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Car stickiness: Heuristics and biases in travel choice

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ABSTRACT

We conduct a laboratory experiment to investigate the factors determining travel mode choice. Two different scenarios are considered. In the first scenario, subjects have to decide whether to commute by car or by metro. Metro costs are fixed, while car costs are uncertain and determined by the joint effect of casual events and traffic congestion. In the second scenario, subjects have to decide whether to travel by car or by bus, whose costs are determined by a different combination of chance and traffic congestion. Subjects receive feedback information on the actual travel times of both modes. We find that individuals show a marked preference for cars, are inclined to confirm their first choice and exhibit travel mode stickiness. We conclude that travel mode choice is subject to cognitive heuristics and biases leading to robust deviations from rational behaviour.

1. Introduction

The rational model of travel mode choice assumes that the optimal decision is to maximise individual utility subject to time and budget constraints. This approach requires that travellers correctly process all the available information and are not affected by cognitive biases. In contrast, non-standard theories of decision-making under uncertainty depart from strict definitions of rationality, especially when individuals face repeated choices (Starmer, 2000). In this setting, behavioural models introduce a great variety of hypotheses regarding information processing and learning based on empirical evidence. In particular, psychological studies indicate that decision makers are boundedly rational, use choice heuristics and are affected by perceptual and cognitive biases (Kahneman and Tversky, 1973).

Field and laboratory researches provide wide evidence that individuals violate the assumption of rationality when travel costs are uncertain. Behavioural models on the determinants of travel mode choice focus on three main areas: information processing and learning, the impact of habit on commuters' decisions, and the effect of travellers' risk attitude.

Most theoretical work concerns the analysis of route choice, which is also the object of a rich experimental literature. Rational route choice is usually modelled as a coordination game in which rational players should converge on equilibrium. The payoff each player can achieve is conditional on the ability to diverge from or to converge with other players' choices. This process depends on the expectations of others' route choices, which are based on prior experience and public information. Some experimental studies show that when subjects choose between two congestible paths, travellers' distribution along each path is close to equilibrium (Iida et al., 1992, Helbing, 2004, Chmura and Pitz, 2004a and 2004b, Selten et al., 2007, Razzolini and Datta Mago, 2011). Lu et al. (2011) confirm this result by showing that *en ruote* real time additional information enhances the optimality of choices in an experimental congested network.[1]

In contrast, when explicitly applied to travel mode choice, empirical and laboratory evidence supports the notion that the activities of information collecting and processing are heterogeneous across individuals and are affected by cognitive biases, which limit choice rationality.

A first source of distortion comes from the fact that the variability of travel times is perceived as less than it really is because it is inferred by experienced times (Kareev et al., 2002). According to the representativeness heuristics (Kahneman and Tversky, 1973), people judge the probability of an event by considering their own experience and not the whole range of possibilities. Empirical research (Srinivasan and Mahmassani (1999); Jong et al., 2003; Abdel-Aty and Abdallah, 2004) shows that information on timetables or travel delays is often inaccurately processed and that real time information is collected and processed sequentially and not instantaneously. Ben-Elia et al.

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[1] Lu et al. (2011) also show that *ex post* information on travel times on non-chosen routes has the opposite impact on choice rationality, by increasing risk-seeking behaviour and route switching.

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(2008) analyze the combined effect of personal experience and real time information on travellers' route choice and conclude that there is substitution, rather than complementarity, between the two. Their key finding is that information is better processed when travellers lack long-term experience on travel time distribution. This result has negative implications for transportation policies, which increasingly rely on the fact that travellers are provided with real-time travel information that is more comprehensive and accurate than information based on personal experience.[2] Travellers' rationality may also be impaired by limited memory. Although travellers adhere to the principle of payoff maximisation, their inability to take into account all previous travel costs leads to a failure in choosing the rational strategy. Kareev et al. (1997) show that individual differences in working-memory capacity imply that decision-makers process samples of different sizes and hold different subjective expectations.

The fact the travel choices are mostly repeated choices also negatively affects travellers' rationality (Gärling, 1998). Habit triggers automatic reactions to information on travel modes that are not based on rational calculation (Aarts et al., 1997). Mahmassani's (1996) survey on the behaviour of commuters points out that they are guided mainly by heuristics rules. Mahmassani and Liu (1998) propose a list of behavioural strategies followed by commuters in route switching decisions and associate them with information provided on delays and departures. Verplanken et al. (1994) and Verplanken and Aarts (1999) show that if habitual behaviour increases in strength, mental and cognitive efforts are reduced to a minimum and additional information is scrutinised less accurately. In a simulation model on route choice, Nakayama and Kitamura (2000) argue that driver-network systems do not converge to equilibrium when these behavioural properties are assumed. The result of their simulations is that network systems do not necessarily converge to equilibrium because drivers develop the habit of choosing the same route repeatedly.

This tendency is particularly pronounced in mode choice. Cars are generally perceived as the means of travel giving status, sense of comfort, control and freedom. The costs associated with car are frequently undervalued because they are not paid entirely simultaneously with car use.[3] These factors explain the common propensity to use private cars and the psychological resistance to reduce it (Van Vugt et al., 1995; Tertoolen et al., 1998; Hensher, 2001; Steg et al., 2001; Bamberg et al., 2003; Steg, 2003; Anable and Gatersleben, 2004). This view is supported by the fact that mode choices are strongly dependent on subjective determinants (Scheiner and Holz-Rau, 2007; Johannson et al., 2006). Individual life styles and differences in people's attitudes and personality traits have such a great impact on these choices to represent a key problem in the implementation of effective transportation policies. Hunecke et al. (2007) calculate a regression model to assess the ecological impact of travel behaviour and find that socio-demographic and psychological factors are significant determinants of mode choice. Klöckner and Friedrichsmeier (2011), in an analysis of student behaviour, show that individual specific attributes are good predictors of car preference.

Finally, in an experiment on route choice, Avineri and Prashker (2006) find that giving travellers more accurate information on actual travel times does not necessarily increase their propensity to choose faster routes. This behaviour is explained in terms of the "payoff variability effect", according to which the increase of travel time variability makes choices more heterogeneous and significantly reduces the maximisation rate. Further evidence confirming this hypothesis is provided by Ben-Elia et al. (2008) and Lu et al. (2011), showing that better information increases risk seeking behaviour, reduces initial exploration and increases heterogeneity of choices. In particular, Ben-Elia et al. (2008) provide laboratory evidence that feedback information of actual travel time has more impact on choices if subjects lack long-term experience on the distributions of travel times. These results support the theory that travellers do not exhibit Bayesian learning in collecting and processing information.

To provide further evidence on the effect of travel information, we conducted an experiment intended to check the robustness of the rational model of travel mode choice and to eventually investigate the heuristics leading to sub-optimal choices. The originality of our contribution lies in the fact that most experimental literature on travel choice (Rapoport et al. 2004, Selten et al. 2007, Ziegelmeyer et al. 2008, Razzolini-Datta 2011) assumes that choices between different routes or modes can be represented as abstract moves in a coordination game which may or not generate Nash equilibria. In contrast, our design made explicit labels of travel modes, such as "car", "metro" or "bus". We expected that this feature led experimental subjects to take into the lab the preferences applied in real life and to rely on heuristic rules to determine their choices.

The rest of the paper is divided into the following sections. Hypotheses and experimental design are described in Section 2. Section 3 illustrates laboratory findings, which are discussed in Section 4. Section 5 concludes by offering some suggestions for policies and future research.

2. Experimental design and hypotheses

According to the rational choice model, travellers should optimise the travel production function by choosing the best combination of monetary costs and expected times. This is given by the minimisation of total travel cost, which is the sum of direct costs (travel mode price) and indirect cost (time expressed by monetary units). Each traveller holds a subjective belief about travel times based on prior experience and public information. When the choice is repeated, this belief is updated rationally on the basis of actual travel times. Following this approach, a sequence of choices is rational if it converges with the mode associated with the lower total travel cost. Although rationality is a broader concept than cost minimisation, in the experiment we treat the latter as a specification of the former. The design consists of two scenarios. In the first, subjects choose repeatedly (50 times) between car and metro. Metro total travel costs, given by the sum of metro price and time cost expressed in monetary units, are fixed, while car total costs are uncertain and determined by the joint effect of traffic congestion and casual events. In the second scenario, subjects repeat for 50 rounds the choice between car and bus, whose costs are both uncertain and determined by the combination of traffic congestion and casual events. In both scenarios, traffic congestion depends on the percentage of commuters choosing the same mode, while the effect of casual events is calculated on the basis of independent drawings from a probability distribution unknown to the subjects. The combination of all these elements implies that car total cost may be greater, equal or lower than metro and bus and is also more random. When making choices, subjects are always informed of

[2] This evolution is due to the increasing use of ATIS (Advanced Traveler Information Systems) technologies, such as broadcast traffic conditions, Variable Message Signs (VMS) and cellular information systems.

[3] Car costs are direct costs such as fuel, parking fees, as well as indirect costs such as usage of tires, maintenance, etc. As they are paid at different times they are not correctly computed to car use. Moreover, external factors such as pollution or social costs due to car accidents are not easily computable and often neglected. Under-evaluation of these costs leads to car use propensity, despite the fact that most public transport systems are heavily subsidised. (Tertoolen et al., 1998)

Table 1
Travel time and costs by treatment.

Treatment	Car expected travel time (minutes)	Car fixed cost[a] (tokens)	Metro scheduled or bus scheduled travel time (minutes)	Metro (fixed) or bus expected travel time (minutes)	Metro or bus fixed cost[a] (tokens)
Metro vs. car	25	1.5	30	30	1.0
Bus 1.0 vs. car	27	1.5	30	32	1.0
Bus 0.8 vs. car	27	1.5	30	32	0.8

[a] Table shows only the fixed component of travel mode costs. The variable component is dependent on the difference between the scheduled time and the realized time. Due to the fixed time of metro, the variable component of this travel mode is zero.

the travel times previously achieved in both modes to investigate if they adjust their expectations.

The experiment was carried out with 62 undergraduate students from the Faculties of Economics and Political Sciences in Florence and adopted a between-subjects design in order to avoid carryover effects from one treatment to the other. The experiment was computerised using a modified version of the Z-tree software (Fischbacher, 2007). We ran three treatments. In the first treatment, we tested the first scenario described above, metro vs. car, with 30 subjects (15 males and 15 females). In the second and third treatment, we submitted to 15 and 17 subjects (equally divided between males and females) the second scenario, bus vs. car, with different bus fixed costs (respectively, 1.0 and 0.8).

Before each session, subjects received an endowment of 150 experimental tokens and written instructions, which were read aloud by the monitor[4] . Prior to the start of the experiment, participants had the opportunity to become familiar with the design in three unpaid rounds. Before and after this preliminary phase, subjects could ask aloud questions on the experimental procedure. At the end of each session, subjects were paid in cash according to the tokens gained during the experiment, which were converted into euro at a pre-established rate made known in advance to the subjects. Average earnings were 18.4 Euro, including the show-up fee.

Before the first round, subjects received the following information (Table 1):

a) The expected/scheduled travel time for each mode. Metro travel time was fixed (30 min), whereas car and bus travel time were uncertain and depended on some casual factors (such as weather, car accidents, road works), randomly chosen by the computer according to a fixed probability distribution. Subjects received information on the expected value of the distribution (25 min in the car/metro treatment), but not on the distribution characteristics. Moreover, for cars and buses a possible traffic congestion delay, as determined by the combined choices of all the subjects, could be added to travel time and imply a monetary cost.
b) The cost of each travel mode that was made by a fixed component and a variable component linked to the difference between the scheduled time and the realized time. The variable component was the penalty to be paid or the reward gained respectively for minutes of delay or in advance of the expected travel.

The relation between traffic congestion and travel time, which is shown in Table 2, was not communicated in advance to the subjects.

[4] A full version of the written instructions (original in Italian and translated in English) can be provided on request.

Table 2
Effect of traffic congestion on car and bus travel times.

	Level of traffic congestion		
	Moderate	Intense	Chaotic
Share of car users	$\leq 55\%$	$> 55\% \leq 75\%$	$> 75\%$
Car travel time variation (in minutes)	0	5	10
	Level of traffic congestion		
	Moderate	Intense/Chaotic	
Share of car users	$\leq 55\%$	$> 55\%$	
Bus travel time variation (in minutes)	0	5	

The same was true for the probability distribution of casual factors determining car and bus travel times, which is shown in Table 3.

For each five minutes of delay (or ahead of time) on expected time, car cost was increased (or decreased) by 0.5 tokens and total cost of the travel mode adjusted. As buses never arrived ahead of scheduled time, bus cost could be only increased.

After each round, subjects were privately informed of:

a) the travel time achieved by both available modes;
b) the level of traffic congestion defined as *moderate*, *intense* or *chaotic*, related to the percentage of subjects choosing the car;
c) the individual total cost in tokens of the travel, given by the sum of fixed cost and eventual penalties or rewards;
d) the residual number of tokens.

By summarizing, subjects were asked to make a binary choice between two travel modes with monetary incentives to choose the less expensive option. Table 4 shows that the choices could be evaluated in term of travel time (t^{tot}) or travel cost (C^{tot}), whose actual values were determined by casual events (for cars and buses) and by traffic congestion (depending on the share of car users).

If the share of car users had not been greater than 55%, car travel time was equal to that randomly drawn from the distribution of Table 3, t*car. If the share had been between 55% and 75%, car travel time was increased by five minutes and, consequently, the total cost increased by 0.5 token, while if the share had been over 75%, car travel time was increased by ten minutes and total cost by 1.0 token. Thus, in absence of congestion, car expected travel time was lower than the public transport scheduled time, and since subjects were informed that each five minutes ahead of time (delay) implied a monetary gain (penalty) of 0.5 tokens, car expected total cost was equivalent to the metro and bus cost of 1.0 token. In the car–metro treatment subjects had a 45% (due to casual events) chance of achieving a car travel time of 20 min, with a gain of 0.5 tokens with respect to the metro cost, but this chance was challenged by other subjects' choices as traffic congestion could offset or even reverse this gain.

Table 3
Effect of casual factors on car and bus travel times.

Metro treatment					
Car travel time (in minutes)	20	25	30	35	40
Probabilities	45%	30%	10%	10%	5%
Bus treatments					
Car Travel time (in minutes)	20	25	30	35	40
Probabilities	30%	30%	20%	10%	10%
Bus Travel time (in minutes)	30	35	40		
Probabilities	70%	20%	10%		

Table 4
Summary of the experimental design.

Treatment	Travel mode	
Metro vs. car	Car	$t^{act}_{car}=t^{*}_{car}+t^{cong}_{car}(N_{car})$ $t^{cong}_{car}(N_{car})=0$ if $N_{car}<N_1$ $t^{cong}_{car}(N_{car})=\alpha$ if $N_1\leq N_{car}\leq N_2$ $t^{cong}_{car}(N_{car})=\beta$ if $N_{car}>N_2$ $C^{tot}_{car}=C^{f}_{car}+C^{v}_{car}$ $C^{V}_{car}=\gamma^{*}(t^{act}_{car}\text{-}t^{sch}_{met})$
	Metro	$t^{act}_{met}=t^{sch}_{met}=t^{f}_{met}$ $C^{tot}_{met}=C^{f}_{met}$
Bus vs. car	Car	$t^{act}_{car}=t^{*}_{car}+t^{cong}_{car}(N_{car})$ $t^{cong}_{car}(N_{car})=0$ if $N_{car}<N_1$ $t^{cong}_{car}(N_{car})=\alpha$ if $N_1\leq N_{car}\leq N_2$ $t^{cong}_{car}(N_{car})=\beta$ if $N_{car}>N_2$ $C^{tot}_{car}=C^{f}_{car}+C^{v}_{car}$ $C^{V}_{car}=\gamma\ {}^{*}(t^{act}_{car}\text{-}\ t^{sch}_{bus})$
	Bus	$t^{tot}_{bus}=t^{*}_{bus}+t^{cong}_{bus}(N_{car})$ $t^{cong}_{bus}\ (N_{car})=0$ if $N_{car}<\ N_1$ $t^{cong}_{bus}\ (N_{car})=\ \alpha$ if $N_{car}\geq N_1$ $C^{tot}_{bus}=C^{f}_{bus}+\ C^{V}_{bus}$ $C^{V}_{bus}=\gamma^{*}(t^{act}_{bus}-t^{sch}_{bus})$

t^{act} $_{car,bus,met}$, Actual travel time.t^{*}_{car}, Casual variable [20,45] representing the effect of casual event on time (see Tables 1 and 3).t^{*}_{bus}, Casual variable [30,45] representing the effect of casual event on time (see Tables 1 and 3).$t^{cong}_{car,bus}$, Congestion time delay.t^{sch} $_{met,bus}$, Scheduled travel time for public transport (30 min, see Table 1) that is the reference time for cars being delay/ahead.t^{f}_{met}, Fixed travel time for metro (30 min).N_{car}, number of cars.C^{tot} $_{car,bus,metro}$, total cost of the transport mode.C^{f} $_{car,bus,metro}$, fixed cost of the transport mode (see Table 1).C^{v} $_{car,bus}$, variable component of travel cost.N_1, first congestion threshold (55%).N_2, second congestion threshold (75%).α, Delay to be added for moderate congestion (5 min).β, Delay to be added for heavy congestion (10 min).γ, Parameter to convert time differences into monetary costs (5 min converted in 0,5 token so that γ =0,1).

Overall, travel costs were as follows:

a) In the metro and bus 1.0 treatment, the expected total costs of car and metro were equivalent if the share of car users was not greater than 55%. Top panel of Fig. 1 shows the effect of congestion and casual events on costs, with solid lines representing the expected costs for metro (horizontal) and car (stepwise) and dashed lines car costs under different casual (randomly chosen) and congestion events.
b) In the bus treatments, the expected total cost of buses and car was also influenced by congestion and casual events. However, for the sake of simplicity, bottom panel of Fig. 1 represents only the effect of congestion on transport mode costs. In case of bus 0.8 treatment, bus cost is permanently 20% lower than car expected total cost.

With respect to the rational model of travel mode choice, we intended to test the following two hypotheses:

HP. 1 Before the first round, subjects are indifferent between the available modes in the metro treatment and in the bus 1.0 treatment, while they prefer bus over car in the bus 0.8 treatment.

$${}_{1}N_{car}=50\%\ \text{(metro and bus 1.0 treatments)}$$
$${}_{1}N_{car}=0\ \text{(bus0.8treatment)}$$

where ${}_{1}N_{car}$ is the share of subjects choosing car in the first round.

HP. 2 After the first round, subjects update their expectations. The expected total costs of the two available modes are equivalent in the metro and bus 1.0 treatments if the percentage of car users is no greater than 55%, otherwise expected car cost is higher than the alternative mode. In the bus 0.8 treatment, bus expected total costs were always lower than car expected costs (Fig. 1). This is equivalent to say that there is a continuum of Nash equilibriums up to the point in which cars are more than 55%, because there is no incentive for each subject to deviate from her/his choice[5]. Thus,

$$0\leq {}_{t}N_{car}\leq 55\%\ \text{(metro and bus 1.0 treatments)}$$
$${}_{t}N_{car}=0\ \text{(bus 0.8 treatment).}$$

where ${}_{t}N_{car}$ is the share of subjects choosing car in rounds other than the first.

3. Results

Findings are presented in three sections, which describe the different patterns of behaviour shown by subjects.

3.1. Preference for cars

As discussed in the introduction, many empirical studies provide evidence that travellers exhibit a propensity to use private cars over alternative modes. The findings support this observation. Fig. 2 shows the share of car users each five rounds.

In the metro treatment, the share of car users is almost never lower than 55%, confirming that car is chosen by the majority of subjects, although it is more costly than metro for the effect of traffic congestion. The share of car users is nearly the same in the first and in the last round, reaching its peak around the 7th–8th round and then fluctuating around the initial value. This result appears to be contingent more on the behavioural inclination to use cars acquired outside the laboratory than on information received during the experiment. Fig. 3 shows the share of car users (left panels) and the cost difference between car and metro or bus (right panels).

In the left top panel, the dark line, representing the share of cars, is almost always above the bottom horizontal line of the 55% congestion threshold[6] and occasionally above the top horizontal line of heavy congestion (more than 75% cars).

The preference for cars is confirmed by looking at actual travel costs. The right top panel of Fig. 3 shows the difference between car and metro costs for each round, which is rarely negative. Although the average car total cost (1.46) is greater than the fixed metro cost (1.00), the ratio between the average shares of car and metro users is nearly two to one.

In the bus (1.0) treatment, cars are chosen on average by the 58% of the subjects (Fig. 2). The middle left panel of Fig. 3 shows the share of car users in each round. Also in this treatment the dark line is mainly above the bottom threshold line.

[5] In the transportation literature, the non cooperative equilibrium is reformulated as the Wardrop Equilibrium, also known as User Assignment Equilibrium (Wardrop 1952). Wardrop's first principle states that every driver chooses a route/mode for which the cost is minimal. As a consequence, the Wardrop equilibrium is defined as a situation in which no driver can unilaterally reduce travel costs by shifting to another route/mode.

[6] The share of cars in metro treatment is statistically (p value=0.000) above the threshold of 55%, as the standard error is 0.014 (t=9.166).

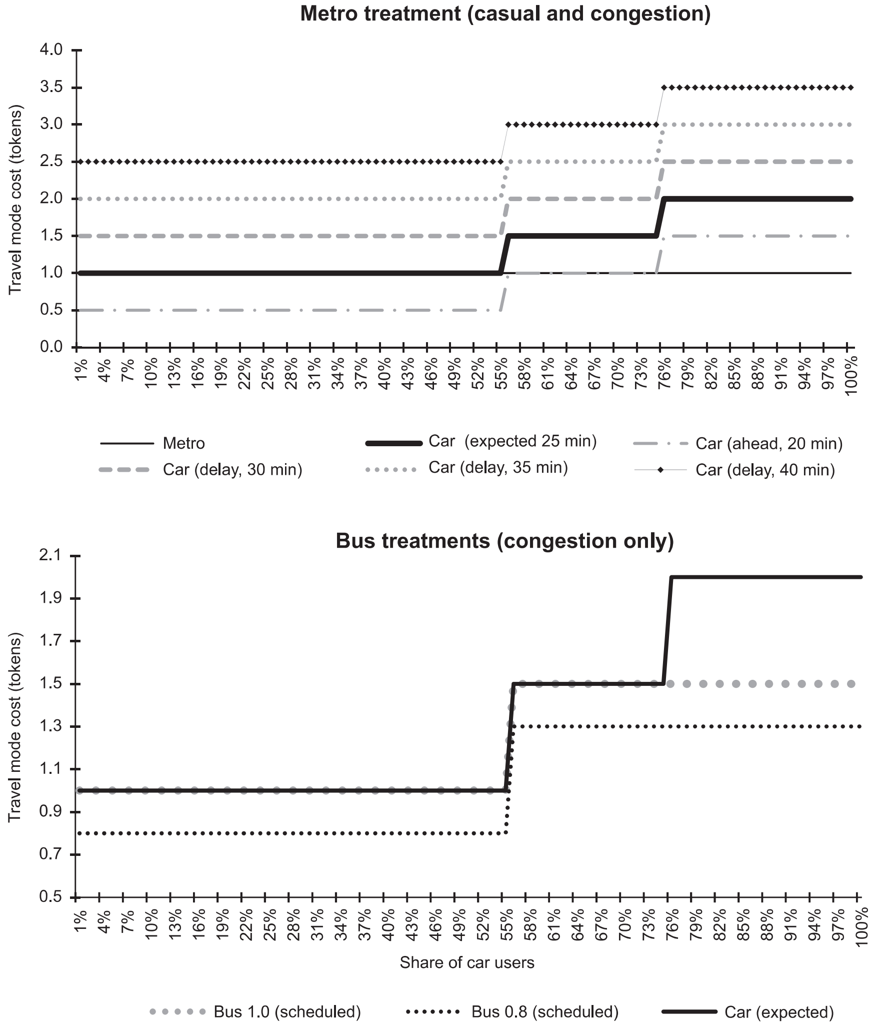

Fig. 1. Effect of congestion and casual events on travel mode costs.

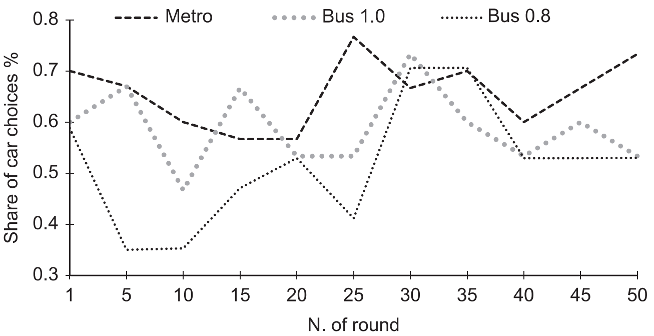

Fig. 2. Share of car users by treatment (every five rounds).

The equivalence between expected total costs of car and bus holds only below the threshold of 55% of car users, but this share is exceeded in 40 rounds out of 50[7]. Actual travel costs in the bus 1.0 treatment are shown by the middle right panel of Fig. 3. On average, car total cost is 1.63, which is 35% greater than bus cost (1.21).

In the bus 0.8 treatment (bottom panels of Fig. 3), the reduction of the fixed bus cost relatively increases the percentage of bus commuters, but the share of car users is greater than 50% in 30 rounds and on average is equal to 50.1, despite the predicted equilibrium of zero car users. Costs shown in the right panel validate the robustness of car preference, since the actual average bus cost (0.96) is considerably lower than car average (1.48).

The dynamics of choices confirms the positive inclination towards car usage, also by looking at the share of car users in rounds following an outlier value of car cost. After rounds in which car costs are very high, subjects react very quickly, but the deterrent effect does not last long. If regret can play a role in travel mode choice, it does not seem relevant in the experiment.

Finally, it is noticeable that cars are more often chosen when the alternative travel mode is metro rather than bus (t=4.708, $p<0.05$ in the bus 1.0 treatment; t=7.86, $p<0.05$ in the bus 0.8 treatment). Table 5 confirms this finding by showing the frequency of rounds by shares of car users.

In the metro treatment, the share of car users is lower than 0.50 only in 10% of the rounds, while this percentage increases to 20% in the bus 1.0 treatment and to 40% in the bus 0.8 treatment.

3.2. First choice effect

Further analysis shows that subjects exhibit patterns of choices corresponding to behavioural rules, which do not necessarily involve

[7] The share of cars in bus1.0 treatment is above the threshold of 55% with a statistical significance of 94% (p value=0.0511, t=1.66).

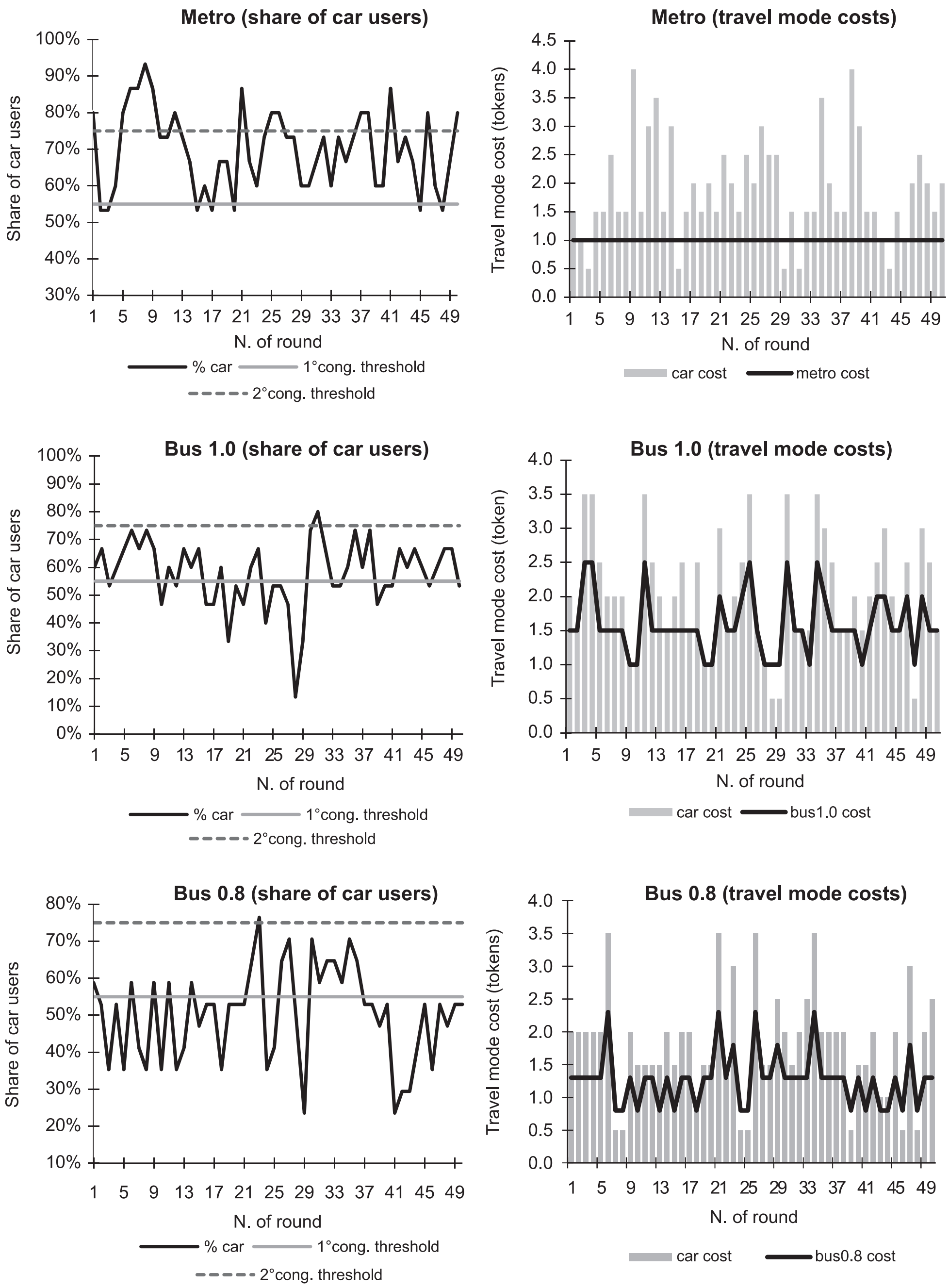

Fig. 3. Share of car users and travel costs by treatment.

Table 5
Frequencies of rounds by proportion of car users and by treatments.

Share of car users	Metro vs. car	Bus 1.0 vs. car	Bus 0.8 vs. car
< 0.50	10	10	20
$\geq 0.50 < 0.60$	10	11	20
$\geq 0.60 < 0.70$	34	23	5
$\geq 0.70 < 0.80$	18	5	5
$\geq 0.80 < 0.90$	25	1	–
≥ 0.90	3	–	–
Total no. of rounds	100	50	50

cost minimisation. In all treatments, the share of car users increases in the second half of each treatment and becomes less erratic. The average share of car users over all rounds and all treatments is almost the same. It increases from 0.57 in the first 25 rounds to 0.59 in the last 25 rounds, while the standard deviation decreases from 0.180 to 0.145. Moreover, the number of subjects changing travel mode in the last 15 rounds is a third lower than the number of subjects switching in the first 15 rounds.

These results might be interpreted as evidence of learning. Subjects would gradually discover the probability distributions determining travel times and this process would decrease choice variability. In contrast, we found that subjects exhibit a clear tendency to confirm their first choice. Top panel of Fig. 4 shows the distribution of subjects by metro choice, divided by car choosers and metro choosers in the first round.

Subjects choosing car in the first round are concentrated on the left of the distribution. 86% of subjects who start by choosing a car choose the metro fewer than 16 times, whereas only 22% of those whose first choice is metro preferred metro fewer than 16

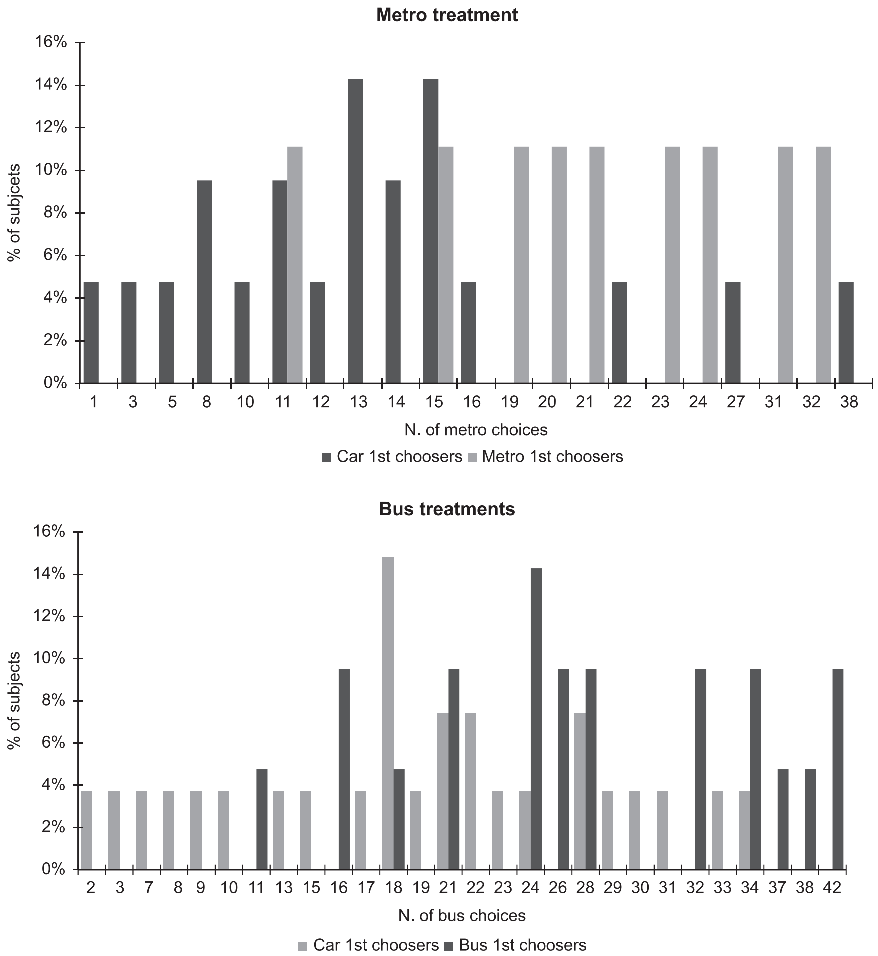

Fig. 4. First choice effect: distribution of public transport choices by type of first choice.

times. Similar choice patterns emerge for the bus treatments (Fig. 4, bottom panel).

3.3. Travel mode stickiness

The first choice effect implies that travellers exhibit an aversion to change travel mode. Fig. 5 shows the distribution of subjects according to the number of mode changes.

Only 28.6% of the subjects in the metro treatment and 39% in the bus treatments change more than 20 times over 50 rounds. On average, subjects change mode 17.7 times in the metro treatment and 18.0 times in the bus treatments.

It can be shown that changes are negatively correlated with the average travel time in both treatments, although this relationship is not statistically significant. In an experiment on route choice, Selten et al. (2007) provide evidence of the positive relationship between route stickiness and aggregate payoff. They also analyze how travellers react to other commuters' choices by defining two different types of responses. In the first type, called *direct response*, travellers switch mode in the next round if travel times in the previous round are relatively high. In the second type, the *contrary response*, travellers change mode if travel times in the previous round are relatively low, on the basis of the expectation that this mode will attract more travellers in the next round and produce more traffic congestion.

To investigate the occurrence of these responses in our experiment, we define travel mode cost relatively *high* if it is higher than the average travel cost of the previous ten rounds and relatively *low* if it is lower than the average travel cost of the previous ten rounds.[8] In the design, traffic congestion depends only on the share of car users and subjects are informed of the total travel costs of both modes. Accordingly, we adopt the definitions of *direct* or *contrary responses* given in Table 6.

For example, in the metro treatment, a change of travel mode is a *direct response* if the subject switches from car to metro upon observing a relatively high car cost or switches from metro to car upon observing a relatively low car cost, while it is a *contrary response* if the subject switches from car to metro after a relatively low car travel cost or switches from metro to car after a relatively high car travel cost. To confirm the metro travel mode over two adjacent rounds is a *direct response* if car costs are relatively high and a *contrary response* if car costs are relatively low.

For each subject i we calculate the Yule–Hamman coefficient H_i, which is given by

$$H_i = \frac{\sum_{j=1}^{n} Direct_{ij} - \sum_{j=1}^{n} Contrary_{ij}}{\sum_{j=1}^{n} \left(Direct_{ij} + Contrary_{ij} \right)}$$

The coefficient H_i varies between -1 and $+1$, so that positive values indicate the prevalence of the direct response mode and negative values of the contrary response mode. If values are concentrated around zero, neither mode prevails over the other.

[8] We assume that subjects make their choices on the basis of the previous ten rounds, because the correlation between the number of car users and the average car cost of the previous ten rounds was higher than the correlation with the average car cost of the previous five rounds or of all previous rounds.

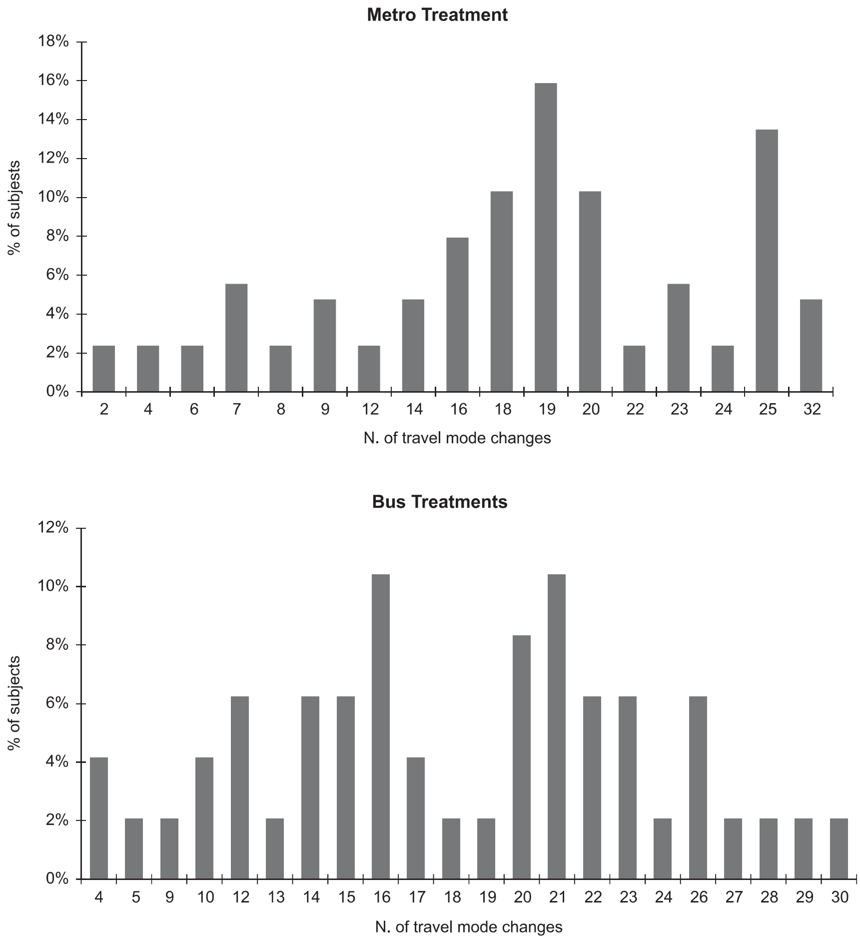

Fig. 5. Number of travel mode changes by treatment.

Table 6
Direct and contrary response modes.

Choices	Travel costs	
	High	Low
Switching from car to metro/bus	Direct (d1)	Contrary (c1)
Switching from metro/bus to car	Contrary (c1)	Direct (d1)
Confirming car	Contrary (c2)	Direct (d2)
Confirming metro/bus	Direct (d2)	Contrary (c2)

Fig. 6 shows the Yule–Hamman coefficient for all subjects in the metro (top panel) and bus treatments (bottom panel).

In both treatments, the coefficient is mostly concentrated around zero. It varies between -0.46 and $+0.13$ in the metro treatment and between ± 0.38 in the bus treatments. According to the classification proposed by Selten et al. (2007), no subject in the experiment can be classified as a *direct* or *contrary responder*, which is the case if Yule–Hamman coefficients are, respectively, lower than -0.5 and greater than $+0.5$. This result is related to the first choice effect, which decreases the tendency to change travel mode. The propensity to travel mode stickiness is further corroborated by the fact that subjects in the middle range of the distributions of Fig. 6 change travel mode less than those in the extreme quartiles. This confirms that subjects' behaviour is more strictly related to prior learning outside the laboratory than to information provided during the experiment.

Finally, a logistic regression model has been run in order to assess the relevance of the first choice effect and stickiness on travel mode choice (car$=$1, public transport$=$0). Table 7 shows the regression results for the three treatments considering the effect of subjects' first choice, the effect of the choice of previous period (the lagged dependent variable) and the effect of total cost (traffic congestion and casual events included) in period $t-1$.

The regression results largely confirm the biases discussed in the previous sections. In the metro and bus 0.8 treatments, the first choice effect is statistically significant. In the bus 0.8 treatment the first choice effect dominates, but a significant contribution of stickiness (choice of the preceding period) is also found. Stickiness and reaction to the cost paid in the previous period are statistically significant in the bus 1.0 treatment. These varied results can be presumably explained by the different characteristics between private and public travel modes among treatments chosen in the experimental design. In metro and bus 0.8 treatments, public transports have specific as well as easy-to-identify positive attributes (i.e., fixed travel time for metro and cost reduction for bus) and only a marked initial inclination can explain the high share of car choices. In bus 1.0 treatment, the uncertainty about travel time influences the individual perception of both travel modes and cost differential appears less evident. As a result, subjects exhibit stickiness but also a stronger reactivity to costs.

4. Discussion

Our key experimental result is that travel mode is significantly affected by heuristics and biases leading to robust deviations from rational behaviour. Whereas the rational choice model postulates

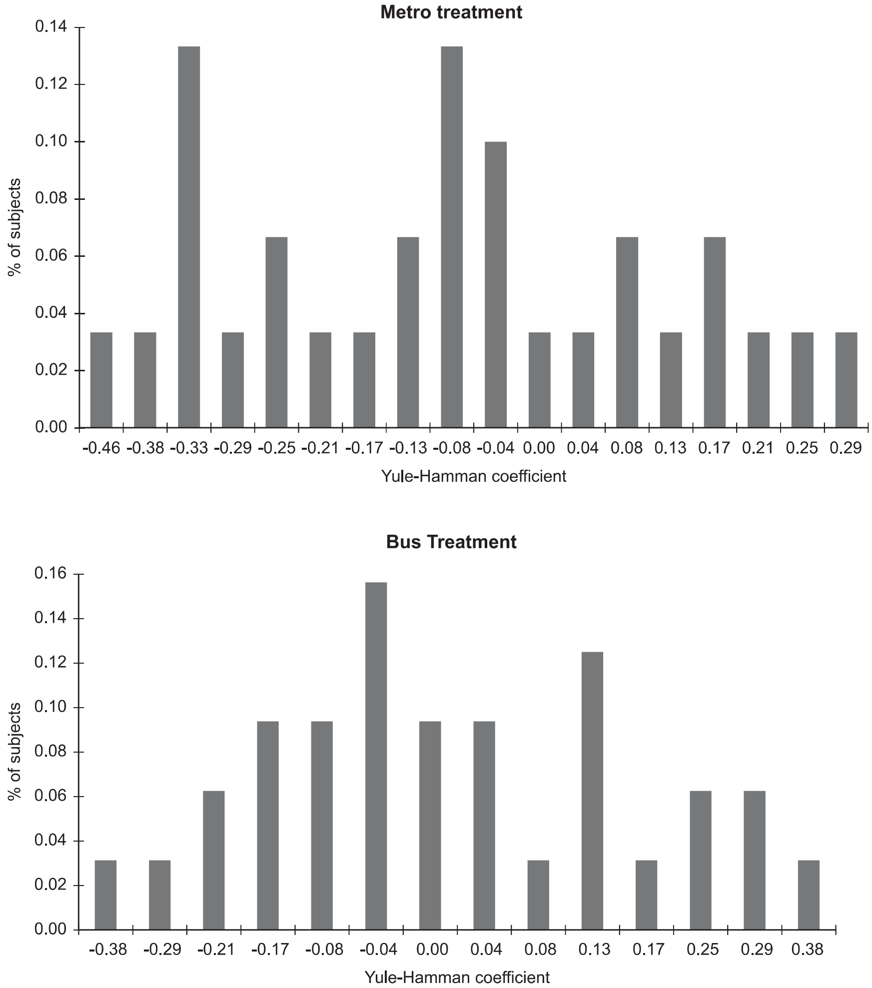

Fig. 6. Yule–Hamman coefficients.

Table 7
Determinants of car choice. Logit regressions.

	Metro vs. car	Bus 1.0 vs. car	Bus 0.8 vs. car
First choice	0.9788	0.319114	0.815
	(0.000)	(0.401)	(0.013)
Choice [1]	0.3376	0.8667	0.5952
	(0.110)	(0.000)	(0.001)
Cost [1]	0.2332	−0.2967	0.1852
	(0.236)	(0.035)	(0.231)
Constant	−0.3596	0.117	−0.9913
	(0.220)	(0.751)	(0.001)
No. obs.	705	705	799
Wald χ	24.93	31.16	28.28
	(0.000)	(0.000)	(0.000)

Note: panel random effect model, *p*- values in parentheses.

that travellers choose the most economical travel mode, we find that individuals use behavioural rules that do not necessarily involve the minimisation of total costs.

The main bias pointed out by data is the car effect, according to which individuals exhibited a preference for cars over metro and bus in contrast with their economic interest. The refutation of the rational model is corroborated by their general inclination to confirm first choices and to travel mode stickiness. These findings were obtained in an experimental setting in which subjects made their choices repeatedly and could learn the probability distributions determining actual travel costs from the feedback information on chosen and non chosen modes. Moreover, they did hardly show persistent signs of regret (Chorus et al. 2011) when car costs were markedly higher than metro or bus costs. Significantly enough, the participants were students of the University of Firenze, a city that opened its first metro line just a few months after the experiment. Hence, they were under the effect of a massive communication campaign in support of metro that might have promoted a positive attitude toward it.

A first explanation of these results is related to the affective dominance of cars, which, as pointed out above, are generally perceived as symbols of status and freedom, as confirmed also by Steg (2003). This attitude would be bolstered by the fact that car costs are often underestimated because they are partially paid delayed over time. This outcome can be mainly attributed to the label effect. In the laboratory, the use of non-professional subjects and monetary incentives should make subjects' innate characteristics largely irrelevant. In our experiment, this purpose seems to be only partially fulfilled. The explicit reference to "car", "bus" and "metro" reveals that subjects are biased towards one of the alternatives and this preference overrides the impact of incentives. As pointed out above, this behaviour depends more on prior experience outside the laboratory than on expected gains in the laboratory. In effect, travel mode choices are routine decisions, taken over and over again. They tend to become habitual choices, which cease to be the consequence of a deliberate process of weighing pros and cons. In the experiment, this attitude is automatically triggered by the cues given to subjects. Once a travel mode is chosen, rational calculation plays a limited role in determining decisions, and subjects' decisions are driven by heuristic reasoning.

The use of labels differentiates our design from Selten et al.'s (2007) experimental analysis of route choice, in which subjects play a game with two available strategies, which are choosing the main road M or the side road S. In their context-free experiment, choices, as abstract moves in a coordination game, generate outcomes very near to the equilibrium. Although mathematical game theory does not use labels, it has been argued that when playing a game in the laboratory subjects inevitably apply their own labels, because laboratory is not a socially neutral context but is itself an institution with its own formal or informal, explicit or tacit, rules (Loewenstein, 1999). By introducing labels, the external validity of experimental findings is improved, especially if one assumes that thinking and problem solving are inherently context-dependent. In our design, labels allow to remind and evoke contexts which activate subjects' emotions and mental associations. Their first choices were indeed reliable indications of their preferences and were generally confirmed during the following rounds.

Such inertia can be explained by referring to the dual process theory (Stanovich and West, 2000, Kahneman and Frederick, 2002, Kahneman, 2011). According to this approach, cognitive activities are of two types, System 1 and System 2. System 1 includes the processes characterised by automatic, associative functioning and heuristic purposes, while System 2 encompasses the rational, rule-based and analytic processes. Although both systems can be biased by prior beliefs, mental models or memory limitations, System 1 is activated immediately and often unconsciously by external stimuli, while System 2 is slower and deliberately controlled. Kahneman and Frederick (2002, p. 53) describe the interaction between the two systems as follows: "Highly accessible impressions [are] produced by System 1 control judgments and preferences, unless modified or overridden by the deliberate operations of System 2." It has also been argued that the rule-based reasoning of System 2 can be internalised by System 1 through experience (Hinton, 1990). By repeating mental associations over time, people generate routinely intuitive responses that could be previously the outcome of sequential steps of analytic thinking. This automaticity provides on account of the so-called "affect heuristics" (Slovic et al., 2002), which is connected to the perception of uncertainty and risk. Even if the rational cognitive processes of System 2 would lead to consider a choice as economically disadvantageous, positive affect associated to the same option by System 1 makes possible that the perceived emotional benefit overrides the assessment of material costs. In the experiment, subjects framed car as the "good" transport mode on the basis of an affective response, which occurs rapidly and automatically. They seem to choose on the basis of an "affect pool" (Finucane et al., 2000) which associates, consciously or unconsciously, a positive tag to car use. This heuristics serve as a cue in the place of the weighing of the pros and cons required from rational calculation, which is a complex task in calculating uncertain travel times. This also explains why subjects were reluctant to switch mode, even when it was rationally justifiable.

5. Conclusions

This experimental study shows that, in repeated travel mode choice, available information is not properly processed, cognitive efforts are generally low and rational calculation play a limited role. These results have relevant implications for the design of transportation policies. Travel mode choices are determined by a variety of psychological factors and subjective attitudes, such as habit and emotions, which should be analysed and taken into account for improving the efficiency of transportation networks. In particular, the preference for cars seems to be relatively resistant to the effect of economic incentives. Consequently, little progress can be expected by asking travellers to voluntarily reduce the use of a car or even by subsidising public transport costs. On one hand, transportation policies should aim at changing the individual cognitive perception of travel modes not by adopting a range of low intensity tactics (such as progressive increases in fuel costs, additional taxes, parking fees), which may be ineffective, but by initiatives which increase individual awareness in making choices. On the other hand, findings confirm previous research on the modest efficacy of "soft" policies based on the provision of information to encourage public transport and sustainable behaviour. This observation can also lead to conclusions favouring the use of "hard" or "command and control" policies, as in limitation of car use such as limited traffic zones, if incentives are not effective in provoking a change of behaviour.

The awareness that affective states are relevant in mode choice situations also raises important questions to be addressed by further research. In particular, experimental methods can be useful to detect the psychological factors explaining both the emotional attachment to car drive and the personal and societal significance of public transportation. It also requires investigating how the provision of more customer-focused and personalised information on transport modes can improve travellers' awareness of the economic consequences of their choices. It is also plausible that individuals' positive affect attached to the car use is directly related to the frequency of car use, as pointed out by Steg (2003). Experimental support of this hypothesis could be useful in supporting the differentiation of public transportation policies between frequent and infrequent car users.

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