

Data challenges: more behavioural and (relatively) less statistical – a think piece

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Abstract

The study of traveller behaviour has blossomed into a multi-disciplinary array of theories, methods and data paradigms all aimed at improving our understanding of drivers of passenger and freight movement in time and space. While progress continues unabated, there remains the challenge of extracting more behavioural richness out of the way in which we work to understand the nuances of preference revelation and hence choice making. In particular, we are a long way from understanding what incentives might work best in attracting behavioural responses that government on behalf of society would like to see as travel outcomes that align with specific policy and strategy objectives. In this paper we discuss a number of informative ways of gaining an increased understanding of behavioural response, which leads into a list of data items worthy of inclusion in new surveys. The paper is designed as a thought piece in line with the role it played as a plenary presentation at the opening of the 2014 International Conference on Travel Survey Methods.

Keywords: data challenges, behavioural response, new survey content, behavioural insight, risk, uncertainty, herding, choice experiment complexity and relevance

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Introduction

The most complex element of travel behaviour studies is the human being. While we may never be in a position to fully explain the next response that each individual might make to a changing set of circumstances designed to influence trip making, in the short, medium and long term, we now have a growing body of theoretical and empirical evidence that is suggestive of possible paths of response and what are some of the key drivers of change and/or reinforcement of habitual behaviour. The extant literature recognises a growing number of areas of fruitful research endeavour that have not been given enough attention in travel behaviour studies and in travel survey design, and which should move from what one might describe as fringe interests to a central role in the toolkit used by travel survey methods specialists.

This paper, as an interpretation of a plenary address, summarises a number of such themes that should be highlighted for serious consideration in the design of travel surveys. The selection of themes includes uncertainty and subjective probability and a return to a greater role for revealed preference data compared to the growing influence of stated choice data, the complexity of choice experiments contrasted with the relevance of information, herding behaviour, behavioural insights and nudging, and the appeal of supplementary response variables in choice studies such as awareness, familiarity, and acceptability of alternatives.

The process for modelling decisions under uncertainty

The great majority of travel choice studies and aligned data sets are snapshot interpretations of choice making activity that typically assume that all decisions taken are associated with risk neutrality. Although it is common to assume that individuals are, on balance, substantially risk averse, with some exceptions under risk taking, the recognition and hence testing for risk attitude should be encouraged, especially where there is a growing relevance attached to circumstances that question the real behavioural value of simplistic assumptions such as certainty of travel times on the road network (i.e., trip time variability¹) and getting a seat on public transport (i.e., the crowding variability effect).

Recognising risk is one thing, but extending the data collection exercise and modelling opportunity to accommodate uncertainty is quite different. Specifically, risk is associated with a known or assumed occurrence (probability) distribution, whereas uncertainty relates to an unknown distribution that is guided by sources of ambiguity aversion (also known as source preference – see Fox and Tversky 1998). Fundamentally, risk is *conditioned by* uncertainty. In seeking out ways to incorporate uncertainty into choice modelling, we begin by asking the question: what sort of data might we need to be able to do this? Central to the answer is evidence on subjective probability associated with the occurrence of attribute levels such as travel times and getting a seat. The most common response is to build this into a stated choice experiment; however given the subjective (or perceived) nature of such information, this may not be possible. Choice experiments impose levels on attributes in general, although they are able to establish revealed levels for an experienced (status quo or reference) alternative but not for the designed alternatives. Fundamentally, uncertainty (linked to subjective probability) is difficult to measure and hence capture (maybe impossible?) in a choice experiment. Taking travel time variability as an example which requires data on travel times and the associated occurrence of each travel time, these two items can be measured as objective or subjective constructs as summarised in Table 1 (from Hensher *et al.* 2015). Given that choice experiments impose attribute levels through a designed structure, it appears not possible to see respondent perceptions on levels of attributes, and thus only level *i* is permissible. Whether objective levels designed into choice experiments can be used as proxies for subjective levels, offering the ability to treat the choice

¹ On two days that I drafted this paper my journey work was 35 mins and 2 hours – the latter due to an accident on the Sydney harbour bridge).

experiment as a source of data to accommodate the role of risk and uncertainty is an empirical issue that has, as far as I am aware, not been systematically investigated.

Table 1 Four levels of subjectivity and objectivity of data

Level <i>i</i>	FO = OPs+OAs
Level <i>ii</i>	PS(1) = OPs+SAs
Level <i>iii</i>	PS(2) = SPs+OAs
Level <i>iv</i>	FS = SPs+SAs

Notes: FO: fully objective, PS(1): Partially subjective; PS(2): Partially subjective, FS: fully subjective; SPs: Subjective probabilities, SAs: Subjective attributes; OPs : Objective probabilities, OAs: Objective attributes
Source preference = sources of uncertainty ambiguity

What this discussion does suggest, however, is that it might be time to revisit revealed preference data with a fresh perspective, given that subjective measures of attributes and their occurrence can be more readily obtained for experienced and non-experienced alternatives. Given the growing recognition of the role of uncertainty as embellished by the classic statement by Ellsberg (1961, p 659), namely “An individual . . . can always assign relative likelihoods to the states of nature. But how does he act in the presence of uncertainty? The answer to that may depend on another judgment, about the reliability, credibility, or adequacy of his information (including his relevant experience, advice and intuition) as a whole.”, the ability of a revealed preference approach to account for uncertainty offers much appeal. The types of data required are best summarised in Figure 1 (from Fox and Tversky 1998, see also Heath and Tversky 1991), which translates into a simple survey instrument such as the screen in Figure 2.

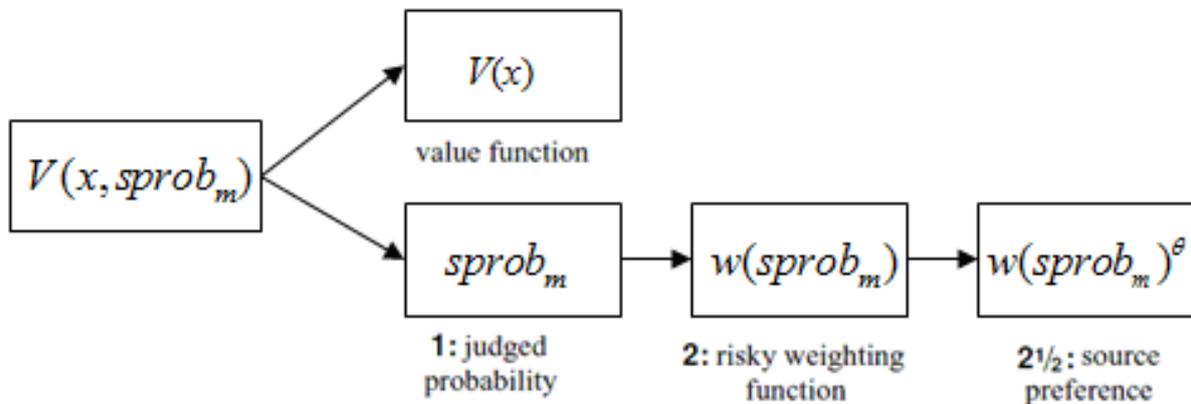


Figure 1 Process to recognise uncertainty in choice making

To obtain data to identify the probability weighting process under uncertainty, the first step is to ask respondents to provide their judged (subjective) probabilities ($sprob_m$) of target events, and the second step is to weight those judged probabilities by using a nonlinear probability weighting function for risk (i.e., risky weighting function) as is common in prospect theory applications (see Rasouli and Timmermans 2014 for a review of the popular functional forms, and Li and Hensher 2015 for a generalised form that can reveal the ‘statistically best’ functional form). The distinction between decision under risk and uncertainty is captured in the further transformation of decision weights, which indicates individuals’ source preference through the source preference parameter (θ) which can itself be a function of other judgments (e.g., beliefs).

A theme that is central to uncertainty and risk is believability of the evidence (Hensher *et al.* 2013). Heath and Tversky (1991) explain what they call a *competence hypothesis*, which states that people prefer to bet on their own vague beliefs in situations in which they feel they have more knowledge. In this context, Fox and Tversky (1998) propose a general belief-based approach to decision making under uncertainty as a transformation of the judged probability, as given in (1).

$$W(A) = (w[P(A)])^\theta \quad (1)$$

$\theta > 0$ is an estimated parameter which is inversely related to the attractiveness of the source, $P(A)$ reflect a person's belief in the likelihood of the outcome, and w^θ reflects a person's preference to bet on that belief. Hence, this latter takes into account for the influence of behavioural sources on preference revelation in terms of deviations from the given and (subjective) judged probabilities for the belief weight function, referred to as uncertainty ambiguity. This parameter can be considered as a function of other characteristics of the individual.

This modelling process integrates two essential components of research in behavioural decision theory: (i) the analysis of decision under risk (e.g., decision weights in Prospect Theory and Rank-Dependent Utility Theory $w(p_i)$), and (ii) the study of judgment under uncertainty (e.g., subjective probability and belief prospects). It also extends Prospect Theory by teasing apart the role of personal belief and source preference (sources of uncertainty ambiguity) in the weighting process. A Model with Source Preference (θ) can be a function of context otherwise it is a sample mean effect. An example of a functional form to be estimated that captures these processes is given in equation (2), where SEEUT is the subjective extended expected utility theoretic model. This model is implemented in Hensher *et al.* (2015).

$$SEEUT(U) = \beta_x [w(p_1)^\theta x_1^{1-\alpha} + w(p_2)^\theta x_2^{1-\alpha} + \dots + w(p_R)^\theta x_R^{1-\alpha}] / (1 - \alpha) \quad (2)$$

Car Commuter

You are qualified for this survey.

You said that you commute by **car as driver** and we know that your travel times will vary each time you travel to work for many reasons such as congestion, accidents, breakdowns, and road works.

Could you please share with us **3 possible travel outcomes** that you believe could occur on your **car trip to work?** (these could be based on your recent experience on your regular commuter trip, or your perceptions of what it is likely to be.)

The 3 possible travel outcomes must include: **one with the longest travel time, one with the shortest travel time and one with the most likely travel times.**

The likelihood of the most likely travel time must be highest amongst 3 possible outcomes and the likelihoods across 3 possible outcomes must add up to 100.

	Outcome 1	Outcome 2	Outcome 3
Door-to-door travel time (minutes)	<input type="text"/>	<input type="text"/>	<input type="text"/>
Travel distance by car (km)	<input type="text"/>	<input type="text"/>	<input type="text"/>
Toll paid (\$)	<input type="text"/>	<input type="text"/>	<input type="text"/>
The likelihood of this outcome actually occurring (%)	<input type="text"/>	<input type="text"/>	<input type="text"/>
Rank possible travel outcomes from 1 (most preferred) to 3 (least preferred)	<input type="text"/>	<input type="text"/>	<input type="text"/>

What is the average fuel consumption of the car that you would use for commuting? litres/100km

How many times in the last 2 months did you drive to work?

You said that you could use **public transport** to commute if you wanted to.

What would be the **3 possible outcomes** of your commuting trip by **public transport?** (use the same principles provided above for car commuting trip to provide your answers)

	Outcome 1	Outcome 2	Outcome 3
Door-to-door travel time (minutes)	<input type="text"/>	<input type="text"/>	<input type="text"/>
Fare (\$)	<input type="text"/>	<input type="text"/>	<input type="text"/>
The likelihood of this outcome actually occurring (%)	<input type="text"/>	<input type="text"/>	<input type="text"/>
Rank possible travel outcomes from 1 (most preferred) to 3 (least preferred)	<input type="text"/>	<input type="text"/>	<input type="text"/>

How many times in the last 2 months did you ride public transport to work?

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Figure 2 Illustrative data screen to obtain data associated with uncertainty

Complexity vs. relevance in choice experiments

There is a great deal of what I would describe as paranoia about the ‘complexity’ of stated choice experiments. There are proponents who would suggest that a few attributes (e.g., three) and two or three alternatives is about as much as a respondent can handle, whilst other analysts are supportive of more attributes and alternatives (see Figure 3 for examples of choice sets with many attributes). What is often missing in the debate are the criteria that should be used in defining the dimensions of choice experiments, apart from the broad belief in choice experiments being ‘comprehensive’ and ‘comprehensible. Some studies partition the attribute set and show respondents a number of different choice sets that contain a partial set of attributes. The issue of transitivity and hence comparability is at risk in such situations.

What should dictate the dimensionality of choice experiments is the ‘relevance’ of attributes and it should prevail over complexity (Hensher 2014). Relevancy suggests comprehensiveness, provided there are no crucial attributes that have been excluded. Indeed, respondents often struggle with a choice response that is a true reflection of their preferences, which are often based on consideration of other attributes that are not revealed but which contaminate the assessment of the offered attributes. The challenge then becomes one of presenting the information in a way that is comprehensible. This requires creative formats and extensive piloting of the instrument to ensure that the data has meaning in the way it is planned to be used.

Characteristics	Status Quo	BPScheme 1	BPScheme 2
Year scheme will be introduced	Implementation of the scheme	2015	2016
Description of the scheme	Current Experience	Carbon Based (\$/day)	Distance Based (\$/km)
Weekly fuel charges	Predicted impact on your monthly	\$ 2.40	\$ 0.00
Annual vehicle registration fee (per annum)		\$ 40.00	\$ 24.00
Annual vehicle registration fee (per annum)		\$ 320.00	\$ 240.00
Driver licence fee (per annum)		\$ 11.00	\$ 6.17 (km)
Off-peak period congestion charge (based on travel by car-act week)		—	\$ 14.40 for 120 km
Off-peak period congestion charge (based on travel by car-act week)		—	\$ 3.00 (\$ 1.50 for 30 km)
Revenue raised will be allocated as:			
improving public transport	30%	60%	0%
improving existing and construct new roads	—	0%	0%
reducing personal income tax	—	0%	80%
general government revenue	65%	20%	0%
general government revenue	15%	0%	20%

Attribute	Car 1a	Car 1b	Car 2a	Car 2b	Attribute	Bus 1a	Bus 1b	Bus 2a	Bus 2b
Time trip starts	8:00 AM	9:00 AM	10:00 AM	8:30 AM	Setting trip start means of transport	10:25 AM	9:05 AM	9:05 AM	8:00 AM
Time you arrive at where car to be parked	9:01 AM	9:01 AM	10:01 AM	8:31 AM	Setting trip start means of transport	9:40 AM	9:00 AM	10:10 AM	8:55 AM
Percentage of seats occupied at time of boarding	25%	60%	50%	80%	Time you board the bus	9:45 AM	9:05 AM	10:15 AM	8:10 AM
Number of people standing at time of boarding	0	0	0	0	Time message to get a seat where you get off	10:00 AM	9:22 AM	10:26 AM	8:27 AM
Time message to get a seat where you get off	\$0.00	\$0.00	\$0.00	\$0.00	Bus fare	\$2.00	\$2.40	\$2.40	\$2.20
Time bus arrives at stop where you get off	\$0.12	\$0.21	\$0.24	\$0.24	Frequency of bus service, every...	10 mins	15 mins	5 mins	15 mins
Frequency of bus service, every...	\$4.00	\$0.00	\$2.00	\$2.00	% Time bus in a bus lane	0%	0%	0%	0%
% Time bus in a bus lane	90%	40%	80%	40%	Setting from main means of transport	10:54 AM	9:25 AM	10:26 AM	8:27 AM
Setting from main means of transport	9:13 AM	9:10 AM	10:10 AM	8:30 AM	Time you arrive at final destination by walking	10:54 AM	9:25 AM	10:26 AM	8:27 AM
Time you arrive at final destination by walking	90%	40%	80%	40%	This arrival time is assumed	75%	30%	70%	30%
This arrival time is assumed	Yes	No	Yes	No	Rank each option from 1 (most preferred) to 8 (least preferred)	Rank	Rank	Rank	Rank
Rank each option from 1 (most preferred) to 8 (least preferred)	Rank	Rank	Rank	Rank	Would this time make you late or early or on time?	Early	On time	Late	On time
Would this time make you late or early or on time?	Early	On time	Late	On time					

Figure 3 Examples of choice scenarios – complex or relevant?

Relevancy does not suggest that all attributes as offered are considered in the revelation of preferences and choices. What is at stake here, however, is the risk of limiting the number of attributes to a common set which results in maintaining some attributes that are not relevant to a sub sample, while excluding some attributes that are relevant to another sub sample. To accommodate this concern, the overlay of attribute processing in the presence of an extended set of attributes provides one way to minimise the possibility that relevant attributes are excluded and hence are not able to be attended to. An example of attribute processing is to allow an attribute associated with an alternative to be greyed out prior to making a choice. It would be ideal if this could be undertaken as part of a larger pilot study, and then the findings used as a basis of establishing the candidate set of attributes that apply to the majority of the sample, allowing removal of any attributes or levels that are likely to add very little

to the overall preference modelling exercise. Importantly, this method not only provides insight in respect of attributes but also in establishing meaningful levels for attributes.

More complex designs, in terms of the number of attributes, also tend to minimise (if not eliminate) the presence of dominance, which is typically the results of a few attributes in a design. This is linked to the debate on the presence of non-trading, which dissipates when one adds attributes. These aspects of the design of choice experiments led Collins *et al.* (2104) to discuss how choice experiments can incorporate behavioural constraints which may in part compromise statistical efficiency, albeit for good reason. One such constraint involves the elimination of choice tasks in which one alternative dominates the others, which can occur in choice experiments and is likely to be more evident in relatively simply designs in respect of only a few attributes.

Challenging attributes that matter - some appealing enhancements to data collection

Acceptability of alternatives

In designing choice experiments, it is common to present a fixed number of alternatives to a respondent and have them rank these alternatives or choose the most preferred alternative. However, the offered alternatives, including the one that is ranked as most preferred, may not always be acceptable (Rose *et al.* 2015, Beck *et al.* 2013); it may simply be the best of a poor set on offer. Although the acceptability of an alternative may influence the processing strategies used by the respondents in revealing their preferences, there has been a limited amount of inquiry into the overall relevance of imposed alternatives in stated choice studies in contrast to the literature on choice set formation, especially in revealed preference studies (Hensher and Ho 2015).

An acceptability of an alternative response is similar to the notion of consideration sets. The inclusion of the acceptability of an alternative (however defined) is effectively an additional endogenous choice response as suggested in recent papers by Hess *et al.* (in progress) and Rose *et al.* (2015). This literature posits that when making decisions, people first identify an acceptable set of alternatives (alternative acceptability), known as a consideration set in the broader literature (especially in marketing research), and it is from this reduced set that the final choice is typically made. This is in line with the literature on choice set formation set out mainly in the context of revealed preference data (see Manski 1977 and Swait and Ben Akiva 1987). Rose *et al.* (2015) show that joint estimation allows the modeller to overcome potential endogeneity bias that may exist between these responses. Their findings suggest a large number of differences between parameters associated with the alternatives deemed to be acceptable and those associated with alternatives reported as being unacceptable to the respondent. The authors also conclude that what might be thought of as preference heterogeneity may be linked to the overall acceptability of an alternative.

Hensher and Ho (2015) investigate the relationship between the attribute levels associated with an alternative offered in a choice experiment and the construction of a respondent's choice set based on the alternatives considered through the acceptability response dummy variable. They find that the attribute dimensionality across the alternatives (i.e., the context-dependent effects) plays a major role in sanitising the full choice set offered, and as a form of preference heterogeneity they suggest that this should improve the predictive performance of the model applications, in contrast to assuming all alternatives offered in a stated choice experiment are always considered by all sampled respondents. This, however, comes with an assumption that factors influencing the consideration set are reasonably stable over time. They conclude that the extent to which the identification of a choice set actually processed by each respondent increases model performance and prediction constitutes a fruitful area for ongoing research.

Herding behaviour

Individuals are often described as ‘creatures of habit’ with a tendency to follow rather than lead. The growing interest in this view, in the finance literature in particular, highlights the strength of following through on the notion of herding behaviour. Essentially, herding recognises that each decision maker looks at the decisions made by previous decision makers in taking their own decision (and can include hypothetical testing). People will be doing what others are doing (or saying they do or plan to do) rather than using their information. For example, academics choose to research on topics that are currently ‘hot’ or ‘very hot’. This phenomenon is also referred to as information cascading. For example, “If they like it then maybe I will like it” and “Getting carried away with the crowd”.

Models of group polarisation (including household and peer influences) should recognise herding effects or information cascades generated by observing others’ choices, as this information may alter the assessed probabilities and consequently affect decisions in the group environment. Even when people have full, accurate, knowledge of the probabilities, observing others’ choices may however create a risky shift which should be captured in choice studies.

Including an attribute in choice experiments that describes the percent take up (like information acceleration) of an alternative (relevant for labelled alternatives) is one possible way of gaining an understanding of the follower mentality aligned with herding behaviour.

Behavioural insights and nudging

Nudge theory (or Nudging) argues that positive reinforcement and indirect suggestions to try to achieve *non-forced* compliance can influence the motives, incentives and decision making of groups and individuals alike, at least as effectively, if not more effectively, than direct instruction, legislation, or enforcement. A nudge, is any aspect of the choice architecture that alters people’s behaviour in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid. Nudges are not mandates. Putting fruit at eye level counts as a nudge. Banning junk food does not. It is closely linked to herd behaviour; for example, “Did you know that Fred [your best mate] tried the bus last week and it was much quicker than the car.”

Nudging as a centrepiece of what is referred to as the literature on ‘behavioural insights’ can provide guidance on how to influence travel behaviour. It does this by taking an evidence-based approach. For example, using behavioural insights can help to maximise the behavioural response to a communications campaign; increase the effectiveness of personalised travel planning or other behaviour change programmes; increase the rate of adoption of a new service; and improve our ability to forecast the impact of measures designed to influence behaviour.

Nudging also relates to the nature of wording in survey instruments, with specific wording designed to influence travel behaviour in a way that some might describe as coercive and targeted. As an example, based on Alverini (2009), we can present three ways to ask a modal choice question (known as framing of choice outcomes):

- A. Commuting by car will take 20 minutes; Cycle-commuting will take 15 minutes,
- B. Commuting by car will take 20 minutes; Choosing to commute by bike, your journey will be 5 minutes shorter, and
- C. Cycle-commuting will take 15 minutes; Choosing to commute by car, your journey will be 5 minutes longer

The so-called rational choice model will view all wording as the same (i.e., classical economics cannot predict differences). It is hence difficult to predict how ‘unframed’ information on the options

(alternative A) will be interpreted and used by the traveller. Framing cycling as a choice that carries possible gain (as illustrated in alternative B), or the even stronger nudge (alternative C) where the choice of commuting by car is framed as a loss, are ways to make cycling appear more attractive than the alternative. None of the information formats impose a restriction of the travel options for the traveller. However, they are encouraged to choose the option which is considered to be preferable. In summary, nudges can help overcome cognitive bias, highlight better choices and increase the effect of behavioural change without restricting choices.

Familiarity and awareness

When the analyst assumes that all attributes offered in a choice experiment are relevant, there is an implicit sense that the respondent has complete familiarity or awareness of both the alternatives on offer and the context within which a choice is being made. A classic example where this fails is the debate on road pricing reform, which is substantively not understood by the majority of respondents, certainly in Australia (Hensher *et al.* 2013). The value of identifying respondent awareness and/or familiarity seems appealing to behavioural study as a way of establishing the extent to which better information will improve awareness and familiarity in a way that might engender greater support for a reform package. This is a sensible position for studies interested in stakeholder buy in.

Survey methodologists should consider this matter and identify the appropriate ways to define awareness and familiarity. In a recent study on road pricing reform, for example, Hensher *et al.* (2013) defined awareness through the question “to what extent are you aware of what road pricing means?”, and familiarity through the question “how familiar are you with the debate on road pricing?”. The response scale of these questions was a score between 0 (totally unaware or unfamiliar respectively) and 100 (totally aware or familiar respectively). Balbontin *et al.* (2015) used this evidence to reconstruct a choice set of alternatives using a number of tested cut-offs for awareness and familiarity as additional endogenous response variables. The acceptability of an alternative was also used to construct a final set of choice alternatives, all of which were subject to a modelling framework that incorporated risk and uncertainty as set out earlier in this paper. The final model focussed only on awareness and not familiarity.

The results, detailed in Balbontin *et al.* (2015) suggest that treating awareness and acceptability as endogenous variables is an appealing approach to analyse the alternative road pricing schemes. They also showed that when people are more aware of what road pricing is, they are more willing to support the schemes. Source preference was considered as a function of the level of familiarity with the debate on road pricing and the number of weekly trips into the central city. When either of these increased, individuals’ had a tendency to underestimate $w(p_i)$ for a smaller range of p_i .

Real time information (acceleration)

This phenomenon is linked to herding in that it reflects the commitment in the future by other people to a particular alternative that is not well known today. This can be considered in travel surveys through an attribute of value in projecting take up in real markets (switching behaviour). Participants can be given information say on take up in 5, 10, 15 yrs of electric vehicles that enables them to observe the desired choice outcomes of others, and they can revise their choices based on these observations.

Conclusions

This paper was prepared as a plenary address designed to highlight some real behavioural opportunities in the study of travel behaviour that can be better informed by specific survey data items that are commonly not included in travel surveys.

Whilst one can always source at least one survey that has considered one or more of the themes addressed in this think piece, it is unlikely that we can witness a widespread uptake on such interesting and potentially important features of the ongoing search for a better understanding of choices made by individuals, households, and organisations more generally. The ongoing agenda should emphasise the reproducibility of empirical evidence to support specific research paths, a cornerstone of good science.

In converting a plenary address to a formal paper there is always the risk that what came across as a strong point in the presentation may end up being somewhat diluted in the challenge to express a point in print. This is indeed the case, and as a result, the messages that have survived in the paper are essentially those that have passed my test of ‘relevant endurance in conversion’.

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