

Valuation of Travel Time

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Abstract

After decades of study, the value of travel time remains incompletely understood and ripe for further theoretical and empirical investigation. Research has revealed many regularities and connections between willingness to pay for time savings and other economic factors including time of day choice, aversion to unreliability, labor supply, taxation, activity scheduling, intra-household time allocation, and out-of-office productivity. Some of these connections have been addressed through sophisticated modeling, revealing a plethora of reasons for heterogeneity in value of time rooted in behavior at a micro scale. This paper reviews what we know and what we need to know. A recurrent theme is that the value of time for a particular travel movement depends strongly on very specific factors, and that understanding how these factors work will provide new insights into travel behavior and into more general economic choices.

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Valuation of Travel Time

Kenneth A. Small

It is difficult to name a concept more widely used in transportation analysis than the value of travel time. Its theoretical meaning and its empirical measurement are fundamental to travel demand modeling, social cost analysis, pricing decisions, project evaluation, and the evaluation of many public policies.

This paper undertakes a selective review of certain aspects, focusing on conceptual issues and interpretation. Why do we care about the subject, and how does the answer guide our understanding of it? Despite the importance of value of time in air and freight transportation, I restrict attention here to surface passenger transportation.

1. Why do we care?

The analysis of value of time is valuable for at least three reasons. First, it is important in decision making about transportation policy, as just mentioned. Second, it sheds light on broader questions about human behavior that are of interest throughout economics. Third, it is a crucial component in travel demand modeling, which is needed for many purposes.

1.1 Investment and policy evaluation

Two of the most prominent goals of transportation investments are time savings and, to a lesser extent, improvements in the reliability (i.e. predictability) of travel time. Insofar as it is possible to quantify “typical” costs of travel, travel time and its unreliability tend to dominate. For example, Small and Verhoef (2007) tally the costs of a typical urban commuting trip in the United States, finding that travel time and reliability together account for 45% of the average social variable cost, compared to vehicle capital costs (19%), vehicle operating costs (16%), and accident costs (16%).

It is not surprising, then, that the majority of investments seek to save travel time by reducing congestion, raising free-flow travel speed, and/or reducing circuitry of travel. It follows that the value of those time savings plays a critical role in investment analyses – second only,

perhaps, to the assumed discount rate. That value is the sum of the time savings across various dimensions—trip purposes, user types, times of day, etc.—each multiplied by a “value of time” (VOT) that captures those particular travelers’ willingness to pay for savings under a particular circumstance.

As is increasingly recognized, when users face uncertain travel times, they care about the probability distribution of the travel times they might encounter. Measuring travel-time reliability amounts to finding a compact way to summarize that distribution, especially its dispersion. Usually a single summary number is sought, but this is not necessary: travelers could, for example, care about both the standard deviation and the 90th percentile value, each having a different implication for the cost of unexpected deviations from a planned travel schedule. Once we have chosen one or more measures of reliability, we can seek to learn travelers’ willingness to pay for improvements in those measures – i.e., the value(s) of reliability (VOR).

Investigations into VOT and VOR raise interesting questions. How strongly correlated are these values with income or wage rate? Is there a stable functional relationship, and if so does it apply equally across individuals within a country, across time, and across countries? How much do these values depend on specific situations? For example, do they vary from day to day even for the same person? Should we expect dramatic changes in VOT resulting from in-vehicle devices that improve productivity, comfort, or the quality of entertainment en route?

Another question is how one is to understand the relationship between VOT and VOR for decisions made in the course of a trip, after the uncertainty of travel time is partially resolved. For example, it is often asserted that a traveler on the way to an airport has a very high VOT. Presumably this results from a high VOR; but to the traveler who has experienced some delay and is fearful of more, it may feel like a high VOT. Can this interaction be understood rigorously? And how does it bear on the value of information that can resolve uncertainty more quickly?

1.2 Connection to broader behavioral questions

Understanding the value of time can illuminate behavioral puzzles that go well beyond travel *per se*. An example is the “harried leisure class,” the revealing title of a small book by Lindler (1970). As economic development proceeds, one might expect that leisure, a normal

good, would be consumed in greater quantities. Yet even as the consumption of leisure goods from video games to yachts has skyrocketed, people seem more hurried than ever, and in many countries including the United States they appear to work as hard as ever.¹ Consistent with these observations, measured values of time continue to rise; the theory behind these measurements helps us understand why leisure might be pursued in a hurried manner.

Another puzzle is how people decide on their activity patterns, which in turn would influence how time-constrained they are in their trips. If most travel is a derived demand, as usually postulated, then it arises from very complex scheduling decisions in which multiple activities are sequenced in ways requiring movement among locations. Modeling how people map out an overlapping set of activity schedules over periods of hours, days, weeks, and even years, all the time accounting for the ever-changing technologies, costs, and service offerings of the transportation system, is a daunting challenge to say the least. Nevertheless, many travel demand researchers believe that only by embedding travel demand into activity choice can trip scheduling and value of reliability be satisfactorily understood.

To complicate the matter further, human genetics appear to have evolved in a context of constant movement. Thus, it is plausible that people have an inherent desire to be on the move. How might this show up in values of time for various types of travel? As one example, Ben-Akiva and Lerman (1985, pp. 174-176) found, using a piecewise linear specification for travel time, that workers may not care at all about reducing the first 20 minutes of their commute—perhaps because they like having time between home and office. Mokhtarian and Salomon (2001) argue, as supported by survey evidence from Ory and Mokhtarian (2005), that a substantial amount of travel is undertaken for the joy of it rather than as a derived demand.

Yet another puzzle is why students and retirees appear to value their time less than people in their most economically productive years. One might think a person's values of time at different life stages would be equalized via some version of a life-cycle theory of consumption, despite the fact that time cannot be borrowed like money. This puzzle has potential implications for how educational services are offered and for the demand for health-care and other services by older people.

¹ More precisely, both paid work and household production work have remained approximately constant over the entire twentieth century in the U.S. These overall statements hide some significant gender-specific changes. See Ramey (2009) and Hammermesh (2012).

A warning: some of these questions are not answered or even fully addressed here. However, one aim of the paper is to show that the theories and empirical techniques used to address VOT and VOR are capable of being adapted to answer broader questions.

1.3 Travel demand modeling

Even if we cared nothing about VOT or VOR for policy evaluation, we would need to understand them simply to predict people's travel decisions. Travel demand models typically find that travel time is one of the most important explanatory variables in terms of statistical and economic significance—more consistently so even than cost. Furthermore, the explanatory power of such models is often improved by judicious interactions of travel time with other variables such as income, trip distance, and mode. The specification of these interactions amounts to choosing, explicitly or implicitly, a model of how VOT varies. Thus, it can be guided by a theory of time allocation aimed at deriving such variations.

A simple example is the early binary probit model of urban commuter mode choice of Lave (1969). Lave specifies utility to be linear in cost and also linear in travel time multiplied by the wage rate. The result is that value of time, defined as the tradeoff between time and cost leaving utility constant, is proportional to the wage rate.² Train and McFadden (1978) go on to derive a continuum of specifications leading to the same proportionality, namely that utility is linear in $C \cdot w^\sigma$ and in $T \cdot w^{1-\sigma}$, where C and T are cost and travel time, w is the wage rate, and σ is the elasticity of utility with respect to goods in a simple Cobb-Douglas utility model of choice between goods and leisure. (Lave's model is the special case where $\sigma=0$.) Thus, one's beliefs about an appropriate model of labor-leisure tradeoff can guide the specification of a travel demand model, with the resulting measurement shedding light on broader questions.³

A recent theme in travel demand modeling is the empirical importance of heterogeneity, including especially cross-sectional differences in the coefficients that determine VOT and VOR. Some heterogeneity is "observed," i.e. explained by measured variables, as in the example just given in which varying wage rates explain differences in VOT. But empirical models often find that "unobserved"

² If conditional indirect utility for a mode is $V=\alpha C+\beta T w$, where C is cost, T is travel time, and w is wage rate, then VOT is $(\partial V/\partial T)/(\partial V/\partial C) = (\beta/\alpha)w$.

³ Train and McFadden find their model fits best empirically when $0.7 \leq \sigma \leq 1.0$, indicating that a majority of "full income" (unearned income plus potential labor income, less commuting cost) is spent on goods rather than leisure.

heterogeneity—that known only through an assumed stochastic distribution of parameters—is much larger. For example, Small et al. (2005) specify utility linear in cost, travel time, and a measure of unreliability, with the coefficients on time and unreliability assumed to have normal distributions (conditional on observed variables such as income or gender); their estimates imply that the resulting unexplained variance in value of time is several times larger than the variance explained by measured variables. Of course, this comparison depends on what explanatory variables are included.

This result could mean that significant modeling improvements are possible by finding new observable explanatory variables. But it may mean that behavior is determined by factors essentially unknowable to the analyst. If the latter, a further question is: Can we expect the measured properties of the stochastic distribution describing unobserved heterogeneity to remain stable across time and locations? The answer—likely to be found in the properties of VOT and VOR—is important to transferability of travel demand models, which greatly affects the cost of acquiring these very practical and widely used tools of transportation planning.

2. What do we know?

2.1 Basic results: theory

Most theories of value of time are elaborations of the time allocation framework of Becker (1965). The basic idea is that people choose how much labor to supply, given a constraint that total time available is divided among work, leisure, and travel. At its bare bones, this model implies that travel time is valued at the after-tax wage rate. This is because the Becker model assumes that time can be transferred freely between work and leisure, so any marginal savings in travel time can be used to increase labor income. If the individual is optimizing, it is sufficient to know its value in that activity to determine the marginal tradeoff between travel time and money.

This model has been elaborated in many directions. A common starting point is DeSerpa (1971).⁴ Utility U is affected by goods consumption G , by times T_k spent in each of K other activities (which can include both travel and leisure pursuits), and by time T_w spent at work (which may increase or decrease utility). Each activity has a minimum time requirement, \bar{T}_k (hence constraint $T_k \geq \bar{T}_k$), plus there is

⁴ Here I follow the exposition of Small and Verhoef (2007, sect. 2.6.1). For reviews of additional theoretical developments, see González (1997), Jara-Díaz (2000, 2007), and Hensher (2011).

also an overall time constraint, $T_w + \sum_k T_k \leq \bar{T}$. The budget constraint is $G \leq Y + wT_w$, where Y is unearned income and the price of goods consumption is normalized at one.

This problem can be solved by formulating a Lagrangian function, in which each constraint is associated with a Lagrange multiplier indicating how tight it is (i.e., the rate at which utility could be increased by relaxing it a little). Let λ , μ , and ϕ_k be the Lagrangian multipliers for the budget constraint, the overall time constraint, and the activity-specific time constraints, respectively. We define the value of travel time as the marginal tradeoff between travel time and unearned income that would leave the traveler indifferent:

$$v_T^K \equiv \left(\frac{dY}{dT_K} \right)_V = - \frac{\partial V / \partial \bar{T}_K}{\partial V / \partial Y} = \frac{\phi_K}{\lambda} \quad (1)$$

where V is the indirect utility function (the utility achieved in the solution to the problem), and K is the label for the activity consisting of traveling.⁵ The last equality follows from the properties of Lagrangian multipliers. The solution to the optimization problem yields:

$$v_T^K = \frac{\mu}{\lambda} - \frac{U_{TK}}{\lambda} = w + \frac{U_{Tw} - U_{TK}}{\lambda} \quad (2)$$

where U_{TK} and U_{Tw} are marginal direct utilities of time spent in travel and at work, respectively.

Equation (2) has a natural interpretation which aids thinking about empirical specifications for value of time. The first equality in (2) tells us that the value of travel time is determined by the relative tightness of time and budget constraints (indicated by μ/λ), modified by any enjoyment or dislike of the travel itself (U_{TK}). We can think of μ/λ as a pure time value, sometimes called the “value of time as a resource,” since it indicates the monetary value of increasing the total time available.⁶ The second equality in (2) tells us further that the value of travel time is greater or less than the wage rate depending on whether work is liked or disliked relative to travel, i.e. on the sign of $U_{Tw} - U_{TK}$. An empirical finding that VOT is less than the

⁵ The value of λ can be estimated using Roy’s identity provided the model includes a variable measuring the monetary cost of travel (Small and Verhoef, 2007, equation 2.24). Even if income appears in the travel choice model, its coefficient would not measure $\partial V / \partial Y$ because other portions of the indirect utility function, namely all those unaffected by the choice being analyzed, contribute to $\partial V / \partial Y$ but are necessarily omitted from the travel choice model.

⁶ That is, $\frac{\mu}{\lambda} = \frac{\partial V / \partial \bar{T}}{\partial V / \partial Y}$.

wage rate can then be taken as evidence that people dislike work more than traveling.⁷ Jara-Díaz et al. (2008) provide more direct evidence for this interpretation, as they develop a method to separately estimate the value of travel time v_T^K and the value of leisure μ/λ . Doing so for samples from three different nations, they achieve insights about possible cross-country differences in the disutility of time at work.

Can workers freely alter their work hours, as posited above? Evidence shows that they often must change jobs to accomplish this, so that limitations on job mobility constrain work hours to some extent (Altonji and Paxson, 1992). One way to address this is to assume that wage w depends on time worked T_w , in which case an added term $T_w \cdot (dw/dT_w)$ appears on the right of (2).⁸ Or one could assume a rigid work-hours constraint, $T_w = \bar{T}_w$, with associated Lagrangian multiplier ϕ_w . This modification adds a term ϕ_w/λ to the value of time as given by (2), thus raising VOT if people are forced to work more than they want and lowering it if they work less than they want. These results are intuitive: if people are either enticed or required to work more than they want to given the prevailing wage rate, they perceive their time as more scarce and hence more highly valued.

This theory can be elaborated to deal with many possible variations of VOT with trip purpose, income, gender, family status, and other factors. For example, for a person with large exogenous time commitments, the overall time constraint will bind more tightly, all else equal, so that μ/λ in (2) is larger; this may be one reason why longer trips seem empirically to have higher VOT (Daly and Carrasco, 2009). Another reason could be that trips become more tiresome the longer they are, so that increasing marginal disutility ($-U_{TK}/\lambda$) sets in, thereby raising VOT according to (2). As another example, Johnson (1966) posits that people with higher wages also tend to have more enjoyable jobs, perhaps causing the value of time to vary more than proportionally with the wage rate since the effect of U_{T_w}/λ in (2) will then rise with the wage rate. Yet another example is when travel time is decomposed into various components such as in-vehicle, walking, and waiting for a transit trip, or such as congested and uncongested time

⁷ This effect could be strong enough to drive VOT to zero, as posited by Mokhtarian and Salomon (2001). In that case, the constraint $T_K \geq \bar{T}_K$ is not binding and travel would be what DeSerpa calls a pure leisure good.

⁸ This can be seen as replacing the average compensation w by the marginal compensation $[w + T_w \cdot (dw/dT_w)]$ as the measure of the economic cost of lost time.

for an automobile trip. It is typically postulated that walking, waiting, and congested time are onerous compared to their in-vehicle or uncongested counterparts, in which case a simple generalization of (2) shows that these components of travel will exhibit higher values of time. Other hypotheses, described later, require greater generalizations of the model.

For business travel, it is natural to turn instead to production theory.⁹ Formulating how a firm's profits are affected by employees' time spent in business travel, Hensher (1977) derives an intuitive equation for value of time savings consisting basically of four additive components. First is marginal product of the time savings to the employer if that time were spent instead at the office, but modified by subtracting the portion of travel time that is spent working (perhaps at reduced productivity). Second is the utility of time if it were spent at work, U_{Tw} . Third is the value to the traveler of the portion of travel time perceived as leisure (this portion is also subtracted from travel time when computing components one and two). Fourth is a quantity reflecting reduced productivity at work due to fatigue from traveling. The second and third components are further corrected to account for personal income taxation. In practice, the use of this formula is hampered by lack of data on some items, so certain parts are typically omitted, namely personal income taxation, productive time while traveling, and the effects of fatigue.

This brief sketch of the production approach to business travel reveals a conclusion that applies to other forms of travel as well. The value of time that affects travel decisions can depend strongly on factors that analysts normally do not observe: individual tax rates, ability to use travel time productively, fatigue from travel, enjoyment of work, tightness of work-hours constraints, and many others. It is no surprise, then, that studies often reveal wide variations in measured value of time, depending on the particular way the studies are formulated.

2.2 Basic results: empirical

The empirical literature is vast; here I extract a few points from the many reviews available such as Small and Verhoef (2007, ch. 2) and Hensher (2011), as well as from the meta-analyses by Shires and de Jong (2009) and Abrantes and Wardman (2011).

⁹ Here I follow the concise presentation of Hensher (2011, pp. 139-141).

First, the value of time for commute trips seems typically to average around one-half the gross wage rate—amazingly close to the early results of Lave (1969). Values also vary widely by trip purpose, typically being highest for business travel and lowest for discretionary leisure travel.

Second, values rise with income or wage rate, but less than proportionally—in contrast to the theory by Johnson (1966) just noted. This variation is well documented in cross-sections (especially across nations) and over time, although not necessarily with identical elasticities. For example, the meta-analysis of Abrantes and Wardman (2011) measures the income elasticity of VOT to be 0.9, based on variations over time within the UK; but studies with mainly cross-sectional variation typically yield elasticities on the order of 0.5.¹⁰ Gunn (2001) finds some evidence that VOT has undergone a secular downtrend independent of income—perhaps due to improved in-vehicle amenities—which could cause some studies to underestimate the income elasticity by confounding income with this secular trend. Another wrinkle is that the relationship of VOT to income at any point in time may not be one of constant elasticity: Börjesson et al. (2012), using repeated cross-sections, find that the income elasticity is close to zero at low incomes and considerably greater than one for higher incomes. If confirmed in other data sets, such a dramatically non-constant income elasticity of VOT would have important implications for the distribution of costs and benefits from various policies.

Third, there are some well-established differences among values of time spent under various circumstances. Automobile drivers value time more highly under congested conditions than under free-flow conditions, by perhaps 25% to 55%.¹¹ (As discussed later, one explanation for this is the additional effort required by drivers to avoid accidents in congested conditions.) The value of walking or waiting time on transit trips is considerably larger than that of in-vehicle time—by multiples of two to three by most assessments, although the multiple is only 1.7 in Abrantes and Wardman (2011, Table 13). Abrantes and Wardman also find an elasticity of VOT with respect to distance of 0.16 (p. 10).

¹⁰ For example, Wardman (2004). See Hensher (2011, pp. 143-146) and Shires and de Jong (2009) for thorough reviews. Shires and de Jong (2009) measure elasticities with respect to gross domestic product per capita, which they believe are driven mainly by cross-sectional variations, of roughly 0.7 for commuting and 0.5 for business and leisure travel. Gunn (2000, p. 444) concludes that the evidence supports a cross-sectional elasticity of 0.5.

¹¹ Based on results reported by Abrantes and Wardman (2011, p. 7) Hensher (2011, Table 7.1), and Rizzi et al. (2012). Interestingly, Rizzi et al. find that the congestion premium appears in their stated preference data only when pictures of congestion are included in the questions posed to survey respondents.

Since VOT is typically measured as a ratio of coefficients, its standard error requires an additional calculation. The simplest method, known as the Delta method, applies a first-order Taylor series approximation to deviations around the point estimate, which is the ratio β_t/β_c of point estimates of coefficients:

$$\frac{Var(\beta_t / \beta_c)}{(\beta_t / \beta_c)^2} \cong \frac{Var(\beta_t)}{(\beta_t)^2} + \frac{Var(\beta_c)}{(\beta_c)^2} - 2 \frac{Cov(\beta_t, \beta_c)}{\beta_t \beta_c}.$$

Daly et al. (2012) show that if β_t and β_c are maximum likelihood estimators of the coefficients, then this approximation is the maximum likelihood estimator for their ratio, so that it is asymptotically consistent just as are the standard estimates of the variances and the covariance of the individual coefficients. Thus there is often no need to apply more complex methods, such as Monte Carlo simulation, which are analyzed by Armstrong et al. (2001).¹² However, simulation may be necessary in more complex models that include error components or in which the value of time is a more complex function of coefficients.

2.3 Heterogeneity and mixture models

In addition to the observed heterogeneity just documented, newer econometric techniques have permitted researchers to measure the remaining unexplained variation, known as “unobserved heterogeneity.” The primary technique is the mixed discrete choice model, in which utility has an error term with two components: the usual one whose distribution defines a particular class of discrete-choice models (such as probit, logit, or generalized extreme value), plus a second component that depends on the data and can have a very general distribution.¹³

For example, a mixed logit model begins with a conditional indirect utility function depicting the value to consumer i of choosing an alternative j having observable characteristics represented by vector z_j :

¹² The Delta method applies also to a much more general class of functions of coefficient estimates, as explained by Daly et al. (2012) with many examples calculated in their Table 1.

¹³ Walker and Ben-Akiva (2011) provide a compact review. Train (2009) provides detailed information about estimation methods, including reasons to prefer using non-random draws (such as from a Halton sequence) for the simulations.

$$V_{ij} = \alpha_j + \beta'_0 z_{ij} + v_{ij}(z_{ij}) + \varepsilon_{ij} \quad (3)$$

where ε_{ij} is a pure random term with an extreme value distribution (hence “logit” in the model’s name) and v_{ij} is another random variable with some “mixing distribution,” so called because the resulting choice probabilities are integrals involving a mixture of the two distributions. Common distributions assumed for v_{ij} include normal, half-normal, log-normal, and triangular—the latter three often chosen in order to restrict coefficients to have the theoretical expected signs.

Estimation involves Monte Carlo simulation to approximate the expected choice probabilities derived from (3), taking advantage of the simplicity of the logit formula for the choice probability conditional on a random draw from the mixing distribution. Compiling results for many random draws provides simulated probabilities for choices, which are approximations to probabilities computed by integration over the two random distributions. From the simulated probabilities, one forms the simulated log-likelihood function, maximization of which provides estimates of the parameters β_0 and the “hyperparameters” σ of the mixing distribution.

McFadden and Train (2000) derive some general properties of this model.

The most commonly assumed functional form for $v_{ij}(\cdot)$ depicts pure randomness in the coefficients β^k of particular variables, z_k , in (3):

$$v_{ij} = \sum_k \sigma_k \phi_k z_{ij}^k$$

where ϕ_k is a standardized random variable with the postulated mixing distribution,¹⁴ σ_k is the standard deviation of that distribution, and z_{ij}^k is the value taken by the k -th variable in data vector z . Equivalently, the coefficient vector β is now viewed as random, with k -th component $\beta_0^k + \sigma_k \phi_k$. Thus σ_k can be considered a measure of dispersion in the k -th coefficient as it varies in an unobservable fashion across the population.¹⁵ Allowing in addition for correlations among the random components, the model can be written:

$$V_{ij} = \alpha_j + \beta' z_{ij} + \varepsilon_{ij}$$

¹⁴ That is, ϕ_k is the postulated random variable after subtracting its mean and dividing by its standard deviation.

¹⁵ In general these random components can be correlated, with their variance-covariance matrix parameterized by a vector σ . A special case of (3) involves variables d_k that are just combinations of alternative-specific constants, defined as one if j is included in a particular combination indexed by k , and zero otherwise. Brownstone and Train (1999) show how this formulation can capture correlations among alternatives similar to those assumed in a nested logit model.

where β is random with mean β_0 and variance-covariance matrix parameterized by some vector σ .

In the context of VOT, one typically specifies travel time, reliability, and/or cost to be variables with random coefficients. Estimating parameters β_0 and σ then permits calculation of all the properties of the distribution of VOT. This calculation can be combined with observed heterogeneity, which arises from interacting time, reliability, and/or cost with other observed variables (like income or trip distance). It can also be combined with the sampling error, summarized in the standard errors of estimated parameters, to obtain the overall uncertainty in VOT or in value of reliability; Small et al. (2005) do this in order to compute percentiles of the distribution of VOT. They find that the greatest source of variation is unobserved heterogeneity, i.e. variation due to the random variables $\{\phi_k\}$.

However, there are at least two significant barriers to successful use of mixed discrete choice models for measuring values of time. Both are amenable to amelioration, but at some cost.

Choice of distribution function. The first barrier is the fact that the assumed distribution function for the random coefficients can strongly influence the resulting coefficient estimates, and in particular such ratios as VOT.¹⁶ The main reason is that commonly used tractable distribution functions vary greatly from one another in the size of their tails, i.e. in the probabilities of large deviations from central values. Data are usually sparse or entirely absent in that region, making it difficult or impossible to determine what distribution best represents the data there.¹⁷

One way to avoid assuming an inappropriate mixing distribution is to estimate part of it nonparametrically. Fosgerau (2006) obtains promising results this way, demonstrating along the way that the distribution's tails are not necessarily identified in a given data set. A possibly more parsimonious approach is the latent class model: assume that the mixing distribution involves

¹⁶ Hess et al. (2005), Fosgerau (2006), and Fosgerau and Bierlaire (2007) provide comparisons among results for various parametric, semiparametric, and seminonparametric distributions using both actual and artificially generated data.

¹⁷ Several of these distributions are censored so to require $VOT \geq 0$, with a probability mass at $VOT=0$ representing people who don't care about travel time. Axhausen and Cirillo (2006) fit several models showing a positive fraction of travelers having zero or even negative values of time, and argue that this is theoretically plausible.

just a few possible values of the parameter vector, each characterizing a latent (i.e. unobservable) class of travelers into which survey respondents are assigned probabilistically depending on their characteristics (Greene and Hensher, 2003).

Implausible distributions of ratios. Another difficulty with mixed models is their tendency to produce implausibly dispersed distributions for ratios of coefficients, which often represent the willingness to pay (WTP) for a characteristic such as travel time. The problem is especially acute if the denominator of the ratio—typically the coefficient of a price variable—is allowed to be random with a distribution whose support includes very small values (for example, a log-normal distribution). For this reason, the cost coefficient is often specified as non-random even if this assumption is contradicted by a statistical test.

An alternative specification reparameterizes utility in “WTP space” so that the assumed randomness occurs in the ratios themselves. For example, we could rewrite (3) as:

$$V_{ij} = \alpha_j + \lambda p_{ij} + \lambda \gamma z_{ij}^- + \varepsilon_{ij} \quad (4)$$

where p denotes price and z^- denotes the vector of all other variables. The model is now nonlinear in parameter λ and parameter vector γ , the latter consisting of direct estimates of WTP. This does not diminish the model’s computational tractability because probabilities conditional on random parameters still have the usual formulas (e.g. logit if ε has the double-exponential distribution), and the joint distribution of the random parameters themselves is estimated using Monte Carol simulation. Train and Weeks (2005) and Hensher and Greene (2011) report that such models produce much smaller dispersion in WTP measures such as VOT. However, they also report that the model in WTP space does not fit the data as well as the model as more usually formulated (i.e. in “coefficient space”). The particular models studied by these authors have complexities that make it difficult to draw a firm conclusion about the significance of this last finding.¹⁸

¹⁸ Train and Weeks estimate some coefficients using a log-normal distribution, with apparently good results in terms of conventional statistical significance (i.e., high t -ratios). However, when they calculate the implied estimated values of the direct “coefficient” of the variable of interest, e.g. $\partial V/\partial p$, none of the resulting values are statistically significant for either the model in preference space or that in WTP space. Hensher and Greene’s WTP-space model has four fewer parameters than their preference-space model, due to restricting the random parameter related to the price coefficient to be uncorrelated with other random parameters— probably a useful restriction from the point of view of statistical power. This restriction may explain why their model in WTP space fits the data less well.

Conclusion on Mixed Discrete Choice Models. It seems clear that heterogeneity in values of time exists, and that an important part of it will always be beyond our ability to explain using observable data. Mixture models provide information on this heterogeneity and so seem certain to continue as a necessary tool. The problem is that the new information needed must describe joint distributions of an unknown form, a task beyond many data sets. To put it more formally, new information can be obtained from a statistical model only at a cost in terms of statistical power, i.e., the ability of a given data set to precisely estimate parameters of interest. While it may be tempting to estimate a very general model, based on the ability to reject simpler ones, this also produces the danger of overfitting. In practice, one must always keep an eye out for signs that desired parameters are simply not well identified in a given data set, in which case some theoretically based restriction may be called for.

2.4 Time of day variation, scheduling choice, and reliability

One source of heterogeneity in value of time is the time of day of travel. Generally, VOT is found to be higher in peak hours than off-peak, although this may reflect unmeasured differences in trip purposes. But what about the effects on VOT of small differences in departure or arrival times?

2.4.1 Scheduling choice and the value of time

Even defining VOT is ambiguous if congestion is changing rapidly at the times during which a trip takes place. This is because travelers may adjust their departure times to meet scheduling goals, thereby making the travel time endogenous. For example, suppose the trip takes place during the rising part of the rush hour, and an improvement to the last link used lowers its (exogenous) travel time by one minute. Suppose also the traveler has been optimizing her departure time in a continuous fashion to meet certain scheduling preferences. Then in response to the improvement, she may further adjust the departure time; this will cause only a second-order utility change (due to the envelope theorem), so it is appropriate to apply the usual VOT analysis to the one-minute time saving. But if the traveler is at a corner solution, such as

needing to maintain a fixed arrival time, the departure-time adjustment will result in encountering more congestion and thus utility will rise by less than the standard calculation.

We can better understand the connection between scheduling and VOT by considering travelers' preferences concerning scheduling. Vickrey (1969) postulates "alpha-beta-gamma" preferences, in which a commuter wishes to arrive exactly at t^* , suffering a scheduling cost at rate β per minute for early arrival or γ per minute for late arrival. Travel time is valued at α . If congestion is changing rapidly, it becomes optimal for some travelers to suffer scheduling cost in order to reduce their travel-time cost. This balance changes if an exogenous transportation improvement reduces travel time at any given time of day. Furthermore, congestion occurs as a result of these scheduling decisions, in a pattern that will itself shift due to the exogenous change in conditions. Thus, to fully analyze the outcome as well as the benefits in a situation of rapidly changing congestion, a model of scheduling decisions and resulting equilibria is needed. Newell (1987) provides a rather general such model; a special case is the "bottleneck model," which postulates identical travelers with alpha-beta-gamma preferences, and congestion determined by a deterministic queue behind a fixed-capacity bottleneck.¹⁹

Where might alpha-beta-gamma preferences come from? And might they vary by time of day as well? Vickrey (1973) provides a key theoretical insight, elaborated by Tseng and Verhoef (2008) and de Palma and Fosgerau (2011). Suppose, for concreteness, a commuter has time-varying preferences for when he conducts activities at home and at work. Perhaps he wants to sleep while it is dark, to interact with children at breakfast, and to be at work when the presence of others makes it the most productive to do so.²⁰ From the traveler's individual point of view, this situation can be described by a time varying rate of utility spent at each location. Following Tseng and Verhoef, let $H(t)$ and $W(t)$ represent the value of a unit of time spent at home or work, respectively, at time t (relative to spending that time traveling); and let T be the travel time between home and work. If $H(t) < W(t+T)$ within a relevant solution region, the worker's choice will be to choose a departure time t_d for which $H(t_d) = W(t_d+T) \equiv H^*$ because this equalizes the

¹⁹ The bottleneck model was first described by Vickrey (1969), and further developed by several authors, especially Fargier (1983), Arnott et al. (1990, 1993, 1998). Alpha-beta-gamma preferences were measured empirically for a sample of commuters by Small (1982).

²⁰ Henderson (1981) and Fosgerau and Small (2012) provide formal equilibrium models of agglomeration in the home and/or workplace that could lead to such apparent preference. Wilson (1988) provides empirical evidence for the productivity benefit of working simultaneously with others.

marginal losses from giving up time at work and time at home. The situation is depicted in Figure 1, for travel time T_0 . If the consumer's travel time is then shifted from T^0 to $T^0+\Delta T$, the lost value increases by $H_0^*\Delta T$.

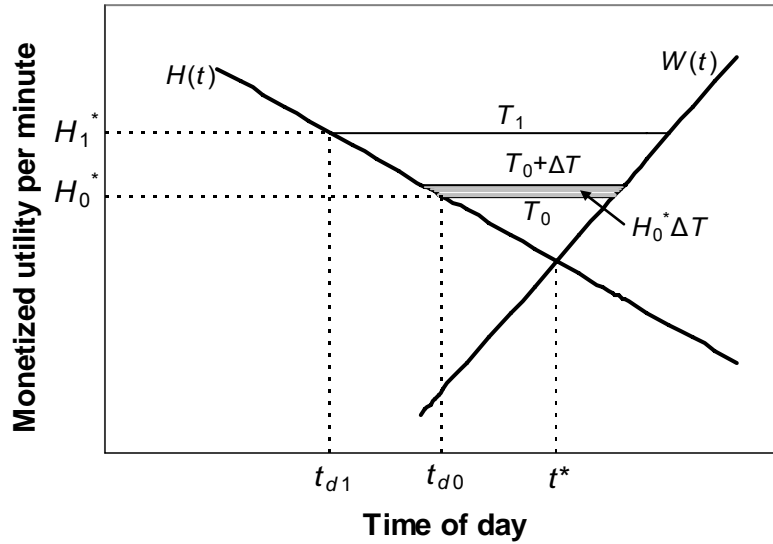


Figure 1. Schedule choices with time-dependent utility

Tseng and Verhoef show that this model yields the alpha-beta-gamma specification as a limiting case where $H(t)$ is constant (equal to α) and $W(t)$ is constant within each of two regions, taking values $(\alpha-\beta)$ for $t < t^*$ and $(\alpha+\gamma)$ for $t > t^*$. The intuition here is that the individual prefers time at home to time traveling by amount α per unit time; prior to t^* work time is less valuable than home time by amount β , but after t^* it is more valuable than home time by amount γ .

As noted by Fosgerau and Engelson (2011), this theory offers a simple explanation of why VOT is observed to increase with trip length. This will occur if $H(t)$ is declining and $W(t)$ is rising in t , since then any increase in travel time forces the traveler to choose a new equilibrium at a higher equalized value H^* . The situation is also depicted in Figure 1, as a rise in H^* when travel time increases from T_0 to T_1 .

2.4.2 Scheduling costs and the value of reliability

How does a traveler come to value reliability? Earlier papers have identified scheduling preferences as the main reason people want predictable travel times.²¹ The traveler suffers not only the occasional costs of unexpected delays, but also suffers some routine costs of choosing an earlier schedule in order to allow a safety margin. Since the precise costs are not known in advance, the travelers is usually assumed to chose a departure time that minimizes the expected value of the sum of these costs, taking into account whatever is known about the distribution of travel times.

Fosgerau and Karlström (2010) provide explicit expressions for the resulting costs, using alpha-beta-gamma preferences, in the case where congestion is not changing over time. It's worth going through the mathematics for the insights we get concerning appropriate measures of reliability.

We wish to find the traveler's cost as a result of changes in the mean travel time or in measures of the dispersion of its distribution. To do so, first consider the traveler's optimization problem. Let $F(T)$ be the cumulative distribution function of random travel times T , with mean μ and standard deviation σ . Normalizing the time axis so that $t^*=0$, it is convenient to define departure by the lead time $D=-t_d$, so that arrival time is $T-D$ and early arrival (arriving before t^*) occurs if $T-D<0$. Then scheduling costs are $-\beta(T-D)$ for early arrival and $\gamma(T-D)$ for late arrival. Travel time cost is αT . Taking expectations, the consumer's decision problem is therefore:

$$\begin{aligned} \text{Min}_D EC &= \alpha\mu - \beta \int_{-\infty}^D (T - D)F'(T)dT + \gamma \int_D^{\infty} (T - D)F'(T)dT \\ &= \alpha\mu + \beta(D - \mu) + (\beta + \gamma) \int_D^{\infty} (T - D)F'(T)dT \end{aligned}$$

where μ is the mean travel time. The solution turns out to be surprisingly simple and enlightening. The first-order condition for minimizing expected cost is:

²¹ For summaries, see Bates et al. (2001) and Li et al. (2010). Most empirical attempts to measure a "planning cost" as an additional cost to unpredictability, once scheduling costs are accounted for, have obtained small and statistically insignificant results (Noland et al., 1998). However a meta-analysis by Tseng (2008) finds some evidence for such planning costs: when scheduling costs are included separately the reliability coefficient is reduced by about 80 percent, but not by 100 percent, compared to when a single reliability variable is included without scheduling cost.

$$\frac{\beta}{\beta + \gamma} = 1 - F(D^*) \equiv P_L^*$$

where D^* is optimal lead time (time allowed between departure and preferred arrival) and P_L^* is the probability of arriving late. This result shows that, remarkably, the optimizing traveler sets P_L^* to a value that is entirely independent of the travel-time distribution.

Fosgerau and Karlström show that this optimization result can be written explicitly for the optimal lead time:

$$D^* = \mu + \sigma\Phi^{-1}(\psi) \quad (5)$$

resulting in expected cost

$$EC^* = \alpha \cdot \mu + (\beta + \gamma) \cdot \Omega_\psi \cdot \sigma \quad (6)$$

where Φ is the cumulative distribution function of the standardized random variable $(T - \mu)/\sigma$,²² and where

$$\Omega_\psi = \int_\psi^1 \Phi^{-1}(p) dp; \quad \psi = \frac{\gamma}{\beta + \gamma}. \quad (7)$$

Equation (6) is the desired expression for the negative of utility in terms of mean travel time and reliability. The quantity Ω_ψ is a property of the standardized distribution, specifically the size of its tail to the right of the 100· ψ percentile. Fosgerau and Karlström interpret Ω_ψ as “the mean lateness in standardised travel time”: more precisely, $\Omega_\psi\sigma$ is the unweighted average of the differences between the p -th percentiles and the mean, for all $p > \psi$. For a conventional choice of parameters of alpha-beta-gamma preferences, roughly based on empirical evidence, $\gamma = 2\alpha = 4\beta$; thus $\psi = 0.8$. Then (5) and (6) involve the tail of the distribution to the right of the 80th percentile.

Thus the Fosgerau-Karlström result gives support to, as well as more specific guidance for, the suggestion that the upper tail of the distribution is a useful measure of reliability. We can factor the last term of (6) into a reliability measure R times its value VOR:

$$EC_S^* = (\beta + \gamma) \cdot [\Omega_\psi \sigma] = (VOR) \cdot [R]. \quad (8)$$

Brownstone and Small (2005) report success in several studies measuring unreliability in a related way, namely the difference (in amount of travel time) between either the 80th and 50th percentiles or between the 90th and 50th percentiles. The Fosgerau-Karlström result supports this

²² That is, Φ is defined by $\Phi[(T - \mu)/\sigma] = F(T)$.

general approach of focusing on the right tail, but suggests a different specific measure, one that averages all the percentiles beyond the 80th (if $\psi=0.8$) and subtracts not the median but the mean. With this decomposition of expected scheduling cost, VOR is purely a behavioral quantity and so should be portable from one situation to another involving a similar population; but R is a mixture of behavioral and distributional properties.

Another way of factoring (8), preferred by Fosgerau and Karlström, is:

$$EC_S^* = [(\beta + \gamma)\Omega_\psi] \cdot \sigma = [\text{VOR}] \cdot R.$$

Here reliability is defined as σ , which coincides with common practice in the applied literature on reliability and is convenient empirically if the shape of the distribution is unknown. The drawback is that now VOR, supposedly a behavioral quantity, depends on the distribution facing the traveler.

Noland and Small (1995) and Koster et al. (2009) derive closed-form expressions corresponding to (5) and (6) for several specific distributions of uncertain travel time. For example, if travel time T follows a uniform distribution with mean μ and standard deviation σ , the optimal departure interval and resulting expected cost are:²³

$$\begin{aligned} D^* &= \mu + (\psi - 1/2)\sqrt{12} \cdot \sigma \\ EC^* &= \alpha\mu + (\beta + \gamma) \cdot \psi \cdot (1 - \psi)\sqrt{3} \cdot \sigma. \end{aligned} \quad (9)$$

Comparing with (5) and (6), we see that for the standardized uniform distribution, the ψ -th percentile value of travel time (when $\psi=0.8$) is $(\psi - 1/2)\sqrt{12} = 1.04$, and $\Omega_\psi = \psi \cdot (1 - \psi)\sqrt{3} = 0.55$. Thus in order to maintain the probability of being late at $(1 - \psi)=0.2$, the traveler chooses a departure with lead time equal to mean travel time plus 1.04 standard deviations, and suffers expected scheduling cost of $(\beta + \gamma) \cdot 0.55 \sigma$. Noland and Small (1995) also present generalizations of these results when there is an additional discrete cost θ of arriving later than the desired time t^* , and when congestion is changing over the course of the time frame of interest.

A different theory of reliability, based on the time-dependent utility theory discussed in the previous subsection, is proposed by Fosgerau and Engelson (2011). This theory helps unify

²³ See Noland and Small (1995), eqn (13), setting $\theta=\Delta=0$. In their notation, $D=T_e$, $\mu=T_m/2$, and $\sigma = T_m / \sqrt{12}$. Their solution is $D^* = \psi T_m = \mu + (\psi - 1/2)\sqrt{12} \cdot \sigma$ and $EC_S^* = 1/2 \beta \psi T_m = 1/2(\beta + \gamma) \frac{\beta \gamma}{(\beta + \gamma)^2} \sqrt{12} \cdot \sigma = (\beta + \gamma) \psi \cdot (1 - \psi) \sqrt{3} \cdot \sigma$.

the understanding of time-varying VOT, scheduling choice, and value of reliability. They assume that the value functions $H(t)$ and $W(t)$ are linear in t (as shown in Figure 1). This leads to two striking results, both of practical interest. First, VOT varies with trip length in a simple way: it is a linear function of travel time T , increasing or decreasing in T depending on whether the slopes of H and W are of opposite or the same signs. Second, if reliability is measured as σ , VOR is a constant, equal to the slope W' , which may be interpreted as the incremental cost of losing time at the destination. An empirical study by Tseng and Verhoef (2008, Fig. 3), using responses by Dutch commuters to hypothetical scenarios, suggests that the assumption of linear H and W is a reasonable approximation.

How big is VOR? Li et al. (2010) review both theoretical and empirical aspects of value of reliability.²⁴ Among other things, they report on measurements of the reliability ratio, defined as the ratio of VOR to VOT when reliability is measured as σ . For the uniform distribution, equation (9) shows that the reliability ratio is $\sqrt{3} \cdot (\beta + \gamma)\psi \cdot (1 - \psi) / \alpha$, or 0.69 with conventional parameter values mentioned earlier. According to Li et al., this ratio is most often found empirically to be between 0.8 and 1.3 for car travel, with somewhat higher values for travel by public transportation. Tseng (2008) obtains a higher value, namely 1.71, from a meta-analysis of VOR studies, when both scheduling and planning motivations are lumped together in a single value. Li et al. suggest that the measured reliability ratio is sensitive to the different ways researchers have used to describe hypothetical distributions of uncertain travel times to survey respondents.

2.4.3 Decisions en route and the value of information

From the theories just presented, we see that anything that reduces the dispersion in the distribution of random travel times reduces scheduling cost. Making traffic information available before the scheduling decision is made is one such measure to reduce dispersion. But what about information provided en route, including information inherent in the travel time actually experienced on portions of the trip already taken?

²⁴ Other reviews include Bates et al. (2001), Noland and Polak (2002) and Batley et al. (2008), the latter being especially comprehensive.

Usually it is too late to alter the scheduling of the trip once it has begun, unless the traveler should decide to make a stop along the way. But it may not be too late to influence some route or mode decisions. For example, one could decide to substitute transit for the last portion of a car trip, or taxi for the last leg of a transit trip. Given the heavy investment cost of information systems, it could well be worthwhile to build such an explicit model of such a process, despite its complexity and the need for fine-grained information.

At any point in the trip, such subsequent decisions may involve tradeoffs among expected travel time savings, their dispersion, and cost. Thus, one could consider the revealed preferences as exhibiting real-time variations in VOT and VOR, depending strongly on scheduling goals. This is the germ of truth in claims like “the value of time is very high when going to the airport.” But is it useful to look at the problem this way? Transportation investments cannot be made in real time, so knowing about such variations is of little help for planning. In principle it could influence real-time decisions in traffic control centers, but it would be impossible to know the specific scheduling constraints facing the thousands of travelers affected. Thus, it’s probably best to recognize that the high values of time that people may feel introspectively as they travel are really reflections of value of reliability.

Information provision has the potential not only to reduce travel-time dispersion for individuals, but to change the pattern of congestion itself. This is because if large numbers of travelers are induced by real-time information to change their decisions, this will change where and when congestion occurs. A number of models suggest that it is helpful, from a network point of view, to have some fraction of travelers informed about where congestion is severe, but also that if market penetration of such a system exceeds some threshold, everyone may be made worse off. The reason is mainly overreaction: unless the information is extremely accurate, traffic tends to move to a few alternative routes which then become too congested.²⁵ Basically this is a market failure due to herd effects; it tends to be quite specific to the situation modeled and assumptions made. The failure is less likely if there are alternate sources of information available, if different travelers react differently to their information, and if the information is presented in such a way as to encourage some randomness in response—rather like mixed strategies in game theory.

²⁵ For examples, see Arnott et al. (1991), Ben-Akiva et al. (1991), and Emmerink et al. (1994, 1998).

Making the information accurate is extremely challenging, because it requires predicting congestion for the duration of a traveler's trip. This in turn requires correctly modeling the behavior of travelers in response to unanticipated congestion and to the information itself. Yang (1998) and Paz and Peeta (2009) develop formal models of such a system.

2.5 Stated preference data

As theory and practice have moved to more fine-grained analyses of preferences, it has become increasingly difficult to measure the needed parameters using data on actual choices made by travelers. These data, known as "revealed preference" (RP), are often considered inherently superior to other sources because they depict choices made in real-world situations where unknowable factors influence decision makers, where good decision making is motivated by actual gains and losses, and where repeated choices provide more opportunity for careful reasoning (or trial and error) than does a short survey.

But RP data have their own problems: they require a great deal of outside knowledge about the environment in which people make decisions, they often produce highly correlated outcomes, and they cannot describe traveler reactions to alternatives not currently offered. For these reasons, much recent research has used data on choices among hypothetical rather than actual situations. Such data are called "stated preference" (SP).²⁶ Considerable effort has gone into developing survey methods that minimize biases caused by people not treating these hypothetical scenarios the same way they would real ones (Hensher, 2010).

A particular case of such potential bias arises in value of time studies. Some studies have found substantial and apparently stable differences between VOT measured from SP versus RP data, usually finding estimates of VOT that are larger when based on RP than on SP data.²⁷ This pattern is confirmed by the meta-analyses of Shires and de Jong (2009) and Abrantes and Wardman (2011): for example, Shires and de Jong find that other things equal, studies using SP

²⁶ Other authors distinguish among different ways the hypothetical situations are presented, reserving "stated preference" for questions in which a tradeoff is explicitly probed in a question, in contrast to "stated choice" when the respondent is asked to choose the best among a set of hypothetical alternatives.

²⁷ Examples include Isacsson (2007), using data from Sweden, and Hensher (2010), using data from Sydney (Australia) and New Zealand.

data obtain a 35 percent smaller value for VOT than do RP studies in the case of commuting, and 24 percent smaller in the case of leisure trips.²⁸

Hensher (2010) finds that such results are sensitive to how SP surveys are designed—including the range of variation presented and whether respondents are given their current situation as one of the alternatives to choose among. For this reason, Hensher is optimistic that further research can narrow the gap between SP and RP results by guiding SP survey design. But Brownstone and Small (2005) offer an explanation that would be harder to overcome. They explore the question of relative VOT estimates from SP and RP data using data from several studies of southern California commuters who have an option to pay to travel in express lanes. Survey respondents in the same locations, in some cases even the same respondents, gave answers that imply values of time about half as large using SP compared to RP data. (A similar difference is found for VOR.) A potential explanation arises from questions asking explicitly what people think is the time loss due to congestion: they are found to overestimate this loss. Thus, they may interpret the time savings presented in SP scenarios as though they were smaller than the value stated in the question and used in the statistical analysis, causing them to understate their willingness to pay for time savings.

2.6 Loss aversion, prospect theory, and the value of small time savings

The usual theory behind value of travel time relies on rational behavior and stable—albeit perhaps complex—preferences. But departures from conventional rationality are well documented in other fields of consumer behavior. What effect could this have on travel demand modeling and, in particular, on measurement of VOT? As it turns out, the answer can help solve a persistent puzzle regarding an apparent variation of VOT with the size of time savings.

²⁸ Because the specification of the meta-analysis is double-logarithmic, I based these calculations on computing $[1 - \exp(-\alpha)]$, where α is the coefficient of the SP dummy (with RP as base) in the random effects models of their Tables 3 and 4 (i.e. $\alpha = -0.43$ for commute, -0.28 for leisure). Abrantes and Wardman's meta-analysis finds that the measured value of in-vehicle time is 18 percent lower, and that of walk and wait time is 31 percent lower, using SP data relative to RP data, as computed from their Table 15: the table's last column shows that the VOT computed using RP is 1.22 times that for SP in the case of in-vehicle time, and approximately 1.44 times for walk/wait time. Thus, relative to RP, SP is underestimated by a fraction $1 - (1/1.22) = 0.18$ for in-vehicle time, and $1 - (1/1.44) = 0.31$ for walk/wait time.

Experimental evidence has shown that people exhibit strong awareness of the status quo, or to some other reference point which they define internally, and that they are averse to negative changes from that point. A famous example is college students demanding more money to relinquish a coffee mug that has been allocated to them than they would be willing to pay to buy the mug from someone else (Kahneman et al., 1990). This phenomenon, much too large to be due to income effects, is named “loss aversion” since people show more aversion to the loss of some consumption item than they show a desire for an equivalent amount of gain.²⁹

A comparable situation in travel behavior is documented by De Borger and Fosgerau (2008) and Hess et al. (2008). Using SP data, find that respondents’ willingness to accept (WTA), measured as the monetary compensation they require to agree to a travel-time increase, is several times larger than the willingness to pay (WTP) for a travel-time reduction of the same amount. Hensher (2011) reports a similar though smaller asymmetry.³⁰ Such asymmetry poses a quandary for measuring value of time, since the standard definition sets it equal to both WTA and WTP.

De Borger and Fosgerau propose a theoretical resolution that retains the concept of a single underlying value of time. It is based on the “prospect theory” of Tversky and Kahneman (1991). Indirect utility depends not on time and cost generically, as is usually assumed, but on deviations t and c in the time and cost of travel alternatives compared to a reference point. It does so through two separate “value functions,” v_t and v_c , each defined to be zero at the origin and each increasing in the corresponding “good” ($-t$ or $-c$). The two variables are assumed connected through a common multiple w , which the authors interpret as a reference-free value of time:

$$u(c, t) = v_c(-c) + v_t(-wt).$$

Each value function is assumed to exhibit loss aversion, i.e. $-v(-x) > v(x)$ for $x > 0$; and to exhibit diminishing sensitivity with respect to gains or losses, i.e. $v''(x)$ has the opposite sign as x . Loss aversion implies that the indifference curves (showing cost as a function of time) are kinked at the origin, which is the reference point by definition. Hence utility is not differentiable there, so the definition of VOT given earlier is invalid.

²⁹ Strictly speaking, this example is the “endowment effect.” Kahneman et al. (1990) propose that it is explained by loss aversion, but other explanations have also been offered: for example, “salience” (Bordalo et al., 2012).

³⁰ Hensher (2011, p. 151). Hensher’s definitions of WTP and WTA are reversed from those used here, as he views the cost change as the one to be accepted or paid for (via time changes).

By making some specific functional form assumptions, De Borger and Fosgerau are able to recover most parameters of the model from SP responses to simple binary choice situations, in each of which cost and time are both anchored somewhere among the choices.³¹ In this way, they are able to verify the properties of loss aversion and strictly diminishing marginal sensitivity, while also testing (and accepting) the additional restriction that the arguments of the two value functions have a ratio w which may vary across the population but does not depend on whether the choice in question represents a gain or a loss in travel time. This kind of restriction helps overcome the objection of Timmermans (2010) that prospect theory is too flexible to be usefully tested.³²

It remains to be seen how the behavior observed in these hypothetical experiments corresponds to actual behavior. Perhaps loss aversion in transportation choice is an artifact of the artificial choices given in SP surveys, and would not apply to real choices. For example, Hu et al. (2012) find a much smaller difference between WTP and WTA in revealed preference data. Even if loss aversion does not apply to real choices, we may still need to account for it in order to model the difference between SP and RP results, which in turn is needed to interpret SP results. If loss aversion does apply to real choices, we need to understand how the subjectively determined reference point is updated with time and experience in order to predict the dynamic path of behavior.

If we succeed in predicting actual behavior using such models, we still face the difficult question of how to make normative judgments. In other applications of behavioral economics, welfare analysis has proven to require very strong assumptions.³³ De Borger and Fosgerau imply that the estimated value of w in their model can be used to evaluate time savings, a procedure

³¹ There are four types of choices; in two of them there is an alternative for which $c=t=0$ (i.e. the reference situation is offered as an alternative) while in the other two each alternative has either $c=0$ or $t=0$ (i.e. each alternative involves some departure from the reference situation). The four types of choices measure directly each of four common measures: WTA for a time loss, WTP for a time gain, equivalent loss (in time) for a cost increase, and equivalent gain (in time) for a cost increase. The rates of diminishing marginal valuations (v') can be measured because the sizes of the gains and losses are varied across the questions posed.

³² Timmermans has several other objections as well. One is that other theories may explain some of the apparent deviations from rationality being accounted for by prospect theory.

³³ A good example is the analysis by Chetty et al. (2009) of an excise tax. They are able to derive an elegant generalization of the usual “Harberger triangle” measuring the welfare consequences of raising a tax from zero to a small value. But to do so, they assume that the only welfare loss is due to non-optimal consumption arising from non-rational behavior; it cannot, for example, arise from cognitive costs in computing the optimum.

recommended explicitly by Fosgerau et al. (2007). Additional empirical evidence is needed to determine whether this specific empirical model applies generally enough for this to be a practical and reliable procedure.

Meanwhile, it appears that the theory of reference-dependent utilities does resolve one conundrum that has plagued the measurement of VOT. It is often, though not universally, observed that the estimated VOT is larger when the time saving being valued is larger. Daly et al. (2011) provide a very thorough and practical review of this issue. Such a result could occur due to nonlinearities in indirect utility within a conventional model, but empirically the variations seem too large to be explained in this way. An older interpretation has been that people do not notice small changes and therefore a smaller VOT should be applied to small travel-time savings. But this raises a number of now well-known inconsistencies (Mackie et al., 2001, Sect. 5.3): for example, a series of small improvements each evaluated separately would lead to smaller benefits than all of them done together. Furthermore, as demographic and geographical changes work their inevitable course, many of the people benefiting from a transportation improvement will never have actually experienced the “reference point” from which the travel-time changes were measured by researchers.

The theory of De Borger and Fosgerau (2008) offers a fully consistent explanation for observed measures of VOT that increase with time savings. This is demonstrated by Hjorth and Fosgerau (2012). Briefly, suppose the value functions postulated by prospect theory not only show diminishing sensitivity (as defined above), but that the rate at which sensitivity diminishes is greater for cost than for time. In other words, as one gets further from the reference point, the marginal importance of cost fades relative to that of time. Then when large potential time savings are presented, the marginal tradeoff between time and cost is greater. Provided one has chosen the correct reference point, one observes VOT apparently increasing with the time savings, even though there is a constant true reference-dependent VOT as postulated by the theory.

Do theories based on reference dependence offer the best route to further progress on measuring VOT? Daly et al. (2011) conclude that reference-dependent effects are important in VOT measurements, and that SP data are especially prone to such effects, so that “the VOT ultimately reported from [an SP study] is a function of the design of the study” (p. 11). This comports with the argument of Hensher (2010) noted in the previous subsection. Because of this problem with SP studies, Daly and his coauthors seem well justified in recommending more

effort to take advantage of recent advances in RP collection methods such as exploiting mobile communications.

3. What do we need to learn?

It is apparent that we know a great deal about how people trade off time, reliability, and money. This knowledge provides a sophisticated basis for using measures of VOT and VOR in policy applications.

Nevertheless, it is striking that the more we learn about these topics, the more apparent it is that the behavioral regularities being sought are subtle and complex. It's not just a matter of measuring a single number, "the" value of time, or even a set of functional relationships showing how it varies with income, age, and so forth. Rather, we need to understand how these tradeoffs are embedded within a complex dynamic decision-making process involving many choice dimensions, all within a context of habit, attitudes, and learning.

I conclude with a short list of topics that are incompletely understood, trying to focus on those that matter and are amenable to research.

- *Observed heterogeneity.* This is not a new issue, but open questions remain. Does VOT have a constant elasticity with respect to income, as postulated by Abrantes and Wardman (2011)? Or is it closer to linear with an intercept, as postulated by MVA Consultancy et al. (1987), or to a sharply increasing step function as in Börjesson et al. (2012)? Can we describe the relationship best using data on wages, income, or gross domestic product per capita? We still lack a theory predicting a specific functional relationship to any of these measures, making it difficult to go beyond *ad hoc* specifications. Other questions about observed heterogeneity are raised in the points below.
- *Unobserved heterogeneity.* The existence of unexplainable heterogeneity is well established. Should we be satisfied with capturing it in mixture models, or is it feasible to explain it using observable data? If the latter, what new variables are needed and would they have useful policy implications? If we continue to use mixture models, are there any guidelines as to the best parametric distributions? When is it better to estimate the distribution non-parametrically? Under

what conditions is unobserved heterogeneity in VOT stable across times and locations? These questions can equally be asked about the measurement of reliability.

- *Labor supply and household decision making.* A few papers have noted important relationships between the transportation system and labor supply: for example, how transportation interacts with job search, and how information on job duration and job search can be used as base for measuring VOT.³⁴ Meanwhile, labor economists have devoted much attention to how life-cycle variations affect the value of time spent in home production or job search (Ghez and Becker, 1975); but little of this has spilled over into transportation economics. Among the questions that could be illuminated are: How do gender, family status, age, and earning abilities of various family members affect an individual's VOT and VOR? And if transportation is improved and this impacts labor supply through the value of time savings, would it then also affect related decisions such as marriage, fertility, and immigration? Answering these questions will require probing decision-making within households, perhaps along the lines adopted by Fortin and Lacroix (1997) for explaining labor supply or those by Hensher et al. (2008) and Beck et al. (2012) for explaining automobile demand.
- *Effort and accident costs.* As already noted, empirical evidence suggests that time driving under congested conditions is more onerous than other driving time, adding a substantial "congestion premium" to VOT. One possible reason is the extra effort required. Steimetz (2008) shows that if this effort is for the purpose of avoiding accidents, it is a part of accident costs which is rarely accounted for in analyses of accident prevention measures, but which can be measured as part of measuring VOT. This is because under congested conditions, VOT as normally measured (the ratio time and cost coefficients) incorporates not only a valuation of travel time itself, but also a valuation of congestion-related accident risk and of the effort expended to lower that risk. The valuation of travel time itself is the part explained by the usual theories of VOT, described earlier; the valuation of accident risk and effort at avoidance requires a theory of demand for safety, effort, and how safety and effort are affected by congestion.

³⁴ Van Ommeren et al. (2000), Van Ommeren and Fosgerau (2009).

Steimetz carries out the relevant decomposition and finds that nearly one-third of the VOT as normally measured is due to accident risk and accident-avoidance effort.³⁵

Thus if the congestion premium in VOT results from accident risk and avoidance effort, as in Steimetz's theory, VOT and the benefits of safety measures are both theoretically and empirically connected. On the one hand, safety-related conditions affect the congestion premium on VOT; and on the other, the measurement of VOT offers an avenue to measuring a component of safety costs. The latter is far from small: Steimetz estimates the accident-related externality in a sample of commuters on a major expressway into San Diego, California, to be \$0.78 per vehicle-mile, about three-fourths as large as his estimate of the travel-time externality and many times larger than typical values calculated from the costs of the accidents themselves.³⁶ Furthermore, under conventional assumptions in the safety literature, accident costs are relatively insensitive to congestion because the increase in accident rate is either zero or is offset by a decrease in accident severity due to lower speeds. Thus most or all of the external cost measured by Steimetz is due to effort, captured only by a theory such as his.

These observations have two very practical implications. First, the congestion premium is likely to change over time and to depend on some measurable factors related to safety; omitting those factors may cause specification error in measuring VOT. Second, measuring the impacts of such factors on VOT may lead to valuable insights into the full benefits of safety measures.

- *Attitudes.* Do travelers' attitudes toward travel alternatives constitute a useful addition to our ability to predict travel demand? It is possible to model rigorously how agents simultaneously form attitudes and make choices, recognizing that causality runs in both directions (Golob, 2001; Ben-Akiva et al., 2002). One can even incorporate the formation of stated preferences, and thus reap the advantages of combining data on attitudes with data on both revealed and stated preferences (Morikawa et al., 2002; Fujii and Gärling, 2003). In principle, such attitudinal data can provide additional information that tightens estimates of true behavioral

³⁵ Calculated by comparing the estimated hourly VOT from Steimetz (2008), Tables 4 and 5, which give \$29.46 using a conventional specification but only \$21.02 when traffic density is also controlled for.

³⁶ Small and Verhoef (2007, Table 3.3) estimate the external cost of accidents at \$0.06 per vehicle-mile (at 2005 price levels) for typical U.S. urban commuters. This is calculated as the difference between marginal social cost (\$0.178) and average private cost (\$0.117).

determinants, and perhaps can help to explain differences between inferences from SP and RP data. However, several questions remain. Which attitudinal traits are both influential and stable enough to be useful for prediction? How much statistical efficiency is gained from incorporating attitudinal information? Does such information tell us more about behavior or about how respondents answer surveys? The importance of this topic is increased by our growing realization that the standard rational economic paradigm is an incomplete and sometimes highly inaccurate description of individual decision-making.

- *Technology.* It is widely believed that better in-vehicle amenities and mobile communications and entertainment devices lower the value of time, by making travel time less onerous or more productive. Yet the evidence is thin, and the ability to predict future impacts is virtually nonexistent. In other arenas, communications advances have failed to have anticipated effects, often because they have spurred larger changes in behavior and social organization. For example, telecommunications has proven to be mainly complementary to rather than a substitute for transportation, as individuals and businesses have transformed the way people interact. Could something similar occur to alter the ability of technology to blur the distinctions among time spent in travel, leisure, and work?
- *Time horizon.* Given the importance of scheduling, it seems likely that decisions underlying VOT and VOR depend critically on the length of time over which behavior can change. On any given day, once a trip plan is made, disruptions to that plan due to scheduling may be quite costly, whereas known time savings may have limited value. Over a long time horizon, by contrast, one can adjust one's activity patterns to accommodate some unreliability, and also to take greater advantage of time savings. These intuitive conditions lead us to expect that over short time spans, VOT may be smaller and VOR larger than over long spans. Peer et al. (2011) indeed find such a pattern and it is quite marked. Better models accounting for the time horizon for decisions are likely to improve empirical work on VOT and VOR in many ways.
- *Activity analysis.* Travel demand forecasting is moving from trip-based models to activity-based models, in which sequencing of trips in both time and space is derived from a

household's desire to undertake certain activities.³⁷ Such models can help us deal with travel dynamics and several other issues already considered here such as scheduling choice, household decision making, and time horizons. Activity-based models contain components, especially mode choice, with familiar tradeoffs between cost, time, and perhaps reliability; so they do not fundamentally change the nature of VOT or VOR. They do, however, offer the possibility of a more detailed and rigorous basis for explaining the many sources of variation in VOT and VOR. Ironically, economists have played little role in these developments, although in principle activity analysis is very much a set of economic decisions. Thus it seems there is room for adding new insights into the values of time and reliability by applying economic tools to activity modeling.

4. Conclusion

Analyzing how people trade off time and money is not only useful for transportation practice, but it provides fundamental insights into several aspects of behavior including time allocation, scheduling decisions, loss aversion, activity patterns, and life-cycle labor supply. The reverse direction of influence is equally critical: better understanding of these diverse phenomena can help us better specify the more prosaic tradeoffs made in travel decisions, which are so important for policy evaluation.

Despite the maturity of the field and the sophistication of existing knowledge, there are fundamental potential gains still awaiting new theoretical and empirical results. Especially, the more that can be done to explain the widespread heterogeneity in how people make these tradeoffs, the more likely we will obtain robust and credible results that can enhance transportation analysis at all levels.

³⁷ Davidson et al. (2007) provide a helpful overview emphasizing practical implementations, of which there are now many. Pinjary and Bhat (2011) provide a review of research issues and specific research models.

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