The Marginal External Costs of Rush-Hour Headaches and Travel Delays

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Abstract

This paper develops a simple empirical framework for estimating two distinct components of the externalities that are generated by peak-period highway travel: time costs and non-time costs. Time costs reflect motorists' willingness to pay for marginal travel-time reductions, whereas non-time costs reflect willingness to pay for marginal traffic-density reductions while holding travel times constant. A key assertion is that the value of traffic-density reductions captures the value of reducing unobservable congestion costs, such as rush-hour headaches and collision-avoidance efforts. Estimates are obtained by analyzing the choices that motorists make in a real market situation where a free-flow alternative to congested travel can be purchased. Results suggest an overall congestion externality of \$1.80 per vehicle mile, of which \$1.00 can be attributed to travel delays and \$0.80 can be attributed to non-travel-time factors. Inter alia, these results demonstrate the importance of considering congestion costs beyond "the value of time" and shed light on valuing the unobservable "risk compensation" component of external accident costs.

Keywords: Congestion pricing, value of time, accidents, travel delays, externalities

*** PRELIMINARY DRAFT ***
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1 Introduction

Urban motorists are well-acquainted with the stress and aggravation of rush-hour traffic. During periods of peak demand they must compete for limited road space and impose a variety of external costs upon one another in the process. Some of these costs are generated by measurable travel delays, while other costs are generated by unobservable or intangible factors. For example, the frequent and sudden stops attendant to "stop and go" conditions can be quite rattling, and navigating through these conditions requires a substantial degree of effort to avoid collisions. There is no conventional label for such costs, but all experienced motorists have incurred them. Some portion of these intangible costs, however, may rightfully be labeled as "accident externalities". As Edlin (2003) puts it, "the costs of stress and tension that we experience in traffic are partly accident avoidance costs and should properly be included in a full measure of accident externality costs".[1] In general, rush-hour motorists bear (and create) a variety of intangible costs when confronted by dense traffic conditions, such as the "stress and tension" induced by a sea of brake lights. But attempting to define the units of "stress and tension" may prove intractable, let alone trying to estimate how motorists value "marginal stress and tension reductions".

Fortunately, the observable and unobservable costs of traffic congestion share a common link: they are increasing functions of traffic densities. This paper develops a simple framework for exploiting this link and applies it to a unique set of micro-level data from a California toll road to estimate how motorists value marginal reductions in traffic densities, separately from how they value marginal reductions in travel times. The basic premise is that estimating how motorists value traffic-density reductions, while controlling for travel times, captures (in reduced form) how they value marginal reductions in the unobservable costs that correspond to dense traffic conditions. In other words, the objective is to estimate a familiar policy parameter, the "value of time" (VOT), along with a new parameter, the "value of density" (VOD). Applying these estimates to a standard congestion-technology framework yields externality estimates in terms of both travel-delays and non-travel-time factors such as stress, tension, accident-avoidance efforts, and any other intangible costs that increase with traffic densities.

Results suggest that a typical rush-hour commuter values travel-time savings at $21 per hour and is willing to pay $0.07 for each vehicle per lane-mile avoided during a given commute. These estimates correspond to congestion externalities of $1.80 per vehicle mile, $1.00 of which is attributable to travel-delays and $0.80 of which is embodied by non-travel-time costs. The finding that these intangible costs represent 44% of peak-period congestion externalities carries substantial implications for efficient road-pricing, investment, and related transportation policies.

The following section provides a cursory review of congestion-technology principles. Sec-

[1] Newbery (1990) remarks that accident-avoidance efforts are "not costless, and the extra care taken by everyone should be properly costed."

tion 3 presents a formal description of how congestion externalities can be decomposed into a travel-delay component and a density-specific component, where the later is designed to capture intangible costs induced by congested travel. This lays the foundation for Section 4, which develops an empirical framework for separately estimating these costs in a discrete-choice context. Section 5 describes the data and estimation procedures used to obtain valuation and cost estimates. These results are reported in Section 6, followed by a discussion of their implications in Section 7. Section 8 offers concluding remarks.

2 Congestion Technology

This paper's empirical framework relies on the ability to estimate how motorists respond to varying traffic densities and speeds, which calls for a brief review of congestion principles. It is important to note from the outset that traffic density is a stock quantity, defined as the number of vehicles per unit of space on a road at a given point in time. The demand for road use (or any economic good) must, however, be expressed in terms of a flow quantity. This is typically accomplished by characterizing demand by the number of vehicles passing a given point on a road per unit of time, which defines the road's traffic "volume" or, appropriately, traffic "flow". The onset of traffic congestion occurs when vehicle flows increase traffic densities to the point where motorists must reduce their speeds in the interest of safety.[2] Figure 1 illustrates this relationship between average vehicle speeds and densities. Traffic densities up to D_0 do not cause a reduction in average speed. Increased traffic densities from $D = 0$ to $D = D_0$ may still, however, decrease motorist welfare. Imagine two types of vehicles on which average speeds are measured: fast cars and slow cars. When traffic density increases, the fast cars will not reduce their speeds but must now maneuver around the slow vehicles. Slow cars also maintain their speeds, but must become increasingly mindful of passing cars when, say, attempting to change lanes. After D_0, however, vehicle flows begin to approach the highway's capacity and vehicles must, on average, reduce their speeds. The density at which vehicle speeds fall to zero represents complete gridlock.

The explicit relationship between volume (V), density (D), and speed (S) is defined by the "fundamental" equation of traffic flow:[3]

$$V = D \cdot S(D) \tag{1}$$

where $\frac{\partial S}{\partial D} \leq 0$. So changes in average vehicle flows can be mapped into changes in average traffic densities and travel times (through changes in average speeds).[4] It will be useful for

[2] This statement illustrates the fundamental relationship between travel-delay externalities and the "collision-avoidance" component of accident externalities.

[3] Haight (1963)

[4] Traffic volumes, densities, and speeds are often measured in vehicle-miles, vehicles per lane-mile, and miles per hour, respectively.

later analysis to describe the impact of traffic volumes on traffic densities by

$$\frac{\partial D}{\partial V} = \frac{1}{S + \frac{\partial S}{\partial D} D} = \frac{1}{S(1 + \varepsilon_{S,D})} \tag{2}$$

where $\varepsilon_{S,D} \equiv \frac{\partial S}{\partial D} \frac{D}{S}$ is the elasticity of speed with respect to density.

Although the concept of volume allows economists to describe road use as a flow quantity, volume alone does not contain enough information to characterize the demand for road use. Consider, for example, two identical single-lane roads leading to the same destination. On one road the density is 100 vehicles per mile carrying vehicles at an average speed of 10 miles per hour. On the other there are 20 vehicles per mile with vehicles traveling at 50 miles per hour. It is easy to argue that motorists would prefer the less congested road (due to its lower "generalized price"). Yet both roads carry identical volumes of 1,000 vehicles per hour. It is only through the impact of volumes on speeds and densities that the costs of road use can be understood. In other words, motorists have a direct sense of how fast they are travelling and how many vehicles are crowding them, but would be hard-pressed to describe the volume of traffic they encounter. Volume, instead, typically serves as a proxy for a more salient demand concept: the number of motorists attempting to enter the road. This demand can be related explicitly to volume, however, when considering a fixed time period such as the "rush hour". In this case, multiplying the traffic volume for that period by the period's duration gives the number of vehicles that travelled during that period.

3 Congestion Costs

Following Walters (1961), the relationship in equation (1) can be used to characterize the demand for and supply of road use as functions of traffic volume. The "price" of road use is often referred to as a " generalized price" because it includes non-pecuniary costs such as motorists' time costs and, as argued here, intangible costs such as stress and driving effort.[5] Figure 2 illustrates this framework.[6] At traffic flows up to V_0, additional vehicles entering the road do not cause travel delays, but short-run marginal cost ($SRMC$) exceeds short-run average variable cost ($SRAVC$) due to the non-travel-time costs that coincide with increased traffic densities. Because motorists only consider the private costs of their trips, represented by the $SRAVC$ curve, they will consume road space up to V_{EQ}.[7] With the given demand curve, V_{EQ} is an inefficient equilibrium due to the external costs represented by the difference between

[5] It can also include other costs, such as pollution and noise, that are not explicitly considered here.

[6] This figure omits a possibly backward-bending portion of the marginal cost curve that could result from a phenomenon known as "hypercongestion" (see Small and Chu (2003) for a review of this literature). Hypercongestion can be handled by dynamic models, as in Arnott et al. (1993), to characterize travel-delay (and schedule-delay) costs in a queuing discipline. Note that figure 1 is still consistent with such models when the demand and cost curves are defined over a single travel period (Arnott et al. (1993)).

[7] Accordingly, average variable cost is sometimes referred to as "marginal private cost".

$SRMC$ and $SRAVC$ at V_{EQ}. An efficient traffic flow occurs at V^*, where traffic congestion is not eliminated but is reduced to a level where the marginal social benefit of another trip equals its marginal social cost.

Figure 1 works "behind the scenes" of Figure 2. As more vehicles enter a given road, there is a point at which traffic density increases and average speed decreases, resulting in travel delays. And it is argued here that the more congested the road becomes, the more "stress and tension" motorists suffer – beyond the stress induced by travel delays. The sources of such stress can vary from collision-avoidance efforts to reduced enjoyment of rush-hour radio broadcasts or fewer sips of coffee. Note that motorists can suffer these intangible costs even in the absence of travel delays. Hensher (2001) makes a particularly important contribution along these lines by demonstrating empirically that motorists are willing to pay more for a *given* amount of travel-time savings when these savings are achieved under more dense traffic conditions. He does so by conducting a survey-based experiment that elicits respondents' choices among alternative travel modes that vary by composition of travel-delay types, such as the proportion of time spent in "slowed down" and "stop/start" conditions. The value of intangible costs such as stress and accident-avoidance efforts are reflected by changes in travel-time valuations that vary with traffic conditions. One of the present study's goals is to separate the value of these intangible costs from the value of travel-time savings.

To formally describe travel-time and intangible costs generated by increased traffic densities, consider a commute period of fixed duration, q, on a given highway. Let $c(T(D(V)), D(V))$ represent short-run average variable cost, in dollars per vehicle, which depends on travel time, T (the inverse of speed), and on average traffic density, D. Travel time is a function of traffic density (as depicted in Figure 1), which is influenced by the extent of road use represented by average traffic volume, V. Assuming one person per vehicle, the qV motorists during the commute period incur a short-run total variable cost of cqV dollars. Short-run marginal cost (corresponding to an additional vehicle) is given by

$$\frac{\partial(cqV)}{\partial qV} = \frac{\partial(cV)}{\partial V} = c + \left[\frac{\partial c}{\partial T}\frac{\partial T}{\partial D} + \frac{\partial c}{\partial D}\right]\frac{\partial D}{\partial V}V \tag{3}$$

The second term on the right-hand side of equation (3) shows explicitly how additional vehicles impose external congestion costs on other commuters (in dollars per vehicle). There are two distinct components to this externality. The first component, $\frac{\partial c}{\partial T}\frac{\partial T}{\partial D}\frac{\partial D}{\partial V}V$, is the travel-delay externality, while the second component, $\frac{\partial c}{\partial D}\frac{\partial D}{\partial V}V$ is a reduced-form expression for the external costs that are generated by increased traffic densities holding travel times constant. The $\frac{\partial T}{\partial D}\frac{\partial D}{\partial V}$ and $\frac{\partial D}{\partial V}$ expressions represent how traffic conditions change with increased vehicle entries; in the context of Figure 1, $\frac{\partial T}{\partial D}\frac{\partial D}{\partial V} = 0$ up to D_0, but $\frac{\partial D}{\partial V} > 0$. Note that, following equation (2), the joint external congestion cost can also be expressed as

$$\left[\frac{\partial c}{\partial T}\frac{\partial T}{\partial D}+\frac{\partial c}{\partial D}\right]\frac{D}{1+\varepsilon_{S,D}} \tag{4}$$

which will be useful for later analysis.

The value of the travel-delay externality depends on $\frac{\partial c}{\partial T}$, which is simply the marginal value of travel-time savings, or "value of time" (VOT). Analogously, the value of the externality generated by increased traffic density, holding travel time constant, depends on $\frac{\partial c}{\partial D}$, which is introduced here as the marginal value of traffic-density reduction, or "value of density" (VOD). Combining estimates of the economic parameters, VOT and VOD, with estimates of the traffic parameters yields marginal external congestion cost estimates in terms of travel delays and intangible factors that increase with traffic densities.

When combined with the demand for road use, this congestion-cost framework can be used to estimate optimal congestion fees. Let $p = D(V')$ represent the road's inverse demand, where $p \equiv c + t$ is the generalized price including a toll of t levied on each commuter. The net benefit to the qV motorists during the commute period is

$$q\left[\int_0^V D(V')dV' - cV\right] \tag{5}$$

Maximizing this difference between total benefit and total variable cost and re-arranging the first-order condition yields

$$\Rightarrow t^* = \left[\frac{\partial c}{\partial T}\frac{\partial T}{\partial D}+\frac{\partial c}{\partial D}\right]\frac{\partial D}{\partial V}V - c \tag{6}$$

which shows that the optimal congestion fee is simply the difference between marginal and average cost. In other words, a toll of t^* will reduce travel demand during the commute period to the economically efficient level, V^*, depicted in Figure 2.

4 Estimation Framework

Consider a rush-hour commuter who faces a choice between two parallel roads: A and B. Road A is uncongested, but the commuter must pay a toll of τ_A to travel it. Road B, on the other hand, suffers from typical rush-hour congestion but may be accessed for a money price of zero. The commuter would be indifferent between the two roads if their generalized prices were equal, i.e., she would be willing to pay a maximum toll, $\tau_A^{\max}$, to enter Road A equal to the congestion costs that she would otherwise face on Road B. Formally, if the difference in traffic levels between the two roads is $dV \equiv V_B - V_A$, then she would be willing to pay

$$\tau_A^{\max} = \left[\frac{\partial c}{\partial T}\frac{\partial T}{\partial D} + \frac{\partial c}{\partial D}\right]\frac{\partial D}{\partial V}dV = \frac{\partial c}{\partial T}dT + \frac{\partial c}{\partial D}dD \tag{7}$$

where $dT \equiv T_B - T_A$ and $dD \equiv D_B - D_A$ are the differences in travel times and traffic densities on the two roads. For given traffic conditions, then, she values her travel-time savings from choosing Road A at a rate of $\frac{\partial c}{\partial T}$, i.e., at her value of time. Likewise, she values the avoidance of increased traffic densities, separately from how she values travel-time savings, at a rate of $\frac{\partial c}{\partial D}$, i.e., at her value of density. These values would be reflected in the tolls she is willing to pay for uncongested travel.

The above scenario lends itself readily to estimating a typical commuter's value of time and value of density in a discrete-choice estimation framework. Write the indirect utility that commuter n receives from choosing Road A as

$$U_{A,n} = \theta f(x_{A,n}, y_n) + \beta T_A + \lambda D_A + \gamma \tau_A + \epsilon_{A,n} = \upsilon_{A,n} + \epsilon_{A,n} \tag{8}$$

where $\epsilon_{A,n}$ is the latent and random component of commuter n's indirect utility, f is a vector of covariates, T_A is travel time, and D_A is traffic density. θ, β, λ, and γ are parameters to be estimated and the (congested) Road B is taken as the normalizing alternative.[8] $\upsilon_{A,n}$ only serves to provide a more compact expression of the commuter's conditional indirect utility. If we assume that the random utility components are drawn independently and identically from a Type I Extreme Value distribution, then the probability that commuter n chooses Road A is given by the familiar logit form

$$P_{A,n} = \frac{1}{1 + e^{\upsilon_{A,n}}} \tag{9}$$

The commuter's value of time is then given by her marginal rate of substitution between tolls and travel-time savings

$$VOT_n = \left.\frac{d\tau_A}{dT_A}\right|_{d\upsilon_{A,n}=0} = -\frac{\partial \upsilon_{A,n}/\partial T_A}{\partial \upsilon_{A,n}/\partial \tau_A} = -\frac{\beta}{\gamma} \tag{10}$$

which is a standard result showing that VOT can be estimated by the ratio of the toll and travel-time coefficients. Analogously, the marginal rate of substitution between tolls and traffic densities yields the value of density, but care must be taken in light of the functional relationship between travel-times and densities. Write the *gross* value of density as

$$\tilde{VOD}_n = \left.\frac{d\tau_A}{dD_A}\right|_{d\upsilon_{A,n}=0} = -\frac{\partial \upsilon_{A,n}/\partial D_A}{\partial \upsilon_{A,n}/\partial \tau_A} = -\left[\frac{\beta}{\gamma}\frac{\partial T}{\partial D} + \frac{\lambda}{\gamma}\right] \tag{11}$$

[8] Note that Road B is normalized by setting $\upsilon_{B,n} = 0$. Accordingly, T_A and D_A are measured as *differences* in travel times and traffic densities for the two roads.

which separates the overall willingness to pay for traffic-density reductions into its travel-time and density-specific components.[9] Note that the quantity $\frac{\partial T}{\partial D}$ is a random variable that must also be estimated. Equation (11) shows explicitly how examining commuters' tradeoffs between tolls and traffic densities can capture the value of the disutility generated by increased traffic densities in terms of both travel-delays and density-specific costs. If the travel-time component, $\frac{\beta}{\gamma}\frac{\partial T}{\partial D}$, can be estimated separately from the density-specific component, $\frac{\lambda}{\gamma}$, then the intangible costs can be separately estimated insofar as these costs are reflected in revealed tradeoffs between tolls and densities. As such, the term "value of density" is used here to mean the value of the disutility generated directly by marginal increases in traffic densities, namely

$$VOD_n = -\frac{\lambda}{\gamma} \tag{12}$$

Equation (12) can be interpreted as a marginal rate of substitution between tolls and traffic densities that has been "purified" of travel-time influences; it is simply the ratio of the density and toll coefficients. Likewise, equation (10) can be interpreted as a value of time that has been "purified" of non-travel-time influences, provided that travel-times are included in the estimation procedure.

Note that equation (11) can be estimated in reduced form if travel-times are omitted from the estimation procedure. In other words, if the influences of travel times and traffic densities cannot be estimated separately, estimating the choice probability in (9) as a function of density, omitting travel times, can be used to jointly estimate travel-time costs and intangible costs. The converse may not hold; omitting densities from the estimation procedure may produce estimates purely on motorists' opportunity cost of time (as they are often intended to). The functional relationship between travel times and densities, however, suggests the likelihood that travel times and densities are statistically correlated. As such, traditional value of time estimates – those that do not control for traffic densities – may reflect some portion of the value of density reductions that are correlated with travel-time savings.[10]

Combining equation (3) with equations (10) and (12), the joint marginal external congestion cost, reflecting both travel-delay and density-specific costs, is given by

$$MEC = -\left[\frac{\beta}{\gamma}\frac{\partial T_B}{\partial D_B} + \frac{\lambda}{\gamma}\right]\frac{\partial D_B}{\partial V_B}V_B \tag{13}$$

in dollars per vehicle. The congestion-technology components of equation (13), $\frac{\partial T}{\partial D}$, $\frac{\partial D}{\partial V}$, and V, are estimated from traffic conditions on the congested Road B because this is where the externalities are borne (recall that Road A is uncongested). If examining a fixed portion of

[9] This follows from Hensher (2001) who demonstrates that density effects can be elicited by an appropriate decomposition of travel time.

[10] This may explain why VOT estimates based on revealed-preference data are typically much higher than those based on stated-preference data, which is discussed in Section 7.4.

highway with length L, then $-\left[\frac{\beta}{\lambda}\frac{\partial T_B}{\partial D_B}+\frac{\lambda}{\gamma}\right]\frac{\partial D_B}{\partial V_B}\frac{V_B}{L}$ gives the marginal external cost in dollars per vehicle-mile. Finally, it is useful for estimation purposes to express this cost as a function of the speed-density elasticity, $\varepsilon_{S,D}$. The estimation equation then becomes

$$MEC=-\left[\frac{\beta}{\gamma}\frac{\partial T_B}{\partial D_B}+\frac{\lambda}{\gamma}\right]\frac{D_B}{(1+\varepsilon_{s,k})L} \tag{14}$$

with the congestion externality given in dollars per vehicle-mile, and can be decomposed into its travel-delay and density-specific components

$$MEC^T = -\frac{\beta}{\gamma}\frac{\partial T_B}{\partial D_B}\frac{D_B}{(1+\varepsilon_{s,k})L} \tag{15}$$

$$MEC^D = -\frac{\lambda}{\gamma}\frac{D_B}{(1+\varepsilon_{s,k})L} \tag{16}$$

5 Empirical Setting

The San Diego I-15 Congestion Pricing Project offers the real-world versions of Road A and Road B from the previous section. The project offers solo drivers an option to pay for using an eight-mile stretch of two uncongested lanes, referred to as "HOT" lanes, adjacent to (but physically separated from) the main lanes along California's Interstate 15, just north of San Diego, California.[11] 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 afternoon commute. Those who choose to enter the facility must travel its entire length as there are no interim exits.

This paper 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.[12] The 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 1 provides a brief summary of respondent characteristics, where population-weighted figures are also presented to account for choice-based sampling. All of the valuation and cost estimates in this paper rely on measures of tolls, travel-time savings, and traffic densities (or, more precisely, differences in travel times and traffic densities), and a handful of other covariates. These variables are given in the upper portion of Table 2 and each warrants a brief explanation of how it is measured.

A unique characteristic of the I-15 HOT lanes is how free-flow traffic conditions are main-

[11] The acronym "HOT" stands for "High-Occupancy / Toll". This nomenclature arises from special consideration typically given to high-occupancy vehicles (carpools). On the I-15 HOT lanes, carpools are allowed to travel without paying a toll.

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

tained along them. Tolls change every six minutes in $0.25 increments to maintain a minimum speed of 64.5 miles per hour (and a maximum volume of 1,548 vehicles per lane-hour). This is accomplished by traffic-flow monitoring from sensors embedded in the highway near each onramp along the main and HOT lanes.[13] Tolls are posted at the entrance to the facility, 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 "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 travel time on the adjacent HOT lanes. The salient time-savings measure is *median* time savings as commuters do not know their actual time savings prior to choosing between the two sets of lanes. Instead, it is assumed that commuters have a feel for their travel-time distributions and base their decisions on typical values, as is now standard in studies that exploit HOT-lane data.[14] These time-savings measures are based on data from sensors that calculate 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 HOT-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 because 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.[15] These additional savings do not strictly depend on traffic densities along the main lanes and, as such, provide a separate and valuable source of overall travel-time variation. This effectively breaks the collinearity between travel times and traffic densities by providing a sufficient degree of independent variation in time savings to reveal the remaining influence of density on commuters' mode choices.

Differences in traffic densities between the two modes are measured as the difference in the average number of vehicles per lane-mile between the two routes. Because the HOT-lane facility

[13] These sensors are called "loop detectors", which sense changes in inductance to calculate how long vehicles are above them ("occupancy") and how many vehicles pass over them ("flow") in a given period.

[14] This approach is adopted by Ghosh (2001), Lam and Small (2001), Brownstone et al. (2003), Small et al. (2005), and Steimetz and Brownstone (2005). Also, see Brownstone and Small (2005) for an assessment of several recent studies based on HOT-lane data.

[15] More precisely, separate time-savings *distributions* are constructed for those entering the I-15 (HOT-lanes or main lanes) at Ted Williams Expressway so that their median time-savings values reflect these additional savings. The waiting times themselves are based on floating-car observations over ten days of the sample period.

is segmented by a series of sensors, 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 as 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 HOT-lane facility that are typical for their travel periods.

The remaining covariates in Table 2 serve as controls and are included based on the "lessons learned" from Steimetz and Brownstone (2005). For example, 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 HOT lanes. Second, there is evidence from recent HOT-lane studies that motorists also care about the "variability" in the time savings they hope to enjoy from entering the HOT lanes.[16] This variability tends to be highest during peak-commute periods, however, making it especially difficult to separate the influence of variability from the influences of travel times and traffic densities. But high levels of variability are presumably less likely to influence 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 controlling for the influence of uncertainty about HOT-lane time savings.

Income data were only collected categorically, from which an indicator variable that equals one for annual household incomes greater than $80,000 is constructed. Trip Distance reflects the total length of each commuter's journey (including the eight-mile stretch of the HOT-lane facility). The trip-purpose and job-status variables accommodate varying levels of schedule flexibility among the sample respondents. The "Female" variable tests a recurring though unexplained theme in the value-of-time literature: that females are more likely to use HOT lanes. Finally, the "Mobile Phone Available" variable controls for those who are inclined to make calls while driving and would prefer to do so under conditions that require less attention to the task of driving. A preview of the coefficient estimates in Table 2 shows that each control variable carries an "expected" sign.

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

[16] It is common in the value-of-time literature to define "variability" as the difference between the 80^{th} or 90^{th} percentile and 50^{th} percentile of the relevant time-savings distribution. This is based on the notion that commuters care much more about unanticipated delays than they do about unexpectedly swift travel.

while meeting budgetary constraints. This presents a sample-selection problem that must be remedied. If equation (9) were estimated under the assumption of an exogenous sampling mechanism, the model would be estimated by maximizing the joint log-likelihood function

$$L(\nu_{i,n}(\phi)) = \sum_{n=1}^{N}\sum_{i=1}^{2} y_{i,n} \ln(P_{i,n}) \tag{17}$$

where ϕ is a vector of parameters and $y_{i,n}$ is an indicator variable for choosing alternative i. Maximum likelihood estimates from equation (17) would generally be inconsistent unless the endogenous sampling mechanism were properly accounted for.[17] Manski and Lerman (1977) show that a consistent estimator for ϕ, known as the Weighted Exogenous Sample Maximum Likelihood Estimator (WESMLE), is the maximand to the weighted log-likelihood function

$$L_w(\nu_{i,n}(\phi), w_n) = \sum_{n=1}^{N}\sum_{i=1}^{2} w_n y_{in} \ln(P_{in}) \tag{18}$$

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

$$w_i = \frac{p_i}{s_i} \tag{19}$$

where p_i and s_i represent the population and sample shares of mode i. Fortunately, however, the surveyed commuters reported the number of days that they traveled along the facility 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 f_{in} be the number of times person n chose mode i in a given week, and f_n be the total number of trips taken by that person that week. The sampling weights are then given by

$$w_n = \alpha \sum_{i=1}^{2} \frac{w_i f_{in}}{f_n} \tag{20}$$

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

$$\Sigma = \Omega^{-1}\Delta\Omega^{-1} \tag{21}$$

[17] Daniel 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 as they are functions of the (expectations of) inconsistently-estimated choice probabilities.

where

$$\Omega = -E\left[\frac{\partial^2 w_n L_n(\nu_{i,n}(\phi))}{\partial\phi\partial\phi'}\right] \tag{22}$$

$$\Delta = E\left[\left(\frac{\partial w_n L_n(\nu_{i,n}(\phi))}{\partial\phi}\right)\left(\frac{\partial w_n L_n(\nu_{i,n}(\phi))}{\partial\phi'}\right)\right] \tag{23}$$

and $L_n(\nu_{i,n}(\phi))$ is the n^{th} observation's (unweighted) contribution to the log-likelihood function given by equation (17). Replacing the expectation operators in equations (22) and (23) with their sample analogues, evaluated at the WESMLE estimates for ϕ, 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 (19) are used in equation (18). The sampling weights would be quite small for the relatively rare mode (HOT lanes), 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. Second, exploiting additional information about the (choice-based) sampling mechanism to employ the sampling weights given by equation (20) somewhat relaxes the variation constraints that would be imposed by the weights in equation (19). This latter point illuminates the value of exploring the sampling mechanism beyond simple mode-shares if choice-based sampling is to be used for future HOT-lane data collection.

6 Estimation Results

The parameter estimates obtained by maximizing (18) over a sample of 602 morning commuters are displayed in Table 2, along with corresponding value-of-time and value-of-density estimates. All of the coefficients are statistically significant beyond the 95% confidence level. As expected, the demand for HOT-lane use decreases with toll levels and increases with the potential for travel-time savings and enjoying reduced traffic densities. The time and density coefficients are each estimated with precision, allowed by the "colinearity-breaking" effect of additional time savings offered by the dedicated HOT-lane onramp at the head of the facility. The coefficient on Trip Distance suggests that when tolls are unusually high, commuters are more likely (ceteris paribus) to use the HOT lanes because unusually high tolls may indicate unusually heavy downstream congestion on the main lanes. The trip-type and work-status coefficients indicate that commuters with more flexible schedules are less likely to travel along the HOT lanes. The results also suggest that females and long-distance commuters are more likely to use the HOT lanes, as are motorists with access to a mobile phone during their commute.

The ratio of the travel-time and toll coefficients gives the value of time for a typical rush-hour commuter, reported in the lower half of Table 2. Because this ratio can be quite sensitive to small changes in coefficient values, VOT is estimated by "bootstrapping" its underlying empirical distribution and taking the median of this distribution as a point estimate. This value is asymptotically equivalent to an optimal Bayesian posterior estimate of median VOT assuming a normal error structure and an uninformative prior. It also allows for characterizing the standard error of the estimate by the standard deviation of the bootstrap distribution. The results suggest that a typical rush-hour commuter's is willing to pay a rate of $21.39 per hour for marginal travel-time savings. Analogously, the ratio of the travel-time and density coefficients gives the value of density for a typical rush-hour commuter, also reported in Table 2 along with its bootstrapped standard error. The interpretation of the VOD estimate is that a typical rush-hour commuter is willing to pay $0.07 for each vehicle per lane-mile avoided on a given stretch of highway *holding travel time constant*.

Combining these VOT and VOD values with (15) and (16) provides separate estimates for the congestion externalities attendant to travel delays and intangible costs such as stress and accident-avoidance efforts. The travel-delay externality is a function of how travel-times change with traffic densities, $\frac{\partial T}{\partial D}$, and both the travel-delay and density-specific externalities depend on the elasticity of average vehicle speeds with respect to traffic densities, $\varepsilon_{S,D}$; these congestion-technology components must be estimated. Table 3 reports the results of a linear least-squares regression model used to estimate $\frac{\partial T}{\partial D}$, and the results of a log-quadratic regression for estimating $\varepsilon_{S,D}$.[18] Of course, the engineering literature on estimating such quantities is voluminous and this approach is not intended as a competing substitute. However, Table 3 shows that the relationships between average speed, travel time, and density are predicted with reasonable degrees of precision. The resulting estimates are presumably accurate enough to demonstrate the magnitudes of the costs described in this paper.

Table 4 reports estimates for the travel-delay externality, MEC^T, and the intangible external costs captured by increased traffic densities, MEC^D. The joint congestion externality is simply the sum of these costs. The results indicate that during a typical rush-hour commute, motorists impose upon one another a travel-delay externality of $1.05 per vehicle-mile. MEC^T is also reported at the quartiles of the sample's traffic densities to illustrate how the magnitude of this externality changes with varying levels of traffic congestion. MEC^D is reported in a similar manner and suggests that rush-hour motorists suffer an external cost of $0.79 per vehicle-mile in terms of intangible congestion costs reflecting the overall frustration induced by crowded urban expressways. The joint congestion externality resulting from rush-hour congestion is $1.84 per vehicle-mile, 44% of which can be attributed to non-travel-time

[18] In general, $\frac{\partial T}{\partial k}$ can be written as $-\varepsilon_{s,k}\frac{L}{ks}$, which might lead some readers to ask why two regressions are necessary. 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 $\frac{\partial T}{\partial k}$ relates densities to travel times, which include onramp queueing delays.

factors.

7 Implications and Discussion

7.1 Value of Time and Value of Density

The finding that travel-time savings are valued at roughly $21 per hour is not surprising given the range of VOT estimates provided by several recent studies based on HOT-lane data. Lam and Small (2001), for example, estimate VOT at $23 to $24 using evidence from HOT-lanes along Southern California's State Route 91 (SR-91). Small et al. (2005) provide VOT estimates of $20 to $25 from a similar set of SR-91 data.[19] Using I-15 data similar to those employed in the present study, Brownstone et al. (2003) estimate VOT at $30, as do Steimetz and Brownstone (2005) based on a later wave of I-15 data. In order to compare estimates across the I-15 and SR-91 results, Brownstone and Small (2005) weight the characteristics of the I-15 commuters to match those of the SR-91 and find that Steimetz and Brownstone's VOT estimate falls to $22.

What may be surprising is that the value of density estimated here implies that nearly half of the overall congestion externality is due to factors beyond the value of travel-time savings. Intuitively, however, the magnitude of these intangible costs is easy to understand. On a daily basis urban commuters encounter sudden stops, near collisions, lane jumpers, road rage, and even rear-view-mirror shavers – all of which coincide with dense traffic conditions. It is easy to imagine why rush-hour commuters would be willing to pay a premium to avoid these conditions, even without the benefit of travel-time savings. In short, congested commutes generate rush-hour headaches that are suffered beyond those induced by travel delays. The "value of density" elicits the cost of such headaches through commuters' willingness to pay for reduced traffic densities. And the magnitude of these costs suggest taking them into consideration when designing road-pricing and investment policies.

The VOT and VOD estimates imply a joint congestion externality of $1.84 per vehicle-mile, 66% of which is attributable to travel-delays and 44% of which reflects "rush-hour headache" costs. These results further indicate that intangible costs are not easily dismissed, and that congestion-pricing mechanisms designed to reduce rush-hour traffic to economically efficient levels may reflect a substantial portion of non-travel-time charges. A portion of these costs are generated by accident-avoidance efforts, which must be considered when measuring external accident costs.

[19] More precisely, Small et al. (2005) find VOT to be $25 based on revealed-preference (RP) data alone. They also combine these data with an overlapping set of stated-preference (SP) data to produce VOT estimates of $20 to $21 in a random-coefficients framework. When estimating from SP data alone, however, VOT falls to $9.

7.2 Accident Externalities

Following Vickrey (1968), the marginal external accident costs of driving are typically viewed as being proportional to the elasticity of accident risk with respect to traffic flow. When traffic flows increase, the total number of accidents will likely increase but the number of accidents per unit of flow might rise, remain unchanged, or even fall in the case of severe accidents. This ratio of observed accidents to traffic volumes is often defined as "accident risk". Researches traditionally compare marginal and average accident rates across roads with varying traffic volumes to characterize how this risk changes with flows and convert the quantity to a speed-flow elasticity. Combining this elasticity with an appropriate valuation measure, such as the "statistical value of life" for fatal accident externalities, estimates the magnitude of the accident externality.[20] Abstracting from the accident costs imposed on pedestrians an non-motorized vehicles, Vickrey (1968) suggests an elasticity of 0.5, while Newbery (1990) splits the difference between Vickrey's estimate and an engineering convention of a zero elasticity to suggest a value of 0.25. More recent evidence generally ranges from negative values for fatal accidents (Elvik (1994)) to a recurring view that the overall risk-flow elasticity is zero (Jones-Lee (1990), Jansson (1994), Mayeres et al. (1996)). Mayeres et al. (1996) summarize this view: "for accidents between two motorized users an accepted convention is to assume that the number of accidents is proportional to traffic volume, such that the elasticities are zero."

A risk-flow elasticity of zero is often interpreted to mean that the accident externality between motorists is zero. It is important to draw a distinction here between "accident risk", which is based on accidents that actually occur, and collision potential, which necessarily increases with traffic levels. As Vickrey notes, increased traffic "induces a greater degree of caution or discipline on the part of drivers", i.e., motorists engage in "risk-compensating" behavior to offset the increased collision potential generated by heavier traffic.[21] A zero risk-flow elasticity thus indicates that motorists completely offset increases in collision potential with increases in accident-avoidance efforts. These efforts are indeed costly and several studies advocate the accounting of such costs (Newbery (1990), Edlin (2003), Steimetz (2004), Hensher (2005)) or demonstrate their importance to characterizing rational motorist behavior (Rotemberg (1985), Boyer and Dionne (1987), Peirson et al. (1998), Mayeres (1999)). So a useful interpretation of accident-externality estimates based solely on risk-flow elasticities is that they describe the external costs attendant to increases in *observed* accident rates, which do not include the external costs attendant to accident-avoidance efforts. Indeed, accidents are relatively rare, but ubiquitous efforts to avoid them are what keep them rare. This interpretation also avoids somewhat paradoxical policy implications, such as a negative elasticity warranting congestion subsidies in the interest of public safety.

[20] See Jannsson (1994) for a formal derivation of Vickrey's framework, and Peirson et al. (1998), and Lindberg et al. (1999) for reviews of this literature.

[21] Peltzman (1975) provides empirical evidence of risk-compensating behavior; Crandall and Graham (1984) and Keeler (1994) provide more recent support.

Estimating the full extent of accident externalities thus requires estimates for the costs of accident-avoidance. Steimetz (2004) attempts to provide these estimates in a value-of-density framework, similar to that developed in the present study. The argument is that all of the disutility generated by increased traffic densities can be traced to collision-avoidance efforts. This assumption may be too strong, however, given the many other sources of (non-travel-time) frustration that result from dense traffic. Value of density is estimated at $0.07, implying a median density-specific externality of $1.05 per vehicle-mile; the present study also arrives at these same estimates. The portion of this externality that is due to collision-avoidance efforts represents the unobservable component of the accident externality. Following Steimetz (2004), Hensher (2005) estimates the value of density in a mixed-logit framework using toll-road data from an urban commute corridor in Sydney, Australia. Hensher provides VOD estimates ranging from $0.14 and $0.19 for automobile traffic and $0.55 for heavy-vehicle traffic, in U.S. dollars per mile.[22] This results in a traffic-weighted average externality, in terms of density-specific costs, of $1.05 per vehicle mile; this cost represents 49% of the overall congestion externality. Although the estimates from Hensher (2005) and those of the present study have somewhat different interpretations and are obtained under different commute conditions, it appears that the international evidence on intangible congestion externalities support each other quite well. And to the extent that they capture the costs of accident avoidance, these estimates provide evidence that the unobservable component of the accident externality may be quite substantial.

7.3 Methodological Issues

This paper's empirical framework is developed, in part, to stimulate further research on the value of time and the value of density in a joint estimation framework. HOT-lane facilities are particularly valuable in this respect because they are capable of generating rich data on motorists' tradeoffs between money prices and congestion costs, and can be matched with the traffic conditions that these motorists face when making such decisions. There are currently five HOT-lane facilities operating in the United States, and several more are in the planning stage.[23] This section provides a methodological discussion on exploiting data from these facilities or other toll roads and interpreting results.

Due to the functional relationship between travel times and traffic densities, colinearity may prevent the separate estimation of their coefficients using a specification like (8). In other words, it may not be possible to separately estimate VOT and VOD, thus precluding separate estimates for MEC^T and MEC^A. However, commuters care about all of the costs that dense traffic

[22] Hensher's estimates are taken from Table 1 of his paper, where they are given in AU dollars per kilometer for VOD estimates AU dollars per vehicle-kilometer for external cost estimates. These values are converted to US dollars per vehicle-mile using an exchange rate of $1 AU = $1.43 US.

[23] The five existing HOT-lane facilities are along portions of Interstate 15 in San Diego County and State Route 91 in Orange County, California, The Katy and the Northwest Freeways in Harris County, Texas, and Interstate 394 in Minneapolis, Minnesota. States with planned HOT-lane facilities include Washington, Virginia, Maryland, and Colorado.

generates, not just the cost of travel delays. Equation (11) demonstrates that estimating the overall value of traffic-density reductions will also capture the value of travel-time reductions, so long as the relationship between traffic densities and travel times is well understood. To illustrate this, the model in Table 2 is re-estimated with the travel-time variable omitted. This results in a *gross* value of density, $\tilde{VOD}$, of \$0.16 per vehicle per lane-mile (with a bootstrapped standard error of \$0.02). The implied congestion externality is \$1.79 per vehicle-mile, which is statistically indistinguishable from the \$1.84 estimated from the complete specification. Thus, if forced to choose between estimating the value of time and the (gross) value of density, the later may be preferable in that it captures the value of time plus the value of intangible congestion costs.

In some cases data on travel times are available, but data on traffic densities are not. Traditional VOT estimates are still attainable and may reflect the value of intangible costs to some extent due to the colinearity between travel times and traffic densities. For instance, re-estimating the model in Table 2 while omitting the traffic density variable – replicating a traditional discrete-choice framework for estimating VOT – produces a VOT estimate of \$31.06 per hour (with a bootstrapped standard error of \$3.51). This implies a travel-delay externality of \$1.54 per vehicle-mile, which is statistically larger than the MEC^D of \$1.05 estimated from the complete specification (and approaches the overall congestion-cost estimate of a \$1.79 produced by the complete model).[24] These results provide loose evidence that traditional VOT might approximate the joint travel-delay and density externality, but perhaps not completely so.

7.4 Revealed and Stated Preferences

In a summary and assessment of recent value-of-time studies based on Southern California HOT-lane data, Brownstone and Small (2005) find that VOT estimates from revealed-preference (RP) data are typically much larger than those from stated-preference (SP) data.[25] For example, Small et al. (2005) estimate VOT using overlapping RP and SP data from the SR-91 HOT-lane facility. Using RP data alone, median VOT is estimated at \$25 per hour, whereas VOT estimated only using SP data falls to \$9. The present study's finding that traditional value-of-time estimates can capture the influence of intangible congestion costs may help to explain this phenomenon. Recall that the median VOT estimate presented here is \$31 when traffic densities are not controlled for, but falls to \$21 when traffic densities are included in the estimation procedure. Section 4 describes how controlling for traffic densities can "purify" the VOT estimate of intangible costs that arise from dense traffic conditions. VOT estimates from SP data may be similarly "purified" to the extent that they are used to estimate pure travel-time

[24] Note that this \$31 VOT estimate is nearly identical to the estimates obtained by Brownstone et al. (2003) and Steimetz and Brownstone (2005) who estimate VOT using a similar I-15 data set but without controlling for traffic densities.

[25] RP data comprise observations on actual motorist behavior, whereas SP data comprise motorist responses to hypothetical travel scenarios.

savings without characterizing *how* these time-savings are achieved. In other words, SP-based estimates may typically capture the opportunity cost of their respondents' time, whereas RP-based estimates may typically capture this time value plus the intangible costs that densities would otherwise control for. It may also follow that RP-based procedures that do control for traffic densities produce VOT estimates that can be interpreted as the value of uncongested travel time, which could explain why peak-period VOT is typically much higher than it off-peak counterpart (Guttman (1975), Small et al. (1999), Hensher (2001), Brownstone and Small (2005)).

The above discussion also suggests some promise for jointly estimating travel-delay and intangible externalities using stated-preference methods, in the spirit of Hensher (2001). A simple example is to present respondents with two distinct scenarios: one elicits preferences from a series of tolls and travel times; the other presents tolls and travel times along with detailed illustrations of the traffic conditions that correspond to each travel time. Differences in the resulting VOT estimates might then reflect the value of the non-travel-time disutility generated by more onerous traffic conditions.[26]

8 Conclusion

This paper's primary contribution is the development of a simple framework for estimating the unobservable and intangible externalities that result from urban rush-hour traffic congestion. It argues that these costs increase with traffic densities and, accordingly, are captured by motorists' willingness-to-pay for marginal reductions in traffic densities when separated from their willingness-to-pay for marginal travel-time savings. Measuring the value of density and the value of time in a joint-estimation framework also serves to extract the influence of intangible costs from VOT estimates, thereby revealing the opportunity cost of motorists' time. These valuations are estimated in a discrete-choice framework where rush-hour commuters are offered a tolled alternative to congested travel in a real market setting. Results suggest that commuters are willing to pay a rate of $21 per hour for marginal travel-time reductions and a rate of $0.07 for marginal density reductions. Combining these values with estimates for congestion-technology parameters implies a marginal travel-delay externality of $1.80 per vehicle-mile and a "rush-hour headache" externality of $0.80 per vehicle-mile. The disutility associated with accident-avoidance efforts represent some portion of these "headache" costs and are appropriately characterized as a form of accident externality, though it is not possible to isolate this accident externality from other intangible costs. This paper's results also offer an explanation for the divergence between traditional value-of-time estimates based on revealed preference and stated preference data, and suggest that peak-period and off-peak VOT can be estimated in a

[26] This approach might, however, fail to capture the external *benefits* associated with increased accident-avoidance efforts under congested conditions.

single framework.

An important caveat is that the estimates provided here are based on a particularly congested commute corridor in a relatively wealthy area at the height of the morning rush hour. One should exercise caution when attempting to generalize these results to other commute settings. Moreover, they do not capture other important externalities such as observable accident costs and the adverse effects of vehicle emissions. Another caveat is that the external-cost estimates are sensitive to their underlying congestion-technology parameters. The parameter estimates used here are largely illustrative, and careful attention should be paid to accurately portraying congestion dynamics before formulating transportation policies from these cost estimates. Ultimately, the estimates presented herein should be viewed as "proof of concept" and call for further research and, perhaps, more sophisticated estimation methods for accurately estimating the parameters of the empirical framework introduced by this paper. A modest degree of methodological guidance is offered for using data from modern congestion-pricing experiments to obtain such estimates.

One valuable extension would be to combine these external congestion-cost estimates with a model of rush-hour demand to obtain a schedule of optimal congestion tolls or, more ambitiously, optimal road pricing and investment levels in a single framework (as in Keeler and Small (1977)). Further research could also focus on how motorists value reductions in traffic densities of various types, following Hensher (2005). This would be particularly relevant for urban commute corridors that carry a substantial flow of commercial truck traffic. It might also be useful to demonstrate how these valuations and costs vary with commuter characteristics in light of the debate on the economic efficiency of HOT-lanes themselves. (see, for example, Small and Yan (2001) and Steimetz and Brownstone (2005)).

Urban traffic congestion continues to grow rapidly and rush-hour headaches are likely to keep pace. This study serves as an early clinical trial toward measuring, pricing, and alleviating these intangible but pervasive rush-hour symptoms.

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FIGURE 1: Speed vs. Density

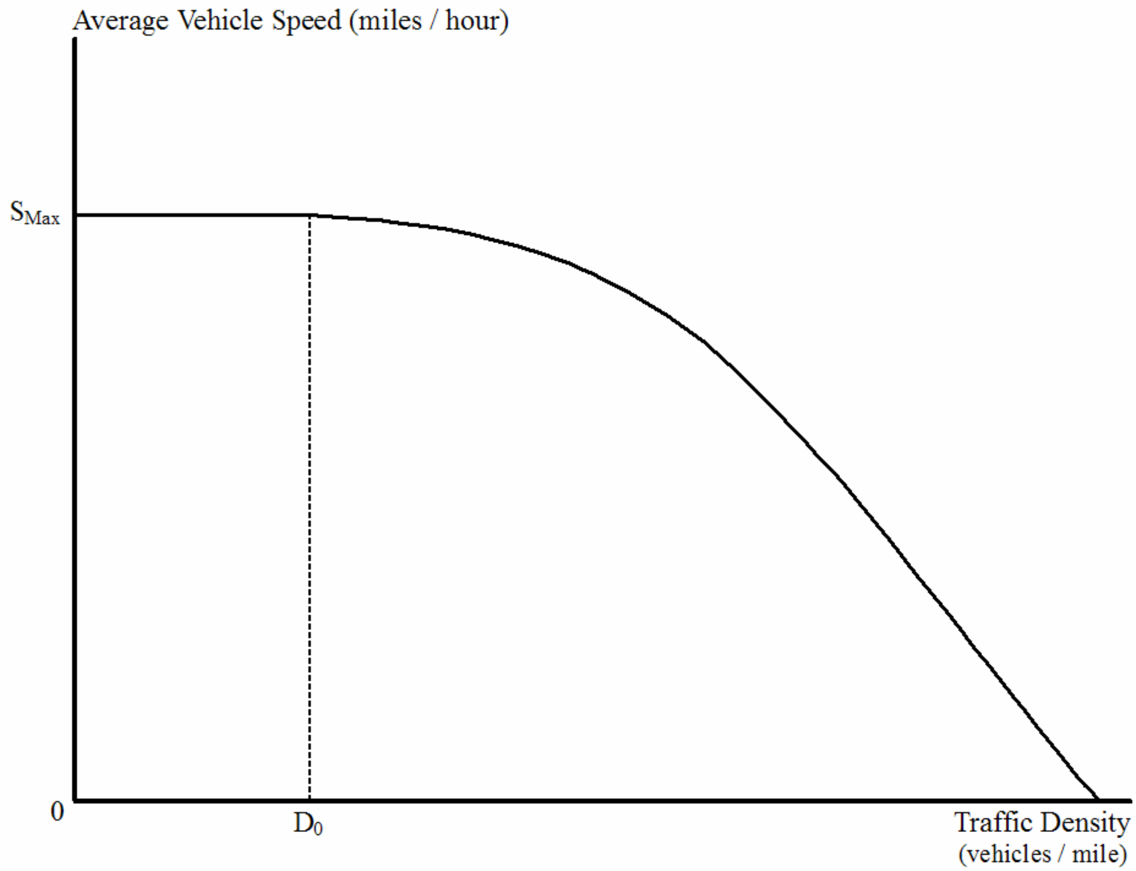

FIGURE 2: Generalized Price vs. Traffic Flow

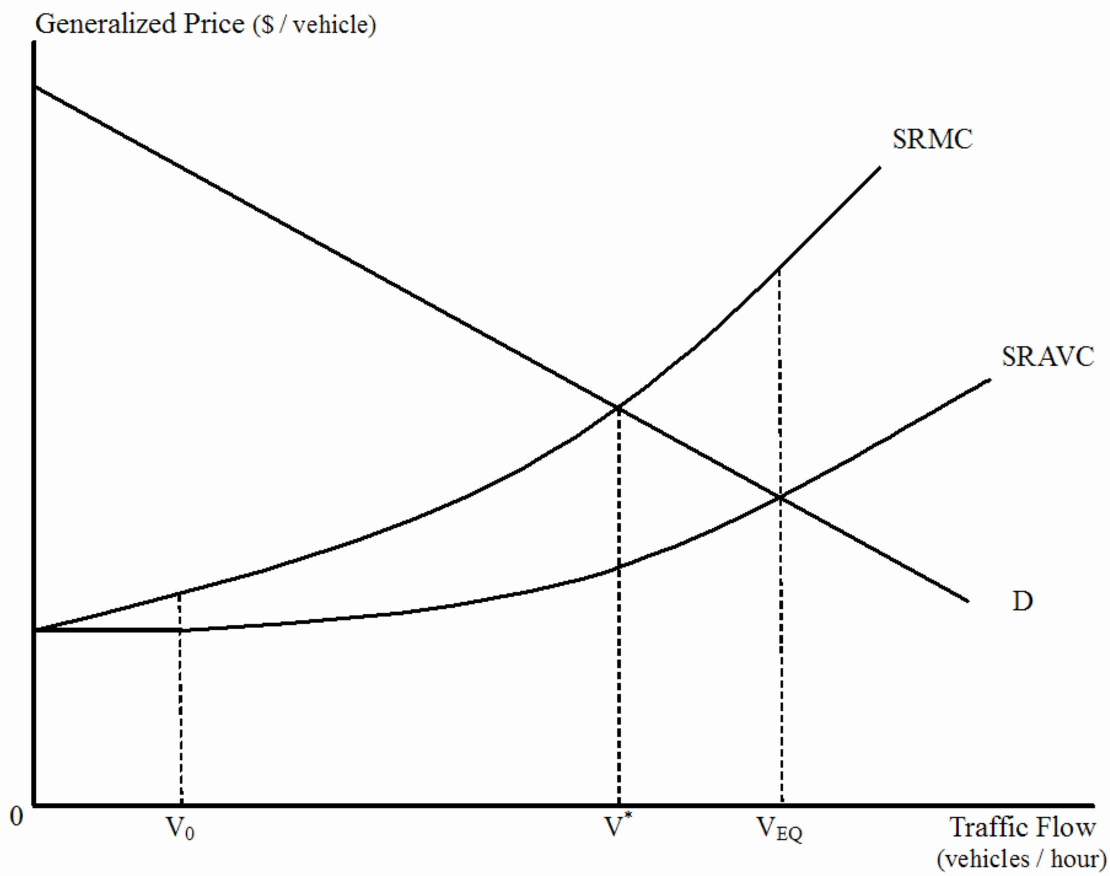

TABLE 1: Summary Statistics

	In Sample	*Weighted to Population*
Mode Share		
Main Lanes	50.17%	84.53%
HOT Lanes	49.83%	15.47%
Posted Tolls Faced ($)		
Mean	1.75	1.65
Standard Deviation	1.18	1.15
Trip Distance (miles)		
Mean	25.02	25.20
Standard Deviation	9.48	9.10
Annual Income ($)		
< $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: Logit and Valuation Estimates

WESMLE Logit Estimates

Independent Variable	**Coefficient**	**Standard Error**	**t-Statistic**
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	

Value of Time and Density Estimates

Value of Time (VOT)[d]	**21.39**
Bootstrapped Standard Error	3.51
Value of Density (VOD)[e]	**0.07**
Bootstrapped Standard Error	0.02

Note: the dependent variable in the 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 over the respondent's trip.

[b] Defined as the median difference between HOT-lane and free-lane travel times over the respondent's trip.

[c] Indicator variable equal to 1 if the condition is true and 0 otherwise.

[d] Calculated using equation (11) in dollars per hour.

[e] Calculated using equation (13) in dollars per vehicle per lane-mile.

TABLE 3: Congestion-Technology Parameter Estimates

Speed vs. Traffic Density[a]

Independent Variables	Coefficient	Standard Error	t-Statistic
Log of Average Traffic Density	-2.67	0.35	-7.57
Squared Log of 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 ($\varepsilon_{S,D}$)[b]	**-0.52**		

Travel Time vs. Traffic Density[c]

Independent Variables	Coefficient	Standard Error	t-Statistic
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
Number of Observations		602	
Adjusted R^2		0.90	
Marginal Effect of Density ($\partial T/\partial D$)[d]	**0.26**		

[a] The dependent variable is the log of average vehicle speed over the commute period. Vehicle speeds are in miles per hour and traffic densities are in vehicles per lane-mile.
[b] Evaluated at the sample mean of the log of average traffic density.
[c] The dependent variable is average travel time over the commute period. Travel times are in minutes and densities are in vehicles per lane-mile.
[d] Evaluated at sample means of the density variables.

TABLE 4: Congestion Externality Estimates

Marginal External Congestion Costs[a]	
Travel-Delay Externality (MEC^T)[b]	
At 25th percentile of traffic density	0.98
At 50th percentile of traffic density	**1.05**
At 75th percentile of traffic density	1.15
Density-Specific Externality (MEC^D)[c]	
At 25th percentile of traffic density	0.74
At 50th percentile of traffic density	**0.79**
At 75th percentile of traffic density	0.86
Joint Congestion Externality ($MEC^T + MEC^D$)	
At 25th percentile of traffic density	1.72
At 50th percentile of traffic density	**1.84**
At 75th percentile of traffic density	2.01

[a] All costs are in dollars per vehicle-mile.
[b] Calculated using equation (16).
[c] Calculated using equation (17).