Analysis of inertial choice behaviour based expected and experienced savings from a real-world route choice experiment

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Abstract

In the context of route choice, inertial behaviour shows that drivers make choices that are satisfactory rather than optimal. Consequently, drivers may not necessarily alter their choice when confronted with a travel time increase on the current choice or a travel time decrease of a choice alternative. As a consequence it can be assumed that driver only alter their choice when the utility difference between alternatives becomes larger than some individual-situation-specific threshold.

Route choice data from a real-world driving experiment was used to study inertial behaviour and estimate inertia thresholds. The data analysis consisted of two parts. One addressing *expected travel time savings* relative to choice alternatives and another addressing *experienced travel time savings* on the current route. With regard to the former it was found that on average roughly one-fourth of the choices were inertial choices. Small travel time differences and dominant non-travel time route attributes had a positive effect on the frequency of inertial choices. Based on lost travel time, inertia thresholds up to 4.5 minutes or 30% of the average travel time were found, while thresholds up to 1.3 minutes or 13% were most common. Considerable differences between OD-pairs and routes indicated that thresholds are probabilistic and dependent on the choice set. Considering *experienced savings*, it was found that on average roughly half of the choices concerned inertial behaviour. Inertia thresholds up to 3.31 minutes or 37% of the average travel time were found, while thresholds up to 1.18 minutes or 11% were more common. Switching behaviour could not be explained by *experienced savings* as participants were much less responsive to *experienced* loss on the current route as opposed to *expected* loss relative to the choice alternative.

Future research opportunities are: moving-average thresholds, inertia thresholds of different situations and driver behaviour types, asymmetry between gains and losses, impact of advanced traffic information systems, and estimation of a model that better matches the route choice data than a simple model that is based on travel time alone does.

Introduction

Background

In the 1970’s and again more recently, behavioural economics is rapidly gaining ground both outside and inside the transportation research arena. Behavioural economics draws on the aspects of (cognitive) psychology, social sciences and economics, and studies the motives and behaviours that explain deviations from rational behaviour (Avineri and Prashker, 2004). In contrast to the rational economic model, human rationality is about our distance from perfection given the observation that people have limited knowledge and constrained cognitive abilities, leading to prejudiced reasoning, biased perception and suboptimal choice behaviour. A generic term for this kind of behaviour is ‘bounded rationality’ that was first introduced by Herbert Simon (Simon, 1955).

From the 1970’s onwards, many researchers showed that bounded rational behaviours are neither random nor senseless, but that they are systematic, consistent, repetitive, and therefore predictable. Most distinguished and frequently cited are works of Kahnemann and Tversky (for an overview see Kahnemann, 2011), and McFadden (e.g. McFadden, 1999). Moreover, it is widely acknowledged that these behaviours have important implications for example on prediction capabilities of choice models and the effectiveness of transport policy. For example, a relevant notion in the context of bounded rational behaviour is that drivers only alter their behaviour or choice when the utility difference in the transportation systems or their trip, is or becomes larger than some individual-specific threshold (Mahmassani and Chang, 1987). Like 'bounded rationality', the term 'threshold' is rather generic. It acknowledges the potential existence of limits, boundaries or cut-offs of perception and consideration of attributes by an individual, as a result of some behavioural mechanism.

Thresholds

Cantillo and Ortuzar (2006) distinguish three different kinds of thresholds:

- *Thresholds as inertia, habit or reluctance to change.* Habit forms when automated cognitive processes take control as the decision maker repeatedly choses the same alternative (Verplanken et al., 1997). Moreover, if the cost of searching for and constructing new alternatives is too high, or if it has too much associated risk, people make an effort-accuracy trade-off and will tend to reuse past solutions that make behaviour easier and less risky (Payne et al., 1993). The formation of habit generates, as a consequence, reluctance to change. Although similar to habit, inertia also acknowledges that the mere action of choosing a particular alternative makes it more probable that the alternative is chosen again on the next day, it adds to this notion that the reason for this repetition may in fact be that the anticipated (expected) quality of an alternative is much higher than that of its competitors (Chorus and Dellaert, 2012). As it were, the so-called inertial effect increases the utility of the current path which means that the same observed behaviour can still prevail after a change (Srinivasan and Mahmassani, 2000).
- *Thresholds defined as minimum perceptible changes.* This means that attribute changes below the threshold do not cause a reaction in the individual (as perceptually the utilities do not change). Theories on 'just noticeable differences' suggest that people may be unable to perceive small differences in the price of products (Monroe, 1970), or just not interested in these differences as it does not pay off to notice them (Levy et al., 2004). This phenomenon is complex since changes can accumulate and eventually exceed the threshold; while in parallel there is might be adjustments in individual behaviour, dependent on the speed of change, which in turn can modify the threshold. Closely related are studies that deal with limited awareness which primarily focus on the discovery of (new) utility differences. Generally, awareness may either result from direct experience (i.e. by having chosen the alternative on one of the preceding days) or from indirectly noticing the change (e.g. from a friend or through a travel information service) (Chorus and Timmermans, 2009).
- *Thresholds as mechanisms of acceptance or rejection of alternatives.* Although it is more common practice to assume that individuals make trade-offs among attributes (Payne et al., 1993), people may actually behave in a non-compensatory manner as in the elimination-by-aspects (EBA) model of (Tversky, 1972) or the satisficing heuristic (Simon, 1955). Based on personal preferences, individuals are assumed to have both a ranking of attributes and minimum acceptable thresholds for each of them; the process begins with the most important attribute, the threshold of which is retrieved and all alternatives with attribute values over the threshold are eliminated. The process is repeated for the remaining attributes in order of importance until one alternative satisfies them all; if none or more than one alternative satisfies all the threshold constraints the preferred one may be selected in a compensatory manner. On top of this process, satisficing behaviour states that decision makers will continue using the chosen alternative as long as it 'suffices' in 'satisfying' (together *satis*ficing) the

decision maker's goals. Moreover, it is assumed that the decision maker will not continue his/her search for a more optimal alternative. Based on the principle of EBA and satisficing, some analysis have shifted their attention from the decision making process to the choice set formation process as pruning of rejected alternatives may improve model predications considerably (Ben-Akiva and Boccara, 1995; Prato and Bekhor, 2007).

Although thresholds may differ in a strict behavioural sense, there are various analytical similarities that make it impossible to empirically distinguish between them based on observed choice alone. The different perspectives on thresholds are very closely related and should be considered complements rather than substitutes, as for example inertia and awareness limitations may exist simultaneously (Chorus and Timmermans, 2009). Yet, the empirical identification of such an integrated model is not trivial. For example, it is impossible to derive, from the observation that a traveller repeatedly chooses one particular route that performs less than another available route, whether this results from individual preferences (rejection of alternatives), satisficing behaviour, limited awareness, perceptual errors, habit or inertia.

Scope and objective

The notion of thresholds is well-known in economics and marketing as it is closely related to price elasticity. As a complement to price elasticity, threshold add the condition that consumers do not respond to small price changes within a 'pricing indifference bands', i.e. a range of possible prices up to which price changes have little or no impact on customer purchase decisions (Cram, 2006). It is argued that this 'range of inattention' along the demand curve gives retailers an incentive for small price increments to increase profit (Levy et al., 2004). Analogically, when applied in the context of transportation, thresholds may give policy makers, road operators and traffic engineers an incentive 'lever' to modify choice attributes (i.e. positive and negative), which in turn will increase the performance of the traffic system (Vreeswijk et al., 2013).

Clearly, the challenge is to collect empirical evidence and estimate the thresholds. However, interest in empirical research has been limited, which is remarkable considering the numerous requests for empirical evidence to validate theories derived from behavioural economics and to develop better descriptive models for travel choice behaviour. Earlier research of the authors addressed the topic of thresholds by studying the influence of perception bias on route choice, and how route attributes and past decisions affect perception (Vreeswijk et al., 2014; 2013). Motivated by these findings and the availability of a data set from a real-world driving experiment (Tawfik and Rakha, 2012), the aim of this paper is to observe the frequency of different choice strategies, to determine how they are influenced by situational variables and to quantify the thresholds associated to the strategies. To understand the underlying reasons for the choice strategies is outside the scope of this paper. The data analysis will examine route switching behaviour and inertial choices in particular, subject to *expected savings* relative to choice alternatives and *experienced savings* on the current route.

The next section describes the setup of the real-world driving experiment to demonstrate how the route choice data were collected. Thereafter the analysis results are presented. First general route choice and route switching statistics are shown, followed by a more in-depth discussion of results on thresholds related to *expected savings* and thresholds related *experienced savings*. The final section presents the conclusions of the study and outlines future research activities.

Data Description

Experimental setup

Data was collected through a real real-world route choice experiment in Blacksburg, Virginia in the United States (Tawfik and Rakha, 2012). A total of 20 participants were involved in this study. Each participant was asked to complete 20 experimental runs over 20 days during regular school week days of the academic spring semester of 2011. Experimental runs were scheduled only during one of three traffic peak hours: morning (7-8 am), noon (12-1 pm), and evening (5-6 pm). It should be noted that the 20 runs for a driver were done at the same time each day. All participants were given the same five Google Map print outs, each map representing one OD-pair and two alternative routes. For each experimental run, participants were asked to drive a research vehicle and make these five OD-pairs assuming that the provided alternative routes were the only routes available between the points of origin and destination. The OD-pairs and the alternative routes were selected to ensure differences in the five choice situations. All driver choices as well as the experienced travel conditions were recorded via a GPS unit placed on board of the vehicle and a research escort that always accompanied the participants. Participants were instructed to behave in the same manner they behave in real life.

After completion of the 20 experiment runs, participants were asked to complete a post-task questionnaire. The post-task questionnaire was divided into two sections. The first section collected information about the participants' perceptions of the traffic conditions on the alternative routes (distance, travel time, travel speed, and traffic level), as well as the participants preference levels of the routes. The pre-task questionnaire collected information about the participants' demographics (age, gender, ethnicity, education level, etc.) and driving experiences (number of driving years, annual driven miles, etc.).

Earlier findings

Analysis results based on the post-task questionnaire combined with aggregated data from the experiment were already reported earlier (Tawfik and Rakha, 2012; 2012). The most important findings are given here.

Experiences vs. Perceptions: driver perceptions of travel speed were more accurate than their perceptions of travel time, while perceptions of distance were least accurate. Looking at the driver perceptions of the travel conditions per OD-pair, the results show that the higher the difference between the two alternative routes is the more accurate are the driver perceptions. In other words, the more salient the signal, the more likely it is to be correctly perceived. It was found that driver perceptions were, in general, around only 60% accurate.

Experiences vs. Choices: recorded choices of the last 5 runs are closer to the declared choices in the post-task questionnaire, than the choices made throughout the entire experiment. This is reasonable as many choices made early in the experiment may have been for exploratory rather than preference reasons. However, expectations of the Stochastic User Equilibrium (SUE) theory seem to hold only for OD-pairs 3 and 5, but not for OD-pairs 1, 2 and 4. In addition, in two cases the actual choice percentages even diverged from the SUE expectations. Hence, expectations of the SUE theory can be very different from the actual reality of choice percentages. Small differences between the two alternative routes and travel time reliability can best explain this. Although the latest route experience was expected to be dominant in driver perceptions, analysis showed that the Markov process updating of experienced travel times was not different from the average-based calculations.

Perceptions vs. Choices: none of the drivers made any irrational choices in OD-pairs 1, 3, and 5 (based on travel time perceptions). Irrational behaviour was identified only for OD-pairs 2 and 4. Compared to travel time, travel speed perceptions provide a better explanation for driver choices in the case of OD-pairs 1, 2 and 4, and on OD-pair 3, traffic perceptions provide a better explanation for driver choices. Considering OD-pair 1 and 4, which are cases with small travel time differences; drivers appear to prefer the faster speed route. In case of OD-pair 3 drivers selected the more reliable route to avoid dense traffic on the university campus.

General data treatment

On the basis of the route choice data together with the pre- and post-task questionnaire, Tawfik and Rakha studied driver experiences, perceptions and choices on an aggregate level. The analysis discussed here is based on a more detailed analysis of the revealed preferences and only uses the route choice data. For each driver and each run this data describes the selected route and the experienced travel time, as illustrated in Figure 1.

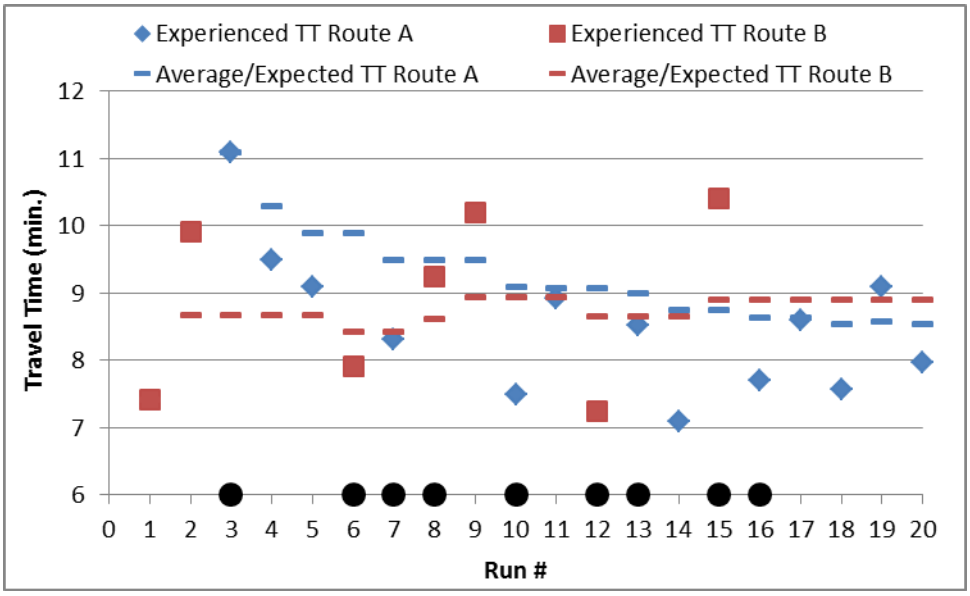


Figure 1 – Example route choice data of 1 individual on 1 OD-pair

From this data it is easy to identify the runs in which a driver switched from one route to the other (indicated by the black dots). For further analysis of route switching behaviour, the average experienced travel time over all past experiences was calculated after each run.

According to literature, there exist different ways drivers integrate pas experiences. One approach is to integrate past experienced cost according to a weighted average (e.g. Horowitz, 1984), for example by assigning equal weights to all past experiences or by assigning weights through exponential smoothing (e.g. Mahmassani and Srinivasan, 1995). Under the myopic adjustment rule, the perceived travel time is a function of the latest day’s outcome exclusively (e.g. Mahmassani and Chang, 1986). The third approach considers perceived travel time as a weighted average of the historically perceived travel time and the time provided by advanced traveller information systems (e.g. Ben-Akiva et al., 1991). However, earlier work by Tawfik and Rakha (2012) on this data set showed that a Markov process updating of experienced travel times was not different from the average-based calculations. For this reason expected travel times are calculated as a uniformly weighted average over all past experienced travel times (see Figure 1).

Limitations

First of all, since data was collected in normal driving conditions on public roads, the experimenters had no control over the traffic conditions and actual travel times while the experienced travel times were dependent on the subsequent choices of the participants. Besides, run by run contextual data that might explain route choice behaviour was not available. For these reasons, the choice situations as revealed in the data (e.g. the average experienced travel times of two routes) were not uniformly balanced but naturalistic.

Secondly, perception data directly obtained from the participants is only available from the pre-task and post-task questionnaires. That is, the data were obtained before and after the 20 runs and therefore are fairly aggregated. As run by run perception data is not available, experienced travel times were used to calculate expected travel times. Note that assuming that these represent the perception of the participants implies that perfectly rational perception is assumed. This is ambiguous and in contrast with earlier statements on perception bias. However, contrasting the experienced and expected travel times with the actual choices of the participants enabled to evaluate the rationality of these choices. Vice versa it enabled to derive conclusions on the accuracy of ‘rational’ perceptions and as such perception thresholds.

Finally, the five routes completed by the respondents were actually part of a trip chain. Although the participants were thoroughly instructed to behave as naturalistic as possible, the realism and importance of the factor arrival time can be questioned.

Overall results

Route characteristics

The table below shows the properties of the 10 routes on the 5 OD-pairs. Travel time difference denotes the average travel time difference between the two routes. Based on Monte Carlo simulation the probability of the odd route being shorter in time and quicker in speed than the even route was determined.

Table 1 – Route characteristics and choice

<table>
<tr><th>OD-pair</th><th>Route</th><th>Average TT</th><th>Travel Time difference</th><th>Probability $TT_a < TT_b$</th><th>Average Speed</th><th>Probability $TS_A > TS_B$</th><th># choices</th><th>% choices</th></tr>
<tr><td rowspan="2">1</td><td>1</td><td>8.5</td><td rowspan="2">0.1
1%</td><td rowspan="2">48.3%</td><td>36.4</td><td rowspan="2">26.6%</td><td>136</td><td>34%</td></tr>
<tr><td>2</td><td>8.4</td><td>43.3</td><td>264</td><td>66%</td></tr>
<tr><td rowspan="2">2</td><td>3</td><td>15.2</td><td rowspan="2">1.5
9-10%</td><td rowspan="2">78.5%</td><td>42.6</td><td rowspan="2">0.1%</td><td>254</td><td>63%</td></tr>
<tr><td>4</td><td>16.7</td><td>63.2</td><td>146</td><td>37%</td></tr>
<tr><td rowspan="2">3</td><td>5</td><td>7.7</td><td rowspan="2">1.6
17-21%</td><td rowspan="2">85.4%</td><td>44.5</td><td rowspan="2">91.8%</td><td>275</td><td>69%</td></tr>
<tr><td>6</td><td>9.3</td><td>37.8</td><td>125</td><td>31%</td></tr>
<tr><td rowspan="2">4</td><td>7</td><td>10.2</td><td rowspan="2">0.6
6%</td><td rowspan="2">35.2%</td><td>29.5</td><td rowspan="2">0.2%</td><td>75</td><td>19%</td></tr>
<tr><td>8</td><td>9.6</td><td>48.2</td><td>325</td><td>81%</td></tr>
<tr><td rowspan="2">5</td><td>9</td><td>10.5</td><td rowspan="2">2.5
24-31%</td><td rowspan="2">5.0%</td><td>33.3</td><td rowspan="2">40.0%</td><td>39</td><td>90%</td></tr>
<tr><td>10</td><td>8.0</td><td>34.0</td><td>361</td><td>10%</td></tr>
</table>

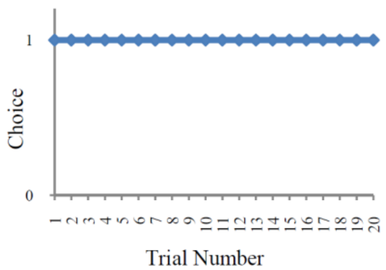
- OD-pair 1: both routes have almost equal travel times, but route 2 has a slightly higher average speed.
- OD-pair 2: route 3 is the shorter time route, but in terms of average speed route 4 is clearly the better alternative.

- OD-pair 3: route 5 outperforms route 6 in both travel time and average speed. However, route 5 is a route with high traffic volumes.
- OD-pair 4: route 8 is a little shorter in time and has a higher average speed. However, route 8 passes through the school campus and there is risk being caught in campus traffic.
- OD-pair 5: route 10 is clearly the shorter time route while the average speed of both routes is nearly equal.

Table 1 shows the choices of the participants which reveal that routes 2, 3 and 5 but specially routes 8 and 10 were the preferred routes. Overall, the choice data shows that in 74% of the cases the average shortest time route was chosen. However, between OD-pairs there are some differences, e.g. 63% for OD-pair 2 and 90% for OD-pair 5. Nonetheless, there remains a considerable amount of choices that cannot be explained by travel time alone.

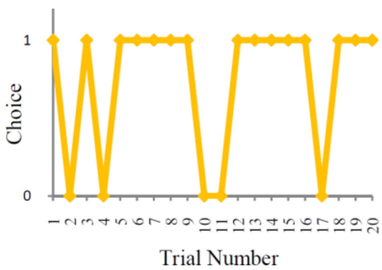
Behaviour types and switching

Based on the pattern of the route choice data as presented in Figure 1 it is possible to distinguish four Driver Behaviour Types (DBT) as first introduced by Tawfik and Rakha (2012). The DBT and their frequency are shown in Figure 2: Stayers, Tryers, Explorers and Switchers. Note that some drivers behaved differently for different OD-pairs. For example, a driver could be a Switcher for OD-pair 1, but a Stayer for OD-pair 4.



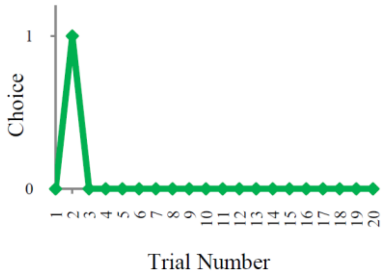
OD1: 25%
OD2: 10%
OD3: 10%
OD4: 45%
OD5: 40%
Total: 26%

Stayers: driver arbitrarily picks a route and uses that same route for the entire 20 runs.



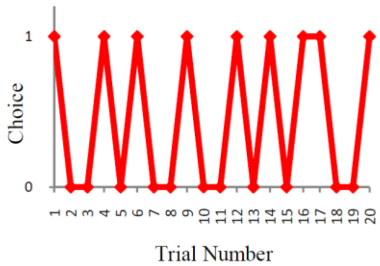
OD1: 15%
OD2: 45%
OD3: 55%
OD4: 30%
OD5: 30%
Total: 29%

Explorers: driver has a clear preferred route but tries the alternative route every now and then.



OD1: 55%
OD2: 35%
OD3: 20%
OD4: 10%
OD5: 25%
Total: 34%

Tryers: driver tries both routes ones or twice and uses the preferred route for remaining runs.



OD1: 5%
OD2: 10%
OD3: 15%
OD4: 15%
OD5: 5%
Total: 10%

Switchers: driver has no clear preferred route and continuously switches between the routes.

Figure 2 – Driver behaviour types

Overall, a majority of the participants had a clear preference for one of the routes and almost never switched (i.e. Stayers or Tryers). These behaviours occur more on OD-pairs with distinct routes such as OD-pairs 4 and 5. There are more Explorers on OD-pairs with routes that are similar, which is the case for OD-pair 1. Lastly, Switchers are mostly observed on

OD-pairs 3 and 4, which are cases in which the shortest time route suffers from dense traffic conditions and unreliable travel times.

Now exploring route switching propensity, the data shows that participants on average switched in 20% of the cases. The number of switches was slightly above average for OD-pairs 1 and 2, and slightly below average on OD-pairs 4 and 5. Remarkably, for OD-pair 4 this is in contrast to the high share of Switchers which might be explained by the risk being caught in campus traffic.

Figure 3 shows that the number of route switches decreased with the number of runs. Hence, the number of switches in the first 10 runs is significantly higher than in the last 10 runs. This shift from explorative choice behaviour to exploiting choice behaviour has been observed by others (e.g. Senk, 2010) and is a sign of learning and convergence. Moreover in an earlier work, Tawfik and Rakha (2012) showed that the percentage of participants choosing a route seems to converge. However, they found that only on OD-pairs 3 and 5 these percentages converged in line with the stochastic user equilibrium expectations. Again this shows that a simple model using travel time alone does not explain the data.

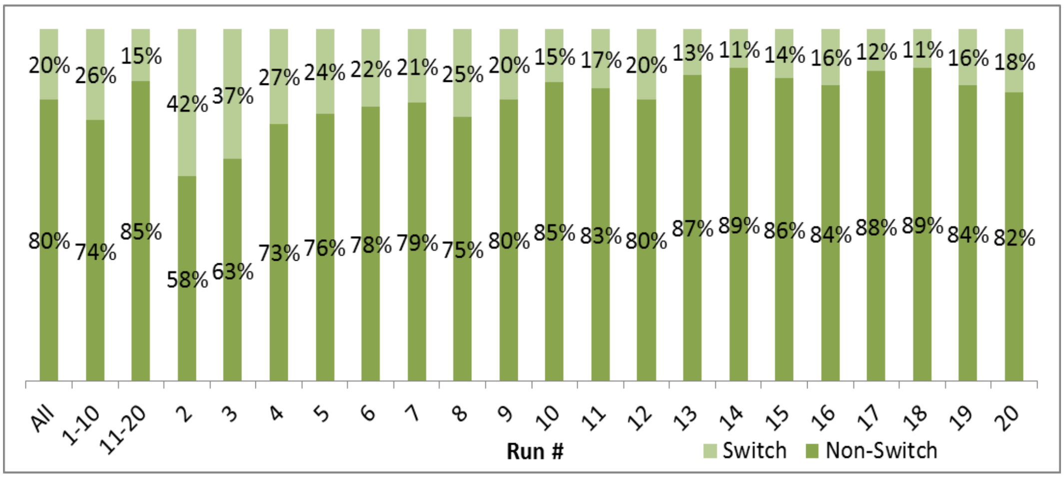


Figure 3 – Evolution of route switching

Choice strategies

In a normal route choice situation it is usually assumed that drivers compare the expected travel time of the available choice alternatives. Alternatively, in case of satisficing or inertia it is assumed that the driver only compares the last experienced travel time of the current choice with the expected travel time of that choice. Based on the available choice data we will evaluate both perspectives by calculating the *expected saving* and *experienced saving* respectively. Considering that these savings are either a gain or a loss, and the decision of the driver is to switch routes or repeat the current choice, four choice strategies can be distinguished:

- Choice strategy 1 (CS1): Gain and stay – the current choice performs better than expected and/or better than choice alternative. The driver repeats the current choice at *t*+1. This behaviour resembles travel time minimizing behaviour.
- Choice strategy 2 (CS2): Loss and stay – the current choice performs worse than expected and/or worse than choice alternative. Yet, the driver repeats the current choice at *t*+1. This behaviour resembles rational travel time minimizing behaviour.

- Choice strategy 3 (CS3): Gain and switch – the current choice performs better than expected and/or better than choice alternative. Yes, the driver switches to the choice alternative t+1. This behaviour resembles compromising behaviour, possibly due to other factors than time.
- Choice strategy 4 (CS4): Loss and switch – the current choice performs worse than expected and/or worse than choice alternative. The driver switches to the choice alternative at t+1. This behaviour resembles rational travel time minimizing behaviour.

As explained earlier, experienced and expected travel times can be derived from the choice data for all time steps. For *expected savings* it is assumed that the difference between the expected travel times of both routes after run t equals the *expected saving* at run t+1 if the driver would repeat the current choice. A positive value indicates a gain (i.e. travel time of the current choice < travel time choice alternative) whereas a negative value indicates a loss. Similarly, for *experienced savings* it is assumed that the difference between the experienced travel time of the current route for run t and the expected travel time of the current route at run t-1 equals the *experienced saving* at run t. A positive value indicates a gain (i.e. experienced travel time < expected travel time) whereas a negative value indicates a loss. Note that for comparison of experienced travel times of both routes, a participant should have chosen both alternative at least ones. This reduced the sample size for assessment 1 from 2000 to 1293.

Example based on Figure* 1: from the perspective of expected savings (compare route alternatives), run 6 is an example of CS4 because gain was expected based on the average experienced travel times after run 5. Vice versa, run 13 is an example of CS3 as loss was expected but the driver switched nonetheless. Run 11 is an example of CS2 and runs 16 to 20 are examples of CS1. From the perspective of experienced savings (compare current route), run 6 is an example of CS4 because gain was experienced but the driver switched. Run 9 is an example of CS1 because loss was experienced but the driver did not switch. Finally, run 17 is an example of CS2 and run 16 is an example of CS3.*

Thresholds related to assessment of choice alternatives

Choice behaviour

Table 2 gives an overview of the frequencies of the choice strategies based on *expected savings*. Based on the sum of CS1 and CS4 the majority of the choices were travel time minimising choices. Differences between OD-pairs and routes can be explained by the average travel time differences between the routes alternatives. For example, the correlation coefficients of CS1 and CS4 with the average travel time difference between routes imply that larger differences in travel time increase the frequency of these 'rational' strategies. This finding is intuitive. Contrarily, the frequency of CS3 decreases when the travel time difference increases. The frequency of CS2, i.e. inertial choices, is highest for OD-pairs with small travel time differences or when the non-shortest time route is competitive with another route attribute like average speed (e.g. routes 2 and 4).

Table 2 - Choice strategies by OD-pair and route

OD-Pair	Route	Avg. ΔTT	CS1	CS2	CS3	CS4	CS1	CS2	CS3	CS4
			Gain	*Loss*	*Gain*	*Loss*	*Gain*	*Loss*	*Gain*	*Loss*
			Stay	*Stay*	*Switch*	*Switch*	*Stay*	*Stay*	*Switch*	*Switch*
1	1	-0.1	41%	29%	15%	15%	27%	13%	35%	25%
	2	+0.1					45%	35%	8%	12%
2	3	+1.5	43%	34%	12%	11%	60%	23%	15%	2%
	4	-1.5					14%	54%	6%	26%
3	5	+1.6	62%	15%	10%	12%	81%	5%	13%	1%
	6	-1.6					1%	48%	3%	48%
4	7	-0.6	38%	33%	14%	15%	6%	30%	17%	47%
	8	+0.6					48%	34%	13%	5%
5	9	-2.5	74%	4%	10%	13%	0%	22%	3%	75%
	10	+2.5					87%	1%	11%	1%
Total			51%	24%	12%	13%	51%	24%	12%	13%
Correl. ΔTT			**0,87**	-0,76	**-0,97**	-0,78	**0,95**	**-0,66**	0,32	**-0,89**
DBT2: Tryers			66%	27%	3%	4%				
DBT3: Explorers			41%	22%	18%	19%				
DBT4: Switchers			27%	19%	27%	27%				

On an aggregated level the data reveals that if gain was *expected* from repeating the current choice (CS1+CS3: 63%), 81% of the participants made a rational choice and stayed at the current choice while 19% decided to switch. In case loss was *expected* (CS2+CS4: 37%), 65% made an inertial choice by staying at the current choice while 35% switched. From a behavioural perspective, if participants did not switch (CS1+CS2: 75%) this can be explained by the *expected saving* in 68% of the cases. Similarly, switching (CS3+CS4: 25%) was 'rational' in 52% of the cases. The relatively low frequency of switching and rational choices suggest that the participants were switch-aversive and not necessarily interested in pursuing travel time gain, but more interested in avoiding the risk and travel time loss. As a result, a considerable share of the choices cannot be explained by travel minimisation alone.

Table 2 also shows the frequency of the choice strategies for the DBT Tryers, Explorers and Switchers. Note that Stayers lack the precondition of at least one experience of both route alternatives. The figures show that the frequency of rational choices (i.e. CS1 and CS4) was highest for Tryers and lowest for Switchers. As Switchers switched the most and Tryers switched the least, this implies that more switching was not necessarily related to more *expected* gain. Moreover, for Switchers the frequencies of the choice strategies are in the same range which underlines the random character of this DBT. Average travel times per driver behaviour type in

Table 3 confirm that Switchers performed the worst, while interestingly Stayers performed the best by far.

Table 3 – Average travel times per driver behaviour type

Average TT [95% conf. int.]	**OD-pair 1**	**OD-pair 2**	**OD-pair 3**	**OD-pair 4**	**OD-pair 5**	**SUM**
Stayers	8.14 [0.24]	15.79 [0.27]	8.95 [0.40]	9.56 [0.15]	8.05 [0.16]	9.25 [0.10]
Tryers	9.91 [0.39]	15.59 [0.23]	7.97 [0.16]	9.87 [0.19]	8.14 [0.19]	10.45 [0.10]
Explorers	8.27 [0.20]	15.91 [0.28]	8.32 [0.24]	9.79 [0.38]	8.37 [0.30]	10.24 [0.12]
Switchers	8.66 [0.50]	16.23 [0.37]	8.53 [0.29]	9.85 [0.26]	10.44 [0.52]	10.67 [0.16]

Besides the frequency of the four choice strategies it is interesting to examine how they evolve relative to the *expected saving* in case of switching (see Figure 4). It clearly shows that with increasing *expected savings* all behaviour becomes rational (i.e. CS1 and CS4). However, for both gains and losses smaller than approximately 1.5 minutes there is no clear difference between the savings intervals. This suggests that within this range all *expected* gains or losses have a similar effect on choice behaviour. Presumably this indicates that drivers' ability to correctly judge situations that involve small travel time differences is limited. Moreover, inertial behaviour (CS2) occurs more with smaller gains.

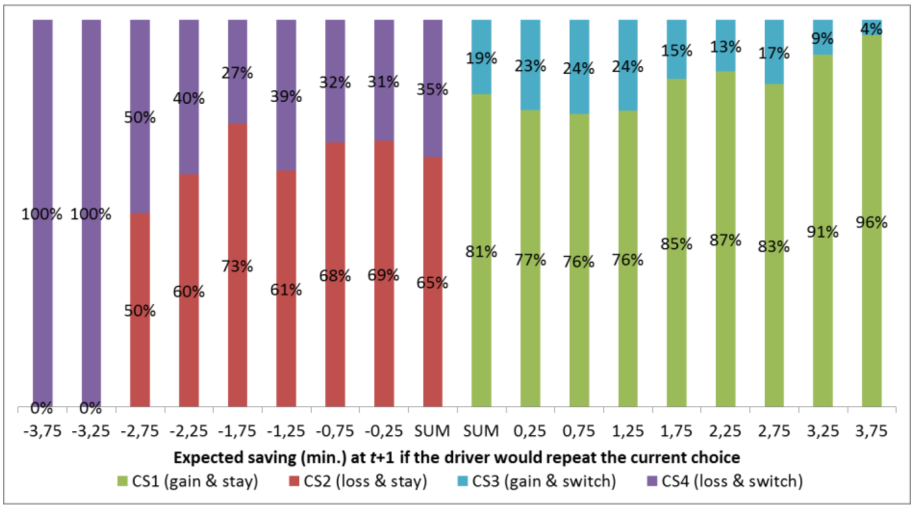


Figure 4 – Frequency of choice strategies by *expected saving* (min.)

Likelihood of switching

To determine the switching likelihood, the number of switches was divided by the total number of decisions, for each saving interval. The result is shown in Figure 5. The average switching likelihood was 25% while the switching likelihood decreases if the *expected* saving decreases and/or becomes negative. This finding is intuitive. Notably, the 95% confidence interval indicates that *expected* loss up to 2.5 minutes do not lead to significantly more switching than average. This bandwidth is an indicator for the inertial threshold. Another observation from the figure is the asymmetry between *expected* gains and *expected* losses which suggest that participants were more sensitive to *expected* loss when staying than to *expected* gain when switching. This is in line with earlier findings and supported by theories of loss aversion (e.g.Kahnemann and Tversky, 1979).

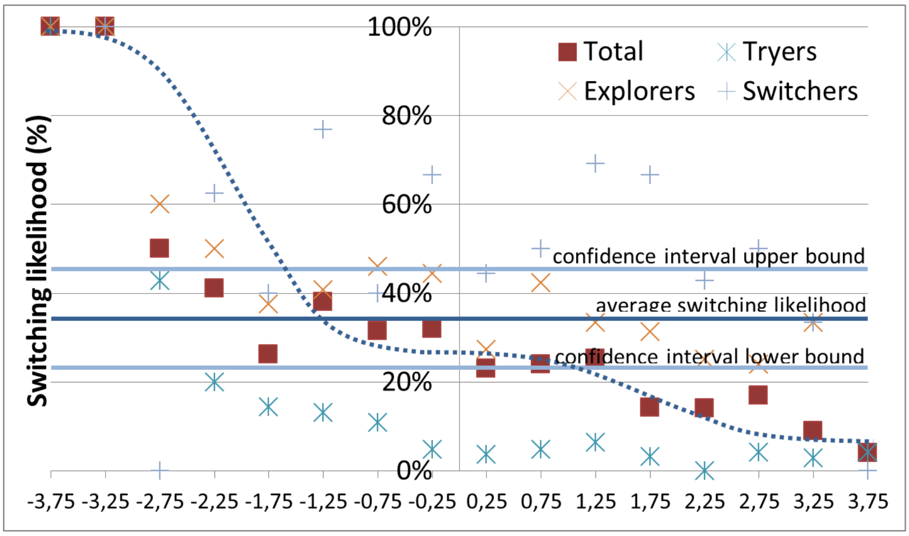


Figure 5 – Switching likelihood by *expected saving* (min.)

Figure 5 also shows the switching likelihood for the driver behaviour types Stayers, Explorers and Switchers (Stayers were excluded because they never switched). Note that the series for the Tryers reflects the one-sample experiences of the route alternative that these drivers had. It shows that if the *experienced saving* on the route alternative was a loss (i.e. the *expected saving* of switching back a gain), the participants were increasingly likely to switch back. Explorers and Switchers were much more likely to switch in general as defined by their type. However, Explorers show an intuitive pattern similar to the overall pattern, while the switching likelihood of Switchers does not seem to reveal any particular pattern. Overall, the results so far suggest that the choice strategies as applied by the participants were not necessarily bad, but could perhaps be improved by applying them in a smart way.

Table 4 – Lost travel time statistics *expected saving*

OD-Pair	**Route**	**Avg.TT**	**CS2**		**CS2**	
			Median	*Max.*	*Median*	*Max.*
1	1	8.5	-0.46	-2.42	-5%	-28%
	2	8.4	-0.44	-2.78	-5%	-33%
2	3	15.2	-0.69	-1.35	-5%	-9%
	4	16.7	-0.99	-2.74	-6%	-16%
3	5	7.7	-0.05	-0.42	-1%	-5%
	6	9.3	-1.22	-2.65	-13%	-28%
4	7	10.2	-0.44	-0.77	-4%	-8%
	8	9.6	-1.08	-2.90	-11%	-30%
5	9	10.5	-0.95	-2.58	-9%	-25%
	10	8.0	-0.78	-0.78	-10%	-10%
CS2 (gain & stay)			-0.71	-1.94	-7%	-19%
CS1 (loss & stay)			0.81	3.29	8%	36%
CS4 (gain & switch)			-0.85	-2.56	-8%	-25%
CS3 (loss & switch)			0.90	2.91	10%	30%

Finally, in addition to earlier findings it is interesting to analyse the lost travel time resulting from inertial choices as an indicator for the inertia threshold. Table 4 shows lost travel time statistics for each route for choice strategy 2 and cumulative statics for all choice strategies. The figures represent the median and maximum *expected saving*, e.g. loss in case of CS2, in minutes and in percent. The table shows that inertia thresholds up to 2.90 minutes and 33% of the average travel time occur. The median values indicate thresholds up to 1.22 minutes and 13% of the actual travel time. This order of magnitude is in line with figures reported in literature (e.g. Srinivasan and Mahmassani, 1999; Mahmassani and Liu, 1999; Mahmassani and Chang, 1985). However, there are considerable differences between OD-pairs and routes. Yet, there is no strong relation between the thresholds and the average travel time or the average travel time differences. This means that other factors, observed and non-observed, also affect thresholds. An important implication from these findings is that no generalised threshold exists, either in minutes or in percentage, but presumably that thresholds are dependent on the choice set and on route characteristics. Finally, Table 5 shows that losses involved in CS3 were generally higher than those of CS1. This suggests that larger losses induce more switching and that switching requires a minimum *expected* gain in return. The latter is another sign of inertial behaviour and thresholds and in line with literature.

Thresholds related to assessment of the current choice

Choice behaviour

Table 5 gives an overview of the frequency of the choice strategies based on *experienced savings*. It shows that the frequency of CS2 (i.e. inertial behaviour) is relatively high for all OD-pairs and higher than was found in

Table 2. This suggests that the participants were less responsive to *experienced* loss on the current route as opposed to *expected* loss relative to the choice alternative. Differences between OD-pairs and routes can be explained by travel time differences between routes. For example, the correlation coefficients imply that larger differences in the average travel time increase the frequency of 'rational' strategies CS1 and CS4 which is intuitive. Accordingly, the frequency of CS3 decreases. The frequency of CS2, i.e. inertial behaviour, is highest for OD-pairs with smaller differences in the average travel time and for non-shortest time routes.

Table 5 – Choice strategies by OD-pair and route

OD-Pair	Route	Avg. ΔTT	CS1	CS2	CS3	CS4	CS1	CS2	CS3	CS4
			Gain	*Loss*	*Gain*	*Loss*	*Gain*	*Loss*	*Gain*	*Loss*
			Stay	*Stay*	*Switch*	*Switch*	*Stay*	*Stay*	*Switch*	*Switch*
1	1	-0.1	46%	33%	13%	9%	37%	28%	21%	14%
	2	+0.1					50%	35%	8%	6%
2	3	+1.5	47%	35%	10%	9%	50%	35%	9%	6%
	4	-1.5					41%	33%	13%	14%
3	5	+1.6	47%	35%	9%	9%	48%	40%	7%	5%
	6	-1.6					45%	23%	15%	18%
4	7	-0.6	48%	37%	8%	7%	39%	19%	24%	19%
	8	+0.6					49%	41%	5%	5%
5	9	-2.5	47%	41%	8%	5%	12%	12%	40%	36%
	10	+2.5					50%	43%	5%	3%
Total			47%	36%	10%	8%	47%	36%	10%	8%
Correl. ΔTT			0,23	0,69	-0,60	-0,63	**0,83**	**0,71**	**-0.86**	**-0.74**
DBT1: Stayers			54%	46%	n/a	n/a				
DBT2: Tryers			54%	40%	4%	2%				
DBT3: Explorers			40%	26%	18%	16%				
DBT4: Switchers			24%	21%	30%	24%				

On an aggregated level the data reveals that if gain was *experienced* (CS1+CS3: 57%), 82% of the participants made a rational choice and stayed at the current choice while 18% decided to switch. In case of *experienced* loss (CS2+CS4: 44%), 82% of the participants made an inertial choice by staying with the current choice while 18% switched. From a behavioural perspective, if participants did not switch (CS1+CS2: 83%) this was an inertial choice in 44% of the cases. Similarly, switching (CS3+CS4: 18%) cannot be explained by the *experienced saving* in 56% of the cases). Table 5 also shows the frequency of the choice strategies for the four driver behaviour types. The figures show that all DBT but the Switchers made more rational choices (i.e. CS1 and CS4) than other choices. Additionally, a counter-intuitive finding is that it seems that participants were a little more likely to switch after experiencing loss than after experiencing gain.

Besides the frequency of the four choice strategies it is interesting to examine how they evolve relative to the *experienced saving* (see Figure 4). It clearly shows that with increasing *experienced* gains all behaviour eventually becomes rational (i.e. CS3). No particular pattern can be observed for *experienced* loss which is a sign that factors other than the *experienced* loss led to switching. Finally, the figure shows that for losses up to 2 minutes there is no clear difference between the intervals. This is an indication of similar behaviour within this range which might be explained by driver' limited ability to correctly judge (or care about) situations that involve small travel time differences. As a consequence, inertial behaviour (CS2) occurs more with smaller gains.

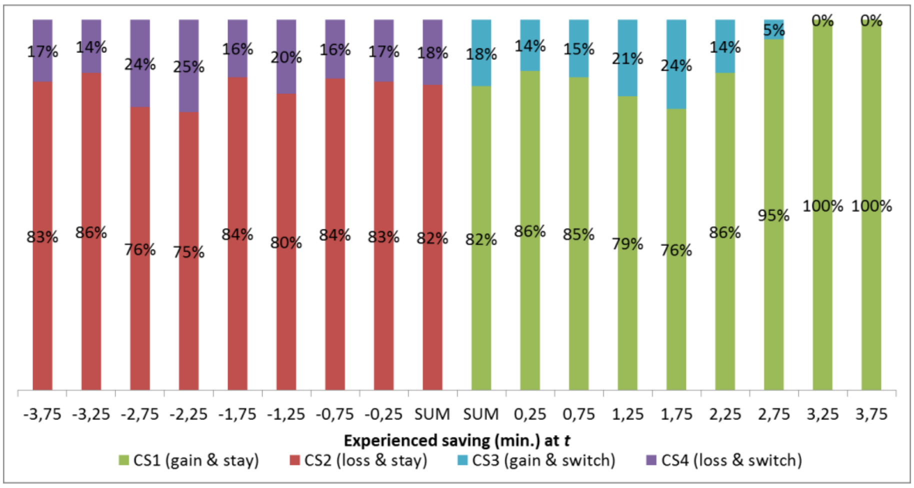


Figure 6 – Frequency of choice strategies by *experienced saving* (min.)

Likelihood of switching

To determine the switching likelihood, the number of switches was divided by the total number of decision, for each saving interval. The result is shown in Figure 7. The average switching likelihood was 20% but the figure does not show a clear pattern in relation to the *experienced saving* as most values are within the 95% confidence interval. The absence of a clear pattern suggests that the *experienced saving* alone is not a major driver for route switching. One explanation might be inertial behaviour, another that the *experienced saving* is likely to be considered conjointly with the availability of choice alternatives and the *expected saving* of these.

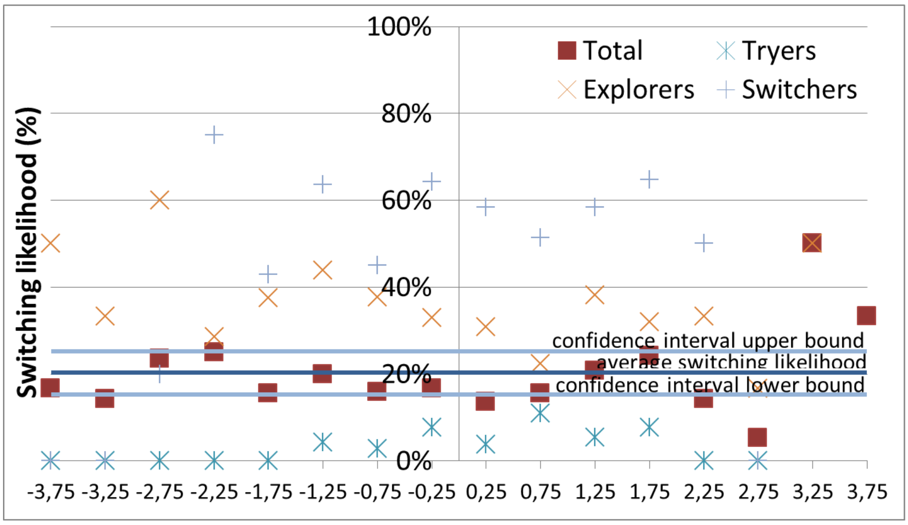


Figure 7 – Switching likelihood by *experienced saving* (min.)

Figure 7 also shows the switching likelihood for the driver behaviour types Stayers, Explorers and Switchers (Stayers were excluded because they never switched). Again it is difficult to derive a pattern although Explorers seem increasingly likely to switch with larger losses.

Table 6 – Lost travel time statistics *experienced saving*

OD-Pair	Route	Avg.TT	CS2		CS2	
			Median	*Max.*	*Median*	*Max.*
1	1	8.5	-0.97	-3.20	-11%	-38%
	2	8.4	-0.76	-3.72	-9%	-44%
2	3	15.2	-0.67	-2.75	-4%	-18%
	4	16.7	-0.62	-3.51	-4%	-21%
3	5	7.7	-0.56	-2.25	-7%	-29%
	6	9.3	-0.51	-3.02	-5%	-32%
4	7	10.2	-0.80	-2.87	-8%	-28%
	8	9.6	-0.70	-3.58	-7%	-37%
5	9	10.5	-0.21	-0.77	-2%	-7%
	10	8.0	-0.59	-3.77	-7%	-47%
CS2 (gain & stay)			-0.64	-3.77	-7%	-30%
CS1 (loss & stay)			0.73	2.78	8%	32%
CS4 (gain & switch)			-0.78	-4.52	-8%	-29%
CS3 (loss & switch)			0.82	4.13	9%	30%

Finally, in addition to earlier findings it is interesting to analyse the lost travel time resulting from inertial choices as an indicator for the inertia threshold. Table 6 shows lost travel time statistics for each route for choice strategy 2 and cumulative statics for all choice strategies. The figures represent the median and maximum *experienced saving*, e.g. loss in case of CS2, in minutes and in percent. The table shows that inertia thresholds up to 3.77 minutes and 47% of the average travel time occur. The median values indicate thresholds up to 0.97 minutes and 11% of the average travel time. Compared to Table 4 the thresholds seem more systematic and repetitive although difference between OD-pairs and routes remain. Generally, thresholds for shortest time routes appear to be larger but this becomes less apparent when other factors than time are at play which is the case for OD-pair 2 and 3. To confirm an earlier finding: values for thresholds cannot be generalised as the data suggests that they are dependent on the choice set and on the route characteristics. Finally, based on CS3 and CS1 Table 6 also confirms that larger losses induce more switching and that switching requires a minimum *expected* gain in return.

Conclusion

Approach

This paper presented the results of a data analysis based on route choice data from a real-world driving experiment. The objective of the analysis was to observe the frequency of different choice strategies, examine route switching behaviour and inertial choices in particular, and to estimate inertia thresholds. For the analysis, average experienced travel times and expected travel times were used to calculate *expected savings* relative to choice alternatives and *experienced savings* on the current route.

Main findings

With regards to the research questions that were defined in the beginning of this paper the main findings are the following: (1) on average about $1/4^{th}$ of the choices concerned inertial behaviour as based on *expected savings*. When two alternatives have similar travel times or when non-travel time attributes are dominant, the amount of inertial choices increases. Based on *experienced savings*, a little more than one-third of the choices concerned inertial behaviour on average. Compared to results from *expected savings* this suggests that the participants were less responsive to *experienced* loss on the current route as opposed to *expected* loss relative to the choice alternative; (2) for *expected savings* and based on lost travel time, inertia thresholds up to 2.90 minutes or 33% of the average actual travel time and a median of 1.22 minutes or 13% of the average actual travel time were found. For *experienced savings*, inertia thresholds up to 3.77 minutes or 47% of the average actual travel time and a median of 0.97 minutes or 11% of the average actual travel time were found. As differences between routes were considerable, it appears that the behavioural principles are general and systematic, but that the magnitude is probabilistic and dependent on the choice set; (3) as loss related to switching was on average higher than loss related to repeating the current choice, switching seems to require a minimum *expected* loss. This is another sign of inertial behaviour and thresholds; (4) for *expected* and *experienced* loss up to 1.5-2 minutes there was no clear difference in the frequency of choice strategies. This might be explained by driver' limited ability to correctly judge (or care about) situations that involve small travel time differences; (5) four driver behaviour types and four choice strategies were distinguished showing that the majority of participants hardly ever switched to adopt a travel time minimising strategy. Nonetheless, for a considerable share of choices a simple model using travel time alone does not explain the data; (6) additionally, it was found that the travel time difference between alternatives, average travel speed and travel time reliability influence choice strategies next to travel time; (7) asymmetry between gains and losses was found in several ways. In general it appeared that respondents were loss-aversive rather than gain-seeking, which made them switch-aversive.

Future research

Several improvements can be made to the research presented in this paper: (1) switching thresholds were defined as a fixed value while in reality it is likely that they are subject to successive good and/or bad experiences. Some moving average as proposed by Van Berkum and Van der Mede Van Berkum and Van der Mede (1993) might better capture drivers' sensitivity based on not only the current or last situation but also other recent ones; (2) as suggested by findings on switching likelihood, it is expected that inertia thresholds are different for choice situation and different driver behaviour types. Additionally, experienced travel times are not only the result of choices but also of stochasticity in the traffic system. To better understand the probabilistic nature of inertia thresholds these relations should be further explored; (3) it is interesting to further explore the effects of the asymmetry between gains and losses and define a framework that integrates theories of loss aversion, indifference bands and driver heterogeneity in relation to switching likelihood; (4) traffic information is expected to affect drivers' perception and route choice behaviour. Therefore it is interesting to study how the presence of advanced traffic information systems affect the findings presented in this paper; (5) lastly it is appropriate to estimate a model based on the results presented in this paper that better matches the data than a simple model that is based on travel time alone does (e.g. Zhang, 2006; Carrion, 2013; Van Essen, 2014). At the same time *expected savings* relative to choice alternative and *experienced savings* on the current routes, and their effect on choice behaviour should be examined simultaneously as in the mind of the driver they are probably not independent from one another either.

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