Estimates of the valuation of travel time savings in Switzerland obtained from pooled data

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ABSTRACT
Reliable measures of the valuation of travel time savings (VTTS) are a crucial input into policy planning in any regional or national context. However, the evidence from secondary or parallel VTTS studies often differs from those of official or national studies. In this paper, we present evidence from a study aimed at merging evidence from four separate VTTS studies conducted in Switzerland. The analysis shows the potential of models estimated jointly on the combined data, and produces very stable results that should be more representative of the overall population.

INTRODUCTION

Travel time savings provide the bulk of the benefits arising from network expansion and capacity additions. For this reason, official guidelines provide approved values to monetarise the predicted travel time savings. These official values are updated at regular intervals and are normally based on extensive empirical studies. However, the official values are only one piece of evidence on the valuation of travel times in a country or region as any concurrent or later study on route, mode, or destination choice will provide further estimates. The differences between these studies with respect to sampling frame, survey protocol, type of data (stated or revealed preference), modelling framework, variables considered or their functional form make direct comparison difficult, but nevertheless raise questions about each of the reported values, especially if the differences in valuation measures are substantial.

The Swiss case is rather typical. Next to an official value of travel time savings (VTTS) study *(1, 2)*, a range of further models have recently provided evidence on travel time valuation. In the present data, we complement the information from the official study (hereafter referred to as the SV study) with data from the ICN study *(3, 4)*, the Kanton study *(5)* and the mobility pricing study *(6, 7)*.

While standard meta-analysis (see for example Lipsey and Wilson *8*) is one approach to merge the information from multiple studies, it is not able to deal adequately with the non-linear effects that are inherent in the discrete choice models underlying the published values of time. These non-linearities relate for example to the substantial changes in VTTS resulting from small changes in model formulation, omitted variable biases, distributional assumptions in mixed logit formulations and other reasons. We also considered the use of Bayesian Belief Networks *(*cf. *9)*, but decided against this approach on the grounds of wanting to stay close to the original framework of the underlying studies. In this paper, we make use of the data combination framework discussed by Ben-Akiva and Morikawa *(10)*, allowing us to use of all the underlying data, while accounting in a systematic way for the differences between the studies.

The purpose of the work reported in this paper is two-fold. Firstly, we aim to explore the suitability of this data fusion approach for a large number of different datasets as set out in Section . Secondly, we aim to provide a consensus estimate of the VTTS for practical application in Switzerland. Given that conflicting evidence about the VTTS is the rule in most countries, this work will help to develop a coherent approach to the fusion of the evidence.

The remainder of this paper is organised as follows. Section presents the various datasets used in the analysis, with modelling methodology discussed in Section . This is followed in Section by a discussion of the estimation results on individual datasets, and in Section by a discussion of the results from the joint estimation. Finally, Section presents the conclusions of the research.

DATA

This study uses four different stated choice datasets which were collected in Switzerland between 2001 and 2006.

The first data set, referred to hereafter as the ICN data, served to predict the changes in travel demand due to the introduction of tilting trains on the Zürich to Lausanne line *(*cf. *3, 4)*. The dataset contains both mode and route choice experiments.

The second dataset, referred to hereafter as the Kanton data *(*cf. *5)*, was collected for the establishment of a new traffic assignment model for the Kanton of Zürich and was used to estimate its underlying route/mode choice parameters.

The third dataset was taken from the Mobility Pricing project *(*cf. *6, 7)* which aimed to

TABLE 1 Summary statistics for datasets used in analysis

	MZ 2000	ICN	Kanton	Mobility Pricing	SV
Date of the survey	2000	Jan-Sept'01	June-Oct'04	Aug '05-Jan'06	June-Oct'02
Number of respondents	27,918	1,042	191	1,987	1,188
Response rate	-	68%	71%	47%	53%
Route choice cases	-	6,454	1,518	3,927	9,606
Mode choice cases	-	7,301	-	9,625	5,784
Male respondents	49%	51%	55.9%	56%	59%
Car always available	77%	59%	61.00%	67.00%	73%
Car sometimes available	15%	22%	21.00%	20.00%	14%
Car never available	8%	19%	18%	13.00%	13%
Resp. with discount ticket	35%	43%	20.60%	41.60%	52%
Resp. with season ticket	6%	11%	9.00%	13.00%	11%
Av. annual income (CHF)	73100	n.a.	n.a.	94753	79816
Income $\leq$ 20k CHF	5.90%	n.a.	n.a.	6.40%	8.70%
Income 20k-40k CHF	14.80%	n.a.	n.a.	6.20%	10.00%
Income 40k-60k CHF	23.40%	n.a.	n.a.	12.60%	16.00%
Income 60k-80k CHF	18.60%	n.a.	n.a.	22.40%	18.90%
Income 80k-100k CHF	17.70%	n.a.	n.a.	19.70%	20.20%
Income 100k-125k CHF	9.50%	n.a.	n.a.	13.30%	12.70%
Income 125k-150k CHF	4.10%	n.a.	n.a.	9.20%	5.90%
Income $>$ 150k CHF	6.00%	n.a.	n.a.	10.30%	7.70%

deliver comprehensive insights into the outcome of a possible introduction of different types of pricing initiatives. Here, we make use of three subsets of the data; one route and departure time experiment and two mode choice experiments, one combined with departure time choice, the other with route choice.

The fourth dataset, referred to hereafter as the SV data (cf. *1, 2*), was designed to estimate the value of travel time savings for Switzerland which were needed in the framework of the new Swiss cost-benefit norms *(11)*. The questionnaire consisted of one route choice and one mode choice experiment.

In line with current practice (see Louviere *et al. 12* or recent European studies such as HCG *13, 14*, Algers *et al. 15*, Kurri and Pursula *16*, Ramjerdi *et al. 17*, Jovicic and Hansen *18* and Mackie *et al. 19*), the SP surveys were based on information from observed trips, with the exception of the Kanton data, where, due to the divergent scope in terms of geographical scale, only 31% of the experiments are based on revealed trips. Table 1 presents some key statistics for the various datasets and compares them with the representative Swiss National Travel Survey *(20)*, or *Mikrozensus* of the year 2000 (MZ 2000). Over all datasets it is obvious that males with public transport season cards and higher incomes are more likely to participate, though this varies over the different studies. As a final observation, it should also be noted that the trips in the ICN and Kanton datasets are on average longer than in the other two datasets.

MODELLING METHODOLOGY

The analysis presented in this paper makes use of standard discrete choice methodology (cf. *21)*, where specifically, we make use of Multinomial Logit (MNL) models. However, there are two important departures from the basic MNL model, in the form of a continuous interaction specification, and in allowing for differences in scale across datasets and subsets within individual datasets. We will now look at these two issues in turn. All models were estimated using BIOGEME *(cf 22)*.

Continuous interactions

In this paper, we make use of a continuous interaction formulation discussed in detail by Mackie *et al. (19)*, and used for example by Hess *et al. (23)* and Axhausen *et al. (2)*. This approach was used as an alternative to simple (and arbitrary) segmentations into different income and distance classes with separate coefficients in different classes. It is a very powerful tool for allowing for deterministic taste heterogeneity, where this is not only preferable for interpretation issues, but in the case of very large datasets has major estimation advantages over random coefficients approaches.

The continuous specification takes the following form:

$$f(y,x) = \beta_x \left(\frac{y}{\hat{y}}\right)^{\lambda_{y,x}} x, \tag{1}$$

where y is the observed value for a given socio-demographic variable, such as income or trip distance, and $\hat{y}$ is a reference value for this attribute, such as the mean value across a sample population. In this example, the sensitivity to an alternative's attribute x varies with y. The choice of the reference value $\hat{y}$ is arbitrary, and has no effect on model fit, or the estimate for $\lambda_{y,x}$. However, the use of the mean value, $\bar{y}$, guarantees that the estimate β_x gives the sensitivity to x at the average value of y in the sample population[1], and helps to stabilise the estimation. The estimate of $\lambda_{y,x}$ gives the elasticity of the sensitivity to x with respect to changes in y; with negative values for $\lambda_{y,x}$, the (absolute) sensitivity decreases with increases in y, with the opposite applying in the case of positive values for $\lambda_{y,x}$. Finally, the rate of the interaction is determined by the absolute value of $\lambda_{y,x}$, where a value of 0 indicates a lack of interaction.

In the present analysis, this approach was used to test for interactions with income and distance, where we used CHF$80,000$ as the base income, with 40km being used as the base distance.

Allowing for differences in scale

When estimating models on data from different sources, it is important to allow for differences in scale across data sources. Indeed, the relative weight of the observed and unobserved parts of utility may vary significantly across datasets, for example as a result of more or less randomness in the choice processes. However, these differences are not just limited to different data sources, but also extend to data from the same sample, but collected with different sub-surveys. As an example, the weight of the unobserved part of utility may be different between a route choice survey and a mode choice survey.

With the formulation used in BIOGEME, the following specification arises. Let $U_{i,d}$ give the utility of alternative i with sample d, where $d = 1, \ldots, D$. Then, we have:

$$\begin{aligned} U_{i,1} &= V_{i,1} + \varepsilon_{i,1} \\ &\ldots \\ U_{i,d} &= V_{d,1} + \varepsilon_{i,d} \\ &\ldots \\ U_{i,D} &= V_{i,D} + \varepsilon_{i,D}, \end{aligned} \tag{2}$$

[1]With $y = \hat{y}$, the term $\left(\frac{y}{\hat{y}}\right)^{\lambda_{y,x}}$ disappears from equation 1.

where $var\left(\varepsilon_{i,d}\right) = \frac{\pi^2}{6\mu_d^2}$.

Using sample 1 as the arbitrary base, we then multiply the utility functions in group d by α_d, where we set $\alpha_1 = 1$. In detail, we then have:

$$\begin{aligned} U_{i,1} &= V_{i,1} + \varepsilon_{i,1} \\ &\ldots \\ \alpha_d\, U_{i,d} &= \alpha_d\, V_{i,d} + \alpha_d\, \varepsilon_{i,d} \\ &\ldots \\ \alpha_D\, U_{i,D} &= \alpha_D\, V_{i,D} + \alpha_D\, \varepsilon_{i,D}. \end{aligned} \tag{3}$$

For estimation as a homoscedastic model, we thus obtain that:

$$var\left(\varepsilon_{i,1}\right) = \alpha_d^2\, var\left(\varepsilon_{i,d}\right). \tag{4}$$

This gives us that:

$$\alpha_d^2 = \frac{var\left(\varepsilon_{i,1}\right)}{var\left(\varepsilon_{i,d}\right)}, \tag{5}$$

which in turn reduces to:

$$\alpha_d = \frac{\mu_d}{\mu_1}. \tag{6}$$

This means that if the estimate for α_d is larger than 1, then the variance of the unobserved utility components in sample d is smaller than in the base sample, with the converse applying if α_d is smaller than 1.

In our analysis, we allow for differences in scale across the various datasets used in the joint models, where we however also allow for differences in scale within datasets, with a division by survey. The expectation would be for the differences across datasets to be larger than the differences within datasets, though exceptions to this rule may exist.

EMPIRICAL ANALYSIS: INDIVIDUAL MODELS

This section presents the estimation results for the dataset-specific models, where in each case, a linear model was estimated alongside the model using the elasticity specification. In each case, other than the continuous interaction terms, a linear-in-attributes specification of the utility function was used, and no segmentations by trip purpose were used at this stage. All t-ratios are calculated using a robust sandwich estimator, with a base value of zero for all parameters other than the α terms, where a base value of 1 was used.

ICN models

The first dataset to be used in the analysis is the ICN data, where we use information on $13,755$ observations collected from $1,042$ respondents taking part in mode choice and route choice experiments, with slightly more observations for the former ($7,301$ compared to $6,454$). The mode choice group was used as the base, such that only $\alpha_{\text{route choice}}$ was estimated. The results of the estimation are summarised in Table 2.

A range of standard marginal utility coefficients were estimated, including the sensitivity to interchanges (β_{changes}), fuel as car running cost (β_{fuel}), headway (β_{HW}), public transport (PT) fare ($\beta_{\text{TC-PT}}$), PT access and transfer time ($\beta_{\text{TT-access}}$ and $\beta_{\text{TT-transfer}}$) and car and PT travel time ($\beta_{\text{TT-car}}$ and $\beta_{\text{PT-car}}$). Additionally, we allowed for an interaction between age and the preference

TABLE 2 Estimation results on ICN data

	Lin. model		Elast. Model	
Observations	13755		13755	
Respondents	1042		1042	
Final LL:	7644.78		7587.86	
par:	22		30	
adj. R	0.01959		0.201	
	est.	asy. t.-rat.	est.	asy. t.-rat.
$\lambda_{\text{changes,dist}}$	-	-	-0.0876	-1.68
$\lambda_{\text{fuel,dist}}$	-	-	-0.2800	-2.69
$\lambda_{\text{HW,dist}}$	-	-	-0.1810	-1.97
$\lambda_{\text{TC-PT,dist}}$	-	-	-0.3871	-7.22
$\lambda_{\text{TT-access,dist}}$	-	-	-0.3245	-4.30
$\lambda_{\text{TT-car,dist}}$	-	-	-0.2734	-3.93
$\lambda_{\text{TT-PT,dist}}$	-	-	-0.2020	-3.62
$\lambda_{\text{TT-transfer,dist}}$	-	-	-0.1911	-1.15
$\alpha_{\text{mode choice}}$	1.00	-	1.00	-
$\alpha_{\text{route choice}}$	2.27	8.14	2.26	8.08
WTP indicators				
TT-car	13.03		13.32	
TT-PT	17.32		14.94	
HW	8.72		7.31	
changes	33.69		24.72	
TT-transfer	5.05		4.01	
TT-access	5.97		4.51	

for PT ($\beta_{\text{age-PT}}$) as well as reliability (delay) effects for either mode ($\beta_{\text{rel-car}}$ and $\beta_{\text{rel-PT}}$).

Alternative specific constants (ASC) were estimated for car in the mode choice experiment (δ_{car}) and the first route in the route choice experiment ($\delta_{\text{route 1}}$). Additionally, we allowed for effects of season ticket and discount ticket ownership for public transport ($\delta_{\text{PT-GA}}$ and $\delta_{\text{PT-HT}}$), car availability ($\delta_{\text{car-car available}}$), and the impact of sex and employment status on the preference for PT ($\delta_{\text{PT-male}}$ and $\delta_{\text{PT-employed}}$). Finally, different rolling-stock constants were also used ($\delta_{\text{PT-comfort 2}}$, $\delta_{\text{PT-comfort 3}}$ and $\delta_{\text{PT-comfort 4}}$).

In terms of non-linear effects, only interactions with trip distance could be allowed for in the absence of income information. Here, we retrieved significant negative interactions, i.e. decreasing sensitivities with distance for β_{fuel}, β_{HW}, $\beta_{\text{TC-PT}}$, $\beta_{\text{TT-access}}$, $\beta_{\text{TT-car}}$ and $\beta_{\text{TT-PT}}$, with interaction effects significant at lower levels of confidence for β_{changes} and $\beta_{\text{TT-transfer}}$.

In terms of actual results, we can see that the VTTS for PT is higher than for car, where the difference is smaller in the elasticity model. The valuation of savings in access time is the highest, while savings in transfer time and headway are much lower. The sensitivity to PT fares decreases more rapidly with distance than the sensitivity to car running costs, while the sensitivity to car travel time decreases more rapidly than the sensitivity to PT travel time,

TABLE 3 Estimation results on Kanton data

	Lin. model		Elast. Model	
Observations	1518		1518	
Respondents	191		191	
Final LL:	-777.66		-721.84	
par:	12		30	
adj. R	0.2495		0.2969	
	est.	asy. t.-rat.	est.	asy. t.-rat.
$\lambda_{\text{changes,dist}}$	-	-	-0.4025	-2.84
$\lambda_{\text{HW,dist}}$	-	-	-0.6297	-4.72
$\lambda_{\text{TC-PT,dist}}$	-	-	-0.7099	-8.40
$\lambda_{\text{TT-access,dist}}$	-	-	-0.2555	-1.95
$\lambda_{\text{TT-PT,dist}}$	-	-	-0.6569	-6.66
$\lambda_{\text{TT-transfer,dist}}$	-	-	-0.1723	-0.62
WTP indicators				
PT travel time	10.1		9.52	
transfer time	11.33		5.86	
access time	26.05		14.09	
headway	7.31		4.71	
interchanges	5.01		2.69	

with the most rapid reduction being observed for access time, suggesting that more outlying departure points become more acceptable on longer journeys. Finally, we can see that the variance of the error term is larger for mode choice than for route choice.

Kanton models

We next look at the results of the estimation on the Kanton dataset, where $1,518$ observations from 191 respondents completing a PT route choice survey were used, where there is also some variation in the type of PT vehicle. The results of this estimation are summarised in Table 3.

The main marginal utility coefficients used in the specification are again the same as for the PT alternative in the ICN data. In addition, an ASC (δ_1) was used for the first alternative, while the type of PT vehicle is accommodated with five additional constants (δ_{bus}, δ_{ICN}, δ_{regional}, $\delta_{\text{s-train}}$, δ_{tram}) with standard train used as the basis.

Again, no income information was available, and distance interactions were retrieved for all six marginal utility coefficients with decreasing marginal sensitivities with increasing distance in each case.

The willingness to pay (WTP) indicators are lower in the elasticity models (at base values for income and distance) than in the linear models, where the decreases are especially marked for transfer time and access time.

Mobility pricing models

Table 4 summarises the estimation results on the mobility pricing data, where $13,552$ observations from $1,987$ respondents were used. Here, two separate mode choice experiments were

TABLE 4 Estimation results on mobility pricing data

	Lin. model		Elast. Model	
Observations	13522		13522	
Respondents	1987		1987	
Final LL:	-6162.05		-6041.6	
par:	28		35	
adj. R	0.341		0.3531	
	est.	asy. t.-rat.	est.	asy. t.-rat.
$\lambda_{\text{changes,dist}}$	-	-	0.0262	-0.27
$\lambda_{\text{HW,dist}}$	-	-	-0.4080	-4.22
$\lambda_{\text{parking,inc}}$	-	-	-0.2276	-1.63
$\lambda_{\text{TC-PT,inc}}$	-	-	-0.2349	-1.72
$\lambda_{\text{toll,dist}}$	-	-	-0.0968	-0.88
$\lambda_{\text{TT-car,dist}}$	-	-	-0.4209	-5.57
$\lambda_{\text{TT-PT,dist}}$	-	-	-0.4055	-9.02
WTP indicators				
car travel time	27.70		27.73	
PT travel time	28.33		32.08	
access time	85.22		64.07	
headway	10.02		7.07	
interchanges	4.93		3.94	

used, along with one route choice experiment.

The main marginal utility coefficients are again the same as in the two previous analyses. However, a large number of additional parameters were estimated. First, $\beta_{\text{car-km}}$ was used to capture the effect of increased annual distances travelled on the utility of the car alternatives in the mode choice surveys. Two additional cost components were also used for the car alternatives, namely parking cost and toll, with coefficients $\beta_{\text{parking cost}}$ and β_{toll} respectively. Here, respondents' attitude towards road pricing is also accommodated through $\beta_{\text{pricing attitude}}$. Schedule delay sensitivities are also included, where separate early coefficients were used for mode choice and route choice, with $\beta_{\text{SDE mode choice}}$ and $\beta_{\text{SDE route choice}}$, with a single late coefficient β_{SDL}. This approach was adopted due to results showing a positive sensitivity to early arrival in the route choice experiments, which could be related to untolled travel at earlier departure times. Constants were associated with the car alternatives in the two mode choice surveys ($\delta_{\text{car 1}}$ and $\delta_{\text{car 2}}$), and with the first alternative in the route choice survey ($\delta_{\text{route 1}}$). Finally, respondents' region of origin was allowed to have an impact on the utility of the car alternative ($\delta_{\text{car french}}$ and $\delta_{\text{car german}}$), while $\delta_{\text{PT-full time}}$ captures an additional effect for PT for full-time employees.

With this data, income and distance information was available, and significant income effects were retrieved for parking cost, road tolls and public transport cost, but not for running cost (fuel) for cars. Decreasing sensitivities with increasing distance were again found for interchanges, headway and the travel time components for car and PT.

Looking at the WTP indicators, the differences between car and PT are very small in the linear model, but increase in the elasticity models, where in both cases, the VTTS for PT is

TABLE 5 Estimation results on SV data

	Lin. model	Elast. Model
Observations	15390	15390
Respondents	1188	1188
Final LL:	-7419.8	-7006.23
par:	21	29
adj. R	0.3025	0.3405

	est.	asy. t.-rat.	est.	asy. t.-rat.
$\lambda_{\text{change,dist}}$	-	-	-0.1478	6.26
$\lambda_{\text{fuel,dist}}$	-	-	-0.5658	14.77
$\lambda_{\text{fuel,inc}}$	-	-	-0.1772	5.27
$\lambda_{\text{HW,dist}}$	-	-	-0.2658	9.71
$\lambda_{\text{TC-PT,dist}}$	-	-	-0.7069	29.37
$\lambda_{\text{TC-PT,inc}}$	-	-	-0.1093	3.53
$\lambda_{\text{TT-car,dist}}$	-	-	-0.4848	10.39
$\lambda_{\text{TT-PT,dist}}$	-	-	-0.3600	14.05

WTP indicators		
car travel time	36.18	32.70
PT travel time	27.34	22.74
headway	17.29	10.85
interchanges	8.67	5.65

higher. The VTTS for access time is again very high, although it drops in the elasticity models. Finally, with the present data, the differences in scale between surveys are not significant at any reasonable levels of confidence.

SV study models

The final dataset to be used is the data from the SV Swiss Value of Time study. Here, we make use of $15,390$ observations, collected from $1,188$ respondents. The data come from a car-train mode choice experiment and 4 route choice experiments; three for train and one for car. The estimation results are summarised in Table 5.

Along with the same coefficients already used for the previous datasets, we now also account for the effects of congestion ($\beta_{\text{congestion}}$) and car user inertia ($\delta_{\text{car inertia}}$), as well as male preference or otherwise for car ($\delta_{\text{car male}}$). Constants are used for the rail alternative in the mode choice survey (δ_{rail}), and for the first route in each of the route choice surveys ($\delta_{\text{route 1}}$, $\delta_{\text{route 2}}$, $\delta_{\text{route 3}}$ and $\delta_{\text{route 4}}$).

In the elasticity models, income for income and trip distance was again available. Decreasing sensitivities with increasing distance were observed for the sensitivities to interchanges, fuel (running costs), headway, PT fares and car and PT travel times. Decreasing sensitivities with increasing income were observed for both cost components.

In terms of scale, we observe greater error variance in the mode choice experiment, while the variance is lowest in the second route choice experiment, which is a car route choice experiment.

Finally, in terms of implied WTP indicators, we observe higher VTTS for car than for PT, while all valuations are lower in the elasticity models when using the afore mentioned base values for income and trip distance.

EMPIRICAL ANALYSIS: JOINT MODELS

In this section, we present the estimation results on the combined dataset. After putting together data from the four individual samples, we obtain a final sample of $44,215$ observations collected from $4,408$ respondents. The estimation results for the resulting models are summarised in Table 6.

The utility specification used in the joint model is based on the individual utility specifications from the dataset-specific models. For each coefficient used in the joint model, Table 6 highlights which dataset-specific utility functions included a given coefficient[2].

Alternative-specific constants still remain dataset-specific, as do some of the dummy interactions with age and other socio-demographic variables. The parameters shared across models are the main marginal utility coefficients and the interaction parameters. Finally, for the scale parameters, the ICN mode choice experiment was used as the base.

We now proceed with our analysis of the actual estimation results, comparing the results from the individual models to those from the joint models.

We begin our comparison by looking at model fit performance, with results summarised in Table 8. The first observation relates to the increases in model fit when moving from the linear models to the elasticity models. Here, we obtain increases in log-likelihood (LL) by between 55.82 units and 618.70 units, which, with increases in the number of parameters between 6 and 12 are all highly significant. This shows the benefits in terms of model performance of allowing for continuous interactions with income and trip distance.

Looking at relative performance across datasets in terms of the adjusted ρ^2 measure, we can see that the best performance is obtained with the mobility pricing data, ahead of the SV data, while the poorest performance is obtained with the ICN data. The advantage of the mobility pricing data over the SV data reduces in the elasticity models given the greater success with this specification in the SV analysis.

A first indication of the performance of the joint models is given by looking at the adjusted ρ^2 measure, where we can see that the model produces performance that is better than that for the ICN data and the Kanton data (only in the linear models), but which is below that obtained with the mobility pricing and SV datasets. A more formal approach is based on a test discussed by Louviere *et al. (12)*, section 8.4.1, which is essentially a likelihood ratio test. Here, we obtain test values of 367.02 and 422.94 for the linear and elasticity models respectively, with critical $\chi^2_1 6$ and $\chi^2_3 3$ values of 26.3 and 47.4 respectively. This means that the homogeneity assumption is rejected rather comprehensively, showing that there are differences between individual datasets that the joint model is not able to accommodate, even with the help of the income and distance interactions. This does not come entirely as a surprise given the earlier discussion about the potential differences between data sources. As such, there is clear evidence of such differences, and the joint model should be seen as being more representative of the overall data than any of the individual models.

The next step in the comparison looks at the various WTP indicators calculated from the model results, with findings summarised in Table 9. Here, it should be noted again that the WTP indicators calculated for the elasticity models are for an annual income of CHF$80,000$

[2]It should be noted that an iterative approach had to be used in the calculation of the standard errors in the elasticity based model, with a covariance matrix calculated separately for the main parameters and for the scale parameters.

TABLE 6 Estimation results on combined data: Part I

					Linear model		Elasticity model	
				Observations:	44,215		44,215	
				Respondents:	4,408		4,408	
				Final LL:	-22,187.80		-21,569.10	
				par:	67		79	
				adj. ρ^2	0.2738		0.2940	
ICN	Kanton	Mob.	SV					
X				$\beta_{\text{age-PT}}$	0.0055	3.06	0.0050	2.79
		X		$\beta_{\text{age-PT}}$	0.0111	6.73	0.0125	9.36
		X		$\beta_{\text{car-km}}$	0.0271	7.14	0.0283	12.97
X	X	X	X	β_{changes}	-0.3207	-16.62	-0.3340	-43.36
			X	$\beta_{\text{congestion}}$	-0.0145	-6.85	-0.0148	-9.75
X		X	X	β_{fuel}	-0.0414	-13.70	-0.0619	-28.66
X	X	X	X	β_{HW}	-0.0093	-15.94	-0.0092	-30.42
		X		$\beta_{\text{parking cost}}$	-0.1957	-11.12	-0.2227	-14.33
		X		$\beta_{\text{pricing attitude}}$	5.8600	7.28	6.2197	30.21
X				$\beta_{\text{rel-car}}$	-0.0061	-1.47	-0.0053	-1.28
		X		$\beta_{\text{rel-car}}$	-0.0323	-5.55	-0.0343	-8.23
X				$\beta_{\text{rel-PT}}$	-0.0067	-1.64	-0.0048	-1.17
		X		$\beta_{\text{rel-PT}}$	-0.0151	-2.34	-0.0151	-2.04
		X		$\beta_{\text{SDE mode choice}}$	-0.0064	-4.27	-0.0065	-5.03
		X		$\beta_{\text{SDE route choice}}$	0.0049	2.69	0.0049	2.98
		X		β_{SDL}	-0.0129	-6.05	-0.0153	-9.72
X	X	X	X	$\beta_{\text{TC-PT}}$	-0.0494	-17.85	-0.0721	-44.25
		X		β_{toll}	-0.1080	-15.93	-0.1202	-29.95
X	X	X		$\beta_{\text{TT-access}}$	-0.0455	-11.06	-0.0450	-11.93
X		X	X	$\beta_{\text{TT-car}}$	-0.0259	-20.37	-0.0335	-46.07
X	X	X	X	$\beta_{\text{TT-PT}}$	-0.0183	-20.13	-0.0245	-49.94
X	X			$\beta_{\text{TT-transfer}}$	-0.0153	-4.87	-0.0168	-5.89
	X			δ_{bus}	-0.5127	-1.61	-0.3875	-1.00
		X		$\delta_{\text{car 1}}$	0.3819	2.65	0.2029	1.40
		X		$\delta_{\text{car 2}}$	0.2024	1.28	0.0868	0.56
X				$\delta_{\text{car available}}$	0.7635	10.34	0.7257	9.69
		X		$\delta_{\text{car available}}$	0.4297	8.54	0.4746	9.76
		X		$\delta_{\text{car french}}$	-0.1512	-1.15	-0.1759	-1.29
		X		$\delta_{\text{car german}}$	-0.5032	-4.08	-0.4760	-3.80
			X	$\delta_{\text{car inertia}}$	0.7288	7.63	0.5529	8.65
			X	$\delta_{\text{car male}}$	-0.0970	-1.96	-0.0743	-1.29
X				δ_{car}	-0.2837	-1.75	-0.2231	-1.45
			X	$\delta_{\text{car-car available}}$	0.2115	3.45	0.1954	2.82
	X			δ_{ICN}	-0.0164	-0.15	0.0286	0.30
X				$\delta_{\text{PT-comfort 2}}$	0.2122	5.15	0.2159	5.63
X				$\delta_{\text{PT-comfort 3}}$	0.2634	7.06	0.2647	8.48
X				$\delta_{\text{PT-comfort 4}}$	0.2288	5.42	0.2319	6.13

TABLE 7 Estimation results on combined data: Part II

ICN	Kanton	Mob.	SV					
X				$\delta_{\text{PT-employed}}$	-0.1396	-2.14	-0.1012	-1.59
		X		$\delta_{\text{PT-full time}}$	0.0658	1.47	0.0690	1.47
X				$\delta_{\text{PT-GA}}$	1.6774	18.04	1.5871	16.48
		X		$\delta_{\text{PT-GA}}$	1.1091	12.14	1.1526	17.01
			X	$\delta_{\text{PT-GA}}$	0.7412	6.37	0.6083	5.66
X				$\delta_{\text{PT-HT}}$	0.9482	15.50	0.8772	14.00
		X		$\delta_{\text{PT-HT}}$	0.5387	9.94	0.5851	11.62
			X	$\delta_{\text{PT-HT}}$	0.5867	7.23	0.5400	8.41
X				$\delta_{\text{PT-male}}$	-0.1989	-3.48	-0.1748	-2.98
			X	δ_{rail}	0.1537	1.89	0.1814	1.84
	X			δ_{regional}	-0.0236	-0.23	0.0399	0.41
X				$\delta_{\text{route 1}}$	0.1406	6.79	0.1363	8.09
		X		$\delta_{\text{route 1}}$	4.3117	7.62	4.7002	29.37
			X	$\delta_{\text{route 1}}$	-0.0093	-0.39	-0.0174	-0.47
			X	$\delta_{\text{route 2}}$	0.0115	1.37	0.0148	1.63
			X	$\delta_{\text{route 3}}$	0.0176	1.02	0.0263	1.22
			X	$\delta_{\text{route 4}}$	-0.0048	-0.41	-0.0049	-0.42
	X			$\delta_{\text{s-train}}$	-0.0424	-0.59	0.0320	0.47
	X			δ_{tram}	-0.0845	-0.24	-0.1476	-0.39
	X			δ_1	-0.1002	-1.52	-0.0231	-0.39
		X		$\lambda_{\text{parking,inc}}$	-	-	-0.2360	-2.60
X	X		X	$\lambda_{\text{TC-PT,dist}}$	-	-	-0.6527	-51.00
		X	X	$\lambda_{\text{TC-PT,inc}}$	-	-	-0.1193	-5.63
		X		$\lambda_{\text{toll,inc}}$	-	-	-0.0011	-0.03
X	X			$\lambda_{\text{TT-access,dist}}$	-	-	-0.3055	-6.78
X		X	X	$\lambda_{\text{TT-car,dist}}$	-	-	-0.4156	-24.59
X	X	X	X	$\lambda_{\text{TT-PT,dist}}$	-	-	-0.3835	-25.73
X	X			$\lambda_{\text{TT-transfer,dist}}$	-	-	-0.2287	-1.44
				$\alpha_{\text{ICN mode choice}}$	1.00	-	1.00	-
				$\alpha_{\text{ICN route choice}}$	3.63	10.60	3.78	23.65
				α_{Kanton}	1.91	6.35	1.93	14.76
				$\alpha_{\text{Mob. pricing mode choice 1}}$	2.73	6.93	2.09	9.50
				$\alpha_{\text{Mob. pricing mode choice 2}}$	4.70	5.20	4.36	13.49
				$\alpha_{\text{Mob. pricing route choice}}$	3.06	8.64	2.53	14.95
				$\alpha_{\text{SV mode choice}}$	1.64	3.11	1.97	13.04
				$\alpha_{\text{SV route choice 1}}$	1.35	3.95	1.21	6.15
				$\alpha_{\text{SV route choice 2}}$	1.26	3.31	1.17	4.94
				$\alpha_{\text{SV route choice 3}}$	1.10	0.64	1.05	1.54
				$\alpha_{\text{SV route choice 4}}$	1.61	4.36	1.45	12.15

WTP indicators		
TT-car	37.47	32.45
TT-PT	22.21	20.38
HW	11.35	7.66
changes	6.50	4.63
TT-transfer	18.56	13.95
TT-access	55.36	37.43

TABLE 8 Model fit comparison for individual and joint models

Linear models

	Null LL	Final LL	par	adj. ρ^2
ICN data	-9,534.24	-7,644.78	22	0.1959
Kanton data	-1,052.20	-777.66	12	0.2495
Mobility pricing data	-9,393.53	-6,162.05	28	0.3410
SV data	-10,667.50	-7,419.80	21	0.3025
Joint model	-30,647.50	-22,187.80	67	0.2738

Elasticity models

	Null LL	Final LL	par	adj. ρ^2
ICN data	-9,534.24	-7,587.86	30	0.2010
Kanton data	-1,052.20	-721.84	18	0.2969
Mobility pricing data	-9,393.53	-6,041.60	35	0.3531
SV data	-10,667.50	-7,006.33	29	0.3405
Joint model	-30,647.50	-21,569.10	79	0.2936

TABLE 9 Comparison of WTP indicators across models (all in CHF/hr, except for CHF/change for reduction in the number of interchanges

Linear models

	Car TT	PT TT	HW	Trans. time	Acc. time	Changes
ICN data	13.03	17.32	5.05	8.72	33.69	5.97
Kanton data	-	10.10	7.31	11.33	26.05	5.01
Mobility pricing data	27.70	28.33	10.02	-	85.22	4.93
SV data	36.18	27.34	17.29	-	-	8.67
Joint model	37.47	22.21	11.35	18.56	55.36	6.50

Elasticity models

	Car TT	PT TT	HW	Trans. time	Acc. time	Changes
ICN data	13.32	14.94	4.01	7.31	24.72	4.51
Kanton data	-	9.52	4.71	5.86	14.09	2.69
Mobility pricing data	27.73	32.08	7.07	-	64.07	3.94
SV	32.70	22.74	10.85	-	-	5.65
Joint model	32.45	20.38	7.66	13.95	37.43	4.63

and a trip distance of 40km, while the results for the individual models are for the average individual in the various samples.

Perhaps the most interesting finding is the ranking of the VTTS components for car and PT. Here, we find that the PT VTTS is higher than the car VTTS in the ICN and mobility pricing models, while the converse is the case in the SV models. In the joint models, the VTTS for car is much higher than that for PT, with the difference being greater than in the SV models, which is very striking indeed. A similarly interesting observation can be made for transfer time, where the valuations in the joint models are higher than those in the individual models. For the

TABLE 10 Comparison of interaction terms across models (asy. t-ratios in brackets

	ICN	Kanton	Mobility pricing	SV	Joint models
$\lambda_{\text{changes,dist}}$	-0.09 (-1.68)	-0.4 (-2.84)	-0.03 (-0.27)	-0.15 (-6.27)	-0.14 (-10.07)
$\lambda_{\text{fuel,dist}}$	-0.28 (-2.69)	-	-	-0.57 (-14.77)	-0.66 (-33.16)
$\lambda_{\text{fuel,inc}}$	-	-	-	-0.18 (-5.27)	-0.16 (-5.85)
$\lambda_{\text{HW,dist}}$	-0.18 (-1.97)	-0.63 (-4.72)	-0.41 (-4.22)	-0.27 (-9.71)	-0.31 (-16.25)
$\lambda_{\text{parking,inc}}$	-	-	-0.23 (-1.63)	-	-0.24 (-2.6)
$\lambda_{\text{TC-PT,dist}}$	-0.39 (-7.22)	-0.71 (-8.4)	-	-0.71 (-29.37)	-0.65 (-51)
$\lambda_{\text{TC-PT,inc}}$	-	-	-0.23 (-1.72)	-0.11 (-3.53)	-0.12 (-5.63)
$\lambda_{\text{toll,inc}}$	-	-	-0.1 (-0.88)	-	0 (-0.03)
$\lambda_{\text{TT-access,dist}}$	-0.32 (-4.3)	-0.26 (-1.95)	-	-	-0.31 (-6.78)
$\lambda_{\text{TT-car,dist}}$	-0.27 (-3.93)	-	-0.42 (-5.57)	-0.48 (-10.39)	-0.42 (-24.59)
$\lambda_{\text{TT-PT,dist}}$	-0.2 (-3.62)	-0.66 (-6.66)	-0.41 (-9.02)	-0.36 (-14.05)	-0.38 (-25.73)
$\lambda_{\text{TT-transfer,dist}}$	-0.19 (-1.15)	-0.17 (-0.62)	-	-	-0.23 (-1.44)

remaining three indicators, the valuations from the joint models are roughly weighted averages across the individual models.

As a final point, we look at the estimates of the continuous interaction terms across models. As discussed in Section , these terms give the elasticity in a given marginal utility coefficient relative to changes in income or trip distance. Here, we can see that the results from the joint model are in general very close to the results from the SV model, and, with the exception of $\lambda_{\text{toll,inc}}$ and $\lambda_{\text{TT-transfer,dist}}$, all estimates in the joint model are highly significant. In detail, we can see that the sensitivities to car and PT travel time decrease at a very similar rate with increasing trip distance, with lower rates for access time and transfer time. Also, the elasticities for travel cost are very similar across the two modes, which lends some extra weight to the findings from the joint model.

PURPOSE-SPECIFIC MODELS

As a next step in our analysis, the generic models from Section are replaced by purpose-specific models, where the sample population is divided into commuters, business travellers, leisure travellers and respondents on shopping trips. In each case, a linear model was estimated alongside the model using the elasticity formulation. A small difference arises between the data used in this analysis and the analysis in Section , in that one respondent (accounting for 9 observations) had to be removed from the data. This respondent was in the business segment but was the only respondent facing the first of the public transport route choice experiments in the SV data, leading to issues in the estimation of an associated scale parameter. For this reason, likelihood ratio tests cannot be used and comparisons are based on the adjusted ρ^2 measure.

Commuter models

The results for the commuter models as well as for the other travel purposes estimated on the pooled data are summarised in Table 11. Here, the full set of parameters from the cross-purpose models was retained. The elasticity model comprehensively outperforms the linear model. The model performance is superior to that of the cross-purpose model in terms of the adjusted ρ^2 measure. In these models, the transfer time coefficient ($\beta_{\text{TT-transfer}}$) is not significant adj. ρ^2

TABLE 11 Estimation results on combined data separated by purpose

	Commuters		Business	
	Lin. model	Elast. Model	Lin. model	Elast. Model
Observations	10158	10158	4529	4529
Respondents	1028	1028	512	512
Final LL:	-4750.50	-4600.23	-2784.61	-1960.24
par:	67	79	62	74
adj. ρ^2	0.3158	0.3354	0.3400	0.3520
WTP indicators				
TT-car	28.7	31.48	106.9	43.3
TT-PT	21.35	22.95	47.15	36.18
HW	7.26	6.81	14.07	9.42
changes	3.38	3.41	7.54	3.92
TT-transfer	3.64	8.62	55.62	53.62
TT-access	23.43	20.81	86.42	58.7

	Leisure		Shopping	
	Lin. model	Elast. Model	Lin. model	Elast. Model
Observations	23168	26168	6351	6351
Respondents	2218	2218	649	649
Final LL:	-12069.62	-11799.40	-2784.61	-2711
par:	63	75	66	78
adj. ρ^2	0.2440	0.2606	0.3525	0.3665
WTP indicators				
TT-car	31.19	25.69	33.39	45.9
TT-PT	18.55	16.39	15.93	23.02
HW	9.53	6.59	6.21	7.17
changes	6.97	4.51	2.94	4.52
TT-transfer	13.45	12.16	18.28	18.49
TT-access	47.15	32.51	20.59	27.75

Business models
The results for the business models estimated on the pooled data are summarised in Table 11. Here, some simplifications in the utility functions were required, and compared to the cross-purpose models, five parameters were dropped, namely δ_{bus}, δ_{car}, $\delta_{\text{PT-employed}}$, $\delta_{\text{route 1}}$ and δ_{tram}. The elasticity model again outperforms the linear model, and the overall model performance is superior to that of the cross-purpose model in terms of the adjusted ρ^2 measure.

Leisure models
The results for the leisure models estimated on the pooled data are summarised in Table 11. Here, some simplifications in the utility functions were required, and compared to the cross-purpose models, four parameters were dropped, namely δ_{bus}, δ_{car}, $\delta_{\text{PT-employed}}$ and δ_{tram}. The elasticity model again outperforms the linear model; however, the overall model performance

is now inferior to that of the cross-purpose model in terms of the adjusted ρ^2 measure.

Shopping models

The results for the shopping models estimated on the pooled data are summarised in Table 11. Here, one simplification in the utility functions was required, and compared to the cross-purpose models, one parameter was dropped, namely δ_{tram}. The elasticity model again outperforms the linear model and the overall model performance is again superior to that of the cross-purpose model in terms of the adjusted ρ^2 measure.

REWEIGHTING

As a final step in the analysis, the WTP estimates produced in Section were reweighted to the population level in terms of income and trip distance classes. The results of this process are summarised in Table 12, where we also give the standard deviation for the indicators[3]. Overall, the indicators are significantly lower than in the sample, which is mainly down to shorter trips in the overall population (average of 11.5km). The low WTP for transfer time for commuters should be put into context by the high standard error for $\beta_{\text{TT-transfer}}$. The high values for access time and transfers for business is mainly due the highly negative values of $\lambda_{\text{transfer}}$ and λ_{access}. Here, one shortcoming of the continuous interaction formulation (Formula 1) becomes obvious: The change of the λ-parameter has only little effect on the gradient in the higher range of distances (survey data) but a very large effect for shorter distances (census). The estimation fits the continuous interaction formulation for the survey data but since the gradient changes severely for short distance the VTTS may be overestimated in this range. Therefore, one has to be careful when interpreting VTTS based on continuous interaction with highly negative values of λ.

GRAPHICAL REPRESENTATION OF VTTS VALUES

Based on the presented results it is possible to draw plots showing the dependency of the VTTS on income and distance. Figure 1 makes clear that the VTTS for business travelers is the most sensitive to travel distance and income while that for commuters is the least sensitive. Since t-test value of $\lambda_{\text{fuel,inc}}$ for shopping trips is not significant the corresponding value was not considered. Therefore, the plot for shopping trips shows only distance dependency. Interestingly, the shape of the VTTS figure for leisure trips is similar to the one for all trips which is not that surprising reflecting the high percentage of leisure trips in Switzerland. Similar plots can be also drawn for all other studied WTP values and will be implemented in the Swiss norm on WTP in transport which will be published later in 2008.

SUMMARY AND CONCLUSIONS

In this paper, we have discussed the estimation of VTTS indicators on a dataset obtained by pooling together evidence from four separate studies conducted in Switzerland in recent years. With various differences across these studies, the aim was to produce a VTTS measure that was more representative of the overall population than that produced by individual studies.

Our analysis has shown that there exist significant differences in results across the four studies and that the joint model is hence outperformed quite comfortably by the individual studies. However, this comes as no surprise, and what is of more interest are the actual findings of the joint model. Here, we obtain very stable parameter estimates both in terms of basic marginal utility coefficients as well as continuous interactions with income and trip distance.

[3]This is calculated as a function of the population distribution of income and trip distance, and is not related to the estimation precision of the individual taste coefficients. As such, the standard deviation relates more to the range of the WTP indicators than to confidence intervals in terms of robustness.

TABLE 12 Weighted WTP indicators for joint models

Weighted WTP indicators (standard deviation)

	Cross-purpose	Commuters	Business	Leisure	Shopping
TT-car	22.23 (5.2)	30.02 (2.65)	30.38 (24.61)	21.05 (6.06)	19.78 (5.71)
TT-PT	3.77 (3.99)	15.35 (4.18)	34.1 (14.63)	11.46 (3.28)	11.76 (0.95)
HW	4.71 (1.77)	4.37 (1.32)	9.43 (2.42)	4.13 (1.59)	4.19 (0.85)
changes	2.34 (1.44)	1.92 (0.79)	3.55 (2.42)	1.94 (1.59)	3.55 (0.85)
TT-transfer	6.16 (5.19)	4.11 (2.53)	81.78 (37.43)	8.9 (2.15)	6.74 (3.95)
TT-access	23.03 (8.66)	22.37 (1.79)	62.0 (15.29)	21.74 (7.24)	10.11 (5.94)

WTP indicators from linear models

	Cross-purpose	Commuters	Business	Leisure	Shopping
TT-car	37.47	28.70	106.90	31.19	33.39
TT-PT	22.21	21.35	47.15	18.55	15.93
HW	11.35	7.26	14.07	9.53	6.21
changes	6.50	3.38	7.54	6.97	2.94
TT-transfer	18.56	3.64	55.62	13.45	18.28
TT-access	55.36	23.43	86.42	47.15	20.59

WTP indicators from elasticity models at base income and trip distance

	Cross-purpose	Commuters	Business	Leisure	Shopping
TT-car	32.45	31.48	43.30	25.69	45.90
TT-PT	20.38	22.95	36.18	16.39	23.02
HW	7.66	6.81	9.42	6.59	7.17
changes	4.63	3.41	3.92	4.51	4.52
TT-transfer	13.95	8.62	53.62	12.16	18.49
TT-access	37.43	20.81	58.70	32.51	27.75

This paper has shown the benefit of merging data from various studies in the estimation of overall WTP measures for use in policy planning. More work remains to be done, for example in terms of recognising the repeated choice nature of the data and in segmenting the data along socio-demographic attributes such as trip purpose. Furthermore, a less restrictive function to cover the sensitivity to alternative attributes with respect to socio-demographic attributes might be helpful in cases where the used elasticity formulation leads to high λ values.

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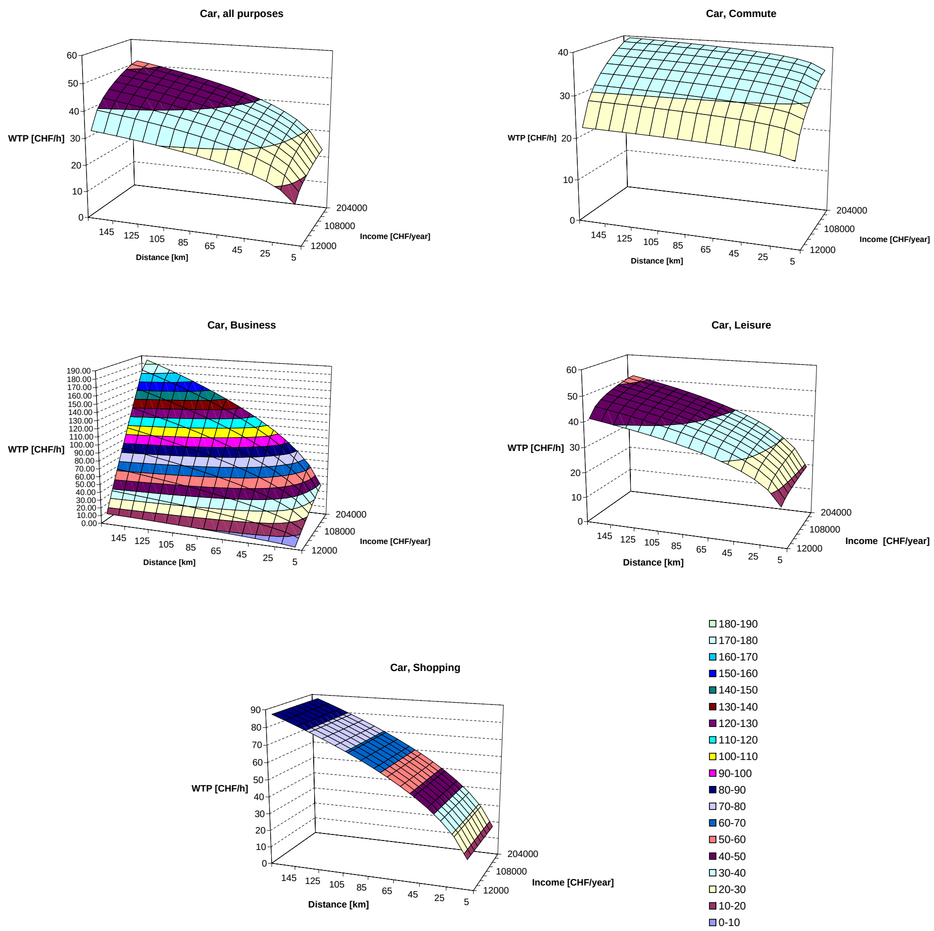
FIGURE 1 VTTS for car travel



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