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Publication Date

2004

UNIVERSITY OF CALIFORNIA, IRVINE

New Methods for Modeling and Estimating
the Social Costs of Motor Vehicle Use

DISSERTATION

Submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Economics

by

Seiji Sudhana Carl Steimetz

Dissertation Committee:
Professor David Brownstone, Co-Chair
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2004

This dissertation of Seiji Sudhana Carl Steimetz
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University of California, Irvine
2004

Dedication

To the memory of my mother, Etsuko Steimetz,
who taught me the meaning of “Gaman”.

To my father, Calvin Steimetz,
who has no formal education,
and is the wisest philosopher I know.

To the memory of my uncle, Shohei Sawada,
whose lifelong dreams were to own a car,
and to do whatever he could to fulfill my dreams.

To the memory of my dear professor, mentor, and friend, David Saurman,
who instilled me with a passion for knowledge, economic intuition, and fine beer.

To Professors Roger Folsom, Rudy Gonzalez, Tom Means, Lydia Ortega,
Mike Pogodzinski, and Thayer Watkins of San Jose State University,
who never doubted me even when they should have.

To my aunt and uncle, Sady and Amy Hayashida,
whose generosity is without limits or prejudice.

To Robert Burbridge,
who watches over my last dollar.

To Jeremy Verlinda,
who watches over my sanity.

To the memories of Tora and Kumo,
who knew that everything I wrote
was important enough to sit on.

To all students of
California Community Colleges,
California State Universities,
and the University of California,
who ought to know how bright their futures can be.

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Acknowledgments

I wish to express the deepest and most sincere gratitude to my committee members, Professors David Brownstone, Kenneth Small, and Kurt Van Dender. David Brownstone taught me how to be an Applied Econometrician; Ken Small taught me how to be a Transportation, Urban, and Environmental Economist; Kurt Van Dender taught me how to reconcile my love and hate of economic research. This dissertation would not have been possible without their tremendous support, guidance, and generosity.

I am particularly grateful to Professor Justin Tobias, whose talent and unusual dedication to teaching enabled me to recognize that I just might have what it takes to complete a Doctoral Degree in Economics.

I also thank all of my dear classmates, and Professors Marigee Bacolod, Arthur DeVany, Kaku Furuya, Michelle Garfinkel, Ami Glazer, Jun Ishii, Geoffrey Iverson, Ivan Jeliaskov, Mark Moore, Dale Poirier, Priya Ranjan, Amelia Regan, Gary Richardson, Stergios Skaperdas, and David Walls, for building the staircase for my ascent from “barely keeping up” to “forging ahead”.

For Chapter One of this dissertation, I thank David Brownstone, Tom Golob, Ken Small, and Jeremy Verlinda for their many valuable insights, and Jia Yan for performing preliminary mixed-logit experiments. For Chapter Two, I thank David Brownstone, Ken Small, Kurt Van Dender, and Jeremy Verlinda for their many insights and helpful suggestions. I am especially grateful to Inge Mayeres for her generous comments on an early draft of the chapter.

This dissertation was made possible by generous financial support from the U.S. Department of Transportation and the California Department of Transportation through the University of California Transportation Center. I am indebted to the University of California Transportation Center for awarding me a Dissertation Grant and numerous Research Fellowships. My research was also supported in part by the Institute for Mathematical Behavioral Sciences and the Department of Economics at the University of California, Irvine.

Any errors or omissions in this dissertation belong solely to me.

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Abstract of the Dissertation

New Methods for Modeling and Estimating

the Social Costs of Motor Vehicle Use

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Seiji Sudhana Carl Steimetz

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Professors David Brownstone and Kenneth Small, Co-Chairs

The body of this dissertation comprises two standalone essays, presented in two respective chapters.

Chapter One develops estimates of how motorists value their travel-time savings and characterizes the degree of heterogeneity in these values by observable traits. These estimates are obtained by analyzing the choices that commuters make in a real market situation, where they are offered a free-flow alternative to congested travel. They are generated, however, in an empirical setting where several key observations are missing. To overcome this, Rubin's Multiple Imputation Method is employed to produce consistent estimates and valid statistical inferences. These estimates are then compared to those produced in a "single imputation" scenario to illustrate the potential hazards of single imputation methods when multiple imputation methods are warranted. A preferred model suggests that the median commuter is willing to pay \$30 to save an hour of travel

time. However, taking observed heterogeneity into account, median estimates range from \$7 to \$65 according to varying, observable motorist characteristics.

Chapter Two develops a theoretical framework for jointly modeling the marginal external accident and travel-delay costs of driving. The framework explicitly accounts for the optimal tradeoffs that motorists make between accident risk and risk-reducing effort. Accident and travel-delay externalities are decomposed into components that correspond to physical accident risk, efforts to offset this risk, and their effects on travel times. An empirical model is developed from this framework, suggesting that joint external costs are \$1.80 per vehicle-mile and external accident costs are \$0.80 per vehicle-mile during a typical peak-period commute. The analysis does not require observations on accident rates and illustrates how the commonly-adopted approach to modeling accident externalities tends to understate these costs.

Introduction

Motorists impose external costs on each other in terms of accidents and travel delays. There is little debate on the importance of identifying and measuring these costs. There is, however, much disagreement on their magnitudes. This thesis sets out to improve upon conventional methods for modeling, estimating, and characterizing accident and travel-delay externalities between motorists.

Travel delays represent the bulk of the external costs that motorists face during peak commute periods. The extent of these costs is typically characterized by motorists' willingness-to-pay for marginal reductions in travel times, traditionally referred to as "the value of time" (VOT). A modern approach to estimating these values is to exploit data from recent congestion-pricing experiments such as California's "High-Occupancy / Toll" (HOT) facilities along Interstate 15 and State Route 91 in San Diego and Orange Counties. Commuters at these facilities are offered, for a toll, free-flow travel along these HOT lanes, revealing their tradeoffs between various combinations of prices and traffic conditions.

The data from these experiments, however, are often plagued by missing or unreliable data. Chapter One develops a framework for overcoming such difficulties by employing Rubin's Multiple Imputation Methodology. The exercise demonstrates how to generate consistent estimates from problematic data while advancing the ongoing "value of time" debate. Despite missing observations on key variables, the median commuter's VOT is estimated at \$30 per hour, which is consistent with the range of estimates reported in related congestion-pricing studies.

The value of HOT-lane facilities themselves, however, is also subject to debate. Some argue that a Pareto-efficient policy is to open HOT lanes for free

use. A cogent response is that the option for free-flow travel, at a premium, has its own value insofar as it caters to varying commuter preferences. As such, the empirical efforts in this chapter focus on characterizing the extent to which VOT varies by observable traits. Taking this observed heterogeneity into account, median VOT estimates range from \$7 per hour for low-income, part-time workers taking non-work trips, to \$65 per hour for high-income, full-time workers on their daily commutes. Moreover, the analysis suggests that low-income work-trip commuters value travel-time reductions more so than high-income non-work-trip commuters do. It shows that high-income and low-income work-trip commuters alike stand to gain substantially from the option to purchase a free-flow alternative to congested travel. This serves to dispel the politically visible argument that HOT lanes only benefit “rich” motorists.

The data from these HOT-lane experiments are particularly well suited for producing reliable VOT estimates since they reveal motorists’ preferences for congestion relief in real-market settings. It is important to note, however, that commuters who purchase free-flow travel receive more than just travel-time reductions in the bargain. Most experienced motorists are quite familiar with the stress and aggravation that rush-hour traffic can generate. One particular source of this aggravation is the constant vigilance that is required of motorists to maintain safety margins between themselves and the many potential collision partners surrounding them. Free-flowing HOT lanes thus provide a combination of more rapid travel and less defensive-driving effort (corresponding to fewer potential collision partners). Since travel times and effort levels are both increasing in traffic levels, traditional VOT estimates generated from HOT-lane data will also reflect the value of “defensive-effort relief” to some extent. Generating “pure”

VOT estimates from HOT-lane data thus requires a method for extracting the value of the safety amenities that HOT-lanes provide from the value of the travel-time savings that they offer. This lays the foundation for the analysis in Chapter Two where HOT-lane data are used to estimate the extent to which motorists impose accident externalities on one another.

The current literature on accident externalities is relatively thin, despite a wide range of beliefs about their magnitudes. While some deem these costs to be of first-order importance, many consider them to be negligible. The latter view is more pronounced in the literature on accident externalities specifically between motorists, where an accepted convention is that no such costs exist. This convention is based on a modeling approach that focuses solely on observed accident rates, which ignores rational driving behavior in the face of risk. When road conditions become more hazardous, motorists naturally respond by driving more carefully, thereby mitigating observable accident risk. This increase in defensive effort generates true economic costs regardless of how many accidents actually occur. It suggests that the conventional approach to modeling accident externalities is likely to understate their magnitudes. Moreover, defensive driving typically corresponds to slower driving, implying a natural relationship between the costs of accident risk, defensive efforts, and travel delays – a relationship that warrants their joint modeling.

To address these issues directly, Chapter Two presents a theoretical framework that characterizes accident and travel-delay costs with explicit components for physical risk, travel delays, and the defensive efforts that link them. It then develops an empirical model from this framework to estimate accident and travel-delay costs (both jointly and separately) in a manner that does not re-

quire observations on accident rates. This is accomplished by exploiting the aforementioned relationship between risk, effort, and travel times. Commuters who purchase travel along free-flowing HOT-lanes are essentially purchasing relief from external accident and travel-delay costs. The analysis explicitly models their choices along these separate dimensions and demonstrates the degrees to which these choices are influenced by travel-times and non-travel-time factors such as risk and effort.

The results suggest that external accident costs represent 44% of the overall externalities generated during a typical peak-period commute, challenging the traditional approaches to modeling them. In turn, these results are also used to analyze related issues such as the impact of non-travel-time factors on existing “value of time” estimates and discrepancies between estimates generated from revealed-preference and stated-preference data.

Together these chapters represent a paradigm shift in how the marginal external costs of accidents and travel-delays are modeled, estimated, and interpreted. This thesis is devoted to improving upon existing methods for estimating these costs, with resulting implications for road-pricing, highway capacity expansion, and related transportation policies.

1 Heterogeneity in Commuters' "Value of Time" with Noisy Data: a Multiple Imputation Approach

1.1 Chapter Introduction

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

In turn, such studies have generated controversy over the “value of value-pricing” itself³, where offering toll-lanes might reduce welfare relative to the norm of offering all lanes at a uniform price of zero.⁴ In response, Small and Yan (2001) and Small, Winston and Yan (2002) illustrate that these purported welfare losses are driven by assuming homogenous preferences across motorists (which amounts to saying that they all have identical VOTs). Instead, they show that accounting for heterogeneity in motorists preferences can reveal substantial welfare gains in a value-pricing setting, and that these gains are often increasing in the degree of het-

¹Small (1999).

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

³Small and Yan (2001).

⁴Liu and McDonald (1999).

erogeneity. Moreover, recognizing this heterogeneity might enable policymakers to overcome current political impediments to offering toll-lanes by ameliorating distributional concerns through policies that cater to varying preferences.⁵ Thus, identifying heterogeneity in VOT and the degree to which it may be present has importance beyond estimating VOT itself.

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

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

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

This paper is organized as follows: Section 1.2 describes the empirical setting for the study. Section 1.3 describes how to generate multiply-imputed data

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

to overcome the problem of missing time-savings data for many respondents. Section 1.4 describes the study’s mode choice model and how to apply it to these imputed data toward obtaining valid statistical inferences. The results of this estimation process follow in Section 1.5. Section 1.6 illustrates some of the hazards of employing only a single imputation when multiple imputations are warranted. Section 1.7 offers a few concluding remarks.

1.2 Empirical Setting: The San Diego I-15 Congestion Pricing Project⁶

This value-pricing project offers solo drivers an option to pay to use an eight mile stretch of two free-flowing lanes (“Express Lanes” or “HOT” lanes) adjacent to (but physically separated from) the main lanes along California’s Interstate 15, just north of San Diego. It offers solo drivers a premium alternative to the typically congested conditions along that section of the I-15 - an alternative that carpools enjoy for free. The Express Lanes are reversible and operate in the southbound direction during the morning commute (inbound to San Diego) and northbound during the afternoon commute. Tolls are posted in both directions at the Express Lane entrance and about one mile prior. Those who choose to enter the facility must travel its entire length since there are no interim exits.

This study focuses on morning (inbound) commuters who traveled the entire eight-mile length on or adjacent to the Express Lane facility during October and November of 1999.⁷ The observation period corresponds to the fifth wave of the project’s panel survey that gathers the necessary information about I-15 commuters required to conduct mode-choice analysis. The proportion of commuters who actually pay to use the Express Lanes is relatively small, so choice-based

⁶See Brownstone et al. (2003) for a more detailed description of this project.

⁷Only weekday and non-holiday trips are considered.

sampling is employed in order to obtain a sufficient amount of variation in the data while meeting budgetary constraints. Table 1-1 summarizes these choice shares, along with demographic information about survey respondents in our sample.

1.2.1 Dynamic Tolls

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

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

1.2.2 Time Savings

Time savings are defined here as the difference between travel times on the main lanes adjacent to the Express Lane facility and travel times on the Express Lanes

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

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

themselves. The salient time-savings measure in this study is *median* time-savings since commuters are incapable of knowing their actual time savings prior to making a mode choice. Instead, it is assumed that commuters have a feel for their travel time distributions and base their decisions on typical values, as is standard in value-pricing studies.¹⁰

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

The first is that loop detector data often result in implausible speed estimates (such as the “Formula 1” speeds encountered in our sample). Through changes in inductance, loop detectors sense how long a vehicle is above them (“occupancy”) and how many vehicles pass over them (“flow”) in a given period. In order to estimate speeds from these data, loop detector algorithms often assume homogeneous vehicle speeds during each period (six minutes in the present case) and, perhaps more heroically, that “typical” vehicle lengths are known.¹¹ Given the mix of passenger cars, trucks, light-duty vehicles, and so forth typically observed on interstates, it is not difficult to see how loop detectors might yield unreliable speed estimates. It is worth noting, however, that if speeds are fairly homogeneous within each period, then speed variation across periods is likely to be fairly

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

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

well represented.

As an alternative to loop detector data, speed data from floating-car experiments are available and are considered to be reliable. These data were collected professionally and involved driving the length of the main and HOT lanes repeatedly in fifteen minute intervals. But, due to budget constraints, such data are only available for five days of the sample period. However, the variation in loop-detector speed data offers a means to predict these “missing” floating-car data, as described in Section 1.3.

The second objection is the existence of a dedicated Express Lane onramp at Ted Williams Expressway on the northern end of the facility. Those wishing to enter the I-15 at Ted Williams (over a third of our sample) can enjoy additional time savings by using the express lanes since the dedicated onramp enables them to bypass the queues that typically form at the metered entrance to the main lanes.¹² Indeed, the average observed wait time at this onramp is roughly equal to the average observed time savings from using the Express Lanes themselves, warranting their inclusion when calculating median time-savings.¹³ Unfortunately, observations on Ted Williams onramp wait times are only available for ten days of the sample period. Section 1.3 describes how to predict these missing data.

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

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

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

savings data. This challenge is addressed in the following section.

1.3 Multiple Imputations

Figure 1-1 aids in depicting the types of main-lane travel time data available for estimating time savings. As previously noted, the sample includes loop detector data for the entire sample period (two months). However, only ten days worth of Ted Williams onramp queue times and five days worth of floating car data are available, both of which are deemed reliable. The task at hand is to predict floating-car time savings and Ted Williams queue times by conditioning on loop detector data. In cases where queue times are available, but floating car times are missing, floating car time savings can be predicted by conditioning on both loop detector and queue data.

The segment labeled “A” in Figure 1-1 shows where it is appropriate to predict floating car time savings from both loop detector and queue data. Segment “B” shows where neither floating car or queue data are available, and must therefore be predicted from loop detector data alone.¹⁴ Segment “C” shows where no prediction is required - these observed values are retained in the estimation process.¹⁵

Express Lane travel times are typically measured by assuming a constant vehicle speed (usually 65 to 75 MPH) since the free-flow conditions in these lanes offer little variation.¹⁶ In this study, average speeds (by time of day) are calculated from Express Lane floating-car data and are taken as representative

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

¹⁵Note that loop detector data are collected in six minute intervals, while floating car and queue data are collected in fifteen minute intervals. To make these data compatible, floating car and queue data are interpolated into six minute intervals.

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

of Express Lane speeds. This can be seen as a compromise between assuming a constant speed across time periods, and fully imputing these speeds (which is likely to be fruitless, given the minor degree of variation in observed speeds). This compromise buys an additional (though small) degree of variation in travel time savings, which is desirable since the key variables of time savings and tolls tend to be highly correlated.

1.3.1 Imputation Procedure

The general procedure for imputing missing data is to draw them from their appropriate asymptotic conditional distributions. In this case, linear regression models are used to estimate these distributions.

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

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

Note that these logit transformations are “undone” when calculating predicted time savings.

1.3.1.1 Floating Car Data Conditioned on Loop Detector and Queue Data

Segment “A” in Figure 1-1 illustrates the empirical setting for these imputations. The analysis proceeds by regressing floating car data on both loop detector

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

and queue data, along with all other available covariates. For parsimony, only covariates with significant explanatory power are retained in the model.

The right column of Table 1-2 shows the estimation results for this regression. Note that the model fits quite well, although the reported R^2 of 0.57 might be misleading. Keep in mind that this value is calculated in the logit-space of the dependent variable, thereby reducing in-sample variation and generating a much lower R^2 than would result from a level-space calculation.

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

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

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

1. Draw σ_*^2 by dividing the residual sum of squares ($\hat{u}'\hat{u}$) from regression (2) by an independent draw from a χ^2 distribution with degrees of freedom equal to the dimension of λ .
2. Draw a vector of residuals u_* from a $N(0, \sigma_*^2 I_N)$ distribution.
3. Draw λ_* from a $N(\hat{\lambda}, \hat{V}_{F^{LQ}})$ distribution.
4. Construct $F_*^{LQ} = X\lambda_* + u_*$.

This process is repeated to obtain the desired number of imputations (m) required for the estimation process described in Section 1.3.2.

1.3.1.2 Floating Car and Queue Data Conditioned on Loop Detector Data

Segment “B” in Figure 1-1 illustrates the cases for which both floating car and queue time savings must be imputed from loop detector data. The procedure is analogous to that of the preceding section, where one might be tempted to impute these data from equation-by-equation least-squares estimators. However, doing so would fail to account for the error correlation across these equations when using them to impute the missing data.¹⁸ To account for this correlation, Zellner’s Seemingly Unrelated Regressions estimator is employed.¹⁹ The left column of Table 1-2 gives the estimation results for these simultaneous regressions.

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

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

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

To better explain the imputation procedure in this case, write

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

¹⁸A Breusch-Pagan test confirms this error correlation across the two regressions.

¹⁹Zellner (1962).

²⁰Note that the dimension of S is $2N \times 1$.

and note that

$$\nu^F \sim N(0, \Sigma_{11} I_N) \quad (5)$$

$$\nu^Q \sim N(0, \Sigma_{22} I_N)$$

It follows from the standard properties of multivariate normal distributions that

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

The procedure to generate single vectors of imputed floating car time savings and Ted Williams queue times follows as²¹

1. Draw ν_*^F from its marginal distribution given in (5).
2. Using the draw in the previous step, draw ν_*^Q from its *conditional* distribution given in (6).
3. Draw $\delta_* = \begin{bmatrix} \delta_*^F \\ \delta_*^Q \end{bmatrix}$ from a $N(\hat{\delta}, \hat{V}_S)$ distribution.
4. Construct $\begin{bmatrix} F_*^L \\ Q_*^L \end{bmatrix} = \begin{bmatrix} X^F & 0 \\ 0 & X^Q \end{bmatrix} \begin{bmatrix} \delta_*^F \\ \delta_*^Q \end{bmatrix} + \begin{bmatrix} \nu_*^F \\ \nu_*^Q \end{bmatrix}$.

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

1.4 Estimation Procedure

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

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

imputation” methods, however, treat the imputed values as known and fail to account for the additional estimation error introduced by the imputation process. In order to obtain valid and consistent estimates, the Multiple Imputation Method given in Rubin (1987) is employed.²² Section 1.6 illustrates how estimates from identical models can differ between single and multiple imputation procedures.

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

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

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

The frequentist version (or “randomization-based” version, as Rubin puts it) of this method is used to obtain estimates.²³ Schenker and Welsh (1988) show that the imputation procedure outlined in Section 1.3.1 is equivalent to drawing from the Bayesian predictive-posterior of the missing data ($f(Y_{mis}|Y_{obs})$) when the

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

²³This is done mainly for computational convenience. Moreover, these estimates are based on 537 observations, suggesting that they would not differ in numerical significance from those produced by a Bayesian approach with relatively flat priors.

regressions exhibit a normal error structure with standard uninformative priors. What remains is a valid frequentist estimator that averages a series of m estimates over these m imputations (for $m \geq 2$), analogous to equation (7).

Let $\tilde{\theta}_r$ denote a single estimate obtained from a complete set of data, including a single set of imputed values, and let $\tilde{\Omega}_r$ denote its associated covariance estimate. Rubin’s Multiple Imputation Estimators are given by

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

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

where

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

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

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

Rubin (1987) shows that $\hat{\theta}$ is a consistent estimator of θ for $m \geq 2$, and $\hat{\Sigma}$ is a consistent estimator for the covariance of $\hat{\theta}$.²⁴ Equation (9) shows that the precision of $\hat{\theta}$ improves with the number of imputations by a factor of $\frac{B}{m}$, suggesting that “many” imputations should be drawn. However, there is no formal stopping rule to suggest how large “many” should be. An approach

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

adopted by Brownstone et al. (1999) is to note from Rubin (1987) that the Wald test statistic for the null hypothesis that $\theta = \theta_0$ is given by

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

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

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

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

The stopping rule adopted by Brownstone et al. (1999) is to increase m until τ is large enough for the standard asymptotic χ^2 distribution of Wald test statistics to apply. They find that $m = 20$ is sufficient to meet this condition. In this study, however, computing time is relatively cheap so $m = 200$ is chosen to effectively minimize the $\frac{B}{m}$ component of $\hat{\Sigma}$ such that $\hat{\Sigma} \simeq U + B$.

This multiple imputation framework enables the analysis to proceed toward consistently estimating θ in the study's mode choice model and to construct consistent value of time-savings estimates, which depend on $\hat{\theta}$.

1.5 Mode Choice and Value of Time Savings

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

1.5.1 Conditional Logit Mode Choice Model

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

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

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

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

where θ is a vector of parameters to be estimated, as prescribed in Section 1.3.2. Each $\tilde{\theta}_r$ and $\tilde{\Omega}_r$ estimate is obtained by maximizing the joint log-likelihood function for the $N = 537$ commuters in our sample, given by

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

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

1.5.2 Alternative Models

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

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

Another consideration is that the inconvenience of obtaining a FasTrak transpon-

der is modeled as an implicit cost of using the Express Lanes.²⁵ An alternative model, such as the nested-logit form, would assume that this effort has its own random determinants by specifying it as an explicit choice dimension. In this spirit, Lam and Small (2001) estimate VOT with the conditional logit and nested logit forms, but obtain only very small differences between the estimates. Ghosh (2001) experiences the same using the same wave of our I-15 data. Hence, the more parsimonious conditional logit form is adopted.

1.5.3 Value of Time Savings

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

$$VOT_n \equiv \left. \frac{dC_{in}}{dT S_{in}} \right|_{\bar{V}_{in}} = - \frac{\partial V_{in} / \partial T S_{in}}{\partial V_{in} / \partial C_{in}} \quad (18)$$

Equation (18) shows that VOT is also a function of any characteristics that are interacted with either time savings or tolls. This is how heterogeneity in VOT is observed across commuters through varying characteristics such as income group, work status, and trip distance.

It is important to point out that most value-pricing studies attempt to estimate the value of reducing the variability in these time savings, often referred to as the “value of reliability” (VOR). Aside from its policy implications, doing so is appropriate since any such valuation is likely to appear in VOT estimates if variability in time savings is not properly controlled for. These studies typically focus on the “upper tails” of time savings distributions, with variability

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

measures such as the difference between the 90th and 50th percentiles of these distributions, since it is reasonable to assume that commuters are only sensitive to relatively large travel delays.²⁶

This study, however, is unable to detect a significant or economically meaningful direct effect of variability across a variety of measures, including those defined in previous value-pricing studies. This is at least partially due to the high degree of collinearity between tolls, time savings, and variability endemic to these types of studies. The SR-91 studies are able to overcome this collinearity since tolls follow a fixed schedule, allowing a degree of independent time-savings variation. Carpools in these studies are also subject to tolls, which can then be converted to per-passenger costs, providing additional independent variation. Unfortunately, this study's sample has no such luxuries since I-15 tolls are dynamic and carpools travel for free.

Perhaps more importantly, the estimates presented here suggest that commuters use these posted tolls to acquire information about travel conditions on the main lanes (captured by the "Low-Toll Signal" variable in Table 1-3).²⁷ When travel conditions are particularly bad, Express Lane tolls are particularly high, which is likely to make commuters less averse to variability in time savings since they are able to better predict the time savings they can enjoy on the Express Lanes. Moreover, those who normally travel during peak periods (when variability is greatest) but are averse to small chances of late arrival can use the Express Lanes as a "backstop" when relatively high tolls suggest doing so.²⁸ If a

²⁶Brownstone et al. (2003), Lam and Small (2001), Ghosh (2001), and Brownstone et al. (1999) use this definition of variability; the latter three of these studies use I-15 data with limited results. Small, Winston, and Yan (2002) define variability as the difference between the 80th and 50th percentiles of their SR-91 time savings distributions.

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

²⁸I thank Kenneth Small for suggesting this possibility.

large enough proportion of commuters exhibit this behavior, then high levels of variability and their attendant high tolls will coincide with a greater propensity to use the Express Lanes.²⁹

Accordingly, VOR is not estimated since even a significant direct effect of variability would result in negative VORs for this sample. Instead, the importance of controlling for variability is recognized by including in the estimation process the conventional “90th-50th percentile” measure (interacted with trip distance).

1.5.4 Estimation Results

1.5.4.1 Parameter Estimates

The first series of columns in Table 1-3 give the estimation results from a conditional logit model with multiple imputations. All of the relevant parameter estimates have the expected signs and are statistically significant at the 95% confidence level, except for the “wrong” coefficient sign on variability interacted with trip distance.³⁰

In the table, the columns entitled “Estimation Covariance Shares” give the shares of the total statistical error for each estimate that are attributable to the imputation process (corresponding to equation (11)) and the estimation process alone (corresponding to equation (10)). These covariance shares, as presented, are defined as $diag(\hat{\Sigma}^{-1}B)$ and $diag(\hat{\Sigma}^{-1}U)$, respectively. Reporting these shares aids in understanding the composition of the standard errors that accompany the parameter estimates – Section 1.6 expand on this.

We focus on the FasTrak choice variables since this is where the marginal

²⁹This notion is supported by preliminary experiments in which variability coefficients carried the “wrong” (positive) sign.

³⁰A priori, we would expect commuters to be averse to time savings variability for any trip distance. However, the discussion in Section 1.4.3 sheds light on why this sign appears.

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

The “Low-Toll Signal” variable is included to control for the traffic-condition signalling effects discussed in the previous section. Specifically, this is an indicator variable equal to one if the posted toll is lower than the average toll across the sample period for that time of day. This particular form is chosen due to the inertia exhibited by a large portion of the FasTrak users in the sample.³¹ The intuition is that many of these commuters are accustomed to travelling solo in the express lanes and will deviate from this behavior when posted tolls signal that traffic conditions in the main lanes are relatively mild. The estimates presented here indicate a measurable toll-signal effect.

The “Free-Lane Traffic Rating” is an attempt to control for the aggravation (disutility) associated with driving in congested conditions, which could bias VOT estimates upwards if not controlled for.³² It is also included to separate its effect from the toll-signal effect. Respondents were asked to rate the traffic conditions on the free lanes on a scale from one to ten, where one represented “bumper-to bumper traffic” and ten represented “no traffic problems at all”. As

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

³²VOT estimates can be thought of as reduced-form expressions for travelers’ willingness to pay for all of the amenities that are provided by the time-saving good. This study attempts to more accurately estimate the “time-savings only” dimension of VOT by controlling for perceptions about traffic conditions, which are believed to be correlated with “congestion aggravation”.

expected, the estimates suggest that worsening traffic conditions correspond to higher propensities for using Express Lanes.

Consistent with the previously cited SR-91 and I-15 studies, it is found that home owners and those with greater education are more likely to use the Express Lanes. Those with flexible arrival times are less likely to use the Express Lanes. In contrast, no significant effect for females is found, and the traditional “middle-age” indicator variable is excluded since it appears to be collinear with the sample’s income and home ownership variables.

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

1.5.4.2 Value of Time-Savings Estimates

From the multiple imputation parameter estimates, VOT estimates are generated for each respondent in the sample using equation (18). The interaction terms involving time savings and tolls, and their statistically significant coefficients, reveal a significant degree of observable heterogeneity in how commuters value the time savings provided by the I-15 Express Lanes. The left-hand side of Table 1-4 summarizes these VOT estimates, sorted into work and non-work trips. Since income plays a prominent role in observing VOT heterogeneity, Figure 1-2 is included to show the (in sample) distribution of income categories

across distances, lending further insights to these estimates.

It is important to note that estimated VOT is a highly nonlinear function of parameter estimates, which is evident from equation (18). Accordingly, small variations in parameter estimates can lead to relatively large changes in VOT estimates (with or without imputations). Hence, a more “robust” estimate of each median VOT is its expected value taken over the sampling distribution of its underlying parameters. The sampling distribution of VOT has no closed-form expression and generally cannot be characterized without using Monte Carlo methods. “Bootstrapping” this sampling distribution provides VOT estimates based on a thorough exploration of their underlying parametric distribution rather than estimating VOT from point estimates of these parameters. This is asymptotically equivalent to calculating an optimal Bayesian posterior estimate of each median VOT (with non-informative priors) and is reported in the “Bootstrap Median” column of Table 1-4. These are taken as preferred median VOT estimates.

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

Let W_i represent these “pure” choice-based weights, T_{in} be the number of times person n chose mode i in a given week, and T_n be the total number of trips

³³These shares are reported in Ghosh (2001).

taken by that person that week. The adjusted choice-based weights are given by

$$W_{in} = \sum_{i=1}^3 \frac{W_i T_{in}}{T_n} A \quad (19)$$

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

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

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

Back to the present study, interacting median time savings with distance offers an additional dimension of observable heterogeneity in VOT, which gives rise to the “inverted U” shape illustrated in Figure 1-3. Figure 1-3 plots median VOT

for work-trip travelers against distance, where income group and employment status vary; a similar pattern is exhibited for non-work trips (not shown in the figure). The quadratic form is appealing since the downward-sloping portion of the function accounts for the possible self-selection of low-VOT commuters who are willing to spend more time on the road and thus travel greater distances. Counteracting this effect is the increasing scarcity of leisure time as travel time cuts into it, or possibly that VOT is lower for shorter trips since people might appreciate some transition time between home and work;³⁴ both of these notions help to explain the upward-sloping portion of the function.

As expected, Figure 1-3 shows that higher incomes correspond to higher VOTs for a given work status. What may be slightly surprising is the magnitude by which higher income groups place a higher value on their time savings. It is possible that these higher income commuters are more also willing to purchase additional amenities that the Express Lanes offer. For instance, Golob (2001) uses an earlier wave of I-15 data to show that FasTrak users perceive a real safety advantage to using the Express Lanes, which is plausible since these lanes are physically separated from the main lanes. This physical separation might also hinder the ability of highway patrol officers to issue tickets to those speeding in the Express Lanes. Additionally, Brownstone et al. (2003) propose that using FasTrak signals wealth - a signal that those with higher incomes might purchase more readily.

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

³⁴Small (1999).

Table 1-4 includes interquartile ranges and their attendant percentiles next to each estimate. These figures characterize the sampling distributions of the parameter estimates, not the distributions of VOTs within the sample. The interquartile ranges reported in the table reflect the degree of uncertainty in estimating VOT due to statistical error in estimating its underlying parameters. They are determined by Monte Carlo draws from the sampling distributions of the parameter estimates, i.e., they are “bootstrapped”.

To illustrate the role that the imputation process plays in generating this statistical error, the left-hand side of Table 1-5 decomposes the degree of this error, characterized by interquartile ranges, into two parts: dispersion based on the estimated total covariance of the parameter estimates and dispersion based on the covariance generated by the imputation process alone. Specifically, the second column in the table is constructed by “bootstrapping” these VOT distributions with draws from a $N(\hat{\theta}, U)$ distribution (see equation 10), which accounts only for the within-imputation covariance produced by parameter estimation alone. Subtracting the resulting interquartile ranges from those in the first column yields the amount of total dispersion due to the imputation process alone. These values are divided by the values in the first column to present them as shares of the total dispersion, given by the third column in the table. The columns labeled “Estimation Covariance Shares” in Table 1-3 provide a similar decomposition for the parameter estimates themselves.

1.6 Multiple Imputations vs. Single Imputation

Tables 1-3 and 1-4 include sets of estimates based on a single imputation. They are included to illustrate the potential hazards of basing estimates on a single set of imputed data when multiple imputations are warranted. These single-

imputation estimates are derived from the same mode-choice model and VOT estimators employed previously with multiply-imputed data.

This single imputation is essentially drawn according to the procedure outlined in Section 1.3.1, with $m = 1$. However, this study sheds the best possible light on the single-imputation scenario - to facilitate a “fair” comparison - by drawing these imputations directly from the means of their asymptotic conditional distributions, given in Table 1-2, and adding the appropriate residuals. The right-hand side of Table 1-3 displays the parameter estimates for the mode choice model in the single-imputation case. Note that the reported t-Statistics in this model are generally higher, illustrating that inferences based on these estimates will be “too sharp” since they do not account for the error introduced by the imputation process, i.e., uncertainty due to measurement error.

The right-hand side of Table 1-4 reports VOT estimates for the single-imputation case. These estimates are uniformly lower than their multiple imputation counterparts. Although this is an artifact of this particular scenario, it illustrates the potential biases that can be introduced by treating the single set of imputed values as known. Also, the last column of Table 1-4 characterizes the degree of statistical error in estimating VOT for the single-imputation case. Since the uncertainty due to measurement error is overlooked here as well, the reported dispersion measures are uniformly lower than their multiple imputation counterparts. This demonstrates that VOT inferences will also be “too sharp” when its underlying sampling variability is understated.

Table 1-6 reflects the degree to which this understatement occurs. Its first column gives a measure of estimation uncertainty that would be reported in a single-imputation scenario without properly accounting for underlying sampling

variability. The second column shows the degree to which this would understate the estimation uncertainty that appropriately accounts for dispersion introduced by the imputation process itself. In this study, failing to perform multiple imputations would produce median VOT estimates that are 23% to 73% “too sharp”, thereby reporting a misleading degree of estimation precision.

1.7 Chapter Conclusion

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

Of course, obtaining these estimates requires a way to construct valid statistical inferences when reliable time savings data are missing for most of our sample. This study demonstrates how to apply Rubin’s Multiple Imputation Method under such circumstances in order to procure valid and consistent estimates. It also illustrates the extent to which the “single imputation method” understates the degree of uncertainty in estimating VOT by failing to account for its underlying

³⁵Small, Winston, and Yan (2002).

sampling variability.

The study's median VOT estimates are plausible, intuitive, and within the range of estimates presented by previous value-pricing studies. Their confidence intervals, however, encompass those of the previous studies, making it difficult to resolve discrepancies among them. Perhaps this study's findings will encourage wider public acceptance of value-pricing projects, hopefully yielding more reliable data for resolving such discrepancies.

2 Defensive Driving and the External Costs of Accidents and Travel Delays

2.1 Chapter Introduction

Road users impose external costs on each other in terms of accidents and travel delays. With travel-delay externalities, marginal increases in travel times are related to traffic levels in order to estimate the magnitudes of these costs. With accident externalities, the focus is on how accident *risk* changes with increasing traffic levels.³⁶

In current practice, estimating the magnitudes of external accident costs involves a comparison between marginal and average accident rates across various traffic volumes. This relationship is typically converted to an expression of the elasticity of accident risk with respect to traffic flow. In what I refer to as the “traditional approach” to modeling accident externalities, cost estimates are directly proportional to these elasticities. And since these elasticities are typically estimated to be zero, the traditional approach often concludes that drivers do not impose external accident costs on one another.

However, this approach overlooks the rational behavior of road users. When driving conditions become more hazardous due to increased traffic levels, rational drivers offset this risk, to some extent, by driving more carefully.³⁷ This defensive effort results in additional economic costs – costs that are widely recognized by the literature on accident externalities but typically abstracted from. Moreover, cautious driving usually coincides with slower driving, which compounds

³⁶“Accident risk” refers to the probability that a road user will be involved in an accident of a particular type. Risk is generally considered to be an increasing function of traffic volume, and the observed ratio of total accidents to volume is typically used to measure the level of this risk.

³⁷In the traffic-safety literature, this phenomenon is known as “offsetting” or “risk compensating” behavior.

the costs of defensive effort with additional travel-time costs. Positive accident externalities can thus exist even when observed accident elasticities are zero (or even negative) since these observed elasticities reflect the tradeoffs between risk and effort that motorists face.

This paper first develops a theoretical model that characterizes these tradeoffs and their effects on accident and travel-delay externalities. An empirical framework is then generated from this model by recognizing that accident risk, defensive effort, and travel delays are linked by traffic densities. Although defensive effort is not measurable, observed traffic densities enable the costs of risk, effort, and travel delays to be jointly estimated by exploiting micro-level data from existing congestion-pricing experiments. The resulting analysis demonstrates that accident externalities between motorists are substantial during peak-period commutes. More generally, this paper suggests a paradigm-shift for modeling, estimating, and interpreting the external costs of accidents and travel-delays.

The paper is organized as follows. Section 2.2 formally reviews the traditional approach to modeling accident externalities. Section 2.3 develops a simple theoretical model in which rational drivers choose an optimal balance of accident risk and defensive effort. Its results are then used to extend the traditional approach by incorporating them into a joint model of accident and travel-delay externalities where several distinct components of these costs are identified. Section 2.4 describes how data from existing congestion-pricing experiments can be used to develop estimates from this theoretical framework. Section 2.5 employs this approach and presents external cost estimates, along with related valuation estimates; its results imply Pigouvian tolls of \$1.80 per vehicle-mile to jointly correct accident and travel-delay externalities, and \$0.80 per vehicle-mile to cor-

rect accident externalities alone. Section 2.6 discusses the implications of these results and compares them to those of previous studies. Suggestions for further research and concluding remarks are offered in Sections 2.7 and 2.8.

2.2 The “Traditional Approach”

In current practice, external accident cost estimates are dictated by estimates for the ratio of marginal to average accident rates or, alternatively, the elasticity of accident risk with respect to traffic flow. To formally illustrate (a simplified version of) this traditional risk-flow approach, consider a single road link in a given time period with only one type of accident and one type of vehicle (ignoring pedestrians). Let A represent the number of accidents between two vehicles on the roadway and v the flow of vehicles traveling that road per unit of time. Additional vehicles on the road increase the number of “encounters” (potential collisions) between vehicles, leading to a greater number of accidents described by

$$A = \gamma v^\rho \tag{20}$$

where γ is a proportionality constant and ρ is the degree to which accidents depend on traffic levels. Marginal and average accident rates are then given by

$$\frac{\partial A}{\partial v} = \rho \gamma v^{\rho-1} \tag{21}$$

$$\frac{A}{v} = \gamma v^{\rho-1} \tag{22}$$

Letting $R(v)$ represent (average) accident risk ($\frac{\partial R(v)}{\partial v} > 0$),

$$A = R(v)v = \gamma v^\rho \tag{23}$$

$$\implies \varepsilon_{R,v} = (\rho - 1) \tag{24}$$

where $\varepsilon_{R,v} \equiv \frac{\partial R(v)}{\partial v} \frac{v}{R(v)}$. Thus, the ratio of marginal to average accident rates is given by ρ , and the elasticity of accident risk with respect to traffic flow is given by $\rho - 1$.

It is important to draw a clear distinction between *flow*, the (average) number of vehicles passing a point on the road per unit of time, and *density*, the (average) number of vehicles on the road per unit of distance at a given time. The above framework is couched in terms of vehicle flows, which allows the “supply” of accidents to be represented as a flow quantity. This framework is largely built on contributions from William Vickrey and David Newbery. For instance, Newbery (1988) suggests that typically “accidents increase as the square of traffic flow”, i.e., $\rho = 2$ is the “natural” degree to which accident rates increase with traffic volumes. This approach is analogous to that used in kinetic gas theory, where the number of collisions between “particles in a box” is proportional to the square of the number of particles in the box. In other words, it is understood in the above model that increasing the number of vehicles on the road causes an increase in the potential for collisions by increasing the *density* of vehicles on the road at each time, which captures what is meant by an increase in the number of “encounters”.

Vickrey (1968) offers some of the first empirical estimates of these quantities by examining marginal and average accident rates on California highways; he suggests $\rho = 1.5$.³⁸ Newbery (1988) notes that highway engineering estimates accept as convention that accident rates are proportional to traffic flow, i.e., $\rho = 1$.³⁹ In light of this, Newbery compromises between the engineering estimates

³⁸Vickrey also notes that accident risk is not directly proportional to volume since increased traffic “induces a greater degree of caution or discipline on the part of drivers.”

³⁹Newbery (1990) also suggests that $\rho = 1$ “would be the case if one took seriously the explanation of ‘risk compensation’, according to which road-users choose a desired level of perceived risk with which they are comfortable - too little risk is boring, too much is frightening. Im-

and Vickrey's estimate and settles on $\rho = 1.25$. These figures are often used as benchmarks in efforts to estimate external accident costs.⁴⁰

Jansson (1994) makes a vital contribution to this literature by building on Vickrey's and Newbery's work to develop a formal model of marginal external accident costs. Much of the recent research on accident externalities employs Jansson's approach in one form or another; Mayeres et al. (1996), Lindberg et al. (1999), and Lindberg (2001) are among recent studies adopting this approach. The model in Jansson (1994) for a single vehicle type (car) is summarized as follows (in simplified form).

Let M_R represent a typical road user's willingness to pay to reduce her accident risk to zero, which can include her dependents' willingness to pay for the same. Additional social costs resulting from an accident, such as net-output losses and administrative costs, should also be accounted for (which Jansson's approach does) but are abstracted from here to keep the analysis simple.⁴¹ Total, marginal private, and marginal social accident costs are given by

$$TSC^t = M_R A = M_R R(v)v \quad (25)$$

$$MPC^t \equiv \frac{TSC^t}{v} = M_R R(v) \quad (26)$$

$$MSC^t \equiv \frac{\partial TSC^t}{\partial v} = M_R \left[R(v) + \frac{\partial R}{\partial v} v \right] \quad (27)$$

where the superscript t denotes that these expressions are in the context of the traditional approach to modeling these costs.⁴² Accordingly, marginal external

provements in road safety then induce compensating increases in risk taking, while deteriorating road conditions (ice, snow, heavier traffic) induce more caution."

⁴⁰For example, Newbery (1988), Jansson (1994), and Peirson et al. (1998) adopt this estimate for their analyses.

⁴¹These costs are often referred to as "cold-blooded costs" in the accident literature. They represent a relatively small portion of total accident costs. Representing these costs with c , their contribution to external accident costs are given by $cR(v)$.

⁴²Transportation economists usually make the simplifying assumption that marginal private

accident costs are given by

$$MEC^t \equiv MSC^t - MPC^t = M_R R(v) \varepsilon_{R,v} \quad (28)$$

which also gives the Pigouvian toll required to achieve an efficient level of traffic in terms of accident risk. It is clear from equation (28) that the magnitude of the accident externality is directly proportional to the accident elasticity $\varepsilon_{R,v}$. Hence, under this approach, empirical estimates of these elasticities are critical in determining the extent to which road users impose accident costs on one another. For instance, from equation (24), the “square-law” referred to by Newbery implies that this elasticity is unity, whereas Vickrey’s estimate implies an elasticity of 0.5. Newbery’s compromise between Vickrey’s estimate and the engineering-based convention of zero implies an elasticity of 0.25.

However, adopting an elasticity of zero has become pervasive in public policy, as reflected by U.S. Federal Highway Administration (1982) and Department of Transport COBA 9 (1981-1993). This is supported by Vitaliano and Held (1991) who estimate marginal to average accident-rate ratios as approximately unity, from which they conclude that “no significant accident externality exists”. Elvik (1994) reviews several empirical studies on the relationship between accidents and traffic levels and concludes that “no precise relationship can be detected”; he then suggests that the accident elasticity is negative for fatal accidents and zero for non-fatal accidents.

This view has also been applied in studies that attempt to estimate the overall external costs of road use. Mayeres et al. (1996) note “for accidents between two motorized road users an accepted convention is to assume that the number costs and average (variable) costs are equal. This is readily defended by noting that the derivative of total private cost with respect to volume is relatively small, while the resulting quantity is multiplied by a value that is relatively large when describing total costs.

of accidents is proportional to traffic volume, such that the elasticities are zero.” If this is the case, then equation (28) tells us that an accepted convention of the traditional approach to modeling accident externalities is to assume that no such externalities exist (between motorized road users). Newbery (2002) cites evidence from Department of Transport (1996) that the ratio of marginal to average accident rates is less than one, implying a negative accident elasticity (as Elvik (1994) suggests for fatal accidents). In this case the traditional approach suggests that driving should be subsidized in the interest of public safety.

However, an observed elasticity of zero does not imply that motorists create no additional hazards for each other (as discussed by Vickrey and Newbery - see footnotes 38 and 39). It instead indicates that motorists offset increased physical risk, to some extent, by driving more carefully. This notion is supported empirically by several studies that attempt to detect “offsetting behavior”. Peltzman (1975) is among the first to provide such evidence and Keeler (1994) provides more recent support.⁴³

As noted in Newbery (1988), these defensive efforts are “not costless, and the extra care taken by everyone should be properly costed.” The traditional approach, however, overlooks these costs - costs that are incurred regardless of the observed relationship between accident risk and traffic levels.

⁴³Efforts to detect offsetting or “risk compensating” behavior is not limited to the economics literature. Engineering-based studies such as Farmer et al. (1997), Sagberg et al. (1997), Meeker et al. (1997), Leden et al. (1998), Assum et al. (1999), and Thiffault and Bergeron (2002) detect risk compensation under a variety of circumstances such as road surface and lighting improvements, driving monotony, railroad-crossing control improvements, and before-and-after studies of anti-lock brake installations.

2.3 A Theoretical Model of Accident and Travel-Delay Externalities with Defensive Drivers

Little research has been devoted to understanding offsetting behavior in the context of accident externalities, though there are a few notable studies. Peirson et al. (1998) adjust existing estimates of external accident costs with a model that incorporates an assumed degree of offsetting behavior. Their approach suggests that existing estimates are overstated given the cost reductions that defensive drivers confer on one another. They acknowledge, however, that these implied cost reductions are not balanced by the costs of exerting risk-reducing effort, such as “congestion and reduced pedestrian mobility”.

The few studies that explicitly address the costs of defensive effort do so theoretically. Rotemberg (1985) explores the effects of defensive effort by modeling optimal tradeoffs between effort and risk reduction through increased following distances and their associated time costs. Boyer and Dionne (1987) use costly “self-protection activities” in an expected utility framework to characterize optimal insurance levels. Mayeres (1999) develops an externality model in which motorists purchase a “defensive commodity” to reduce “exogenous accident risk”.⁴⁴

This section builds on some of the insights from Rotemberg (1985), Boyer and Dionne (1987), Peirson et al. (1998), and Mayeres (1999) to explicitly model tradeoffs between accident risk and defensive effort. It then employs the results of this optimization process in a model that describes the joint contribution of physical accident risk and defensive effort, with its attendant time-costs, to external accident and travel-delay costs.

The “margin” of these marginal external costs is traffic volume. As discussed

⁴⁴Outside the economics literature, Calabresi (1970) explains from a regulatory perspective how defensive driving should be considered in legal reforms.

in Section 2.2, however, (physical) accident risks are influenced by volumes only to the extent that these volumes affect traffic densities. Likewise, vehicle speeds (and their corresponding travel times) are influenced by volumes through their effect on densities.⁴⁵ To emphasize these principles, the modeling efforts in this section focus on traffic densities, but are compatible with the traditional risk-flow approach since these densities are presented as functions of traffic volumes.

2.3.1 Optimal Defensive Effort

Consider a representative driver of a given vehicle type on a single road link with other vehicles of the same type. Let D represent the driver's level of defensive effort - the care she takes to ensure some degree of her own safety, including the level of attention she pays to the task of driving. The risk of an accident between two vehicles is $R \equiv R(k, D)$, where $k \equiv k(v)$ is the average density of vehicles during some time period and v is the average flow of vehicles over that period. This risk depends both on the physical quantity k and the driver's own behavior (through D), i.e., accident risk is endogenous. Also, let w be the driver's initial wealth and $l \equiv l(k)$ be the loss she incurs in an accident. Note that R only gives the probability of a collision and does not specify which type of accident might result (e.g. fatal or serious injury). Instead, the level of l dictates the type of accident under consideration, which is assumed to be a non-linear function of traffic density - initially rising then falling. For example, the likelihood of a collision might be quite high under very dense traffic conditions,

⁴⁵These statements can be represented formally through a "fundamental" relationship between volumes, speeds, and densities: $v = ks(k) \Rightarrow k = \frac{v}{s(k)}$. A more rigorous representation would include dynamic models that account for a phenomenon called "hypercongestion". In these models, average travel times are also increasing in "input flows", as are average densities for road segments that extend beyond the length of any queue that might be generated. See Small and Chu (2003) for an economic review of the "hypercongestion" literature.

but the loss associated with such a collision is likely to be quite low; fatal accidents are assumed to be rare in heavily congested conditions.⁴⁶

Since defensive effort typically involves speed reduction, travel time $T \equiv T(k, D)$ is given in terms of this effort, along with physical characteristics such as the roadway capacity that vehicles consume (proxied by k). Accordingly, $C(T, D)$ represents the (non-stochastic) disutility that results from exerting defensive effort, both directly from effort itself and through its effect on travel time.

The model's main assumptions are summarized as follows:⁴⁷

$$\frac{\partial R}{\partial k} > 0, \frac{\partial R}{\partial D} < 0 \quad (29)$$

$$\frac{\partial T}{\partial k} > 0, \frac{\partial T}{\partial D} \geq 0 \quad (30)$$

$$\frac{\partial C}{\partial D} > 0, \frac{\partial C}{\partial T} > 0 \quad (31)$$

The assumptions state the following: (a) physical accident risk is increasing in traffic density, but can be offset to some extent by defensive effort;⁴⁸ (b) increased traffic density increases travel time as does defensive effort insofar as it induces speed reduction; (c) defensive effort and travel time are costly in terms of utility.

A state-dependent utility framework provides a simple way to relate motorist behavior to the above variables and assumptions. Write expected utility as

$$U^e = R(k, D)U^a(w - l) + [1 - R(k, D)]U^{-a}(w) - C(T(k, D), D) \quad (32)$$

where U^a and U^{-a} are (sub)utilities with and without the occurrence of an accident. The driver will choose a level of defensive effort that balances the marginal

⁴⁶This statement must be tempered by the possibility that under queuing conditions the risk of a fatal accident might be relatively high given an increased probability of slamming into the vehicles at the end of the queue.

⁴⁷More precisely, $\frac{\partial R}{\partial k} > 0 \forall k < k_j$ where k_j is a ‘‘jam density’’ indicating stopped traffic. This accounts for the fact that a vehicle cannot initiate a collision when it is not moving.

⁴⁸‘‘Physical accident risk’’ or ‘‘exogenous risk’’ refers only to the portion of risk that is influenced by density. More formally, if \bar{D} is some fixed level of defensive effort, then an increase in physical risk is represented by $\frac{\partial R(k, \bar{D})}{\partial k} > 0$.

benefit of risk-reduction with the marginal cost of exerting this level of effort, which includes a travel-time component. That is, she will choose the level of D satisfying the first-order condition:

$$\frac{\partial R}{\partial D}[U^a(w-l) - U^{-a}(w)] = \frac{\partial C}{\partial D} + \frac{\partial C}{\partial T} \frac{\partial T}{\partial D} \quad (33)$$

This implicitly defines the optimal level of defensive effort D^* as a function of k , i.e., $D^* = D(k)$. Accordingly, the driver's optimal level of accident risk is given by $R^* = R(k, D(k))$. Note that

$$\frac{dR(k, D(k))}{dk} = \frac{\partial R}{\partial k} + \frac{\partial R}{\partial D} \frac{dD}{dk} \begin{matrix} \geq 0 \\ < 0 \end{matrix} \quad (34)$$

which illustrates an indeterminate change in the driver's resulting level of overall risk after an increase in traffic density. Physical road hazards may increase with traffic flows ($\frac{\partial R}{\partial k} > 0$), but the magnitude and direction of the net change in risk depends on the extent to which driver's offset this physical risk ($\frac{\partial R}{\partial D} \frac{dD}{dk} < 0$).

The result illustrates why empirical studies using the traditional approach might report a zero (or even negative) accident elasticity. Such studies presume to observe $R(v, \bar{D})$ when they more reasonably observe $R(k, D(k))$. In other words, researchers can only observe changes in accident risk net of any offsetting effects, where the net effect results from drivers' optimal tradeoffs between risk and effort.

2.3.2 External Accident and Travel-Delay Costs

The preceding analysis suggests that it is appropriate to model accident and travel-delay externalities together since they jointly involve speed reduction. At a drivers optimal level of defensive effort $D(k)$, travel time is given by $T(k, D(k))$, which illustrates how density provides a link between accident and travel-delay

externalities.⁴⁹

Consider the road environment described in the previous section. M_T is the marginal value of travel time savings (the “value of time”). Analogous to this is M_D , the value of a marginal reduction in the effort required to maintain a preferred level of risk.⁵⁰ M_R is the value of a marginal reduction in the risk of a loss resulting from an accident; in the case of accidents with a single fatality, the main component of M_R is often referred to as the “statistical value of life”.

The total social cost of driving that motorists bear, in terms of accidents and travel-delay, during a commute period of duration q , is given by:⁵¹

$$TSC = M_R R(k, D(k))qv + M_T T(k, D(k))qv + M_D D(k)qv \quad (35)$$

The marginal private cost during this period is

$$MPC \equiv \frac{TSC}{qv} = M_R R(k, D(k)) + M_T T(k, D(k)) + M_D D(k) \quad (36)$$

in dollars per vehicle. The marginal social cost of adding another vehicle to the road is thus

$$\begin{aligned} MSC &\equiv \frac{dTSC}{d(qv)} = \frac{d}{dv} [M_R R(k, D(k))v + M_T T(k, D(k))v + M_D D(k)v] \\ &= M_R \left[\left(\frac{\partial R}{\partial k} + \frac{\partial R}{\partial D} \frac{\partial D}{\partial k} \right) \frac{\partial k}{\partial v} v + R(k, D(k)) \right] \\ &\quad + M_T \left[\left(\frac{\partial T}{\partial k} + \frac{\partial T}{\partial D} \frac{\partial D}{\partial k} \right) \frac{\partial k}{\partial v} v + T(k, D(k)) \right] \\ &\quad + M_D \left[\frac{\partial D}{\partial k} \frac{\partial k}{\partial v} v + D(k) \right] \end{aligned} \quad (37)$$

⁴⁹This should not be confused with the additional congestion externality that results when an accident actually occurs, which is omitted from the present analysis.

⁵⁰Appendix A shows how M_T and M_D can be formally derived. It involves a slightly more complex utility framework, which is left to the appendix since it does not affect the results of the present analysis.

⁵¹This analysis abstracts from other societal losses that accidents create, such as “warm-blooded” and “cold-blooded” costs. Although they could be readily incorporated into the analysis, they are omitted for clarity.

Accordingly, marginal external costs ($MEC \equiv MSC - MPC$) during this period are given by

$$\begin{aligned}
MEC = & M_R \frac{\partial R}{\partial k} \frac{\partial k}{\partial v} v + M_R \frac{\partial R}{\partial D} \frac{\partial D}{\partial k} \frac{\partial k}{\partial v} v \\
& + M_T \frac{\partial T}{\partial k} \frac{\partial k}{\partial v} v + M_T \frac{\partial T}{\partial D} \frac{\partial D}{\partial k} \frac{\partial k}{\partial v} v + M_D \frac{\partial D}{\partial k} \frac{\partial k}{\partial v} v
\end{aligned} \tag{38}$$

in dollars per vehicle.

Equation (38) separates external accident and travel-delay costs into five components. The first term is identical to the cost put forth by the traditional approach to modeling accident externalities. Likewise, the third term shows the travel-delay externality in traditional link-flow congestion models. The second term, however, illustrates an external *benefit* that an incremental driver confers when she offsets physical risk by driving more cautiously. But this benefit is not without its own costs. The fourth term shows caution adding to travel-delay costs through increased travel times. Adding to this is the fifth term, which gives the direct value of the disutility that defensive driving entails.

To compare equation (38) with equation (28) used by the traditional approach, the first two terms can be combined as a risk-flow elasticity $\varepsilon_{R,v} \equiv \frac{dR}{dv} \frac{v}{R}$. Letting MEC' denote only the portion of external costs that are attributable to accident risk and its attendant offsetting behavior gives:

$$MEC' = M_R R \varepsilon_{R,v} + M_T \frac{\partial T}{\partial D} \frac{dD}{dv} v + M_D \frac{dD}{dv} v \tag{39}$$

Equation (39) shows that empirical studies using the traditional approach will tend to understate external accident costs by $M_T \frac{\partial T}{\partial D} \frac{dD}{dv} v + M_D \frac{dD}{dv} v$ unless drivers decline to offset physical accident risk. This is contrary to Peirson et al. (1998), who suggest that offsetting behavior implies that the traditional approach tends to overstate these costs. Essentially, it demonstrates that an observed risk elas-

ticity of zero does not imply zero external costs. And in the case of where $\varepsilon_{R,v}$ is negative, drivers can only confer net external benefits upon each other if the value of their risk-reduction ($-M_R R \varepsilon_{R,v}$) exceeds the combined effort and travel-delay costs that this risk reduction creates. As can be seen from the last two terms in equation (39), what drives these results are the costs that accompany the “greater degree of caution” that Vickrey discussed more than thirty years ago.

2.4 Road Pricing and “Value Pricing”

Ideally, “first-best” road pricing could correct the externalities presented in equation (38) by charging each road user a Pigouvian toll equal to *MEC*. At first, this would seem infeasible since defensive effort is difficult, if not impossible, to measure. However, the components of equation (38) are linked by traffic densities, which are observable quantities that are often available in the data used to conduct “value pricing” experiments.

“Value pricing” refers to highway projects that offer motorists an opportunity to purchase a free-flow alternative to congested travel.⁵² These projects typically involve two parallel road segments: “HOT-lanes” and “free-lanes” or (“main lanes”).⁵³ Tolls to enter the HOT-lanes are set at levels that maintain “free-flow” conditions along these lanes. Data collected from these projects allow researchers to observe the choices that commuters make between segments of equal length but with different prices and traffic conditions.

⁵²Brownstone and Small (2003) provide an excellent summary and assessment of several recent “value pricing” studies.

⁵³The acronym “HOT” stands for “High-Occupancy / Toll”. Typically, value-pricing projects give special consideration to high-occupancy vehicles (carpools), such as a discount on the price of entering the tolled lanes. This leads to the convention of referring to such toll-lanes as “HOT-lanes”.

In this context, define the difference between the average vehicle densities on the free-lanes (k_{free}) and HOT-lanes (k_{HOT}) during a period of duration q as $dk \equiv k_{free} - k_{HOT}$, where $k_{free} \geq k_{HOT}$. The total (non-monetary) cost increase (dC) that a motorist would incur by jumping from the HOT-lanes to the free-lanes (in terms of safety, defensive effort, and travel-delay) is given by differentiating equation (36) totally with respect to k :

$$dC = \left[M_R \left(\frac{\partial R}{\partial k} + \frac{\partial R}{\partial D} \frac{dD}{dk} \right) + M_T \left(\frac{\partial T}{\partial k} + \frac{\partial T}{\partial D} \frac{dD}{dk} \right) + M_D \frac{dD}{dk} \right] dk \quad (40)$$

Each motorist would be willing to pay up to dC to enter the HOT-lanes. Following equation (38), marginal external costs with respect to safety and travel-delay are then given by

$$MEC = \frac{dC}{dk} \frac{\partial k}{\partial v} v_{free} \quad (41)$$

in dollars per vehicle, or $\frac{dC}{dk} \frac{\partial k}{\partial v} \frac{v_{free}}{L}$ in dollars per vehicle-mile, where L is the length of the Express Lane facility. The term $\frac{dC}{dk}$ can be estimated, for example, with a random-utility based discrete-choice model that specifies the (indirect) utility from choosing the HOT-lanes as a function of money-cost (toll) and traffic density; these variables are often available in value-pricing data. In this framework, $\widehat{\frac{dC}{dk}}$ estimates each motorist's marginal rate of substitution between money-price and traffic density, which I refer to as "the marginal value of a unit reduction in average traffic density" or, more compactly, the "value of density" (VOD). This is the general framework used to develop the estimates described in Section 2.5.3. And, aside from estimating Pigouvian tolls, the results of this process can be used in evaluating the benefits of highway expansion projects, which would jointly reflect travel-delay and safety benefits as advocated by Larsen (1994).⁵⁴

⁵⁴Larsen (1994) formally illustrates that optimal road investment based on time-savings ben-

It is important to point out that this approach will reflect the disutility of *all* that is correlated with marginal increases in traffic densities. It is assumed, however, that travel delay, physical risk, and defensive effort represent the bulk of the disutility associated with these densities. And intangible quantities such as “stress levels” are considered to be generated primarily by these factors.

Also note that this approach models choices between prices and densities, where the densities are influenced by traffic volumes. However, since volume data are available in value-pricing data, one might ask why choices between prices and volumes are not modeled directly. To see this, suppose a motorist faced a choice between two parallel, single-lane roads with identical physical dimensions. On one road there is an average of 100 vehicles per mile and its cars are travelling at 10 miles per hour. On the other, there are only 20 vehicles per mile and its cars are moving along at 50 miles an hour. If both roads were toll-free, most would agree that the motorist would likely choose the less congested road. Yet both roads have equal traffic volumes of 1000 vehicles per hour according to the “fundamental” relationship

$$v = ks(k) \tag{42}$$

where $s(k)$ is the average speed on each road. Hence, traffic volumes can fail to predict mode choices under fairly typical traffic conditions for HOT-lane facilities. Densities, however, give a direct sense of how vehicles are liable to “encounter” each other, and relate to speeds (and therefore travel times) in a predictable manner.

To explicitly account for this relationship between densities and speeds, through

efits alone lead to under-investment since they fail to account for the increased safety benefits of capacity expansion.

the influence of volumes, write the $\frac{\partial k}{\partial v}$ term in equation (41) as

$$\frac{\partial k}{\partial v} = \frac{1}{s(k) + \frac{\partial s}{\partial k}k} = \frac{1}{s(k)(1 + \varepsilon_{s,k})} \quad (43)$$

where $\varepsilon_{s,k} \equiv \frac{\partial s(k)}{\partial k} \frac{k}{s(k)}$ is the elasticity of speed with respect to density. Equation (41) can then be expressed as

$$MEC = \frac{dC}{dk} \frac{v_{free}}{s(k)(1 + \varepsilon_{s,k})} = \frac{dC}{dk} \frac{k_{free}}{1 + \varepsilon_{s,k}} \quad (44)$$

in dollars per vehicle, or $\frac{dC}{dk} \frac{k_{free}}{1 + \varepsilon_{s,k}} \frac{1}{L}$ in dollars per vehicle-mile, which is used in the empirical sections of this paper.

Of course, the individual components of this external cost, such as those directly attributable to effort, would not be identified by this model. Instead, it would generate a “reduced-form” estimate of external accident and travel-delay costs. Moreover, without specifying densities for specific vehicle types, this estimate would essentially average the influences of various vehicle types. Nonetheless, it offers a way to measure the level of the externality in a manner that accounts for the net impact of defensive effort.

At this point it is worth noting that existing “value of time” studies using value-pricing data might already capture these external costs to some extent. For instance, in a random-utility framework, the utility that a motorist derives from entering a HOT-lane facility is typically written (in its simplest form) as

$$U_{HOT,n} = X_n\delta + \beta TS_{HOT,n} + \gamma Toll_{HOT,n} + \epsilon_{HOT,n} \quad (45)$$

where X is a vector of demographic covariates; TS and $Toll$ are the travel-time savings and money prices of using the HOT lanes. δ, β, γ are parameters to be estimated and ϵ is the stochastic component of U_{HOT} . In this framework, the marginal value of time savings (corresponding to M_T above) is

$$\frac{dToll_{HOT,n}}{dTS_{HOT,n}} = -\frac{\partial U_{HOT,n}/\partial TS_{HOT,n}}{\partial U_{HOT,n}/\partial Toll_{HOT,n}} = -\frac{\beta}{\gamma} \quad (46)$$

However, TS is implicitly a function of traffic density k , as are omitted terms such as those involving accident risk and defensive effort. Accordingly, variation in traffic density influences “value of time” estimates by its effect on utility through TS . Likewise, this variation would influence utility through its impact on accident risk and defensive effort. So if utility is specified as in equation (45) then “value of time” estimates are likely to reflect additional disutility from accident risk and defensive effort to the extent that β reflects the correlation between travel time and these omitted components (through k).⁵⁵ Hence, corrective tolls and highway-expansion benefit measures that are based on estimates from existing “value of time” studies are likely to reflect some degree of the benefits from reducing risk and effort levels. This matter is further examined in Section 2.6.2.

2.5 An Empirical Analysis of Accident and Travel-Delay Externalities

2.5.1 Empirical Setting

The estimates presented later in this paper employ the methods developed above and are based on data from a particular value-pricing experiment: The San Diego I-15 Congestion Pricing Project. This project offers solo drivers an option to pay to use an eight mile stretch of two free-flowing lanes (“Express Lanes” or “HOT” lanes) adjacent to (but physically separated from) the main lanes (or “free lanes”) along California’s Interstate 15, just north of San Diego. It offers solo drivers a premium alternative to the typically congested conditions along that section of the I-15. The HOT lanes are reversible and operate in the southbound direction during the morning commute (inbound to San Diego) and northbound during the

⁵⁵This might also help to explain why “value of time” estimates based on stated-preference data tend to differ significantly from those based on revealed-preference data. This is further explored in Section 2.6.2.

afternoon commute. Those who choose to enter the facility must travel its entire length since there are no interim exits.

The present study focuses on morning (inbound) commuters who traveled the entire eight mile length on or adjacent to the HOT lane facility during October and November of 1998.⁵⁶ This period corresponds to the third wave of the project's panel survey that gathers the necessary information about I-15 commuters required to conduct mode-choice analysis. Table 2-1 provides a brief summary of respondent characteristics.

All of the valuation and cost estimates in this paper are functions of mode-choice parameter estimates that correspond to tolls, travel-time savings, or traffic densities (or, more precisely, differences in traffic densities between the two modes). These variables are given in the first column of Table 2-2 and each warrants a brief explanation of how it is measured.

A unique characteristic of the I-15 Express Lanes is how free-flow traffic conditions are maintained along them. Tolls change every six minutes in \$0.25 increments to maintain "Level of Service C", as required by California Law for HOT lanes.⁵⁷ This is accomplished by traffic-flow monitoring from loop detectors embedded in the highway near each onramp along the facility.⁵⁸ Tolls are posted at the entrance to the Express Lanes, as well as a mile before, and range from \$0.50 to \$4.00 in the estimation sample with a median of \$1.50. The actual toll faced by respondents in the sample is obtained by matching the time that they reported reaching the facility with toll data collected from the California Department of Transportation (CALTRANS). These tolls are then converted to

⁵⁶Only weekday and non-holiday trips are considered.

⁵⁷Level of Service C is defined by a minimum speed of 64.5 MPH and a maximum service flow rate of 1,548 passenger cars per hour per lane.

⁵⁸ Loop detectors, through changes in inductance, sense how long a vehicle is above them ("occupancy") and how many vehicles pass over them ("flow") in a given period.

“effective tolls”, where they are set to zero if the respondent reports that their tolls are paid for by someone else (such as their employer).

Time savings are defined here as the difference between travel time on the main lanes adjacent to the HOT lanes and travel time on the HOT lanes themselves. The salient time-savings measure in this study is *median* time savings since commuters do not know their actual time savings prior to making a mode choice. Instead, it is assumed that commuters have a feel for their travel-time distributions and base their decisions on typical values, as is standard in value-pricing studies.⁵⁹ These time-savings measures are based on data from loop detectors, which estimate vehicle speeds on the main lanes and HOT lanes in six minute intervals, corresponding to the intervals between toll changes.

An additional and important source of time savings is provided by a dedicated Express Lane onramp at Ted Williams Expressway on the northern end of the facility. Those wishing to enter the I-15 at Ted Williams can enjoy additional time savings by using the HOT lanes since the dedicated onramp enables them to bypass queues that typically form at the metered entrance to the main lanes. In fact, the average observed wait time at this onramp is about 39% of the average observed time savings from using the HOT lanes themselves. Waiting times at this onramp are incorporated into time-savings measures for those who entered the I-15 at Ted Williams Expressway.⁶⁰ The waiting times themselves are based on floating-car observations over ten days of the sample period.

Related to travel-time differences between the HOT lanes and main lanes are

⁵⁹This approach is adopted by Brownstone et al. (2003), Steimetz and Brownstone (2003), Small, Winston, and Yan (2002), Ghosh (2001), Lam and Small (2001), and Brownstone et al. (1999).

⁶⁰Specifically, separate time-savings distributions are constructed for those entering the I-15 at Ted Williams Expressway so that their median time-savings values reflect these additional savings.

differences in average traffic densities, taken here as the difference in the average number of vehicles per lane-mile between the two modes. Since the Express Lane facility is segmented by a series of loop detectors, each sensor measures densities only for its corresponding section of highway. For mode-choice analysis, this requires the operational assumption that commuters' responses to varying traffic densities along the facility are captured by average traffic densities over the length of the facility, as well as over the time interval corresponding to each trip. These assumptions are defended by observing that section-by-section densities are quite stable for each six-minute interval in the estimation sample, as are densities across adjacent intervals. And, analogous to the case for travel-time savings, mode-choice estimates are based on median density differences since commuters are not able to observe the facility's actual traffic conditions prior to making their choices. Instead, commuters presumably respond to conditions along the Express Lane facility that are typical for their travel periods.

The remaining covariates in Table 2-2 serve as controls and are included based on the "lessons learned" from Steimetz and Brownstone (2003). For instance, the "Toll Signal" variable, defined as the difference between the posted toll and average toll for a given time period, serves two purposes. First, posted tolls change every six minutes according to varying traffic levels, which provides motorists with information about downstream traffic conditions. Traffic that is heavier than usual coincides with unusually high tolls, thereby influencing the choice to enter the Express Lanes. Second, there is evidence from recent value-pricing studies that motorists also care about the "variability" in the user-cost savings they hope to enjoy from entering the HOT lanes.⁶¹ However, this variability

⁶¹It is common in the value-pricing literature to define "variability" as the difference between the 80th or 90th percentile and 50th percentile of the relevant time-savings distribution. This is based on the notion that commuters care much more about unanticipated delays than they

tends to be highest during peak-commute periods when traffic densities and tolls are highest, making it especially difficult to separate the influence of time-savings variability on mode choice from the influence of traffic density. But high levels of variability are presumably less likely to influence mode choices when unusually heavy traffic conditions can be predicted, to some extent, by unusually high tolls. In this sense, the “Toll Signal” variable can be thought of as an alternative approach to modeling how commuters respond to uncertainty about the user-cost savings that the Express Lanes can offer.

The income and distance variables are self-explanatory. The trip-purpose and job-status variables accommodate varying levels of schedule flexibility among the sample respondents. The “Female” variable tests a recurring theme in the value-pricing literature: that females are more likely to use HOT lanes. Finally, the “Mobile Phone” variable serves as a “quick and dirty” test of the notion that those who are inclined to make calls while driving would prefer to do so under conditions that require less attention to the task of driving (i.e., less defensive effort). A preview of the coefficient estimates in Table 2-2 shows that each control carries the “expected” sign.

These variables can be viewed as a minimal set of mode-choice predictors, where the goal is to generate a series of estimates that are comparable across model specifications. Any underlying heterogeneity in the following valuation and costs parameters is acknowledged, but implicitly averaged for the sake of clarity.

do about unexpectedly swift travel.

2.5.2 Econometric Framework

Consider a sample of solo drivers on approach to the I-15 Express Lane facility who can choose between the following alternatives: (1) travel in the free lanes parallel to the HOT lanes, and (2) travel in the HOT lanes for a toll.⁶² To characterize these choices, let $U_{in}(Z_{in})$ represent the utility that person n enjoys from choosing alternative i , and write:

$$U_{in}(X_{in}) = V_{in}(X_{in}) + \epsilon_{in} = Z_{in}\theta + \epsilon_{in} \quad (47)$$

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

$$P_{in} = \frac{e^{Z_{in}\theta}}{\sum_{j=1}^2 e^{Z_{jn}\theta}} \quad (48)$$

where θ is a vector of parameters to be estimated. With an exogenous sampling mechanism, θ would be estimated by maximizing the joint log-likelihood function

$$L(\theta, Z_{in}) = \sum_{n=1}^N \sum_{i=1}^2 y_{in} \ln(P_{in}) \quad (49)$$

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

The proportion of commuters who actually pay to use the HOT lanes is relatively small, so choice-based sampling is employed to obtain a sufficient amount

⁶²Note that carpooling commuters, who are exempt from HOT lane tolls, are excluded from the estimation sample.

of variation in the data while meeting budgetary constraints. Accordingly, maximum likelihood estimates from equation (49) will generally be inconsistent unless this endogenous sampling mechanism is properly accounted for.⁶³ To this end, Manski and Lerman (1977) show that a consistent estimator for θ , known as the Weighted Exogenous Sample Maximum Likelihood Estimator (WESMLE), is the maximand to the weighted log-likelihood function

$$L_w(\theta, Z_{in}, w_n) = \sum_{n=1}^N \sum_{i=1}^2 w_n y_{in} \ln(P_{in}) \quad (50)$$

where w_n is the weight given to the n^{th} observation's contribution to the log-likelihood, which is equal to the inverse-probability of observation n being included in the sample. If the only information available for constructing weights were mode shares over the population and sample, then the appropriate choice-based weights would be

$$w_i = \frac{p_i}{s_i} \quad (51)$$

where p_i and s_i represent the population and sample shares of mode i . However, the commuters in the I-15 panel reported the number of days that they traveled on the I-15 corridor in a given week, as well as the number of those days that they used each mode. To more thoroughly reflect the probability that each type of respondent was included in the estimation sample, weights are constructed as follows. Let t_{in} be the number of times person n chose mode i in a given week, and t_n be the total number of trips taken by that person that week. The sampling weights are then given by

$$w_n = \alpha \sum_{i=1}^2 \frac{w_i t_{in}}{t_n} \quad (52)$$

⁶³Daniel McFadden shows that in a conditional-logit model with a full set of alternative specific constants, only the coefficient estimates on the constants themselves will be inconsistent when choice-based sampling is employed (see Manski and Lerman (1977)). However, it is not clear if the standard errors on all of the parameter estimates would be estimated consistently since they are functions of the (expectations of) inconsistently-estimated choice probabilities.

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

The WESMLE asymptotic covariance matrix is given by

$$\Sigma = \Omega^{-1} \Delta \Omega^{-1} \quad (53)$$

where

$$\Omega = -E \left[\frac{\partial^2 w_n L_n(\theta, Z_{in})}{\partial \theta \partial \theta'} \right] \quad (54)$$

$$\Delta = E \left[\left(\frac{\partial w_n L_n(\theta, Z_{in})}{\partial \theta} \right) \left(\frac{\partial w_n L_n(\theta, Z_{in})}{\partial \theta'} \right) \right] \quad (55)$$

and $L_n(\theta, Z_{in})$ is the n^{th} observation's (unweighted) contribution to the log-likelihood function given by equation (49). Replacing the expectation operators in equations (54) and (55) with their sample analogues, evaluated at the WESMLE estimates for θ , yields consistent estimates of Σ .

It is worth noting that the standard errors on WESMLE estimates are typically large in practice, which tend to offset the benefits of choice-based sampling. It is easy to see how the weighting process can do this. Suppose the weights given by equation (51) are used in equation (50). The sampling weights would be quite small for the relatively rare mode, thereby constraining the log-likelihood contributions from the sample variation within this mode. However, the WESMLE estimates generated from this study's sample are reasonably sharp. Two key factors aid in overcoming the "error inflation" that the WESMLE procedure can often produce. First, there is a reasonable degree of variation among the key variables within the relatively rare mode (HOT-lanes). Second, exploiting additional information about the (choice-based) sampling mechanism to employ the sampling weights given by equation (52) somewhat relaxes the variation constraints that would be imposed by the weights in equation (51). This latter

point illuminates the utility of exploring the sampling mechanism beyond simple mode-shares if choice-based samples are to be used.

2.5.3 Valuation and External Cost Estimates

2.5.3.1 Combined Accident and Travel-Delay Costs

As described in Section 2.4, estimating the marginal external costs described by equation (38) entails estimating how motorists value marginal reductions in traffic densities. To this end, let K_{in} be the median difference in average densities between the HOT lanes and free lanes for person n 's travel period, and write:

$$U_{in} = V_{in} + \epsilon_{in} = X_n\delta + \lambda K_{in} + \gamma Toll_{in} + \epsilon_{in} \quad (\text{Model 1})$$

The “value of density” (VOD) for commuter n is then defined by

$$VOD \equiv \left. \frac{dToll_{in}}{dK_{in}} \right|_{\bar{V}_{in}} = -\frac{\partial V_{in}/\partial K_{in}}{\partial V_{in}/\partial Toll_{in}} \quad (56)$$

which is estimated by $-\frac{\hat{\lambda}}{\hat{\gamma}}$. Hence, $-\frac{\hat{\lambda}}{\hat{\gamma}} \frac{k_{free}}{1+\hat{\epsilon}_{s,k}} \frac{1}{L}$ jointly estimates the marginal external costs, in dollars per vehicle-mile, associated with accident risk, travel-delay, and driving effort attendant to larger traffic densities on the free lanes.

Since $\epsilon_{s,k}$ is a random variable, it must also be estimated to calculate the magnitude of this externality. This is accomplished by a log-quadratic regression of speed against density, the results of which are given in Table 2-3. For this regression, average daily speeds and densities in the sample are used to mitigate potential problems with using the static relationship $v = ks(k)$ in a dynamic setting. Of course, the literature on estimating speed-flow relationships is voluminous, and this approach is not intended as a competing substitute. However, Table 2-3 shows that the relationship between speed and density is predicted with a reasonable degree of precision. The resulting elasticity estimate is presumably

accurate enough to demonstrate the magnitudes of the costs described in this paper. This comes with the caveat that the estimate essentially averages across the traffic regimes of daily peak-period commutes.

The first set of columns in Table 2-2 report coefficient estimates for the above model, along with their corresponding (WESMLE) standard errors and t-statistics. Note that travel in the free lanes is the reference mode. All of the coefficients have intuitively correct signs and are statistically significant beyond the 95% confidence level (with the exception of “Trip Distance”).

It follows from these parameter estimates that the median commuter is willing to pay \$0.16 for a marginal reduction in average traffic density during peak morning commute periods. This result is reported in Table 2-2, along with its standard error of \$0.02, which is calculated by “bootstrapping” its underlying empirical distribution. The table also reports corresponding estimates for the combined external costs of accidents and travel-delay, in dollars per vehicle-mile, that an additional vehicle imposes on other motorists. These values are calculated as $-\frac{\hat{\lambda}}{\hat{\gamma}} \frac{k_p}{1+\hat{\varepsilon}_{s,k}} \frac{1}{L}$, where k_p is the p^{th} percentile from the distribution of average daily traffic densities on the free lanes. They suggest that the an additional vehicle generates external costs of \$1.67 to \$1.95 per vehicle mile during a typical morning commute. The discussion in Section 2.6 sheds light on the magnitudes of these estimates.

2.5.3.2 Separating Accident and Travel-Delay Costs

Consider the utility specification

$$U_{in} = V_{in} + \epsilon_{in} = X_n \delta + \beta T S_{in} + \lambda K_{in} + \gamma T oll_{in} + \epsilon_{in} \quad (\text{Model 2})$$

where the salient difference between this specification and that of Model 1 is the inclusion of the time-savings variable TS_{in} .⁶⁴ The resulting marginal value of density-reduction is given by

$$VOD' \equiv \left. \frac{dToll_{in}}{dK_{in}} \right|_{\bar{V}_{in}} = -\frac{\partial V_{in}/\partial K_{in}}{\partial V_{in}/\partial Toll_{in}} = -\left[\frac{\beta}{\gamma} \frac{\partial TS_{in}}{\partial K_{in}} + \frac{\lambda}{\gamma} \right] \quad (57)$$

Here VOD' is separated into two components; $-\frac{\beta}{\gamma} \frac{\partial TS_{in}}{\partial K_{in}}$ controls for the influence of density on utility through its influence on time savings, thereby allowing estimates of $VOD^A \equiv -\frac{\lambda}{\gamma}$ to directly estimate each commuter's willingness-to-pay for marginal reductions in costs such as physical risk and defensive effort through marginal reductions in traffic densities.⁶⁵ Accordingly, external accident costs, denoted MEC^A , are given by

$$MEC^A = -\frac{\lambda}{\gamma} \frac{k_p}{1 + \varepsilon_{s,k}} \frac{1}{L} \quad (58)$$

when utility is specified as in Model 2.

The remaining term in equation (57), $-\frac{\beta}{\gamma} \frac{\partial TS_{in}}{\partial K_{in}}$, likewise can be used to estimate travel-delay externalities, where $\frac{\partial TS_{in}}{\partial K_{in}}$ must also be estimated. Alternatively, note that $-\frac{\beta}{\gamma}$ directly gives the value of a marginal reduction in travel time (the "value of time"). External travel-delay costs, denoted MEC^T , are then estimated with

$$MEC^T = -\frac{\beta}{\gamma} \frac{\partial T}{\partial k} \frac{k_p}{1 + \varepsilon_{s,k}} \frac{1}{L} \quad (59)$$

where T and k are main-lane travel times and densities. Table 2-4 shows the regression used to estimate the (average) marginal effect of density on travel time

⁶⁴Note that the parameters will have different values and interpretations across the various models specified in this paper. The same symbols are used across these models, however, to keep the exposition as simple as possible.

⁶⁵This approach will reflect all of the additional influences that are correlated with density. However, I maintain the assumption that marginal increases in physical accident risk and defensive effort generate the bulk of the non-travel-time disutility from marginal increases in traffic densities. Hence, the term "accident externality" is used here to describe the costs associated with these two factors.

$(\frac{\partial T}{\partial k})$ using median values of T and k from the free lanes along the Express Lane facility.⁶⁶

The second set of columns in Table 2-2 give the coefficient estimates for this specification. At first glance, it might seem peculiar that β and λ are estimated with such precision since TS and K are functionally related. Recall that the dedicated Express Lane onramp at the facility’s entrance provides an additional source of (potential) time savings for a portion of the estimation sample. This onramp serves as a “collinearity breaker” that provides a sufficient degree of independent variation in time savings to reveal the remaining influence of density on mode choice.

Table 2-2 also reports that the resulting VOD^A estimate, which gives the median commuter’s marginal value of density-reduction while controlling for time-savings, is \$0.07. Its standard error of \$0.02 is also reported. At the bottom of this column is the marginal value of reduced travel time, VOT^k , estimated at \$21.39 per hour with a standard error of \$3.51. The superscript “ k ” reminds the reader that this measure of the “value of time” is from a model that explicitly controls for the influence of traffic density. In this sense, VOT^k can be thought of as having been “purified” of density-related influences such as risk and effort.

The table also provides corresponding MEC^A and MEC^T estimates. They suggest that an additional vehicle during a typical morning commute creates external accident costs of \$0.74 to \$0.86 and external travel-delay costs of \$0.98 to \$1.15 per vehicle-mile. Together, the externality is \$1.72 to \$2.01 per vehicle-

⁶⁶In general, $\frac{\partial T}{\partial k}$ can be written as $-\varepsilon_{s,k} \frac{L}{k_s}$, which might lead some readers to ask why the regression in Table 4 is needed. Recall, however, that travel times in this particular setting include queueing times for those entering the I-15 at Ted Williams Expressway. Overall, $\varepsilon_{s,k}$ is used to relate densities to volumes, while $\frac{\partial T}{\partial k}$ given in Table 4 relates densities to travel times, which include onramp queueing delays. The end result is an estimate for $\frac{\partial T}{\partial k} \frac{\partial k}{\partial v} v$, which is required in conjunction with the “value of time” to estimate MEC^T .

mile.

2.5.3.3 The “Value of Time”

Until now, economists have primarily used value-pricing data to estimate how commuters value marginal reductions in travel times using methods similar to those described in Section 2.4. The section also describes how these “value of time” (VOT) estimates can include values associated with risk and effort reductions. To investigate this empirically, utility is specified as

$$U_{in} = V_{in} + \epsilon_{in} = X_n\delta + \beta TS_{in} + \gamma Toll_{in} + \epsilon_{in} \quad (\text{Model 3})$$

which is identical to the utility specification in Model 2, except the density term K_{in} is omitted. This is the basic form that nearly all value-pricing based VOT studies use to estimate the marginal value of time savings given by

$$VOT = \left. \frac{dToll_{in}}{dTS_{in}} \right|_{\bar{V}_{in}} = -\frac{\partial V_{in}/\partial TS_{in}}{\partial V_{in}/\partial Toll_{in}} = -\frac{\beta}{\gamma} \quad (60)$$

This method is often used with revealed-preference (RP) and stated-preference (SP) data alike.⁶⁷

The last set of columns in Table 2-2 give the results for this model. The corresponding VOT estimate is \$31.06 per hour, with a standard error of \$4.59, which is 45% greater than the \$21.39 estimate for VOT^k . The \$31.06 estimate also implies a travel-delay externality of \$1.43 to \$1.67 per vehicle-mile, which are comparable to the total MEC estimates developed in the preceding sections. This warns against interpreting the VOT and MEC^T estimates generated from Model 3 as being strictly attributable to travel delays.

⁶⁷ Revealed-preference data are those that include the actual choices that commuters makes in real-market situations. Stated-preference data are generated from responses based on hypothetical travel scenarios.

2.6 Implications and Comparison with Previous Studies

2.6.1 Accident Externalities

The preceding analysis suggests Pigouvian tolls on the order of \$1.80 per vehicle-mile to jointly correct accident and travel-delay externalities, and \$0.80 per vehicle-mile to correct accident externalities alone. These figures are within the context of the external costs that motorized vehicle users impose on one another when traveling urban freeways during peak commute periods.⁶⁸ More generally, the analysis indicates that commuters are typically willing to pay around \$0.16 for marginal reductions in average traffic densities. Of this, \$0.07 can be attributed to factors such as physical accident risk and defensive effort. The remaining factor, travel-time savings, is valued at \$21 per hour. Each of these figures can also be used to estimate the relevant benefits of highway expansion, jointly or separately. And they are generated in a manner that does not require observations on accident rates.

These results imply that external accident costs account for roughly 44% of the combined cost estimate. This is particularly noteworthy in light of the fact that typically observed accident risks are fairly stable in the face of increased traffic levels. Under the “traditional approach”, this would imply that motorists generally do not create external accident costs for each other. In the present study, however, it would imply that nearly all of the external accident costs are in the form of increased defensive efforts. The intuition behind why these costs can be so “large” is that motorists continuously exert defensive effort during any given trip, which is why observed accident risks are stable in the first place.

Peirson et al. (1998) make a valuable contribution by formally recognizing

⁶⁸They do not consider the external costs that motorists impose on pedestrians and cyclists, nor do they include the “cold-blooded” costs mentioned previously.

that defensive effort plays an important role in measuring accident externalities. However, they focus on the external safety benefits that attentive drivers confer on one another, analogous to the $(M_R \frac{\partial R}{\partial D} \frac{dD}{dk} v)$ term in equation (38). This has the effect of adjusting accident cost estimates downward relative to what the traditional approach would yield. But they are unable to account for the degree to which the costs of defensive effort itself offset this benefit, which are illustrated by the $(M_T \frac{\partial T}{\partial D} \frac{dD}{dk} v)$ and $(M_D \frac{dD}{dk} v)$ terms in equation (38). They do, however, acknowledge the importance of accounting for these offsetting costs.

Peirson et al. (1998) also provide an excellent summary of the existing empirical literature on accident externalities, which aids in understanding the magnitudes of the estimates in Table 2-2. Their summary includes estimates of car-related accident costs from Newbery (1987), Jones-Lee (1990), Pearce (1993), and Jansson (1994), along with those from their own “PSVALM 1” and “PSVALM 2” models.⁶⁹ Each of these studies follows the traditional approach in some form⁷⁰; the “PSVALM” models modify the traditional approach to loosely accommodate physical risk-reductions due to defensive effort, but without considering the costs associated with this effort.

The estimates in Pearce (1993) and Jones-Lee (1990) follow the convention that motorized-vehicles do not impose external accident costs on each other, and range from \$0.05 to \$0.06 per vehicle-mile.⁷¹ Newbery (1987) and Jansson (1994) both assume a risk-flow elasticity of 1.25, which allows for accident externalities between motorized vehicles and yields an estimate of \$0.07 (including

⁶⁹ “PSVALM” is an acronym for “Peirson-Skinner-Vickerman Accidents in London Model”

⁷⁰ Pearce (1993) does not model accident externalities formally. Instead, he suggests that the accident costs borne by non-motorized users be used as a minimal measure of external accident costs. This can be viewed as following the traditional approach with the assumption that $\varepsilon_{R,v} = 0$.

⁷¹ These and all other estimates adapted from Peirson et al. (1998) are converted from 1991 British Pounds per vehicle-kilometer to 1998 U.S. Dollars per vehicle-mile.

externalities on non-motorized users). The PSVALM 1 and PSVALM 2 models developed by Peirson et al. (1998) also assume a risk-flow elasticity of 1.25, but with downward-adjustment mentioned previously. The external accident cost estimates from these studies range from \$0.04 to \$0.06 per vehicle-mile.

Mayeres et al. (1996) estimate the marginal external travel-delay and accident costs generated by peak-period cars in 1996 and 2005 (for Brussels, Belgium). Their 1996 estimates, in dollars per vehicle-mile, are \$0.63 for travel-delay and \$0.19 for accidents, or \$0.82 combined ; corresponding estimates for 2005 are \$3.25 and \$0.23, totalling \$3.48.⁷²

Although none of these results are directly comparable with those developed in this paper, they illustrate the magnitudes of the cost estimates that prevail in the literature on accident externalities. The median estimate of \$0.80 per vehicle-mile suggests that motorists generate external accident costs during peak periods that are much larger than indicated by preceding studies. This holds despite the fact that these studies reflect the additional costs borne by pedestrians and cyclists, which are outside the context of the empirics presented here.

Overall, the analysis in this paper demonstrates that accident externalities can exist even if observed accident risks do not change with increased traffic levels. In this case, external accident costs would be attributed to the costs of the efforts required to hold observed risks constant. This lends intuition to why the estimates presented here are large by comparison. The results from the previous studies presented in this section are based on observed accident rates. However, accidents are relatively rare events, but the defensive efforts that make these accidents rare are ubiquitous.

⁷²These figures are converted from 1990 European Currency Units per vehicle-kilometer to 1998 U.S. Dollars per vehicle-mile.

2.6.2 Travel-Delay Externalities and The “Value of Time”

When tradeoffs between travel times and HOT-lane tolls are examined with (Model 3), without controlling explicitly for traffic densities, the resulting “value of time” estimate is \$31 per hour. Brownstone et al. (2003) obtain a similar median VOT estimate of \$30 using the same wave of I-15 data; Steimetz and Brownstone (2003) also report a median VOT estimate of \$30 per hour using a later wave of the I-15 panel. Overall, these results are in line with the \$21 to \$40 range of RP-based estimates from studies using the I-15 panel or data from a similar value-pricing experiment on California’s State Route 91 in Orange County (see Brownstone and Small (2002) for a comprehensive review and assessment of these studies). However, the estimate falls to \$21 per hour when densities and time savings are both explicitly controlled for.

In the current “value of time” literature, it is generally understood that VOT estimates are only relevant to the particular travel scenario under consideration. For example, in-vehicle delays appear to be less onerous than the time costs associated with waiting at bus stops (and walking to them), presumably because vehicles offer additional amenities that bus-stops may not, such as guaranteed shelter and seating.⁷³ In this sense, VOT estimates can be thought of as “reduced-form” approximations for not only the marginal value of time-savings itself, but also the value of amenities that are correlated with time savings.

A particularly relevant finding along these lines is that peak-period travel time is valued more highly than off-peak, as reported by Guttman (1975) and Small et al. (1999). Even more relevant is Hensher (2001) who finds across a variety of empirical models that “slowed down” and “stop/start” travel times are

⁷³See Small (1996), pp. 43-46.

valued at roughly four and eight times that of free-flow travel. The discussion in Section 2.4 and results from Section 2.5.3.3 provide an explanation for this phenomenon by demonstrating how VOT estimates based on models like the one specified in Model 3 are likely to capture some degree of how commuters value marginal reductions in factors such as risk and effort. Since these factors are correlated with time savings through traffic densities, off-peak VOT estimates might simply reflect lower levels of risk and effort in off-peak periods. This is further illustrated in the finding that the implied travel-delay externalities based on Model 3 resemble the total external costs implied by the models that directly account for traffic densities. Remarkably, it also suggests that when both travel times and traffic densities are explicitly controlled for, the resulting “value of time” can be interpreted as an off-peak VOT estimate.

This discussion might also help to resolve a controversial issue in the “value of time” literature: the discrepancies between VOT estimates that are based on revealed-preference and stated-preference data. RP-based VOT estimates are typically much larger than their SP-based counterparts, even when both sets of data are generated from the same respondents.⁷⁴ Brownstone and Small (2002) hypothesize that this discrepancy is at least partially due to a systematic misperception of travel times by SP respondents. They suggest, among other things, that impatience with heavy traffic conditions causes these respondents to exaggerate the magnitudes of their travel delays.

The approach taken here toward resolving this controversy is to more closely examine how factors such as “impatience with heavy traffic conditions” are generated. Dense traffic requires a substantial degree of “stop-and-go” effort to

⁷⁴For example, see Brownstone and Small (2002) for a review of several RP and SP estimates from studies using value-pricing data, where RP estimates are typically twice as large.

avoid collisions; the reader is most likely familiar with the disutility that a sea of brake-lights and aggressive lane-jumpers can create. However, it is quite possible that SP questionnaires are unable to adequately depict the “stop-and-go” conditions that would naturally accompany their hypothetical travel delays. Typical SP-based VOT estimates might resemble something closer to their respondents’ opportunity cost of time rather than their overall willingness to pay for lighter travel conditions.

To see how the estimates in Section 2.5.3 relate to this hypothesis, consider the value-pricing studies of Ghosh (2001) and Small et al. (2001). With I-15 data, Ghosh (2001) develops both RP-based and SP-based VOT estimates using the same empirical framework and respondents for each. Small et al. (2001) conduct a similar experiment with SR-91 data. Ghosh finds that his SP-based median VOT estimate is 0.40 times that of its RP counterpart; the ratio is 0.45 for the median VOT estimates in Small et al. Recall that VOT is estimated at \$31 using Model 3 and \$21 per hour using Model 2. We might say that the \$21 estimate excludes the influence of factors that generate “impatience with” relatively dense traffic conditions, which is 0.68 times the \$31 estimate that includes some degree of influence from these factors. A similar story might be told for the SP estimates in Ghosh (2001) and Small et al. (2001). If the hypothetical travel scenarios presented to their respondents focus primarily on travel times while overlooking dimensions such as risk and effort, then we might expect the resulting VOT estimates to be on the order of 0.68 times that which would have been achieved had these responses been (more) influenced by these additional dimensions. We see that the 0.40 and 0.45 SP-to-RP estimate-ratios in Ghosh (2001) and Small et al. (2001) are roughly of this order, with additional room to explain discrepancies

between the two types of estimates.

The analysis also reveals a potential problem with the common approach of simply adding external travel-delay cost estimates to separate estimates for external accident costs. Since travel-delay costs based on existing VOT estimates might already capture some degree of accident costs, simply adding the two together can result in some degree of “double counting” when calculating their joint costs. Ironically, however, this practice might approximate combined accident and travel-delay costs fairly well when adopting the convention that motorists do not impose external accident costs on each other.

2.6.3 Choosing the “Correct” Model

Table 2-2 presents three different models for estimating accident and travel-delay costs. These models differ by the extent to which travel times and traffic densities are controlled for. Model 2 given in the table’s second column is preferable since it allows accident and travel-delay costs to be separated. It is also a more “complete” specification in the sense that it controls explicitly for both travel times and traffic densities. However, statistically significant estimates for the influences of these components are achieved through a “collinearity-breaking” effect provided by the onramp queues that form at the northern end of the Express Lane facilities. It would not be reasonable to assume that researchers would typically have access to such fortuitous data. This leaves the remaining models in the table, Models 1 and 3, to contend when the influences of travel times and traffic densities cannot be separated.

The combined externality estimated from Model 1 is statistically indistinguishable from that of the more “complete” Model 2. Although it does not identify separate accident and travel-delay components, road-pricing and expan-

sion policies are more likely to be concerned with the combined estimate. Hence, one might advocate the practice of estimating the “value of density” in usual empirical settings to generate “reduced-form” external cost estimates.

Another “reduced-form” approach is provided by Model 3 in the last column of Table 2-2. This type of model is typically used to estimate “the value of time”, and reflects factors such as risk and effort insofar as they are correlated with travel times (through traffic densities). In this sense, the MEC^T estimates produced by Model 3 can be interpreted as “reduced-form” estimates of the combined externality. However, these values are somewhat smaller than the combined externality estimates generated by Models 1 and 2. So traditional “value of time” estimates seem to serve as somewhat reasonable “reduced-form” approximations for combined external costs if density data are not available. But the similarity of the combined estimates from Models 1 and 2, where traffic densities are considered directly, suggest that densities provide more accurate cost estimates and should be used if available.

2.7 Suggestions for Further Research

2.7.1 Mixed Traffic

The theoretical model developed in this paper focuses on homogeneous vehicle types. It can be readily extended, however, to accommodate mixed traffic. For instance, consider a road environment with only two vehicle types: “Heavy” and “Light”, where qv_H and qv_L denote the number of each type on the road in a given period of duration q . With the expressions for defensive effort and accident risk in mind, the following are examples of questions that would be of concern for public policy. First, do heavy vehicles present greater hazards to other road users than do light vehicles, i.e., is $\frac{dR}{d(qv_H)} > \frac{dR}{d(qv_L)}$? For instance, occupants of

relatively light vehicles are likely to sustain greater losses in a collision than those of relatively heavy vehicles.⁷⁵ This might lead to less cautious driving by heavy-vehicle operators, thereby creating a relatively larger accident risk. On the other hand, these drivers might exercise a relatively large degree of caution since they could face greater liabilities in the event of a collision. This leads directly to the question: do heavy vehicles incite greater defensive effort by other road users than do light vehicles, i.e., is $\frac{dD}{d(qv_H)} > \frac{dD}{d(qv_L)}$? One might expect the driver of a Mini Cooper to react more defensively to a Hummer H2 than she would to a Volkswagen Beetle. Then again, this might not be the case if she observes that Hummer H2 owners tend to drive more carefully than her fellow Mini Cooper owners.

In either case, the care that each driver exercises is associated with reduced speed. So another relevant question is: do heavy vehicles increase travel times more than light vehicles do, i.e., is $\frac{dT}{d(qv_H)} > \frac{dT}{d(qv_L)}$? It is often assumed in the congestion literature that large vehicles, such as busses, have a greater impact on travel times since they consume more roadway capacity. In the context of defensive effort, however, the question asks if drivers tend to slow down around heavy vehicles more so than they do around light vehicles.

The answers to these questions are empirical in nature, but investigating these answers is feasible under this paper's empirical framework with additional data on vehicle-types. Given recent policy concerns over matters such as the prevalence of sport-utility vehicles on the road, these efforts might be warranted and could be used to develop road-pricing policies across several vehicle classes.

A broader scope, beyond this paper's empirical approach, would include risk

⁷⁵Kockelman and Kweon (2002) find that sport utility vehicles are associated with less severe injuries for their occupants and more severe injuries for their collision partners.

and effort externalities that motor vehicles impose on “unprotected” users, such as pedestrians and bicyclists. And expanding the time-frame for the decision-margin of defensive effort could include, for example, costs such as purchasing more “vehicle protection” by upgrading to a Hummer H2.

2.7.2 Isolating Effort Costs

In policy applications, it might be desirable to isolate the defensive-effort component of the costs discussed in this paper. For instance, since 1998 Daimler-Chrysler has equipped several of its Mercedes-Benz passenger cars with its “DISTRONIC Proximity Control” system. These models have front-mounted radar sensors that enable them to automatically maintain a specified following distance in congested conditions. To date, more than 40,000 passenger vehicles worldwide are equipped with this system, which purportedly “contributes significantly to comfortable, stress-free and safe driving”.⁷⁶ In the public sector is the U.S. Department of Transportation’s Intelligent Vehicle Initiative, which seeks to “facilitate accelerated development and deployment of crash avoidance systems”.⁷⁷ As long as resources are devoted to reducing “driver workload” in the face of accident risk, there will be a need to estimate how such programs are fully valued. Of course, any such valuation should properly account for the additional costs that these programs can create. For instance, suppose I is some measure of the level of “Intelligent Vehicle” equipment that a motorist uses. Accident risk might then be written as $R(k, D(k, I))$, where $\frac{\partial D}{\partial I} < 0$. This shows how the net impact of these systems on overall accident risk might be indeterminate and illustrates how such systems can reduce the external safety benefit described by

⁷⁶Source: Daimler-Chrysler press release posted at <http://www.mbnz.org>.

⁷⁷2001 Annual Report of the Intelligent Vehicle Initiative.

the second term in equation (38).

Perhaps dynamic traffic-simulators could provide a useful approach. For example, subjects in a real-time commuting simulation could repeatedly be given choices between two (differently-priced) routes with identical travel times, where one of the routes involves a greater degree of driving effort. This would require some meaningful measure of effort - possibly the number of mechanical movements required or, more complexly, the total amount of time that eyes are focussed on the “road”. One might also envision a real-world analogue to this with appropriately equipped vehicles. The resulting tradeoffs between tolls and effort could then yield estimates for the value of effort reductions, with their implications for measuring accident externalities and the value of programs such as the Intelligent Vehicle Initiative.

2.7.3 RP vs. SP

The discussion in Section 2.6.2 suggests that SP-based “value of time” estimates typically fall short of their RP counterparts because SP respondents might generally be unable to perceive the non-travel-time factors that would influence their choices. A crude test of this hypothesis would be to present respondents with two distinct scenarios: one elicits preferences from a series of tolls and travel times; the other presents identical tolls and travel times but also includes detailed pictures of the traffic conditions that correspond to each travel time. The resulting VOT estimates could then be compared.

Hensher (2001) takes a more sophisticated approach by constructing an SP experiment that elicits choices among modes that vary by composition of travel-delay types, such as the proportion of time spent in “slowed down” and “stop/start” conditions. As mentioned previously, he finds that marginal travel-time reduc-

tions under dense traffic conditions are valued much more heavily than in free-flow traffic. This illustrates that characterizing *how* time savings are achieved by a particular mode can elicit responses that reflect non-travel-time factors that accompany dense traffic conditions, such as physical risk and driving effort. And not only does this offer at least a partial explanation for differences in RP and SP-based “value of time” estimates, it also offers some promise of jointly estimating accident and travel-delay externalities using stated-preference methods.

2.7.4 Automobile Insurance

Up to this point, the fact that motorists usually purchase automobile insurance has been abstracted from. A more complete theoretical analysis would include the impact of various insurance schemes on the external costs of road use (a la Boyer and Dionne (1987)). This impact would not only enter pecuniarily (by, say, modeling accident loss as $l(k, y)$, where y measures a level of insurance coverage). It would influence each motorist’s optimal level of defensive effort since, for example, a heavily-insured motorist might be less inclined to drive carefully. On the other hand, an uninsured motorist who knows that several other motorists are heavily insured might also drive less carefully, or at least have less incentive to self-insure. These types of behavior would then influence the levels of the accident externalities discussed in this paper’s theoretical model. Note, however, that the empirical estimates developed herein presumably capture the net effect of these influences.

2.8 Chapter Conclusion

Most experienced motorists are quite familiar with the frustrations of traffic congestion. Densely populated highways lead to travel delays and sometimes travel

rescheduling. They also require drivers to pay more attention to maintaining safety margins between themselves and their many potential collision partners. And many of these drivers might gladly accept, say, a marginal increase in their risk of a fatal accident in exchange for alleviating some of these frustrations with less-congested travel. This illustrates the hazards of basing external accident cost estimates on observed risk elasticities without properly accounting for the tradeoffs that generate these observations. Moreover, it shows how accident and travel-delay externalities are essentially two sides of the same coin, which warrants their joint consideration.

This paper addresses these issues by jointly modeling the external costs of accidents and travel delays, and by explicitly considering the impact of defensive effort on these costs. An empirical framework is developed from this model by recognizing that accident risk, defensive effort, and travel delays are linked by traffic densities, which are observable in data from existing congestion-pricing experiments. The resulting analysis indicates that during a typical peak-period commute, motorists generate external accident and travel-delay costs of roughly \$1.80 per vehicle-mile. About 44% of these costs can be attributed to increases in physical accident risk and efforts to offset this risk (along with the value of any additional disutility that increased traffic congestion creates).

Overall, the paper demonstrates that (1) external accident costs are generally understated by the traditional approach to estimating them, and (2) travel-delay cost estimates are likely to reflect accident costs, to some extent, through the influences of accident risk and defensive effort. It advocates the use of traffic densities in estimating overall congestion externalities, and the use of separate density and travel-time measures (whenever possible) to derive separate estimates

for accident and travel-delay costs. And through this interplay between accident and travel-delay costs, the analysis illustrates the hazards of constructing estimates for the overall costs of road use by simply adding together independent estimates for these components. This interplay can also help to explain differences in “value of time” estimates generated from revealed-preference and stated-preference data.

This study is the first to use micro-level data to estimate the marginal external accident costs of road use and their relationship to external travel-delay costs. It is written with the hope of stimulating further research on its implications for road pricing, capacity expansion, and related transportation policies.

Conclusion

Transportation Economists have long recognized the importance of measuring the extent to which motorists fail to pay the full social cost of their road use. Each commute period spawns a full complement of externalities, the bulk of which are generated between motorists in terms of travel delays and accidents. To correct these market failures, policymakers need to know how much motorists are willing to pay for marginal reductions in traffic levels. Unfortunately, few observable markets exist for eliciting such preferences. Researchers have instead relied heavily on results from hypothetical markets or "stated preference" experiments.

Recent experiments such as the I-15 San Diego Congestion Pricing Experiment, however, enable researchers to observe markets in which motorists can purchase congestion relief and its accompanying cost reductions. Data from these experiments have been used primarily for estimating the "value of time" (VOT) – a critical parameter for travel-delay cost estimation. The disaggregate, revealed-preference nature of these data are particularly well suited for developing plausible VOT estimates. This is often limited, however, by missing observations on key variables since the equipment used to measure them are prone to failure.

In response, the first chapter in this thesis demonstrates how to overcome such limitations by developing a multiple imputation procedure for constructing consistent VOT estimates when critical data are missing or unreliable. It also demonstrates the extent to which more common remedies, such as single-imputation methods, can overstate the precision of the estimates that they generate. The analysis essentially guides future researchers on how to continue benefiting from congestion-pricing data by overcoming the reliability problems that plague them.

Recent studies have also demonstrated that congestion-pricing experiments have value beyond the data that they generate. These “High Occupancy / Toll” (HOT) facilities can yield welfare gains by offering a differentiated product to heterogeneous consumers. The extent of these gains depends on the extent to which commuter preferences vary. In this spirit, Chapter One of this thesis develops a framework for estimating the extent to which commuter preferences are heterogeneous across observable characteristics. It shows that the value commuters place on marginal reductions in travel times can differ widely by income, trip distance, trip purpose, and employment status. The analysis yields estimates that can guide policymakers in their efforts to achieve welfare improvements through product differentiation.

These estimates, like all VOT estimates generated from congestion-pricing data, are accomplished by observing the tradeoffs that commuters make between money prices (tolls) and travel-time savings. The second chapter in this thesis demonstrates, however, that these estimates are likely to reflect more than just the value of travel-time savings. As discussed formally in the chapter, HOT-lanes provide a vector of amenities that influence commuters’ choices, including relief from non-travel-time costs such as accident risk and defensive effort. Since travel times, risk, and effort levels are all increasing in traffic densities (a measure of congestion levels), these VOT estimates are likely to reflect all of the disutility that increased congestion generates. This helps to explain why revealed-preference based VOT estimates are typically much larger than their stated-preference counterparts, which the chapter discusses in detail.

One source of disutility attendant to increased congestion levels is the additional effort required to contend with an increased number of vehicles available to

collide with. The value of this disutility dictates the magnitude of the accident externality that is created. Traditionally, external accident cost estimates are based on observed changes in accident rates with respect to changes in traffic levels. Observed rates, however, are affected by motorists rationally driving more carefully as conditions become more congested and hazardous. Thus, traditional accident externality estimates can only capture the costs that result when accidents actually occur. They overlook the costs that motorists incur from increased efforts to offset increased collision opportunities. As such, traditional estimates are likely to be understated. Transportation Economists have long acknowledged that the costs of exerting such defensive efforts should be included in external accident cost estimates, just as pollution abatement costs should be included in estimating environmental externalities. But this is traditionally abstracted from since defensive efforts are typically unobservable.

Despite the inability of researchers to observe these defensive efforts, they still influence motorists' decisions to purchase free-flow travel along HOT lanes where less defensive effort is required. This notion is exploited in Chapter Two, which develops an empirical framework for using HOT-lane data to estimate the overall value that commuters place on reduced congestion overall – not just the value of travel-time reductions associated with reduced congestion. What results are estimates for the value of congestion relief, which include the value of travel-time reductions and the value of non-travel-time amenities such as risk and effort reductions. And since accident and travel-delay externalities are determined jointly, estimating them jointly is appropriate – if not essential.

These estimates can be interpreted as reduced-form estimates for the value of all the cost savings that marginal reductions in traffic levels provide. Chapter

Two demonstrates, however, that in some cases the value of travel-time and non-travel-amenities can be estimated separately while jointly modeling their influences on commuter choices. This yields separate valuation estimates for marginal reductions in travel times and non-travel-time factors such as risk and effort. To the extent that these non-travel-time factors reflect risk and effort, the analysis suggests that accident externalities represent a substantial share of the costs that motorists impose on each other during peak-commute periods. This is contrary to the prevailing view in the literature that no such costs are generated between motorists.

Together, these chapters attempt to reshape how various components to the social costs of road use are characterized, modeled, and estimated. They yield direct and immediate implications for road pricing, investment, and related transportation policies. As such, this thesis is devoted to a better understanding and remedying of the market failures that crowd our highways each day.

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Appendix A: VOT and VOD Derivation

For the road environment described in Section 2.3, write expected utility as

$$U^e = R(k, D)U^a(w - l, X) + [1 - R(k, D)]U^{-a}(w, X) - C(D, T(k, D)) \quad (61)$$

where X is a composite commodity and all other terms are as defined previously. The representative driver maximizes this utility function subject to several constraints. One is that she cannot spend more than her accumulated wealth on good X , net of any accident losses.⁷⁸ Another is that she only has a total amount of time \bar{T} to allocate between travel time $T = T(k, D)$ and the time it takes to consume good X , denoted by T_X . Also, travel to any given destination requires some minimum amount of travel time T^M , and such travel requires that some minimum amount of attention D^M be paid to safely operating the vehicle. These constraints are assumed to be binding and are given by

$$w \geq l + X \quad (62)$$

$$\bar{T} \geq T + T_X \quad (63)$$

$$T \geq T^M \quad (64)$$

$$D \geq D^M \quad (65)$$

where the price of the composite commodity is normalized to one. The Lagrangian for this maximization problem is

$$L = U^e + \lambda[w - l - X] + \mu[\bar{T} - T - T_X] + \gamma[T - T^M] + \phi[D - D^M] \quad (66)$$

where λ, μ, γ , and ϕ are the Lagrangian multipliers that correspond to each constraint. The first-order conditions with respect to D and T are

$$\frac{\partial R}{\partial D}[U^a(w - l, X) - U^{-a}(w, X)] - \frac{\partial C}{\partial D} \quad (67)$$

⁷⁸For the sake of simplicity, assume that the agent lives off of her accumulated wealth and does not spend any time earning wages.

$$-\frac{\partial C}{\partial T} \frac{\partial T}{\partial D} - \mu \frac{\partial T}{\partial D} + \gamma \frac{\partial T}{\partial D} + \phi = 0 \quad (68)$$

$$-\frac{\partial C}{\partial T} - \mu - \gamma = 0 \quad (69)$$

Combining (68) with (69) yields expressions for the marginal value of travel time savings M_T and the value of a marginal reduction in defensive effort M_D :

$$M_T \equiv \frac{\gamma}{\lambda} = \frac{1}{\lambda} \frac{\partial C}{\partial T} + \frac{\mu}{\lambda} \quad (70)$$

$$M_D \equiv \frac{\phi}{\lambda} = \frac{1}{\lambda} \frac{\partial C}{\partial D} - \frac{1}{\lambda} \frac{\partial R}{\partial D} [U^a(w-l, X) - U^{-a}(w, X)] \quad (71)$$

Each of these expression describes the marginal values of time savings and risk reduction as comprising two components. The first term in equation (70) gives the direct value of the disutility from travel time. The second term shows the effect of a binding constraint on the total amount of time available. In equation (71), the first term gives the direct value of the disutility from defensive effort. Its second term shows an opportunity cost in terms of reducing the expected utility loss associated with both pecuniary and non-pecuniary costs of being involved in an accident.

Appendix B: Figures

Figure 1-1: Data Structure

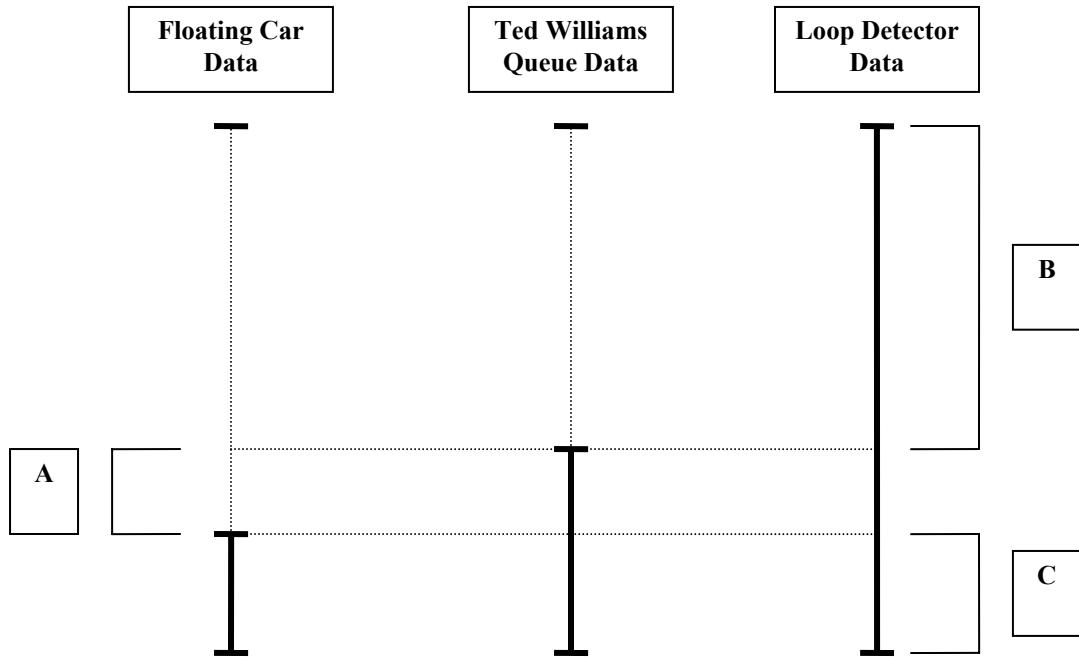


Figure 1-2: Income Category vs. Trip Distance

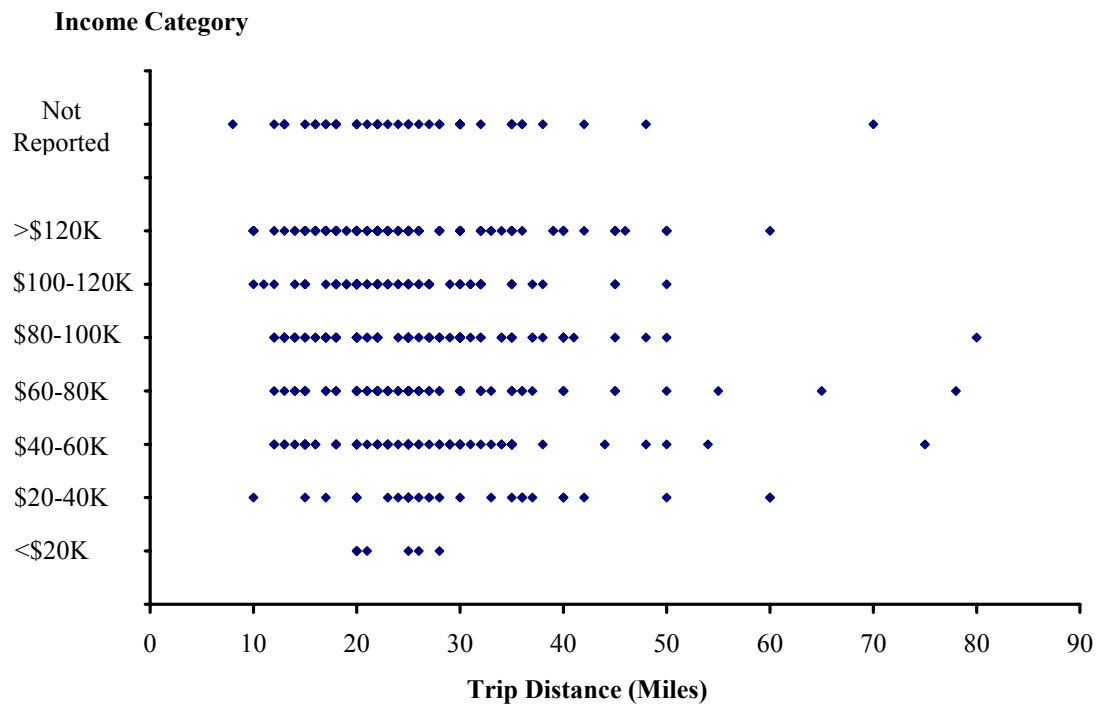
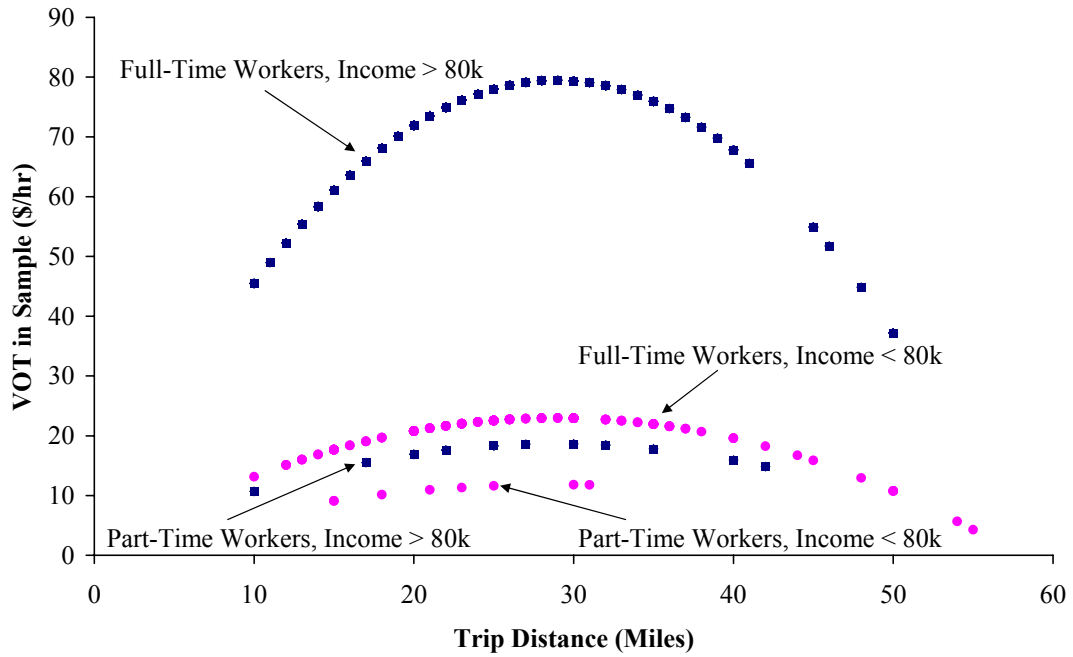


Figure 1-3: Work-Trip VOT vs. Trip Distance



Appendix C: Tables

Table 1-1: Summary Statistics

<i>Trip Characteristics</i>		
	<i>In Sample</i>	<i>Weighted to Population</i>
Mode Share		
Solo in the Main Lanes	48.60%	72.95%
Solo using FasTrak	37.80%	15.67%
Carpool	13.59%	11.38%
Share of Trips in Each Time Period		
5:00-6:00 AM	2.42%	3.63%
6:00-7:00 AM	27.56%	27.26%
7:00-8:00 AM	40.97%	41.88%
8:00-9:00 AM	25.33%	22.70%
9:00-10:00 AM	3.72%	4.53%
Trip Distance		
Mean	26.02	25.99
Standard Deviation	9.99	10.22
Trip Purpose		
Work Related	93.48%	92.46%
Non-Work Related	6.52%	7.54%
<i>Respondent Characteristics</i>		
	<i>In Sample</i>	<i>Weighted to Population</i>
Age		
18-24	1.83%	2.76%
25-34	10.24%	13.07%
35-44	37.48%	36.21%
45-54	32.54%	29.18%
55-64	13.89%	14.57%
65 +	3.84%	4.17%
Refused to Answer	0.18%	0.05%
Sex		
Male	60.34%	62.14%
Female	39.66%	37.86%
Annual Income		
< \$20K	1.30%	1.97%
\$20-40K	5.21%	6.74%
\$40-60K	13.22%	15.52%

\$60-80K	16.39%	17.37%
\$80-100K	17.69%	18.76%
\$100-120K	13.97%	12.60%
> \$120 K	24.02%	18.18%
Refused to Answer	8.19%	8.86%
Home Ownership		
Owns Home	83.05%	78.97%
Does Not Own Home	16.95%	21.03%
Education		
Graduate Degree or Higher	62.94%	57.37%
Less than Graduate Degree	37.06%	42.63%
Work Status		
Full Time	94.23%	93.86%
Part Time	5.77%	6.14%
Household Size		
Mean	3.07	3.07
Standard Deviation	1.26	1.28
Workers per Household		
Mean	2.05	2.06
Standard Deviation	0.69	0.72
Flexible Arrival Time		
Yes	80.82%	81.94%
No	19.18%	18.06%
Number of Respondents		537

Table 1-2: Imputation Models**Floating Car Time Savings and Ted Williams Onramp Wait Times (SUR)^a**

Dependent Variable			
Logit of Floating Car Time Savings			
Independent Variables	Coef.	Std. Err.	t-Stat.
Logit of Loop Detector Time Savings	0.6621	0.2216	2.9900
Toll	-2.8130	0.6735	-4.1800
Logit of Loop Detector Time Savings x Toll	-0.2911	0.1228	-2.3700
Minutes Past 5:00 A.M.	0.1002	0.0211	4.7400
Minutes Past 5:00 A.M. Squared	-0.0007	0.0002	-3.7100
Minutes Past 5:00 A.M. Cubed	0.0000	0.0000	2.8200
Minutes Past 5:00 A.M. x Toll	0.0165	0.0037	4.5100
Monday ^b	-3.4591	1.0350	-3.3400
Tuesday ^b	0.5879	0.2708	2.1700
Friday ^b	0.8318	0.2921	2.8500
Monday x Toll	0.8842	0.2986	2.9600
Tuesday x Toll	-0.6156	0.1638	-3.7600
Friday x Toll	-0.6353	0.2202	-2.8900
Logit of Loop Detector Time Savings x Monday	-0.9934	0.3221	-3.0800
Constant	-5.4512	0.8691	-6.2700
R ²	0.56 ^c		
Root Mean Squared Error	0.72		
Dependent Variable			
Logit of Ted Williams Wait Time			
Independent Variables	Coef.	Std. Err.	t-Stat.
Logit of Loop Detector Time Savings	0.4892	0.1397	3.5000
Mean Toll	-1.3220	0.1650	-8.0100
Minutes Past 5:00 A.M.	0.1904	0.0101	18.8300
Minutes Past 5:00 A.M. Squared	-0.0006	0.0000	-20.0300
Monday ^b	-3.8032	1.4177	-2.6800
Tuesday ^b	1.2273	0.2320	5.2900
Thursday ^b	1.0100	0.2082	4.8500
Monday x Toll	0.9393	0.3948	2.3800
Logit of Loop Detector Time Savings x Monday	-1.1881	0.4405	-2.7000
Constant	-12.4428	0.7802	-15.9500
R ²	0.79 ^c		
Root Mean Squared Error	1.04		

Floating Car Time Savings (OLS)

Dependent Variable			
Logit of Floating Car Time Savings			
Independent Variables	Coef.	Std. Err.	t-Stat.
Logit of Loop Detector Time Savings	0.6559	0.2294	2.8600
Logit of Ted Williams Wait Time	-0.1908	0.0861	-2.2200
Toll	-3.5244	0.7950	-4.4300
Logit of Loop Detector Time Savings x Toll	-0.2116	0.1141	-1.8500
Logit of Ted Williams Wait Time x Toll	0.2273	0.0781	2.9100
Minutes Past 5:00 A.M.	0.1238	0.0264	4.6800
Minutes Past 5:00 A.M. Squared	-0.0008	0.0002	-3.9600
Minutes Past 5:00 A.M. Cubed	0.0000	0.0000	3.0300
Minutes Past 5:00 A.M. x Toll	0.0226	0.0048	4.7200
Monday ^b	-3.2380	1.1079	-2.9200
Tuesday ^b	0.8275	0.3017	2.7400
Friday ^b	0.3381	0.1926	1.7600
Monday x Toll	0.9883	0.3104	3.1800
Tuesday x Toll	-0.9152	0.2012	-4.5500
Logit of Loop Detector Time Savings x Monday	-0.8593	0.3456	-2.4900
Constant	-6.4719	1.1988	-5.4000
R ²	0.57		
Root Mean Squared Error	0.75		

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

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

^c Keep in mind that this value is calculated in the logit-space of the dependent variable. This reduces in-sample variation, generating a lower R² than would result from a level-space calculation. Note that these logit transformations are "undone" when imputations are generated.

Note: Each model is based on 190 observations.

Table 1-3: Conditional Logit Mode-Choice Model Estimates

Independent Variables	Multiple Imputations				
	Coef.	Std. Err.	t-Stat.	Covariance Shares	
				Parameter Estimation	Imputation
<i>FastTrak Choice</i>					
Constant	-0.5007	0.5222	-0.9589	1.0000	0.0000
Worktrip ^a x Toll	-0.7250	0.1847	-3.9252	0.7338	0.2662
Non-Worktrip ^a x Toll	-1.5643	0.4572	-3.4212	0.9883	0.0117
Part-Time Worker ^a x Toll	-0.6824	0.3123	-2.1848	0.9918	0.0082
Income > \$80K ^a x Toll	0.5156	0.1487	3.4681	0.9962	0.0038
Income Not Reported ^a x Toll	0.5091	0.2395	2.1261	0.9948	0.0052
Median Timesavings x Distance	0.0192	0.0050	3.8504	0.9085	0.0915
Median Timesavings x Distance Squared	-0.0003	0.0001	-2.3575	0.8672	0.1328
Timesavings Variability ^b x Distance	0.0047	0.0022	2.0988	0.8129	0.1871
"Low Toll" Signal ^{a,c}	-0.7951	0.2238	-3.5536	0.9703	0.0297
Free-Lane Traffic Rating ^d	-0.2260	0.0525	-4.3086	0.9996	0.0004
Flexible Arrival Time ^{a,e}	-0.5087	0.2648	-1.9212	1.0000	0.0000
Home Owner ^a	1.0217	0.3597	2.8406	0.9839	0.0161
College Degree or Higher ^a	0.5091	0.2320	2.1947	0.9917	0.0083
<i>Carpool Choice</i>					
Constant	-0.1164	0.5005	-0.2325	0.9895	0.0105
Median Timesavings	0.2390	0.0609	3.9243	0.8627	0.1373
Free-Lane Traffic Rating	-0.2078	0.0675	-3.0784	1.0000	0.0000
Single Worker Household ^a	-1.9294	0.4191	-4.6034	0.9992	0.0008
Dual Worker Household ^a	-1.3886	0.3523	-3.9411	0.9979	0.0021
People per Vehicle in Household	0.5022	0.2051	2.4484	0.9953	0.0047
Mobile Phone Available ^a	-0.6085	0.3037	-2.0038	0.9992	0.0008
Number of Observations	537				
Number of Imputations	200				
(Average) ^f Log-Likelihood	-425.36				
(Average) ^f Pseudo R ²	0.28				

Single Imputation

Independent Variables	Coef.	Std. Err.	t-Stat.
<i>FastTrak Choice</i>			
Constant	-0.6622	0.5250	-1.2614
Worktrip ^a x Toll	-0.9560	0.1972	-4.8473
Non-Worktrip ^a x Toll	-1.8649	0.4653	-4.0083
Part-Time Worker ^a x Toll	-0.6318	0.3141	-2.0113
Income > \$80K ^a x Toll	0.5627	0.1490	3.7762
Income Not Reported ^a x Toll	0.5245	0.2396	2.1886
Median Timesavings x Distance	0.0259	0.0047	5.5599
Median Timesavings x Distance Squared	-0.0006	0.0002	-3.8043
Timesavings Variability ^b x Distance	0.0127	0.0038	3.3571
"Low Toll" Signal ^{a,c}	-0.9199	0.2251	-4.0869
Free-Lane Traffic Rating ^d	-0.2120	0.0522	-4.0634
Flexible Arrival Time ^{a,c}	-0.4789	0.2664	-1.7979
Home Owner ^a	0.9876	0.3569	2.7670
College Degree or Higher ^a	0.5263	0.2320	2.2685
<i>Carpool Choice</i>			
Constant	-0.2337	0.5027	-0.4649
Median Timesavings	0.2657	0.0604	4.3964
Free-Lane Traffic Rating	-0.2030	0.0677	-2.9972
Single Worker Household ^a	-1.8519	0.4200	-4.4097
Dual Worker Household ^a	-1.3531	0.3525	-3.8386
People per Vehicle in Household	0.4947	0.2051	2.4124
Mobile Phone Available ^a	-0.6144	0.3041	-2.0205
<hr/>			
Number of Observations	537		
Number of Imputations	1		
(Average) ^f Log-Likelihood	-423.13		
(Average) ^f Pseudo R ²	0.28		

^a These are indicator variables equal to one if the condition is true, zero otherwise.

^b Timesavings Variability is defined as the difference between the 90th and 50th percentiles of the (conditional) timesavings distributions.

^c Equals one if the difference between the posted toll and (conditional) mean toll is negative, zero otherwise.

^d Respondents were asked to rate the traffic conditions on the free lanes on a scale from 1 to 10, where 1 represented "bumper-to bumper traffic" and 10 represented "no traffic problems at all".

^e Equals one if late arrival did not carry serious consequences, zero otherwise.

^f For the multiple imputations mode-choice model, the reported log-likelihood and pseudo R2 values represent averages of these statistics across imputations.

Table 1-4: Value of Time Estimates and Estimation Uncertainty

	Multiple Imputations			
	Median Estimate	Bootstrap Median^a	75%-ile , 25%-ile^b	Interquartile Range^c
Full Sample	45.47	29.68	45.69 , 18.81	26.88
Full Sample at Mean Distance	67.18	38.77	60.88 , 21.93	38.95
<i>Work Trips:</i>				
Income > \$80k	71.93	64.90	111.78 , 41.48	70.30
Income < \$80k	21.95	21.52	28.79 , 16.21	12.58
Income Not Reported	69.78	45.29	88.91 , 20.62	68.29
Full-Time Workers	58.33	44.12	70.36 , 25.81	44.55
Part-Time Workers	15.89	15.65	21.50 , 11.58	9.92
<i>Non-Work Trips:</i>				
Income > \$80k	14.37	14.35	21.35 , 10.37	10.98
Income < \$80k	9.63	9.60	12.92 , 7.16	5.76
Income Not Reported	14.88	14.87	22.34 , 10.23	12.11
Full-Time Workers	10.45	10.83	14.43 , 7.97	6.46
Part-Time Workers	7.28	7.25	9.57 , 5.53	4.04

Single Imputation

	Median Estimate	Bootstrap Median^a	75%-ile , 25%-ile^b	Interquartile Range^c
Full Sample	17.39	18.36	25.01, 14.56	10.45
Full Sample at Mean Distance	28.68	24.91	36.94, 16.29	20.65
<i>Work Trips:</i>				
Income > \$80k	39.69	39.69	55.91, 29.91	26.00
Income < \$80k	15.87	15.74	19.85, 12.62	7.23
Income Not Reported	32.38	31.70	50.12, 20.59	29.53
Full-Time Workers	25.77	25.08	36.31, 16.17	20.14
Part-Time Workers	13.76	12.97	17.07, 9.86	7.21
<i>Non-Work Trips:</i>				
Income > \$80k	12.26	12.64	12.64, 9.70	2.94
Income < \$80k	8.14	8.31	10.38, 6.51	3.87
Income Not Reported	11.65	12.03	16.94, 9.07	7.87
Full-Time Workers	8.72	9.08	11.40, 7.22	4.18
Part-Time Workers	6.51	6.47	8.27, 5.15	3.12

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

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

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

Table 1-5: Decomposition of VOT Estimation Uncertainty

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

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

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

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

Table 1-6: Understatement of VOT Estimation Uncertainty by Single-Imputation Approach

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

Table 2-1: Respondent Summary Statistics

	<i>In Sample</i>	<i>Weighted to Population</i>
Mode Share		
Free Lanes	50.17%	84.53%
HOT Lanes	49.83%	15.47%
Posted-Toll Considered		
Mean	1.75	1.65
Standard Deviation	1.18	1.15
Trip Distance		
Mean	25.02	25.20
Standard Deviation	9.48	9.10
Annual Income		
< \$80,000	37.87%	47.96%
≥ \$80,000	62.13%	52.04%
Trip Purpose		
Work, School, or Appointment Trip	98.34%	97.35%
Other	1.66%	2.65%
Job Status		
Part Time	3.32%	3.31%
Other	96.68%	96.69%
Sex		
Female	41.36%	36.79%
Male	58.64%	63.21%
Mobile Phone Available		
Yes	79.57%	72.21%
No	20.43%	27.79%

Table 2-2: Mode-Choice, Valuation, and External Cost Estimates

WESMLE Binary Logit Estimates

Independent Variable	MODEL 1		
	Coef.	Std. Err.	t
Median Traffic-Density Difference ^a	0.20	0.03	7.37
Median Travel-Time Savings ^b	-	-	-
Effective Toll	-1.26	0.18	-7.12
Toll Signal	1.39	0.39	3.53
Trip Distance	0.02	0.02	1.30
Annual Income > \$80,000 ^c	0.86	0.29	3.01
Work, School, or Appointment Trip ^c	3.84	1.17	3.28
Part-Time Worker ^c	-2.74	0.67	-4.09
Female ^c	0.66	0.29	2.24
Mobile Phone Available ^c	0.87	0.34	2.55
Constant	-12.46	1.70	-7.35

Number of Observations 602

Independent Variable	MODEL 2		
	Coef.	Std. Err.	t
Median Traffic-Density Difference ^a	0.11	0.03	3.38
Median Travel-Time Savings ^b	0.56	0.10	5.70
Effective Toll	-1.57	0.22	-7.23
Toll Signal	1.69	0.37	4.54
Trip Distance	0.05	0.02	2.71
Annual Income > \$80,000 ^c	0.87	0.30	2.87
Work, School, or Appointment Trip ^c	4.09	1.21	3.38
Part-Time Worker ^c	-2.86	0.73	-3.94
Female ^c	0.69	0.31	2.20
Mobile Phone Available ^c	0.94	0.34	2.80
Constant	-11.50	1.75	-6.57

Number of Observations 602

Independent Variable	MODEL 3		
	Coef.	Std. Err.	t
Median Traffic-Density Difference ^a			
Median Travel-Time Savings ^b	-	-	-
Effective Toll	0.70	0.09	8.01
Toll Signal	-1.35	0.23	-5.76
Trip Distance	1.39	0.38	3.63
Annual Income > \$80,000 ^c	0.05	0.02	3.19
Work, School, or Appointment Trip ^c	0.77	0.29	2.62
Part-Time Worker ^c	3.80	1.15	3.32
Female ^c	-2.59	0.69	-3.75
Mobile Phone Available ^c	0.68	0.30	2.23
Constant	0.89	0.33	2.72
	-8.29	1.30	-6.36
Number of Observations	602		

*Valuation and External Cost Estimates**

	MODEL 1	MODEL 2	MODEL 3
VOD	0.16	-	-
(Bootstrap) Std. Err.	0.02	-	-
VOD^d	-	0.07	-
(Bootstrap) Std. Err.	-	0.02	-
MEC			
25%	1.67	1.72	-
50%	1.79	1.84	-
75%	1.95	2.01	-
MEC^d			
25%	-	0.74	-
50%	-	0.79	-
75%	-	0.86	-
MEC^T			
25%	-	0.98	1.43
50%	-	1.05	1.54
75%	-	1.15	1.67
VOT	-	-	31.06
(Bootstrap) Std. Err.	-	-	4.59
VOT^k	-	21.39	-
(Bootstrap) Std. Err.	-	3.51	-

Note: the dependent variable in each mode-choice model is equal to 1 if the respondent entered the HOT lanes and 0 otherwise.

^a Defined as the median difference between HOT-lane and free-lane traffic densities for the respondent's travel period.

^b Defined as the median difference between HOT-lane and free-lane travel times for the respondent's travel period.

^c Indicator variables equal to 1 if the condition is true and 0 otherwise.

* VOD is the "Value of Density", estimated by $dToll/dK$

VOD^A is the direct Value of Density when Travel Times are controlled for.

MEC is the combined Accident and Travel-Delay Externality, estimated by $(dToll/dK)(dK/dv)v$ with Model 1 and by $MEC^A + MEC^T$ with Model 2.

MEC^A is the Accident (risk and defensive effort) component of the combined externality, estimated by $(dToll/dK)(dK/dv)v$ with Model 2.

MEC^T is the Travel-Delay component of the combined externality, estimated by $(dToll/dTS)(dT/dk)(dk/dv)v$

VOT is the Marginal Value of Travel Delay (the "Value of Time"), estimated by $dToll/dTS$.

VOT^k is the "Value of Time" when Traffic Densities are controlled for.

Table 2-3: Speed vs. Traffic Density

Ordinary Least Squares Estimates

Dependent Variable			
Log of Daily Average Vehicle Speed			
Independent Variables	Coef.	Std. Err.	t
Log of Daily Average Traffic Density	-2.67	0.35	-7.57
Squared Log of Daily Average Traffic Density	0.28	0.05	6.01
Constant	9.92	0.66	15.08
Number of Observations		27	
Adjusted R ²		0.88	

Speed-Density Elasticity Estimate^a

$\epsilon_{s,k}$ -0.52

^a Evaluated at the sample median of the log of daily average traffic density. Speeds are in miles per hour and Densities are in vehicles per lane-mile.

Table 2-4: Travel Time vs. Traffic Density

Ordinary Least Squares Estimates

Dependent Variable			
Independent Variables	Coef.	Std. Err.	t
Median Travel Time			
Median Traffic Density	-0.364	0.038	-9.570
Median Traffic Density Squared	0.006	0.000	14.030
Ted Williams Expressway Onramp Indicator	-8.908	1.829	-4.870
Indicator x Median Traffic Density	0.408	0.079	5.160
Indicator x Median Traffic Density Squared	-0.003	0.001	-3.960
Constant	10.767	0.839	12.830
<hr/>			
Number of Observations		602	
Adjusted R ²		0.90	

Time-Density Derivative Estimate^a

∂Time / ∂Density 0.26

^a Travel Times are in minutes and Traffic Densities are in vehicles per lane-mile. The estimated derivative is the average marginal effect of density from the above regression.