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Propensity for voluntary travel behavior changes: An experimental analysis

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Abstract

In this paper we analyze individual propensity to voluntary travel behavior change combining concepts from theory of change with the methodologies deriving from behavioral models. In particular, following the theory of voluntary changes, we set up a two-week panel survey including soft measure implementation, which consisted of providing car users with a personalized travel plan after the first week of observation (before) and using the second week to monitoring the post-behavior (after). These data have then been used to estimate a Mixed Logit for the choice to use a personal vehicle or a light metro; and a Multinomial Logit for the decision to change behavior. Results from both models show the relevance of providing information about available alternatives to individuals while promoting voluntary travel behavioral change.

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Keywords: Soft Measure; Personalized Travel Plan; Behavioral models; Theory of change.

1. Introduction

The reduction of financial resources for investment in the public transport sector, both for ensuring existing services and providing new ones poses yet another challenge, that is to convince an increasingly large number of travelers to opt for public transport, especially for daily trips. To encourage people to make better use of existing transport services, by choosing, where is possible and reasonable, to use alternative transport of private car, increased demand that equates to increased revenue, thereby achieving the objective of maintaining the current

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level of services provision even when faced with a significant reduction in the resources available for managing them. In this context, in many situations today the transport services provided are underutilized even when they offer a convincing and better alternative to private car use. Our research focuses on this topic, and aims to test the introduction of so-called Soft Measures to promote the use of public transport.

Soft measures, also referred to as “Voluntary Travel Behavior Change programs” (VTBC) (Ampt, 2003) or “smarter choices” (Cairns et al., 2004), are aimed at motivating individual voluntary car use reduction in terms of either mode shift, switch of destination and mode or trip evaporation (not making a trip at all) (Sloman et al., 2010).

A common aspect of soft measures in general, is the need for a rigorous detection of behavioral changes so as to evaluate their effectiveness. In most commercial interventions, a behavior change is measured by independent firms (other than soft measures developers) as the change in household travel mode and the reduction in car travel distance before and after the intervention. However, there is no general consensus regarding the definition of “behavioral change” (see Workshop B2 at the International Congress on transport survey methods, scoping the future while staying on track, 2011).

The objective of this work is to contribute to the debate on behavioral change, analyzing the propensity of individuals for voluntary travel behavioral change, by exploratory analyses of observed behaviors before and after a soft measure implementation and modeling the underlying factors that cause a behavioral change.

From a methodological standpoint, two models are proposed. The first model is a Mixed Logit model that combines before and after data (drawn from wave 1 and wave 2 respectively), because two sets of revealed preferences are gathered on the choice of car-only vs. park-and-ride. The difference with a traditional revealed/stated preference discrete choice model successfully is that, a possible mode change (from car-only to light metro) is not due to some attributes variation (as in the traditional model with reference point) but to an increased level of information and awareness of the other (existing) alternative.

The second model presented in this paper, is a Multinomial Logit that describes the behavioral change process through the decision to not to change behavior at all, to change in the weeks to come, to change in the monitoring week. Specifically, the choice of car-only users to switch to park-and-ride alternative (1) during the one-week after survey, (2) in the following weeks or (3) not to change at all is estimated. This second model compared to the first one moves the attention to an individual level (as opposite to the trip attribute level) offering the opportunity to estimate the individual characteristics underlying the process of change.

The rest of the paper is organized as follows: Section 2 reports an overview of the existing literature on behavioral theories and behavioral change models, Section 3 reports the methodology proposed in this paper to analyze travel behavioral change, Section 4 describes the data collection and reports an exploratory analysis of the data. Section 5 discusses the model results, and finally Section 6 reports conclusions and suggestions for further research.

2. Literature overview

There is no general theory of human behavioral change, including travel behavioral change. However, many alternative theories originating from different fields (*i.e.* psychology, health, leisure, physical activity, *etc.*) have been proposed and reported in the literature leading to *Models of behavior* and *Theories of change* (Parker et al., 2007, Anable et al., 2006, Darnton, 2008). *Models of behavior* identify the underlying factors of specific choice events or a specific behavior, as opposed to *Theories of change* that try to detect how behaviors change over time and through steps. In this perspective the second approach is more pragmatic because it aims to promote and encourage a behavioral change.

Despite these differences, there are many overlaps between the two bodies of theories and they can be considered complementary; understanding both is necessary in order to develop effective approaches to behavior change (Darnton, 2008).

Briefly, the most important *Models of behavior* are built upon standard economic theory which refers to those choice behaviors – as for example travel behavior – based on a rational evaluation of alternatives' costs and benefits (utility maximization). Over the time this theory has been combined with powerful analytical techniques able to model current choices and forecast future ones. However, a number of studies, mainly from psychological field have highlighted deviation from the rational behavior (“bounded rationality”, Simon, 1982). Indeed, the behavioral economy integrates the economic theory with psychological studies to represent the individual decision making as constrained by contextual factors (see Cherchi, 2012 for a recent review).

In particular, it is now recognized that consumers have inherent preferences (a favored combination of attributes) and through trial and error learn what they like; preferences stabilize over time but can change under external circumstances that force individuals to rethink of the reasons of their initial choice. This behavior has been extensively studied as part of the habit/inertia problem both in presence of (real or hypothetical) changes in the external environment (e.g. Morikawa 1994; Swait et al., 2004; Bradley & Daly 1997; Cantillo et al., 2007; Srinivasan & Bhargavi, 2007; Yáñez et al., 2009; Cherchi & Manca, 2011) or under stable conditions, *i.e.* no external changes (Ramadurai & Srinivasan, 2006; Cherchi & Cirillo, 2008; Cherchi et al., 2013). These studies pointed out that at past behavior is a strong predictor of future behavior, in particular, if there are no external changes, individuals will repeat exactly the same choices. On the other hand, presenting a choice context in a way that helps the individuals to overcome their own preconceptions highlights the potential benefits and supports their choices, without limiting personal freedom (Thaler & Sustain, 2008). But no works have yet studied the effect of this voluntary behavior in a mode choice model.

The so-called *Theories of change* (*i.e.* which study the dynamical evolution of the individual behavior across time) are essentially learning programs directed primarily at achieving behavior change, by breaking habits, or pursuing organizational change (Lewin's Change Theory, Darnton, 2008). For example, a theory of change represented by the “*Staged Models*” describes the change as a process articulated in a number of phases that lead to the final change (Prochaska & Velicer, 1997).

In addition to these theories, a number of policies have been implemented by Governments to incentivize behavioral changes among existing alternatives. The social marketing is often used to involve the community in the behavioral change programs, in particular to achieve relevant social objectives in the context of health (Gardner & Stern, 1996) and environment (Defra, 2008). In the transportation field, the behavioral change programs have been applied through the Travel Demand Management (also referred as Mobility Management, Cairns et al., 2008) and further through the so called soft measures (Bamberg et al., 2011) also called Voluntary Behavioral Changes Programs (VTBC) (Ampt, 2003). The latter are based on social marketing techniques and information to motivate, support and encourage behavioral change.

Under various names and different details VTBC have been implemented mainly at a personal and community level (mass communication), in different countries, especially in Australia, UK, Japan, Germany, Austria, *etc.* (Richter et al., 2011). The mass communication programs are also referred as Travel Awareness Campaigns (Jones and Sloman, 2003) and Public Transport Information and Marketing (PTIM) (INPHORMM, 1998, TravelWise UK; see Cairns et al., 2004 for a review of PTIM). The former have the objective to increase individual awareness of each one's travel choice effects on environment and health; the PTIM are more or less promotional campaigns that try to increase the attractiveness of public transport. As opposed to mass communication, various programs defined as Personalized Travel Planning (PTP) aim at providing individuals with travel-related information that is specifically based on their daily activity-travel needs. Some examples of PTP are Travel Feedback Programs (Fuji & Taniguchi, 2006), Individualized Marketing and Travelsmart (Brög et al., 2009), Personal Journey Plans (Halden, 2008), and Travel Blending (Ampt, 2003).

PTP programs can be defined as based on a set of motivational drivers (social, economical, psychological, etc.) drawn by classical behavioral models and on a number of steps to follow in order to change habits and decisions as in theories of change.

The contribution of this work is to provide a first explorative analysis of the results from a Personalized Travel Planning, using two different modeling approaches.

The first one interprets the underlying factors of the choice of car-only vs. park-and-ride (as “*Models of behavior*”). The second estimates which are the individual’s variables involved in a behavioral change described as a dynamic process in the time (as *Theories of change*).

3. A model for the voluntary changes

3.1. A mixed Logit mode choice model to account for the effect of personal information

In order to measure the effect of the information on the mode choice behavior, a joint mixed Logit (ML) model that uses data collected before and after providing the information, has been estimated. In particular, the specification includes the car-only vs. park and ride (“P&R”) choice, using before (wave 1) and after (wave 2) data. The goal of this model is to test the effect on the mode choice of the personal information provided to each individual between the first and the second week. This is achieved by specifying in the utility of the P&R, in the wave 2, a variable for the personalized plan effect.

Although the data in the two waves are collected with the same method and in the same context, a scale effect can occur due to unknown effects. To account for that a joint model is estimated, following the typical theory of the joint revealed/state preference model, estimating the scale factor between the two waves. As well known, the scale factor also in the mixed Logit model is inversely related to the variance of the extreme value type 1 (EV1) error terms and it allows to get equal variance across datasets.

The joint ML model used in this paper has the following formulation:

$$\begin{aligned} U_{qj,d}^{w1} &= V_{qj,d}^{w1} + \mu_{qj}^{w1} + \varepsilon_{qj,d}^{w1} \\ U_{qj,d}^{w2} &= \phi(V_{qj,d}^{w2} + \mu_{qj}^{w2} + \varepsilon_{qj,d}^{w2}) \end{aligned} \quad (1)$$

Where $w1$ and $w2$ are respectively wave 1 “before” and wave 2 “after” the individual has been provided with the new information about P&R; q is the individual, j are the alternatives and d is the day of the trip (as all the trips for the same individual have been recorded along a week in both waves). So V^{w1} and V^{w2} are the systematic components of utility for wave 1 and 2 respectively; ε^{w1} and ε^{w2} are EV1 random terms, which represent the typical MNL probability; μ^{w1}, μ^{w2} are the additional random term normally distributed with zero mean and variance $\sigma_{\mu^{w1}}^2, \sigma_{\mu^{w2}}^2$ to be estimated. It allows to account for panel correlation (*i.e.* among answers from the same individual).

Finally, ϕ is the scale parameter that allows the two utilities to have the same variance.

In theory, as the data refer to both before (wave 1) and after (wave 2) there is no need to consider the scale factor. However, in this study, as the users were presented with their personalized travel plan prior to conducting wave 2, the process of evaluating the alternatives may be different and this justifies at least testing for heteroskedasticity.

The systematic utilities are specified as followed:

$$\begin{aligned}
 V_{qj,d}^{w1} &= \beta_{TT}^{w1} TT_{qj,d}^{w1} + \beta_C^{w1} C_{qj,d}^{w1} \\
 V_{qj,d}^{w2} &= \beta_{TT}^{w2} TT_{qj,d}^{w2} + \beta_C^{w2} C_{qj,d}^{w2} + \beta_{Benefits}^{w2} Benefits_{qj,d}^{w2}
 \end{aligned}
 \tag{2}$$

Where $TT_{qj,d}^{w1}$ and $TT_{qj,d}^{w2}$ are the vectors of travel time; $C_{qj,d}^{w1}$ and $C_{qj,d}^{w2}$ are the vectors of travel cost. In particular for the CAR alternative:

$$\begin{aligned}
 \beta_{TT}^{w1} TT_{qCAR,d}^{w1} &= \beta T_{CAR} \cdot (T_{car-only}) + \beta_1 T_{PARK} \cdot (Tp) + \beta T_{WALK} \cdot (Tw) \\
 \beta_{TT}^{w2} TT_{qCAR,d}^{w2} &= \beta T_{CAR} \cdot (T_{car-only}) + \beta_2 T_{PARK} \cdot (Tp) + \beta T_{WALK} \cdot (Tw)
 \end{aligned}
 \tag{3}$$

where:

- $T_{car-only}$ is the travel time by car-only (from origin to destination),
- T_p is the travel time by car looking for parking,
- T_w is the walking time from car parking to destination.

$$\begin{aligned}
 \beta_C^{w1} CC_{qCAR,d}^{w1} &= \beta C \cdot ((C_{car_{km}} \cdot dist_{Or-Dest}) + C_{park}) \\
 \beta_C^{w2} CC_{qCAR,d}^{w2} &= \beta C \cdot ((C_{car_{km}} \cdot dist_{Or-Dest}) + C_{park})
 \end{aligned}
 \tag{4}$$

where:

- $C_{car_{km}}$ is the travel cost by car per km,
- $dist_{Or-Dest}$ is the distance between the origin and the final destination,
- C_{park} is the parking cost.

For the P&R alternative:

$$\begin{aligned}
 \beta_{TT}^{w1} TT_{qP\&R,d}^{w1} &= \beta T_{P\&R} \cdot (T_{car} + T_{wait} + T_m) + \beta_1 T_{WALK_1} \cdot (T_{walk_1}) + \beta T_{WALK_2} \cdot (T_{walk_2}) \\
 \beta_{TT}^{w2} TT_{qP\&R,d}^{w2} &= \beta T_{P\&R} \cdot (T_{car} + T_{wait} + T_m) + \beta_2 T_{WALK_1} \cdot (T_{walk_1}) + \beta T_{WALK_2} \cdot (T_{walk_2})
 \end{aligned}
 \tag{5}$$

where:

- T_{car} is the travel time by car from origin to park-and ride,
- T_{wait} is the waiting time at the Metro station,
- T_m is the travel time by Metro,
- T_{walk_1} is the walking time from park-and ride to Metro station,
- T_{walk_2} is the walking time from Metro station to destination.

$$\begin{aligned}
 \beta_C^{w1} CC_{qP\&R,d}^{w1} &= \beta C \cdot ((C_{car_{km}} \cdot dist_{Or-P\&R}) + C_{ticket}) \\
 \beta_C^{w2} CC_{qP\&R,d}^{w2} &= \beta C \cdot ((C_{car_{km}} \cdot dist_{Or-P\&R}) + C_{ticket})
 \end{aligned}
 \tag{6}$$

where:

- $C_{car_{km}}$ is the travel cost by car per km,
- $dist_{Or-P\&R}$ is the distance between the origin and the park-and ride,
- C_{ticket} is the ticket metro cost.

$Benefits_{qj,d}^{w2}$ is a variable that measure the benefit presented in the personal travel program (PTP). For car users, it represents the benefit achievable from switching from car-only to park and ride. $\beta_{Benefits}$ is the relative

parameter that measures the effect of providing the personalized plan. In particular, the benefits specified in the model are the monetary saving and the calories consumptions, then equation (2) becomes:

$$\begin{aligned}
 V_{qj,d}^{w1} &= \beta_{TT}^{w1} TT_{qj,d}^{w1} + \beta_C^{w1} C_{qj,d}^{w1} \\
 V_{qj,d}^{w2} &= \beta_{TT}^{w2} TT_{qj,d}^{w2} + \beta_C^{w2} C_{qj,d}^{w2} + \beta_{Beuro}^{w2} Beuro_{qj,d}^{w2} + \beta_{Bcal}^{w2} Bcal_{qj,d}^{w2}
 \end{aligned}
 \tag{7}$$

Where $Beuro_{qj,d}^{w2}$ is a variable that represents, for the individual q , the benefits associated with the alternative j . This variable is specific to the P&R alternative in wave 2 for the user prospective P&R. In particular:

$$Beuro_{qj,d}^{w2} = |C_{qCAR,d} - C_{qP\&R,d}|
 \tag{8}$$

Where:

- $C_{qCAR,d}$ is the annual cost of the car only trip,
- $C_{qP\&R,d}$ is the annual cost of the P&R trip mode.

$Bcal_{qj,d}^{w2}$ is a variable that represents, for the individual q , the benefits expressed in terms of calories burned, and associated with the alternative j . This variable is specific to the P&R alternative in wave 2 for the user prospective P&R. In particular:

$$Bcal_{qj,d}^{w2} = |Cal_{qCAR,d}^{w1} - Cal_{qP\&R,d}|
 \tag{9}$$

Where:

- $Cal_{qCAR,d}^{w1}$ are the calories consumed by each individual, in the first week, computed on the basis of the number of meters walked from and to the place where the car was parked,
- $Cal_{qP\&R,d}$ are the calories consumed by each individual, computed on the basis of the number of meters walked from and to the metro station.

From a certain standpoint this method, especially for the attribute of cost, can be interpreted as a reference point (Kanheman & Tversky, 1979 and 1984; Masiero & Hensher, 2011), as it accounts for the difference between the attribute experimented in wave 1 and the attribute proposed in the personalized travel plan.

The quantitative feedback (value of the benefit) may have an important effect in this context since most of the users could have a mistaken perception of his/her reference point. In particular, what is interesting is that the reference values of these attributes are observed by the analyst during wave 1 (passive collection) and not revealed by the user during the survey (active collection).

3.2. A MNL to measure the voluntary travel behavior change

The second model estimated is a Multinomial Logit (MNL) to measure the trade-off between car-only and park-and ride. Differently from the standard applications in the mode choice context, in this case we estimate the probability of changing mode in the coming weeks versus the probability of not changing. This can then be interpreted as a propensity to change.

The variables used to determine the propensity to change, are those related to the answers provided by the participants in the questionnaires handed out at the beginning and at the end of the survey. These are discrete variables that are also coded as dummy in order to test the best specification.

Let $q=(1,2,\dots,Q)$ and $i=(1,2,\dots,I)$ be the indexes respectively for the individuals and for the behavior change options, The following equation represents the structural equation of the choice model:

$$U_{qi} = \beta_i \mathbf{x}_{qi} + \varepsilon_{qi} \quad (10)$$

In equation (5) U_{qi} is the random utility associated with the alternative i for the q^{th} individual, \mathbf{x}_{qi} is a column vector of the attributes (including a constant), β_i the corresponding coefficient vector (column), and ε_{qi} the EVI error term that captures the unobserved effects of the utility function associated with the choice i .

In particular in the following model the index i represents the three alternatives available to the car user: (1) change travel mode in wave 2, (2) change travel mode in the coming weeks (3) not change and not willing to change. The vector \mathbf{x}_{qi} of the attributes simply contains the individuals' personal and travel characteristics and not the specific characteristics of the alternative.

4. Data Analysis

The data used in this study is derived from the implementation of a Personalized Travel Planning (PTP) conducted in Cagliari (Italy) from February 2011 to February 2012, which promoted the usage of a light metro, in service since 2008.

The program involved in two-weeks data collection (before and after the soft measure implementation) of activity travel patterns using a GPS active data logger (smart phone with built-in GPS and activity diary application), called Activity Locator (Meloni *et al.*, 2011). The survey also collected detailed information on individual and household socio-demographic and attitudes.

The behavior change suggested by the soft measure implementation was related to mode switch from car-only to park-and-ride (using the light metro) for the trips observed during one week activity-travel diary (before intervention, wave 1). The participants' responses to the proposed soft measure were monitored during a second week, which immediately follows introduction of the measure (after intervention, wave 2). At the end of the wave 2 all participants were also asked, in the event no behavior changes were detected during the second week, whether they were considering changing in the weeks to come.

The behavioral change in this work was suggested by supplying each participant with a personalized travel plan between the first and the second week of survey. From a conceptual point of view, this study assumed that, following the submission of a personalized travel plan, individuals might reconsider their own mode choice behavior (change their behavior). Each personalized travel plan was created on the basis of the activity-travel information gathered during the first wave and distributed in a pocket size pamphlet. It included: (1) general information on the light metro service (change of mode parking facilities, stations, schedules, where to purchase tickets, ticket types *etc.*), (2) detailed information about the recommended travel plan (which parking facilities to use, at which station to board the train, travel time, at which station to alight and walking time from station to destination), (3) a cost/benefits table comparing current travel mode (car alone) with the recommended travel plan (car + light metro). The cost/benefits table was constructed on the basis of the observed/stated frequency of one or more trips and shows the potential variation between travel attributes of current behavior and of behavior ensuing from changing to the park & ride mode, *i.e.* (1) time spent in car, time spent in light metro, *etc.*, (2) cost of the trip (including cost of parking indicated by the user), (3) Calories burned, (4) CO2 emitted.

4.1. Sample description

The analysis included 85 participants, 21 park and rider users (P&Rs) and 64 car-only users, with a female slight preponderance in both groups (54.1% against 45.9% males). Considering the age groups, the whole sample is uniformly distributed among 18–30 (31.8%), 31–40 (35.3%) and over 41 (32.9%). The age groups are similarly

distributed among P&Rs and car users. As for employment status, P&Rs are students (19.0%), employees (66.7%) or self-employed (14.3%), whereas car users are students (15.6%), employees (51.6%), self employed (28.1%) and unemployed (4.7%). The majority of P&Rs are unmarried (85.7%) as opposed to the car users where marital status is more evenly balanced (51.6% single, 48.4% married). All participants possess a driving license and are car owners, but the kilometers traveled by car by each individual annually vary: 76.2% of the P&Rs travel less than 15,000 km (9.5% 15,000–20,000 km, 14.3% more than 20,000 km) against 50% of the car users (32.8% 15,000–20,000 km, 17.2% more than 20,000 km). Regarding household characteristics, household size in both groups is: 1–2 people (41.2%, 28.6% for P&Rs and 45.4% for car users), 3–4 (48.2%, 61.9% for P&Rs 43.8 for car-only), while the remainder is composed of 5 or more members (10.6%, 9.5 for P&Rs and 10.5% for car-only). Children are present in 28.2% of the families (both P&Rs and car-only), 23.8% for P&Rs 29.7% for car-only. Lastly, 68.2% of the households in both classes owns from 1 to 2 cars while the remainder owns 3 or more.

4.2. Travel dataset

A total of 614 trips (324 in the wave 1 and 290 in the wave 2) were collected. Travel mode distribution in wave 1 was 67% for car as driver and 33% P&R. In wave 2, after the provision of personalized travel plan, the P&R mode registered a positive change, increasing by 10% from 33% to 43%, against a 10% decrease in car driver, to 57%. Table 1 provides a description of the level of service of the park & ride alternative and for the car-only mode.

Table 1. Travel mode distribution for waves 1 and 2 and overall

	Over all		Wave 1		Wave 2	
	Nb.	Modal Split	Nb.	Modal Split	Nb.	Modal Split
Car-only	382	62%	218	67%	164	57%
Park and Ride	282	46%	106	33%	126	43%
Total	614	100%	324	100%	290	100%

The cost of travelling by car (for the car as driver mode and P&R alternative), has been calculated proportionately to the distance traveled for a kilometer cost of 0.40 Euros. At the end of wave 2, all the car users were invited to complete a final questionnaire for providing feedback on their experience and especially their propensity to change. Table 2 shows the relative frequency distribution of the car users answers at the end of the second wave: more than 89% of the sample had decided to change, 34% actually already changed during the monitoring week.

Table 2. Decision to change travel behaviour

	Car-only users	
	N	%
Decision not to change behavior at all	7	11%
Decision to change in the weeks to come	35	55%
Decision to change in the monitoring week	22	34%
Total	64	100%

5. Model results

5.1. The mixed Logit model to account for the effect of the PTP

In this section we describe the results of the mode choice models between car and P&R, Table 3 reports the best specifications obtained after an extensive analysis, where we carefully tested many different utility specifications.

In particular, as expected, we found that the scale parameter was not significantly different from 1. It was then set equal to 1 in the final estimation, and then not reported in the table 3. We note that the sign of all the coefficients is consistent with the microeconomic theory or the expectations. In particular, all the parameters associated to the level-of-services (LOS) are negative and highly significant (t-test >1.96), except for the time spent looking for parking in both waves. The difference in significance of the same parameter between wave 1 and wave 2 can be related to a poor relevance allocated to searching for parking among car users. For what concerns the socioeconomic variables, the only coefficients significant at 95% are marital status (“married”) (wave 1 and 2) and gender (“Male”) (wave 1 and 2).

The variables Beuro and Bcal, which describe the effect of personalized information related to P&R alternative have been included as specific of the park-and ride alternative in wave 2, in order to associate them to the behavior change. We note that the parameter associated to the “personalized information” is positive, which reveals that given the same LOS attributes in wave 1 and wave 2, the utility to park-and ride increases with the level of information related to the light metro alternative. Regarding the significance, the coefficient of Bcal is significant at 95% while for the coefficient of Beuro we can reject the hypothesis that it is different from zero only at 86% (in a one-tail test). This is consistent with the fact that an economic benefit is not too high corresponding to a trade-off from car-only to park-and ride because the car user must sustain anyhow the costs relating to the use of the car from the origin to the light metro parking.

Note that the constants (wave 1 and wave 2) are not really significant, which indicates that the parameters are able to reproduce the phenomenon under study. Finally, we calculated the Subjective Value of Time (SVT) for both alternatives, SVT is the amount that a traveller would be willing to pay in order to save one unit of time, in this case we have:

$$SVT = \frac{\frac{\delta V_{P\&R}}{\delta T_{P\&R}}}{\frac{\delta V_{P\&R}}{\delta C_{P\&R}}} = \frac{\beta T_{P\&R}}{\beta C} = 0.764, \quad SVT = \frac{\frac{\delta V_{CAR}}{\delta T_{CAR}}}{\frac{\delta V_{CAR}}{\delta C_{CAR}}} = \frac{\beta T_{CAR}}{\beta C} = 1.476 \tag{11}$$

Where:

$$T_{P\&R} = T_{car} + T_{wait} + T_m$$

$$T_{CAR} = T_{car-only}$$

Results shows clearly that the car-only users SVT is greater than P&R users SVT, which means that car-only users have a willingness to pay higher than P&R users to reduce travel time.

Table 3. Mixed Logit model results

ML	Estimate	t-test
Constant_P&R (wave 1)	-5.18	-1.31
Constant_P&R (wave 2)	-5.47	-1.56
P&R Attributes		
Travel time by car from origin to park-and ride plus waiting time plus travel time by Metro (wave 1 & wave 2)	-0.17	-1.94
Walking time from park-and ride to Metro station(wave 1)	-4.64	-3.45
Walking time from park-and ride to Metro station(wave 2)	-4.13	-3.19
Walking time from Metro station to destination (wave 1 & wave 2)	-0.96	-3.04
Car-only Attributes		
Travel time by car-only (from origin to destination) (wave 1 & wave 2)	-0.62	-3.75
Walking time from car parking to destination (wave 1 & wave 2)	-1.21	-4.54
Travel time by car looking for parking (wave 1)	-0.21	-1.03
Travel time by car looking for parking (wave 2)	-0.15	-0.84
P&R and Car only Attributes		
Travel cost (wave 1 & wave 2)	-1.71	-2.54
Individual characteristics		
Gender "Male" (wave 1 & wave 2)	3.95	2.45
Marital Status "Married" (wave 1 & wave 2)	4.11	2.61
Personalized information		
Beuro - Personalized information (wave 2)	0.002	1.48
Bcal - Personalized information (wave 2)	19.1	1.96
L(max)		-63.572
L(C)		-313.404
ρ^2		0.808
N. individuals		85
Sample size		614

5.2. The MNL to measure the Voluntary travel behavior change

Table 4 reports the results obtained estimating a MNL model that describes the behavioral change process, *i.e.* the probability to change mode in the monitoring week or sometime later in the future, as opposite to the decision to not resign the car usage. In particular, the attributes are defined at individual level and include (1) individual characteristics, (2) household socioeconomic, (3) travel behavior and cost, and (4) pro-environmental efforts (measured in a deterministic way and not by using indicators, as acquired from questionnaires). Finally, a measure of the daily monetary saving reported in the personalized travel plan (difference between trip cost by car and trip cost by light metro) has been included.

Looking at the results in the table, individuals from households with kids are more likely to change in general and slightly more in the weeks to come. This can still be related to the monetary saving involved and shows that some time is required to re-arrange activity-travel patterns in families with high household responsibilities.

Additionally, individuals with high monthly expenditure are more likely to change, probably due to the higher relevance for them of the monetary saving involved in the mode trade-off.

Further individuals who don't live in the central urban area (Living in Metropolitan area and Living in Suburb area parameters) are more likely to change in the weeks to come.

For what concerns travel behavior and cost parameters, individuals who travel more than 25k kilometers each year, are less likely to change their travel mode behavior. This indicates, as expected, that travel behaviors highly based on car usage are difficult to be modified (inertia effect). However, individuals with high work trips frequency are more likely to change (at least in the second week). This fact is connected to the number of work activities located around the light metro corridor.

An interesting set of parameters is represented by the pro-environmental efforts. It appears that individuals that usually devote high effort to recycling and energy saving are more likely to change behavior, indicating that acquiring pro-environmental styles in different daily habits can be relevant to stimulate also travel behavioral changes. The last parameter estimated in the model is related to the monetary daily savings involved if the suggested mode is integrated in the individual travel behavior. As showed in the table, individuals presented with a saving are more likely to change mode.

Finally, as shown in the first row of the table, the alternatives to change in the weeks to come or to change in the second week (week 2) have significant and negative constants. This result appears to suggest a general low preference among participants to change travel mode (probably also due to habits), and especially to change in the weeks to come. This aspect confirms the presence of inertia factors in car use behaviors and confirms the importance of policies that promote voluntary behavior change through marketing campaign and information about available alternatives. A last note worth to be highlighted is the accordance between parameters' signs between the option to change in the weeks to come and during the monitoring week. This result seems to indicate many similarities between who has immediately changed and those who have admitted to need more time to change their behavior. These correspondences are promising for a final positive outcome among a wider group of individuals. This is confirmed by a post-survey started three months after the end of the project that has revealed how a percentage of the individuals that stated to plan on changing in the weeks to come has actually changed mode behavior.

Table 4. Results of the behavioral change model

	Not to change at all	Change in the weeks to come	Change in the second week
Constant	-	-7.36 (-5.88)	-3.82 (-3.94)
Presence of children	-	5.70 (5.88)	3.97 (4.50)
Monthly expenditure for transport (>100euro)	-	2.32 (2.79)	1.82 (2.36)
Living in Metropolitan area	-	2.34 (2.29)	-
Living in Suburb area	-	1.15 (1.92)	-
Km traveled > 25,000 km/year	-	-	-1.71 (-2.61)
High Recycling efforts	-	2.30 (3.35)	-
High Energy saving effort	-	3.08 (3.47)	2.59 (3.16)
High trip frequency for work	-	-	1.74 (3.56)
Monetary saving involved in the mode shift	-	-	0.93 (2.20)
L(max)		-105.766	
L(C)		-180.172	
ρ^2		0.413	
N. individuals		64	

6. Conclusion

The objective of this work is to contribute to the debate on behavioral change, analyzing the propensity of individuals for voluntary travel behavioral change. Two models have been estimated, the first measures the effect of personal travel programs in the mode choice behavior, the second one analyses the voluntary travel behavior change choice. Both models showed how the information provided during a personalized travel plan is significant on increasing the utility of the proposed alternative and on stimulating a change in behavior. An important result is related to the type of information presented to car-users. Indeed, quantitative measures of benefits involved in a behavior change have been found significant.

From a methodological standpoint, the results presented in this paper reinforce the basic assumption that behavioral model and theories of change can work together in order to make voluntary behavior change programs more effective. Further, from a conceptual point of view, the positive effect of the information provided on the mode choice and behavioral change needs to be taken into account from the governments when planning new policy intervention. Most of the car drivers are in fact not aware of their alternatives and most of the times they are not able to quantify possible benefits deriving from behavior changes. Changing travel behavior, especially for a car user requires great efforts and supporting the behavioral change process needs it's a critical aspect.

Another result of this study highlighted that there are individual habits, such as pro-environmental efforts, that characterize a higher probability to change also travel mode behavior. This is an interesting aspect, since it means that educating the community to adopt sustainable behavior of any type will have an indirect effect on individuals' propensity to change travel behavior as well.

Finally, the work presented in this paper will be further improved jointly estimating the two proposed models in order to properly study the relation between the preference for a certain mode and the propensity for changing.

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