Travel Choice Inertia:
The Joint Role of Risk Aversion and Learning

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Travel choice inertia: The joint role of risk aversion and learning

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Abstract

This paper shows how travellers that are faced with a series of risky choices become behaviourally inert due to a combination of risk aversion and learning. Our theoretical analyses complement other studies that conceive inertia as resulting from the wish to save cognitive resources. We first present a model of risky travel mode choice. We show that if travellers dislike risk, and part of the quality of travel alternatives is only revealed upon usage, inertia emerges due to a learning-based lock-in effect. We extend our analyses to capture forward-looking behaviour and the provision of travel information.

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1.0 Introduction

For many years, there has been a considerable interest among travel behaviour researchers in understanding inertia (see Gärling & Axhausen (2003) for a relatively recent overview). As a result, many studies have illuminated the role of inertia in the context of route-choices (for example Srinivasan & Mahmassani, 2000) and especially mode-choices (for example Gardner, 2009). This amount of effort put into understanding traveller inertia reflects transportation policy-makers' ambitions to change travel behaviour away from established patterns with an aim to increase the efficiency and sustainability of transport network usage (Commission of the European Communities, 2007); such behavioural adaptation is by definition difficult to achieve when travellers are inert (Chorus et al., 2006a). Predominantly, transportation researchers frame inertia as resulting from the wish to save cognitive resources: considering alternative travel options, and exploring and testing new ones consumes time, effort and attention. Since these are scarce resources (Simon, 1978), most inertia-models postulate that it is a good decision-strategy to stick with an alternative that one knows to perform reasonably well, whereas one could also try to find the best performing option for each new trip.

In this paper we show that the emergence and growth of inertia can be explained without making these assumptions of effort-accuracy trade-offs. We show that even travellers that do consider alternative travel options for each trip exhibit inertia, as long as i) they dislike risk[1] and ii) part of the quality of travel alternatives is only revealed upon usage. The intuition behind this result can be put as follows: travelers learn about a travel mode's quality by observing the

[1] In this paper, we use the terms 'risk' and 'uncertainty' interchangeably. As highlighted in the scope-demarcation, we do assume that individuals hold subjective probabilities to the quality of travel alternatives.

performance of a chosen alternative. Given risk aversion this implies that repeatedly choosing the same alternative from an initial set of equally risky alternatives is a rewarding strategy.

The paper's scope is determined as follows: first, in line with most inertia-related research and policy-making, we focus on a travel mode choice between a car and a train option. However, obtained results are informative for other, multinomial, contexts as well – for example involving travellers' departure time- and route-choices. Second, we assume that travellers hold subjective probabilities with respect to the performance, or quality, of an alternative. Quality is conceived as a composite function of tastes, and of different quality-aspects, some of which are 'tangible' (for example travel times, costs) whereas others are less tangible (for example scenery, feeling (un)safe in a train at night). By making observations, the traveller gets an increasingly good idea of how much he likes an alternative. Specifically, we consider the situation where a traveller faces a trip towards a new destination for the first time, so that uncertainty about the quality of travel alternatives is due to a lack of experience with the alternatives, rather than being due to day-to-day variability. Third, we formally derive this learning-based cognitive lock-in effect within the context of Bayesian, myopic Expected Utility maximization-based travel-choices, although we discuss why the lock-in effect is likely to also apply to other styles of decision-making and learning (as long as decision-makers are risk averse and learn from their observations).

Section 2 provides a brief review of models used for modelling traveller learning and decision making under uncertainty, and provides a rationale for our framework. Section 3 shows how inertia emerges when travellers dislike risk. Section 4 extends this model to incorporate (myopic) forward-looking behaviour, and in section 5, we discuss how the presence of multimodal travel information impacts inertia strength. Section 6 presents conclusions.

2.0 A brief review of research into traveller behaviour under uncertainty, and a rationale for our framework

2.1 Learning models for travel behaviour research

When going through the literature on (models of) traveller learning of the quality of different alternatives, it appears that the large majority of modelling approaches can be labelled as either Bayesian belief updating models, non-Bayesian belief updating models, or reinforcement learning models (or hybrid versions of two of the above).

The Bayesian approach, after a slow start in the 1990s, has gained much popularity in the last decade (for example Kaysi, 1991; Sun et al., 2005, Chorus et al., 2009). Although especially outside the domain of mainstream microeconomics the use of the Bayesian approach as a descriptive model of learning is fiercely debated, many recent studies suggest that while Bayesian belief updating may not be an accurate model of actual learning *processes*, the *outcomes* of these processes (such as choices) are often fairly well in line with Bayesian predictions (see Xu and Tenenbaum (2007) for a recent contribution to this line of literature.

Of all non-Bayesian belief updating models, the concept of weighted average learning has probably been the commonly most used approach to model travellers' learning behaviour. However it seems as though this approach has lost some of its popularity lately (for example, Horowitz, 1984; Ben-Akiva et al., 1991). This type of models generally assume that a traveller's perception of an uncertain variable (like travel time) is composed out of a series of previous observations and information uptakes, each of which is associated with a weight which depends on the salience of the observation in addition to a range of other potential determinants and can (in theory at least) be estimated.

Reinforcement learning is intrinsically different from the two types of belief updating introduced above, because there is no explicit link with (the updating of) beliefs. In reinforcement learning studies, learning implies that a decision-maker remembers whether or not a chosen alternative performed well, and that alternatives with a strong performance on day t are (more likely to be) chosen on day $t+1$. As such, models of reinforcement learning in a sense 'skip' the updating of perceptions of attributes and operate at the level of preferences directly. Recently, there has been a growing interest in modelling traveller behaviour using reinforcement learning-notions (for example, Arentze & Timmermans, 2003; Ziegelmeyer et al., 2008), although the approach has received less attention than (non-)Bayesian models of belief updating.[2]

2.2 Models for travel choice under uncertainty with forward looking behaviour

It appears that the default option for modelling travellers' choices under uncertainty is to build on Expected Utility-maximization premises (for example Noland & Small, 1995; de Palma & Picard, 2005). It goes without saying that the usefulness of the EU-maximization approach as a descriptive choice-model has been fiercely debated outside the transportation domain (see Starmer (2000) for an excellent review of this debate). In travel behaviour research, this debate has recently resulted in one alternative choice-perspective gaining ground rapidly: that of Prospect Theory (PT, Kahneman & Tversky, 1979 – see Avineri & Prashker (2003) and Schwanen & Ettema (2009) for recent application in the travel choice domain). Whereas some of these empirical studies find evidence for non-EU maximization behaviour, others don't. It seems

[2] Although it has been shown (Arentze & Timmermans, 2003) that travel choice inertia emergence can be effectively modeled using reinforcement learning, the model's premises do not allow for modeling the interplay between learning and risk aversion that we wish to highlight here. As a result, the reinforcement learning approach is not considered an appropriate learning model given the scope of this paper.

that at this point, the evidence of applicability of EU and PT for analyzing travel choices does not yet allow for drawing of general conclusions. In that sense, there is little difference between the status quo in the travel behaviour research domain and the often varying and inconclusive evidence in other branches of the social sciences (for example, Harrison & Rutström, 2009).

Compared to the heated debate in the travel choice behaviour domain about the usefulness of EU- and PT-models of choice under uncertainty, much less attention has been devoted to the usefulness of different ways to model travellers' forward-looking behaviour. Studies that aim to model forward looking travellers generally have done so using a myopic approach, which assumes that travellers only consider the value of acquiring information or making observations with respect to the forthcoming choice situation, instead of looking further ahead (for example, de Palma & Picard, 2006; Chorus et al., 2006b). In other branches of the social sciences, empirical applications of myopic models (for example, Gabaix et al., 2006) as well as of non-myopic models (Erdem et al. (2005)) are available.

2.3 Selecting a modelling framework, and general applicability of results

At this point it is clear that no matter the (combination of) models selected for our formal analyses, there is contrasting empirical evidence within the domain of travel behaviour research. Given this situation of empirical ambiguity, we choose to select our modelling approach based on predominantly pragmatic reasons. Firstly, we choose to model learning behaviour by means of Bayesian updating-models. The pragmatic advantage of the Bayesian approach over weighted average learning lies in the former perspective's formal tractability: the Bayesian approach relies on one central equation to simultaneously update means and variances, and consumes no additional parameters which need to be fixed at some arbitrary value. Second, we model choice by means of a mean-variance linearization of Expected Utility in light of its compatibility with the Bayesian approach – the latter is used to update means and variances of risky variables, which may then directly enter the linearized Expected Utility-function to describe subsequent choice behaviour. For modelling forward-looking behaviour, we adopt a myopic perspective to remain in line with previous work in travel choice research and to keep the tractability of our model and its derivations at a reasonable level.[3]

At this point it is worth stressing that, although the formal analyses presented in the remainder of this paper are performed within the context of the selected modeling approach, our main finding (if travelers dislike risk, and part of the quality of travel alternatives is only revealed upon usage, inertia emerges due to a learning-based lock-in effect) generalizes over this modeling context. Although space limitations do not allow us to provide formal proofs for multiple models, we discuss in detail the intuition behind each of the formal results obtained for our model. These interpretations of results help establish credibility to our claim of obtaining results that are more general than the adopted modeling perspective only. We consider formal derivation of our results in the context of competing models of learning and choice as a fruitful avenue for further research.

3.0 Inertia among Bayesian, Expected Utility-maximizing travellers

3.1 A model of Bayesian, Expected Utility-maximizing travel mode-choice behaviour

Consider a traveller that has changed jobs and faces a choice between two travel modes – car and train – for his daily commute towards his new work location. The quality x of each mode – being

[3] Note that there is recent empirical evidence for the combination of linearized myopic EU-maximization behavior in the travel choice domain (Chorus et al., 2010).

a function of tastes and attributes that are relevant to the traveller – is anticipated by the traveller as a risky variable given the absence of experience with both modes in the context of the changed commute destination. Assume that car and train quality are both anticipated in terms of a normal distribution whose mean ($\hat{x}$) and variance (VAR) represent expected quality and quality uncertainty, respectively: $f\left(x_{car}^{t}\right) = N\left(\hat{x}_{car}^{t}, \sqrt{VAR_{car}^{t}}\right)$, $f\left(x_{train}^{t}\right) = N\left(\hat{x}_{train}^{t}, \sqrt{VAR_{train}^{t}}\right)$, where t denotes trip number (or day number, when we assume that each day a trip is made). Note that although many other distributions may be used here, the normal distribution is convenient when specifying a Bayesian learning process. We assume that the traveller evaluates travel modes based on a mean-variance linearization[4] of Expected Utility (*EU*). In the context of non-forward-looking behaviour, *EU* is equated with *instantaneous* Expected Utility ($E\tilde{U}$: with the term instantaneous, we mean to reflect that the utility of a particular travel mode is only based on its anticipated performance during the current trip):

$$E\tilde{U}_{car}^{t} = \beta_x \cdot \hat{x}_{car}^{t} - \beta_{VAR} \cdot VAR_{car}^{t}, \; E\tilde{U}_{train}^{t} = \beta_x \cdot \hat{x}_{train}^{t} - \beta_{VAR} \cdot VAR_{train}^{t} \tag{1}$$

Here, β_x and β_{VAR} are nonnegative, the latter reflecting the level of risk aversion. To account for slight day-to-day contextual differences in the traveller's choice situation (on a particular day, the traveller may for example be carrying luggage which may affect perceived quality of different travel modes) iid error terms ε_{car}^{t} and ε_{train}^{t} are added to the modes' utility, which are drawn from

[4] Note that in the context of normally distributed quality-levels, and assuming that the function mapping quality to utility is exponential (implying Constant Absolute Risk Aversion), Expected Utility is in fact given by a mean-variance formulation (de Palma and Picard, 2006).

an Extreme Value Type I distribution with variance $\pi^2/6$ (implying that the scale of the utility is normalized to one). This specification results in the standard binary logit formulation of probabilities $P\left(y^t = car\right)$ and $P\left(y^t = train\right)$, where y^t denotes the option chosen during trip *t*.

Upon choosing one of the travel modes (for example the car mode) and executing the trip, the traveller makes an observation ($\breve{x}_{car}^t$) of the mode's quality. The traveller knows that this observation will help him provide a more accurate assessment of the mode's quality. However, the traveller also believes that he is unable to make a perfectly reliable assessment of an alternative's quality by making only one observation (remember that quality is defined as a function of the traveller's tastes and a number of tangible and less tangible quality-aspects). Formally, assume that a quality observation is a noisy signal of actual quality x_{car} in the sense that $f\left(\breve{x}_{car}^t \middle| x_{car}\right) = N\left(x_{car}, \sqrt{VAR_{obs}}\right)$. That is, the traveller believes that, if the actual quality-level equals x_{car}, observed quality during trip *t* is normally distributed with mean equalling x_{car} (in other words: he believes observations provide unbiased measurements of actual quality), and variance equalling VAR_{obs}. The magnitude of VAR_{obs} reflects the extent to which the traveller believes that an observation of quality during the execution of an alternative is an unreliable measurement of actual quality. In other words: higher levels of VAR_{obs} reflect that the traveller distrusts his own observations and believes that it takes time to 'get to know' the alternative and appreciate its quality. We assume that VAR_{obs} does not differ between the car and the train mode, hence the absence of a mode-specific superscript.

Given these assumptions, the travellers updated perception of quality of the car mode, after having made trip *t* using the car mode and having observed a quality level $\breve{x}_{car}^t$, denoted

$f\left(x_{car}^{t+1}\middle|\breve{x}_{car}^{t}\right)$, is given by applying Bayes' Theorem (for example Edwards et al., 1963): $f\left(x_{car}^{t+1}\middle|\breve{x}_{car}^{t}\right)=N\left(\hat{x}_{car}^{t+1},\sqrt{VAR_{car}^{t+1}}\right)$, where:

$$\hat{x}_{car}^{t+1}=\frac{\left(VAR_{car}^{t}\right)^{-1}\cdot\hat{x}_{car}^{t}+\left(VAR_{obs}\right)^{-1}\cdot\breve{x}_{car}^{t}}{\left(VAR_{car}^{t}\right)^{-1}+\left(VAR_{obs}\right)^{-1}} \text{ and } VAR_{car}^{t+1}=\frac{VAR_{car}^{t}\cdot VAR_{obs}}{VAR_{car}^{t}+VAR_{obs}} \tag{2}$$

In words: updated quality perceptions are a weighted average of prior beliefs and observed quality. Weights reflect perceived reliability of prior beliefs and observations, respectively: when the traveller distrusts (trusts) his own observations, updated perceptions of quality are relatively close to initially anticipated quality (observed quality).

3.2 Inertia: underlying behavioural mechanisms

Before analyzing the behavioural mechanisms underlying inertia among rational travellers, it is of much importance to clearly define what we mean by the term itself. Although it is tempting to define inertia in terms of a decision-maker repeatedly choosing the same alternative, 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. As a result, defining inertia in terms of repetition alone is not very meaningful. Intuitively, we want to define inertia in a way that acknowledges that the mere *action of choosing* a particular alternative makes it more probable that the alternative is chosen again on the next day. In the context of the model presented above we can formalize this intuition as follows: a traveller exhibits inertia when the probability of choosing car over train during day t+1 is higher than the same probability during day t, under the condition that a) car is chosen during trip t and b) the level of car quality that was observed during the trip matches the expected level of quality. Inertia strength is defined in terms of the difference between these two choice probabilities. In notation (in the remainder of this paper, unless stated otherwise, we consider car-inertia):

Definition 1a: A traveller exhibits inertia when $P\left(y^{t+1}=car \middle| y^t=car, \breve{x}^t_{car}=\hat{x}^t_{car}\right) > P\left(y^t=car\right)$ or, in expected utility terms, when $\left(EU^{t+1}_{car} \middle| y^t=car, \breve{x}^t_{car}=\hat{x}^t_{car}\right) - \left(EU^{t+1}_{train} \middle| y^t=car, \breve{x}^t_{car}=\hat{x}^t_{car}\right) > \left[EU^t_{car}-EU^t_{train}\right]$.

Definition 1b: Inertia strength equals $P\left(y^{t+1}=car \middle| y^t=car, \breve{x}^t_{car}=\hat{x}^t_{car}\right) - P\left(y^t=car\right)$. Alternatively, inertia strength, defined in terms of expected utilities, equals: $\left[\left(EU^{t+1}_{car} \middle| y^t=car, \breve{x}^t_{car}=\hat{x}^t_{car}\right) - \left(EU^{t+1}_{train} \middle| y^t=car, \breve{x}^t_{car}=\hat{x}^t_{car}\right)\right] - \left[EU^t_{car}-EU^t_{train}\right]$.

Note that by providing these definitions we contribute to the literature on traveller inertia, where inertia is mostly defined rather loosely in terms of repetitive behaviour, or lack of willingness to switch to alternative routes and modes. Having defined inertia (strength), we can now explore when, to what extent and why the rational traveller presented in section 2.1 exhibits inertia. We do so by deriving two results.

Result 1: Under the condition that β_{VAR}, VAR_{car}^{t} and VAR_{obs} are all strictly positive, the rational traveller presented in section 2.1 exhibits inertia. Inertia strength – defined in terms of expected utilities – equals $\beta_{VAR} \cdot \left(VAR_{car}^{t}\right)^2 \Big/ \left(VAR_{car}^{t} + VAR_{obs}\right)$.

The intuition behind the first part of this result is as follows: the rational traveller learns about risky quality by observing the quality of a chosen travel mode. Given risk aversion this implies that choosing a travel mode, and observing that quality is as expected, leads to less quality uncertainty (and: higher utility) during the next trip: inertia arises as a cognitive lock-in effect. The intuition behind the second part of result 1 is as follows: it is obvious that a higher degree of risk aversion (β_{VAR}) and increased uncertainty (VAR_{car}^{t}) will both lead to more pronounced lock-in effect. The effect of observation unreliability (VAR_{obs}) on inertia strength can be explained as follows: remember that the key driver of inertia among rational travellers is the opportunity to learn from observations (in combination with risk aversion). Now, higher values of VAR_{obs} imply that observed quality during trip *t* is perceived by the traveller as a relatively unreliable signal of actual quality, which in turn implies that less weight is attached to these observations in the traveller's Bayesian learning process. As a result, to the extent that the traveller perceives observations to be unreliable signals, there is little opportunity for learning and the cognitive lock-in effect causing inertia is suppressed.

Result 2: Under the condition a) that β_{VAR}, VAR_{car}^{t} and VAR_{obs} are all strictly positive, and b) that the observed level of quality is Δ units lower than expected, a choice for the car mode during day

t implies an increased choice probability for the car mode during day t+1 as long as $\beta_{VAR} > \frac{\beta_x \cdot \Delta}{VAR_{car}^t}$.

The intuition behind this result is as follows: even when quality is lower than expected, the fact that quality uncertainty is reduced by learning from observations may imply a net gain in utility. Higher levels of initial uncertainty and of risk aversion imply higher gains. However, when the disappointment in terms of quality – or the traveller's marginal valuation of quality – are too large, the net gain becomes a net loss and the probability that the traveller chooses the car-mode is lower during trip t+1 than it was during trip t.

4.0 Inertia among forward-looking travellers

4.1 A model of (myopic) forward-looking travel mode-choice behaviour

Until now, we have assumed that the expected utility (*EU*) associated with choosing a travel mode-alternative is a function of anticipated mean and variance during the current trip t alone (hence: instantaneous Expected Utility). We now present a formulation of forward-looking travel choice-behaviour that acknowledges that (the traveller anticipates that) choosing a particular mode during the current trip has consequences (because of *anticipated* learning dynamics) for the anticipated instantaneous Expected Utility that may be derived from the next trip. In short: we assume that a traveller, when planning trip t, knows that the observation of the chosen mode's quality during that trip may help him derive more utility from his mode choice during trip t+1. The myopically forward-looking traveller maximizes (linearized) Expected Utility, where a travel mode's Expected Utility is the sum of the instantaneous Expected Utility defined in (1), and the product of a forward-looking parameter γ and the anticipated instantaneous Expected Utility associated with the next trip (which in turn is conditional on having chosen the considered travel mode during the current trip):

$$
\begin{aligned}
&EU_{car}^{t} = E\tilde{U}_{car}^{t} + \gamma \cdot E\tilde{U}^{t+1} \left| \left(y^{t} = car \right) \right. \\
&EU_{train}^{t} = E\tilde{U}_{train}^{t} + \gamma \cdot E\tilde{U}^{t+1} \left| \left(y^{t} = train \right) \right.
\end{aligned}
\tag{3}
$$

When γ approaches zero, the traveller is only concerned with the current trip, and (3) reduces to (1). When γ approaches one, the traveller is concerned with making a good choice during the next trip as much as he is concerned with the current trip's utility. The anticipated instantaneous Expected Utility associated with the next trip, conditional on having chosen a particular travel mode during the current trip, is denoted as:

$$
\begin{aligned}
&E\tilde{U}^{t+1} \left| \left(y^{t} = car \right) \right. = \int_{\breve{x}_{car}^{t}} \left[\max \left\{ E\tilde{U}_{car}^{t+1} \left| \left(\breve{x}_{car}^{t} \right) \right., E\tilde{U}_{train}^{t} \right\} \cdot f\left(\breve{x}_{car}^{t} \right) \right] d\breve{x}_{car}^{t} \\
&E\tilde{U}^{t+1} \left| \left(y^{t} = train \right) \right. = \int_{\breve{x}_{train}^{t}} \left[\max \left\{ E\tilde{U}_{car}^{t}, E\tilde{U}_{train}^{t+1} \left| \left(\breve{x}_{train}^{t} \right) \right. \right\} \cdot f\left(\breve{x}_{train}^{t} \right) \right] d\breve{x}_{train}^{t}
\end{aligned}
\tag{4}
$$

Here, $E\tilde{U}_{car}^{t+1} \left| \left(\breve{x}_{car}^{t} \right) \right. = \beta_{x} \cdot \hat{x}_{car}^{t+1} - \beta_{VAR} \cdot VAR_{car}^{t+1}$ and $E\tilde{U}_{train}^{t+1} \left| \left(\breve{x}_{train}^{t} \right) \right. = \beta_{x} \cdot \hat{x}_{train}^{t+1} - \beta_{VAR} \cdot VAR_{train}^{t+1}$, where updated perceptions of quality (uncertainty) are as defined in (2). In words, the traveller knows that when choosing a travel mode (for example the car mode) during trip *t*, he will make a noisy observation of its quality $\breve{x}_{car}^{t}$ – of course, he does not know what quality level he will observe, hence the integration over $f\left(\breve{x}_{car}^{t}\right)$. He also knows that he will use this noisy observation to update his beliefs about car quality, and that he will base his choice between the car and train mode during the next trip on these updated beliefs. The traveller's beliefs regarding what level of quality he will observe during trip t equal his initial beliefs about car quality, that is: $f\left(\breve{x}_{car}^{t}\right)=f\left(x_{car}^{t}\right)$.

Finally, note that the right-hand-side of (4) implies that it is assumed that a travel mode's anticipated instantaneous Expected Utility during trip t+1, conditional on choosing *the other* mode during day t, equals the instantaneous Expected Utility during trip t. This assumption follows from the notion that travellers are assumed to only learn about a mode's quality by means of direct observation[5]. Choice probabilities are given by using the binary logit model presented in section 2.1. Upon choosing one of the travel modes, a noisy observation is made of the quality of the chosen mode, leading to updated beliefs regarding the chosen mode's quality.

4.2 Inertia among myopically forward-looking travellers (simulation)

Because the integrals over $f\left(\breve{x}_{car}^{t}\right)$ and $f\left(\breve{x}_{train}^{t}\right)$ do not have a closed form solution we discuss inertia among forward-looking travellers by means of a numerical simulation. Importantly, because shown numerical simulation outcomes partly depend on arbitrarily chosen values for relevant variables, we will be as careful and conservative as possible when interpreting obtained simulation results. Assume the following settings: $\hat{x}_{car}^{t}=\hat{x}_{train}^{t}=0$, that is: expected quality of both the car and the train mode, as anticipated when planning trip t, equals zero. Furthermore,

[5] The next section shows how this assumption may be relaxed to acknowledge the role of secondary learning from travel information.

$VAR^t_{car} = VAR^t_{train} = 5$, implying that during trip *t*, both car and train quality are anticipated to fall, with a probability of 67 per cent (95 per cent), within the interval [-5,5] ([-10,10]). Quality is evaluated in terms of one util per unit (β_x=1). Finally, VAR_{obs} = 2.5. Given these settings, the following result is obtained (note that a series of sensitivity analyses show that the result is robust with respect to varying one or more of the above parameter settings):

Result 3a: For small magnitudes of β_{VAR}, higher values of γ (that is, values close to 1) imply lower levels of inertia strength, potentially leading to negative inertia.

Result 3b: For higher values of β_{VAR}, inertia strength increases, and the effect of γ on inertia vanishes.

Figure 1 illustrates these results (β_{VAR} is varied from 0 to 1 (this latter extreme being the value of β_x), while simultaneously γ is also varied from 0 to 1). The dependent variable, inertia strength, is measured (in line with definition 1) in terms of the probability that car is chosen during trip *t*+1, given a choice for the car during trip *t* and an associated observation of car quality that exactly matches expectations, minus the probability of choosing the car during trip *t* (which equals 50 per cent). Integration over the density functions that represent what observations the traveller expects to make when choosing a particular mode is performed by means of Monte Carlo simulation (100 pseudo-random draws are made from each density function – sensitivity analysis showed that this number is sufficiently high). Software package GAUSS 7.0 is used for performing the simulation.

It is immediately seen that, as stated in result 3, the negative effect of γ on inertia strength only becomes noticeable when the degree of risk aversion approaches zero. For these low levels of risk aversion, positive values of γ may lead to negative levels of inertia strength (a choice for the car mode during trip *t* leads to a reduction in probability of choosing the car mode again during the next trip). However, when risk aversion grows, the negative effect of γ on inertia strength rapidly decreases.

The intuition behind these results is as follows: in the absence of (substantial levels of) risk aversion, the traveller is predominantly concerned with choosing the mode with highest *expected* quality. Given the Bayesian learning process defined in section 2.1, the observation of car quality during trip *t* results in an improved estimate of expected car quality (although expected quality itself is unchanged, given that $\breve{x}_{car}^{t} = \hat{x}_{car}^{t}$). As a result, when planning trip *t*+1, the traveller is still indifferent between the two modes in terms of expected quality, but he does face a choice between on the one hand a further decrease in car quality uncertainty (implied by a choice for the car mode), and on the other hand a decrease in train quality uncertainty (implied by a choice for the train mode). Intuition, as well as Bayes' Theorem, state that the latter decrease in uncertainty will be larger than the former, because a second observation of an uncertain phenomenon provides less information than the first observation. As a result, when planning trip *t*+1, a traveller that has chosen the car mode during trip *t* knows that he should choose the train mode during trip *t*+1 if he wants to be as sure as possible that he will make the right choice, in terms of maximizing expected quality, during trip *t*+2.

In the presence of substantial levels of risk aversion, the argumentation changes. First, as was shown in section 2, higher levels of risk aversion lead to higher levels of inertia strength due to the learning-based cognitive lock-in effect. Second, the intuition behind the result that when risk aversion is non-negligible the effect of γ on inertia strength rapidly approaches zero, is as follows: a risk averse traveller, having chosen a particular travel mode during trip *t*, has developed a preference for this mode as a result of the learning-based cognitive lock-in effect. When planning trip *t*+1, the traveller anticipates (to the extent that he is forward-looking) that a choice for the other mode will bring the uncertainty level of that mode to the same level as that of the mode chosen during trip *t*. However, he also knows that he is able to further decrease the uncertainty associated with the mode chosen during trip *t*, by again choosing this mode during trip *t*+1. To the extent that risk aversion is present, this additional decrease in uncertainty counterbalances the potential gains in terms of getting a better estimate of expected quality, resulting from choosing a different mode during trip *t*+1. As a result, in the presence of risk aversion, increasingly forward looking behaviour does not lead to lower inertia strength.

5.0 Inertia in the presence of multimodal travel information

Until here, we have assumed that travel choices are made in the absence of information. Clearly, broadening this assumption towards acknowledging the presence of information would lead to a better correspondence with most actual choice situations faced by travellers nowadays. In this section, we study how the presence of pre-trip personalized multimodal information about travel mode-quality impacts inertia emergence.

5.1 A model of travel choice behaviour in the presence of multimodal travel information

Assume, without loss of generality, that pre-trip information becomes available (or: noticed by the traveller) after the traveller has made the first trip *t* towards his new working location.

Assume that he has chosen to use the car mode for this first trip. When planning trip $t+1$, the traveller receives multimodal quality information in the form of messages $\overline{x}_{car}^{t+1}$ and $\overline{x}_{train}^{t+1}$. As a result, his beliefs concerning the quality of both the car and the train mode (the former of these already updated once as a result of observed car quality during trip t) are updated.

Assume that the traveller believes that the information provider is unable to faultlessly assess quality (for example because the information provider is only partially able to correctly assess the traveller's tastes). Specifically, we postulate that $f\left(\overline{x}_{car}^{t+1}\left|x_{car}\right.\right)=N\left(x_{car},\sqrt{VAR_I}\right)$ and that $f\left(\overline{x}_{train}^{t+1}\left|x_{train}\right.\right)=N\left(x_{train},\sqrt{VAR_I}\right)$, VAR_I being a measure of anticipated information unreliability. This formulation implies that information is perceived to be unbiased (that is: the expected quality message equals expected quality) and that perceived information reliability does not vary across modes[6]. As a result, reception of information leads to the following updates in quality anticipations: $f\left(x_{car}^{t+1}\left|\breve{x}_{car}^{t},\overline{x}_{car}^{t+1}\right.\right)=N\left(\hat{x}_{car}^{t+1},\sqrt{VAR_{car}^{t+1}}\right)$ and $f\left(x_{train}^{t+1}\left|\overline{x}_{train}^{t}\right.\right)$ = $N\left(\hat{x}_{train}^{t+1},\sqrt{VAR_{train}^{t+1}}\right)$, where:

[6] There is some indirect evidence supporting this latter assumption: a web survey held by the first author among 488 travelers (Chorus et al., 2007 – results discussed in this footnote are not published), who were asked to identify themselves as either car-drivers or Public Transport users, shows that perceptions of travel information reliability did not differ much between the two groups, and that travelers' perception of information reliability concerning the other than their usual mode of transport did not differ a lot among the two groups as well.

$$\hat{x}_{car}^{t+1} = \frac{\left(VAR_{car}^{t+1}\right)^{-1} \cdot \hat{x}_{car}^{t+1} + \left(VAR_I\right)^{-1} \cdot \overline{x}_{car}^{t+1}}{\left(VAR_{car}^{t+1}\right)^{-1} + \left(VAR_I\right)^{-1}} \text{ and } VAR_{car}^{t+1} = \frac{VAR_{car}^{t+1} \cdot VAR_I}{VAR_{car}^{t+1} + VAR_I}$$

$$\hat{x}_{train}^{t+1} = \frac{\left(VAR_{train}^{t}\right)^{-1} \cdot \hat{x}_{train}^{t} + \left(VAR_I\right)^{-1} \cdot \overline{x}_{train}^{t+1}}{\left(VAR_{train}^{t}\right)^{-1} + \left(VAR_I\right)^{-1}} \text{ and } VAR_{train}^{t+1} = \frac{VAR_{train}^{t} \cdot VAR_I}{VAR_{train}^{t} + VAR_I} \tag{5}$$

Here, $\hat{x}_{car}^{t+1}$ and VAR_{car}^{t+1} are as defined in (2). Note the difference in superscripts between the car and train-mode: for the car-mode, the updated quality perceptions are a combination of the received message and perceived quality after having chosen the car mode during trip t (which itself is a combination of initial anticipations and observed quality). For the train mode, the updated quality perception is simply a combination of the received message and initial quality anticipations.

For a non-forward looking traveller, the story ends here. However, to the extent that the traveller is concerned – when planning trip t – with the instantaneous utility to be derived from trip t+1, the presence of information has a second order effect: the traveller, when planning trip t, anticipates that he will receive travel information again before trip t+1 and that this information will lead him to once again update his perceptions before planning trip t+1. Of course, he does not know beforehand what messages he will receive. However, he does know that there is a formal relationship between on the one hand the probability of receiving particular messages $\overline{x}_{car}^{t+1}$ and $\overline{x}_{train}^{t+1}$ when planning trip t+1 and on the other hand his anticipation of car and train quality after having made trip t, in combination with his anticipation of information reliability. As a result of this relationship, the traveller's anticipations of what message he might receive when planning trip t+1 differ between the two modes, since his anticipation of messages is conditional on the anticipated observation to be made during trip t. In notation, the traveller knows that, should he for example choose the car mode during trip t and make an observation $\breve{x}^t_{car}$, his anticipations of what messages $\overline{x}^{t+1}_{car}$ and $\overline{x}^{t+1}_{train}$ he will receive when planning trip t+1 are:

$$
\begin{aligned}
f\left(\overline{x}^{t+1}_{car} \middle| \breve{x}^t_{car}\right) &= \int\limits_{x^{t+1}_{car}} \left[f\left(\overline{x}^{t+1}_{car} \middle| x^{t+1}_{car}\right) \cdot f\left(x^{t+1}_{car} \middle| \breve{x}^t_{car}\right) \right] dx^{t+1}_{car} \\
f\left(\overline{x}^{t+1}_{train} \middle| \breve{x}^t_{car}\right) &= \int\limits_{x^t_{train}} \left[f\left(\overline{x}^{t+1}_{train} \middle| x^t_{train}\right) \cdot f\left(x^t_{train}\right) \right] dx^t_{train}
\end{aligned}
\tag{6}
$$

Here, $f\left(x^{t+1}_{car} \middle| \breve{x}^t_{car}\right)$ is as presented in (2). Furthermore, in line with the argument presented right before equation (5), $f\left(\overline{x}^{t+1}_{car} \middle| x^{t+1}_{car}\right) = N\left(x^{t+1}_{car}, \sqrt{VAR_I}\right)$ and $f\left(\overline{x}^{t+1}_{train} \middle| x^t_{train}\right) = N\left(x^t_{train}, \sqrt{VAR_I}\right)$. Finally, note that $f\left(\overline{x}^{t+1}_{car} \middle| \breve{x}^t_{train}\right)$ and $f\left(\overline{x}^{t+1}_{train} \middle| \breve{x}^t_{train}\right)$ are derived in the same fashion as $f\left(\overline{x}^{t+1}_{car} \middle| \breve{x}^t_{car}\right)$ and $f\left(\overline{x}^{t+1}_{train} \middle| \breve{x}^t_{car}\right)$.

Given these anticipated probabilities of receiving particular messages, we can derive the forward-looking traveller's anticipation of instantaneous Expected Utility associated trip t+1, conditional on having made a particular observation during trip t:

$$
E\tilde{U}^{t+1} \left| \left(\breve{x}^t_{car}\right) \right. = \int\limits_{\overline{x}^{t+1}_{car}} \int\limits_{\overline{x}^{t+1}_{train}} \left[\max \begin{Bmatrix} E\tilde{U}^{t+1}_{car} \left| \left(\overline{x}^{t+1}_{car}, \breve{x}^t_{car}\right), \right. \\ E\tilde{U}^{t+1}_{train} \left| \left(\overline{x}^{t+1}_{train}\right) \right. \end{Bmatrix} f\left(\overline{x}^{t+1}_{car} \middle| \breve{x}^t_{car}\right) f\left(\overline{x}^{t+1}_{train} \middle| \breve{x}^t_{car}\right) \right] d\overline{x}^{t+1}_{car} d\overline{x}^{t+1}_{train}
$$

$$
E\tilde{U}^{t+1} \left| \left(\breve{x}^t_{train}\right) \right. = \int\limits_{\overline{x}^{t+1}_{car}} \int\limits_{\overline{x}^{t+1}_{train}} \left[\max \begin{Bmatrix} E\tilde{U}^{t+1}_{car} \left| \left(\overline{x}^{t+1}_{car}\right), \right. \\ E\tilde{U}^{t+1}_{train} \left| \left(\overline{x}^{t+1}_{train}, \breve{x}^t_{train}\right) \right. \end{Bmatrix} f\left(\overline{x}^{t+1}_{car} \middle| \breve{x}^t_{train}\right) f\left(\overline{x}^{t+1}_{train} \middle| \breve{x}^t_{train}\right) \right] d\overline{x}^{t+1}_{car} d\overline{x}^{t+1}_{train}
$$

(7)

Conditional instantaneous Expected Utilities are derived by applying the updating rule given in (5) and entering updated perceptions in (1). Substituting (7) in (4) and subsequently substituting (4) and (1) in (3) gives the Expected Utilities for the two modes. Based on these Expected Utilities, choice probabilities are derived using the binary logit model presented in section 2.1. Upon choosing one of the travel modes, based on these anticipations of quality observations during trip *t* and resulting messages to be received when planning tip *t*+1, a noisy observation is made of the quality of the chosen mode, leading to updated beliefs regarding the chosen mode's quality.

5.2 Inertia in the presence of multimodal travel information (simulation)

Because the derivation of choice probabilities among forward-looking travellers in the presence of information involves the evaluation of several integrals without a closed form solution, we study inertia by mans of numerical simulation. Assume the following settings: like in section 3.2, $\hat{x}^t_{car} = \hat{x}^t_{train} = 0$, $VAR^t_{car} = VAR^t_{train} = 5$, $VAR_{obs} = 2.5$ and $\beta_x = 1$. Risk aversion parameter β_{VAR} = 0.25. Given these settings, the following results are obtained (note that a series of sensitivity analyses show that these results are robust[7] with respect to varying one or more of the above parameter settings):

[7] An exception is the level of risk aversion: as was established in result 3b, high levels of risk aversion imply that the effect of γ becomes negligible, irrespective of the value of VAR_I.

Result 4a: Inertia strength is an increasing function of information unreliability (VAR_I). For large magnitudes of VAR_I, higher values of γ imply lower levels of inertia strength.

Result 4b: For small values of VAR_I (implying reliable information), the effect of γ on inertia strength vanishes.

Figure 2 illustrates this result. VAR_I is varied from 0 to 5 (this latter extreme being the value of VAR_{car}^t and VAR_{train}^t which implies that the information is anticipated to be equally unreliable as the traveller's own initial knowledge. Simultaneously, γ is varied from 0 to 1. The dependent variable, inertia strength, is measured (in line with definition 1) in terms of the probability that car is chosen during trip t+1 (given a choice for the car mode during trip t and an associated observation of car quality that exactly matches a priori expectations) minus the probability of choosing the car during trip t (which equals 50 per cent). Integration over the density functions that represent what observations the traveller expects to make when choosing a particular mode is performed by means of Monte Carlo simulation (100 pseudo-random draws for each density). Messages are also simulated by making 100 pseudo-random draws from the pdfs presented in (6). Crucially, to reflect that the traveller anticipates that received messages are conditional on his (potentially updated) perceptions of quality after having made a trip (see (6)), messages are conditioned on anticipated quality levels. That is, for each possible quality level drawn, 100 messages are drawn, which results in 10,000 messages being drawn in total. Sensitivity analyses showed that these numbers were sufficiently high. Figure 2 shows simulated levels of inertia strength (note that the scale of the Z-axis differs from that in Figure 1).

The positive effect of information unreliability on inertia strength is clearly visible. The intuition behind this result is straightforward: as discussed in section 2.2, inertia arises from a lock-in effect based on travellers' ability to learn from observing a chosen mode's quality level. However, these observations becomes less important when information becomes more and more reliable, and as a result the cognitive lock-in effect causing inertia becomes less pronounced. Take the extreme situation where a traveller believes that he will receive fully reliable information at the start of each trip: in that case, paying attention to quality levels observed during trips made is of no use as it does not add to the learning process. As a result, the cognitive lock-in effect based on learning from observations vanishes.

When information is unreliable, the negative effect of γ on inertia strength is clearly visible as well. This effect is in line with result 3a as illustrated in Figure 1 (note that to the extent that information is anticipated to be unreliable, the 'with information' case becomes equivalent to the 'without information' case): forward-looking travellers are relatively prone to explore new alternatives, because they know that observing their quality levels helps them achieve higher levels of expected quality in future choices. To the extent that information is anticipated to be reliable, the effect of γ on inertia strength rapidly diminishes because reliable information not only diminishes the usefulness of observing quality during the current trip, but also the usefulness of anticipated observations during the next trip (the traveller knows that information will also be available during the next trip).

6.0 Conclusions and discussion

This paper shows how travellers that are faced with a series of risky choices become behaviourally inert due to a combination of risk aversion and learning. We first present a model of risky travel mode choice and show that if travellers dislike risk, and part of the quality of travel alternatives is only revealed upon usage, inertia emerges due to a learning-based lock-in effect. We go on to show how the interplay between forward-looking behaviour and risk aversion determines the level of inertia among forward-looking travellers. In addition, we show how the costless provision of multimodal travel information may slow down inertia emergence, but only to the extent that the information is considered reliable.

The main message this paper tries to convey is that the usually invoked postulates of effort-accuracy trade-offs (sticking to a good enough alternative that has been chosen before arises from the wish to save effort, time and attention) are not necessary to explain inertia in a travel mode choice context. We show that inertia emerges rapidly and forcefully among travellers that consider all alternatives available in their choice set. Of course, there is no reason to conclude from the analysis presented here that inertia has little to do with effort-accuracy trade-offs – on the contrary: we acknowledge the intuitive notion of inertia arising from travellers' wish to economize on cognitive resources. In fact, we believe that actual patterns of traveller inertia are the result of an interplay between such trade-offs and the learning-based lock-in effects described in this paper.

From a theoretical perspective, we believe that a particularly fruitful direction for further research would be to incorporate strategic behaviour. As recent experimental studies point out, car-drivers are likely to consider (anticipated) choices made by other travellers when choosing which route to take (Ziegelmeyer et al., 2008). Intuitively, one would expect that there is a link between such strategic behaviour and inertia emergence, although further research is needed to gain detailed insights into this relation. Notwithstanding that the presented model leaves room for theoretical model extensions like the one discussed directly above, we consider empirical testing to be the paramount direction for further research.

To conclude, we believe that the results and overall conclusion we present here have an important practical implication: they suggest that inertia might be even more difficult to ‘break’ then we thought. Whereas transport policy-makers often assume that helping make travellers consider all available alternatives (for example by providing travel information; see Chorus et al. (2006a) for an overview of such attempts) will reduce inertia, our results suggest that such an approach will not be very helpful. On the other hand, our analyses do highlight the potential of other measures, such as the promotion of alternative (sustainable) travel modes when travellers are forced to abandon their usual mode. Our results suggest that travellers may be quite good in quickly learning ‘good’ habits.

References

Arentze, T.A., Timmermans, H.J.P., 2003. Modeling learning and adaptation processes in activity-travel choice. *Transportation*, 30(1), 37-62

Avineri, E., Prashker, J.N., 2003. Sensitivity to uncertainty: need for a paradigm shift. *Transportation Research Records*, 1854, pp. 90-98

Ben-Akiva, M., De Palma, A., Kaysi, I., 1991. Dynamic network models and driver information systems. *Transportation Research Part A*, 25, 251-266

Chorus, C.G., Molin, E.J.E., van Wee, G.P., 2006a. Travel information as an instrument to change car-drivers’ travel choices: A literature review. *European Journal of Transport and Infrastructure Research*, 6(4), 335-364

Chorus, C.G., Arentze, T.A., Molin, E.J.E., Timmermans, H.J.P., van Wee, G.P., 2006b. The value of travel information: Decision-strategy specific conceptualizations and numerical examples. *Transportation Research Part B*, 40(6), 504-519

Chorus, C.G., Molin, E.J.E., Arentze, T.A., Timmermans, H.J.P., van Wee, G.P., 2007. Travelers' need for information in traffic and transit: results from a web-survey. *Journal of Intelligent Transportation Systems*, 11(2), 1-11

Chorus, C.G., Arentze, T.A., Timmermans, H.J.P., 2009. Traveler compliance with advice: A Bayesian utilitarian perspective. *Transportation Research Part E*, 45(3), 486-500

Chorus, C.G., Walker, J.L., Ben-Akiva, M.E., 2010. The value of travel information: A search-theoretic approach. *Journal of Intelligent Transportation Systems*, 14(3), 154-165

Commission of the European Communities, 2007. *Green Paper: Towards a new culture for urban mobility.* Brussels, Belgium

de Palma, A., Picard, N., 2005. Route choice decision under travel time uncertainty. *Transportation Research Part A*, 39, 295-324

de Palma, A., Picard, N., 2006. Equilibria and information provision in risky networks with risk-averse drivers. *Transportation Science*, 40(4), pp. 393-408

Edwards, W., Lindman, H., Savage, L.J., 1963. Bayesian statistical research for psychological research. *Psychological Review*, 70, pp. 193-242

Erdem, T., Keane, M.P., Öncü, T.S., Strebel, J., 2005. Learning About Computers: An Analysis of Information Search and Technology Choice. *Quantitative Marketing and Economics*, 3, 207-246.

Gabaix, X., Laibson, D., Moloche, G., Weinberg, S., 2006. Costly information acquisition : Experimental analysis of a boundedly rational model. *American Economic Review*, 96, 4, pp. 1043-1068

Gardner, B., 2009. Modelling motivation and habit in stable travel mode contexts. *Transportation Research Part F*, 12(1), pp. 68-76

Gärling, T., Axhausen, K.W., 2003. Introduction: Habitual travel choice. *Transportation*, 30, pp. 1-11

Han, Q., Dellaert, B., van Raaij, F., Timmermans, H.J.P., 2007. Modeling strategic behavior in anticipation of congestion. *Transportmetrica*, 3(2), pp. 119-138.

Harrison, G.W., Rutström, E.E., 2009. Expected utility theory and prospect theory: One wedding and a decent funeral. *Experimental Economics*, 12, 133-158

Kahneman, D., Tversky, A., 1979. Prospect Theory: An analysis of decision under risk. *Econometrica*, 47, 263-291

Kaysi, I., 1991. *Framework and models for provision of driver information system*. PhD-thesis, Massachusetts Institute of Technology, Cambridge, MA

Noland, R.B., Small, K.A., 1995. Travel-time uncertainty, departure time choice and the cost of morning commutes. *Transportation research Record*, 1493, pp. 150-158

Schwanen, T., Ettema, D., 2009. Coping with unreliable transportation when collecting children: Examining parents' behavior with cumulative prospect theory. *Transportation Research Part A*, 43(5), 511-525

Simon, H.A., 1978. Rationality as process and as product of thought. *American Economic Review*, 68(2), pp. 1-16

Srinivasan, K.K., Mahmassani, H.S., 2000. Modelling inertia and compliance mechanisms in route choice behaviour under real-time information. *Transportation Research Record*, 1725, pp. 45-53

Starmer, C., 2000. Developments in non-expected utility theory: the hunt for a descriptive theory of choice under risk. *Journal of Economic Literature*, 38, pp. 332-382

Sun, Z., Arentze, T.A., Timmermans, H.J.P., 2005. Modeling the impact of travel information on activity-travel rescheduling decisions under conditions of travel time uncertainty. *Transportation Research Record*, 1926, 79-87

Xu, F., Tenenbaum, J.B., 2007. Word learning as Bayesian inference. *Psychological Review*, 114 (2), pp. 245-272

Ziegelmeyer, A., Koessler, F., My, K.B., Denant-Boèmont, L., 2008. Road traffic congestion and public information: An experimental investigation. *Journal of Transport Economics and Policy*, 42(1), 43-82

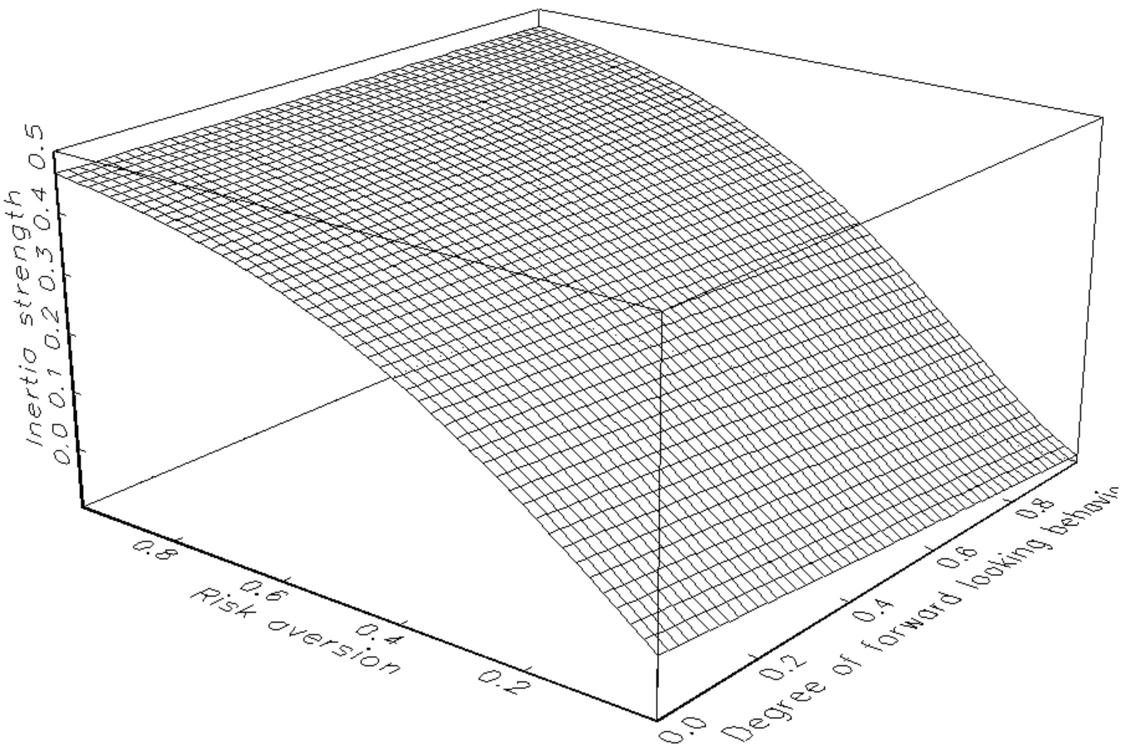

Figure 1: Inertia among forward looking travellers

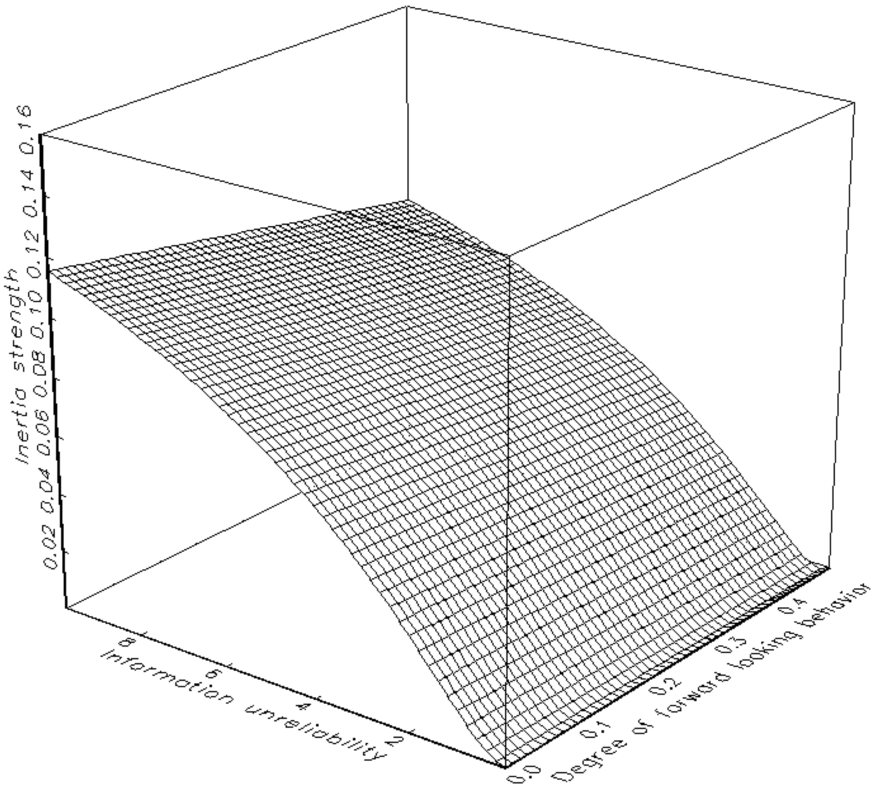

Figure 2: Inertia in the presence of multimodal travel information

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