developed by Manski and Lerman (1977). Their Weighted Exogenous Sample Maximum Likelihood Estimator (WESMLE) is the maximand of the weighted likelihood function:

$$\sum\nolimits_{n} \omega_n \, L_n(\theta, x_n), \qquad (3)$$

where L_n is the log likelihood function for the n^{th} observation and the sampling weight, ω_n, is the inverse of the probability that the n^{th} observation (individual) would be chosen from a completely random sample of the population. Of course, if the sampling scheme were completely random, then all of the sampling weights would be equal and the WESMLE would simply be the usual maximum likelihood estimator.

Manski and Lerman (1977) show that the WESMLE is consistent and asymptotically normal, but not fully efficient (see Imbens, 1992 for fully efficient alternative estimators). Manski and Lerman's proof actually shows that the WESMLE's properties hold for any regular maximum likelihood estimator as long as the sampling weights are known with certainty. The asymptotic covariance of the WESMLE is given by:

$V = \Psi^{-1}\Lambda\Psi^{-1}$, where

$$\Psi = -E\left(\partial^2 \omega_n \, \mathrm{L}_n(\theta, \mathrm{x}_n) \big/ \partial\theta\partial\theta' \right) \quad \text{and} \qquad (4)$$

$$\Lambda = E\left(\left(\partial \omega_n L_n(\theta, x_n) \big/ \partial \theta \right) \left(\partial \omega_n L_n(\theta, x_n) \big/ \partial \theta' \right) \right).$$

This covariance matrix can be consistently estimated by replacing the expectations in equation (4) with sample moments evaluated at the WESMLE estimates.

A major advantage of the WESMLE is that it can be computed easily by modifying existing maximum likelihood programs. The WESMLE for both the linear regression model and the conditional logit model can be computed by appropriately weighting the variables and applying standard maximum likelihood programs. Unfortunately, this procedure yields downward biased standard error estimates, but the consistent estimates given by equation (4) are straightforward to compute. This downward bias can be substantial in common applications. The incorrect standard errors for the models in Section 6 are typically downward biased by 50 percent relative to the correct standard errors in equation (4).[4]

For a simple choice-based sample, the WESMLE weights are just given by the ratio of the population mode share divided by the sample mode share. This is just the inverse of the sampling probability multiplied by the sample size divided by population size to make the sum of the weights equal the sample size. Note that these weights are also equal to the standard post-stratification weights for the choice-based design. For many transportation applications the population mode shares are available from traffic and passenger counts. Table 3.1 gives the relevant shares and weights for the I-15 panel used in Section 6 of this paper. Note that the FasTrak users are oversampled, which results in their getting a very low weight.

Table 3.1: Mode Share and Weights

Mode	Population share	Sample share	Weight
Drive Alone	80.8	43.5	1.86
FasTrak	3.5	39.9	0.09
Carpool	15.7	16.6	0.95

4 Measurement Models

The loop detector data described in Section 2.3 can give very inaccurate estimates of the actual time savings commuters get from taking the HOT lanes. Depending on the traffic flows between the loop detectors (which are miles apart on the I-15 corridor) actual speeds can be either over or under-predicted. Since these measurement errors will generally be larger when the road is congested, the measurement errors in time savings

[4] A STATA program for computing the WESMLE and the correct standard errors is available from the corresponding author.

are likely to be larger for FasTrak and carpool lane users. Since time saved using the HOT lanes is a key dependent variable in the choice models in Section 6, this measurement error will bias key parameter estimates.

This section considers two different approaches to correcting the measurement errors in loop detector speeds. Section 4.1 uses data from cars that drove down the I-15 corridor at 15 minute intervals during the last week of October, 1998. These data are used to fit an imputation model which we use to multiply impute corrected time savings in Section 6. Section 4.2 uses data on commuters' perceived time savings. These data were only collected for FasTrak customers, but there are enough in our sample to fit some interesting models.

4.1 Time Savings Imputation Models

Driving down a corridor with a stopwatch and clipboard, called the "floating car method," is generally considered the most accurate way to measure travel times and speeds. However, floating car observations are expensive and expose surveyors to liability in case of accidents. Therefore it is rare when there are enough floating car data to examine the distribution of travel times as in Figure 2.

We use the five days in late October where we have both floating car and loop detector data available to fit a model which we use to predict floating car travel time for the other seven weeks of our survey period. These predicted floating car data are then used to fit mode choice models in Section 6.2. This approach assumes that the floating car data are correct, and we will use multiple imputations to correct for the measurement error caused by imperfect predictions.

The floating car data are collected at 15 minute intervals while the loop detector data are at 6 minute intervals. To make these data compatible, we interpolated the floating car data into 6 minute intervals. Figure 4 shows box and whisker plots of the distribution of time savings from the two methods over the morning commutes from October 26 through October 30, 1998. The floating car estimates are generally more than twice as large as the loop detector time savings, which shows that the loop detector estimates are badly biased for this corridor.

Figure 4: Distribution of HOT Lane Time Savings

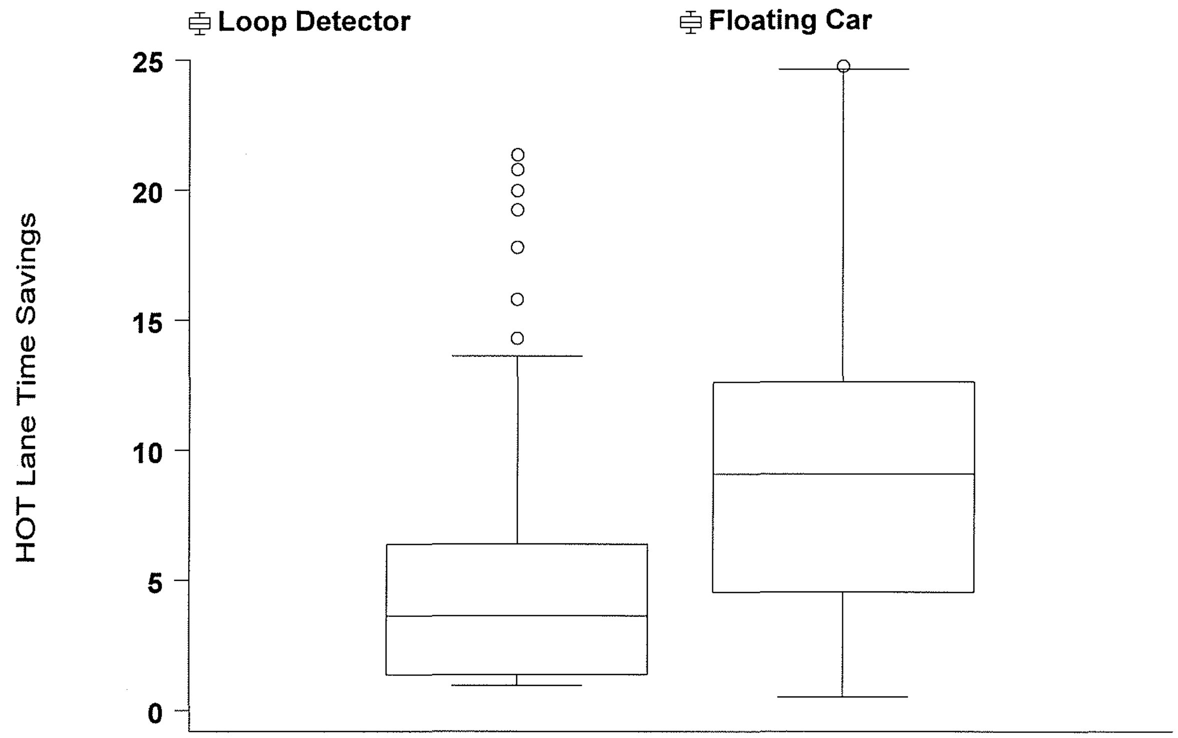


Table 4.1 shows the best fitting linear regression model for predicting floating car HOT lane time savings. To avoid unreasonable predictions we first transform both time savings measures to keep them bounded between zero and 35 minutes, which is the maximum observed loop detector time savings. The exact transformation for both time savings variables is given by the following transformed logit:

$$\log\left(\left(\frac{t}{35}\right)\Big/\left(1+\frac{t}{35}\right)\right). \tag{5}$$

We tried a number of different specifications including higher order terms in loop detector time savings and toll variables, but none of them significantly improved the fit of the model. We also experimented with lagged values, but the cubic polynomial in time effectively removes the autocorrelation in the time savings measures. Since the purpose of this model is accurate prediction, we are looking for the most parsimonious model with the best fit.

Although the variables involving the tolls are not individually significant, they are jointly significantly different from zero at the one percent level. If they are excluded from the model, then the R^2 drops slightly to .89. However, excluding the loop detector data reduces the R^2 to .82 and increases the MSE of the residuals to .46.

Table 4.1: Imputation Model for Floating Car HOT Lane Time Savings

Dependent Variable: Logit of Floating Car Time Savings			$R^2 = 0.90$ Root MSE = 0.36
Independent Variables:	Coef.	Std. Err.	*t*-Stat.
Logit of Loop Detector Time Savings × Minutes Past 5:00 A.M.	0.0029	0.00031	9.3
Minutes Past 5:00 A.M.	0.222	0.0149	14.8
(Minutes Past 5:00 A.M.)^2	-0.00138	0.000121	-11.4
(Minutes Past 5:00 A.M.)^3	2.73E-06	2.91E-07	9.38
Toll	-0.229	0.188	-1.22
Toll × Minutes Past 5:00 A.M.	0.00222	0.00126	1.77
Constant	-11.4	0.52	-22.1

There are two general approaches for estimating a behavioral model with measurement error in the explanatory variables: joint maximum likelihood of the behavioral and measurement models, or Rubin's multiple imputation approach. Joint maximum likelihood would be very difficult for the model in Section 6.2 since the actual explanatory variables are complicated non-differentiable transformations of the variable explained by the measurement model in Table 4.1. We will therefore implement the multiple imputation approach as given in Rubin (1987 and 1996). Brownstone (1998) gives more detail using the same notation as this section. Rubin developed his methodology for missing data, and in our application floating car time savings are missing for approximately 80 percent of our respondents.

Suppose we are interested in estimating an unknown parameter vector θ. If no data are missing, then we would use the estimator $\tilde{\theta}$ and its associated covariance estimator $\tilde{\Omega}$. If we have a model for predicting the missing values conditional on all observed data, then we can use this model to make independent simulated draws for the missing data. If m independent sets of missing data are drawn and m corresponding parameter and covariance estimators, $\tilde{\theta}_j$ and $\tilde{\Omega}_j$, are computed for each of these imputed data sets, then Rubin's Multiple imputation estimators are given by :

$$\hat{\theta} = \sum_{j=1}^{m} \tilde{\theta}_j / m \qquad (6)$$

$$\hat{\Sigma} = U + (1 + m^{-1}) B, \qquad (7)$$

where

$$B = \sum_{j=1}^{m} (\tilde{\theta}_j - \hat{\theta})(\tilde{\theta}_j - \hat{\theta})' / (m-1) \qquad (8)$$

$$U = \sum_{j=1}^{m} \tilde{\Omega}_j / m. \qquad (9)$$

Note that B is an estimate of the covariance among the m parameter estimates for each independent simulated draw for the missing data, and U is an estimate of the covariance of the estimated parameters given a particular draw. B can also be interpreted as a measure of the covariance caused by the nonresponse (or measurement error) process.

Rubin (1987) shows that for a fixed number of draws, $m \geq 2$, $\hat{\theta}$ is a consistent estimator for θ and $\hat{\Sigma}$ is a consistent estimator of the covariance of $\hat{\theta}$. Of course B will be better estimated if the number of draws is large, and the factor $(1 + m^{-1})$ in equation (7) compensates for the effects of small m. Rubin (1987) shows that as m gets large, then the Wald test statistic for the null hypothesis that $\theta = \theta^0$,

$$\left(\theta - \theta^0\right)' \hat{\Sigma}^{-1}\left(\theta - \theta^0\right), \tag{10}$$

is asymptotically distributed according to an F distribution with K (the number of elements in θ) and ν degrees of freedom. The value of ν is given by:

(8) $$\nu = (m - 1)(1 + r_m^{-1})^2 \text{ and } \quad r_m = (1 + m^{-1}) \, \mathrm{Trace}(BU^{-1})/K. \tag{11}$$

This suggests increasing m until ν is large enough (e.g. 100) so that the standard asymptotic Chi-squared distribution of Wald test statistics applies. We used this stopping rule and found that the models in Section 6.2 required m=20 multiple imputations. Meng and Rubin (1992) show how to perform likelihood ratio tests with multiply-imputed data. Their procedures are useful in high-dimensional problems where it may be impractical to compute and store the complete covariance matrices required for the Wald test statistic (equation 10).

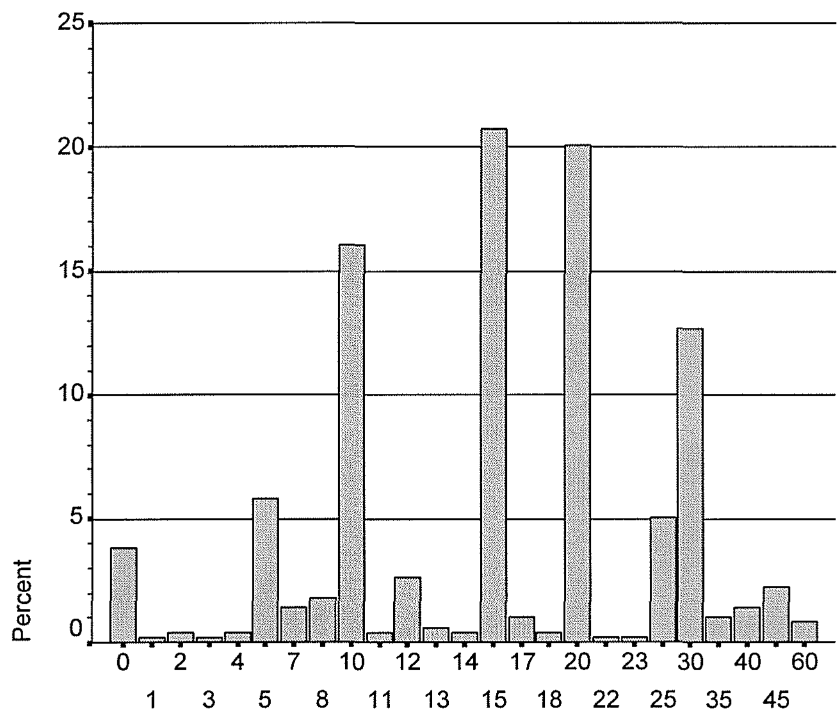
To draw one set of imputed values for the missing floating car data, first draw one set of slope and residual variance parameters from the asymptotic distribution of the linear regression estimators from Table 4.1. The slope parameters are drawn from the joint normal distribution centered at the parameter estimates with covariance given by the usual least squares formula ($s^2(X'X)^{-1}$). The residual variance, σ_*^2, is drawn by dividing the residual sum of squares by a draw from an independent χ_d^2 distribution, where d is the residual degrees of freedom. An imputed residual vector is then drawn from independent normal distributions with mean zero and variance equal to σ_*^2. The imputed values are then computed by adding this imputed residual to the predicted value from the regression using the imputed slope parameters. Additional sets of imputed values are drawn the same way beginning with independent draws of the slope and residual variance parameters. Observations where floating car data are observed are fixed at these observed values across all imputations. This imputation method, which Schenker and Welsh (1988) call the "normal imputation" procedure, is equivalent to drawing from the Bayesian predictive posterior distribution when the dependent variable and the regressors follow a joint normal distribution with standard uninformative priors.

For each imputed value we add the mean time savings for those respondents using the Ted Williams Parkway entrance. The medians and 90th percentiles across each month are computed for each 6-minute time interval. These medians and the difference between the 90th percentiles and the medians are then used to estimate the parameters of the choice model in Section 6.2. The multiple imputation procedure described here has been implemented in STATA, and it could be programmed in most modern statistical packages.

4.2 Perceived Time Savings

Another approach to measuring time savings is to ask commuters directly. Panel respondents who were FasTrak customers were asked: "About how much time, if any, do you think using FasTrak saves you on a one-way, south-bound trip, compared to using the regular lanes during the times you normally travel?" The distribution of responses to this question is shown in Figure 5. Most respondents round to the nearest five minutes, and the most frequent responses were 15 and 20 minutes, followed by 10 and 30 minutes. In general, the perceived values are higher than time savings estimates from loop detector and floating car data.

Figure 5. Perceived Time Savings resulting from FasTrak Use for the Southbound Trip in Minutes (N = 497)



Perceived time savings should be a positive monotonic function of objective time savings. One component of objective time savings is the time difference attributable to travel in the HOT lanes, as opposed to the regular lanes of I-15, estimates of which are available from the time savings imputation models that correct loop detector speed data using floating car data. A second component of objective time savings is relevant for FasTrak users entering the I-15 freeway at Ted Williams Parkway at the north end of the HOT Lane facility. Their perceived time savings should also be a function of the objective measurement of onramp delay times, as described in Section 2.3.

We conducted regression analyses of perceived time savings as a function of different measures of the distribution of corrected HOT lanes time savings and floating car measurements of time savings at the Ted Williams Parkway onramp, plus demographic variables. The candidate measures of objective time savings included the median and 90^{th} percentiles of the corrected HOT lanes time savings for six-minute arrival intervals over one month, and the median, 90^{th} percentile, and maximum values of onramp time savings for 15-minute ramp arrival times for ten days of observations. Quadratic and interaction terms were also tested, and the results are shown in Table 4.2. We did not use multiple imputations to account for the prediction error in the time savings variables, and we used the best point prediction from the model in Table 4.1 together with a simulated residual. Therefore the standard errors in the models presented in this subsection are downward biased. Qualitatively similar results can be obtained using loop detector data.

The best explanation of perceived time savings only achieved an adjusted R^2 of .092. It involved using the one-month median of imputed HOT lanes time savings and the maximum value of time savings at the Ted Williams Parkway onramp. For some unknown reason, females were found to perceive almost four minutes more savings than males for the same level of objective time savings. This gender effect is significant at $p < .001$. The positive constant term confirms that FasTrak users perceive time savings to be greater than objective time savings by a substantial amount.

Table 4.2: Regression of Perceived FasTrak Times Savings on Time Savings Estimated from Loop Detectors and Floating Cars, Plus Demographics (N = 386)

Independent Variables:	Coef.	Std. Err.	*t*-Stat.
Median corrected HOT Lanes time savings over one month	0.478	0.134	3.56
Maximum time savings at Ted Williams Pkwy onramp	0.294	0.144	2.04
Female	3.883	1.006	3.86
Constant	11.269	4.553	2.82

Since mode choice behavior involving FasTrak usage is likely to be related to perceived travel time savings, and not just objective time savings, we analyzed the relationship between the residual computed from the regression of Table 4.2 and a categorical variable defined as the proportion of each FasTrak users previous week's trips that were made using FasTrak to pay for solo use of the HOT lanes. This FasTrak demand variable has five categories: 0 (10.4 % of the sample), .2 (7.8 %), .4 (13.0%), .6 (6.0%), .8 (4.9 %) and 1 (58.0%). The polyserial correlation coefficient between FasTrak demand measured this way and the regression residual is 0.313, which is significant at $p < .001$. The polyserial correlation coefficient is one of the most appropriate estimates of the strength of a relationship between an ordered-categorical variable and a continuous variable (Olsson, Drasgow and Dorans, 1982; Bollen, 1989).

We can conclude that FasTrak demand is positively associated with the difference between users' perceived time savings and the value of their perceived time savings predicted using available objective time savings measures and demographic variables. This indicates that demand for FasTrak cannot be explained solely in terms of objective time savings and other variables. Perceived time savings probably also plays a role in forming behavior, but perceptions can also be a function of behavior.

To test the role of objective time savings in jointly explaining both perceived time savings and FasTrak demand while simultaneously testing the direction of the causality between FasTrak demand and perceived time savings, we next constructed a structural equations model (SEM). The SEM has two endogenous variables, FasTrak demand and perceived time savings. The five exogenous variables in the SEM model are the four variables in the regression of Table 4.2 plus a spatial Ted Williams Parkway user dummy variable, to test for effects that are not captured by the objective onramp time savings variable alone. We postulated that perceived time savings were a function of objective time savings and the demographic variables, and FasTrak demand was a function of perceived time savings and demographic and spatial variables. In such a recursive model, objective time savings only affects demand through perceived time savings. Demand is a function of both the explained and unexplained portions of perceived time savings. We also specified an alternative model with causality from FasTrak demand to perceived time savings, to test the hypothesis that greater time savings are perceived as a rationalization of behavior, consistent with the theory of cognitive dissonance (Festinger, 1957; Golob, Horowitz and Wachs, 1979).

In the SEM, the endogenous FasTrak demand variable was treated as a two-limit Tobit model (Maddala, 1983), and all the other variables were treated as ordinary continuous variables. The SEM was estimated using ADF-WLS (arbitrary distribution function weighted least squares), as described in Bollen (1989) and Jöreskog and Sörbom (1993). The ADF-WLS method yields consistent parameter estimates which are asymptotically efficient with asymptotically correct covariances, and the model fit will produce correct chi-square test values (Browne, 1982 and 1984).

The postulated direct links that define the optimal SEM are shown with their estimated coefficients in Figure 6. The chi-square value for the fitted model is 4.278 with 5 degrees of freedom (corresponding to $p = 0.510$). This indicates that the fitted model cannot be rejected at the $p = .05$ level (the null hypothesis is that the model represents the true covariance structure, and differences between this true structure and the sample are due only to chance). Results show that perceived time savings is explained by the two measures of objective time savings plus gender, in a manner consistent with the regression described in Table 4.2. FasTrak demand is explained by perceived time savings, an income dummy, and a dummy signifying access to I-15 and the HOT lanes at Ted Williams Parkway. Objective time savings and gender explain demand via the path through perceived time savings. The total effects, or coefficients of the reduced-form equations, computed by solving the equations in terms of the exogenous variables, are listed in Table 4.3.

Figure 6. Flow Diagram of Structural Equations Model of Perceived Times savings and FasTrak Demand

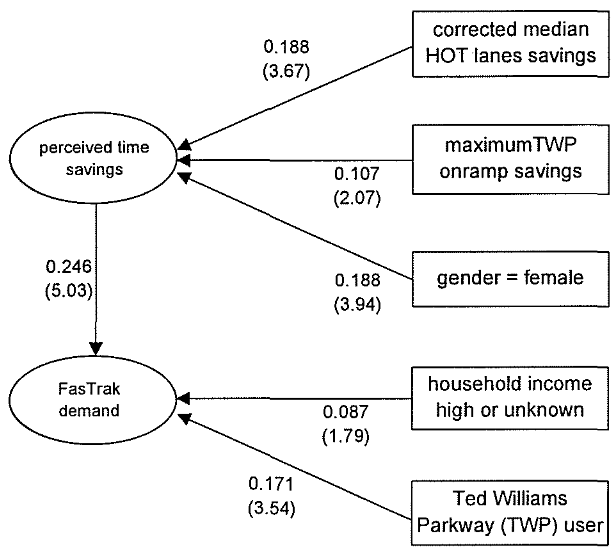


Table 4.3. Coefficients of the Reduced-form Equations, or Total Effects (*t*-statistics in parentheses; N = 386)

Endogenous Variable	Corrected median HOT lanes savings	Maximum TWP onramp savings	Gender = female	Household income high or unknown	Ted Williams Parkway user
Perceived time savings	0.188 (3.67)	0.107 (2.07)	0.188 (3.94)		- -
FasTrak demand	0.046 (3.02)	0.026 (1.92)	0.046 (3.05)	0.087 (1.79)	0.171 (3.54)

The SEM is still identified if a direct effect is added from FasTrak demand to perceived time savings. Adding this link drops the fitted model chi-square to 3.743 with 4 degrees of freedom. The estimated parameter of the "feedback" link from demand to perceived time savings is positive, as predicted by the theory of cognitive dissonance, but it is not significant at the $p = .05$ level. The significance of the overall improvement in the model can also be tested using the difference in chi-square values, because the two models are nested. This difference, which is 0.535 with 1 degree of freedom, is not significant at the $p = .05$ level. Further research is required to better understand this complex relationship between objective estimates of time savings, perceived time savings, and demand.

5 Attrition Model

The 39% attrition rate between Waves 2 and 3 of our panel is not unusual for transportation panel surveys (Raimond and Hensher, 1997). The high attrition might be due to the required detailed questions about the commute trip which respondents find difficult to answer and/or intrusive. Although new respondents (the refreshment sample) are recruited each wave to maintain sample size, it is crucial to account for attrition when analyzing these data. Once the data are collected there is nothing to be done about the loss of efficiency due to the decreased sample size, but there are flexible modeling techniques to identify and correct for non-ignorable attrition.

The simplest approach is to compare the non-attriters (or panel sample) with the refreshment sample. Table 5.1 compares the mean of key variables across these samples for our data. There do not appear to be striking differences, but the panel sample appears to have slightly higher income and longer commute distance. Since the samples are approximately equal size, it is also possible to fit the choice model in Section 6.1 separately for each sample. The hypothesis that attrition is ignorable is then equivalent to the hypothesis that the coefficients of the choice model are equal across the samples. A standard likelihood ratio test shows that this hypothesis cannot be rejected at any reasonable significance level for these data.

If there is no reasonable size refreshment sample, or if the data are used for dynamic analysis, then the attrition process can be modeled using the initial wave of the panel. Table 5.2 gives the results of fitting a binomial logit model to the attrition process. The results show that the only significant predictors of attrition are refusal to disclose income, distance, and proportion of FasTrak use during the previous week. Commute distance enters as a quadratic term that has a maximum negative effect on attrition at 42 miles. This implies that for the relevant range of the data longer distance commuters are less likely to attrite. Proportion of FasTrak use is an endogenous variable in our choice models, so its significance in the attrition model implies that the attrition process is non-ignorable. The higher attrition of FasTrak users might be related to the substantial number of additional survey questions administered to this group. The marginally significant results in Table 5.2 also imply that respondents who do not change work or home locations are less likely to attrite. Previous FasTrak panel members (those who also completed the first wave of the survey) are less likely to attrite between the second and third waves.

The attrition model results in Table 5.2 indicate that the attrition process is non-ignorable for mode-choice modeling, so we need to use inference methods that are consistent with non-ignorable attrition. Our method is based on the fact that the WESMLE described in Section 3.2 yields consistent inference as long as the weights are known. Although we can consistently estimate these weights by $W = 1/(1-\hat{P})$ (where $\hat{P}$ are the predicted attrition probabilities from the attrition models), these estimates are subject to substantial estimation error. Therefore WESMLE estimates using weights W will provide consistent parameter estimates, but the estimated standard errors of these estimates will be downward biased since they neglect the estimation errors in the weights.

Table 5.1: Comparison of Panel and Refreshment Samples Mean Values

Wave 3 Variable	Panel sample	Refreshment sample
Income ≥ $100,000	0.34	0.30
Income < $40,000	0.04	0.07
Income-refused/Don't Know	0.09	0.11
Female	0.40	0.43
Age between 35 and 45	0.39	0.40
Has Graduate Degree	0.30	0.28
Household owns home	0.86	0.85
Distance	26.11	24.84
Toll paid by someone else	0.04	0.06
Used FasTrak last trip	0.40	0.40
Used carpool last trip	0.17	0.16
Sample Size	337	362

(All variables are indicators except for distance.)

Fully consistent inference can be achieved by multiply imputing the weights from the binomial logit attrition model and combining the estimates using Rubin's multiple imputation Methodology (see equations 6-9). The weights can be multiply imputed by drawing independently from the asymptotic joint normal distribution of the parameter estimates from the logit model and then using these draws to compute a new set of estimated attrition probabilities.

Table 5.2: Binomial Logit Attrition Model (positive favors attrition)

Wave 2 Variable	Coef.	Std. Err.	t-Stat.	Mean Values: Attrite	Mean Values: Panel Sample
Number of observations	792				
Pseudo R2	0.04				
Log likelihood	-507.9				
Income ≥ $80,000	0.115	0.216	0.53	0.44	0.46
Income < $40,000	0.077	0.241	0.32	0.22	0.23
Income-refused/Don't Know	0.664	0.274	2.42	0.17	0.10
Age/10*	-0.554	0.439	-1.26	4.30	4.41
(Age/10) squared*	0.053	0.047	1.13	19.68	20.57
Workers per vehicle	0.127	0.348	0.37	0.79	0.79
Household owns home	-0.272	0.221	-1.23	0.80	0.84
Female	-0.005	0.160	-0.03	0.44	0.43
Vehicles per driver*	0.174	0.197	0.88	1.18	1.18
Has Graduate Degree	-0.027	0.173	-0.15	0.31	0.30
Distance/10*	-0.607	0.239	-2.55	2.57	2.73
(Distance/10) squared*	0.071	0.031	2.31	7.92	8.56
Single worker household	0.385	0.286	1.35	0.35	0.31
Two worker household	0.266	0.247	1.08	0.53	0.54
Proportion of FasTrak use*	0.460	0.229	2.01	0.33	0.26
Proportion of Carpool use*	-0.117	0.263	-0.45	0.13	0.15
FasTrak panel	-0.270	0.189	-1.43	0.31	0.33
I-15 panel	-0.063	0.194	-0.32	0.25	0.29
Enters at Ted Williams Parkway	0.164	0.186	0.88	0.40	0.31
Toll paid by someone else	0.365	0.340	1.07	0.07	0.05
Works full or part time	-0.002	0.374	-0.01	0.95	0.94
Size of household ≥ 4	0.386	0.229	1.68	0.16	0.11
Changed location of work/school in past 6 mos.	0.323	0.253	1.28	0.12	0.09
In current residence more than 6 mos.	-0.551	0.341	-1.62	0.93	0.96
Constant	1.772	1.129	1.57		
Proportion of Sample				0.39	0.61
Predicted Attrition Probability*				0.43	0.37
Standard Deviation of Predicted Attrition Probability*				0.12	0.10

(All variables are indicators except those marked with *.)

If the attrition model is correctly specified, then the resulting multiple imputation parameter and covariance estimators, $\hat{\theta}$ and $\hat{\Sigma}$, are consistent whether the attrition process is ignorable or not. The standard unweighted maximum likelihood estimators, $\bar{\theta}$ and $\bar{\Sigma}$, which ignore the attrition weights, are efficient if both the sampling and attrition processes are ignorable, but inconsistent otherwise. Therefore the statistic:

$$T = \left(\hat{\theta} - \bar{\theta}\right)' \left(\hat{\Sigma} - \bar{\Sigma}\right)^{-1} \left(\hat{\theta} - \bar{\theta}\right), \qquad (12)$$

is a valid Hausman (1978) test statistic for the null hypothesis that both the attrition processes is ignorable. Under the null hypothesis, T has a chi-squared distribution with degrees of freedom equal to the rank of $\left(\hat{\Sigma}-\overline{\Sigma}\right)$. When applied to the choice models in Section 6, this Hausman test fails to reject the hypothesis of ignorable attrition for either the panel sample or the merged panel and refreshment sample.

Relative to joint maximum likelihood estimation of the attrition and choice model, the methodology described above is inefficient. However, this methodology is much easier to calculate than joint maximum likelihood, which is frequently intractable in complex models. Simple Hausman (1978) tests can be applied to test for the non-ignorability of the attrition (or missing data) process. Since the WESMLE was originally designed to provide consistent estimates with choice (or response)-based sampling designs, the methodology proposed here can be trivially modified to yield consistent estimates and forecasts for choice-based panels with non-ignorable attrition. The attrition weights for each mode need to be multiplied by a constant so average weight for each mode equals the choice-based weights given in Section 3.2

The tests for non-ignorable attrition described in this section depend critically on the model being estimated. In our application the attrition process is clearly non-ignorable, but the magnitude of the resulting bias is small relative to the error in our parameter estimates. Clearly this result can change if there is any change in model specification.

6 Choice Model Results

Sections 6.1 and 6.2 compare mode choice model estimates correcting for measurement error and choice-base sampling. We use a model derived from the specification in Kazimi *et. al.* (1999). The main difference in the specifications is that here we include a variable identifying sample respondents who do not pay their own tolls. Any teenager knows that if someone else is paying (typically the employer), then they will be less sensitive to the price.

In addition to the parameter estimates, we also report value of time (VOT) estimates for the models in Sections 6.1 and 6.2. Since toll enters the specification both linearly and interacted with variability (the difference between the 90th percentile and the median of time saved by taking the HOT lane over the month), the VOT in dollars per hour saved is given by:

$$\left(60 \times \theta_{timesavings}\right) \Big/ \left(\theta_{toll} + \theta_{toll*Variability} \times Variability\right). \tag{13}$$

Since VOT varies across respondents, we give the distribution across respondents weighted by the choice-base sampling weights to match the population of morning commuters. We also give this VOT evaluated at the weighted mean of Variability. This latter quantity is useful for comparison with other studies which typically do not report the variable in equation (13).

6.1 Loop Detector Time Savings

The top portion of Table 6.1 gives parameter estimates for the mode choice model using loop detector time savings. Most of the parameters in the unweighted model are precisely estimated, although this is not surprising given the extensive specification search needed to find the model in Kazimi *et. al.* (1999). High-income, home-owning, middle-aged females with a graduate degree are the most likely group to pay for FasTrak. Large households with not enough cars per worker are most likely to carpool. Both carpoolers and FasTrak users have similar positive coefficients for time savings, but the reduction in Variability from HOT lane use is not significant. However, if Variability is removed from the model then the toll coefficient drops and becomes insignificant. Relative to solo driving, commute trip drivers are more likely to choose FasTrak and non-commute trip drivers are more likely to carpool.

The weighted estimates are computed using the WESMLE estimator described in Section 3.2. The parameter estimates are similar to the unweighted estimates except for the FasTrak constant. This is not surprising since the unweighted estimates for the mode-choice constants are inconsistent. The standard errors for the weighted FasTrak choice parameters are almost three times larger than the unweighted estimates. This is due to the low weight given FasTrak users, and it shows that WESMLE estimates can be quite inefficient when the sample mode proportions are much different than the population proportions. Imben's (1992) efficient estimator should be more accurate in this setting.

The bottom portion of Table 6.1 gives various estimates of the value of travel time reduction. The first block gives the weighted distribution of the value of time calculated in equation (13). Note that the distribution is skewed and there is substantial variance across the population. The median values are much higher than Calfee and Winston'2 (1998) estimates, and they are on the high end of the estimates reviewed in Small (1992). These medians are similar to equation (13) evaluated at the weighted sample mean variability (labeled "VOT at Mean Variability" in Table 6.1 and 6.2). This is the number typically presented in studies where VOT varies according to observed variables. Since this is just a scalar, it is straightforward to estimate the standard error of this estimate (caused by parameter estimation error) using the delta method. Although this estimate is significantly different from zero, the standard error is large enough to include almost all previous estimates. Calfee and Winston do not report standard errors for their VOT estimate of $5.00, but the unweighted VOT estimates in Table 6.1 are more than two standard errors away from their point estimate.

6.2 Predicted Floating Car Time Savings

Table 6.2 gives the results of estimating the choice model using the predicted floating car data and multiple imputation algorithm described in Section 4.1. The coefficient estimates are roughly similar to those in Table 6.1, but the key coefficients of toll and time savings for commuters are reduced in magnitude and significance. Overall the standard errors are considerably larger than in Table 6.1. This is of course due to the component of error caused by the error in the prediction model used to generate the predictions.

Table 6.1: Mode Choice Model Using Loop Detector Data

Number of obs. = 699	Unweighted Estimates Pseudo R^2 = 0.21 Log likelihood = -606.56			Weighted Estimates Pseudo R^2 = 0.53 Log likelihood = -357.89		
FasTrak choice	**Coef.**	**Std. Err.**	***t*-Stat.**	**Coef.**	**Std. Err.**	***t*-Stat.**
Constant	-5.978	1.994	-3.00	-10.251	8.824	-1.16
Income ≥ $100K + DK/REF	0.855	0.183	4.68	0.924	0.559	1.65
Income < $40K	-0.621	0.505	-1.23	-0.551	1.864	-0.30
Female	0.730	0.183	3.98	0.845	0.557	1.52
Age between 35 & 45	0.423	0.179	2.36	0.428	0.540	0.79
Has Graduate Degree	0.741	0.195	3.80	0.842	0.575	1.47
Household owns home	0.754	0.293	2.57	0.747	1.002	0.75
Distance	0.019	0.010	1.86	0.025	0.029	0.85
Toll paid by someone else	1.747	0.454	3.85	2.013	0.885	2.27
Toll	-0.787	0.220	-3.58	-0.930	0.693	-1.34
Median total time savings for commuters	0.182	0.047	3.87	0.177	0.115	1.54
Median total time savings for non-commuters	0.417	0.216	1.93	0.532	0.866	0.61
Toll × Variability	0.135	0.035	3.83	0.158	0.094	1.68
Commute trip	3.395	1.939	1.75	4.428	8.677	0.51
Carpool Choice						
Constant	-2.265	1.006	-2.25	-3.163	1.326	-2.38
Workers per vehicle	1.005	0.366	2.74	0.979	0.414	2.37
Distance	0.102	0.056	1.82	0.105	0.076	1.38
Distance squared	-0.001	0.001	-1.27	-0.001	0.001	-0.98
Single worker household	-0.973	0.350	-2.78	-0.914	0.435	-2.10
Two worker household	-0.522	0.289	-1.81	-0.520	0.357	-1.46
Commute trip	-1.762	0.414	-4.25	-1.655	0.449	-3.68
Median total time savings	0.144	0.045	3.19	0.134	0.055	2.43
Carpool ramp bypass	0.556	0.278	2.00	0.733	0.353	2.08
Variability of solo drive time	0.098	0.076	1.29	0.081	0.102	0.80
Value of Time ($/hour)	Percentile	Largest		Percentile	Largest	
95%	105.60	693.26		83.19	430.56	
90%	73.63			58.86		
75%	35.27	Smallest		28.71	Smallest	
50%	23.37	-254.14		19.13	-239.55	
25%	16.55			13.59		
10%	14.43			11.86		
5%	14.08			11.58		
	Mean	Std. Dev.		Mean	Std. Dev.	
	32.64	94.29		23.64	67.74	
VOT at Mean Variability	25.96	7.70		21.23	17.11	

Table 6.2: Multiply Imputed Mode Choice Model Using Predicted Floating Car Data

Number of obs. = 699	Unweighted Estimates Pseudo R^2 = 0.20 Log likelihood = -611.27			Weighted Estimates Pseudo R^2 = 0.53 Log likelihood = -360.57		
FasTrak choice	**Coef.**	**Std. Err.**	***t*-Stat.**	**Coef.**	**Std. Err.**	***t*-Stat.**
Constant	-7.179	3.342	-2.15	-11.318	12.063	-0.94
Income ≥ $100K + DK/REF	0.830	0.271	3.06	0.852	0.603	1.42
Income < $40K	-0.591	0.536	-1.10	-0.524	1.912	-0.27
Female	0.704	0.251	2.81	0.801	0.597	1.34
Age between 35 & 45	0.445	0.210	2.12	0.532	0.562	0.95
Has Graduate Degree	0.747	0.266	2.81	0.792	0.611	1.30
Household owns home	0.812	0.355	2.29	0.884	1.049	0.84
Distance	0.015	0.011	1.39	0.023	0.031	0.75
Toll paid by someone else	1.816	0.633	2.87	2.112	1.045	2.02
Toll	-0.600	0.387	-1.55	-0.665	0.665	-1.00
Median total time savings for commuters	0.074	0.037	2.04	0.089	0.084	1.06
Median total time savings for non-commuters	0.297	0.200	1.49	0.371	0.712	0.52
Toll × Variability	0.090	0.053	1.69	0.102	0.077	1.33
Commute trip	4.495	3.004	1.50	5.303	11.693	0.45
Carpool Choice						
Constant	-2.139	1.145	-1.87	-2.645	1.492	-1.77
Workers per vehicle	0.982	0.435	2.26	0.970	0.485	2.00
Distance	0.099	0.060	1.64	0.083	0.078	1.07
Distance squared	-0.001	0.001	-1.23	-0.001	0.001	-0.73
Single worker household	-1.005	0.426	-2.36	-1.003	0.506	-1.98
Two worker household	-0.548	0.318	-1.72	-0.589	0.389	-1.52
Commute trip	-1.747	0.588	-2.97	-1.655	0.616	-2.69
Median total time savings	0.056	0.033	1.71	0.067	0.041	1.63
Carpool ramp bypass	0.634	0.315	2.01	0.820	0.406	2.02
Variability of solo drive time	0.039	0.076	0.51	0.096	0.107	0.90
Value of Time ($/hour)	Percentile	Largest		Percentile	Largest	
95%	108.70	333.36		95.37	141.16	
90%	72.12			65.04		
75%	31.30	Smallest		27.71	Smallest	
50%	18.71	-190.35		17.69	-547.43	
25%	10.30			9.14		
10%	-20.72			-19.69		
5%	-83.02			-123.92		
	Mean	Std. Dev.		Mean	Std. Dev.	
	25.63	74.75		7.54	81.49	
VOT at Mean Variability	18.63	13.88		20.88	28.41	

Since the floating car time savings are generally larger than the corresponding loop detector measures, we would expect that the value of time estimates would drop relative to Table 6.1. The bottom portion of Table 6.2 confirms this expectation and shows that the VOT estimates have dropped $5 - $7 from those in Table 6.1. Note that this change is quite significant from a policy perspective, but the change is not statistically significant given the large standard errors of these measures.

If the error in the prediction model is ignored and only one set of predictions is used, then the standard errors are downward biased by over 50 percent for this model. Even though the prediction model in Table 4.1 fits very well, the prediction error is still an important component of the total estimation error.

7 Conclusion

This paper reviews techniques for handling attrition, choice-based sampling, and measurement error in panel surveys. Although we concentrate on commuter surveys and value of time measurement, the techniques are general and can be applied in other settings.

The analysis of panel attrition in Section 5 shows that although the attrition process is not ignorable, the resulting biases in the choice model estimates are negligible. This result depends critically on the particular choice model we used, and attrition might be important for a more accurate model. In any case, the 40 percent attrition rate in the San Diego panel will clearly reduce the sample size for dynamic analysis. The transportation research community needs to find cost-effective methods for reducing the attrition rate even if we are capable of effectively monitoring the attrition process. One possible approach is to give respondents small GPS receivers coupled with a logging device to more accurately record trip details without requiring lengthy recall diary questions.

The WESMLE estimator is an easily applied estimator for non-ignorable samples. However the high standard errors reported in Sections 6.1 and 6.2 show WESMLE's inefficiency can be important in cases where the weights vary over a broad range. We will experiment with Imben's (1992) efficient estimator to see if this remedies the problem. For the conditional logit models used in this paper, choice-based sampling only biases the mode-specific constants. The unweighted estimates are therefore consistent for estimating value of travel time reduction (VOT), but they can not be used to predict market shares in response to a change in tolls (or any other quantity that depends on the parameters of the mode-specific choice constants).

Section 4 shows that measurement error in travel time is a serious problem for mode-choice models. The relatively cheap measures, loop detectors and respondents' perceptions of time savings, are both badly biased. When we collect additional data on all respondents' perceptions, then we can add these perceptions to our imputation models. In any case the multiple imputations approach used here to integrate the measurement error and choice models is a good general tool for these sorts of problems. Ignoring the component of error in the choice model parameters caused by the prediction model leads to serious underestimates of the precision of the choice model parameters.

The substantive conclusions from the models in Section 6 are largely negative. We cannot estimate value of travel time reduction accurately enough to resolve current controversies. In particular, the confidence bands from our estimates cover all existing estimates even though the differences between these estimates are important for planning new transportation infrastructure investments. We are planning additional work combining perceived time savings, loop detector time savings, and floating car time savings using data from more recent waves of the I-15 panel. We are also asking stated preference questions to our sample (similar to those in Calfee and Winston, 1998) so that we can jointly model their responses to hypothetical and real HOT lanes. Hopefully these enhanced models will yield more accurate estimates.

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