Analysis of driver's response to real-time information in Switzerland

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Abstract

We present behavioral models designed to capture the response of drivers to real-time traffic information. In 2003, we have conducted a survey in Switzerland in order to collect both Revealed Preferences (RP) and Stated Preferences (SP) about choice decisions in terms of route and mode. The RP data contains socioeconomic characteristics of the individuals in our samples, their actual usage of ITS as well as their actual route and mode choice behavior. The SP data provide us with stated route and mode choices when drivers are faced with different hypothetical choice situations involving real-time information about the state of the network. First we present a Mixed Binary Logit

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model with panel data to analyze the drivers' decisions when traffic information is provided during their trip by the mean of Radio Data System (RDS) or variable message signs (VMS). This model is referred to *en-route choice* model. Second we present Nested Logit models capturing the behavior of drivers when they are aware of traffic conditions before their trip. These last models allow to predict *pre-trip route choice* decisions with regard to route and mode when traffic information is available. The calibrated models are subsequently included in a simulator which predicts travelers' behavior in specific scenarios (described by adjustable parameters) allowing the sensitivity analysis of the demand with regard to the variations of various parameters. In this paper, we discuss the results of the estimation process, including some comments about the Value of Travel Time Savings (VTTS) and present some scenarios developed with our simulator.

1 Introduction

Intelligent Transportation Systems (ITS) are aiming at the improvement of transportation systems through advanced information and control technologies. Namely, Dynamic Traffic Management Systems (DTMS) combine those technologies with the appropriate decision-aid tools.

Demand models play a central role in such systems. Indeed, the impact of ITS on travelers' behavior must be captured, understood and explicitly predicted. In this context, representing transportation demand through (possibly dynamic) origin-destination matrices is not sufficient. A disaggregate representation is necessary, where individuals are considered with their characteristics (trip purpose, available ITS equipment, etc.) and with their decisions in terms of route and mode choice.

Most recent methodologies for the evaluation and management of ITS are based on behavioral models, predicting the response of users to the ITS environment. Among them, we can cite the software systems developed at the Massachusetts Institute of Technology: MITSIM Laboratory (Ben-Akiva et al., 1997) for the evaluation of DTMS and DynaMIT (Ben-Akiva et al., 2001) for real-time traffic information and prediction. Other tools, like VISSIM or AIMSUM in Europe, and DYNASMART and TRANSIM in the US are also based on a disaggregate representation of the demand.

The use of such tools allows for an operational approach of telematics, which optimizes the impact of existing infrastructures, such as Variable Message Signs (VMS), RDS, etc. Disaggregate demand models also help to analyze the impact of longer term strategies such as road-pricing, congestion-pricing, diversion strategies, etc.

During the last decade, various behavioral models have been proposed in the literature to capture response to traffic information. Although various methodologies have been used, such as cluster analysis (Conquest et al., 1993) or Poisson regression (Khattak et al., 2003), most approaches are based on discrete choice models (see, among others, Khattak et al., 1996, Zhao, 1996, Wardman et al., 1997, Mahmassani and Liu, 1999, Dia, 2002, Chatterjee et al., 2002) or mixtures of discrete choice models (e.g. Karthik et al., 2003).

In this paper, we also adopt a discrete choice approach and present behavioral models capturing the response of Swiss travelers to traffic information, designed to be used in a DTMS. The models presented here are the result of a research project conducted between 2002 and 2004. The research team was composed of two engineering consulting firms (Robert-Grandpierre et Rapp, SA, Lausanne, and Büro Widmer, Frauenfeld), IVT (Institute for Transport Planning and Systems), ETHZ, and the Operations Research Group ROSO, EPFL.

The data collection process is described in Section 2. The model for en-route behavior is presented in Section 3 while the models for pre-trip behavior are presented in Section 4. Before concluding in Section 6, we illustrate examples of how these models can be used in a simulator in Section 5.

2 Data collection

Data was collected in two phases. In the first phase, the respondents were asked to report one day's worth of travel in a diary, their associated use of advanced information systems, and their socioeconomic characteristics.

The usual set of diary question was expanded to include items about the use of information systems, trip planning, time constraints, the route taken and alternative routes. It was clearly more difficult for the respondents than the usual diary. The revealed preference (RP) questionnaire included a question about the respondent's willingness to participate in the second phase of the study, involving a stated preferences (SP) experiment based on the answers in the RP diary. Each phase was separately pre-tested for response behavior and question quality. The surveys were undertaken in the spring (pre-test RP), summer (main study RP) and autumn (pre-test and main study SP) of 2003.

As the interest of the study lay in longer distance trips, three groups were targeted:

- commuters and car drivers in the French speaking canton Vaud. The addresses were provided by SIEMENS and the automobile club, TCS, which sent our diaries and reminders;

- commuters and car drivers in the German speaking canton Zürich. The addresses were provided by the automobile club, TCS, which sent our diaries and reminders;

- owners of a second home in Ticino from the German speaking part of the country, as they are very likely to undertake long-distance leisure journeys. The diary was adjusted to ask about the last relevant journey. The sample was constructed from public records about the owners of second homes in this canton south of the Alps.

The response to the RP survey is summarized in Table 1. A questionnaire was not considered useful if the description of the trips was not detailed enough, or if the reported trips were shorter than 7 km, a distance deemed necessary for information systems to have an impact on drivers' behavior.

The response rates are low, both because only one reminder was possible and because of the complexity of the diary. The contrast between the travelers to the Ticino, for whom a congested journey is a regular occurrence and who already benefit from radio-distributed information, and the rest

Response	Vaud	Zürich	Ticino	Total
Total sent	826	600	323	1749
Total received	232	195	147	574
Without reminder	180	110	62	352
After reminder	52	85	85	222
Usable	223	182	137	542
Share of usable responses [%]	27	30	42	31

Table 1: Pre-test and main RP surveys: Response behavior

of the sample is striking. The increased response indicates an increased interest. The TCS based sample includes persons not working, as well as those never faced with congestion in the more rural parts of the respective cantons. Given that the changes between pre-test and main study were minor we included the usable responses from the pre-tests for the further analysis.

The stated preferences experiments were generated based on the longest reported trip, the reference trip of each respondent. Each received seven hypothetical pre-trip choice situations (route and mode choice) and seven hypothetical en-route choice situations (route choice only). In the pre-trip case, we assume that traffic information is available two hours before the trip starts. Three alternatives were offered for in each case: the base alternative, an alternative recommended by the information system and a realistic public transportation alternative derived from the official timetable. The attribute values of the base alternative are those of the reported trip, in order to remind the respondent the choice context. The attributes of the two other alternatives were based on an orthogonal experimental design corrected for dominant alternatives.

The attributes for the road-based alternatives are

- departure time,
- estimated non-congested travel time
- estimated congested travel time

- estimated total travel time (the sum of the previous two)
- percentage of error for the predicted times,
- expected arrival time (departure time plus total travel time),
- cost (operating costs including fuel, oil and maintenance).

The attributes of the public transportation alternative are

- Departure time from the closest public transportation stop.
- Travel time to the final stop (closest to the destination)
- Arrival time at the final stop (the sum of the two previous)
- Fare (accounting for yearly passes and specific discounts)

In the en-route case, we assume that traffic information is available during the trip. We also suppose that the radio is turned on and that there are VMS along the route. Two alternatives are included: the base alternative and alternative recommended by the information system. Their attributes are

- Estimated travel time to the destination from the current location
- Percentage of error on the predicted time
- Type of road to the destination: motorway and similar (labeled *national*), other roads (labeled *non-national*), or both,
- Source of information: Radio or Variable Message Signs (VMS)

The response to the SP survey is summarized in Table 2. A further 21 usable SP returns were obtained from the participants of the RP pre-test.

The response is a satisfactory 69%, which is normal after respondents have committed themselves to further participation. Table 9 compares the samples' characteristics with the Mikrozensus 2000, the national travel survey (Bundesamt für Raumentwicklung and Bundesamt für Statistik, 2001) for the usable 542 responses from the RP, and for the 186 SP questionnaires actually used in the pre-trip model. The shift in the sample structure is noticeable.

Response	Vaud	Zürich	Ticino	Total
Total sent	103	91	86	280
Total received	71	65	72	208
Without reminder	52	31	36	119
After 2 reminders	19	34	36	89
Usable (en-route model)	65	63	66	194
Usable (pre-trip model)				186
Share of usable responses [%]	63	69	77	69

Table 2: Main SP survey: Response behavior

3 En-route model

A mixed logit model (see Train, 2003) for panel data has been estimated using the software package Biogeme (Bierlaire, 2003, Bierlaire, 2005). The model specification is reported in Table 3, where "radio" is 1 if information is received by the radio, 0 otherwise; "VMS" is 1 if information is received by VMS, 0 otherwise; "non-national" is 1 if the trip to the destination is using non-national roads, 0 otherwise; "frequent_usage" is 1 if the traveler frequently uses the radio to get traffic information, 0 otherwise; "unfrequent_usage" is "1-frequent_usage", that is 1 if the traveler does not frequently use the radio to get traffic information, 0 otherwise.

A total of 1358 observations have been used (7 questions per respondent, 194 respondents). The estimated parameters are reported in Table 4.

All parameters are significant. We briefly discuss each of them.

β_{current} is the Alternative Specific Constant associated with the first alternative. It is positive as expected. This captures a type of inertia to change.

β_{time} is negative, as expected.

$\beta_{\text{error\_radio\_freq}}$, $\beta_{\text{error\_radio\_unfreq}}$, $\beta_{\text{error\_vms}}$ are all negative, capturing the impact of uncertainty on travelers' choice, as people do not favor alternatives for which imprecise information is available. Comparing

	Current route	Alternative route
$\beta_{current}$	1	0
σ_{panel}	1	0
β_{time}	remaining time	remaining time
$\beta_{error\_radio\_high}$	error * radio * frequent_usage	error * radio * frequent_usage
$\beta_{error\_radio\_low}$	error * radio * unfrequent_usage	error * radio * unfrequent_usage
β_{error_vms}	error * VMS	error * VMS
$\beta_{non\text{-}national}$	non-national	non-national

Table 3: En-route model specification

the three values, it appears that a same level of error is more penalized for a VMS than for the radio. Also, travelers who currently listen and use traffic information from the radio have a tendency to penalize the errors made by this media less. This could be explained by the fact that travelers have a better experience of radio than VMS.

$\beta_{\textbf{non-national}}$ is negative, capturing the fact that travelers are reluctant to leave the main road network. However, its absolute value is less than $\beta_{current}$, showing that, everything else being equal, travelers prefer their current route on non-national roads, rather than an alternative itinerary using national roads.

$\sigma_{\textbf{panel}}$ is significant, showing that it was important to include intra-personal effects in the model. Its sign is irrelevant.

Note that we have tried to estimate separate models for each subsample, but they did not appear to be significantly different.

4 Pre-trip models

We have estimated a joint nested logit model, combining a model for the Ticino sample (second home owners) and the rest of the sample (we did not discover any significant difference between the French and German

Name	Value	Std error	t-test
β_{current}	0.552	0.110	5.015
β_{time}	-0.133	0.012	-10.869
$\beta_{\text{error\_radio\_freq}}$	-0.055	0.016	-3.405
$\beta_{\text{error\_radio\_unfreq}}$	-0.076	0.023	-3.352
$\beta_{\text{error\_vms}}$	-0.078	0.016	-4.938
$\beta_{\text{non-national}}$	-0.270	0.101	-2.679
σ_{panel}	-0.716	0.156	-4.576

K= 7
$\mathcal{L}(0)$= -940.601
$\mathcal{L}(\beta^*)$= -701.949
$\rho^2 = 0.254$
$\bar{\rho}^2 = 0.246$

Table 4: Estimated parameters of the en-route model

speaking parts). A total of 1302 observations have been used (7 questions per respondent, 186 respondents). A total of 34 parameters have been estimated: 2 nest parameters, one scale parameter, 11 parameters specific to the Ticino model, 16 specific parameters to the other model, and 4 parameters common to both models: β_{cost}, β_{error}, $\beta_{\text{radio\_usage}}$ and $\beta_{\text{profession}}$.

- Initial log-likelihood: $\mathcal{L}(0) = -1399.63$
- Final log-likelihood: $\mathcal{L}(\beta^*) = -767.245$
- Rho-square: $\rho^2 = 0.451824$

Although jointly estimated, we present the results separately.

The specification of the Ticino model is reported in table 5, where "frequent_usage" is 1 if the traveler frequently uses traffic information, 0 otherwise; "aware" is 1 if the traveler was informed by radio about the traffic state during the reference trip, 0 otherwise; "impact" is 1 if the traveler has actually used traffic information during the reference trip, 0 otherwise; "half-fare ticket" is 1 if the traveler owns a ticket which entitles to a 50% rebate on all main line services, 0 otherwise; "people" is the

	Nest A		Nest B
	Route 1	Route 2	Public transportation
$\beta_{\text{ASC1-Ticino}}$	1	0	0
$\beta_{\text{ASC2-Ticino}}$	0	1	0
β_{cost}	cost	cost	-
β_{error}	error	error	-
$\beta_{\text{time\_jam1-Ticino}}$	time in jam	-	-
$\beta_{\text{time\_jam2-Ticino}}$	-	time in jam	-
$\beta_{\text{radio\_usage}}$	frequent_usage	-	-
$\beta_{\text{aware-Ticino}}$	-	aware	-
$\beta_{\text{impact-Ticino}}$	-	impact	-
$\beta_{\text{half\_fare-Ticino}}$	-	-	half-fare ticket
$\beta_{\text{people\_nbr-Ticino}}$	-	-	people
$\beta_{\text{car\_nbr-Ticino}}$	-	-	cars
$\beta_{\text{profession}}$	-	-	manager
$\beta_{\text{income-Ticino}}$	-	-	income(>8000CHF)
$\beta_{\text{public\_transportation-Ticino}}$	-	-	usage_percentage

Table 5: Specification of the pre-trip model for Ticino

number of persons within the traveler's household; "cars" is the number of cars in the household; "manager" is 1 if the traveler is working as a manager or working at home, 0 otherwise; "income(>8'000 CHF)" is 1 if the monthly household income is above 8'000 CHF[1], 0 otherwise; "usage_percentage" is the percentage of public transportation trips among all trips to the second home.

Note that there is not enough variability in travel time and cost for the public transportation alternative in the Ticino sample, explaining why these attributes are not included in the model.

The results of the estimation are reported in Table 6. All parameters are significant at the 95% level of confidence, except $\beta_{\text{aware-Ticino}}$. However, the t-test is close to the 1.96 threshold. Therefore, we have decided to keep

[1] In 2005, 1 CHF ≈ 0.645 €

Name	Value	Std error	t-test
β_{cost}	-0.145	0.034	-4.214
β_{error}	-0.021	0.009	-2.209
$\beta_{\text{radio\_usage}}$	0.401	0.125	3.218
$\beta_{\text{profession}}$	-2.297	0.409	-5.613
$\beta_{\text{ASC1-Ticino}}$	12.11	3.225	3.754
$\beta_{\text{ASC2-Ticino}}$	12.67	3.293	3.847
$\beta_{\text{half\_fare-Ticino}}$	2.386	0.862	2.768
$\beta_{\text{income-Ticino}}$	3.186	1.314	2.425
$\beta_{\text{aware-Ticino}}$	-0.354	0.182	*-1.942*
$\beta_{\text{impact-Ticino}}$	0.505	0.196	2.579
$\beta_{\text{people\_nbr-Ticino}}$	-1.210	0.391	-3.094
$\beta_{\text{car\_nbr-Ticino}}$	-1.173	0.446	-2.634
$\beta_{\text{public\_transportation-Ticino}}$	0.190	0.053	3.579
$\beta_{\text{time\_jam1\_Ticino}}$	-0.048	0.014	-3.322
$\beta_{\text{time\_jam2\_Ticino}}$	-0.073	0.025	-2.967
$\mu_{\text{Nest A-Ticino}}$	4.057	0.971	3.147^*
λ_{scale}	0.580	0.151	-2.787^*

Superscript * means that the t-test is against 1

Table 6: Estimated parameters for the Ticino pre-trip model

the parameter in the model.

β_{cost} is negative, as expected for a travel cost coefficient.

β_{error} is negative, as expected. Same conclusion as in the en-route model.

$\beta_{\text{radio\_usage}}$ is positive. It seems to show that the inertia is larger for frequent users of the traffic information at the radio. It is not clear if it is a feature of the model, or if the frequent usage of the radio indeed encourages inertia, because of bad experiences. This requires more investigation.

$\beta_{\text{profession}}$ is negative, illustrating the aversion of managers and home-working persons to use public transportation.

$\beta_{\text{ASC1-Ticino}}$ and $\beta_{\text{ASC2-Ticino}}$ are the Alternative Specific Constants. There are positive, illustrating the attractiveness of the car versus public transportation.

$\beta_{\text{half\_fare-Ticino}}$ is positive, showing a propensity to use public transportation by the owners of a half-fare ticket.

$\beta_{\text{income-Ticino}}$ is positive, showing an attractivity of public transportation for households with a high income. It may be due to the relatively high cost of long distance trips by public transportation in Switzerland, which only high incomes can afford when traveling with the whole family.

$\beta_{\text{aware-Ticino}}$ is negative, capturing an inertia, a preference toward the current alternative for more informed people. This is consistent with the comments about $\beta_{\text{radio\_usage}}$ (note that $\beta_{\text{aware-Ticino}}$ is in the utility function of the alternative route).

$\beta_{\text{impact-Ticino}}$ is positive, showing that people who have used traffic information to modify their decision during the reference trip have a propensity to change. It seems to support the assumption about the bad experience proposed in the analysis of the sign of $\beta_{\text{radio\_usage}}$.

$\beta_{\text{people\_nbr-Ticino}}$ is negative. Indeed, the marginal cost of one more person in the family is much more important for public transportation than for private transportation.

$\beta_{\text{car\_nbr-Ticino}}$ is negative. Indeed, the more cars in the household, the less likely the use of public transportation.

$\beta_{\text{public\_transportation-Ticino}}$ is positive, showing an attractivity for the public transportation by the most frequent users of public transportation.

$\beta_{\text{time\_jam1\_Ticino}}$ and $\beta_{\text{time\_jam2\_Ticino}}$ are both negative. The sensitivity to the predicted time in jam for the alternative route is more important. Note also that the free flow travel time did not appear significant in the model. It is due to the very low variability of this attribute for the Ticino sample.

The specification of the commuters model is reported in Table 7, where "d(0-50)" is 1 if the trip length is between 0 and 50km, 0 otherwise; "d(50-100)" is 1 if the trip length is between 50 and 100km, 0 otherwise; "frequent_usage" is 1 if the traveler frequently uses traffic information, 0 otherwise; "aware" is 1 if the traveler was informed by radio about the traffic state during the reference trip, 0 otherwise; "manager" is 1 if the traveler is working as a manager or working at home, 0 otherwise; "early_arrival" is the number of minutes between the arrival by public transportation and the scheduled arrival time; "fare" is the public transportation fare; "timetable" is the scheduled travel time from the timetable; "age(0-40)" is 1 if the traveler is younger than 40, 0 otherwise; "car_as_mode" is 1 if the car was the chosen mode for the reference trip, 0 otherwise; "car_availability" is 1 if a car is available to the traveler, 0 otherwise; "car_type" is 1 if a company car has been used during the reference trip, 0 otherwise; "kilometers" is the number of kilometers traveled by car per year.

The results of the estimation are reported in Table 8. All parameters are significant to the 95% level of confidence, except $\beta_{\text{internet\_usage}}$ and β_{fare}. However, the t-tests are close to the 1.96 threshold value, and we have decided to keep them in the model.

Parameters $\beta_{\mathbf{cost}}$, $\beta_{\mathbf{error}}$, $\beta_{\mathbf{radio\_usage}}$ and $\beta_{\mathbf{profession}}$ have been discussed above.

$\beta_{\mathbf{ASC1}}$ and $\beta_{\mathbf{ASC2}}$ are the Alternative Specific Constants for the two first alternatives. They are negative, which is difficult to interpret. Indeed, the cost and time parameters are alternative specific. For instance, if we compare alternatives with a cost of 10 CHF, a travel time of 50 minutes (both for car and public transportation), the probability of choosing the public transportation is significantly smaller than the probability to choose the car, as expected.

$\beta_{\mathbf{mode}}$ is negative, meaning that people reporting to use their car have a preference toward the car, so it affects negatively the public transportation alternative.

$\beta_{\mathbf{availability}}$ is negative, meaning that people who have a car available have a tendency to use it, so it affects negatively the public transportation alternative.

$\beta_{\mathbf{type}}$ is negative, for the same reason as described above.

$\beta_{\mathbf{internet\_usage}}$ is negative, showing that people who use Internet to access the information have a propensity to switch route. It is interesting to note that the parameter $\beta_{\mathrm{radio\_usage}}$ is positive in comparison.

$\beta_{\mathbf{aware}}$ is positive, showing that people who are aware of alternative routes, have a propensity to switch. Note that, in comparison to the Ticino model, the commuter model deals with situations where the number of feasible routes is usually higher.

$\beta_{\mathbf{age}}$ is negative, showing that people younger than 40 have a preference for the car.

$\beta_{\mathbf{kms}}$ is negative, showing that the more the car is used per year, the less appealing public transportations are.

$\beta_{\mathbf{early}}$ is negative, capturing the inconvenience of mismatch between the actual arrival time and desired arrival time when using public transportation.

$\beta_{\mathbf{fare}}$ is negative, as expected for a cost coefficient. Note that it is less negative than the cost coefficient for the car alternatives.

$\beta_{\mathbf{timetable}}$ is negative, as expected for a travel time coefficient.

$\beta_{\mathbf{time\_jam\_medium}}$, $\beta_{\mathbf{time\_jam\_short}}$, $\beta_{\mathbf{time\_free\_medium}}$, $\beta_{\mathbf{time\_free\_short}}$ are all negative, as expected. As discussed below, although they have the correct sign, we are somehow suspicious about the parameters estimates for the short trips. Indeed, there are plenty of context-specific constraints associated with short trips that are not accounted for in this model. The fact that travel time in free flow conditions is more penalized than travel time in jam is counter-intuitive. In the "medium" case (trips between 50 and 100km), travel time in traffic jam is more penalized than travel time in free flow conditions.

It is interesting to analyze the Value Travel Time Savings (VTTS), as provided by the commuter model. As we use a linear specification, this quantity is simply given by the ratio between the travel time coefficient and the travel cost coefficient.

VTTS (CHF/min)	Free flow	in Jam
Short distance ($\leq$ 50km)	*50.7*	34.8
Medium distance ($>$ 50km)	27.3	36.5

The values for the medium distances are comparable with the results provided by Koenig et al. (2004): 35.9 CHF, assuming an income of 10'000 CHF/month and a business trip of 75km. However, for the short distance, our values are significatively higher. Koenig et al. (2004) obtain 24.22 CHF, assuming an income of 10'000 CHF/month and a business trip of 25km. Clearly, in our model, we have a low granularity of distances and travel times for short distance trips. The approach by Koenig et al. (2004) is more appropriate to estimate VTTS for short trips. Anyway, the value 50.7 CHF, reported in italic above, does not seem valid to us. We believe the time and cost parameters capture other effects associated with short trips, that should be explicitly analyzed.

Note that it appeared that adding an error component to capture the panel data effect was not useful for the pre-trip models, as individual characteristics are already captured by fixed coefficients.

5 Simulation

We have implemented a simulator for the models. We illustrate here some examples based on the en-route model.

In Figure 1, the x-axis represents various values between 15 and 35 minutes for the remaining time on the alternative route. The error on the information is 5 minutes for both alternatives. The value of the other attributes are reported above the chart. Among other things, it is interesting to note that the 50% probability is reached when the alternative route is 25 minutes, compared to the 30 minutes on the usual route. Also, if both routes are said to be 30 minutes, the probability to switch route is only about 34%, illustrating the inertia to change.

In Figure 2, the x-axis represents various values between 5 and 15 minutes for the error on the information about the alternative route, given that the error on the information about the usual route is 10 minutes. The travel time on the usual route is predicted to be 35 minutes, while it is predicted to be 30 minutes on the alternative route. The 50% is reached for a value of about 8.5. If both errors are 10 minutes, the probability to switch is about 47%.

Figure 3 is the same scenario as Figure 2, except that the information about the usual route is obtained from a VMS instead of the radio. We note that the 50% value shifts from about 8.5 to about 11.5, illustrating that travelers have less confidence in VMS, everything else being equal.

6 Conclusions

We have estimated a model capturing the response to en-route information, and two models capturing the response to pre-trip information, based on data collected in Switzerland during 2003.

The en-route model enables to measure the level of inertia to en-route switching and the preference toward national roads, among other things. It has been illustrated using some examples of the simulator.

In the pre-trip models, the heterogeneity of the sample has been emphasized. Indeed, the socioeconomic characteristics play a significant role in these models. First, a model for the owners of a second home in Ticino has been estimated. It allows to capture and predict the important role of traffic information, and of public transportation in this specific context, and may help to design appropriate focused policies for long distance, non-work related, trips. Second, a model for commuters has been estimated. While the model seems valid for medium distance trips, we have significant suspicions of its validity for short distance trips. More investigation is necessary to better understand the constraints and the choice context of such trips. The attributes included in our SP experiments are probably not sufficient to explain them.

The models that have been estimated are advanced random utility models. The en-route model is a mixed binary logit model with panel data. The pre-trip models are heterogeneous nested logit models. They have all been estimated using the Biogeme software package.

We conclude by mentioning some potentially interesting streams of investigations:

- The diversity of behaviors emphasized in this study suggests the development of regular surveys to better understand this phenomenon. The cost of collecting such data being important, organizing regular surveys would also bring very valuable information at a low marginal cost. Moreover, it would allow to analyze the behavioral dynamics, in order to understand how travelers change their behavior as they experience the use of ITS.

- The abnormally high VTTS for short distance trips should be investigated. For instance, mixed GEV models could be considered, along the lines discussed by Hess et al. (2005).

- It appears from the models that the level of error in an information system significantly influences its perception. However, this concept has been kept at an abstract level in our surveys, and would deserve a deeper analysis.

- Our sample is biased toward private car users. A more systematic analysis of mode choice would require more public transportation users in the sample.

The use of demand models is more and more critical in the ITS context. The models estimated in this paper allows to better understand and predict the response of travelers to traffic information.

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	Nest A		Nest B
	Route 1	Route 2	Public transp.
β_{ASC1}	1	0	0
β_{ASC2}	0	1	0
β_{cost}	cost	cost	-
β_{error}	error	error	-
$\beta_{\text{time\_jam-short}}$	time in jam * d(0-50)	time in jam * d(0-50)	-
$\beta_{\text{time\_jam-medium}}$	time in jam * d(50-100)	time in jam * d(50-100)	-
$\beta_{\text{time\_free-short}}$	fr. flow time * d(0-50)	fr. flow time * d(0-50)	-
$\beta_{\text{time\_free-medium}}$	fr. flow time * d(50-100)	fr. flow time * d(50-100)	-
$\beta_{\text{radio\_usage}}$	frequent_usage	-	-
$\beta_{\text{internet\_usage}}$	frequent_usage	-	-
β_{aware}	-	aware	-
β_{early}	-	-	early arrival
β_{fare}	-	-	fare
$\beta_{\text{timetable}}$	-	-	timetable
$\beta_{\text{profession}}$	-	-	manager
β_{age}	-	-	age(0-40)
β_{mode}	-	-	car_as_mode
$\beta_{\text{availability}}$	-	-	car_availability
β_{type}	-	-	car_type
β_{kms}	-	-	kilometers

Table 7: Specification of the pre-trip model for commuters

Name	Value	Std error	t-test
β_{cost}	-0.145	0.034	-4.214
β_{error}	-0.021	0.009	-2.209
β_{radio_usage}	0.401	0.125	3.218
$\beta_{profession}$	-2.297	0.409	-5.613
β_{ASC1}	-3.054	1.144	-2.670
β_{ASC2}	-2.780	1.141	-2.436
β_{mode}	-1.390	0.297	-4.683
$\beta_{availability}$	-3.659	1.081	-3.386
β_{type}	-3.016	1.093	-2.760
$\beta_{internet\_usage}$	-0.239	0.125	*-1.910*
β_{aware}	0.708	0.156	4.523
β_{age}	-1.197	0.341	-3.513
β_{kms}	-0.041	0.012	-3.420
β_{early}	-0.033	0.011	-3.166
β_{fare}	-0.037	0.022	*-1.674*
$\beta_{timetable}$	-0.066	0.009	-7.019
$\beta_{time\_jam\_medium}$	-0.088	0.019	-4.543
$\beta_{time\_jam\_short}$	-0.084	0.015	-5.582
$\beta_{time\_free\_medium}$	-0.066	0.011	-5.752
$\beta_{time\_free\_short}$	-0.122	0.015	-8.081
$\mu_{Nest\ A}$	1.951	0.311	3.051^*
λ_{scale}	0.580	0.151	-2.787^*

Superscript * means that the t-test is against 1

Table 8: Estimated parameters for the pre-trip commuters model

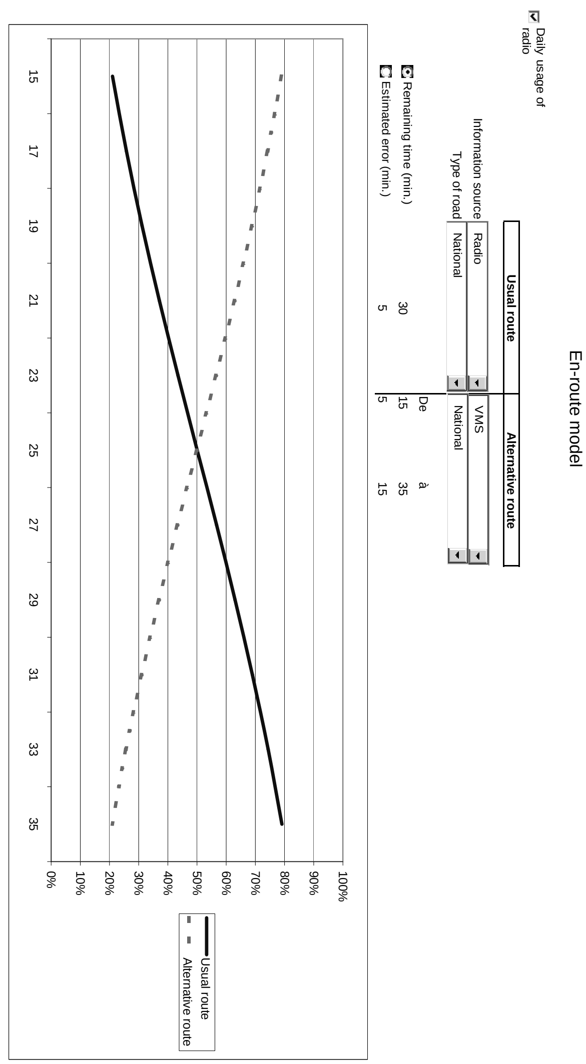

Figure 1: First scenario

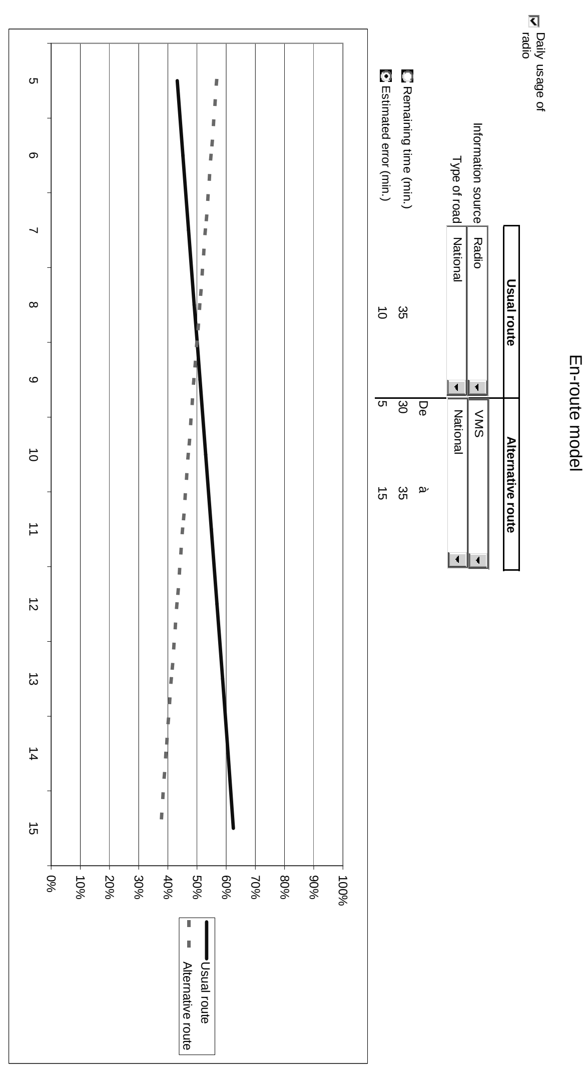

Figure 2: Second scenario

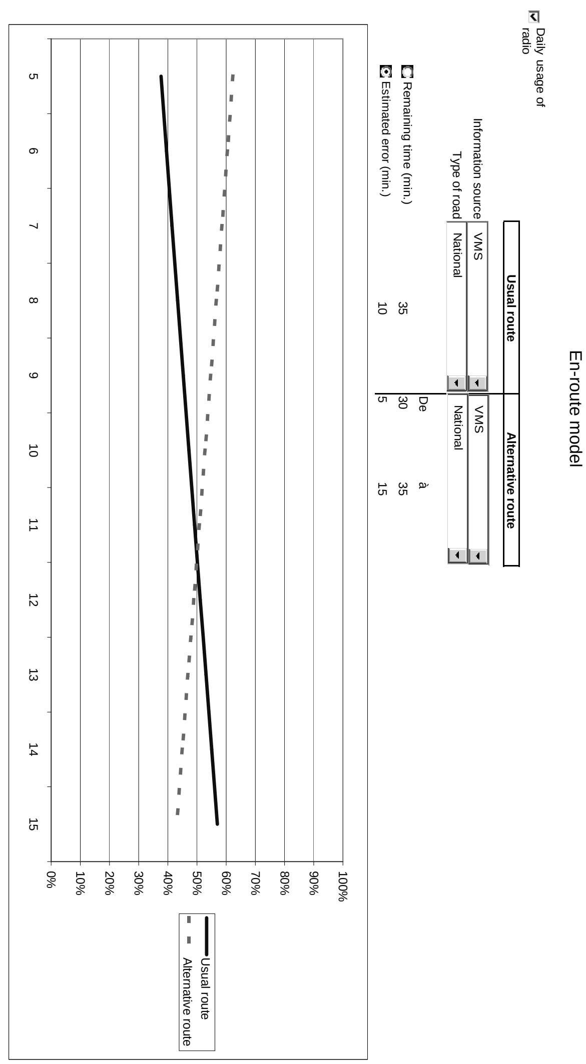

Figure 3: Third scenario

	Nat. Travel survey 2000	Usable RP		SP used	
Sex					
Male	46.4%	354	65.3%	122	65.6%
Female	53.7%	188	34.7%	64	34.4%
Education					
Primary+lower secondary	34.0%	30	5.5%	4	2.2%
Vocational training	40.7%	252	46.5%	76	40.9%
A-level, tertiary	25.3%	260	48.0%	106	57.0%
Working status					
None	47.4%	113	20.8%	36	19.4%
Employed	46.8%	358	66.1%	126	67.7%
Self-employed	5.8%	71	13.1%	24	12.9%
Driving licence					
Yes	78.4%	493	91.0%	176	94.6%
No	21.6%	49	9.0%	10	5.4%
Railpass ”General abonment”					
Yes	6.0%	61	11.3%	20	10.8%
No	94.0%	481	88.7%	166	89.2%
Half-fare card					
Yes	34.8%	379	69.9%	138	74.2%
No	63.2%	163	30.1%	48	25.8%
Income [CHF]					
¡ 2K	3.1%	5	0.9%	0	0.0%
2K-4K	14.8%	34	6.3%	8	4.3%
4K-6K	22.5%	90	16.6%	23	12.4%
6K-8K	16.2%	125	23.1%	46	24.7%
8K-10K	9.7%	109	20.1%	51	27.4%
10K-12K	5.2%	51	9.4%	21	11.3%
12K-14K	2.6%	42	7.7%	17	9.1%
¿ 14K	4.0%	45	8.3%	17	9.1%
No response	21.9%	41	7.6%	3	1.6%

Table 9: Socioeconomic characteristics