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Abstract

The treatment of the opportunity cost of travel time in travel cost models has been an area of research interest for many decades. This analysis develops a methodology to combine the travel distance and travel time data with respondent-specific estimates of the value of travel time savings. The individual travel time values are elicited with the use of discrete choice stated preference methods. The travel time valuation procedure is integrated into the valuation exercise to create a two equation structural model of site valuation. Since the travel time equation of the structural model incorporates individual preference heterogeneity full structural model provides a travel cost site demand model based upon individualized values of time. The methodology is illustrated in a study of recreational birdwatching, more specifically, visits to a stork village in Poland. We show that the usual practice of basing respondents' value of travel time savings on their wage rate is largely unfounded.

Keywords:

contingent valuation, stated preference, validity, incentive compatibility

JEL:

Q26, Q51, Q57

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1. Introduction

This analysis proposes a structural model of the travel cost demand approach (TCM) that includes two components. One component is used to estimate the value of travel time for each individual in the sample. The second component incorporates that value of travel time into the travel cost variable that is used in the estimation of the site demand. While the travel cost demand curve is estimated using the widely applied count methodology, the travel time component of the model is based on a discrete choice stated preference method. Our approach avoids arbitrary assumptions about an individual's value of time in an appealing way. It also allows quite intricate valuations since the stated preference portion of the model can accommodate a wide range of travel modes, time constraints, family situations and other considerations that can affect the value of one's time when traveling for recreation.

The individual level approach to valuing travel time utilized in this analysis is made possible by relatively recent advances in modeling preference heterogeneity in stated preference studies. The advances allow the derivation of posterior estimates of *each individual's taste parameters*. We argue that utilizing individual-specific values of travel time savings, based on respondents' stated preferences, provides a superior method for empirically incorporating the value of travel time into travel cost demand studies. Through an empirical illustration we show that the proposed approach is feasible and tractable. All it requires is the inclusion of only a few discrete choice experiment questions (DCE) in a TCM survey and a proper econometric treatment.

1.1. Valuing the opportunity cost of travel time in recreation demand models – previous research

The incorporation of the value of travel time in the TCM studies has been a source of concern since the earliest applications of this method (e.g., Clawson and Knetsch 1966, Johnson 1966). Researchers disagreed not only about how much the travel time is worth but also whether it should be included in the model at all. Cesario (1976) provided an early cogent discussion of the incorporation of the value of time into travel cost models. Despite the decades of research into the value of time Randall's (1994) observation that "the cost of travel time remains an empirical mystery" remains valid and estimating the value of travel time (or, in most cases, rather the opportunity cost of time) remains a frequently discussed problem in the literature on TCM (e.g., Hanley and Barbier 2009, Fletcher, Adamowicz, and Graham-Tomasi 1990, Garrod and Willis 1999).

Early on McConnell (1975) stressed the need to estimate the value of time before incorporating it in the demand function. However, uncovering the rate of substitution between money and time was long considered empirically intractable (as these trade-offs are endogenous and unobservable), even if conceptually possible. Cesario's (1976) suggestion that commuter's travel time values of 25–50% of an individual's wage rate was widely adopted. Using a fraction of wage rate has remained probably the most common approach, with the compromise value of 33% being the most broadly accepted level (Hellerstein and Mendelsohn 1993, Englin and Shonkwiler 1995a, Englin and Cameron 1996, Garrod and Willis 1999, Gürlük and Rehber 2008, Egan et al. 2009, Huhtala and Lankia 2012). Critics of the wage-based approach note that it makes little sense for those without reported wages, the method would suggest their marginal utility of time is zero. That is clearly not the case. (Feather and Shaw 1999, Parsons 2003).

Englin and Shonkwiler (1995b) developed a model linking a count travel cost to a confirmatory factor analytic model. The confirmatory factor analytic portion allowed a travel time value to be imputed for each individual and incorporated into the cost of travel. In a further development, Feather and Shaw (1999) used shadow wages (the values of extra units of leisure time) as the opportunity cost of travel time and compared this with previous approaches (using a fraction of wage rate and hedonic wage equations). On average, their estimates were better adjusted to the observed wage rates for different employment categories of respondents, compared with the wage rate predicted by the hedonic model.

Recent work has focused on the relationship between one's work and life schedule and the value of time in recreational travel. The early discussion of these issues was put forth by Bockstael, Strand, and Hanemann (1987) who proposed a general framework on how to incorporate time in TCM studies, based on insights from the labor literature. Demand for time depends on whether an individual can freely substitute recreation for work (interior solution) or has fixed work hours (corner solution). Most recently, Larson and Lew (2014) empirically implemented a system of joint labor–recreation equations to capture these effects. Palmquist, Phaneuf, and Smith (2010) employed a joint revealed stated preference approach to deal with fundamental lack of substitutability of recreation time for other forms of time. Both of these efforts seek a structural analysis of the value of time that looks at the relationship between the demand for time and hence value and flexibility to substitute time.

A second recent strand of work has focused on revealed valuations of travel time. Fezzi, Bateman, and Ferrini (2014) utilized a natural experiment where recreationists had a choice of a toll road which was faster or not paying a toll and taking more time to reach the recreation site. This is a novel

approach and very robust but it is also specific to a particular site and so will be subject to the usual limitations if the values are transferred to other settings. Wolff (2014) utilized speeding behavior as a function of gasoline price to identify the value of time. This is also revealed preference approach and so is excellent for the area studied but again the values must be transferred to use in other settings.

Early suggestions to combine TCM with contingent valuation or contingent behavior questions (Cameron 1992a, b, Adamowicz, Louviere, and Williams 1994, Englin and Cameron 1996) explored the methodological issues without paying specific attention to the opportunity cost of time. For example, Englin and Cameron (1996) added contingent behavior questions to a TCM study but these questions referred to general trip costs and not specifically to the opportunity cost of time. Nevertheless, such an approach makes it possible to impose exogenously varying travel costs and could be applied to opportunity cost of time too. Álvarez-Farizo, Hanley, and Barberán (2001) adopted contingent valuation to estimate the value of leisure time for use in recreational models and confirmed a significant variation in leisure time values. Building on Shaw (1992), Casey, Vukina, and Danielson (1995) offered an alternative approach, indicating that individual preferences regarding time are better reflected by the opportunity costs of time associated with a particular aspect of recreation than the wage. After all, the latter measures the trade-off between work and leisure more generally. They complemented a standard travel cost survey with a contingent valuation question about peoples' willingness to accept compensation to forgo a precisely defined recreational experience and used these results to derive the value of leisure time. Ovaskainen, Neuvonen, and Pouta (2012) directly elicited a stated value of time using a contingent valuation survey.

In light of the above challenges of incorporating meaningful estimates of the opportunity cost of time into recreational demand models, in what follows we propose to combine TCM with a DCE that would indicate how much each respondent values travel time. Compared to most of the above ideas, ours is more flexible and it is very precise in that we obtain specific estimates on the opportunity cost of time for each respondent in any potential setting. We explain this approach by first reviewing the methodology required by the TCM and DCE studies, with a particular focus on econometric derivation of individual-specific values of travel time savings. We then move to an empirical illustration of our approach which is compared with traditional treatments of value of travel time savings. Our case study not only serves as an example of the methodology we propose, but also illustrates that the usual approach of assuming that respondents' values of travel time savings are proportional to their wages is largely unfounded. The last section offers discussion of the results and conclusions.

2. Methods and econometric treatment

2.1. The travel cost method

The individual travel cost method treats trips to a site as the quantity demanded, while the cost of the trip as the price of access to the site. These assumptions result in a demand function of the following form:

$$r_i = f(p_i, z_i), \quad (1)$$

where r_i is the number of trips taken by individual i to a given site during a given time period, p_i is the cost of access to the site (which usually consists of the cost of travel and opportunity cost of travel time), and z_i is a vector of individual characteristics that are believed to influence the number of trips an individual takes.

In this setting, the consumer surplus associated with accessing the site by an individual i is represented by:

$$CS_i = \int_{p_i^0}^{p_i^*} f(p_i, z_i) dp_i, \quad (2)$$

where p_i^0 is the current trip cost to the site and p_i^* is the cost level at which the number of trips goes to zero, also called individual i 's 'choke price'.

A standard practice is to model single-site recreation demand functions using count data distributions. The two most frequently used count models are Poisson and Negative Binomial. These models are flexible enough to handle truncation, a large number of zero trips in the data, and preference heterogeneity. The main advantage of the Poisson model is that it is a member of the linear exponential family and so its parameters are unbiased as long as the underlying demand relationship is linear exponential. However, the Poisson distribution has the property of equi-dispersion – the first two moments of a distribution are equal, i.e., $E(Y) = \mu = V(Y)$. If a particular data set does not satisfy this assumption then more efficient estimates of the parameters can be obtained from the negative binomial distribution as it does not require equi-dispersion.

A second area of consideration is the method used to sample the trip data. If the data was sampled on-site the frequency of visitation by a user affects the likelihood of being in the sample. This sampling bias is referred to as endogenous stratification. The more frequently one visits a site the

more likely they are to be sampled. A second issue is that only visitors can possibly be sampled. As a result the sample is also truncated at zero. The problem of endogenous stratification and truncation in the context of travel cost modeling has been addressed for the Poisson model by Shaw (1988). Englin and Shonkwiler (1995a) extended the analysis to the truncated and endogenously stratified negative binomial model. Englin and Shonkwiler (1995a) accommodated three features of on-site samples concerning count data: over-dispersion, truncation at zero, and endogenous stratification due to oversampling of frequent users of the site. In this model, the probability of individual i making y_i trips to the site is given by:

$$Pr(y_i | y_i > 0) = y_i \frac{\Gamma(y_i + \alpha_i^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha_i^{-1})} (\alpha_i^{y_i} \lambda_i^{y_i-1}) (1 + \alpha_i^{-1} \lambda_i)^{-(y_i + \alpha_i^{-1})}, \quad y_i = 1, 2, \dots, \quad (2)$$

where Γ represents the gamma function, λ_i is the mean, which is typically modeled as a function of explanatory variables and α_i is the over-dispersion parameter. Amoako-Tuffour and Martínez-Espíñeira (2012) took this reasoning further and allowed the over-dispersion parameter α_i to vary according to respondent characteristics (and they used their survey data to indicate which fraction of the wage rate best represented the respondents' opportunity cost of travel time, making also this parameter a function of the respondents' characteristics).

2.2. Discrete choice experiments

In environmental economics stated preference methods are commonly used for modeling consumers' preferences and valuation. Respondents' choices are typically modeled in a random utility framework (McFadden 1974), which assumes that the utility associated with any choice alternative can be divided into a sum of contributions that can be observed by a researcher, and a component that cannot, hence is assumed random. Specifically, consider the following empirical specification of a random utility multinomial choice model:

$$U_i(\text{Alternative} = j) = U_{ij} = \beta_i' \mathbf{x}_{ij} + \varepsilon_{ij}, \quad (3)$$

where U_{ij} represents respondent i 's utility associated with selecting alternative j out of a set of J available alternatives, $\mathbf{x}_{ij}$ is a vector of respondent- and alternative-specific choice attributes, i.e. goods or their characteristics, and β_i represents a vector of individual-specific taste parameters associated with marginal utilities of the choice attributes. Assumptions regarding parametric

distributions of the taste parameters, such that $\beta_i \sim f(\mathbf{b}, \Sigma)$, where $\mathbf{b}$ is a vector of sample means and Σ is a variance-covariance matrix, allows to account for unobserved preference heterogeneity and possibly – correlations between random taste parameters.

The stochastic component of the utility function (ε) may be interpreted as resulting from researcher's inability to observe all attributes of choice and all significant characteristics of respondents (McFadden 1976), or as decision maker's choice from a set of his decision rules (Manski 1977). Random utility theory is transformed into different econometric models by making assumptions about the distribution of the random error term and the random parameters. Typically, ε_{ij} is assumed to be independently and identically (iid) Extreme Value Type 1 distributed across individuals and alternatives. When unobserved preference heterogeneity is allowed in a way presented above, this leads to a Mixed Logit (MXL) model (McFadden and Train 2000).

In what follows, we utilize Bayesian framework for estimating MXL model and deriving individual-level taste parameters and, as a result, individual-specific values of travel time savings (VTTS). In our case, the choice of Bayesian approach provided greater flexibility in selecting bounded distributions for some of the random taste parameters (cost), as the economic theory dictates that distribution of taste parameters associated with these attributes has no support in negative values (Train and Sonnier 2005). In addition, some of the advantages of Bayesian over classical estimation include easier identification of a global maximum of the likelihood function, and handling correlated random parameters (Huber and Train 2001). Last but not the least, in a Bayesian approach identification of individual-level parameters is less of an issue than in classical approach, since in extreme cases the prior can provide the necessary information.

Bayesian estimation procedures for the random parameters logit do not require simulating choice probabilities. Instead, the likelihood of observing individual i making a sequence of T choices $\mathbf{Y}_i = \{y_{i1}, \dots, y_{it}, \dots, y_{iT}\}$ is the product of standard logit formulas, conditional on β :

$$L(\mathbf{Y}_i | \beta_i) = \prod_{t=1}^{T_i} \frac{\exp(\beta_i' \mathbf{x}_{iy_{it}t})}{\sum_{j=1}^{J_{it}} \exp(\beta_i' \mathbf{x}_{ijt})} . \quad (4)$$

The unconditional probability is the integral of (4) with respect to all values of β_i , weighted by their multivariate probability density $\psi(\beta_i)$:

$$P(\mathbf{Y}_i | \mathbf{b}, \Sigma) = \int L(\mathbf{Y}_i | \beta_i) \psi(\beta_i | \mathbf{b}, \Sigma) d\beta_i . \quad (5)$$

The Bayesian approach requires specifying priors for the model parameters $\mathbf{b}$, Σ and β_i for all $i=1..N$. Typically, a diffuse normal distribution (with zero means and diagonal matrix of arbitrarily large variances Θ , allowing for almost flat distribution) is used as a prior for $\mathbf{b}$, $\mathbf{b} \sim MVN(0, \Theta)$, and inverted Wishart distribution (with the number of degrees of freedom K equal to the length of $\mathbf{b}$, and parameter $K\mathbf{I}$, where $\mathbf{I}$ is a K -dimensional identity matrix) is used as a prior for Σ , $\Sigma \sim IW(K, K\mathbf{I})$. The priors for each individual's taste parameters β_i are proportional to the assumed (population-level) distributions of taste parameters times the priors on $\mathbf{b}$ and Σ ; as an aside, because of this hierarchy of parameters this procedure is often referred to as hierarchical Bayes. As a result, denoting choice sequences of all individuals at all choice occasions as $\mathbf{Y}$, the joint posterior distribution on $\mathbf{b}$, Σ and each β_i is:

$$\Lambda(\beta_i \text{ for all } i=1..N, \mathbf{b}, \Sigma | \mathbf{Y}) \propto \prod_{i=1}^N L(\mathbf{y}_i | \beta_i) \mu(\beta_i | \mathbf{b}, \Sigma) N(\mathbf{b} | 0, \Theta) IW(\Sigma | K, K\mathbf{I}) . \quad (6)$$

Since using the parametric distributions which impose bounds on taste parameters may make direct drawing from the joint posterior distribution difficult, some variant of Metropolis-Hasting algorithm is usually used (Train 2009, Chib and Greenberg 1995).

Interestingly, the results of the estimation procedure are asymptotically equivalent to the classical, maximum likelihood estimator. The results can thus be given a dual – classical and Bayesian – interpretation (Geweke 1989).

The approach that we propose in this paper extends the traditional TCM by utilizing individual-specific VTTS. In order to make this possible and, at the same time, allow for preference heterogeneity it is crucial to obtain individual-level taste parameter estimates. Although in this paper we adopt a Bayesian approach, Huber and Train (2001) showed that reliable individual-level parameters for discrete choice models can be obtained irrespectively of the estimation or inference framework. Within a Bayesian framework, the distribution of coefficients across population is estimated and used as a prior, which combined with individual's choices results in posterior estimates of each individual's tastes (Rossi, McCulloch, and Allenby 1996, Allenby and Rossi 1998). Similarly, in a classical setting, applying Bayes theorem, i.e. combining maximum likelihood estimates of the population distribution with individual choices, makes derivation of individual-specific parameter estimates possible (Revelt and Train 2000). Huber and Train (2001) showed that these approaches lead to largely equivalent results.

3. Empirical illustration

In order to investigate differences resulting from applying individual-level estimates of travel time versus the traditionally assumed value of time we designed and implemented a joint TCM-DCE study in the context of recreational birdwatching.

3.1. Study site, experimental design and survey administration

The study site selected for this application was Żywkowo, one of Polish ‘stork villages’. A stork village is a common name for a village with a white stork (*Ciconia ciconia*) breeding colony, often inhabited by more storks than people. Żywkowo, the best known stork village in Poland, has approximately 40 white stork nests and 10 households, however, it receives approximately 2,000 – 5,000 tourists annually, many of whom come from abroad. Żywkowo lays in the north-east of Poland, on the periphery of one of the most attractive parts of the country to tourists, the Masurian Lake District. It is not located near any major tourist attraction and is relatively far from larger cities; in addition, since there are no other attractions in the village it is visited solely because of birds, and more specifically – because of white storks.

The questionnaire was designed to collect the usual data necessary for a TCM study. We asked where the tourists came from, distinguishing between their most recent stop (if they visited more than one place during their trips) and their place of residence. We also asked how long the travel took, what means of transportation were used and the number of people travelling in a party. In order to identify respondents who, in general, had positive willingness to pay for travel time savings we asked if they had wished their travel time was shorter. After that, respondents who expressed general interest in making their travel time shorter were asked to participate in hypothetical discrete choice tasks designed to reveal their WTP for travel time savings. Finally, respondents were asked socio-economic questions, providing information about their age, gender, income, level of education, and basic birdwatching preferences. Questionnaires were available in Polish, German and English.¹

The DCE part of the survey utilized up to 6 choice tasks per respondent. Each choice task consisted of 3 alternatives – one status quo alternative associated with no travel time savings and no costs, and two additional alternatives represented by different travel time savings and cost. To make the questionnaires more efficient we prepared 4 versions of the DCE questions which differed in the

¹ More details about the survey are available in Czajkowski et al. (2014).

utilized attribute levels; each respondent was presented with one of the versions depending on the length of the travel time he declared earlier. The design of each DCE version was generated using NGENE 1.0.2. We optimized the design for D-efficiency of an MNL model using Bayesian priors (Ferrini and Scarpa 2007) and all prior estimates were assumed to be normally distributed, with their means derived from the MNL model estimated on the dataset from the pilot survey, and standard deviations equal to 0.25 of each parameter mean.

Tourists visiting Żywkowo were surveyed on site between April and September of 2011, i.e., from when the storks returned from their spring migration to when they left for autumn migration. Questionnaires were available to tourists visiting an exhibition room. Tourists were prompted to take part in the study by local employees and, additionally, by interviewers who assisted the local staff at times when the tourists were the most numerous. In 2011, 2,850 tourists visited the exhibition room, of whom 583 agreed to complete the questionnaire, resulting in a response rate above 20%.²

3.2. Deriving respondent-specific values of travel time savings with discrete choice experiment approach

We start by presenting the results of the discrete choice experiment estimated for respondents who indicated that they wished their journey to the study site had been shorter. The MXL model was estimated using the Bayesian procedures described in section 2.2. The choice attributes included travel time savings (*TTS*), cost (*FEE*) and an alternative specific constant associated with the status quo alternative (*SQ*). All taste parameters were assumed random and possibly correlated. Since economic theory indicates that utility associated with (negative) cost and travel time savings (for respondents who indicated that they wished their journey had been shorter) cannot be negative, we tried several bounded distributions to represent population-level parameters of these attributes, including lognormal, triangular and truncated normal in which cumulative probability associated with negative values were amassed at zero. Of these, the truncated normal displayed the best fit to our data. The *SQ* was assumed to follow normal distribution.

² Unfortunately, the available visitor statistics do not provide detailed information on the characteristics of visits (e.g., the length of stay) nor on the socio-demographic characteristics of visitors. As a result we have no definite check on how representative our sample is, despite the relatively large share of surveyed visitors, and the fact that we performed the interviews throughout the entire season.

The estimation was performed in Matlab.³ In our application, we used 100,000 iterations for ‘burn-in’ (the iterations used by Metropolis-Hasting algorithm within which the draws converge to the target, conditional posterior distribution), and after that we retained every 11th iteration result for the total of 100,000 iterations used to conduct inference, i.e. from a classical perspective, deriving estimates of the parameters.⁴ Finally, we used 10,000 draws per individual to simulate the estimated distributions of random parameters and to calculate simulated log-likelihood value. The step length for the Metropolis-Hasting algorithm was set to 0.3, well within the range suggested by Gelman et al. (2003).

The estimation results are presented in Table 1. The first column represents the reference MNL model. All parameters of this model are highly significant and of expected sign. The improvement in model fit from the MNL to the MXL model with correlated parameters, as indicated by Akaike information criterion (AIC) and McFadden’s pseudo R^2 , is an evidence of substantial heterogeneity in respondents’ preferences. This is confirmed by relatively large estimates of standard deviations of population parameters. The results of a likelihood ratio tests showed that indeed, all parameters should be modeled as random and correlated.

Table 1. The results of the discrete choice model (standard deviations / standard errors given in parentheses)

	Multinomial logit	Mixed logit	
	Taste parameters	Means of random taste parameters	Standard deviations of random taste parameters
<i>SQ</i>	0.7437*** (0.0905)	-0.4801 (0.5562)	7.3009*** (1.0764)
<i>TTS</i>	0.5626*** (0.0731)	1.3692*** (0.5407)	1.7275 (1.7048)
<i>FEE</i>	2.1369*** (0.4087)	14.3263*** (2.6824)	14.4804** (7.1327)
Model characteristics			
Simulated log-likelihood	-1,463.6052	-986.2775	
McFadden’s pseudo R^2	0.0703	0.3732	
AIC/ <i>n</i>	2.0470	1.3888	
<i>n</i> (observations)	1,433	1,433	
<i>k</i> (parameters)	3	9	

³ The dataset and Matlab codes for the models used in this paper are available from http://blind_review.blind_review/ under CC BY 4.0 license.

⁴ We retained only every 11th draw in order to reduce the amount of correlation among the draws.

The estimation results presented above allowed us to derive individual-specific parameters in a fashion described in section 2.2. These parameters were in turn used to simulate⁵ individual-level willingness to pay for travel time savings, following Hanemann (1984) and Small and Rosen (1981):

$$CV = \frac{1}{\mu} \left\{ \ln \sum_1^n \exp(\beta' \mathbf{x}_0) - \ln \sum_1^n \exp(\beta' \mathbf{x}_1) \right\}, \quad (7)$$

where μ is the marginal utility of income (the parameter on price), β is vector of estimated parameters of the indirect utility function, $\mathbf{x}_0$ are the levels of the attributes in the reference situation and $\mathbf{x}_1$ are the levels of the attributes in the improved situation. In our case, we assumed two alternatives ($n = 2$; status quo and non-status quo) and the improvement in the form of 1 hour travel time reduction, which occurred in the non-status quo alternative of $\mathbf{x}_1$.

Descriptive statistics of these individual-specific values of travel time savings for the sample of our respondents are presented in Table 2. For comparison, the table also includes the statistics for respondents' wage rates. These results can be compared to mean WTP obtained from the MNL model of 11.34 PLN (with confidence interval of 7.81 – 14.85 PLN).⁶

Table 2. Descriptive statistics of respondent-specific values of travel time savings and wage rates [PLN/h]

	Value of travel time savings		Wage rate	
	All respondents	Respondents who wished their journey was shorter	All respondents	Respondents who wished their journey was shorter
Mean	4.2966	9.7001	12.6677	12.2781
Median	0.0000	6.8703	12.5000	12.5000
Standard deviation	8.7571	10.9921	7.7456	7.7459
0.025 quantile	0.0000	0.0028	2.8125	2.8125
0.975 quantile	27.1533	38.8924	28.1250	28.1250

⁵ Only respondents who declared that they wished their journey was shorter were included in this analysis; the others were assumed not to be willing to pay for travel time savings (VTTS = 0). In simulation we accounted for effective means of the distributions which were modelled as truncated normal.

⁶ 1 PLN $\approx$ 0.25 EUR $\approx$ 0.33 USD

The results of this exercise allow for a few interesting conclusions. First of all, even a relatively simple discrete choice experiment can result in reliable respondent-specific values of travel time savings. The descriptive statistics presented in Table 2 show that individual-specific values of WTP for travel time savings are well behaved for virtually all respondents in our sample who had stated that they wished their travel time had been shorter.

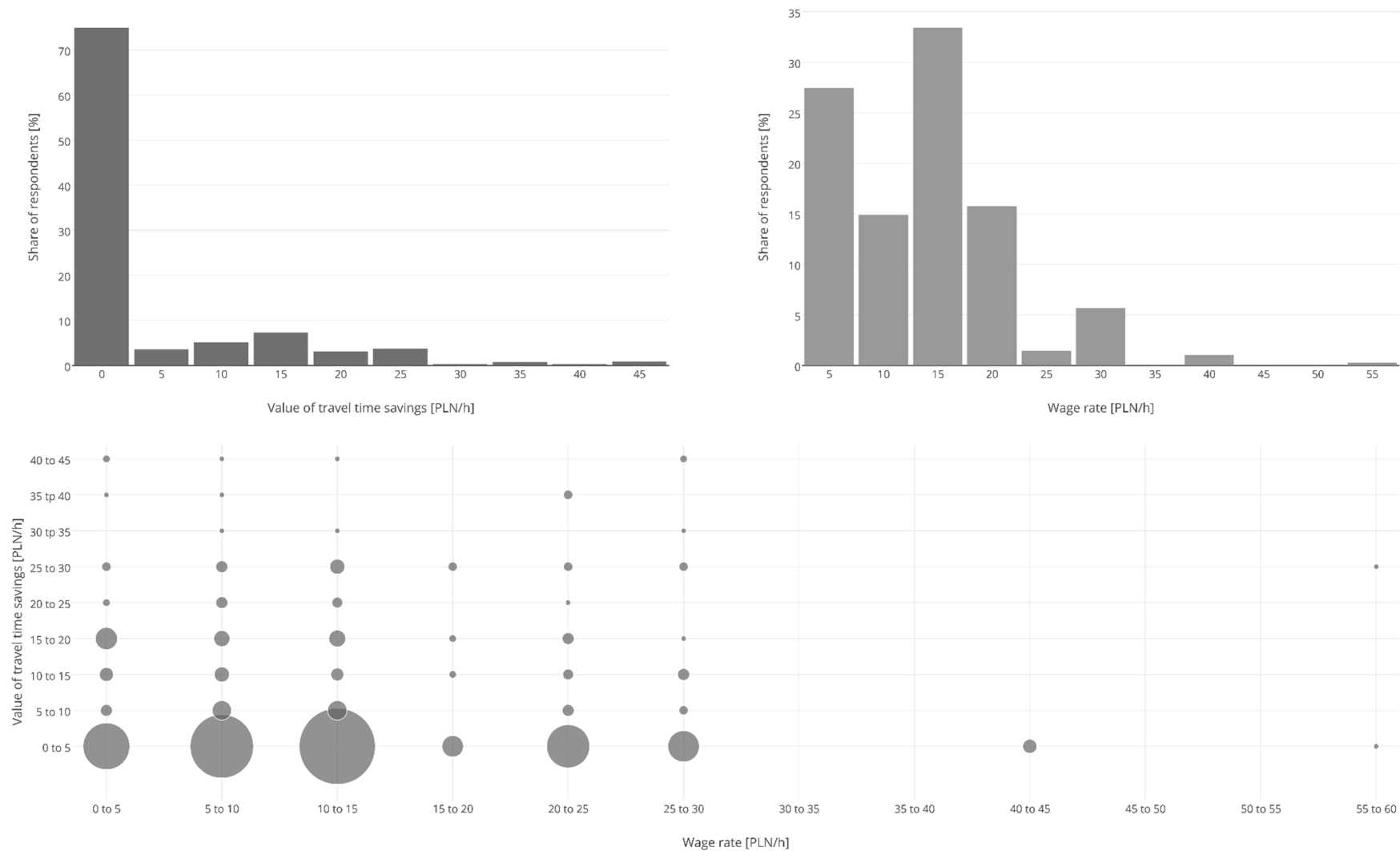
Secondly, we find that respondents' mean value of 1 hour travel time savings is very close 1/3 of their mean wage rate. This seems to support the usual rule of thumb applied in many empirical studies (cf. literature review provided in section 1.1). However, on closer inspection, we find that this assumption is largely unfounded. Note, that only slightly less than 50% of respondents declared that they wished their journey was shorter, implying VTTS = 0. In addition, substantial share of those who were generally in the market for shortening their travel times still made choices which implied very low VTTS (e.g., did not choose the costly improvement alternative in any of the choice tasks). Finally, the correlation of respondents' VTTS and their wage rate is very low (0.0074 for all respondents, 0.0578 for those who declared they wished their journey was shorter).

We investigate the relationship between respondents' VTTS and wage rate further using graphical illustration provided in Figure 1. The first two panels present histograms of observed VTTS and wage rates. The distributions are indeed very different. The distribution of individual-specific VTTS appears close to lognormal, with a probability spike at zero. This implies a high level of asymmetry. As a result, utilizing mean values (of wage, VTTS) for all respondents could substantially bias the results, especially if the higher or lower values of VTTS are correlated with the length of the trip or the number of trips a respondent makes.

The bubble chart presented below is possibly even more telling. The area of each bubble represents the number of respondents who were classified to each of the VTTS-wage rate combination bins. If VTTS and wage rates were correlated, we would expect a positive linear relationship. Instead, we find that respondents' WTP for shortening their trip is largely independent of their wage rate.

Overall, our results do not support using respondents' wage rate as a proxy for respondents' VTTS. We therefore argue for utilizing stated preference methods for measuring individual level VTTS and in what follows, we demonstrate substantial differences resulting from utilizing individual-level vs. aggregated vs. traditional assumptions regarding the value of travel time in travel cost models.

Figure 1. Respondents' wage rates and implied values of travel time savings



3.2.1. Individual heterogeneity with respect to VTTS

In order to provide an insight into respondents' heterogeneity with respect to their VTTS we present the logit model for 'market participation' – respondents' answers to the question if they (in general) would prefer that their journey was shorter and a simple linear regression model in which individual-specific VTTS are explained with respondents' socio-demographic variables (Table 3).

Table 3. The analysis of respondents' heterogeneity with respect to VTTS

	Probit model for respondents willingness to shorten their journey	Linear regression model of respondents' VTTS
<i>Constant</i>	-0.6739** (0.3216)	-4.0390** (1.7993)
<i>Travel time</i>	0.2745*** (0.0634)	2.1241*** (0.4090)
<i>Travel time²</i>	-0.0202*** (0.0066)	-0.1543*** (0.0431)
<i>Household size</i>	0.0330 (0.0529)	1.3633*** (0.3434)
<i>Number of children</i>	-0.0444 (0.0731)	-1.4646*** (0.4691)
<i>Age</i>	-0.0100*** (0.0035)	-0.0105 (0.0087)
<i>Male</i>	0.1614 (0.0994)	0.0211 (0.6483)
<i>Education – medium</i>	0.5716*** (0.2094)	1.3289 (1.2876)
<i>Education – high</i>	0.6211*** (0.2102)	3.0507** (1.2996)
<i>Wage rate</i>	-0.0098 (0.0070)	0.0507 (0.0454)

The results show that respondents whose journeys were longer were more likely to answer that they indeed wished their journey had been shorter; the relationship is convex, as indicated by the negative coefficient associated with the travel time squared. These results coincide with individual specific VTTS – respondents who had to travel longer were willing to pay more to shorten their journey (although at a decreasing rate). Additionally, we find that older respondents are generally less likely, while respondents with medium or high level of education are more likely to state that they wish their journey was shorter. Respondents with the university degree are also statistically willing to pay more for travel time reduction, similarly to respondents from larger households –

although this last effect is counterfeited for respondents with children. Finally, we note that respondents' wage was not a significant explanatory variable of neither willing to shorten ones journey, nor their individual VTTS.

These results have profound implications. Since respondents whose traveling times are larger have higher WTP for shortening their journey it clearly follows that using mean VTTS for every respondent in the sample will negatively bias the cost of travel time. This is because observations with higher individual-specific VTTS have higher weights in the utility function (more hours multiplied with higher cost per hour). In addition, since respondents' VTTS appears statistically independent from their wage, using individual-specific wage rates as a proxy of VTTS is not convincing approach either. We illustrate this finding with the comparison of different modeling approaches in the next section.

3.3. Travel cost method with consumer-specific values of travel time savings

In this section we present the estimation results of 5 travel cost models with different assumptions with respect to respondents' VTTS. Generally, visitor i 's expected number of trips can be calculated as:

$$\lambda_i = \exp(\beta_{TC} TC_i + \beta'_z \mathbf{Z}_i), \quad (8)$$

which serves as our travel cost recreation demand function. The TC_i represents individual i 's cost associated with reaching the stork village and $\mathbf{Z}_i$ is a vector of individual characteristics that are considered to influence the number of trips i takes (in our case, since we intended to keep our approach as simple as possible, we only used a constant).

The average cost of traveling 1 km was assumed to be 0.45 PLN⁷; however, when calculating cost per person we took a travelling party size into account. As far as the VTTS is concerned, the following alternative specifications were used:

- (1) VTTS = 0;
- (2) VTTS = 1/3 of respondent's wage rate;
- (3) VTTS = respondent's wage rate;

⁷ We used the official average operating cost according to the Polish Automobile Association. This rate is commonly used for reimbursing employees who use private vehicles for official business.

(4) VTTS = mean WTP derived from the MNL model;

(5) VTTS = individual-specific WTP derived from the RPL model.

In all cases, we only included the cost associated with the travel time for respondents who indicated that they wished their journey was shorter. The resulting travel costs, calculated under different assumptions with respect to VTTS, are presented in Table 4.

Table 4. Respondents' travel costs under different assumptions with respect to VTTS [PLN]

Respondents' travel cost when:	$VTTS_i = 0$	$VTTS_i = 1/3$ wage rate	$VTTS_i = \text{full}$ wage rate	$VTTS_i$ derived from the MNL model	$VTTS_i$ derived from the MXL model
Mean	23.54	28.80	39.32	38.41	36.58
Median	15.40	16.00	20.56	19.83	16.00
Standard deviation	33.71	40.19	56.54	53.28	60.94
0.025 quantile	2.60	2.60	2.60	2.60	2.60
0.975 quantile	137.15	180.55	222.48	223.54	221.39

We estimated the count data models in a Bayesian framework, applying the independence chain Metropolis-Hastings algorithm with a multivariate t distribution (with mean $(\hat{\beta})$ equal to the mode of the posterior kernel, and variance equal inverted negative Hessian resulting from the maximum likelihood estimator subroutine evaluated at $\hat{\beta}$)⁸ as a candidate-generating density (Chib, Greenberg, and Winkelmann 1998, Davis and Moeltner 2010). The Gibbs Sampler was implemented with 100,000 burn-in draws and 10,000 retained draws.⁹

⁸ The tuner elements for these t-distributions were set as the degrees of freedom = 8 for means and a scalar 2 for the variance. These settings led to acceptance rates of approximately 50% and to desirable efficiency measures.

⁹ As an aside, we have also tried to combine the two estimation steps into one. This can theoretically be done by saving the appropriate number of iteration- and individual-specific parameters from the discrete choice part (and hence iteration- and individual-specific VTTS values) and utilizing them for each of the iterations conducted in step 2. In other words, each iteration in the estimation of the count data model would use a different explanatory vector, thus preserving the conditionality that links the two equations. However, this approach turned out to be infeasible, due to a large probability mass of the cost parameter at 0 which resulted in many iteration- and individual-specific VTTS being undefined or plus/minus infinity. As a result, the estimation of the count data model could not proceed without additional assumptions (such as assuming that VTTS of such respondents was 0, or sample mean). In addition to the independence chain version of the Metropolis-Hastings algorithm which requires optimizing the LL function (and hence evaluating gradients) for each iteration and causes additional problems if some of the observations are not real numbers, we tried a simpler, random walk version of this algorithm. This approach also turned out infeasible for simultaneous estimation because even without the necessity to calculate gradients the value of the log-likelihood function was often undefined.

The estimation results are presented in Table 5. As expected, the travel cost coefficient is negative and statistically significant at the 1% level in all the models. The constant and the over-dispersion parameter α_i are also highly significant.¹⁰ All models are characterized by reasonably good fit (pseudo- R^2 , AIC/n), however, it is impossible to directly compare them in terms of fit, as each one is essentially estimated on a different dataset. A common theme is that the intercept term is relatively stable across specifications ranging from -5.5253 to -5.6916, virtually indistinguishable from each other statistically. The over-dispersion parameters are also indistinguishable from each other. The slope parameters while not statistically distinguishable from each other at conventional test levels follow the usual pattern of higher values of time flattening the slope of the estimated demand curve.

Table 5. The TCM models estimation results

	Model 1 ($VTT S_i = 0$)	Model 2 ($VTT S_i = 1/3$ wage rate)	Model 3 ($VTT S_i = \text{full}$ wage rate)	Model 4 ($VTT S_i$ derived from the MNL model)	Model 5 ($VTT S_i$ derived from the MXL model)
$\beta_{constant}$	-5.4337*** (1.0276)	-5.4048*** (1.0356)	-5.4122*** (1.0355)	-5.4194*** (1.0363)	-5.4921*** (1.0258)
β_{TC_i}	-6.0055*** (1.7298)	-5.3977*** (1.5206)	-3.9725*** (1.1376)	-3.9758*** (1.1395)	-3.0694*** (1.0375)
α_i^*	4.5479*** (1.0360)	4.5396*** (1.0436)	4.5438*** (1.0437)	4.5527*** (1.0447)	4.5582*** (1.0337)
Model characteristics					
Simulated log-likelihood	-429.109	-428.861	-429.75	-430.073	-432.366
McFadden's pseudo R^2	0.5509	0.5512	0.5502	0.5499	0.5475
AIC/n	1.4875	1.4866	1.4897	1.4908	1.4987
n (observations)	581	581	581	581	581
k (parameters)	3	3	3	3	3

We now turn to presenting the welfare measures associated with the different VTTS assumptions made in Models 1 to 5. Consumer surpluses (CS) per person per trip were calculated as an inverse of the estimated travel cost parameter ($-1/\beta_{TC}$). The standard errors and corresponding 95% confidence intervals were obtained using the delta method. The results are reported in Table 6.

¹⁰ On a technical note, since the candidate parameters for the count data model are derived from a multivariate t distribution, we found that with sufficiently large variance, every so often the candidate draw for the α parameter was negative. This caused numerical problems, as the gamma function (see eq. (2)) is only defined for positive values. In order to impose this theory-driven constraint we revised equation (2) in such a way, that $\alpha = \exp(\alpha^*)$ and optimized for α^* . This proved a convenient way to ensure that α has no support for negative values, while not changing the log-likelihood function.

Table 6. Consumer surplus estimates [PLN]

	Model 1 ($VTT S_i = 0$)	Model 2 ($VTT S_i = 1/3$ wage rate)	Model 3 ($VTT S_i = \text{full wage}$ rate)	Model 4 ($VTT S_i$ derived from the MNL model)	Model 5 ($VTT S_i$ derived from the MXL model)
CS (st.err.)	166.51 (47.9633)	185.26 (52.1913)	251.73 (72.0894)	251.52 (72.0917)	325.8 (110.1244)
95% c.i.	72.51 – 260.52	82.97 – 287.56	110.44 – 393.03	110.22 – 392.82	109.96 – 541.65

As the parameter estimates for the demand functions suggest will happen the welfare estimates for flatter demand curves (ones with higher values for time) are higher. The individual random parameters model provides the highest welfare measures.

4. Discussion and conclusions

In this paper we propose to combine the usual TCM data with respondent-specific estimates of the value of travel time savings. Although slightly more complicated and more strenuous for respondents, this approach is much more informative than utilizing values of times derived from respondents' wage rate or stated preference results assuming common value for all individuals in the sample.

Our approach is different from those proposed so far in that we do not just extrapolate the appropriate wage rate based on the respondents' socio-economic data combined with other sources, nor any structural analysis of the value of time for our respondents. Our DCE questions are more flexible than those asked by others Fezzi, Bateman, and Ferrini (2014), in that they are general and not specific to our study. At the same time, this approach limits the scope of researcher judgment necessary to estimate the opportunity cost of travel time, and it reduces the need for external data to be combined with survey data in an attempt to calculate the opportunity cost of travel time in a structural way.

In light of the difficulties and ambiguities related to the opportunity cost of travel time, some authors decided not to incorporate time costs in their travel cost models (Hanley, Bell, and Alvarez-Farizo

2003, Fleming and Cook 2008, Alberini, Zanatta, and Rosato 2007, Alberini and Longo 2006).¹¹ One of the reasons for this approach is the apprehension that incorporating time might bias the coefficient on the price downwards. Another problem might be that time spent in travel might have a value on its own – travelling might be generating utility for some travelers (e.g., enjoying changing landscapes or deriving pleasure from using a particular means of transportation; Chavas, Stoll, and Sellar 1989). In our study, almost 45% of respondents were willing to pay to reduce their travel time. However, even though 55% declared they were not willing to pay anything, our results show that even the most common practice of assuming VTTS to equal 1/3 of wage rate, seems to underestimate the true travel cost, and hence consumer surplus. We found that the respondents' who were willing to pay to shorten their journey were willing to pay the amounts to a large extent not directly related to their hourly wage rate, and often more than the full hourly wage.

Our study indicates that it is not necessary nor adequate to use a fraction of hourly earnings because the opportunity cost of time can be measured more accurately by allowing respondents to express their preferences regarding the time they spend in travel. In this way, we move even further with the argument that the opportunity cost of travel time is defined endogenously – it is a function of visitor's characteristics. We explicitly account for the opportunity cost of travel time *perceived* by respondents, as opposed to the real cost of travel time they may incur (Amoako-Tuffour and Martínez-Espíñeira 2012). Such a flexible approach allows us to account for the fact that travel time is decided by each individual who can choose longer or shorter routes, taking into account the consumptive value of travel time. Indeed, the idea that the valuation of travel time is highly subjective was present in the discussion already since Cesario (1976). Indeed, we observed substantial heterogeneity in respondents' preferences in our study.

Many applied researchers are rather conservative in their assumptions about how much the opportunity cost of time might add to the value of a visited site and preferred to use the lower bounds of the wage rate (Neher, Duffield, and Patterson 2013). For example, Hynes, Hanley, and O'Donoghue (2009) suggested that it would be useful to determine individual opportunity costs of travel time to avoid a potential bias related to assuming an excessively high wage fraction as a reference. Meanwhile, a comparison of our approach with the key alternative specifications of the

¹¹ An alternative to using the opportunity cost of time was proposed by Shrestha, Seidl, and Moraes (2002) and later applied by Hanley and Barbier (2009). They included travel time in hours as an extra variable, alongside travel cost. The estimated time that respondents would be willing to spend in travel can then be translated into economic value, when combined with information about their willingness to pay money in a utility-theoretic framework (Larson, Shaikh, and Layton 2004). In addition to a travel cost model, one can also develop a separate model of transportation mode choice to estimate the value of travel time, providing information on how time is valued versus the cost of travel (Hausman, Leonard, and McFadden 1995).

opportunity cost of time show that recreationists may actually value their time higher than it has been expected so far. Consumer surplus calculated with the MXL model was almost twice as high as in the case of not including the travel time at all, and 1.78 as high as when the opportunity cost of travel time was assumed to be 1/3 of the wage rate. It was even 30% higher than if the opportunity cost of travel time equaled full wage rate.

More broadly, our study indicates a need to incorporate various components of the travel cost and to do so in a respondent-specific way. It also shows an opportunity to integrate different valuation methods and thus practically use the fact that they refer to different issues and can provide complementary information. Our empirical illustration of valuing recreational birdwatching in a stork village demonstrates the feasibility of this approach.

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