DIFFERENTIATED ROAD PRICING, EXPRESS LANES, AND CARPOOLS:

EXPLOITING HETEROGENEOUS PREFERENCES IN POLICY DESIGN

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Introduction

The U.S. highway system, largely constructed with public funds from the fuel tax, could be characterized as a public good if it were rarely congested. But like many public goods that are available at little or no charge, its quality has deteriorated with the intensity of use. Today, the nation's road system has turned into a "tragedy of the commons" as road users experience nearly 4 billion hours of annual delay (Schrank and Lomax, 2005). Of course, even an efficient road system would force motorists to incur some delays, but the current level is regarded by most observers as excessive.

Historically, the public has had a status-quo bias against economists' recommendations to use the price mechanism to reduce congestion.[1] Policymakers have therefore pursued other approaches such as allocating reserved lanes to vehicles carrying two or more people. But recent evidence indicates that these "high-occupancy-vehicle" (HOV) lanes sometimes carry fewer people than general-purpose lanes, attract many family members who would ride together anyhow, and shift some travelers from vanpools or buses to low-occupancy carpools (Orski 2001, Poole and Balaker 2005). As a result, HOV lanes are losing favor among state departments of transportation.

A recent innovation is to fill the reserved capacity not used by HOVs with solo drivers willing to pay a toll. These so-called "high-occupancy-toll" (HOT) lanes can be found in the Los Angeles, San Diego, Houston, and Minneapolis–St. Paul metropolitan areas, and they are currently under consideration in other areas including Denver, Seattle, San Francisco, and Washington, DC.

[1] Small, Winston, and Evans (1989), Mohring (1999), and the papers in Santos, ed. (2004) provide recent discussions of road pricing.

HOT lanes appeal to a broad set of motorists who are sufficiently inconvenienced by congestion to pay a sizable toll to travel on less congested lanes, either daily or as dictated by their schedules. Although the adoption of HOT-lanes in some urban areas indicates that the public is no longer opposed to all forms of congestion pricing, HOT lanes are questionable on welfare grounds for two reasons. First, motorists continue to impose high congestion costs on each other because most of the highway is unpriced. Second, the express lanes are still underutilized because a big price differential exists between the two roadways (Small and Yan, 2001). Indeed, simulations show that HOT lanes sometimes *lower* welfare compared with keeping all lanes in general use, particularly if they are priced high enough to allow motorists to travel at approximately free-flow speeds—a condition that is achieved to promote the service advantages of the lanes among the public.

In short, HOV and HOT policies do not appear to have answered the long-standing call for efficient yet politically viable road pricing policies. In this paper, we seek to identify such policies by analyzing the behavior of motorists traveling on California State Route 91 (SR91) in Orange County. These travelers have the option of traveling solo on the general lanes, paying a toll to use the HOT express lanes, or forming a carpool to use the express lanes at a discount. Because travelers are likely to vary in their preferences for speedy and reliable travel, we model the situation accounting for both observed and unobserved preference heterogeneity.[2] We find that users of SR91 have high average values of travel time and travel-time reliability, and that the distributions of these values exhibit considerable dispersion.

[2] Previous empirical studies that allow for heterogeneous preferences among motorists include Calfee, Winston, and Stempski (2001), Hensher (2001), Jiang and Morikawa (2004), Steimetz and Brownstone (2005), Hess, Bierlaire, and Polak (2005), and Small, Winston, and Yan (2005a). Simulation studies incorporating heterogeneity to analyze pricing scenarios include Small and Yan (2001), Verhoef and Small (2004), and De Palma and Lindsey (2004).

We then show that by designing differentiated pricing schemes for general and express lanes that cater to such varying preferences, it is possible to capture some of the efficiency that HOV and HOT policies sacrifice while generating welfare disparities among road users that are not only smaller than more efficient pricing policies generate but small enough to be comparable to policies that have actually passed the test of politically acceptability in a few urban areas.

Empirical Model of Travel Choices

California State Route 91 is a major limited-access expressway used heavily by long-distance commuters. A 10-mile stretch in Orange County includes four free lanes and two express lanes 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. Carpools of three or more could use the express lanes at a 50 percent discount at the time covered by our surveys.[3] Unlike the regular lanes, the express lanes have no entrances or exits between their end points.

We assembled a data set from surveys of travelers on the corridor, describing the lane choices they actually make and the choices they would hypothetically make in different circumstances. In an earlier paper using the same data (Small, Winston, and Yan 2005a), we modeled motorists' lane choice only. Here we model three simultaneous decisions by motorists: (i) whether to acquire a transponder, which gives them the flexibility to use the express lanes whenever they desire; (ii) whether to travel on the express or free lanes for the trip in question; and (iii) how many people to travel with in their vehicle. We include transponder acquisition as a

[3] Starting late May 2003, these carpools could travel for free except weekday afternoons outbound from 4-6 p.m., when they receive a 50 percent discount. Current information is available on the Orange County Transportation Authority's "91 Express Lanes" website at http://www.91expresslanes.com.

separate choice because it captures a legal requirement to use the express lanes. Whether a motorist decides to meet the requirement may depend on other characteristics than those explaining day-to-day travel choices, and may cause more persistence in travel behavior than would otherwise be the case. We include vehicle occupancy so that we can explore the effects of various policies that depend on it.

The three choices are assumed conditional on related choices including travel mode (car vs. public transport), residential location, and time of day of travel. In our context, mode choice is unimportant because public transportation has a very small share of travelers on the corridor served by SR91. Residential location may indeed be important, but it is a longer-run response that introduces complexities that are difficult to capture in a tractable empirical model. We would like to model the choice of what time of day people travel but are unable to do so because we lack information on how congestion varies on roads that people use besides the SR91 study corridor. We describe later some statistical tests that indicate that our results are not particularly sensitive to our assumption that travel occurs at a given time of day.

In the empirical analysis that follows, we combine data that describe motorists' actual decisions for their morning commute with data indicating hypothetical choices between the express and free lanes under varying travel conditions. This strategy permits us to extract information about the *distribution* of preferences that would otherwise be impossible to extricate from other random influences on behavior. The mechanism at work is that an individual who answered the hypothetical questions provides responses for up to eight different scenarios; hence, we can effectively infer that individual's preferences through his unique pattern of responses to tradeoffs among cost, time, and reliability. We estimate common coefficients of the tradeoffs that are shared among individuals and coefficients of the tradeoffs that vary among individuals, enabling us to measure the key distributions of the value of time and value of reliability in our sample.

Formally, traveler n faces a choice whether to have a transponder (T) or not (N); whether to travel on a general (free) lane (G) or express lane (X); and whether to travel with 1, 2, or 3 people in the vehicle (where 3 means three or more). The three choice dimensions define 2x2x3=12 alternatives, but only nine of them are available because a highway traveler must have a transponder to use the express lane, thereby eliminating combinations *NX*1, *NX*2, and *NX*3.

Following standard discrete-choice modeling, we specify the indirect utility of traveler n choosing an alternative j to be random:

$$U_{jn} = X_{jn}\beta_n + \varepsilon_{jn}\,. \tag{1}$$

In this equation, X_{jn} is a vector of attributes associated with alternative j including the toll, travel time, and reliability that apply to the traveler's trip; β_n is a vector of parameters that captures the traveler's preferences for those attributes; and ε_{jn} is an error term capturing unobserved influences. We measure preference heterogeneity by allowing parameter vector β_n to vary across individuals according to both observed characteristics and random (i.e. unobserved) influences:

$$\beta_n = W_n\gamma + \mu_n\,. \tag{2}$$

In this equation, W_n is a vector of explanatory variables relating to traveler n, while μ_n is a vector of random variables; γ is a vector of parameters, to be estimated statistically, describing how preferences depend on observed characteristics. The random terms μ_n are assumed to be independent normal random variables, with variances to be estimated. Thus the terms $W_n\gamma$ and μ_n describe observed and unobserved heterogeneity, respectively, in preferences toward travel characteristics.

If ε_{jn} in (1) were independently distributed according to identical extreme-value distributions, then equations (1) and (2) would constitute a conventional mixed-logit model where each choice probability can be expressed as a standard multinomial logit choice probability (conditional on β_n), integrated over the distribution of μ_n (which determines β_n).[4] Our model is more complicated because we specify the structure of ε_{jn} to account for certain special features of the data. One is the decision structure inherent in our choice alternatives; another, which we describe later, is that we merge our data from several sources.

As noted, the decision structure involves three choice dimensions. Thus it is unlikely that the alternative-specific preferences ε_{jn} for the nine permitted alternatives are independent of each other. Rather, a natural approach is to specify random preferences for groups of alternatives as described by Brownstone and Train (1999).[5] We let ε_{jn} include four distinct preferences: for a transponder (T), for the express lane (X), for a two-person carpool ($H2$), and for a three-person carpool ($H3$). Thus:

$$\varepsilon_{jn} = \Delta_j^T \nu_n^T + \Delta_j^X \nu_n^X + \Delta_j^{H2} \nu_n^{H2} + \Delta_j^{H3} \nu_n^{H3} + \eta_{jn} \tag{3}$$

where Δ_j^T denotes a dummy variable equal to one if alternative j is one of those characterized by a transponder, and so forth. The four variables ν_n^k are independent normal random variables, each with mean zero and a standard deviation σ^k to be estimated. (For parsimony, we impose $\sigma^{H2}=\sigma^{H3}\equiv\sigma^{HOV}$.) The remaining random terms, η_{jn} in (3), are assumed to be independent random

[4] Small and Winston (1999) and Train (2003) contain expositions of the logit and mixed-logit models. The (normalized) extreme-value distribution for a random variable ε is defined by the probability Prob[$\varepsilon \leq$x] = exp(e^{-x}).

[5] An alternative approach would be to use a nested-logit specification. The approach here is more flexible, is typically better behaved numerically, and is easier to implement given that we are using mixed logit.

variables (one for each alternative) with identical extreme-value distributions, just like in a logit model.

Naturally, one can expect to estimate the *distribution* of only a few of the many behavioral parameters contained in a model like this. We choose two key parameters, which means there are two components of μ_n in equation (2) with non-zero variances. One (μ_n^{Time}) is part of the coefficient of travel time, while the other (μ_n^{Rel}) is part of the coefficient of (un)reliability. Their standard deviations, to be estimated, are denoted σ^{Time} and σ^{Rel}.

To summarize the stochastic part of the model, we specify six independent normal random terms (ν's and μ's) with five distinct unknown standard deviations (σ's) to be estimated.

We define the value of travel time (VOT) and value of reliability (VOR) for individual *n* as the ratios of marginal utilities of travel time and reliability, respectively, to the marginal utility of money cost. That is,

$$VOT_n = \frac{\beta_n^{Time}}{\beta_n^{Cost}} \tag{4}$$

$$VOR_n = \frac{\beta_n^{\mathrm{Re}l}}{\beta_n^{Cost}} \ , \tag{5}$$

where β_n^{Time} , $\beta_n^{\mathrm{Re}l}$, and β_n^{Cost} are the coefficients of travel time, reliability of travel time, and toll in equation (1). These values depend on observables W_n and random components μ_n through equation (2).

Data Set and Econometric Issues

We combine survey data from three samples of people traveling between 4:00 am and 10:00 am on the California State Route 91 corridor westbound who have the option of using the express lanes. The surveys were taken over a 10-month period in 1999 and 2000. The first survey was a telephone survey generating 435 observations pertaining to actual travel on a particular day, conducted by researchers at California Polytechnic State University at San Luis Obispo (CalPoly) with our participation (Sullivan *et al.* 2000). Thus it consists of revealed preference (RP) data.

The second and third samples are from a two-stage mail survey collected by us through the Brookings Institution. The initial stage collected RP data from 79 respondents on actual trips taken during a week of travel, while a follow-up stage presented to each respondent eight stated preference (SP) scenarios.[6] In each SP scenario, the respondent was asked to choose between two otherwise identical routes with specified hypothetical tolls, travel times, and probabilities of delay; an illustrative scenario is presented in the appendix. The SP sample contains 78 respondents, who generated 610 observations; 54 of these people also answered the RP questions. Detailed descriptions of the samples are presented in Small, Winston, and Yan (2005b).

By constructing a sample that contains both RP and SP observations, we can overcome the main drawbacks of each type of data. The use of RP data is often hindered by strong correlations among travel cost, time, and reliability; whereas SP data raise concerns about whether the behavior exhibited in hypothetical situations applies to actual choices. By specifying some parameters to be identical and others different in the utility functions generating RP and SP choices, we can improve the precision in estimating common parameters (due to low

[6] 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 percent 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.

correlations designed into the SP questions) while allowing for expected behavioral differences in other parameters.

Table 1 presents some statistics on socioeconomic variables and trip distance. The Brookings RP sample appears 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.[7] We estimate the average wage rate to be $23/hour.[8] The CalPoly sample has higher household incomes and shorter trip distances than the Brookings samples, evidently being drawn from a smaller and more affluent geographical area. These sampling differences should not affect our parameter estimates because our model includes income and trip distance as explanatory variables.

Table 2 presents the choice shares of the nine alternatives associated with each RP sample. We observe a difference among carpooling propensities between the CalPoly and Brookings samples, with many fewer carpools in the latter. To better understand the difference, the CalPoly sample is disaggregated into four subsamples representing different ways of finding respondents (Sullivan *et al.* 2000). The "Random" subsample was obtained by telephone interviews drawn randomly from lists of telephone exchanges in the relevant area; the other three CalPoly subsamples came ultimately from license plates observed on the highway and are therefore choice-based (some were purposely carpool-enriched). Even in the CalPoly "Random"

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[7] Our sample's median income is $46,250, whereas the average incomes in the two counties where our respondents lived were $36,189 and $39,729 in 1995, as estimated by the Population Research Unit of the California Department of Finance.

[8] Data from the US Bureau of Labor Statistics (BLS) for the year 2000 record the mean hourly wage rate by occupation for residents of Riverside and San Bernardino Counties. We combine the BLS occupational categories into six groups that match our survey question about occupation, and assign to each person in our sample the average BLS wage rate for that person's occupational group. We then add 10 percent to reflect the higher wages likely to be attracting these people to jobs that are relatively far away.

subsample, however, the combined carpool shares are considerably higher (24%) than in the Brookings RP sample (6%), despite both being obtained from random telephone calls. The CalPoly Random shares are much closer to the observed peak-period carpool shares on the SR91 roadway (Sullivan *et al.* 2000), so we conclude that the Brookings sample undersampled people who carpool — possibly because the telephone screening questions to determine eligibility for the survey were originally designed to only find solo drivers and subsequently modified. Thus, we use the CalPoly Random subsample as our measure of the population choice shares, and correct for choice-based sampling in our estimates by applying carpool-share weights to the other subsamples (Manski and Lerman 1977).

We recognize that SR91 has a higher share of carpoolers than most other highways in the nation have. Later we perform sensitivity analysis on the share of carpoolers to explore how our analysis applies to other metropolitan areas.

Specification and Estimation

We posit that motorists' joint choices are influenced by their socioeconomic characteristics and the characteristics of their journey, including the total trip distance and the toll, travel time, and (un)reliability of travel time on the portion of the journey where a lane choice exists.

The express lane toll for a given trip is the published toll for the time of day the motorist reported passing the sign that indicates the toll level. It is discounted by 50% if the trip was in a carpool of three or more. (We asked respondents, even in the SP survey, to indicate their vehicle occupancy for actual trips.)

Our ability to measure individuals' preferences depends critically on capturing the different conditions they face when traveling at different times of day. Therefore, we sought to measure those conditions carefully to construct variables for the RP portion of the analysis. We measured the reliability of service encountered by a traveler, as well as the travel time itself, by taking field measurements at many different times on eleven different days, corresponding approximately to the travel periods covered by our surveys. The field measurements consist of travel times clocked by students attending the University of California, Irvine, who drove the road repeatedly. Thus we were able to measure the median travel time observed across the eleven days, at any given time of day, as well as the entire distribution of travel times across those days, again as a function of the time of day. For our travel-time variable, whose coefficient is β^{Time} in equation (4), we use the median value; for our measure of unreliability of travel time, denoted *Rel* in (5), we use the difference between the 80th and 50th percentiles of the distribution of travel times across days. This measure captures the behavioral notion that people are more concerned with unexpected late arrivals than early arrivals; the measure also is less closely correlated with median travel time than a symmetric measure of dispersion such as the variance. Small, Winston, and Yan (2005b) discuss the procedures used to estimate these measures and to validate their accuracy.

The variables describing the individual include age, sex, household size, per-capita income, total trip distance, and trip purpose (viz. a dummy for work trip). We explored other variables describing arrival-time flexibility, occupation, education, and size of the workplace, but found that they have little explanatory power and that omitting them did not materially influence the other parameter estimates.

The variables used in the SP analysis are defined, with one exception, identically to those in the RP data set—although the travel descriptors are of course generated differently, being specified in the survey questions instead of measured in the field. The one exception is reliability. We did not think we could explain percentiles of a probability distribution to survey respondents, so in the SP scenarios we described reliability as the frequency of being delayed 10 minutes or more; we convert the responses into probabilities for purposes of analysis. The reliability variable therefore has different units and meaning in the RP and SP scenarios, so distinct RP and SP coefficients for it are estimated; however it is the RP coefficients that we use to describe resulting values of reliability and to simulate policy scenarios.

A number of specification issues arise when we combine the RP and SP data sets. The RP analysis is described by equations (1)-(3), to which we append superscript *RP* to distinguish those observations. The SP analysis, however, is different because we asked each respondent to express only a choice between the express or regular lanes; and we asked for this choice in eight different scenarios (each with different hypothetical values of travel variables). Because the SP choice is binary, it is convenient in the case of SP respondents to replace (1) by the utility *difference* between the express and regular lane. Thus in each choice scenario t, the respondent n chooses the express lane if and only if

$$U_{nt}^{SP} \equiv X_{nt}^{SP} \beta_n^{SP} + \varepsilon_{nt}^{SP} \geq 0\,, \qquad (6)$$

with β_n^{SP} given by (2) with the addition of *SP* superscripts on each of the symbols there. Note that β_n^{SP}, representing the preferences of individual *n*, does not vary across the different choice scenarios *t* presented to that individual.

We account for three additional effects that may arise due to the nature of the SP sample and to combining it with the RP samples. First, we expect the random influence ε_{nt}^{SP} to exhibit a typical panel structure. That is, it contains one random term, which we denote ξ_n, common to all the choice scenarios considered by individual *n*; and another, denoted η_{nt}^{SP}, that is unique to each choice scenario. Second, in the 55 cases where the same individual answered both the RP and SP questions, we expect some correspondence between the unobserved influences on their actual behavior and their hypothetical responses. To capture this, we assume that part of the random utility is common between them. Specifically, we assume the SP error ε_{nt}^{SP}, expressing random preference for the express lane as revealed in SP responses, contains a term proportional to ν_n^X from equation (3), representing random preference for travel in the express lane as revealed in observed (RP) behavior. Accounting for both of these effects results in the SP error in equation (6) given by:

$$\varepsilon_{nt}^{SP} = \xi_n + \theta \nu_n^X + \eta_{nt}^{SP} \qquad (7)$$

where ξ_n is normally distributed with zero mean and variance normalized to one; θ is a parameter to be estimated; and η_{nt}^{SP} has a logistic distribution with standard deviation σ^{SP}.[9]

Finally, we follow standard practice in combining RP and SP data by allowing for differences between revealed and stated choices in the variance of random preferences. That is, the random factors affecting revealed choices may be larger or smaller than those affecting stated choices. For similar reasons, we allow for a difference between the two RP data sets in the variance of the random term in equation (1). The two data sets are Brookings RP (denoted BR) and CalPoly (denoted C). Thus the three standard deviations describing the three parts of our

[9] The logistic distribution describes the difference between two extreme-value variates, which is what we obtain because utility in (6) is the difference between the random utilities of express and regular lanes. Train (2003), p. 39 illustrates this point.

data (BR, C, and SP) are connected by two ratios which we estimate: $\tau^{BR} \equiv \sigma^{SP}/\sigma^{BR}$ and $\tau^{C} \equiv \sigma^{SP}/\sigma^{C}$. The ratios are described in our estimation results as "scale parameters".[10]

We compute the log-likelihood function for our sample as the summation of logarithms of choice probabilities for RP observations (choice among nine alternatives) and for SP observations (binary choice), with the common error term ν_n^X entering both RP and SP choices for those people who are members of both Brookings samples. As noted, each choice probability is expressed in the usual manner for mixed logit as an integral of a multinomial or binary logit probability, conditional on normal random variates, over the distribution of those variates. We obtain parameter estimates by maximizing this log-likelihood function using Monte Carlo simulation to compute the integrals.[11]

Identification

Every statistical model must make explicit or implicit "identifying assumptions" about which environmental factors are held constant as others are varied, thus enabling the analyst to isolate the parameters of interest. Our model's parameters are identified by assuming that the unobserved influences on transponder, vehicle occupancy, and lane choice do not vary systematically by time of day; if they did, they would be correlated with the cost, time, and reliability of travel and their presence would bias those coefficients. The validity of this assumption depends to a large extent on how well our observed variables capture taste variation across time of day. Fortunately, it appears that such variation is reflected in several of our variables. For example, a motorists' sex is correlated with the time of day of travel: females

[10] As in the binary logit model, one of these standard deviations can be normalized, typically by setting it equal to $\pi/\sqrt{3}$ for mathematical convenience: Train (2003), pp. 44-46. We normalize σ^{SP} in this way.

[11] This is the *maximum simulated likelihood estimator* developed by Lee (1992) and McFadden and Train (2000) and exposited by Train (2003), pp. 148-149.

constitute only 15% of those people traveling during the interval 4:00-5:00 am, but 39% of the 7:00-8:00 am group. Similarly, the proportion of respondents whose trips are work trips varies from 100% at the earliest time to 58% at the latest time.

In Small, Winston, and Yan (2005a), we conducted a formal test of whether unobserved taste variation by time of day affects our estimates of cost and travel-time coefficients. The test consisted of estimating models of lane choice that included five time-of-day dummy variables. The findings indicated that values of time and reliability were not affected very much by the inclusion of the dummy variables. We do not include the time-of-day dummies in the current model because in the previous work they reduced the precision of the estimates.

Estimation Results

Estimation results are presented in Table 3. We group the RP parameters as those for generic variables that influence all three choice dimensions (transponder, lane, and vehicle occupancy), and those that influence just one of those dimensions. We also group separately those parameters influencing only the SP lane choice and those having a common effect on RP and SP choices.[12] Most influences are statistically significant and have the expected signs. As indicated by the generic RP coefficients and the SP coefficients, motorists pay close attention to the toll, travel time, and reliability when choosing among the available alternatives.

[12] We conducted an extensive exploration of alternative specifications and functional forms for the explanatory variables, including removing the equality constraints between certain RP and SP parameters reflected in the "combined estimates" in the table. The model presented here is robust to such variations and is not rejected by statistical tests against more general models.

Observed heterogeneity in preferences is indicated by "interaction variables" formed by multiplying a generic variable by a socioeconomic or distance variable.[13] For example, toll is multiplied by a dummy variable for income, and median travel time is multiplied by various functions of trip distance. The results show that, as expected, motorists with higher incomes are less responsive to the toll, a statistically significant effect for RP respondents. The deterrent effect of travel time varies with distance in an inverted U pattern, initially rising but then falling for trips greater than 32 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 commutes, but we find the difference to be negligible.

We also find observed heterogeneity in alternative-specific preferences. The estimates listed under "RP Coefficients" in the table show that middle-aged females and commuters are more inclined than other motorists to acquire a transponder. Middle-aged females with large families are more likely than other motorists to carpool, perhaps because they are more likely to make trips where family members ride together. Finally, as indicated by the "Combined Coefficients," women, middle-aged motorists, and motorists in smaller households are more likely than others to choose the toll lanes, even after accounting for differences in transponder acquisition and car occupancy.[14]

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[13] That is, we multiply a component of variable vector X_{jn} in equation (1) by a component of variable vector W_n in equation (2), as required by substituting (2) into (1). The resulting coefficient is a component of parameter vector γ in (2).

[14] To better understand why women are more likely to use the toll lanes, we tried including an interaction of four variables: gender, age, household size, and either the express-lane dummy or the travel-time-uncertainty variable. This interaction sought to test whether working mothers with children might prefer the toll lanes or be more averse to unreliability due to tighter schedules. However, we could not find a measurable effect.

Substantial unobserved heterogeneity in preferences over travel characteristics is indicated by the size and statistical significance of the estimated standard deviations σ^{Time} and σ^{Rel}. Similarly, there is unobserved heterogeneity over absolute preferences for the express lanes ($\sigma^{X\text{-}RP}$) and for carpooling (σ^{HOV}). We tried also to estimate a random coefficient for the toll, but we were unable to obtain stable results. The standard deviations are estimated with good precision and are substantial in magnitude, ranging from roughly one-fourth of the corresponding mean coefficient to a multiple of it.[15] The scale and correlation parameters that describe the error structure are also estimated precisely and show, among other things, that the RP and SP responses from a single individual are strongly correlated.

We use our parameter estimates to compute properties of the distributions across individuals of motorists' implied value of time (VOT) and reliability (VOR).[16] In table 4, we provide summaries for all road users combined and for users of the express lanes and the free lanes separately. We use the Brookings RP sample for enumeration because it best represents the population, as argued previously. (There is no bias from choice-based sampling here because we use information only about respondents' characteristics, not their choices.) We characterize heterogeneity in VOT and VOR by the interquartile range (i.e., the difference between the 75th and 25th percentile values) across individuals and across values of random parameters; this measure is relatively robust to the high upper tails typically found in distributions of ratios of random variables. The results are obtained by sampling across people in the enumeration sample

[15] The ratio of standard deviation to the mean coefficient is directly estimated for (un)reliability at 1.32. In the case of travel time, the estimated standard deviation of 0.39 may be compared with the SP coefficient of travel time of about -0.36 and with the derivative of utility with respect to RP median travel time, which is -0.76 at the mean trip distance of the Brookings RP sample.

[16] These computations use the individual estimates for RP responses, which are derived according to (3) from the estimates of the mean coefficients from the section "RP Coefficients: Generic Variables" in Table 3 and from the estimates of standard deviations from the section "Combined Coefficients". Note that the latter estimates make use of both RP and SP responses.

and, for each, making repeated random draws from all estimated distributions; the same method is used, and described in greater detail, by Small, Winston, and Yan (2005a).

All of the 90% confidence intervals in the second column are strictly positive, which indicates that all the reported estimates are statistically different from zero using a one-sided test at a five percent significance level. We find that the median value of time is $19.63/hour, which is about 85% of the average wage rate and thus near the upper end of the range expected from previous work (Small 1992, pp. 43-45). The median value of reliability is $20.76/hour.[17] Motorists also exhibit a wide range of preferences for speedy and reliable travel, as total heterogeneity in VOT and VOR is nearly equal to, or greater than, the corresponding median value. On average, express-lane users have higher values of travel time and reliability than do users of the free lanes—as expected—but wide and overlapping ranges exist within these two groups, resulting from the strong heterogeneity in preferences.

Simulating Highway Policies

We explore the policy implications of preference heterogeneity by developing a simulation model that uses our econometric results. It allows us to examine current HOT and HOV policies and alternative pricing policies. We begin with a situation closely resembling the SR91 road-pricing experiment. Two 10-mile roadways, Express and Regular, are assumed to connect the same origin and destination and to have the same free-flow travel time of 8.0 minutes.[18] We model a four-hour peak period of 5:00-9:00 a.m.

[17] Note that reliability is measured in hours because it is formed from percentiles of the distribution of travel time — which is measured in hours. Nevertheless reliability, like travel time, is a property of the entire trip (more precisely, of the portion of the trip occurring on the section of the corridor we study).

[18] This is the observed travel time on the section we study at 4:00 a.m., corresponding to a speed of 75 miles per hour.

We find equilibria by iterating between the supply and demand sides of the model. The supply side is a standard static congestion model in which travel delays are proportional to the fourth power of the volume-capacity ratio (US Bureau of Public Roads 1964). Capacity is 2,000 vehicles per hour per lane. Unreliability is assumed to be a constant fraction 0.3785 of travel delay (travel time minus free-flow travel time) — the fraction observed in our data on the free lanes averaged over 5-9 a.m.

The demand side is obtained from the estimated demand model by sample enumeration, using the Brookings RP sample which, as noted, is random and mostly representative of the population. The enumeration sample is assumed to represent a fixed population of size *N* potential commuters.

Our estimated demand model, of course, is conditional on travel in this corridor. However, we want to include the possibility of individuals altering their decision to travel in the corridor in response to policies we simulate, because other studies have shown that such responses can strongly affect the relative benefits of alternative pricing strategies (Verhoef, Nijkamp, and Rietveld 1996). Therefore we extend our estimated model by adding an "outside choice" representing non-travel (on the corridor).

The full procedure for this extension is described in the Appendix. Briefly, we postulate an "outside" or "non-travel" alternative labeled -1 (which could represent no trip, a trip outside the four-hour time period, or a trip on one of the other corridors that are some distance from the one we are modeling). Its utility is simply a constant $\bar{\delta}_{-1}$ plus a random term $\eta_{-1,n}$. The random terms for the other alternatives, i.e., the terms η_{jn} in equation (3), are assumed to be more closely correlated with each other than with η_{-1}, just like in a nested logit model; a new parameter λ

indicates the strength of this correlation. Choice probabilities (conditional on random parameters) are nested logit.[19]

Calibrating the Expanded Demand Model

To use our model for simulation, we need to calibrate three parameters: the alternative-specific constant for the outside choice ($\overline{\delta}_{-1}$), the coefficient of the inclusive value of travel (λ), and the population size (N). Because we expect the travel alternatives to be much closer substitutes for each other than for non-travel, we choose λ as small as possible without causing numerical instability: namely, λ=0.2. This choice does not seem to have much effect on the nature of the results. We calibrate the other two parameters ($\overline{\delta}_{-1}$ and N) to replicate observed traffic conditions during the morning peak on SR91 in the summer of 2000, which took place with an express-lane toll of $3.30 with 50% discount for HOV3. The key traffic conditions are a travel-time difference between the express and the free lanes of 3.4 minutes (according to our field measurements), and non-travel share of 10%.[20] The parameters that achieve these results are shown in the first column of numbers in Table 5, along with the resulting travel times and the implied elasticity of traffic volume with respect to the full cost of travel.[21] The middle column

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[19] The choice probabilities are expressed in the appendix equations (A.2a-d).

[20] The 10% figure is a plausible estimate based on the likelihood that a small portion of trips were foregone due to congestion, that an alternative route available for some travelers (SR241) had about 8%-9% share of the CalPoly sample, and that the share of public transit is less than 1%.

[21] Full cost is toll plus the traveler's value of travel time and unreliability faced. We computed the full-cost elasticity by using our expanded demand model, with initial calibrated parameters just described, to simulate changes in total travel under a no-toll scenario and under a scenario where travel time and reliability are both increased 10 percent for all alternatives. We also computed the implied money-price elasticity of express-lane travel, which is -1.12, for comparison to the value of the same quantity reported in Yan, Small, and Sullivan (2002), which is -0.7 to -0.8 but based on a model that did not account for preference heterogeneity. We believe the higher elasticity calculated here is realistic because preference heterogeneity creates a subset of people who are quite ready to shift into or out of the express lanes in response to tolls, even though they are not very likely to shift from travel to non-travel.

shows the travel times produced by simulating the base (No-toll) policy with those parameters: namely 12.03 minutes, indicating a speed of 50 miles per hour.

We recognize, however, that most areas considering new pricing or express-lane policies have far worse congestion than was observed on SR91 in 2000 —which was only five years after a 50 percent increase in the road's capacity. We therefore raise population *N* enough to reduce average speed to 30 miles per hour under a no-toll scenario. In setting the parameters for this starting situation, we hold constant not $\bar{\delta}_{-1}$ but instead the total traffic elasticity under a no-toll situation, shown in the last row. That elasticity (-0.36) may be compared with the value of -0.58 estimated under the actual pricing scheme in effect on SR91 in 2000, based on the CalPoly data and using a model with no heterogeneity (Yan, Small, and Sullivan 2002).

The calibration exercise just described leads finally to the parameters shown in the last column of the table, which we use in our policy simulations. We perform sensitivity tests, described later, using different values of the elasticity of total traffic volume, including a value of zero.

Defining Policies

Based on our equilibrium model of supply and demand, we simulate results for several pricing and operational policies. For each, we calculate tolls, travel times, traffic volumes, revenue, changes in consumers' surplus, and total change in social welfare. In our base-case or "no-toll" policy, the two roadways are not distinguished. We compare policy scenarios that have the same number of total lanes (six), and thus do not investigate whether the benefits of a particular policy would merit adding new lanes in order to implement it.

The change in consumer surplus for traveler *n*, relative to the base case, is determined by the log-sum rule for nested logit (Choi and Moon 1997):

$$\Delta CS_n = \frac{1}{m_n}\Delta \ln\left[\exp\left(\bar{\delta}_{-1}\right) + \exp\left(\lambda I_n\right)\right], \tag{8}$$

where Δ indicates the difference between a given scenario and the base scenario, I_n is the inclusive value of the nine travel alternatives, and m_n is the individual's marginal utility of income, determined from the coefficient of the toll variable using Roy's identity.[22] The change in social welfare is the sum of expected changes in all individuals' consumer surplus and in toll revenues.

Besides the base policy ("No toll"), we first consider five other policies:

- <u>HOV:</u> a conventional "carpool-lane" policy in which the express lanes are open at no charge to carpools of two or more people;
- <u>HOT:</u> the express lanes are open both to carpools and to anyone willing to pay a toll;
- <u>One-route toll:</u> the express lanes are open to anyone willing to pay a toll, but with no discount for carpools;
- <u>Two-route toll:</u> all lanes are tolled, but with two different toll levels;
- <u>Two-route HOT:</u> same as Two-route toll except carpools can use either type of lane without charge.

For those policies requiring a toll, the toll is chosen to maximize social welfare subject to the constraints that define the policy; in the case of the HOT lane, the resulting optimal toll is smaller than would be charged under criteria typically used in current implementations.

The specific alternatives that are available for each policy are enumerated in Table 6. Because their availability varies across policies, we must consider a feature of welfare analysis using discrete choice models: namely, adding more options increases welfare beyond any

[22] The equation for I_n is given as equation (A.2c) in the Appendix. We report all results on a per-trip basis, so Roy's identity equates m_n to minus the coefficient of the toll. Based on the results of Table 3, m_n = -(-2.4042+1.3869*H_n), where H_n represents a traveler's value of the high household income dummy.

improvement in travel conditions that may actually result. This feature derives from the nature of a random utility model that assumes there are unobservable characteristics, captured by ε_{jn} in (1), that differ among alternatives. We see from Table 6 that some of our policies offer options with or without a transponder, while others offer express lanes as well as regular lanes. Our demand model was estimated in a situation including all nine possible alternatives described earlier; but when we simulate other policies, certain of these alternatives are eliminated from the choice set. This affects expected utility because the unobservable characteristics of eliminated alternatives are valued by some travelers. For example, some travelers in a HOT-lane environment value the day-to-day flexibility of lane choice that owning a transponder provides, whereas they do not have such flexibility in the No-toll or HOV policies.

Simulation Results

Simulation results are presented in Table 7. To facilitate understanding of the findings, we begin by presenting a detailed summary of the HOT-lane policy. The welfare-maximizing express toll for this policy is $9.23 per trip (first row). It produces a big reduction of travel times on the express lanes compared with the base policy (from 20.0 to 12.4 minutes), and a much smaller reduction on the general lanes (from 20.0 to 19.2 minutes). The next set of numbers gives the shares of selected combinations of alternatives (in which the shares for alternatives with and without a transponder are added together). Thus, for example, 3.4 percent of the N potential travelers choose not to travel on this corridor; just 2.6 percent pay the toll in order to travel alone on the express lanes (alternative $TX1$); and 52.5 percent travel alone in the general lanes (alternatives $TG1$ and $NG1$).

The consumer-surplus change for this policy, relative to No toll, averages \$2.01 per person—largely reflecting the reduced congestion caused by the shift to carpools (which is nearly as great as in the HOV policy, given that solo vehicles must pay a high express toll). The average, however, masks a wide dispersion in the gains to travelers, indicated by the percentiles shown next: the median traveler gets a \$0.62 increase in consumer surplus, whereas the 75th percentile traveler gets a much larger \$2.71 while the 25th percentile traveler gets only \$0.26. Finally, the toll revenue collected from the HOT lane is just \$0.24 per person, reflecting the small percentage paying the high toll. Adding the average consumer surplus change of \$2.01 to the average toll revenue of \$0.24 gives the total welfare change per person, \$2.25, shown in the last row.

We now compare the welfare properties of the policies. The introduction of HOV lanes improves efficiency by encouraging carpooling—more than doubling its share from the base case (row labeled "All HOV"). This policy significantly reduces travel time on the express lanes, but leaves the general lanes very congested (third and fourth rows). In all likelihood, the policy would be much less effective in a smaller metropolitan area: Dahlgren (1998) finds that HOV lanes are favorable (in terms of reducing total person delay) only when initial congestion is substantial (delays of 35 minutes or more) and when the initial modal share of carpools is sizable (20 percent or more). We explore the welfare properties of HOV lanes under these conditions when we perform sensitivity analysis.

Allowing solo motorists to use the express lane if they pay a toll (HOT) generates a small welfare improvement over the HOV policy by enabling a small share of travelers to switch lanes and drive faster. In the HOT-like policy without an HOV exemption (One-route toll), the general lane becomes even more congested and the welfare improvement over the initial HOV policy is negligible. The Two-route toll and Two-route HOT policies generate considerably more welfare gains, as expected. But they do so at the cost of imposing large consumer-surplus losses on many travelers: the distribution in the population shows that the "Two-route toll" reduces consumer surplus for three-fourths of all travelers (because the 75th percentile traveler gains $0.00), while the "Two-route HOT" reduces it for between one-fourth and one-half of them (because the 25th percentile gain is negative but the median gain is positive).

Table 8 provides more perspective on the distributional effects of the policies by showing how consumer surplus varies between and within two different income groups. The dispersion within each group is quite large: for example, in the HOT policy the inter-quartile range is from $0.67 to $6.80 for the high-income group and from $0.22 to $2.10 for the low-income group. Note that these distributions show a great deal of overlap: for example, the one-quarter of the low-income group with the largest gains (i.e., those above the 75th percentile) receive consumer surplus benefits of $2.10 or more, exceeding the gains of those at or below the median in the high-income group. As indicated previously, such findings reflect the considerable heterogeneity in VOT, VOR, and alternative-specific preferences that we found even controlling for income. Evidently there are many reasons besides income why some travelers strongly prefer one option over another.

Notwithstanding their sacrifice of economic efficiency, variants of HOV, HOT, and One-route pricing policies have attained a certain degree of public acceptance, suggesting that their distributional features are compelling enough to allow implementation. The first-best policy of tolling both lanes (Two-route toll) produces a sizable gain in welfare over HOV and HOT policies, largely because it greatly reduces congestion on both lanes. However, it causes travelers to suffer high and disparate losses in consumer surplus, averaging $2.36 per trip and over $5.36

per trip for one-fourth of all travelers. Furthermore, the largest losses are associated with the lowest income groups, who tend to have the lowest values of time and reliability. These features obviously contribute to efficient pricing's lack of political appeal.

However, we find that policymakers can achieve most of the gains from first-best pricing, while partly addressing distributional concerns, by adding a carpool exemption to the Two-route pricing policy (making it "Two-route HOT").[23] The carpool share, already high in two-route pricing because of its financial incentives, increases even more, while congestion on both routes compares with the levels under two-route pricing. Remarkably, travelers on average obtain a substantial gain in consumer surplus ($0.98) from Two-route HOT (compared with no toll); nevertheless, the policy is vulnerable to the concern that a substantial fraction of people incur sizable losses — those in the most disadvantaged quartile of users lose at least $1.91 per trip.

It is important to point out that if we assumed that travelers were homogeneous, our findings would change considerably, along the same lines as in Small and Yan (2001) and Verhoef and Small (2004). With homogeneous preferences, the relative welfare gain from the one-route toll, whose efficiency relies mainly on creating differential services, would drop significantly; HOT would become nearly identical in effect to HOV (because no additional benefits would result from separating users based on their preferences); and the one-route toll would be set much lower (because it cannot rely on attracting users just from the upper tail of the VOT and VOR distributions). In general, the reason that accounting for heterogeneity greatly

[23] This policy, like others involving an express lane, incorporates the absolute preferences for the express lane from our demand model, which on average are slightly positive. For this reason, traffic is equilibrated when the express lane is slightly slower than the general lane, even though the express lane has a (moderately) higher price. While this may appear anomalous, it reflects other advantages of the express lanes on SR91, such as lack of trucks and intermediate entrances and exits, which we think would apply in many other express-lane applications.

affects policy comparisons is that diversity in users' preferences creates the opportunity to improve social welfare by providing differentiated services.

<u>Toward a Better Policy Compromise</u>

Our findings on the distribution of benefits and costs raise the question of whether it is possible to craft a policy that achieves an even better compromise between efficiency and political feasibility than the policies explored thus far. In particular, we seek a more efficient policy with the same attractive distributional features as the "One-route toll". We choose "One-route toll" as a benchmark for political feasibility because at least two cases exist in North America where a policy resembling it has been successfully implemented. One case is SR91 itself: although carpools did not all pay full fare on SR91, those with only two occupants did and those with three or more occupants paid half the fare during most of the time when the original private toll road was in operation.[24] The other case is Highway 407 in the Toronto area. This is a publicly built highway (later sold to a private firm) that runs through the suburbs paralleling, a few miles away, a very congested east-west route through the city known as Queen Elizabeth Way. Projects such as these, and several others being actively considered, suggest that the public is willing to tolerate a toll road without HOV exceptions if a free alternative is available. In our simulation of the One-route toll, the free alternative exists in the form of a roadway immediately adjacent to the priced one, so this policy should be at least as acceptable as Highway 407.

We therefore quantify a benchmark for political viability as the 25th percentile of consumer-surplus change experienced by travelers under the "One-route toll" policy. Table 7

[24] Although there were complaints about the high tolls and about charging HOV3+ vehicles, they do not appear to have undermined the stability of the arrangement, which had a strikingly high acceptance level in various polls. What did eventually undermine the private operation was an unrelated issue: the franchise allowed the private operator to veto any capacity improvements in the corridor, which it did through a lawsuit in a highly publicized dispute with the California Department of Transportation. As a result, the express-lane franchise was purchased in 2003 by a public agency, which has retained most of the toll policies of its private predecessor.

shows that this is -$0.98 per trip. We then define an alternate version of two-route pricing that sets the two toll levels to maximize welfare, subject to the consumer surplus loss of the 25^{th} percentile traveler not exceeding $0.98 per trip. The result is the "Limited two-route HOT" policy shown in the last column in Tables 7 and 8. It results in a sharply differentiated toll: for the express lane its magnitude ($9.65) compares with that in the Two-route toll policy, but for the general lane it is only $1.90, much lower than either of the other two-route pricing policies. The policy achieves a general-lane speed of 36 miles per hour, intermediate between those of the no-toll and the two-route policies. It also achieves greater efficiency than any of the policies that leave the general lanes unpriced.

Motorists in the "Limited two-route HOT" policy achieve a consumer surplus *gain*, on average, of $1.36 compared with no tolls. This exceeds the gain achieved by any other two-route pricing policy. Furthermore, travelers are treated much more evenly than in the other two-route pricing policies, with the inter-quartile range only modestly greater than with HOT or HOV. Thus, the Limited two-route HOT policy succeeds in improving efficiency more than most other policies, while maintaining the attractive distributional characteristics comparable to policies that have been found to be political feasible.

We stress that our policy simulations are based on an experiment concerning only a single ten-mile stretch of highway. Most significant congestion affects a much broader region. If the distributional advantages of differentiated pricing enable it to be broadly adopted, its welfare gains will be greatly magnified.

<u>Sensitivity Analysis for Simulation Results</u>

The simulation results presented so far are based on a full-cost elasticity for total traffic of -0.36. Tables A.1 and A.2 in the appendix present simulation results where we assume the full-cost elasticity of total corridor traffic is -0.60 and zero, respectively. For the case of zero elasticity, the model has no outside option and so there is no parameter $\bar{\delta}_{-1}$ to calibrate. In the other case, the two parameters N and $\bar{\delta}_{-1}$ are simultaneously calibrated, as in the main results, to achieve the desired elasticity and travel-time differential with no toll. The results show that the welfare rankings of various policies, and the nature of their distributional impacts, do not depend on this assumed elasticity. We caution that specific numerical results are not necessarily comparable with different assumed elasticities because they imply different starting shares for HOV.

A more important area for sensitivity analysis, in our view, is varying the initial carpool share. As noted, many metropolitan areas have much smaller carpool shares than Los Angeles, with its large size and relatively long work trips. We therefore present an alternate simulation in which we change the parameters governing the alternative-specific utilities for HOV alternatives so as to produce HOV shares about half those of our primary scenario (Table 7), under both the no-toll and HOV policies.[25] Results are shown in Table 9. The policies do not perform as well as those in our main simulation, either in total welfare gain or in direct impact on consumers. For example, the median consumer-surplus change is uniformly negative. The smaller efficiency gains and less favorable distributional properties occur because the policies cannot induce as much carpool formation and therefore they achieve less relief from congestion. The HOV policy, especially, is much less effective—it produces a *negative* total welfare change and substantial consumer surplus losses both to the median and, especially, the 25th percentile traveler. This

[25] We do this by adjusting: the HOV dummy and its standard deviation. (The HOV3 dummy is adjusted proportionally to the HOV dummy.) The HOV share can be estimated approximately for about 20 existing corridors with HOV lanes in US metropolitan areas from data in Pratt *et al.* (2000), Tables 2-2, 2-7, and 2-9; almost all are between 15% and 30%, whose midpoint (22.5%) is almost exactly half the share predicted by our HOV policy simulation in Table 7.

striking finding is consistent with policymakers' growing dissatisfaction with HOV lanes and growing interest in HOT lanes throughout the country.

What about the "Limited two-route HOT" policy? Can it outperform HOT? Although we found that it cannot meet its political acceptability, as indicated by HOT's 25th percentile consumer surplus loss, it can improve on HOT's efficiency if we define political acceptability relative to the 25th percentile consumer-surplus loss of HOV instead. Thus, the possibility for an improved policy compromise exists for other metropolitan areas in the country, although we cannot be as sanguine about political feasibility as before.

Conclusion

Methodological advances in microeconometrics have enriched our understanding of consumer behavior by recognizing that consumers are not homogeneous. Applications have shown that accounting for heterogeneity is important when assessing policies in many domains, such as economic deregulation, job training, and poverty programs. We find that heterogeneity plays a similarly important role in policy toward highway transportation. Accounting for it creates the opportunity not only to introduce HOT lanes, as has been previously recognized, but to introduce more far-reaching pricing policies within the limits of distributional effects that appear to be politically acceptable in certain circumstances. We have been able to design a differentiated road-pricing scheme that fills in the gap between optimal but socially unpopular first-best pricing and pragmatic but less efficient policies like carpool or HOT lanes.

Recent experiments have shown that policymakers are no longer unwilling to use the price mechanism to allocate scarce road capacity. The changing times give cause for optimism that more efficient policies, offering choices that appeal to diverse users, will become serious candidates for implementation.

Table 1. Descriptive Statistics

	Value or Fraction of Sample		
	Cal Poly-RP	Brookings-RP	Brookings-SP
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
>60,000	0.62	0.17	0.17
Female Dummy	0.32	0.37	0.37
Mean Actual Trip Distance (Miles)	34.2	44.8	42.6
Number of Respondents	435	79	78
Number of Observations	435	369	610

Table 2. Choice Shares of Calpoly and Brookings RP Samples

Alter-native	Calpoly Sample				Brookings RP sample (%)
	Random (%)	New Plates (%)	Repeat (%)	UCI (%)	
*NG*1	41	28	17	11	51
*TG*1	16	26	33	39	23
*TX*1	19	15	16	22	20
*NG*2	7	9	3	0	0
*TG*2	3	8	16	6	2.5
*TX*2	8	5	7	22	1
*NG*3	3	3	0	0	0
*TG*3	1	3	3	0	0
*TX*3	2	3	5	0	2.5
All carpool	24	31	34	28	6
No. of Obs.	201	191	58	18	79

Legend:
Transponder acquisition: N=No, T=yes
Lane: G=General (free) lane, X=Express lane.
Car occupancy: 1=solo, 2=HOV2, 3=HOV3+

Table 3 Estimation Results for Demand Model

Variable	Coefficient (standard error)[a]
RP coefficients	
Generic variables:	
Toll (\$)[b, c]	-2.4042 (0.3994)
Toll[b, c] × dummy for high household income (> \$60K)	1.3869 (0.3395)
Median travel time (min.)[b] × trip distance (units of 10 miles)	-0.5753 (0.1751)
Median travel time[b] × trip distance squared	0.1128 (0.0394)
Median travel time[b] × trip distance cubed	-0.0050 (0.0020)
Travel-time uncertainty (80%-ile minus the median) (min.)[b]	-0.7489 (0.2668)
Transponder choice:	
Transponder dummy× Brookings dummy	-2.0101 (0.7472)
Transponder dummy × Calpoly dummy	-3.6342 (0.7374)
Female dummy × age30-50 dummy × transponder dummy	1.8535 (0.7979)
Commute dummy × transponder dummy	1.2502 (0.6967)
Standard deviation of transponder dummy (σ^T)	0.3276 (0.9422)
Lane choice:	
Express lane dummy × Brookings dummy	0.2564 (1.1386)
Express lane dummy × Calpoly dummy	0.2264 (1.1691)
Standard deviation of express lane dummy ($\sigma^{X\text{-}RP}$)	3.7879 (0.8261)
Carpool choice:	
Carpool dummy × Brookings dummy	-11.5192 (1.0339)
Carpool dummy × Calpoly dummy	-11.6719 (0.8883)
Female × age30-50 × household size × carpool	1.4404 (0.3563)
HOV3 dummy × Brookings dummy	-9.2262 (0.9886)
HOV3 dummy × Calpoly dummy	-7.4263 (0.9909)
Common standard deviation of HOV dummies (σ^{HOV})	10.3225 (0.7837)
SP coefficients	
Express lane dummy	-3.0651 (1.1953)
Standard deviation of express lane dummy ($\sigma^{X\text{-}SP}$)	1.0530 (0.5237)
Toll (\$)[b, c]	-1.4165 (0.3028)
Toll[b, c] × dummy for high household income (> \$60K)	-0.2492 (0.4808)
Travel time (min.)[b] × long commute dummy (> 45 minutes)	-0.3538 (0.0812)
Travel time[b] × (1 - long commute dummy)	-0.3843 (0.0616)
Travel-time uncertainty[d]	-7.1139 (1.4507)

(Table 3 – continued)

Combined coefficients	
Female dummy × express lane dummy	2.2434 (0.8384)
Age30-50 dummy × express lane dummy	1.9277 (0.7955)
Household size (number of people) × express lane dummy	-0.7371 (0.2117)
Standard deviation of travel-time coefficient (σ^{Time})	0.3866 (0.0694)
Ratio of std. dev. to mean of coefficient of travel-time uncertainty ($\sigma^{Rel}/\gamma^{Rel}$)	1.3233 (0.3805)
Correlation parameter between RP and SP express lane choice (θ)	1.4808 (0.3209)
Parameters associated with scaling	
Scale parameter: Calpoly sample (τ^C)	0.4143 (0.0902)
Scale parameter: Brookings RP sample (τ^{BR})	0.6064 (0.2029)
Number of observations	1124
Number of persons	538
Log-Likelihood	1059.63

[a] Standard errors reported are the "sandwich" estimate of standard errors from Lee (1995). That is, each is the square root of the corresponding diagonal element in the matrix $\hat{V} = (-H)^{-1} P (-H)^{-1}$, 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 the simulation error in the likelihood function.

[b] All cost, travel-time, and unreliability variables are entered as the difference between values for toll and free lanes. In the RP data, the cost for free lanes is zero, travel time for toll lanes is 8 minutes, and unreliability for toll lanes is zero. In the SP data, cost, travel time, and unreliability are specified in the questions.

[c] Value of "cost" for the toll lanes is the posted toll for a solo driver (for RP data) or the listed toll in the survey question (for SP), less 50% discount if car occupancy is 3 or more. For SP, car occupancy is determined from a question asking whether the respondent answered as a solo driver or as part of a carpool, and if the latter what size carpool.

Table 4. Implied Values of Time and Reliability for the Brookings Sample

	Median Estimate	**90% Confidence Interval [5%-ile, 95%-ile]**
Value of time ($/hour)[a]		
Median for:		
Entire sample	19.63	[8.75, 34.61]
Express lane users	25.51	[11.50, 39.99]
Free lane users	18.63	[7.76, 29.08]
Total heterogeneity[b] for:		
Entire sample	19.02	[12.57, 30.96]
Express lane users	29.30	[14.65, 55.97]
Free lane users	17.73	[11.37, 28.05]
Value of reliability ($/hour)[a]		
Median for:		
Entire sample	20.76	[8.37, 40.71]
Express lane users	23.78	[10.01, 48.29]
Free lane users	19.50	[5.73, 34.54]
Total heterogeneity[b] for:		
Entire sample	35.51	[14.95, 66.71]
Express lane users	44.70	[18.27, 84.24]
Free lane users	32.95	[13.70, 62.01]

[a] Calculated from Equations (4) and (5) using estimates of β_n^{Time}, β_n^{Rel}, and β_n^{Cost} applicable to RP responses (but note those estimates rely on both RP and SP data because they depend on σ^{Time} and σ^{Rel}).

[b] Heterogeneity is expressed here as the inter-quartile range of the quantity in question across both individuals in the enumeration sample and random draws from the estimated distributions of the β's, in order to account for observed and unobserved heterogeneity, respectively.

Table 5. Initial Calibration

	Summer 2000 conditions		More congested conditions
	HOT-lane policy	No-toll policy	No-toll policy
Assumed toll:[a]			
Express lanes	\$3.30	\$0	\$0
Free lanes	\$0	\$0	\$0
Calibrated parameters:			
N	17,570	17,570	24,710
$\bar{\delta}_{-1}$	-12.65	-12.65	-23.41
Travel time (min.):			
Express lanes	9.83	12.03	20
Free lanes	13.23	12.03	20
Arc elasticity of total corridor traffic volume with respect to full cost[b]	-0.40	-0.36	-0.36

[a] HOV3+ pays half of the toll.

[b] Based on 10 percent increase in time, unreliability, and cost for each travel option.

Table 6. Availability of Alternatives by Policy

Alternative				Policy			
Number	Description: Mode	Transponder?	Lane	No Toll	HOV	HOT; One-route toll	Two-route toll; Two-route HOT
0	Solo	N	G	x	x	x	
1	Solo	T	G			x	x
2	Solo	T	X			x	x
3	HOV2	N	G	x	x	x	
4	HOV2	T	G			x	x
5a	HOV2	N	X		x		
5b	HOV2	T	X			x	x
6	HOV3	N	G	x	x	x	
7a	HOV3	T	G			x	x
7b	HOV3	N	X		x		
8	HOV3	T	X			x	x

Note: x means that the alternative is available in that scenario. T indicates a transponder, N indicates none. G indicates the general lanes; X the express lanes.

Table 7. Policy Simulation Results

	No toll	HOV	HOT	One-route toll	Two-route toll	Two-route HOT	Limited two-route HOT
Toll on Express Lane	$0	$0	$9.23	$8.69	$10.14	$6.33	$9.65
Toll on General Lane	$0	$0	$0	$0	$8.16	$5.34	$1.90
Travel times (min.):							
Express Lane	20.00	11.8	12.4	11.6	11.6	13.1	12.5
General Lane	20.00	18.8	19.2	22.6	12.8	12.5	16.5
Aggregated choice shares (%):							
No travel on corridor	7.4	3.3	3.4	6.4	8.5	3.0	3.3
Solo on Express Lane	24.8	0	2.6	8.9	8.0	7.6	1.7
Solo on General Lane	49.6	52.0	52.5	54.5	27.9	25.0	46.3
HOV2 on Express Lane	5.1	32.6	30.0	15.4	16.3	23.1	31.7
HOV2 on General Lane[a]	10.3	2.9	3.0	7.2	22.1	26.8	6.6
HOV3+ on Express Lane	0.9	8.8	8.1	6.7	8.5	6.9	8.9
HOV3+ on General Lane[b]	1.9	0.6	0.4	0.9	8.8	7.6	1.4
All HOV3+	2.8	9.4	8.5	7.6	17.3	14.5	10.3
All HOV	18.2	44.8	41.5	30.2	55.7	64.5	48.6
Consumer surplus change ($/person)[c]:							
Average	0	2.11	2.01	0.50	-2.36	0.98	1.36
Distribution in population							
75%-ile	0	2.92	2.71	0.65	0.00	3.51	2.80
50%-ile	0	0.77	0.62	-0.27	-2.68	0.52	0.33
25%-ile	0	0.26	0.26	-0.98	-5.36	-1.91	-0.98
Toll revenue ($/person)[c]	$0	$0	$0.24	$1.64	$5.35	$1.81	$1.05
Welfare change ($/person)[c]	$0	$2.11	$2.25	$2.14	$2.99	$2.79	$2.41

[a] In the HOT and One-route toll policies, this row combines shares for two alternatives, with and without a transponder: namely, alternatives 3 and 4 in Table 6.

[a] Same as not a, but combines alternatives 6 and 7 in Table 6.

[c] Consumer surplus and social welfare are measured relative to the no-toll scenario. They and toll revenue are each divided by the total number of potential travelers *N*. Social welfare is the sum of consumer surplus plus revenue.

Table 8. Consumer surplus distribution by income group ($/person)

	No toll	HOV	HOT	One-route toll	Two-route toll	Two-route HOT	Limited two-route HOT
High income (≥ 60K)							
75%-ile	0	6.47	6.80	6.01	5.16	8.30	6.88
50%-ile	0	1.68	1.61	1.27	0.92	4.48	2.47
25%-ile	0	0.72	0.67	-0.92	-3.34	0.15	0.04
Low income (< 60K)							
75%-ile	0	2.50	2.10	0.29	-0.55	2.47	2.00
50%-ile	0	0.64	0.51	-0.37	-3.20	0.11	0.08
25%-ile	0	0.22	0.22	-0.98	-5.60	-2.19	-1.04

Table 9. Simulation Results with Low HOV Share

	No toll	HOV	HOT	One-route toll	Two-route toll	Two-route HOT	Limited two-route HOT
Toll on Express Lane	$0	$0	$8.03	$8.20	$11.10	$9.47	$8.35
Toll on General Lane	$0	$0	$0	$0	$7.94	$7.02	$1.98
Travel times (min.):							
Express Lane	20.00	9.31	12.38	12.28	12.07	13.37	12.64
General Lane	20.00	25.38	22.95	24.04	15.87	15.50	20.75
Aggregated Choice shares (%):							
No travel on corridor	7.49	13.31	7.84	9.26	18.37	13.23	9.08
Solo on Express Lane	27.88	0	14.66	17.75	16.80	15.57	14.59
Solo on General Lane	55.77	64.09	61.43	61.55	48.38	47.43	58.47
HOV2 on Express Lane	2.47	16.71	11.84	5.90	6.70	12.70	12.58
HOV2 on General Lane	4.94	1.12	1.21	3.22	5.89	6.26	1.72
HOV3 on Express Lane	0.48	4.61	2.77	1.85	2.41	3.29	3.17
HOV3 on General Lane	0.97	0.16	0.25	0.47	1.45	1.52	0.39
All HOV3	1.45	4.77	3.02	2.32	3.86	4.81	3.56
All HOV	8.86	22.60	16.07	11.44	16.45	23.77	17.86
Consumer surplus change ($/person):							
Average	0	-0.50	0.41	-0.20	-4.22	-2.81	-0.67
Distribution in population							
75%-ile	0	0.30	0.68	0.28	-1.98	-0.16	0.00
50%-ile	0	-1.12	-0.35	-0.69	-5.27	-3.86	-1.98
25%-ile	0	-2.51	-1.14	-1.66	-7.01	-5.81	-2.51
Toll revenue ($/person)	$0	$0	$1.18	$1.75	$6.44	$4.82	$2.38
Welfare change ($/person)	$0	$-0.50	$1.59	$1.55	$2.22	$2.01	$1.71

Notes: See Table 7.

Appendix

Stated Preference Survey Questionnaire

Eight hypothetical commuting scenarios were constructed for respondents who travel on SR91. Respondents who indicated their actual commute was less (more) than 45 minutes were given scenarios that involved trips ranging from 20-40 (50-70) minutes. An illustrative scenario follows:

Free Lanes	**Express Lanes**
Usual Travel Time: 25 minutes	Usual Travel Time: 15 minutes
Toll: None	Toll: $3.75
Frequency of Unexpected Delays of 10 minutes or more: 1 day in 5	Frequency of Unexpected Delays of 10 minutes or more: 1 day in 20
Your Choice (check one):	
Free Lanes ☐	Toll Lanes ☐

Extended Demand Model for Simulations

Let Ω={-1,0,1,…,8} denote the choice set for a potential road user, where alternative -1 is the outside choice and alternatives 0–8 represent the different combinations of routes, transponder acquisition, and car occupancy defined previously. It is convenient to let $\tilde{\Omega}$={0,1,…,8} denote the subset of choices involving travel on the corridor.

The utility of individual *n* choosing alternative *j* is:

$$U_{-1n} = \overline{\delta}_{-1} + \eta_{-1n} \tag{A.1a}$$

$$U_{nj} = X_j^{RP} \beta_n^{RP} + \varepsilon_{jn}^{RP}, \; j \geq 0 \tag{A.1b}$$

with β_n^{RP} and ε_{jn}^{RP} as given by equations (2)-(3). Thus each traveler's utility for non-travel is divided into a mean $\bar{\delta}_{-1}$, which is constant for all commuters, and random deviation ε_{-1n}; whereas the utility for each alternative involving travel is the same as in the RP part of our estimated model (1)-(3). We henceforth omit the superscript *RP* for simplicity.

The random preferences for individual *n* are therefore represented by the vector $\Psi_n = (\eta_n, \nu_n, \mu_n)$, where $\eta_n = (\eta_{-1n}, \eta_{0n}, ..., \eta_{8n})$, $\nu_n = (\nu_n^T, \nu_n^X, \nu_n^{H2}, \nu_n^{H3})$, and $\mu_n = (\mu_n^{Time}, \mu_n^{\mathrm{Rel}})$. The density function of Ψ_n is specified as $\rho(\Psi_n) = \rho_\eta(\eta_n) \cdot \rho_{\nu\mu}(\nu_n, \mu_n)$; here $\rho_{\nu\mu}(\cdot)$ is a product of independent normal random variables with standard deviations as estimated, while $\rho_n(\cdot)$ takes the nested-logit form in which the outside alternative -1 is one nest and the travel alternatives $\widetilde{\Omega}$ are another nest with similarity parameter λ. This specification captures the idea that the substitution pattern between any two travel choices may be different from that between non-travel and travel. The market share of alternative $j \in \widetilde{\Omega}$, within the sub-market represented by people with characteristics of traveler n in our enumeration sample, is found by integrating the nested-logit probability formula, conditional on random parameters ν_n and μ_n, over the distribution function of those random parameters:

$$S_{jn} = \int_{(\nu_n, \mu_n)} S_{jn}^{(\nu_n, \mu_n)} \cdot \rho_{\nu\mu}(\nu_n, \mu_n) d(\nu_n, \mu_n) \tag{A.2a}$$

where

$$S_{jn}^{(\nu_n, \mu_n)} = \frac{\exp(X_{jn}\beta_n / \lambda)}{\exp(I_n)} \cdot \frac{\exp(\lambda I_n)}{\exp(\bar{\delta}_{-1}) + \exp(\lambda I_n)} \tag{A.2b}$$

is the share conditional on values of the normal random variates, and

$$I_n = \ln \sum_{j=0}^{8} \exp(X_{jn}\beta_n / \lambda) \tag{A.2c}$$

is the inclusive value of travel choices. The non-travel share is

$$S_{-1n} = \frac{\exp\left(\bar{\delta}_{-1}\right)}{\exp\left(\bar{\delta}_{-1}\right) + \exp\left(\lambda I_n\right)}. \tag{A.2d}$$

The total demand for an alternative j is therefore

$$D_j = \sum_n w_n S_{jn}, \tag{A.3}$$

where w_n is the number of people represented by motorist n. This number is just w_n=N/79, where N is the total population size, since our enumeration sample consists of 79 equally-weighted individuals. The traffic volume arising from those individuals who choose a travel alternative j involving occupancy O_j is $V_j \equiv D_j/O_j$.

Table A.1. Alternate Simulation Results: Elasticity=-0.60

	No toll	HOV	HOT	One-route toll	Two-route toll	Two-route HOT
Toll on Express Lane	$0	$0	$8.41	$8.53	$9.41	$6.02
Toll on General Lane	$0	$0	$0	$0	$7.01	$5.32
Travel times (min.):						
Express Lane	20.0	12.4	13.0	11.3	11.4	13.8
General Lane	20.0	19.8	20.0	22.9	13.0	12.8
Aggregated choice shares (%):						
Outside choice	16.5	9.8	10.8	15.9	19.7	9.8
Solo on Express Lane	22.2	0	2.8	7.4	7.2	7.9
Solo on General Lane	44.3	47.9	48.0	48.9	26.7	21.9
HOV2 on Express Lane	4.8	30.8	27.9	14.1	14.1	20.4
HOV2 on General Lane	9.6	2.7	3.0	6.9	18.8	26.7
HOV3 on Express Lane	0.9	8.5	6.9	5.9	7.2	6.0
HOV3 on General Lane	1.7	0.4	0.6	0.9	6.3	7.3
All HOV3	2.6	8.9	7.5	6.8	13.5	13.3
All HOV	17.0	42.4	38.4	27.8	46.4	60.5
Consumer surplus change ($/person relative to No Toll):						
<u>*Average*</u>	0	1.50	1.47	0.46	1.77	0.49
<u>*Distribution in population*</u>						
75%-ile	0	2.04	1.94	0.56	0.03	2.73
50%-ile	0	0.10	0.03	-0.14	-1.76	0.08
25%-ile	0	0.03	0.01	-0.87	-4.61	-1.94
Toll revenue ($/person)	$0	$0	$0.24	$1.40	$4.24	$1.63
Welfare change ($/person)	$0	$1.50	$1.71	$1.86	$2.47	$2.13
Consumer surplus distribution by income group ($/person)						
High income (≥ 60K)						
75%-ile	0	5.04	5.04	5.16	4.85	6.67
50%-ile	0	0.23	1.08	1.02	1.47	3.50
25%-ile	0	0.08	0.02	-0.65	-2.28	0.18
Low income (< 60K)						
75%-ile	0	1.75	1.42	0.20	-0.02	1.86
50%-ile	0	0.09	0.02	-0.25	-2.26	0.00
25%-ile	0	0.03	0.01	-0.89	-4.83	-2.28

Notes: See Table 7.

Table A.2. Alternate Simulation Results: Elasticity=0 (no outside choice)

	No toll	HOV	HOT	One-route toll	Two-route toll	Two-route HOT
Toll on Express Lane	$0	$0	$8.47	$8.64	$10.46	$6.17
Toll on General Lane	$0	$0	$0	$0	$9.29	$5.19
Travel times (min.):						
Express Lane	20.0	11.0	11.6	11.6	11.8	12.3
General Lane	20.0	18.1	18.3	22.1	12.4	12.3
Aggregated choice shares (%):						
Outside choice	0	0	0	0	0	0
Solo on Express Lane	26.6	0	3.5	10.4	9.7	8.8
Solo on General Lane	53.2	54.3	54.5	57.6	26.6	26.6
HOV2 on Express Lane	5.6	31.7	28.7	15.2	16.4	21.7
HOV2 on General Lane	11.3	4.2	4.5	8.5	26.4	28.1
HOV3 on Express Lane	1.1	8.9	7.9	7.0	8.9	6.6
HOV3 on General Lane	2.2	0.8	0.9	1.3	11.9	8.2
All HOV3	3.3	9.8	8.8	8.3	20.9	14.9
All HOV	20.2	45.7	42.0	32.0	63.4	64.6
Consumer surplus change ($/person relative to No Toll):						
Average	0	2.94	3.09	1.17	-2.39	1.87
Distribution in population						
75%-ile	0	4.07	4.00	1.15	0.12	4.45
50%-ile	0	1.47	1.64	0.14	-3.05	1.29
25%-ile	0	0.56	0.91	-0.44	-5.78	-1.48
Toll revenue ($/person)	$0	$0	$0.24	$1.40	$4.24	$1.63
Welfare change ($/person)	$0	$1.50	$1.71	$1.86	$2.47	$2.13
Consumer surplus distribution by income group ($/person)						
High income (≥ 60K)						
75%-ile	0	8.35	8.68	6.70	6.04	9.81
50%-ile	0	3.06	4.02	1.79	1.49	5.30
25%-ile	0	1.42	2.23	0.13	-3.10	0.93
Low income (< 60K)						
75%-ile	0	3.38	3.04	0.71	-0.94	3.46
50%-ile	0	1.22	1.40	0.01	-3.60	0.77
25%-ile	0	0.49	0.82	-0.50	-6.08	-1.73

Notes: See Table 7.

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