

A Methodology for the Estimation of Value-of-Time Using State-of-the-Art Econometric Models

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Abstract

Value-of-time (VOT) measures are valuable in a wide range of public transport policy and planning applications. However, VOT is a latent variable that cannot be measured directly. In this research, state-of-the-art econometric models are developed within a methodological framework that allows for the estimation of the VOT. Ordered and binary discrete choice models have been developed. Furthermore, a mixed effects model that accounts for the unobserved heterogeneity across different individuals has also been specified. The models have been applied to short intercity trips between two medium-size cities (Agrinio and Patras) in Greece. The model specification combines trip-based characteristics (mode, travel time, and travel cost), with socioeconomic characteristics, such as profession, education, and car ownership. A stated-preference survey has been designed and administered to a random sample of 289 people. The estimated coefficients from the developed models have been used to estimate VOT measures and the overall performance of the ordered logit and the generalized linear mixed model has been found to be superior to the binary logit model.

Introduction

Value-of-time (VOT) measures are valuable in a wide range of public transport policy and planning applications. Public transportation infrastructure projects can be justified through the quantification of the generalized benefits to society, including reduction of harmful emissions, conservation of energy, and recovery of productivity lost in congestion. Quantification of each of these components is a complicated process, which involves estimates of the gains in each category. To develop a single overall figure, these components need to be translated into a single unit, which is usually a monetary currency. Delay and travel time can be converted to dollar amounts through the concept of VOT. For example, Lehtonen and Kulmala (2002) used VOT figures to estimate the travel time savings due to signal prioritization and real-time passenger information enhancements along two transit lines in the city of Helsinki, Finland. Grant-Muller et al. (2001) review the state-of-the-art in the economic appraisal of transport projects, drawing on national practice in Western European countries. While there are substantial cultural and economic differences, one of the key commonalities is the principle of monetizing direct transport impacts. In their review of valuation studies of railway rolling stock, Wardman and Whelan (2001) demonstrate the importance of VOT measures.

While VOT is a very important notion in transportation planning and infrastructure management, it is a latent theoretical construct that cannot be easily quantified or measured. As a result, methodologies for the indirect assessment of the VOT have been developed. Different socioeconomic characteristics, trip purpose, and other attributes result in very heterogeneous traveler populations and therefore potentially in very different VOTs across individuals. For example, affluent travelers may be willing to pay a steep toll to save trip time, while students may not have this option. One approach to quantify VOT is to develop discrete choice models based on data collected by surveys and then use the estimated coefficients for the cost and duration of travel to compute a VOT measure.

This article develops models for the estimation of VOT using state-of-the-art econometric models and demonstrates their application in a medium-size city in Greece. Ordered logit models and mixed effects models are developed, and compared with a more widely used binary logit model. The more advanced models are found to be superior to the binary logit model often used in such applications. Besides providing a resource for researchers, this research can be readily used by

practitioners, thus helping bridge the gap between state-of-the-art and state-of-the-practice.

The remainder of this article is structured as follows. The next section presents a review of relevant literature. Previous studies with Greek data are also shown to establish the range of VOT values available in the literature. This section is followed by an outline of the application methodology and data collection process. Model specification and estimation results for the entire data are shown next, followed by models using indicative subsets of the data. The article concludes with findings and directions for further research.

Literature Review

VOT is a very volatile measure that depends on several parameters and changes from country to country, industry to industry, and even from individual to individual. The objective of this literature review is to present the state-of-the-art in the modeling of VOT in terms of data collection and models used. Specific VOTs are only mentioned for the applications that refer to Greece, in order to establish the range of VOT obtained by other studies. Models developed for the estimation of VOT for other applications (such as commercial motor carriers) are also presented as they are often methodologically very similar.

Kawamura (2000) used stated-preference data from California to estimate the VOT of commercial motor carriers, using a modified logit model in which the coefficients were assumed to be distributed log-normally across the population. The questionnaire included questions about the characteristics of the motor carrier company and 10 stated-preference choices between options with tolls and without tolls. Kurri et al. (2000) present the results of two separate studies for the estimation of freight-specific VOTs for road and rail transport, using the same methodology. Stated-preference data was used, in which hypothetical choice situations between two road or rail transport alternatives were presented to transport managers in manufacturing companies in Finland. A logit model was employed for the estimation of the coefficients that were used for the determination of the VOT.

In the past decade, several VOT studies have been conducted in Europe, including The Netherlands (Gunn and Rohr 1996), Norway (Ramjerdi et al. 1997), Sweden (Alger et al. 1996), the United Kingdom (Gunn et al., 1996), and Switzerland (Axhausen et al., 2004). Wardman (1998) presents a meta-analysis of VOT derived

from 105 travel demand studies using revealed-preference and/or stated-preference methods. Kumar et al. (2004) developed multinomial logit models for the estimation of the VOT, the service headway and the comfort levels for trip-makers traveling along rural bus routes in India. Data were collected through a stated-preference survey. While trip characteristics and socioeconomic characteristics of the respondents were collected, they were not included in the final models.

Diamandis et al. (1997) estimated the VOT for Greek drivers. The survey was based on revealed preferences made by participating travelers in choosing between alternative modes with different prices and travel times. The collected data were analyzed with the use of the multinomial logit model. Finally the evaluated VOT for nonprofessional trips range between US \$3.72/hr and US \$4.32/hr and for professional trips between US \$5.42/hr and US \$6.42/hr. (Dollar amounts represent original figures from the paper and have not been adjusted for inflation.)

Polydoropoulou et al. (2000) present the results of a large-scale study in Greece. The survey used stated-preference data collected via a telephone survey. The scenarios that were presented to the participants included choices between car, bus, train, ship, and airplane. The attributes that were chosen to describe each alternative were mode, time, and cost. The authors identify the incorporation of socioeconomic data into the model formulation as a useful direction for further research. The selected data were analyzed with the use of multinomial logit and mean VOTs were evaluated for each mode: US \$6.6/hr, car; US \$4.92/hr, bus; US \$4.32/hr, train; US \$5.64/hr, ship; and US \$20.76/hr, airplane. (Dollar amounts represent original figures from the paper and have not been adjusted for inflation.)

Bierlaire and Thémans (2005) developed models for the prediction of travel decisions and consequently transportation demand with regard to different strategies of traffic management. A combination of revealed-preference and stated-preference data were analyzed using mixed logit models. The VOT was evaluated for short-distance (<50km) and medium-distance trips. The influence of several socioeconomic characteristics was evaluated.

In conclusion, most of the studies aiming at the estimation of VOT for freight and passenger travel use discrete choice models. Due to practical reasons, most studies use logit models, while recent studies (such as that of Bierlaire and Thémans 2005) use more advanced models such as mixed logit. In terms of data, most studies use stated-preference data, no doubt due to the difficulty of obtaining revealed-preference data. The inclusion of socioeconomic characteristics into the model

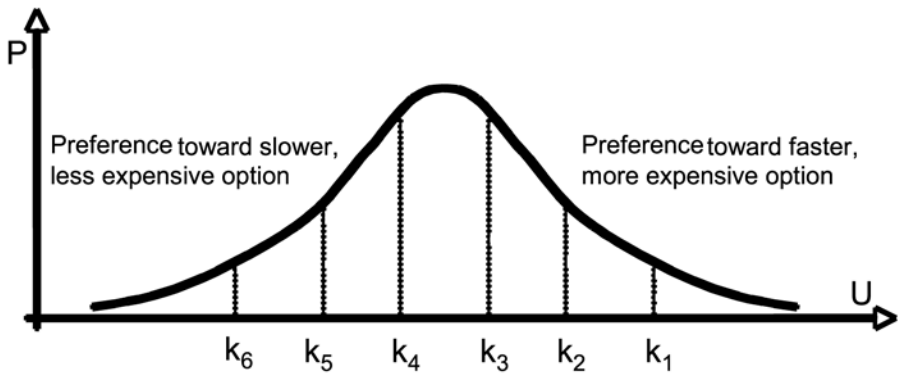
formulation is recommended. Richardson (2002) demonstrated the use of adaptive stated-preference surveys using simulated data.

Methodology

Model Formulation

Survey respondents are often asked to express their preferences in a rating scale. Such scales are often called Likert scales (Likert 1932; Richardson 2002). A multinomial logit model could be specified with each potential response coded as an alternative. However, the ordering of the alternatives violates the independence of the errors for each alternative, and therefore the Independence for Irrelevant Alternatives (IIA) assumption of the logit model. Nested or cross-nested models are one approach to overcoming this issue.

Figure 1 shows the distribution of the choice probability P as a function of the utility U . Assuming a ranking scale with seven levels, there are six thresholds or critical values that separate the choices.



**Figure 1. Distribution of Respondents' Preferences
(adapted from Train 2002)**

In the case of repeated observations (such as the case of stated-preference surveys with multiple responses), one often needs to consider the heterogeneity across individuals (often referred to as "unobserved heterogeneity"). In general, pooling data across individuals while ignoring heterogeneity (when it is present) will lead

to biased and inconsistent estimates of the effects of pertinent variables (Hsiao 1986). Several approaches have been developed to incorporate these effects in the model formulation. One is to estimate a constant term for each individual and each choice, which is referred to as a “fixed effects” approach (Chamberlain 1980). Perhaps the main drawback to this approach is the large number of parameters (and consequently large number of required observations per individual). A more tractable approach is to assume that the fixed term varies across individuals according to some probability distribution, which is referred to as a random effects specification (Heckman 1981; Hsiao 1986). The most common assumptions for this distribution are the normal and the lognormal. One drawback to this approach, however, is that it does not allow for a closed-form expression for the choice probabilities, thus leading to numerical complications. Models combining fixed effects and random effects are called mixed effects models.

Suppose the following general formulation for the systematic component of the utility function is used:

$$V = \beta_0 + \beta_{\text{cost}} * \text{travel_cost} + \beta_{\text{time}} * \text{travel_time} + \dots (1)$$

where:

- β are the coefficients to be estimated
- travel_cost and travel_time are the variables associated with travel cost and travel time, respectively
- ... corresponds to additional explanatory parameters in the model.

The coefficient of the cost and the coefficient of the travel time capture the sensitivity of the travelers’ utility toward changes in the travel time and the cost. Their ratio can therefore be used to capture the trade-off between travel time and the travel cost; in other words the VOT. The following explanation provides more insight into this. The utility is in general unitless. To simplify notation, it is sometimes useful to express it in an imaginary unit of “utils.” Assuming that the travel cost is measured in \$ and the travel time is measured in minutes, the units of the respective coefficients would then be utils/\$ and utils/min, respectively. The ratio of the coefficient for the travel time over the coefficient for the travel cost would have units of \$/min (or \$/hr if multiplied by 60), which is the expected unit for a VOT measure:

$$VOT = \frac{\beta_{time}}{\beta_{cost}} \cdot 60 \left(\frac{utils/min}{utils/\$} = \$/min \right) \quad (2)$$

Modeling involves inherent trade-offs of complexity versus performance. The addition of appropriate terms in a model can improve its performance; similarly, more elaborate model structures may be better able to model complicated processes. On the other hand, parsimonious models have lower data and computational requirements and thus can be more easily applied. Rigorous statistical tests and appropriate goodness-of-fit measures are available to ensure that additional variables and elaborate modeling techniques are indeed appropriate. Arguably the simplest discrete choice model is the binary logit model, which can be used as a benchmark against which more involved models can be measured, so that their marginal contribution can be concretely quantified.

Survey Design and Administration

Collected data may be either revealed-preferences (RP) or stated-preferences (SP) data. RP data represent the actual behavior of travelers and can be obtained through travel surveys, diaries, and field experiments. SP data represent the behavior of the travelers in hypothetical situations; such data can be obtained through SP surveys and simulators. The power of SP data lies in their ability to provide insight into nonexistent alternatives, as well as driver choice data in situations where RP data are limited (Louviere et al. 2000). Examples of studies using SP data include Abdel-Aty et al. (1997), Mahmassani et al. (2003), and Ettema and van de Horst (2005). While SP data are widely used, they are viewed with skepticism by some analysts. Adamowicz and Deshazo (2006) and Louviere (2006) discuss several issues related to SP methods.

To take advantage of a flexible experimental design that also includes nonexistent alternatives, an SP survey was developed and administered via personal interviews in the city of Agrinio, Greece, in December 2005. Wattam et al. (2005) provide the key steps for the design of such a survey: setting of alternatives, selection of measures for each attribute, selection of number of levels for each attribute, and development of scenarios.

The sample of survey respondents was random and over a period of three weeks the total number of participants was 289. The questionnaire contained two parts.

The first included 15 questions about socioeconomic characteristics, such as demographic characteristics and usual preferences in driving. The second part included 10 hypothetical binary questions in which respondents were asked to indicate their choice in a seven-point rating scale (ranging from strong preference for the first alternative through indifference between the two alternatives to strong preference for the second alternative). The choice of a seven-point rating scale is supported by Richardson (2002), who compares several rating scales for the problem of VOT estimation and concludes that a seven-point scale results in lower bias and variance than five- and nine-point scales.

Each respondent was presented with 10 scenarios resulting in a total of 2,890 observations. The scenarios included various combinations of modes, costs, and time. The range of travel times used in the SP experiments is between 60 and 120 minutes, and their difference in the experimental design ranges between 20 and 60 minutes (so that it can also reflect the sensitivity to the magnitude of the difference). Costs for the alternatives ranged between 6 and 10 Euro (roughly \$7 and \$12) while cost differences ranged from €1,5 to €5,5. These travel times and costs represent realistic values for the intercity trips that were considered (i.e., between the Greek cities of Agrinio and Patras, which are 84km apart). Two scenarios involved car trips, two scenarios involved bus trips, and six scenarios involved choices between car and bus.

A first version of the questionnaire was tested on a random sample of 30 respondents. Based on the analysis of these questionnaires, the survey was improved especially regarding the ease and speed of completion. The survey was administered in the form of an interview; that is a researcher asked the questions and wrote down the respondent's answers. This approach minimized errors that could be made by inexperienced subjects and also sped up the process, thus making the response rate higher. Only subjects who had done an intercity trip longer than 1hour in the past three months were included in the survey. Furthermore, only drivers older than 18 years of age were eligible, as car was one of the alternatives. The duration of the interview ranged between 5 and 10 minutes per respondent, with a response rate of about 55 percent. Approximately 40 percent of those who declined to participate were not interested in participating in this survey, while the remaining 60 percent of those who declined, stated that they had not done any intercity trip in the past three months.

The resulting data is consistent with the socioeconomic characteristics of rural cities in Greece. For example, gender representation was balanced, as 52 percent of the sample were male. In terms of age, 20 percent of the respondents were between 18 and 25 years old, 45 percent were between 25 and 45 years old, 22.5 percent were between 45 and 64 years old, and 12.5 percent were older than 65. Five percent of the sample had no car, 35 percent had one car, 32 percent had 2 cars, and 28 percent had access to more than 3 cars.

A sample question from the second part of the questionnaire is shown in Figure 2.

Please state your preference toward these options:

Option A		Option B	
Mode: Car		Mode: Bus	
Time: 60 min		Time: 120 min	
Cost: 10,00 €		Cost: 6,00 €	

1	2	3	4	5	6	7
Strong preference for A	Moderate preference for A	Slight preference for A	No preference	Slight preference for B	Moderate preference for B	Strong preference for B

Figure 2. Sample Question from the SP Questionnaire

Model Estimation Results

Three models have been considered and compared with respect to their applicability to the estimation of VOT using data from a survey in the city of Agrinio, Greece:

- A binary logit model was estimated as a benchmark, reference model. To estimate a binary logit model, the seven-point scale of the response was reduced to a binary choice. Responses with varying preferences for option A (respectively B) were grouped into preference for choice A (respectively B). Furthermore, responses with no preference for either choice were removed, as it would not be reasonable to attribute these responses to either of the binary alternatives. As a result, the final number of observations for the binary logit model was 2,789, instead of 2,890 for the ordered logit model.

- An ordered logit model, in which the ordered response is used directly as the dependent variable.
- A generalized linear mixed effects model, allowing for a random intercept, capturing unobserved heterogeneity among individual respondents.

All models were estimated using the R Software for Statistical Computing, version 2.4.0 (R Development Core Team 2006) with the *MASS* package (Venables and Ripley 2002) for the logit models and the *repeated* package for the generalized linear mixed model.

To obtain interpretable models, it was necessary to rearrange the collected data so that the fastest (and more expensive) mode was always first. As a result, a positive coefficient for a parameter implies that an increase in that attribute is associated with an increased preference for the faster alternative. This choice was arbitrary and the opposite convention could be used as well; of course, in that case the sign and the interpretation of the estimated coefficients would differ.

The results of the estimation for the three models are reported in Table 1. All coefficients are significant at the 95 percent level, except for the travel time and travel cost coefficients, which have t-values between 1.1 and 1.2 (in absolute value) in the ordered logit model and between 1.2 and 1.4 for the generalized linear mixed model. Higher travel times and cost result in a lower tendency of travelers to pick the mode in question. The intuitive negative signs of these two coefficients, along with the meaningful VOT figure obtained from this process, support the model results. The results of the binary logit model are similar, with a decrease in the significance of the travel time and travel cost coefficients. The gradual increase in the significance of the travel time and travel cost differences from the binary logit to the ordered logit and to the generalized linear mixed model indicate that the increased complexity of these models indeed improves the fit and provides additional benefits. In the final model (generalized linear mixed model), the travel time coefficient is significant at the 85 percent level, and the travel cost at the 80 percent level.

The large standard errors of travel time and cost coefficients seem problematic. On the one hand, these may be due to the correlation between repeated observations from the same respondent. This is only partly captured by the mixed effects model, which allows for a randomly distributed intercept. The estimated standard deviation of the intercept is very significant, which implies that indeed there is heterogeneity between individuals or—put differently—correlation among the

Table 1. Estimated Coefficients and Statistics

	Binary Logit		Ordered Logit		Generalized Linear Mixed Model	
	Est. coef.	z-value	Est. coef.	t-value	Est. coef.	t-value
Intercept	N/A	N/A	-1.426	-9.146	N/A	N/A
k ₆	N/A	N/A	-0.6064	-3.954	N/A	N/A
k ₄	N/A	N/A	-0.1517	-0.9914	N/A	N/A
k ₃	N/A	N/A	-0.0371	-0.2427	N/A	N/A
k ₂	N/A	N/A	0.442	2.887	N/A	N/A
k ₁	N/A	N/A	1.1632	7.545	N/A	N/A
Intercept	-0.1325	-0.692	N/A	N/A	-3.678	-31.551
Intercept Standard deviation	N/A	N/A	N/A	N/A	1.345	54.104
Variable	Est. coef.	z-value	Est. coef.	t-value	Est. coef.	t-value
Travel time (min)	-0.01097	-0.8	-0.01296	-1.204	-0.0113	-1.376
Travel cost (€)	-0.09757	-0.65	-0.1349	-1.142	-0.1136	-1.256
Mode	0.2411	2.18	0.4485	5.154	0.4075	6.113
Education: Basic (Base)	---	---	---	---	---	---
Education: High school	1.017	7.301	0.9789	8.532	0.962	10.434
Education: Technical	1.884	6.827	1.932	8.727	0.693	10.955
Education: College	1.417	7.337	1.677	10.225	1.28	10.653
Education: University	1.801	10.964	1.562	12.29	1.714	17.36 1
Profession: self - empl.(Base)	---	---	---	---	---	---
Profession: private empl.	-0.5911	-3.444	-0.5287	-3.96	-0.249	-2.456
Profession: student	-1.002	-6.765	-0.9225	-8.526	-0.857	-10.905
Profession: public empl.	-0.6075	-3.475	-0.4888	-3.96	-0.443	-4.286
Profession: homemaker	-1.215	-6.689	-1.031	-7.266	-1.118	-9.741
Profession: unemployed	-1.106	-4.298	-0.8592	-4.066	-1.066	-6.992
Profession: retired	-1.012	-5.789	-1.202	-8.514	-1.284	-11670
Peak time	-0.3183	-3.397	-0.3191	-4.283	0.419	-7.462
Car ownership	0.1217	2.89	0.1229	3.936	0.0995	4.291
Summary statistics						
Number of observations	2789		2890		2890	
Residual deviance	3024		8924.78		10966	
Residual degrees of freedom	2773		2869		2872	
Log -likelihood	-1512.007 (16 d.o.f.)		-4483.39 (21 d.o.f.)		-5483.162 (18 d.o.f.)	
Akaike Information Criterion (AIC)	3056.01		8966.781		11002	

N/A: Not applicable

responses of the same individual. On the other hand, the number of respondents may not be sufficient to provide sufficient information for the estimated coefficients.

Summary statistics are also presented in Table 1. However, as the models are non-nested, comparisons using these statistics are not appropriate.

Using equation 2 the VOT was calculated as:

1. 5,99 €/h (approx. US \$7.2/h) with the use of the generalized linear mixed model,
2. 5,77 €/h (approx. US \$6.9/h) with the use of the ordered logit model, and
3. 6,76 €/h (approx. US \$8.1/h) with the use of the binary logit model.

The binary logit model provides the highest estimate for the VOT. A comparison of the obtained VOT from the three models provides further evidence that the ordered logit and generalized linear mixed model provide superior performance in this context and for this dataset. For comparison, Diamandis et al. (1997) estimated values between US \$3.72/hr and US \$6.42/hr (in 1996 dollars) and Polydoropoulou et al. (2000) estimated US \$4.92/hr for bus and US \$6.6/hr for car (in 2000 dollars).

In the remainder of this section, the estimated coefficient values for the generalized linear mixed model are discussed to provide some further insight into the model. The Mode variable is coded as the difference between the two modes. Dummy variables have been created for each mode (carA and carB), taking the value 1 if the mode is car and 0 otherwise. If both modes are the same (both car or both bus), their difference is equal to 0. If one of the modes is bus (and it will have to be mode B, as it is assumed that bus is always slower), then $\text{carA} - \text{carB} = 1 - 0 = 1$ and it takes value of 1. The positive estimated coefficient captures the underlying preference toward choosing private car over public transit.

Education has been entered into the model as a factor taking five values (basic education, high school, technical education, college, university). The lowest level of education (basic education or elementary school and junior high school) has been used as a base. In general, as the level of education increases, the preference toward faster modes tends to increase. Using basic education as the base, there is a clear increase for high school graduates, and then another level where the preferences of those with technical school and college and university degrees cannot

be clearly distinguished. This is a reasonable finding as higher education may be considered a proxy to income.

The respondent's profession has been included in the models as a factor with seven levels: self-employed, private employee, student, public employee, homemaker, unemployed, and retired. Using self-employed people as the base, the other factor levels have negative coefficients, implying that they have a lower tendency toward faster (and expensive) options. Self-employed travelers show the highest interest for fast options, followed by private employees. This is an intuitive finding, as these groups of professionals can be expected to have the highest value of time. Students and public employees follow, while the lowest preference toward fast, expensive options is exhibited by unemployed and retired people (who have low disposable income and not so many pressing obligations). These are all reasonable findings and demonstrate how profession can be used as a proxy to income.

An additional variable (*Peak_time*) captures whether the majority of the trips that the respondent makes are within peak periods. If a person travels mostly during peak periods, then this variable takes the value 1, otherwise it takes the value 0. This variable is associated with a negative coefficient, showing a lower tendency of those who travel during peak periods for fast, premium options. This might be related with the fact that premium services offer lower perceived benefits during peak periods (e.g., due to overall congestion).

Variable *Car_ownership* reflects the number of cars available in the household. The estimated coefficient is positive, confirming the intuitive expectation that travelers with higher car ownership have a higher preference toward the faster (and more expensive) options. Besides the practical benefit of having access to cars when they need them, car ownership acts as a proxy to income.

Subset Analysis

The developed methodology also allows analysis of the VOT of subgroups of the sample population through the estimation of model coefficients using a subset of the survey data. For example, models for young travelers, as well as travelers who mostly travel for leisure, are estimated in this section and the resulting VOTs are calculated. Model estimation results for these two subset are shown in Table 2.

Table 2. Estimated Coefficients and Statistics for Subset Mixed Models

Variable	Young Individuals		Leisure Trips	
	Est. coef.	t-value	Est. coef.	t-value
Intercept	2.534	5.303	4.846	31.027
Intercept standard deviation	1.361	21.788	1.417	43.449
Travel time (min)	-0.0191	-1.078	-0.0195	-1.909
Travel cost (€)	-0.2463	-1.265	-0.187	-1.665
Mode	0.7029	4.895	0.374	4.519
Education: Basic (Base)	---	---	---	---
Education: High school	0.2681	0.734	1.473	12.429
Education: Technical	1.466	3.554	1.866	9.541
Education: College	-0.248	-0.551	1.517	10.081
Education: University	1.466	1.427	2.079	17.038
Profession: Self -empl.(Base)	---	---	---	---
Profession: Private empl.	0.43	1.296	-0.13	-1.005
Profession: Student	-1.246	-3.838	-0.937	-9.487
Profession: Public empl.	-0.931	-3.349	-0.361	-2.59
Profession: Homemaker	N/A	N/A	-1.358	-9.987
Profession: Unemployed	-1.44	-4.607	-1.663	-8.891
Profession: Retired	N/A	N/A	-0.515	-3.584
Peak time	-1.727	-12.967	0.12	1.663
Car ownership	0.303	4.468	0.245	7.581
Summary Statistics				
Number of observations	580		1770	
Residual deviance	2150.4		6619	
Residual degrees of freedom	564		1752	
Log -likelihood	-1075.182 (16 d.o.f.)		-3309.521 (18 d.o.f.)	
Akaike Information Criterion (AIC)	2182.4		6655	

N/A: Not applicable as none of the surveyed young people were homemakers or retired

The estimated VOT for young individuals is found to be equal to 4.66€/h (5.6\$/h), while for individuals who travel mostly for leisure in the area covered by the survey the VOT is calculated as 6.27€/h (approximately 7.5\$/h). For reference, the average VOT estimated from the complete model is equal to 5.99€/h (or about 7.2\$/h). These results are intuitive and consistent with the literature, thus providing further validation of the developed approach. The VOT of younger persons is lower than the average, as these individuals in general have fewer obligations and lower disposable income. The interpretation of the VOT for leisure trips is a bit more involved. One could argue that work-related trips involve a higher VOT, as there are presumably constraints (e.g., the worker needs to arrive at work by a fixed time,

or needs to complete some activities within some given time). Leisure trips, on the other hand, have no explicit constraints. However, time spent/saved during such trips is “quality” time that the individual can spend with his or her family, or performing other enjoyable activities. As a matter of fact, evidence in the literature (e.g., Feather and Shaw 2000; Jara-Diaz et al. 2006) suggests that VOT for leisure trips is generally higher than for work-related trips.

Conclusion

A methodology for the estimation of value-of-time using stated-preference surveys and various econometric models (including ordered discrete choice models and generalized linear mixed models) has been presented. An application in the interurban trips between the cities of Agrinio and Patras in Greece has resulted in reasonable estimates for the VOT. Ordered logit and binary logit models have been estimated and it has been shown that, in this particular application, the ordered logit model provides superior performance. A generalized linear mixed model that also considers correlation among responses from the same respondent is also presented. In this application, the mixed model is found superior than the other two models. As recommended by previous studies, this research incorporates socioeconomic data into the specification of the models.

The main contribution of this article is the application of advanced econometric models (ordered logit model, generalized linear mixed effects model) within a methodology for the estimation of VOT. The developed models are found to be superior to the binary logit model often used in such applications. Besides providing a resource for researchers, this research can be readily used by practitioners, thus helping bridge the gap between state-of-the-art and state-of-the-practice.

Future research may include both modeling and application enhancements. In terms of modeling, refinements to the discrete choice models could be used to more fully account for the unobserved heterogeneity and taste variation between the survey respondents (the current fixed effect model only allows for a randomly distributed intercept). Explicit modeling of the correlation between the answers of each respondent with respect to other parameters in the model (panel data) could improve the estimation accuracy and significance of the estimated coefficients. One of the requirements for such an analysis includes a larger dataset. In addition, the approach should be further validated through its application to other datasets, including different data collection techniques, such as adaptive

survey design (see e.g., Richardson 2002) and combination of stated-preference questionnaires with revealed-preference questions.

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