Economics of Transportation 4 (2015) 256–265

Contents lists available at ScienceDirect

Economics of Transportation

journal homepage: www.elsevier.com/locate/ecotra

Memory, expectation formation and scheduling choices

Paul Koster [a,b,*], Stefanie Peer [c], Thijs Dekker [d]

[a] Department of Spatial Economics, VU University Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands
[b] Tinbergen Institute, Gustav Mahlerplein 117, 1082 MS Amsterdam, The Netherlands
[c] Vienna University of Business and Economics, Welthandelsplatz 1, 1020 Vienna, Austria
[d] University of Leeds, Institute for Transport Studies, 36-40 University Road, Leeds LS2 9JT, UK

ARTICLE INFO

Article history:
Received 12 January 2015
Received in revised form
29 June 2015
Accepted 1 September 2015

Keywords:
Memory
Transience
Expectation formation
Retrieval accuracy
Scheduling
Value of reliability

ABSTRACT

Limited memory capacity, retrieval constraints and anchoring are central to expectation formation processes. We develop a model of adaptive expectations where individuals are able to store only a finite number of past experiences of a stochastic state variable. Retrieval of these experiences is probabilistic and subject to error. We apply the model to scheduling choices of commuters and demonstrate that memory constraints lead to sub-optimal choices. We analytically and numerically show how memory-based adaptive expectations may substantially increase commuters' willingness-to-pay for reductions in travel time variability, relative to the rational expectations outcome.

1. Introduction

Imperfect knowledge regarding the true distribution of stochastic state variables, like product quality or travel times, induces individuals to form expectations based on personal experiences and external sources of information. Memory processes are known to influence expectation formation processes (Hirshleifer and Welch, 2002; Mullainathan, 2002; Wilson, 2003; Sarafidis, 2007) and anchoring constitutes a persistent phenomenon in human behaviour (Wilson et al., 1996; Strack and Mussweiler, 1997; Furnham and Boo, 2011).[1]

This paper develops an adaptive expectations model which explicitly accounts for limited cognitive abilities of decision makers. Expectation formation in our model has the following properties. First, decision makers are assumed to have limited memory, such that only a fixed number of past experiences can be stored. Second, retrieving experiences from memory is probabilistic and decision makers experience difficulty in retrieving more distant experiences; a phenomenon often referred to as transience (Horowitz, 1984; Barucci, 1999, 2000; Schacter, 2002). Third, retrieval may be inaccurate, meaning that retrieved experiences may not correspond to the original experiences. Transience and retrieval inaccuracy are both forms of memory decay. Fourth, decision makers prime their expectations using exogenous anchors. The inclusion of past experiences, limited cognitive abilities and anchoring in the expectation formation model provides a significant deviation of the rational expectations model.

We apply the model to scheduling decisions of commuters facing stochastic daily travel times. Commuters experience dis-utility from travel time variability, as it induces them to depart and/or arrive earlier or later than preferred (Vickrey, 1969; Small, 1982, 1992; Noland and Small, 1995). The developed model provides a better understanding of empirical findings that hint at the presence of adaptive expectations and anchors in the context of travel related scheduling decisions. For example, Bogers et al. (2007) and Ben-Elia and Shiftan (2010) provide evidence that recently experienced travel times have an over-proportionally large influence on travel decisions. Peer et al. (2015) find that commuters take into account the long-run travel time average as well as day-specific traffic information in their scheduling decisions.

The value commuters attach to a marginal reduction in travel time variability is referred to as the value of (travel time) reliability and can be inferred from observed scheduling choices (Fosgerau and Karlström, 2010; Fosgerau and Engelson, 2011). Typically, the value of reliability is derived using the presumption that commuters have

* Corresponding author at: Department of Spatial Economics, VU University Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands. Tel.: +31 20 5982369.

E-mail addresses: p.r.koster@vu.nl (P. Koster), stefanie.peer@wu.ac.at (S. Peer), t.dekker@leeds.ac.uk (T. Dekker).

[1] Often anchors corresponds to the information that is obtained first, which is then used as a reference point in subsequent decisions (Tversky and Kahneman, 1974). Ariely et al. (2003), for instance, demonstrated that individuals can be primed to anchors that are as random as the last two digits of their social security number.

http://dx.doi.org/10.1016/j.ecotra.2015.09.001
2212-0122/

rational expectations and an infinite memory. We find that with adaptive travel time expectations this value of reliability is higher, because sub-optimal scheduling decisions are made. Therefore, improvements in reliability are associated with larger benefits, because they make commuters depart and arrive closer to the times they prefer and decrease the variability in departure times. Empirical revealed preference studies using reduced-form utility functions are likely to already capture these behavioural biases in the coefficient that is estimated for travel time variation. Our results are therefore mainly important for current stated preference practice that ignores the process of expectation formation: our numerical illustration shows that these values of reliability can underestimate our bounded rationality value of reliability by up to 45%, suggesting that the welfare effects of memory biases may be substantial.

Underestimation of the value of reliability may have significant implications for cost-benefit assessments of transport policies. Namely, the benefits from improvements in travel time reliability in road-related transport projects amount to ca. 25% of the benefits related to travel time gains (Peer et al., 2012). Benefits from travel time gains, in turn, are estimated to constitute on average 60% of total user benefits in transport appraisals (Hensher, 2001).

While we apply our model to scheduling choices of commuters, it may very well be relevant to other fields of economics, such as for the study of the impacts of heterogeneous expectation formation on (dis) equilibrium in dynamic economic systems (see Hommes (2013)) or for the analysis of repetitive consumer choices with uncertain product quality. Note that bounded rationality in our model is exclusively caused by limited cognitive abilities rather than judgement errors due to selective memory (Gennaioli and Shleifer, 2010) or probability weighting. Therefore this paper stands apart from works modelling bounded rationality as a result of satisficing (Simon, 1955; Caplin et al., 2011), self-deception (Bénabou and Tirole, 2002), or optimal belief formation when the decision utility is affected by anticipatory emotions (Brunnermeier and Parker, 2005; Bernheim and Thomadsen, 2005) as well as by (ex-post) disappointment (Gollier and Muermann, 2010).

The remainder of the paper is structured as follows. Section 2 describes the general setup of the model, Section 3 applies that model to the specific case of scheduling decisions. Section 4 provides numerical estimates of the biases that may result from memory limitations and anchoring. Finally, Section 5 discusses the modelling assumptions and concludes.

2. General description of the model

Consider a decision-maker who decides on x_0, where the subscript 0 indicates that the decision is made for the time period to come. Outcome utility $U(x_0, s_0)$ is assumed to be continuous and strictly concave in x_0, and depends on the stochastic state s_0. Let $f(s_0|\omega_0)$ be the probability density function of s_0, where ω_0 is a vector of parameters that characterizes $f(\cdot)$. Expected outcome utility is then defined as

$$\mathbb{E}(U(x_0, s_0)) = \int U(x_0, s_0) f(s_0|\omega_0)\, ds_0. \tag{1}$$

With rational expectations, the decision maker knows the distribution $f(s_0|\omega_0)$ and maximizes Eq. (1) to decide on x_0. In what follows, we denote ${x_0}^{re}$ as the optimal choice under rational expectations, and $\mathbb{E}(U_{re}) \equiv \mathbb{E}(U(x_0^{re}, s_0))$ as the corresponding maximal expected utility. Deviations from rational expectations are introduced by assuming that the decision maker has imperfect knowledge regarding $f(s_0|\omega_0)$. In our model, she forms adaptive expectations regarding s_0, using past experiences in combination with primed expectations. Past experiences are denoted by past stochastic realisations of s_k, which are drawn from $f(s_k|\omega_k)$. A higher value of the index k refers to a more distant experience. Primed expectations enter the model in the form of an anchor state s_A. In contrast to the states stored in the decision maker's memory and the corresponding retrievals, the anchor is assumed to be non-stochastic and is a stable element in the expectation formation process.

The decision maker is assumed to have limited cognitive abilities. First, it is assumed that she has a *limited* memory, meaning that only K past experiences $s_1 \dots s_K$ are stored in memory. Second, it is assumed that the realisation of s_k is correctly stored in memory, but a stored state can only be retrieved with a probability $\rho_k > 0$. Following Schacter (2002), this allows us to assume that more recent experiences can be retrieved more easily, i.e. $\rho_1 > \rho_2 > \dots > \rho_K$. We refer to this phenomena as *transience*. Third, retrieval of the stored states $s_1 \dots s_K$ may be *inaccurate*. Instead of $s_1 \dots s_K$, the decision maker retrieves $\bar{s}_1 \dots \bar{s}_K$ from her memory. Let $g_k(\bar{s}_k|s_k, \phi_k)$ be the retrieval density function, with ϕ_k and s_k as its characterizing parameters. Fourth, *anchoring* is present. The anchor reflects an exogenous, stable belief concerning travel time that is independent of new experiences and the current traffic situation. While we do not model the origin of the anchor explicitly in order to keep the model generic, the anchor could for example be driven by stable publicly available information.

Eq. (2) defines the expected decision utility as the weighted average of utilities across the anchor and the set of retrieved states

$$U^d = \tau U(x_0, s_A) + (1-\tau) \sum_{k=1}^{K} \rho_k U(x_0, \bar{s}_k), \tag{2}$$

where $\sum_{k=1}^{K} \rho_k = 1$. In this equation, τ is the weight assigned to the anchor. When $\tau = 0$, expectations are fully adaptive and when $\tau = 1$, the decision maker ignores her earlier experiences and expected decision utility is solely based on the anchor s_A and the choice of x_0. Eq. (2) mimics Eq. (1) when $\tau \to 0$, $\rho_k = 1/K$, $\overline{s_k} = s_k$ and $K \to \infty$. Rational expectations are therefore a special case of our model. The decision maker maximizes Eq. (2) with respect to x_0. Denote this optimal x_0 by ${x_0}^{ae}$, where the *ae* superscript refers to the fact that the decision maker uses adaptive expectations.[2] Decisions on x_0 are sub-optimal whenever $x_0^{ae} \neq x_0^{re}$. Nevertheless, the situation could arise where $x_0^{ae} = x_0^{re}$, i.e. the decision maker 'coincidentally' makes the optimal choice.

Suppose that we need to make a prediction of the expected outcome utility of the decision maker. This prediction has to account for the fact that the state in time period 0, the states in memory and the corresponding retrievals of these states are stochastic. To obtain the predicted expected outcome utility, we take the expected value over all possible combinations of experienced and retrieved states. Mathematically this is tedious, since it involves a $2K+1$ dimensional integral over all possible values of the $K+1$ realised states $s_0 \dots s_K$, and the K possible values of retrieved states $\bar{s}_1 \dots \bar{s}_K$

$$\mathbb{E}(U_{ae}) \equiv \mathbb{E}\left(U(x_0^{ae}, s_0)\right) = \int \dots \int \left(\int \dots \int U(x_0^{ae}, s_0) \prod_{k=1}^{K} g_k(\bar{s}_k|s_k, \phi_k) d\bar{s}_1 \dots \bar{s}_K \right) \prod_{k=0}^{K} f(s_k, \omega_k) ds_0 \dots ds_K. \tag{3}$$

This equation obviously has the disadvantage that it is less parsimonious than its rational expectations counterpart, i.e. Eq. (1) with ${x_0}^{re}$. Nevertheless, its generic set-up helps to structure our thoughts about how earlier experiences and retrieval inaccuracy affect predictions of the expected outcome utility. The next section makes analytical progress by imposing more structure on the utility function $U(\cdot)$ and derives an analytical representation of the

[2] A unique solution for ${x_0}^{ae}$ exists since Eq. (2) is a weighted average of strictly concave functions.