Econometrica, Vol. 73, No. 4 (July, 2005), 1367–1382

UNCOVERING THE DISTRIBUTION OF MOTORISTS' PREFERENCES FOR TRAVEL TIME AND RELIABILITY

BY KENNETH A. SMALL, CLIFFORD WINSTON, AND JIA YAN[1]

We apply recent econometric advances to study the distribution of commuters' preferences for speedy and reliable highway travel. Our analysis applies mixed logit to combined revealed and stated preference data on commuter choices of whether to pay a toll for congestion-free express travel. We find that motorists exhibit high values of travel time and reliability, and substantial heterogeneity in those values. We suggest that road pricing policies designed to cater to such varying preferences can improve efficiency and reduce the disparity of welfare impacts compared with recent pricing experiments.

KEYWORDS: Mixed logit, stated preference, congestion pricing, product differentiation, value of time.

1. INTRODUCTION

EFFICIENT PRICING IS RARELY USED to ameliorate highway congestion, probably because of its immediate adverse impact on a representative traveler. Recent experiments in the United States have therefore tried to make pricing more appealing by giving motorists the option to travel free on regular lanes or to pay for congestion-free travel on express lanes—a policy sometimes called value pricing.

Theory suggests that the benefits of differentiated road pricing depend critically on the cross-sectional variation in motorists' preferences for speedy and reliable travel (Small and Yan (2001) and Verhoef and Small (2004)). However, econometric evidence on travelers' preference variation is quite limited. Value-of-time studies often capture *observed* heterogeneity by allowing estimated values to depend on the wage rate, income, and other factors (Small and Winston (1999), Wardman (2001)), but the previous studies have limitations. Those based solely on data describing actual choices, i.e., revealed preference (RP) data, have been hampered by collinearity among cost and travel-time variables; consequently they rarely have accounted for reliability (i.e., the predictability of travel time) and they have not accounted for heterogeneity in cost or travel-time elasticities arising from *unobserved* sources. Calfee, Winston, and Stempski (2001) and Hensher (2001) measure the extent

[1]The authors are grateful to the Brookings Center on Urban and Metropolitan Policy and the University of California Transportation Center for financial support. We thank Edward Sullivan for access to data collected by California Polytechnic State University at San Luis Obispo, with financial support from the California Department of Transportation and the U.S. Federal Highway Administration's Value Pricing Demonstration Program. We also are grateful for comments from David Brownstone, Jerry Hausman, Charles Lave, Steven Morrison, and Randy Pozdena; from participants in seminars at UC Irvine, Northwestern University, the American Economic Association, and the University of Maryland at College Park; and from the referees and a co-editor of this journal.

of unobserved heterogeneity using stated preference (SP) data that describe hypothetical responses, but SP data are tainted by doubt whether behavior exhibited in hypothetical situations applies to actual choices.

In this paper, we estimate the distribution of values of travel-time savings and reliability, allowing for both observed and unobserved heterogeneity. We do so by analyzing a sample of motorists who can participate in a value-pricing experiment in the Los Angeles area. These motorists face considerable variation in tolls and other factors. We enrich that variation by combining RP data from actual choices with SP data from hypothetical situations that are aligned with the pricing experiment. Combining the two types of data enables us to obtain statistically precise estimates while still allowing for possible differences between actual and hypothetical behavior.

We find that commuters differ substantially in how they value travel time and reliability. We find also that the average valuation of both is quite high, and is considerably higher when measured in real as opposed to hypothetical scenarios. We suggest that these findings offer possibilities to design differentiated pricing schemes that are more efficient and that create smaller disparities among users than do current value-pricing experiments.

2. EMPIRICAL SETTING AND DATA OVERVIEW[2]

The route of interest is California State Route 91 (SR91) in greater Los Angeles. A 10-mile portion of the route in Orange County, used heavily by long-distance commuters, includes four regular freeway lanes (91F) and two express lanes (91X) in each direction. Motorists who wish to use the express lanes must set up a financial account and carry an electronic transponder to pay a toll, which varies hourly according to a preset schedule.

We combine three samples of people traveling on this corridor, based on surveys taken over a 10-month period in 1999 and 2000. The first is a telephone RP survey conducted by researchers at California Polytechnic State University at San Luis Obispo (Cal Poly) with our participation (Sullivan et al. (2000)). It includes both commuting and other trips. The second and third samples are from a two-stage mail survey collected by us through the Brookings Institution. It used the data base of a market research firm, along with a prescreening survey, to obtain a random sample of potential rush-hour commuters on the corridor. The first stage of the Brookings survey collected RP data on actual trips. The second stage presented eight SP scenarios where the respondent could choose between two otherwise identical routes with specified hypothetical tolls, travel times, and probabilities of delay. Our econometric design allows us to treat each RP observation and each of the multiple SP observations for

[2]Additional details of our data collection and methodological procedures are contained in our supplement on the *Econometrica* web site.

TABLE I
DESCRIPTIVE STATISTICS

	Value or Fraction of Sample		
	Cal Poly RP	Brookings RP	Brookings SP
Choose 91X (RP dependent variable)	0.26	0.25	
Time period of trip (RP)			
4:00–7:00 am	0.56	0.54	
7:00–8:00 am	0.20	0.21	
8:00–10:00 am	0.24	0.25	
Age (years):			
<30	0.11	0.12	0.10
30–50	0.62	0.62	0.64
Household income ($/year):			
<60,000	0.38	0.83	0.83
>100,000	0.22	0.02	0.04
Female dummy	0.32	0.37	0.37
Mean actual trip distance (miles)	34.2	44.8	42.6
Number of respondents	438	84	81
Number of observations	438	377	633

any given individual as separate observations with appropriate error correlations. The final sample consisted of RP data on 522 distinct individuals and SP data totaling 633 observations on 81 distinct individuals (55 of whom also answered the RP questions).

Table I presents some summary statistics. The Cal Poly and Brookings RP samples have nearly identical shares of people using the express lanes. The Brookings samples appear to represent well the population characteristics of the SR91 catchment area, tracking census information for the two relevant counties except for household income—which, naturally, is higher for our respondents because most of them are commuters. The Cal Poly sample has higher household incomes and shorter trip distances than the Brookings samples, evidently being drawn from a narrower and more affluent geographical area; we therefore condition our choice model on these two variables.

3. ECONOMETRIC FRAMEWORK

Our basic model specifies the choice between express and regular lanes as conditional on related choices including residential location, travel mode (car or public transport), time of day, and car occupancy. The choice is also conditional on transponder acquisition for SP respondents, but is unconditional on transponder acquisition for RP respondents.[3] Integrating all these decisions with lane choice would enrich the analysis, but would probably not affect the results of interest here. For instance, mode choice is unimportant because public transportation has a very small share of travelers in this corridor. Location choice is typically a long-run decision and the express lanes had been open only a few years. We discuss later the effects of endogenous choices of car occupancy, transponder acquisition, and time of day; the latter is the most critical because our ability to identify the effects of cost, time, and reliability depends on their variation throughout the rush-hour period.

Formally, individual i, facing an actual or hypothetical instance t of choice between lanes, chooses express lanes whenever the following random utility difference is positive:

$$U_{it} \equiv \theta_i + \beta_i X_{it} + \varepsilon_{it}. \tag{1}$$

Variables in X_{it} may include measures of the toll difference C_{it}, travel-time difference T_{it}, and (un)reliability difference R_{it} between the two alternatives. We define the values of travel time and reliability for individual i as

$$\mathrm{VOT}_i = \frac{\partial U_{it}/\partial T_{it}}{\partial U_{it}/\partial C_{it}}, \quad \mathrm{VOR}_i = \frac{\partial U_{it}/\partial R_{it}}{\partial U_{it}/\partial C_{it}}. \tag{2}$$

Our specification precludes these values from varying across t; however, they may depend on whether the respondent is answering a RP or a SP question, a distinction we add to the notation shortly.

To capture heterogeneity, we specify scalar θ_i and vector β_i in (1) as

$$\theta_i = \bar{\theta} + \phi W_i + \xi_i, \quad \xi_i \sim N(0, \sigma_\xi^2), \tag{3}$$

$$\beta_i = \bar{\beta} + \gamma Z_i + \zeta_i, \quad \zeta_i \sim N(0, \Omega), \tag{4}$$

with Ω a diagonal matrix with up to 3 nonzero elements. Observed heterogeneity in behavior is captured by the effects of observed variables W_i and Z_i, while unobserved heterogeneity is captured by the random variables ξ_i and ζ_i. (It is only Z_i and ζ_i that affect heterogeneity in VOT and VOR.) As indicated, we specify the components of ζ_i as normally distributed; we also tried log-normal and truncated normal distributions, but similar to others (Train (2001)), we were unable to obtain convergence.

[3]SP respondents were instructed to assume they had a transponder, so if they followed this instruction their lane choice is conditional on having a transponder. If instead they took as given their *actual* transponder status, then we could have selection bias to the extent that their actual transponder status is correlated with unobserved preferences for the express lane. We assume that any selection bias arising in this way is controlled for by specifying a random constant for lane choice by SP respondents, as we describe in this section. We found that results were not affected by adding a control variable to describe the transponder status of the SP respondent's actual commute.

We denote our three data subsets by superscripts BR (Brookings RP), BS (Brookings SP), and C (Cal Poly). All the RP observations have a single choice instance t, so we can write $\varepsilon_{it}^{\mathrm{BR}} = \varepsilon_i^{\mathrm{BR}}$ and $\varepsilon_{it}^{\mathrm{C}} = \eta_i^{\mathrm{C}}$.[4] We further split $\varepsilon_i^{\mathrm{BR}}$ and $\varepsilon_{it}^{\mathrm{BS}}$ into components (denoted by ν and η), with one part in common, to allow for correlation between RP and SP observations of the same individual (determined by a multiplier ρ) and among multiple SP observations from one individual (determined by the relative variances of ν_i^{BS} and η_{it}^{BS}). These assumptions transform (1), after substituting (3) for θ_i, into the system

(5a) $$U_i^{\mathrm{BR}} \equiv \bar{\theta}^{\mathrm{BR}} + \phi^{\mathrm{BR}} W_i^{\mathrm{BR}} + \beta_i^{\mathrm{BR}} X_i^{\mathrm{BR}} + \nu_i^{\mathrm{BR}} + \eta_i^{\mathrm{BR}},$$

(5b) $$U_{it}^{\mathrm{BS}} \equiv \bar{\theta}^{\mathrm{BS}} + \phi^{\mathrm{BS}} W_i^{\mathrm{BS}} + \beta_i^{\mathrm{BS}} X_{it}^{\mathrm{BS}} + \rho \nu_i^{\mathrm{BR}} + \xi_i^{\mathrm{BS}} + \eta_{it}^{\mathrm{BS}},$$

(5c) $$U_i^{\mathrm{C}} \equiv \bar{\theta}^{\mathrm{C}} + \phi^{\mathrm{C}} W_i^{\mathrm{C}} + \beta_i^{\mathrm{C}} X_i^{\mathrm{C}} + \eta_i^{\mathrm{C}},$$

where random parameters β_i are as in (4) and $\nu_i^{\mathrm{BR}} \sim N(0,1)$. We have set $\xi_i^{\mathrm{BR}} = \xi_i^{\mathrm{C}} = 0$ in (3) because, with only one observation per individual, these two random variables are redundant with η_i^{BR} and η_i^{C}. We assume that η_i^{BR}, η_{it}^{BS}, and η_i^{C} have independent logistic distributions, yielding the familiar logit formula for the choice probability conditional on other random parameters; our treatment of unobserved heterogeneity is, therefore, an example of the mixed-logit model described by McFadden and Train (2000) and Train (2003).

As is usual in combining RP and SP data sets (Ben-Akiva and Morikawa (1990)), we allow the variances of η_i^{BR} and η_{it}^{BS} to differ, indicating that there may be different sources of random preferences over revealed and stated choices. As a precaution we also let η_i^{C} have its own distinct variance. All this is accomplished by normalizing the variance of η_i^{BR} to $\pi^2/3$ (as in binary logit) and estimating the ratios

(6) $$\mu^k \equiv \sigma^{\mathrm{BR}}/\sigma^k, \quad k = \mathrm{BS}, \mathrm{C},$$

where σ^k is the standard deviation of η_{it}^k or η_i^k. The normalization of η_i^{BR} therefore combines with that of ν_i^{BR} to give (5a) an imposed error variance that is different from, but no less general than, that usually assumed in mixed-logit models.[5]

[4]The Brookings RP sample actually contains information for all commuting trips made within the survey week, which could be treated as separate observations. However, 87% of the respondents made the same choice every day and nearly all of the others varied on only one day. So we simplify, with little information loss, by creating a binary response variable equal to one if the respondent chose the express lanes for half or more of the days reported. We tried variants of this response variable with virtually no changes in results.

[5]Normalizing the variance of ν_i^{BR} involves no loss of generality because each of the two equations containing it also contains an additional individual-specific error term. Thus in (5a), the normalization of ν_i^{BR} becomes part of the overall system normalization, as just described, while in (5b) it merely affects the estimated variance σ_ξ^2.

Our specification allows for considerable generality in how choices are determined relative to each other in the three data samples. Of course, combining these samples can improve statistical efficiency only if the model imposes some constraints. We assume that certain coefficients are identical in two or more of the samples, thereby enabling the SP responses to help identify some heterogeneity parameters whose effects would be obscured by multicollinearity in RP-only data (as occurred when we estimated models on these data). Specifically, although we allow for different mean coefficients on travel variables in the RP and SP samples, we constrain the heterogeneity in the RP and SP coefficients to be identical as measured either by the standard deviation (for travel time) or by the ratio of standard deviation to mean (for reliability). We also tried to include random coefficients on cost, but found that model unstable and concluded that it was too rich for our data set.

The parameters of the model are estimated by maximizing a simulated log-likelihood function, as developed in McFadden and Train (2000). We obtained stable results by performing simulations using 4,500 random draws of parameters ν_i^{BR}, ξ_i^{BS}, and ζ_i^k ($k = \mathrm{BR}, \mathrm{BS}, \mathrm{C}$) for each individual i.

4. SPECIFICATION OF INDEPENDENT VARIABLES

The express-lane toll for a given trip is the published toll for the time of day the commuter reported passing the sign that indicates the toll level, discounted by 50% if the trip was in a carpool of three or more.[6] Other potentially important influences on lane choice include trip distance, annual per capita household income, age, sex, household size, and a dummy variable (based on identical questions in the two RP surveys) that indicates whether the commuter had a flexible arrival time—which may control somewhat for endogeneity of the time-of-day choice. We also explored a number of other variables, such as occupation, education, vehicle occupancy, and size of workplace, but they are omitted here because they had little explanatory power and did not influence the other coefficients.

We give special attention to measures of travel time and reliability. Theory suggests that a traveler's expected total travel cost rises with travel-time uncertainty if it is costly to arrive early or late at the destination (Noland and Small (1995)). If being late is more onerous than being early, as confirmed by empirical results, expected travel cost is especially sensitive to the right tail of the distribution of travel times. We sampled from the distribution of travel times across all weekdays of the year, a distribution we assume is known to travelers based on their experience. We assume that motorists consider the central tendency and the dispersion of that distribution. Because this is a binary choice

[6]We asked respondents, even in the SP survey, their vehicle occupancy for actual trips. Those who did not report it are assumed not to have carpooled. To guard against systematic bias from this assumption, we included a dummy variable that identified these respondents, but it had no explanatory power, so it is omitted here.

and there is essentially no dispersion in express-lane travel time, we need consider only the distribution of travel-time *savings* from taking the express lanes.

Plausible measures of central tendency include the mean and the median; we find the model fits slightly better using the median. We measure dispersion as the difference between the 80th and the 50th percentiles, which accords with the aforementioned theory and results in our model fitting better than with alternate measures such as standard deviation.

Data to estimate the measures were obtained from field measurements on SR91 taken at many times of day on 11 different days. Students drove repeatedly on the free lanes, clocking the travel time between prescribed points. We use a type of nonparametric smoothing known as local linear quantile regression (Koenker and Bassett (1978)) to estimate various percentiles of the distribution of travel-time savings across days, each as a function of the time of day. The measurements are simplified because traffic in the express lanes was observed to move freely at all times of day, enabling us to assume a constant travel time of 8 minutes.

Figure 1 characterizes the measures, along with the raw data points and 90% confidence bands. Median time savings is measured quite precisely; dispersion somewhat less so. Median savings reaches its peak considerably earlier than

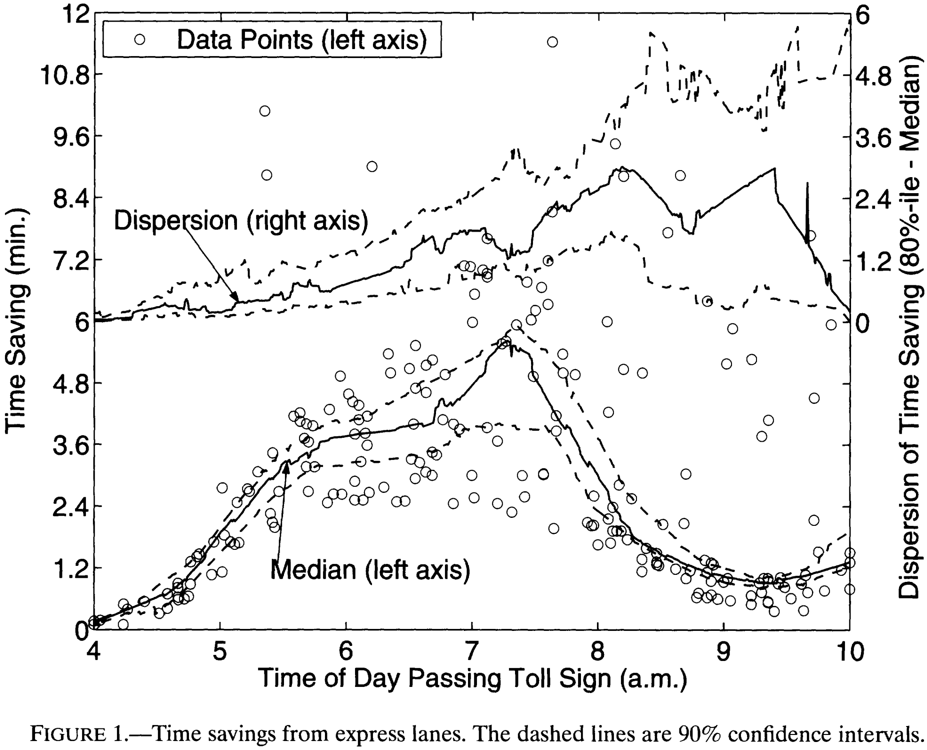

FIGURE 1.—Time savings from express lanes. The dashed lines are 90% confidence intervals. Dispersion is the difference between the 80th and 50th percentiles.

does dispersion—a difference in pattern that causes them to have only a weak correlation in our data. This relationship can be explained by two features of the raw data on time savings. First, the scatter in those data points grows in magnitude until quite late in the peak period (presumably due to long-lasting effects of random incidents occurring early). Second, during the height of the rush hour there are substantial negative deviations of the travel-time savings from their median, indicating unusually good days for traffic. Our measure of dispersion, however, is unaffected by negative deviations, consistent with the view that they impose only small costs on travelers.

Most SP variables correspond in definition to the RP variables. An exception is the measure of unreliability. We did not think survey respondents would understand statements about percentiles of a probability distribution, so in our SP scenarios we specified the frequency of being delayed 10 minutes or more, which we convert into a probability for analysis.

5. ESTIMATION RESULTS

Estimation results are presented in Table II. Most influences are statistically significant and have the expected sign. Both the RP and SP coefficients indi-

TABLE II

PARAMETER ESTIMATES OF LANE-CHOICE MODEL

Dependent Variable: 1 if Toll Lanes Chosen; 0 Otherwise Independent Variable	Coefficient (Standard Error)[a]
RP variables	
Constant	
Brookings subsample ($\bar{\theta}^{BR}$)	0.1489 (0.8931)
Cal Poly subsample ($\bar{\theta}^{C}$)	−1.6349 (1.1040)
Cost ($)	−1.8705 (0.5812)
Cost × dummy for medium household income ($60–100,000)	0.5438 (0.2549)
Cost × dummy for high household income (>$100,000)	1.1992 (0.3849)
Median travel time (min) × trip distance (units: 10 mi)	−0.4088 (0.1536)
Median travel time × (trip distance squared)	0.0695 (0.0276)
Median travel time × (trip distance cubed)	−0.0029 (0.0012)
Unreliability of travel time (min)	−0.5778 (0.2435)
SP variables	
Constant ($\bar{\theta}^{BS}$)	−1.6107 (0.8943)
Standard deviation of constant (σ_ξ)	0.4800 (0.6305)
Cost	−1.0008 (0.2849)
Cost × dummy for medium household income ($60–100,000)	−0.2317 (0.5407)
Cost × dummy for high household income (>$100,000)	0.2842 (0.9714)
Travel time (min) × long-commute dummy (>45 min)	−0.1965 (0.0522)
Travel time × (1 − long-commute dummy)	−0.2146 (0.0618)
Unreliability of travel time (probability of late arrival)	−5.6292 (2.3819)

Continues

TABLE II–*Continued*

Dependent Variable: 1 if Toll Lanes Chosen; 0 Otherwise Independent Variable	Coefficient (Standard Error)[a]
Pooled variables	
Female dummy	1.3267 (0.6292)
Age 30–50 dummy	1.2362 (0.5121)
Flexible arrival-time dummy	0.5903 (0.6994)
Household size (number of people)	−0.5497 (0.2248)
Standard dev. of coeff.'s of travel time (in Ω)	0.1658 (0.0457)
Ratio of std. dev. to mean for coeff.'s of unreliability (in Ω)	1.0560 (0.2754)
Other parameters	
Scale parameter	
Cal Poly sample (μ^{C})	0.4118 (0.1688)
SP sample (μ^{BS})	1.3368 (0.3741)
Correlation parameter, Brookings RP and SP (ρ)	3.2882 (0.8320)
Summary statistics	
Number of observations	1,155
Number of persons	548
Number of replications (R)	4,500
Log-likelihood	−501.57
Pseudo R^2	0.3704
Implied elasticities of demand for express lane[b]	
Toll in express lanes	−1.588 (0.504)
Median travel time in free lanes	0.727 (0.331)
Unreliability in free lanes	0.374 (0.166)

[a] Standard errors are the "sandwich" estimates of Lee (1995), obtained from $\hat{V} = (-H)^{-1}P(-H)^{-1}$, where H is the Hessian of the simulated log-likelihood function and P is the outer product of its gradient vector (both calculated numerically). This estimate accounts for simulation error in the likelihood.

[b] Express lane usage is computed by aggregating individual choice probabilities over the Brookings RP sample. Each probability is calculated by simulated integration over the distributions defined by (4), conditional on all estimated parameters of the model; the calculation is then repeated after a 10% increase in the toll, median travel-time saving, or unreliability facing each individual, and an elasticity is calculated. This process is repeated for each of 1,000 random draws of the estimated parameters from their sampling distribution. The numbers reported are the empirical mean and standard deviation across the 1,000 resulting elasticities.

cate that commuters are deterred from the express lanes by a higher toll and are deterred from the free lanes by longer median travel times and greater unreliability—findings that hold throughout the range of the interaction variables.

The implied elasticities of express-lane usage with respect to toll, travel-time savings, and unreliability are shown at the bottom of the table. All three variables have a substantial impact on the decision to use the express lanes. To better understand the price elasticity of −1.59, consider that the private operator of the express lanes maximizes profit by setting a price so that marginal revenue equals short-run marginal cost, which on the express lanes is near zero. However, the marginal revenue is less than that given by the usual formula that involves the demand elasticity, because each additional car using the express lanes reduces the attraction of those lanes to others by relieving congestion on the regular lanes. If that congestion is severe, the elasticity of demand must be substantially greater than 1 in magnitude to produce marginal revenue near 0 as required for a profit-maximizing equilibrium.

Observed heterogeneity is captured by interactions between cost and income, and between time and three powers of trip distance—these are the variables Z in (4). Consistent with expectations, motorists with higher incomes are less responsive to the toll. The negative of the RP coefficient of median travel time varies with distance in an inverted U pattern, initially rising but then falling for trips greater than 45 miles. Following Calfee and Winston (1998), we conjecture that this pattern results from two opposing forces: the increasing scarcity of leisure time as commuting becomes longer and the self-selection of people with lower values of time into farther out residences. For SP, we allow the coefficient on travel time to differ between people with long and short actual commutes, but the difference is negligible.

We also find observed heterogeneity in alternative-specific preferences via variables W in (3)—listed under "pooled variables" in the table. Women, middle-aged motorists, and motorists in smaller households are more likely to choose the toll lanes. Others such as Parkany (1999) have also found that women are more likely to use toll lanes. To better understand why, we tried interacting gender, age, and household size under the hypothesis that working mothers prefer the toll lanes, or are more averse to unreliability, due to tighter schedules, but we could not find a measurable effect. We also fail to find a significant effect of having a flexible arrival time, either as a shift variable (as shown) or interacted with reliability—possibly because this variable is correlated with omitted job characteristics that counter its influence.

Turning to the stochastic part of the model, substantial unobserved heterogeneity is indicated by the standard deviations of the random parameters (also listed under "pooled variables"). They are estimated with good precision and are substantial in magnitude, amounting to roughly 25–100% of the corresponding mean coefficients.[7] The scale and correlation parameters that describe the error structure ("other parameters" in the table) are also estimated quite precisely and show that the RP and SP responses from a single individual are strongly correlated.

The value of combining RP and SP data became apparent when we tried to estimate the RP portion of the model using just the RP data: we were unable to obtain convergence when the model included unobserved heterogeneity. If we excluded unobserved heterogeneity, we obtained nearly identical RP results using either RP data alone or combined RP and SP data. We conclude

[7]In the case of unreliability, this ratio is estimated directly, as shown, at 1.056. In the case of travel time, the estimated standard deviation of 0.166 may be compared with the SP coefficient of median travel time of about -0.2 and with the derivative of utility with respect to RP median travel time, which is -0.69 at median trip distance.

that the combination of RP and SP data provides additional power to identify heterogeneity, while not biasing results for the rest of the model.

Values of Time and Reliability

We use our parameter estimates to compute various properties of the distributions of motorists' implied values of time (VOT) and reliability (VOR) across individuals. Results are shown in Table III. As shown by the 90% confidence intervals in the second column, all of the reported estimates are statistically different from zero using a one-sided test.

We use the Brookings samples for these computations because they best represent the population. We characterize heterogeneity in VOT and VOR by the

TABLE III

DISTRIBUTIONS OF VALUES OF TIME AND RELIABILITY

	Base Model		Model with Time-of-Day Dummy:	Model with Occupancy, Transponder Choice:
	Median Estimate	90% Confidence Interval [5%-ile, 95%-ile]	Median Estimate[a]	Median Estimate[a]
	RP estimates			
Value of time ($/hour)				
Median in sample	21.46	[11.47, 29.32]	27.44	23.64
Observed heterogeneity	4.04	[2.60, 8.34]	5.07	5.35
Unobserved heterogeneity	7.12	[3.15, 16.87]	7.34	8.64
Total heterogeneity in sample	10.47	[5.82, 24.11]	11.22	12.52
Value of reliability ($/hour)				
Median in sample	19.56	[6.26, 42.80]	24.31	24.59
Total heterogeneity in sample[b]	26.49	[8.60, 60.40]	29.76	28.49
	SP estimates			
Value of time ($/hour)				
Median in sample	11.92	[7.09, 21.06]	11.99	10.88
Observed heterogeneity	2.60	[0.24, 8.86]	4.21	2.79
Unobserved heterogeneity	12.32	[6.90, 23.30]	14.50	12.39
Total heterogeneity in sample	13.31	[7.41, 23.88]	15.96	12.94
Value of reliability ($/incident)				
Median in sample	5.40	[3.26, 10.12]	5.54	5.23
Total heterogeneity in sample[b]	7.95	[4.65, 14.38]	7.75	6.52

[a]The 90% confidence intervals are not shown to save space; they are quite similar to the ones shown in column 2 and in no case does the confidence interval include zero.

[b]Total and unobserved heterogeneity of VOR, as defined here, are identical (i.e., there is no observed heterogeneity) despite the dependence of VOR on income. This is because observed heterogeneity in VOR arises only from variation in the dummy variable for income categories, and the 25th and 75th percentile values of VOR (across i) happen to come from the same income category (namely, the lowest).

interquartile range (i.e., the difference between 75th and 25th percentile values) across individuals, a measure that is relatively robust to the high upper tails typically found in ratios of random variables. The results are obtained by combining multiple draws from the sampling distribution of estimated parameters ($\bar{\beta}$, γ, Ω) in (4), sample enumeration across values of Z_i in (4), and a single random draw of ζ_i in (4) for each individual in that enumeration conditional on ($\bar{\beta}$, γ, Ω). Each row of Table III shows a different property of the distribution of VOT or VOR across individuals, while the first two columns show properties of the sampling distribution of the quantity named in that row. Separate magnitudes of observed and unobserved heterogeneity are measured by restricting (4): we set $\zeta_i = 0$ to account for only observed heterogeneity, or we replace Z_i by its sample mean to account for only unobserved heterogeneity.

Based on commuters' revealed preferences, we find that the median value of time is \$21.46/hour or about 93% of the average wage rate, which is near the upper end of the range expected from previous work (Small (1992)). The median RP value of reliability is \$19.56/hour. To put these figures in perspective, in our data the median time saving for the express lanes averages 3.3 minutes during the 5:00–9:00 am peak period, while unreliability in the free lanes averages 1.6 minutes (see Figure 1). Thus, the average commuter during those hours would pay \$1.18 for the time savings and \$0.52 for the improved reliability, implying that reliability accounts for roughly one-third of the attraction of the express lanes—less during the early and middle parts of the rush hour and more during the later part.

Commuters exhibit a wide range of preferences for speedy and reliable highway travel. Total heterogeneity in VOT and VOR ranges from about half to more than 100% of the corresponding median value. Most of the heterogeneity is from unobserved sources, verifying the importance of using random parameters to capture motorists' taste variation. Of course, if we could measure additional sources of preference variation, we presumably would find less unobserved and more observed heterogeneity.

The implied SP values of time are much smaller on average than the RP values, possibly reflecting a tendency of travelers to overstate the travel time they experience during times of congestion (evidence confirming this tendency is reported in Sullivan et al. (2000, p. xxiii)). Thus, a motorist considering a 10-minute time saving in an SP question may envision a real-world situation where the time saving is only 5 minutes and answer accordingly—yielding an SP value of time only half the RP value. As for reliability, the median motorist in our SP sample exhibits a willingness to pay of \$0.54 per trip to reduce the frequency of 10-minute delays from 0.2 to 0.1.

Sensitivity to Identifying Assumption and Alternative Specifications

We have implicitly assumed that any unobserved influences on lane choice do not vary systematically by time of day; if they did, they would be correlated with cost, time, and reliability, and therefore bias those coefficients. The validity of this assumption depends partly on how well our observed variables capture taste variation across times of day. Fortunately, we have many variables that play this role, including income, trip distance, trip purpose, flexibility of arrival time, sex, age, household size, occupation, marital status, and education. For example, a motorist's sex is likely to be an important source of taste variation; we know it is correlated with time of day because females constitute only 15% of those commuters traveling during the interval 4:00–5:00 am, but 39% of the 7:00–8:00 am group. Similarly with trip purpose: the proportion of respondents whose trips are work trips varies from 100% at the earliest time to 58% at the latest time.

A more formal test takes advantage of the fact that 55 members of the SP sample, providing 433 observations, told us the time of day at which their actual trip normally took place. In the SP sample, travel time and reliability are uncorrelated with the time of day as part of the survey design, so we can include time-of-day dummies in an SP-only model restricted to these observations while still measuring other parameters with precision. We can then compare the results with and without these dummies to see whether VOT and VOR are affected. We used five time-of-day dummies, one for each hour of the morning period other than a base hour defined as 7:00–8:00 am. Their estimated coefficients were not jointly significantly different from zero. Moreover, including the dummies decreased the median SP values of time and reliability less than 10% and increased the amount of unobserved heterogeneity (as measured by the interquartile range) less than 8%. Hence, based on the SP data our results are robust to omitted time-of-day-related influences.

We performed a further check by reestimating the joint RP/SP model, using all the data and including a dummy variable for travel at 7:00–8:00 am, the one period that appeared different from all the others in the SP-only experiment just described. (We set this dummy variable to zero for those 26 people not answering the time-of-day question and treated them like a separate sample, with their own alternative-specific constant and error variance.) The estimated coefficient for the time-of-day dummy is -1.64 with standard error 1.29. The third column of Table III shows the resulting VOT and VOR estimates; the 90% confidence intervals, not shown, still exclude zero in all cases. Including the time-of-day dummy increases modestly the estimated median RP values of time and reliability, and also increases slightly the amount of unobserved heterogeneity in those values. Therefore, our main conclusions—that values of time and reliability are high and contain considerable unobserved heterogeneity—are if anything strengthened. We do lose precision by incorporating the time dummy, so we offer the base model as containing our best estimates.

It is also possible that the demand *elasticity* for the toll road varies by time of day, in a way that is not captured by our observables. Thus, if the toll-lane operator systematically sets prices higher than they otherwise would be whenever the elasticity is small in magnitude and if unobservable factors are correlated with both the level and the elasticity of demand, then price would not be exogenous and its coefficient would be over- or underestimated depending on the signs of the correlations. Any resulting bias to the estimated VOT and VOR would be smaller, because the time savings and unreliability variables are causally related to price through congestion in the regular lanes, so their coefficients would be biased in the same direction as that of price.

We examined the robustness to assumed cross-equation constraints by estimating models both with fewer and with more constraints relative to the RP and SP coefficients. We computed the resulting distributions of the values of time and reliability, obtaining results virtually indistinguishable from those of the base model. Furthermore, we found using likelihood ratio tests that we could not reject our preferred specification against less constrained models. Indeed, we found that we could have imposed an additional constraint to equate the cost coefficients, but we preferred not to do so because this coefficient is critical to our VOT and VOR calculations.

Finally, we explored potential simultaneity bias by estimating a model that explains the simultaneous choice of vehicle occupancy, transponder acquisition, and lane by RP respondents, as well as lane only by SP respondents. We created nine alternatives from the permitted combinations of these choices. Conditional on the random coefficients, including a random constant for the transponder, choice among the nine alternatives is multinomial logit, but this is less restrictive than it appears because our error structure mimics a nested logit, as described by Brownstone and Train (1999). The resulting VOT and VOR distributions, summarized in the last column of Table III, are similar to those from the base model and support our earlier arguments that other choices would have little impact on our findings. It is useful to note that the joint RP model can be expressed as a selection model in which transponder choice determines whether lane choice is observed. The random constant for transponder choice then allows the correlation between the selection equation and the lane-choice equation to be estimated, rather than being imposed by the logit functional form. (As it happens, we could not reject the hypothesis that the random constant has zero variance.) However, the selection model contains exclusion restrictions based solely on statistical insignificance, so we are assuming that it is identified by the mixed-logit functional form with the random constant.

6. CONCLUSION

By combining the power of RP and SP data, using a random-parameters model, and constructing improved measures of reliability, we are able to measure properties of travel preferences that have eluded other studies. We find that travel time and its predictability are highly valued by motorists and that there is significant heterogeneity in these values.

Motorists' varying preferences for travel time and reliability have important implications for road pricing policy. As noted earlier, theoretical studies find that substantial heterogeneity is necessary for value pricing as currently practiced to create significant benefits. The amount of heterogeneity found here is likely to generate such benefits. For example, in Small and Yan (2001), an interquartile difference of half the median value of time (roughly what we find in revealed behavior) approximately quadruples the maximum benefit attainable from second-best pricing when there is no heterogeneity.

Accounting for preference variation could also enhance the political viability of pricing. We show in a companion paper (Small, Winston, and Yan (2005)) that differentiated road prices can be designed, based on the distributions of values of time and reliability obtained here, to produce greater efficiency gains than current experiments while retaining or even increasing their distributional advantages over comprehensive road pricing. Thus there may be a politically feasible compromise between value pricing as now practiced, which is not very efficient, and first-best congestion pricing, which introduces severe disparities in direct welfare impact.

In a nutshell, our confirmation of significant preference heterogeneity among travelers offers policymakers a long-awaited opportunity to address the stalemates that impede transportation policy in congested cities.

Dept. Economics, University of California, Irvine, CA 92697-5100, U.S.A.; ksmall@uci.edu; http://www.socsci.uci.edu/~ksmall/,

Brookings Institution, 1775 Massachusetts Avenue, N.W., Washington, DC 20036, U.S.A.; cwinston@brook.edu,

and

Dept. of Logistics, Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong; lgtjiay@polyu.edu.hk.

Manuscript received August, 2002; final revision received January, 2005.

REFERENCES

BEN-AKIVA, M., AND T. MORIKAWA (1990): "Estimation of Travel Demand Models from Multiple Data Sources," in *Transportation and Traffic Theory*, ed. by M. Koshi. New York: Elsevier, 461–478.

BROWNSTONE, D., AND K. TRAIN (1999): "Forecasting New Product Penetration with Flexible Substitution Patterns," *Journal of Econometrics*, 89, 109–129.

CALFEE, J., AND C. WINSTON (1998): "The Value of Automobile Travel Time: Implications for Congestion Policy," *Journal of Public Economics*, 69, 83–102.

CALFEE, J., C. WINSTON, AND R. STEMPSKI (2001): "Econometric Issues in Estimating Consumer Preferences from Stated Preference Data: A Case Study of the Value of Automobile Travel Time," *Review of Economics and Statistics*, 83, 699–707.

HENSHER, D. A. (2001): "The Valuation of Commuter Travel Time Savings for Car Drivers: Evaluating Alternative Model Specifications," *Transportation*, 28, 101–118.

KOENKER, R., AND G. S. BASSET (1978): "Regression Quantiles," *Econometrica*, 46, 33–50.

LEE, L. (1995): "Asymptotic Bias in Simulated Maximum Likelihood Estimation of Discrete Choice Models," *Econometric Theory*, 11, 437–483.

MCFADDEN, D., AND K. TRAIN (2000): "Mixed MNL Models for Discrete Response," *Journal of Applied Econometrics*, 15, 447–470.

NOLAND, R. B., AND K. A. SMALL (1995): "Travel-Time Uncertainty, Departure Time Choice, and the Cost of Morning Commutes," *Transportation Research Record*, 1493, 150–158.

PARKANY, E. A. (1999): "Traveler Responses to New Choices: Toll vs. Free Alternatives in a Congested Corridor," Ph.D. Dissertation, University of California at Irvine.

SMALL, K. A. (1992): *Urban Transportation Economics. Fundamentals of Pure and Applied Economics Series*, Vol. 51. Reading, U.K.: Harwood Academic Publishers.

SMALL, K. A., AND C. WINSTON (1999): "The Demand for Transportation: Models and Applications," in *Essays in Transportation Economics and Policy: A Handbook in Honor of John R. Meyer*, ed. by J. Gomez-Ibanez, W. Tye, and C. Winston. Washington, DC: Brookings Institution Press, 11–55.

SMALL, K. A., C. WINSTON, AND J. YAN (2005): "Differentiated Pricing, Express Lanes, and Carpools: Exploiting Heterogeneous Preferences in Policy Design," Working Paper, Department of Economics, University of California at Irvine.

SMALL, K. A., AND J. YAN (2001): "The Value of 'Value Pricing' of Roads: Second-Best Pricing and Product Differentiation," *Journal of Urban Economics*, 49, 310–336.

SULLIVAN, E., K. BLAKELY, J. DALY, J. GILPIN, K. MASTAKO, K. A. SMALL, AND J. YAN (2000): "Continuation Study to Evaluate the Impacts of the SR 91 Value-Priced Express Lanes: Final Report," Department of Civil and Environmental Engineering, California Polytechnic State University at San Luis Obispo, available at *http://ceenve.ceng.calpoly.edu/sullivan/SR91/*.

TRAIN, K. (2001): "A Comparison of Hierarchical Bayes and Maximum Simulated Likelihood for Mixed Logit," Working Paper, Dept. of Economics, University of California at Berkeley, available at *http://elsa.berkeley.edu/ train/papers.html*.

——— (2003): *Discrete Choice Methods with Simulation*. Cambridge, U.K.: Cambridge University Press.

VERHOEF, E. T., AND K. A. SMALL (2004): "Product Differentiation on Roads: Constrained Congestion Pricing with Heterogeneous Users," *Journal of Transport Economics and Policy*, 38, 127–156.

WARDMAN, M. (2001): "A Review of British Evidence of Time and Service Quality Valuations," *Transportation Research E: Logistics and Transportation Review*, 37, 107–128.