Estimating Commuters' "Value of Time" with Noisy Data: a Multiple Imputation Approach

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Abstract

We estimate how motorists value their time savings and characterize the degree of heterogeneity in these values by observable traits. We obtain these estimates by analyzing the choices that commuters make in a real market situation, where they are offered a free-flow alternative to congested travel. We do so, however, in an empirical setting where several key observations are missing. To overcome this, we apply Rubin's Multiple Imputation Method to generate consistent estimates and valid statistical inferences. We also compare these estimates to those produced in a "single imputation" scenario to illustrate the potential hazards of single imputation methods when multiple imputation methods are warranted. Our results show the importance of properly accounting for errors in the imputation process, and they also show that value of time savings varies greatly according to motorist characteristics.

Keywords: value of time, congestion pricing, heterogeneous consumers, product differentiation, missing data, multiple imputation

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1 Introduction

Typically the dominant component of benefits from a transportation project is travel-time savings.[1] This alone illustrates the need to accurately measure how such time savings are valued, resulting in a large empirical effort to estimate "the value of time" (VOT) for highway motorists. However, few of these studies examine how motorists respond to actual prices, such as tolls. Fortunately, recent "value-pricing" projects, such as those of State Route 91 (SR-91) and Interstate 15 (I-15) in Southern California, offer unique opportunities to study the preferences of motorists who can purchase a free-flow alternative to congested travel in the form of toll-lanes.[2]

In turn, such studies have generated controversy over the "value of value-pricing" itself[3], where offering toll-lanes might reduce welfare relative to the norm of offering all lanes at a uniform price of zero.[4] In response, Small and Yan (2001) and Small, Winston and Yan (2002) illustrate that these purported welfare losses are driven by assuming homogenous preferences across motorists (which amounts to saying that they all have identical VOTs). Instead, they show that accounting for heterogeneity in motorists preferences can reveal substantial welfare gains in a value-pricing setting, and that these gains are often increasing in the degree of heterogeneity. Moreover, recognizing this heterogeneity might enable policymakers to overcome current political impediments to offering toll-lanes by ameliorating distributional concerns through policies that cater to varying preferences.[5] Thus, identifying heterogeneity in VOT and the degree to which it may be present has importance beyond estimating VOT itself.

Unfortunately, value-pricing studies are often plagued by poorly-measured or missing travel-time data, as is the case for this paper. This problem must be overcome in a manner that

[1] Small (1999).

[2] Typically value-pricing experiments give special consideration to high-occupancy vehicles (carpools). For instance, carpools on the I-15 are exempt from paying tolls, while vehicles with three or more occupants on the SR-91 can travel at 50% of the posted toll. This leads to the convention of referring to such toll-lanes as "high occupancy / toll" lanes, or "HOT" lanes.

[3] Small and Yan (2001).

[4] Liu and McDonald (1999).

[5] Specifically, these distributional concerns are that offering toll-roads can involve a greater loss in consumer surplus for lower VOT motorists (see Small, Winston, and Yan (2002)). Additionally, there is the public perception that HOT lanes mostly benefit high income motorists, who tend to have higher VOTs. Mohring (1999) cites a case in Minneapolis where "widespread public opposition to publicly provided 'Lexus lanes' has postponed - perhaps permanently - plans to convert one HOV lane into a HOT lane."

yields valid statistical inferences.

In light of the above, this paper serves dual roles: (1) estimating VOT and characterizing its heterogeneity by identifiable components, and (2) describing how to apply Rubin's Multiple Imputation Method to overcome data problems and produce consistent estimates yielding valid inferences.

We find that median VOT is $30 per hour, but ranges from $7 to $65 according to varying motorist characteristics. In our case, these estimates are higher than those produced by imputing a single set of values to replace "missing" time-savings data - an artifact of this particular analysis but illustrative of the potential biases created by treating imputed data as known. We also show the degree to which this "single imputation" method understates the degree of uncertainty in estimating VOT by failing to account for the estimation error introduced by the imputation process.

This paper is organized as follows: Section 2 describes the empirical setting for our study. Section 3 describes how to generate multiply-imputed data to overcome the problem of missing time-savings data for many respondents. Section 4 describes our mode choice model and how to apply it to these imputed data to obtain valid statistical inferences. The results of this estimation process follow in Section 5. Section 6 illustrates some of the hazards of employing only a single imputation when multiple imputations are warranted. Section 7 offers a few concluding remarks.

2 Empirical Setting: The San Diego I-15 Congestion Pricing Project[6]

This value-pricing project offers solo drivers an option to pay to use an eight mile stretch of two free-flowing lanes ("Express Lanes" or "HOT" lanes) adjacent to (but physically separated from) the main lanes along California's Interstate 15, just north of San Diego. It offers solo drivers a premium alternative to the typically congested conditions along that section of the I-15 - an alternative that carpools enjoy for free. The Express Lanes are reversible and operate in the southbound direction during the morning commute (inbound to San Diego) and northbound

[6] See Brownstone et al. (2003) for a more detailed desciption of this project. A map of the HOT lanes and more information are available at: http://argo.sandag.org/fastrak/index.html

during the afternoon commute. Tolls are posted in both directions at the Express Lane entrance and about one mile prior. Those who choose to enter the facility must travel its entire length since there are no interim exits.

Our study focuses on morning (inbound) commuters who traveled the entire eight mile length on or adjacent to the Express Lane facility during October and November of 1999.[7] This period corresponds to the fifth wave of the project's panel survey that gathers the necessary information about I-15 commuters required to conduct mode-choice analysis. The proportion of commuters who actually pay to use the Express Lanes is relatively small, so choice-based sampling is employed in order to obtain a sufficient amount of variation in the data while meeting budgetary constraints. Table 1 summarizes these choice shares, along with demographic information about survey respondents in our sample.

2.1 Dynamic Tolls

A fascinating characteristic of the I-15 Express Lanes is how they maintain free-flow traffic along them. Tolls change every six minutes in $0.25 increments to maintain Level of Service C, as required by California Law for HOT lanes.[8] This is accomplished by traffic flow monitoring from loop detectors embedded in the highway near each onramp along the facility. Posted tolls in our sample range from $0.50 to $4.25, with a median of $2.50 during the peak of rush-hour.

Solo drivers who wish to use the Express Lanes subscribe to "FasTrak" accounts and obtain transponders that are used to debit their accounts each time they use the facility. The actual toll faced by respondents in our sample is obtained by matching the time that they reported reaching the facility with toll data collected from the California Department of Transportation (CALTRANS). These tolls are then converted to "effective tolls", where they are set to zero if the respondent reports that their account is paid for by someone else (such as their employer or benevolent wife).[9]

[7] Only weekday and non-holiday trips are considered.

[8] Level of Service C is defined by a minimum speed of 64.5 MPH and a maximum service flow rate of 1,548 passenger cars per hour per lane.

[9] This method provided a better empirical fit than assigning indicator variables for these cases.

2.2 Time Savings

Time savings is defined here as the difference between travel time on the main lanes adjacent to the Express Lane facility and travel time on the Express Lanes themselves. The salient time-savings measure in our study is *median* time-savings since commuters are incapable of knowing their actual time savings prior to making a mode choice. Instead, we assume that commuters have a feel for their travel time distributions and base their decisions on typical values, as is standard in value-pricing studies.[10]

We asked commuters how much time they would have saved if they used the Express Lanes for their last commute trip. Even accounting for the tendency to round off to 5 and 10 minute intervals, many of the respondents gave implausibly high answers. These answers also varied depending on whether the respondent actually took the Express Lanes for the last trip. Ghosh (2001) used the reported time savings estimates to try and estimate models similar to those reported in this paper, but he was unable to get any reliable results. We therefore use engineering estimates for this study, and we note that these engineering estimates are more valid for project evaluation.

We have a complete set of data from loop detectors, which estimate vehicle speeds on the main lanes and Express Lanes in six minute intervals, corresponding to the intervals between toll changes. Ideally, these data could be collected across the sample period to obtain time savings distributions for each time of day (during commute periods), as is done in Ghosh (2001) and Brownstone et al. (2003). There are two major reasons, however, for rejecting this procedure.

The first is that loop detector data often result in implausible speed estimates (such as the "Formula 1" speeds encountered in our sample). Through changes in inductance, loop detectors sense how long a vehicle is above them ("occupancy") and how many vehicles pass over them ("flow") in a given period. In order to estimate speeds from these data, loop detector algorithms often assume homogenous vehicle speeds during each period (six minutes in the present case) and, perhaps more heroically, that "typical" vehicle lengths are known.[11]

[10] This approach is adopted by Brownstone et al. (2003), Small, Winston, and Yan (2002), Ghosh (2001), Lam and Small (2001), and Brownstone et al. (1999).

[11] More accurately, a "mean effective vehicle length" or "G-factor" is assumed, where "effective vehicle length" is defined as the product of velocity and "occupancy" for a given vehicle.

Given the mix of passenger cars, trucks, light-duty vehicles, and so forth typically observed on interstates, it is not difficult to see how loop detectors might yield unreliable speed estimates. It is worth noting, however, that if speeds are fairly homogeneous within each period, then speed variation across periods is likely to be fairly well represented. Most of the problems we found with loop detector data in this project could be alleviated by using paired detectors and spacing these paired detectors closer together, but time and budget constraints precluded these measures.

As an alternative to loop detector data, we have speed data from floating-car experiments that we consider to be reliable. These data were collected professionally and involved driving the length of the main and HOT lanes repeatedly in fifteen minute intervals. But, due to budget constraints, we only have such data for five days of the sample period. However, the variation in loop-detector speed data offers a means to predict these "missing" floating-car data, as described in Section 3.

The second objection is the existence of a dedicated Express Lane onramp at Ted Williams Expressway on the northern end of the facility. Those wishing to enter the I-15 at Ted Williams (over a third of our sample) can enjoy additional time savings by using the express lanes since the dedicated onramp enables them to bypass the queues that typically form at the metered entrance to the main lanes.[12] Indeed, the average observed wait time at this onramp is roughly equal to the average observed time savings from using the Express Lanes themselves, warranting their inclusion when calculating median time-savings.[13] Unfortunately, we only have observations on Ted Williams onramp wait times for ten days of the sample period. We describe how to predict these missing data in Section 3.

The challenge ahead, as evident from the preceding section, is to construct valid statistical inferences with a complete set of "bad" (loop detector) time-savings data and an incomplete set "good" (floating-car and onramp-queue) time-savings data. This challenge is addressed in the following section.

[12] Brownstone et al. (1999) multiply impute floating car time savings data conditioned on loop detector data, but do not properly account for Ted Williams queue times in estimating time-savings distributions.

[13] Specifically, we construct separate time-savings distributions for those entering the I-15 at Ted Williams Expressway so that their median time-savings values reflect these additional time savings.

3 Multiple Imputations

As previously noted, we have loop detector data for the entire sample period (two months). However, we only have ten days worth of Ted Williams onramp queue times and five days worth of floating car data, both of which we take as reliable. The task at hand is to predict floating car time savings and Ted Williams queue times by conditioning on loop detector data.[14] In cases where queue times are available, but floating car times are missing, floating car time savings can be predicted by conditioning on both loop detector and queue data.[15]

Express Lane travel times are typically calculated assuming a constant vehicle speed (usually 65 to 75 MPH) since the free-flow conditions in these lanes offer little variation.[16] In our study, we take average speeds, by time of day, from Express Lane floating car data as representative Express Lane speeds. This can be seen as a compromise between assuming a constant speed across time periods, and fully imputing these speeds (which is likely to be fruitless, given the minor degree of variation in observed speeds). This compromise buys an additional (though small) degree of variation in travel time savings, which is desirable since the key variables of time savings and tolls tend to be highly correlated.

3.1 Imputation Procedure

The general procedure for imputing our missing data is to draw them from their appropriate asymptotic conditional distributions. In our case, linear regression models are used to estimate these distributions. Each set of imputed values must be drawn so that the first and second moments (and all cross-moments with other variables in the model) match those of the missing data. This insures that the estimates computed from any set of imputed values are consistent. Since we use linear regression models, we need to make sure that the models condition on all relevant variables. We also need to add a simulated residual to each set of imputations so that the variance of the imputed values is equal to the variance of the missing data.

[14] More precisely, all such prediction models condition on all available information in the sample.

[15] Note that loop detector data are collected in six-minute intervals, while floating car and queue data are collected in fifteen minute intervals. To make these data compatible, we interpolate the floating car and queue data into six-minute intervals. Although these interpolated data could contain less variation than the actual six-minute data, the six-minute loop detector data do not change very quickly over the range of our data collection.

[16] Brownstone et al. (2003), Small, Winston, and Yan (2002), Ghosh (2001), Lam and Small (2001), and Brownstone et al. (1999) all follow this convention.

To avoid unreasonable predictions, the dependent variables in these regressions (floating car time savings and Ted Williams onramp queue times) are transformed to bound these predictions between zero and 20 minutes - a bit more than the maximum observed loop detector time savings. Letting t represent the time savings measure of interest, this transformation takes the logit form:[17]

$$\ln\left[\frac{t/20}{1-(t/20)}\right] \tag{1}$$

Note that these logit transformations are "undone" when calculating predicted time savings. Simple predictions from a linear model only fall outside the zero-to-twenty minute range a few times. However, it is important to impose the range restrictions because the imputation procedures described below draw different parameter values and add a simulated residual for each set of imputations. Without range restrictions many of these imputed values would be unreasonably high or low.

3.1.1 Floating Car Data Conditioned on Loop Detector and Queue Data

We proceed by regressing our floating car data on both loop detector and queue data, along with all other available covariates. For parsimony, only covariates with significant explanatory power are retained in the model.

The right column of Table 2 shows the estimation results for this regression. Note that the model fits quite well, although the reported R^2 of 0.57 might be misleading. Keep in mind that this value is calculated in the logit-space of the dependent variable, thereby reducing in-sample variation and generating a much lower R^2 than would result from a level-space calculation.

To impute floating car time savings from these results, write this regression model as

$$F^{LQ} = X\lambda + u \tag{2}$$

where F^{LQ} is a vector of observed floating car time savings, X is a matrix of covariates, including loop detector and queue data, λ is a vector parameters to be estimated, and u is a vector of residuals. Let $\hat{V}_{FLQ} = \hat{\sigma}^2(X'X)^{-1}$ denote the (standard) estimated covariance matrix for this model, where $u \sim N(0, \sigma^2 I_N)$. The procedure to impute a single vector of floating car time savings follows as

[17] This approach follows Brownstone et al. (1999).

1. Draw σ_*^2 by dividing the residual sum of squares $(\hat{u}'\hat{u})$ from regression (2) by an independent draw from a χ^2 distribution with degrees of freedom equal to the dimension of λ.

2. Draw a vector of residuals u_* from a $N(0, \sigma_*^2 I_N)$ distribution.

3. Draw λ_* from a $N(\hat{\lambda}, \hat{V}_{F^{LQ}})$ distribution.

4. Construct $F_*^{LQ} = X\lambda_* + u_*$.

This process is repeated to obtain the desired number of imputations (m) required for the estimation process described in Section 3.2.

3.1.2 Floating Car and Queue Data Conditioned on Loop Detector Data

Imputing both floating car and queue time savings from loop detector data is analogous to that of the preceding section, where one might be tempted to impute these data from equation-by-equation least-squares estimators. However, doing so would fail to account for the error correlation across these equations when using them to impute the missing data.[18] To account for this correlation, we use Zellner's Seemingly Unrelated Regressions estimator.[19] The left column of Table 2 gives the estimation results for these simultaneous regressions.

To impute floating car time savings and queue times from these results, write the model as

$$S = \begin{bmatrix} F^L \\ Q^L \end{bmatrix} = \begin{bmatrix} X^F & 0 \\ 0 & X^Q \end{bmatrix} \begin{bmatrix} \delta^F \\ \delta^Q \end{bmatrix} + \begin{bmatrix} \nu^F \\ \nu^Q \end{bmatrix} = X\delta + \nu \qquad (3)$$

where F^L and Q^L are vectors of observed floating car and queue data, X is a matrix of covariates including loop detector data, δ^F and δ^Q are parameters to be estimated, and ν^F and ν^Q are residual vectors corresponding to each equation in the system.[20] Let $\hat{V}_S = (X'(\hat{\Sigma} \otimes I_N)X)^{-1}$ represent the estimated covariance matrix for this model, where $\nu \sim N(0, \Sigma \otimes I_N)$. In model (3), the residuals (elements of ν) are distributed independently across observations, but are correlated across regressions (F^L and Q^L), which is reflected in the 2×2 matrix Σ.

[18] A Breusch-Pagan test confirms this error correlation across the two regressions.
[19] Zellner (1962).
[20] Note that the dimension of S is $2N \times 1$.

To better explain the imputation procedure in this case, write

$$\Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix} \tag{4}$$

and note that

$$\begin{aligned} \nu^F &\sim N(0, \Sigma_{11} I_N) \\ \nu^Q &\sim N(0, \Sigma_{22} I_N) \end{aligned} \tag{5}$$

It follows from the standard properties of multivariate normal distributions that

$$\nu^Q | \nu^F \sim N\left(\frac{\Sigma_{12}}{\Sigma_{11}} \nu^F, \left(\Sigma_{22} - \frac{(\Sigma_{12})^2}{\Sigma_{11}} \right) I_N \right) \tag{6}$$

The procedure to generate single vectors of imputed floating car time savings and Ted Williams queue times follows as[21]

1. Draw ν_*^F from its marginal distribution given in (5).

2. Using the draw in the previous step, draw ν_*^Q from its *conditional* distribution given in (6).

3. Draw $\delta_* = \begin{bmatrix} \delta_*^F \\ \delta_*^Q \end{bmatrix}$ from a $N(\hat{\delta}, \hat{V}_S)$ distribution.

4. Construct $\begin{bmatrix} F_*^L \\ Q_*^L \end{bmatrix} = \begin{bmatrix} X^F & 0 \\ 0 & X^Q \end{bmatrix} \begin{bmatrix} \delta_*^F \\ \delta_*^Q \end{bmatrix} + \begin{bmatrix} \nu_*^F \\ \nu_*^Q \end{bmatrix}$.

Repeating this procedure m times produces m sets of completed data. These imputations are used in the estimation process described in the following section.

3.2 Estimation Procedure

A common way to handle missing data (aside from deleting or ignoring these cases) is to impute a single set of missing data from "hot-deck imputations", or from the procedures outlined in the previous section ($m = 1$). These "single imputation" methods, however, treat the imputed

[21] Technically speaking, the first step should be to draw Σ_* from an appropriately parameterized Inverse Wishart distribution. The following steps would then employ the elements of this drawn matrix. This step is omitted, however, for computational convenience since it is unlikely to have a measurable impact on the final estimation results.

values as known and fail to account for the additional estimation error introduced by the imputation process. In order to obtain valid and consistent estimates, we employ the Multiple Imputation Method given in Rubin (1987)[22]. Section 6 illustrates how estimates from identical models can differ between single and multiple imputation procedures.

The theoretical justification for multiple imputations is couched in Bayesian estimation theory. Following Rubin and Schenker (1986), let Y_{obs} and Y_{mis} denote sets of observed and missing values in a particular sample. Also, let θ represent the population parameter to be estimated. The posterior density function of θ is given by

$$h(\theta|Y_{obs}) = \int g(\theta|Y_{obs}, Y_{mis}) f(Y_{mis}|Y_{obs}) dY_{mis} \tag{7}$$

where $g(\cdot)$ is the complete-data posterior density of θ and $f(\cdot)$ is the predictive-posterior density of the missing values. We see from (7) that the posterior distribution of θ can be obtained by averaging its complete-data posterior over the predictive-posterior density of the missing values. Another way to view this procedure is to interpret Y_{mis} as a nuisance parameter, which is integrated out of the posterior density of θ.

We use the frequentist version (or "randomization-based" version, as Rubin puts it) of this method to obtain our estimates.[23] Schenker and Welsh (1988) show that the imputation procedure outlined in Section 3.1 is equivalent to drawing from the Bayesian predictive-posterior of the missing data ($f(Y_{mis}|Y_{obs})$) when the regressions exhibit a normal error structure with standard uninformative priors. What remains is a valid frequentist estimator that averages a series of m estimates over these m imputations (for $m \geq 2$), analogous to equation (7).

Let $\tilde{\theta}_r$ denote a single estimate obtained from a complete set of data, including a single set of imputed values, and let $\tilde{\Omega}_r$ denote its associated covariance estimate. As indicated in the previous section, the imputed values are drawn so that each of these estimates are consistent.

[22] More precisely, we use Rubin's Multiple Imputation Method with Ignorable Nonresponse, since there is no reason to posit an endogenous nonresponse mechanism for our missing data. See Rubin and Schenker (1986), Schenker and Welsh (1988), and Rubin (1996).

[23] We do this mainly for computational convenience. Moreover, our estimates are based on 537 observations, suggesting that our estimates would not differ in numerical significance from those produced by a Bayesian approach with relatively flat priors.

Rubin's Multiple Imputation Estimators are given by

$$\hat{\theta} = \frac{1}{m}\sum_{r=1}^{m}\tilde{\theta}_r \quad (8)$$

$$\hat{\Sigma} = U + \left(1 + \frac{1}{m}\right) B \quad (9)$$

where

$$B = \frac{1}{m-1}\sum_{r=1}^{m}(\tilde{\theta}_r - \hat{\theta})(\tilde{\theta}_r - \hat{\theta})' \quad (10)$$

$$U = \frac{1}{m}\sum_{r=1}^{m}\tilde{\Omega}_r \quad (11)$$

Equations (10) and (11) decompose the statistical error in estimating θ into two components. B estimates the covariance *between* the m parameter estimates, which represents the covariance caused by the imputation (or measurement error) process. U, on the other hand, estimates the covariance of the parameter estimates *within* the series of m imputations.

Rubin (1987) shows that $\hat{\theta}$ is a consistent estimator of θ for $m \geq 2$, and $\hat{\Sigma}$ is a consistent estimator for the covariance of $\hat{\theta}$.[24] Equation (9) shows that the precision of $\hat{\theta}$ improves with the number of imputations by a factor of $\frac{B}{m}$, suggesting that "many" imputations should be drawn. However, there is no formal stopping rule to suggest how large "many" should be. An approach adopted by Brownstone et al. (1999) is to note from Rubin (1987) that the Wald test statistic for the null hypothesis that $\theta = \theta_0$ is given by

$$(\theta - \theta_0)'\hat{\Sigma}^{-1}(\theta - \theta_0) \quad (12)$$

and is asymptotically distributed according to an F distribution with k and τ degrees of freedom, where k equals the dimension of θ and τ is given by

$$\tau = (m-1)(1 + \rho_m^{-1})^2 \quad (13)$$

$$\rho_m = (1 + m^{-1})Trace(BU^{-1})k^{-1} \quad (14)$$

The stopping rule adopted by Brownstone et al. (1999) is to increase m until τ is large enough for the standard asymptotic χ^2 distribution of Wald test statistics to apply. They find that

[24] See Rubin (1987), chapter 4, for a detailed explanation of the asymptotic equivalence of this estimator to its Bayesian counterpart.

$m = 20$ is sufficient to meet this condition. In our study, however, we note that computing time is now relatively cheap and choose $m = 200$ to effectively minimize the $\frac{B}{m}$ component of $\hat{\Sigma}$ such that $\hat{\Sigma} \simeq U + B$.

This multiple imputations framework enables us to proceed toward consistently estimating θ in our mode choice model and to construct legitimate value of time-savings estimates, which depend on $\hat{\theta}$.

4 Mode Choice and Value of Time Savings

The mode choice model outlined in this section is estimated 200 times with the $m = 200$ complete datasets constructed from as many sets of imputations, where each estimate corresponds to a particular $\tilde{\theta}_r$ and $\tilde{\Omega}_r$ in the previous section. Our VOT estimates are based on the final estimation results, corresponding to equations (8)-(11) in that section.

4.1 Conditional Logit Mode Choice Model

To estimate how commuters value their time savings in an actual market setting, we model their mode choices between three alternatives: (1) Solo travel in the main lanes parallel to the Express Lanes, (2) Solo travel in the Express Lanes (which we refer to as the "FasTrak" choice to indicate that it involves paying a toll), and (3) Carpooling in the Express Lanes. To characterize these choices, let $U_{in}(X_{in})$ represent the utility that person n enjoys from choosing alternative i, and write

$$U_{in}(X_{in}) = V_i(X_{in}) + \varepsilon_{in} = X_{in}\theta + \varepsilon_{in} \tag{15}$$

where $V_i(X_{in})$ is the indirect utility for those with observed characteristics X_{in}. The remaining term ε_{in} accounts for unobserved (latent) characteristics to accommodate stochastic preferences for alternative i among those with identically observed characteristics. If we assume that each ε_{in} is distributed independently and identically according to a Type I Extreme Value distribution, then the probability P_{in} that person n chooses alternative i, conditioned on characteristics X_{in}, is given by the standard logit form

$$P_{in} = \frac{e^{X_{in}\theta}}{\sum_{j=1}^{3} e^{X_{jn}\theta}} \tag{16}$$

where θ is a vector of parameters to be estimated, as prescribed in Section 3.2. Each $\tilde{\theta}_r$ and $\tilde{\Omega}_r$ estimate is obtained by maximizing the joint log-likelihood function for the $N = 537$ commuters in our sample, given by

$$L = \sum_{n=1}^{N} \sum_{i=1}^{3} I_{in} \ln(P_{in}) \tag{17}$$

where $I_{in} = 1$ if person n chooses alternative i, and $I_{in} = 0$ otherwise.

4.2 Alternative Models

Given the variety of choice models that are available to us, it is worth commenting on why we choose the conditional logit form. The first consideration is the fact that we use a choice-based sample. Maximizing a random-sample likelihood, as in equation (17), can yield inconsistent estimates under these circumstances. However, Manski and Lerman (1977) show that in a conditional logit model with a full set of alternative-specific constants (as we have in our specification), only the coefficients on these constants will be estimated inconsistently. This implies that using an unweighted maximum likelihood estimator for our conditional logit model is appropriate, especially since our VOT estimates do not depend on these alternative-specific constants. This notion is evident in Lam and Small (2001), who compare both weighted and unweighted multinomial logit estimates in a value-pricing context, which only creates differences in their alternative-specific constant estimates, thereby leaving their VOT estimates virtually unchanged.

The next consideration is that our emphasis on revealing heterogeneity in VOT might suggest a form that allows for unobserved heterogeneity, such as the mixed-logit form with random error components. Our preliminary experiments with this form, however, do not exhibit any statistically significant unobserved heterogeneity. Small, Winston, and Yan (2001) experience the same with the revealed-preference portion of their SR-91 data, as does Ghosh (2001) using the same wave of our I-15 data. This does not necessarily imply the absence of unobserved heterogeneity, but it does suggest that the conditional logit form is reasonable for our analysis.

Another consideration is that we model the inconvenience of obtaining a FasTrak transponder as an implicit cost of using the Express Lanes.[25] An alternative model, such as the

[25] Note that FasTrak users are not charged for obtaining transponders and establishing accounts.

nested-logit form, would assume that this effort has its own random determinants by specifying it as an explicit choice dimension. In this spirit, Lam and Small (2001) estimate VOT with the conditional logit and nested logit forms, but obtain only very small differences between the estimates. Ghosh (2001) experiences the same using the same wave of our I-15 data. Hence we adhere to the more parsimonious conditional logit form.

4.3 Value of Time Savings

In accord with equation (15), we estimate how commuters value their time savings by estimating their marginal rates of substitution between time savings TS and the costs of these time savings C (in the form of tolls). The value of time savings (VOT) for commuter n is defined by

$$VOT_n \equiv \left.\frac{dC_{in}}{dTS_{in}}\right|_{\bar{V}_{in}} = -\frac{\partial V_{in}/\partial TS_{in}}{\partial V_{in}/\partial C_{in}} \tag{18}$$

Equation (18) shows that VOT is also a function of any characteristics that are interacted with either time savings or tolls. This is how we are able to observe heterogeneity in VOT across commuters through varying characteristics such as income group, work status, and trip distance. Interpreting equation (18) as the value of time savings assumes that commuters only care about travel time when they decide whether or not to take the HOT lane. If they also perceive safety benefits, then this will make equation (18) overstate the true VOT. However, since any HOT facility will also yield similar safety benefits, the results of equation (18) are still relevant for HOT lane project evaluation. A much more thorough examination of these issues can be found in Steimetz (2004).

It is important to point out that most value-pricing studies attempt to estimate the value of reducing the variability in these time savings, often referred to as the "value of reliability" (VOR). Aside from its policy implications, doing so is appropriate since any such valuation is likely to appear in VOT estimates if variability in time savings is not properly controlled for. These studies typically focus on the "upper tails" of time savings distributions, with variability measures such as the difference between the 90th and 50th percentiles of these distributions, since it is reasonable to assume that commuters are only sensitive to relatively large travel delays.[26]

[26] Brownstone et al. (2003), Lam and Small (2001), Ghosh (2001), and Brownstone et al. (1999) use this

In our study, however, we are unable to detect a significant or economically meaningful direct effect of variability across a variety of measures, including those defined in previous value-pricing studies. This is at least partially due to the high degree of collinearity between tolls, time savings, and variability endemic to these types of studies. The SR-91 studies are able to overcome this collinearity since tolls follow a fixed schedule, allowing a degree of independent time-savings variation. Carpools in these studies are also subject to tolls, which can then be converted to per-passenger costs, providing additional independent variation. Unfortunately, we do not have such luxuries since I-15 tolls are dynamic and carpools travel for free.

Perhaps more importantly, our estimates suggest that commuters use these posted tolls to acquire information about travel conditions on the main lanes (captured by the "Low-Toll Signal" variable in Table 3).[27] When travel conditions are particularly bad, Express Lane tolls are particularly high, which is likely to make commuters less averse to variability in time savings since they are able to better predict the time savings they can enjoy on the Express Lanes. Moreover, those who normally travel during peak periods (when variability is greatest) but are averse to small chances of late arrival can use the Express Lanes as a "backstop" when relatively high tolls suggest doing so.[28] If a large enough proportion of our commuters exhibit this behavior, then high levels of variability and their attendant high tolls will coincide with a greater propensity to use the Express Lanes.[29]

Accordingly, we choose not to estimate VOR since even a significant direct effect of variability would result in negative VORs for our sample. Instead, we recognize the importance of controlling for variability and include the conventional "90th-50th percentile" measure (interacted with trip distance) in our estimates. Fortunately Brownstone and Small (2004) show that the VOT estimates obtained in this paper are very similar to those from the SR91 studies where it is possible to jointly estimate the VOR. Therefore our inability to estimate VOR does

definition of variability; the latter three of these studies use I-15 data with limited results. Small, Winston, and Yan (2002) define variability as the difference between the 80th and 50th percentiles of their SR-91 time savings distributions.

[27] Ghosh (2001) constructs a similar variable to capture this "toll signalling" effect, which yields a statistically significant coefficient estimate.

[28] We thank Ken Small for suggesting this possibility.

[29] This notion is supported by our preliminary experiments in which variability coefficients carried the "wrong" (positive) sign.

not appear to bias our VOT estimates.

5 Estimation Results

5.1 Parameter Estimates

The first series of columns in Table 3 give the estimation results from our conditional logit model with multiple imputations. All of the relevant parameter estimates have the expected signs and are statistically significant at the 95% confidence level, except for the "wrong" coefficient sign on variability interacted with trip distance.[30]

In the table, the columns entitled "Estimation Covariance Shares" give the shares of the total statistical error for each estimate that are attributable to the imputation process (corresponding to equation (10)) and the estimation process alone (corresponding to equation (11)). These covariance shares, as presented, are defined as $diag(\hat{\Sigma}^{-1}B)$ and $diag(\hat{\Sigma}^{-1}U)$, respectively. Reporting these shares aids in understanding the composition of the standard errors that accompany the parameter estimates – Section 6 expand on this.

We focus on the FasTrak choice variables since this is where the marginal rates of substitution between time savings and tolls are observed; the Carpool choice variables primarily serve as controls and are included to enhance the independent variation in our sample. Note that solo travel in the main lanes is the reference choice. As expected, the results show that higher income commuters, those travelling to work or for work-related purposes, and full-time workers are relatively less sensitive to tolls than their counterparts.

The "Low-Toll Signal" variable is included to control for the traffic-condition signalling effects discussed in the previous section. Specifically, this is an indicator variable equal to one if the posted toll is lower than the average toll across the sample period for that time of day. We chose this particular form due to the inertia exhibited by a large portion of the FasTrak users in our sample.[31] The intuition is that many of these commuters are accustomed to travelling solo in the express lanes and will deviate from this behavior when posted tolls

[30] A priori, we would expect commuters to be averse to time savings variability for any trip distance. However, the discussion in Section 4.3 sheds light on why this sign appears.

[31] Of those who reported traveling solo in the Express Lanes at least once during a given week, 62% reported that they traveled solo in the Express Lanes each time they traveled that portion of the I-15 that week.

signal that traffic conditions in the main lanes are relatively mild. Our estimates indicate a measurable toll-signal effect.

The "Free-Lane Traffic Rating" is an attempt to control for the aggravation (disutility) associated with driving in congested conditions, which could bias our VOT estimates upwards if not controlled for.[32] We also include it to separate its effect from the toll-signal effect. Respondents were asked to rate the traffic conditions on the free lanes on a scale from one to ten, where one represented "bumper-to bumper traffic" and ten represented "no traffic problems at all". Our estimates illustrate the expected case where perceptions of worsening traffic conditions correspond to higher propensities for using Express Lanes.

Consistent with the previously cited SR-91 and I-15 studies, we find that home owners and those with higher educations are more likely to use the Express Lanes. Those with flexible arrival times are less likely to use the Express Lanes. In contrast, we do not find a significant effect for females, and exclude the traditional "middle-age" indicator variable since it seems to be collinear with the income and home ownership variables in our sample.

A few additional insights arise from these estimates. One comes from noticing the similarity of the estimates for cases involving higher incomes and those involving cases where income is not reported. This mildly justifies the common practice of including income non-responses with higher-income respondents. Another comes from the negative sign on the carpool choice variable that indicates whether or not the respondent has access to a mobile phone for personal use. We hypothesize that mobile-phone users are more averse to carpooling lest they reveal sensitive information to their fellow carpoolers.

5.2 Value of Time-Savings Estimates

From the multiple imputation parameter estimates, we generate VOT estimates for each respondent in our sample using equation (18). The interaction terms involving time savings and tolls, and their statistically significant coefficients, reveal a significant degree of observable

[32] VOT estimates can be thought of as reduced-form expressions for travelers' willingness to pay for all of the amenities that are provided by the time-saving good. We attempt to more accurately estimate the "time-savings only" dimension of VOT by controlling for perceptions about traffic conditions, which we believe to be correlated with "congestion aggravation". See Steimetz (2004) for a thorough decomposition of how motorists distinctly value travel-time savings and additional amenities provided by time-saving goods.

heterogeneity in how commuters value the time savings provided by the I-15 Express Lanes. The left-hand side of Table 4 summarizes these VOT estimates, sorted into work and non-work trips.

It is important to note that estimated VOT is a highly nonlinear function of parameter estimates, which is evident from equation (18). Accordingly, small variations in parameter estimates can lead to relatively large changes in VOT estimates (with or without imputations). Hence, a more "robust" estimate of each median VOT is its expected value taken over the sampling distribution of its underlying parameters. The sampling distribution of VOT has no closed-form expression and generally cannot be characterized without using Monte Carlo methods. "Bootstrapping" this sampling distribution provides VOT estimates based on a thorough exploration of their underlying parametric distribution rather than estimating VOT from point estimates of these parameters. This is asymptotically equivalent to calculating an optimal Bayesian posterior estimate of each median VOT (with non-informative priors) and is reported in the "Bootstrap Median" column of Table 4. We take these as our preferred median VOT estimates.

Since our estimates are based on a choice-based sample, these VOT estimates are weighted to make them representative of the population of I-15 morning commuters. Population mode shares were estimated with five days worth of count data collected during the sample period.[33] From these, we construct "pure" choice-based weights equal to the ratio of population shares to our sample shares. Additionally, respondents reported the number of days that they traveled on the I-15 corridor in a given week, as well as the number of those days that they used each mode. To properly reflect the probability that each type of respondent was included in our sample, we adjust these "pure" weights as follows.

Let W_i represent these "pure" choice-based weights, T_{in} be the number of times person n chose mode i in a given week, and T_n be the total number of trips taken by that person that week. Our adjusted choice-based weights are given by

$$W_{in} = \sum \frac{W_i T_{in}}{T_n} A \tag{19}$$

[33] These shares are reported in Ghosh (2001).

where A is a constant adjustment factor required to ensure that the sum of these weights equals the sample size.

The median VOT estimate across our sample is \$30 per hour, which falls within the \$18 to \$33 range of median VOT estimates reported by the previous value-pricing studies cited in this paper. However, the considerable degree of heterogeneity in preferences revealed by our analysis yields median VOT estimates ranging from \$7 for part-time workers on non-work trips to \$65 for high-income work-trip commuters.

At first glance, our full-sample median VOT estimate appears to be on the "high end" of those estimated by previous studies. This is likely driven by the relatively higher incomes and shorter trip distances of our I-15 morning commuters. Note that Brownstone et al. (2003) report a median VOT equal to our \$30 estimate using an earlier wave of I-15 data. A more thorough basis of comparison is presented in Brownstone and Small (2004), where our I-15 sample is re-weighted by income and trip distance categories to match those of the SR-91 sample in Small, Winston, and Yan (2002). When our I-15 sample is "matched" to their SR-91 sample, our median VOT estimate across this sample is \$22, which corresponds nicely with their \$20 to \$25 range of median VOT estimates. This is also in line with the \$23 to \$24 range of median VOT estimates from the SR-91 reported in Lam and Small (2001).

Back to the present study, interacting median time savings with distance offers an additional dimension of observable heterogeneity in VOT, which gives rise to the "inverted U" shape illustrated in Figure 1. Figure 1 plots median VOT for work-trip travelers against distance, where income group and employment status vary; a similar pattern is exhibited for non-work trips (not shown in the figure). The quadratic form is appealing since the downward-sloping portion of the function accounts for the possible self-selection of low-VOT commuters who are willing to spend more time on the road and thus travel greater distances. Counteracting this effect is the increasing scarcity of leisure time as travel time cuts into it, or possibly that VOT is lower for shorter trips since people might appreciate some transition time between home and work;[34] both of these notions help to explain the upward-sloping portion of the function.

As expected, Figure 1 shows that higher incomes correspond to higher VOTs for a given

[34] Small (1999).

work status. What may be slightly surprising is the magnitude by which higher income groups place a higher value on their time savings. It is possible that these higher income commuters are more also willing to purchase additional amenities that the Express Lanes offer. For instance, Golob (2001) uses an earlier wave of our I-15 data to show that FasTrak users perceive a real safety advantage to using the Express Lanes, which is plausible since these lanes are physically separated from the main lanes. This physical separation might also hinder the ability of highway patrol officers to issue tickets to those speeding in the Express Lanes. Additionally, Brownstone et al. (2003) propose that using FasTrak signals wealth - a signal that those with higher incomes might purchase more readily.

The figure also illustrates from our estimates that even lower-income full-time workers value their time savings more than all part-time workers do. This relationship holds regardless of trip purpose. It suggests an additional dimension along which policymakers can cater to varying preferences when proposing further projects.

Table 4 includes interquartile ranges and their attendant percentiles next to each estimate. These figures characterize the sampling distributions of the parameter estimates, not the distributions of VOTs within the sample. The interquartile ranges reported in the table reflect the degree of uncertainty in estimating VOT due to statistical error in estimating its underlying parameters. They are determined by Monte Carlo draws from the sampling distributions of the parameter estimates, i.e., they are "bootstrapped".

To illustrate the role that the imputation process plays in generating this statistical error, the left-hand side of Table 5 decomposes the degree of this error, characterized by interquartile ranges, into two parts: dispersion based on the estimated total covariance of the parameter estimates and dispersion based on the covariance generated by the imputation process alone. Specifically, the second column in the table is constructed by "bootstrapping" these VOT distributions with draws from a $N(\hat{\theta}, U)$ distribution (see equation 10), which accounts only for the within-imputation covariance produced by parameter estimation alone. Subtracting the resulting interquartile ranges from those in the first column yields the amount of total dispersion due to the imputation process alone. These values are divided by the values in the first column to present them as shares of the total dispersion, given by the third column in the table. The columns labeled "Estimation Covariance Shares" in Table 3 provide a similar decomposition for the parameter estimates themselves. The relatively small share of error due to estimation uncertainty is due to the good fit of the imputation models.

6 Multiple Imputations vs. Single Imputation

Tables 3 and 4 include sets of estimates based on a single imputation. We include these to illustrate the potential hazards of basing estimates on a single set of imputed data when multiple imputations are warranted. These single-imputation estimates are derived from the same mode-choice model and VOT estimators that generate our "proper" results.

This single imputation is essentially drawn according to the procedure outlined in Section 3.1, with $m = 1$. However, we shed the best possible light on this single-imputation scenario to facilitate a "fair" comparison by drawing these imputations directly from the means of their asymptotic conditional distributions, given in Table 2, and adding the appropriate residuals. The right-hand side of Table 3 displays the parameter estimates for our mode choice model in the single-imputation case. Note that the reported t-Statistics in this model are generally higher, illustrating that inferences based on these estimates will be "too sharp" since they do not account for the error introduced by the imputation process, i.e., uncertainty due to measurement error. Note that the reduction in standard errors between the multiple and single imputation estimates is not as large as would be predicted from the "Estimation Covariance Shares" column in Table 3. This is simply due to the fact that the parameter estimates and standard errors for the single imputation are based on one draw of the imputed values and therefore subject to substantial noise.

The right-hand side of Table 4 reports VOT estimates for the single-imputation case. These estimates are uniformly lower than their multiple imputation counterparts. Although this is an artifact of this particular scenario, it illustrates the potential biases that can be introduced by treating the single set of imputed values as known. In particular, it appears that the particular single imputation we drew for this example lies close to the 25th percentile in the sampling distribution of the VOT estimates.

The last column of Table 4 characterizes the degree of statistical error in estimating VOT for the single-imputation case. Since the uncertainty due to measurement error is overlooked here as well, the reported dispersion measures are uniformly lower than their multiple imputation counterparts. This demonstrates that VOT inferences will also be "too sharp" when its underlying sampling variability is understated.

Table 6 reflects the degree to which this understatement occurs. Its first column gives a measure of estimation uncertainty that would be reported in a single-imputation scenario without properly accounting for underlying sampling variability. The second column shows the degree to which this would understate the estimation uncertainty that appropriately accounts for dispersion introduced by the imputation process itself. In our study, failing to perform multiple imputations would produce median VOT estimates that are 23% to 73% "too sharp", thereby reporting a misleading degree of estimation precision.

7 Conclusion

We observe the choices that commuters make when they are offered the opportunity to purchase a free-flow alternative to their congested daily commutes. In doing so, we are able to estimate how these commuters value their time savings and characterize the degree to which their preferences vary through observable characteristics. And, in accord with Small, Winston, and Yan (2002), this heterogeneity suggests that toll-lanes like the ones in our study have value well beyond enabling economists to better estimate the value of time savings. In particular, our estimates suggest that preferences vary significantly for *every* trip distance - a condition that provides "an opportunity to design pricing policies with a greater chance of public acceptance by catering to varying preferences."[35] Such policies might eventually dispel the public perception of toll-lanes as "Lexus lanes".

Of course, obtaining these estimates requires a way to construct valid statistical inferences when reliable time savings data are missing for most of our sample. We demonstrate how to apply Rubin's Multiple Imputation Method under these circumstances in order to procure valid and consistent estimates. We also illustrate the extent to which the "single imputation method" understates the degree of uncertainty in estimating VOT by failing to account for its

[35] Small, Winston, and Yan (2002).

underlying sampling variability.

Our median VOT estimates are plausible, intuitive, and within the range of estimates from previous value-pricing studies. However, we are unable to definitively resolve the differences between those studies and ours since the confidence intervals around our estimates encompass their estimates as well. Perhaps the notion of offering toll-roads will soon gain wider public acceptance, hopefully yielding more reliable data that can be used to resolve such discrepancies.

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TABLE 1: SUMMARY STATISTICS

Trip Characteristics	*In Sample*	*Weighted to Population*
Mode Share		
Solo in the Main Lanes	48.60%	72.95%
Solo using FasTrak	37.80%	15.67%
Carpool	13.59%	11.38%
Share of Trips in Each Time Period		
5:00-6:00 AM	2.42%	3.63%
6:00-7:00 AM	27.56%	27.26%
7:00-8:00 AM	40.97%	41.88%
8:00-9:00 AM	25.33%	22.70%
9:00-10:00 AM	3.72%	4.53%
Trip Distance		
Mean	26.02	25.99
Standard Deviation	9.99	10.22
Trip Purpose		
Work Related	93.48%	92.46%
Non-Work Related	6.52%	7.54%

Respondent Characteristics	*In Sample*	*Weighted to Population*
Age		
18-24	1.83%	2.76%
25-34	10.24%	13.07%
35-44	37.48%	36.21%
45-54	32.54%	29.18%
55-64	13.89%	14.57%
65 +	3.84%	4.17%
Refused to Answer	0.18%	0.05%
Sex		
Male	60.34%	62.14%
Female	39.66%	37.86%
Annual Income		
< $20K	1.30%	1.97%
$20-40K	5.21%	6.74%
$40-60K	13.22%	15.52%
$60-80K	16.39%	17.37%
$80-100K	17.69%	18.76%
$100-120K	13.97%	12.60%
> $120 K	24.02%	18.18%
Refused to Answer	8.19%	8.86%
Home Ownership		
Owns Home	83.05%	78.97%
Does Not Own Home	16.95%	21.03%
Education		
Graduate Degree or Higher	62.94%	57.37%
Less than Graduate Degree	37.06%	42.63%
Work Status		
Full Time	94.23%	93.86%
Part Time	5.77%	6.14%
Household Size		
Mean	3.07	3.07
Standard Deviation	1.26	1.28
Workers per Household		
Mean	2.05	2.06
Standard Deviation	0.69	0.72
Flexible Arrival Time		
Yes	80.82%	81.94%
No	19.18%	18.06%
Number of Respondents	537	

TABLE 2: IMPUTATION MODELS

Floating Car Time Savings and Ted Williams Onramp Wait Times (SUR)[a]

Dependent Variable			
Logit of Floating Car Time Savings			
Independent Variables	**Coef.**	**Std. Err.**	**t-Stat.**
Logit of Loop Detector Time Savings	0.662	0.222	2.99
Toll	-2.813	0.674	-4.18
Logit of Loop Detector Time Savings x Toll	-0.291	0.123	-2.37
Minutes Past 5:00 A.M.	0.100	0.021	4.74
Minutes Past 5:00 A.M. Squared	-6.63E-04	1.79E-04	-3.71
Minutes Past 5:00 A.M. Cubed	1.18E-06	4.16E-07	2.82
Minutes Past 5:00 A.M. x Toll	1.65E-02	3.65E-03	4.51
Monday[b]	-3.459	1.035	-3.34
Tuesday[b]	0.588	0.271	2.17
Friday[b]	0.832	0.292	2.85
Monday x Toll	0.884	0.299	2.96
Tuesday x Toll	-0.616	0.164	-3.76
Friday x Toll	-0.635	0.220	-2.89
Logit of Loop Detector Time Savings x Monday	-0.993	0.322	-3.08
Constant	-5.451	0.869	-6.27
R^2	0.56[c]		
Root Mean Squared Error	0.72		

Dependent Variable			
Logit of Ted Williams Wait Time			
Independent Variables	**Coef.**	**Std. Err.**	**t-Stat.**
Logit of Loop Detector Time Savings	0.489	0.140	3.50
Mean Toll	-1.322	0.165	-8.01
Minutes Past 5:00 A.M.	0.190	0.010	18.83
Minutes Past 5:00 A.M. Squared	-6.27E-04	3.13E-05	-20.03
Monday[b]	-3.803	1.418	-2.68
Tuesday[b]	1.227	0.232	5.29
Thursday[b]	1.010	0.208	4.85
Monday x Toll	0.939	0.395	2.38
Logit of Loop Detector Time Savings x Monday	-1.188	0.440	-2.70
Constant	-12.443	0.780	-15.95
R^2	0.79[c]		
Root Mean Squared Error	1.04		

Floating Car Time Savings (OLS)

Dependent Variable			
Logit of Floating Car Time Savings			
Independent Variables	**Coef.**	**Std. Err.**	**t-Stat.**
Logit of Loop Detector Time Savings	0.656	0.229	2.86
Logit of Ted Williams Wait Time	-0.191	0.086	-2.22
Toll	-3.524	0.795	-4.43
Logit of Loop Detector Time Savings x Toll	-0.212	0.114	-1.85
Logit of Ted Williams Wait Time x Toll	0.227	0.078	2.91
Minutes Past 5:00 A.M.	0.124	0.026	4.68
Minutes Past 5:00 A.M. Squared	-0.001	0.000	-3.96
Minutes Past 5:00 A.M. Cubed	1.36E-06	4.47E-07	3.03
Minutes Past 5:00 A.M. x Toll	2.26E-02	4.79E-03	4.72
Monday[b]	-3.238	1.108	-2.92
Tuesday[b]	0.827	0.302	2.74
Friday[b]	0.338	0.193	1.76
Monday x Toll	0.988	0.310	3.18
Tuesday x Toll	-0.915	0.201	-4.55
Logit of Loop Detector Time Savings x Monday	-0.859	0.346	-2.49
Constant	-6.472	1.199	-5.40
R^2	0.57		
Root Mean Squared Error	0.75		

[a] Floating Car Time Savings and Ted Williams Wait Times are estimated simultaneously using Zellner's Seemingly Unrelated Regressions Model to account for resdiual correlation across equations.

[b] These are indicator variables equal to one if the condition is true, zero otherwise.

[c] Keep in mind that this value is calculated in the logit-space of the dependent variable. This reduces in-sample variation, generating a lower R^2 than would result from a level-space calculation. Note that these logit transformations are "undone" when imputations are generated.

Note: Each model is based on 190 observations.

TABLE 3: CONDITIONAL LOGIT MODE-CHOICE MODEL ESTIMATES

	Multiple Imputations					Single Imputation		
				Estimation Covariance Shares				
Independent Variables	**Coef.**	**Std. Err.**	**t-Stat.**	**Parameter Estimation**	**Imputation**	**Coef.**	**Std. Err.**	**t-Stat.**
FastTrak Choice								
Constant	-0.501	0.522	-0.96	1.00	0.00	-0.662	0.525	-1.26
Worktrip[a] x Toll	-0.725	0.185	-3.93	0.73	0.27	-0.956	0.197	-4.85
Non-Worktrip[a] x Toll	-1.564	0.457	-3.42	0.99	0.01	-1.865	0.465	-4.01
Part-Time Worker[a] x Toll	-0.682	0.312	-2.18	0.99	0.01	-0.632	0.314	-2.01
Income > $80K[a] x Toll	0.516	0.149	3.47	1.00	0.00	0.563	0.149	3.78
Income Not Reported[a] x Toll	0.509	0.239	2.13	0.99	0.01	0.524	0.240	2.19
Median Timesavings x Distance	1.92E-02	4.99E-03	3.85	0.91	0.09	2.59E-02	4.66E-03	5.56
Median Timesavings x Distance Squared	-3.32E-04	1.41E-04	-2.36	0.87	0.13	-6.02E-04	1.58E-04	-3.80
Timesavings Variability[b] x Distance	4.70E-03	2.24E-03	2.10	0.81	0.19	1.27E-02	3.77E-03	3.36
"Low Toll" Signal[a,c]	-0.795	0.224	-3.55	0.97	0.03	-0.920	0.225	-4.09
Free-Lane Traffic Rating[d]	-0.226	0.052	-4.31	1.00	0.00	-0.212	0.052	-4.06
Flexible Arrival Time[a,e]	-0.509	0.265	-1.92	1.00	0.00	-0.479	0.266	-1.80
Home Owner[a]	1.022	0.360	2.84	0.98	0.02	0.988	0.357	2.77
College Degree or Higher[a]	0.509	0.232	2.19	0.99	0.01	0.526	0.232	2.27
Carpool Choice								
Constant	-0.116	0.500	-0.23	0.99	0.01	-0.234	0.503	-0.46
Median Timesavings	0.239	0.061	3.92	0.86	0.14	0.266	0.060	4.40
Free-Lane Traffic Rating	-0.208	0.068	-3.08	1.00	0.00	-0.203	0.068	-3.00
Single Worker Household[a]	-1.929	0.419	-4.60	1.00	0.00	-1.852	0.420	-4.41
Dual Worker Household[a]	-1.389	0.352	-3.94	1.00	0.00	-1.353	0.353	-3.84
Number of People per Vehicle in Household	0.502	0.205	2.45	1.00	0.00	0.495	0.205	2.41
Mobile Phone Available for Personal Use[a]	-0.608	0.304	-2.00	1.00	0.00	-0.614	0.304	-2.02
Number of Observations	537					537		
Number of Imputations	200					1		
(Average)[f] Log-Likelihood	-425.36					-423.13		
(Average)[f] Pseudo R^2	0.28					0.28		

[a] These are indicator variables equal to one if the condition is true, zero otherwise.
[b] Timesavings Variability is defined as the difference between the 90th and 50th percentiles of the (conditional) timesavings distributions.
[c] Equals one if the difference between the posted toll and (conditional) mean toll is negative, zero otherwise.
[d] Respondents were asked to rate the traffic conditions on the *free lanes* on a scale from 1 to 10, where 1 represented "bumper-to bumper traffic" and 10 represented "no traffic problems at all".
[e] Equals one if late arrival did not carry serious consequences, zero otherwise.

TABLE 4: VALUE OF TIME ESTIMATES and ESTIMATION UNCERTAINTY

	Multiple Imputations				Single Imputation			
	Median Estimate	**Bootstrap Median[a]**	**75%-ile , 25%-ile[b]**	**Interquartile Range[c]**	**Median Estimate**	**Bootstrap Median[a]**	**75%-ile , 25%-ile[b]**	**Interquartile Range[c]**
Full Sample	45.47	**29.68**	45.69 , 18.81	26.88	17.39	18.36	25.01, 14.56	10.45
Full Sample at Mean Distance	67.18	**38.77**	60.88 , 21.93	38.95	28.68	24.91	36.94, 16.29	20.65
Work Trips:								
Income > $80k	71.93	**64.90**	111.78 , 41.48	70.30	39.69	39.69	55.91, 29.91	26.00
Income < $80k	21.95	**21.52**	28.79 , 16.21	12.58	15.87	15.74	19.85, 12.62	7.23
Income Not Reported	69.78	**45.29**	88.91 , 20.62	68.29	32.38	31.70	50.12, 20.59	29.53
Full-Time Workers	58.33	**44.12**	70.36 , 25.81	44.55	25.77	25.08	36.31, 16.17	20.14
Part-Time Workers	15.89	**15.65**	21.50 , 11.58	9.92	13.76	12.97	17.07, 9.86	7.21
Non-Work Trips:								
Income > $80k	14.37	**14.35**	21.35 , 10.37	10.98	12.26	12.64	12.64, 9.70	2.94
Income < $80k	9.63	**9.60**	12.92 , 7.16	5.76	8.14	8.31	10.38, 6.51	3.87
Income Not Reported	14.88	**14.87**	22.34 , 10.23	12.11	11.65	12.03	16.94, 9.07	7.87
Full-Time Workers	10.45	**10.83**	14.43 , 7.97	6.46	8.72	9.08	11.40, 7.22	4.18
Part-Time Workers	7.28	**7.25**	9.57 , 5.53	4.04	6.51	6.47	8.27, 5.15	3.12

[a] These estimates are *expected* values of median VOT taken over the sampling distribution of their underlying parameters.

[b] These figures reflect characteristics of the estimated distributions of the parameter estimates, not the distibutions of VOTs within the sample. The interquartile ranges reported here characterize the degree of uncertainty in estimating VOT due to statistical error in estimating its underlying parameters. They are determined by Monte Carlo draws from the sampling distributions of the parameter estimates, i.e., they are "bootstrapped".

[c] These figures are differences between the 75th and 25th percentiles reported in the preceeding column - not to be confused with VOT heterogeneity within the estimation sample.

TABLE 5: DECOMPOSITION of VOT ESTIMATION UNCERTAINTY

	Multiple Imputations		**Share of Uncertainty**
	IQR[a]	**IQR**[b]	**Due to Imputations**[c]
	$N(\theta,\Sigma)$	$N(\theta,U)$	
Full Sample	26.88	24.36	0.09
Full Sample at Mean Distance	38.95	37.67	0.03
Work Trips:			
Income > $80k	70.30	66.17	0.06
Income < $80k	12.58	11.06	0.12
Income Not Reported	68.29	66.71	0.02
Full-Time Workers	44.55	41.91	0.06
Part-Time Workers	9.92	9.16	0.08
Non-Work Trips:			
Income > $80k	10.98	10.16	0.07
Income < $80k	5.76	5.18	0.10
Income Not Reported	12.11	11.33	0.06
Full-Time Workers	6.46	5.86	0.09
Part-Time Workers	4.04	3.67	0.09

[a] The interquartile ranges reported here characterize the degree of uncertainty in estimating VOT due to statistical error in estimating its underlying parameters.

[b] These IQRs are determined by Monte Carlo draws from a distribution cenetered on the parameter estimates with a covariance reflecting parameter estimation error net of imputation error.

[c] This shows the share of VOT estimation uncertainty, measured by IQR, due to estimation error generated by the imputation process.

TABLE 6: UNDERSTATEMENT of VOT ESTIMATION UNCERTAINTY from SINGLE IMPUTATION

	Single Imputation Reported IQR	**Percentage Lower than Multiple Imputation IQR**
Full Sample	10.45	61.12%
Full Sample at Mean Distance	20.65	46.98%
Work Trips:		
Income > $80k	26.00	63.02%
Income < $80k	7.23	42.53%
Income Not Reported	29.53	56.76%
Full-Time Workers	20.14	54.79%
Part-Time Workers	7.21	27.32%
Non-Work Trips:		
Income > $80k	2.94	73.22%
Income < $80k	3.87	32.81%
Income Not Reported	7.87	35.01%
Full-Time Workers	4.18	35.29%
Part-Time Workers	3.12	22.77%

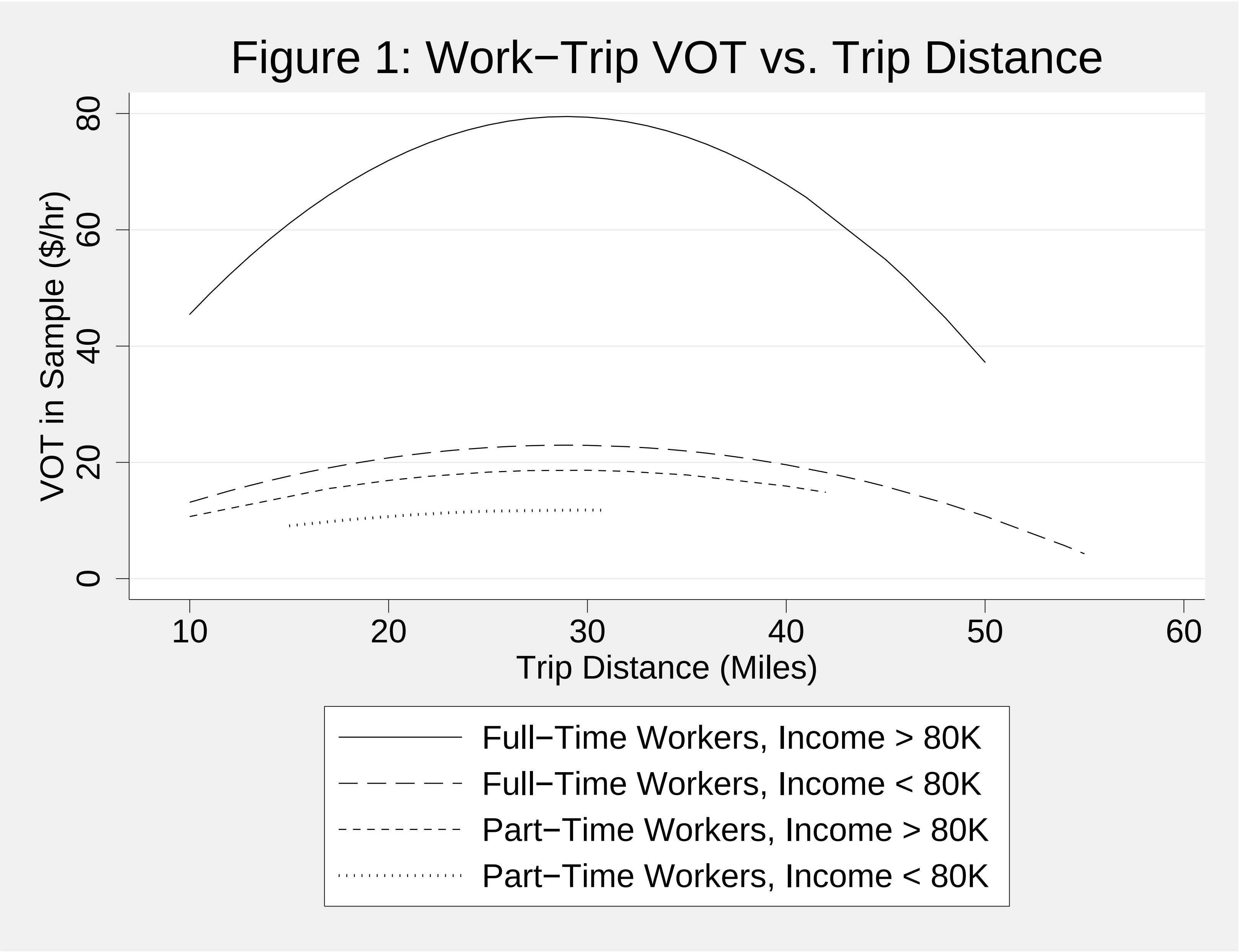
Figure 1: Work−Trip VOT vs. Trip Distance
VOT in Sample ($/hr)
0
20
40
60
80
10
20
30
40
50
60
Trip Distance (Miles)
Full−Time Workers, Income > 80K
Full−Time Workers, Income < 80K
Part−Time Workers, Income > 80K
Part−Time Workers, Income < 80K