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## Dynamic Process Model of Mass Effects on Travel Demand

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### Abstract

Whereas transportation planners commonly predict the negative impacts of mass transportation, there is increasing empirical evidence of the existence of *positive* mass effects, whereby increased use of a mode by the 'mass' will generally increase its attractiveness for future travellers. In this paper we consider the dynamic impact of such an effect on the problem of travel demand forecasting, with particular regards to social network effects. Our proposed modelling approach is inspired by literature from social physics, evolutionary game theory and marketing. For simplicity of exposition, our model is specified for a scenario in which (a) there is a binary choice between two mobility lifestyles, referred to as car-oriented and transit-oriented, and (b) there are two population groups, where one is the "leading" or "innovative" population group and the other the "following" or "imitating" population group. This latter distinction follows the rather well-known Bass model from the marketing literature (1969). We develop the transition probabilities and transition dynamics. We illustrate with a numerical case study that despite lower intrinsic utility for the transit lifestyle, significant changes towards this lifestyle can be achieved by considering congestion, service improvements and mass effects. We further illustrate that mass effects can be positive or negative. In all cases we explore the sensitivity of our conclusions to the assumed parameter values.

Key words: Mass effects, travel demand, long range forecasting, Bass model, social networks, stochastic process model

## 1. Introduction

Over the past decades, town and transportation planners have utilised a large range of policy measures in order to influence the travel decisions of individuals towards more sustainable modes. Foremost among these have been the so-called “hard” measures, such as pricing of the less sustainable modes as well as investments in the infrastructure of the more sustainable modes (e.g. Stopher, 1994; Hensher and Chung, 2011). In order to justify and appropriately target such policies in advance, a range of sophisticated, price-sensitive travel demand models have been developed in order to forecast the likely economic and societal benefits. However, there has been a growing awareness among policy-makers that hard measures are not on their own sufficient; for example, the pricing measures may be politically sensitive, and (especially in periods of economic austerity) the scope of the infrastructure investments may be too limited given the scarce availability of funding.

Such considerations have led to the increasing importance of so-called “soft” measures: communicative, persuasive measures to convince individuals or groups about the need for the modal shift (e.g. Bamberg et al, 2011; Richter et al, 2011; Thørgersen, 2007). Evidence for the increasing policy importance of such soft measures can be seen in the growing interest in “Travel Feedback Programmes” or more generally “Mobility Management” such as TravelSmart in Australia (Zhang et al, 2012) or SmarterChoices in the U.K. (Cairns et al, 2008). Again, travel demand forecasting has a key role, for example in deciding how to target the measures to achieve the desired policy consequences, or how to optimally design and time any complementary hard measures in an integrated package. However, while the modelling of hard measures is now a relatively mature and well-understood subject (Boyce and Williams, 2003), the tools for modelling soft measures are much less advanced, given the much shorter time that they have featured on the policy agenda and given the problem in capturing difficult-to-quantify effects. A particular challenge for modelling the impact of soft measures is that their effectiveness depends on changing travellers’ attitudes. Soft measures may be seen as having their origin in environmental psychology, and as such they do not appeal directly to the existence of a “perceived (and easy to model) utility function”, but to changes in various psychological determinants that form behavioural intention. Following such a line of reasoning, Anable et al (2012), for example, predict

future energy and mobility scenarios based on changes in attitudes, avoiding the need to translate attitudes into “static utilities” (that determine decisions) by developing a reasonable "storyline".

The present paper will seek to explore a feature that we consider to be common to many such soft measures, namely that they implicitly aim for some kind of positive, social *mass effect*, reflecting the emerging role of social networks as a stimulus for travel behaviour decisions (Axhausen, 2008; Carrasco et al, 2008). That is, from the policy-maker’s perspective, one persuades a few to change their behaviour initially in order to encourage a larger number of people to follow later. This has two clear implications: (a) the problem we consider is inherently dynamic, the relevant forecasting question is: ‘how does demand change with time?’, not ‘what is the demand?’ and (b) the decision of an individual at any point in time is dependent on the prior decisions of other individuals. This is not to suggest that travel demand forecasting has never considered dynamic problems. Indeed some thirty years ago, anticipating well the future growth in research interest in dynamic demand forecasting, Clarke et al (1982) suggested a three-way classification of micro-dynamics (detailed scheduling within the day), macro-dynamic modifiers (incorporating habit and lags) and macro-dynamic processes (life processes, from birth to death). This classification reflects the general focus of subsequent travel demand modelling developments, whereby demand is seen essentially as the sum of individualistic processes (aside from perhaps at the household level). The problem of forecasting demand dynamics under social mass effects, however, does not fit into such a classification, as it does not decompose into individualistic dynamic processes.

The main aims of the present paper are, firstly, to propose a potential approach for representing such mass effects among travellers through an extension of existing travel demand forecasting methods. Our second objective is then to use this mathematical description to explore the dynamics of such mass effects in some hypothetical scenarios. While we believe that considering social mass effects is particularly important to encourage sustainable transport developments, we recognise at the same time that they have the potential to lead to unsustainable feedbacks, and the study of this issue forms part of our second objective.

Although the case study explored in this paper is based on some hypothetical scenarios, we believe it provides insights into policy issues for encouraging the shift toward sustainable travel modes. We believe our proposed approach is useful to analyse externalities between policy

measures, i.e., *political externalities*, in which one policy measure has positive or negative impacts on the effects of other measures. As will be shown in this paper, an introduction of a communicative measure might have the potential to subvert the effects of other measures, such as road pricing or service improvements, by strengthening conformity effects excessively. In addition, it is shown that a policy measure targeting one group might have “spill-over” effects on the other group.

The structure of the paper is as follows. The review of Section 2 has two elements: firstly, we review evidence for the existence of positive mass effects, and as a result of this discussion seek to pinpoint the particular phenomena that we aim to capture in the present paper. Secondly, we analyse previous modelling approaches for similar phenomena, both in the transportation literature and elsewhere. This review is used to inform our model formulation in Section 3, where we specify a dynamic forecasting model for users choosing between two ‘mobility lifestyles’. Section 4 analyses the proposed approach in more detail, through numerical examples and by establishing limiting cases, which provide a ‘positioning’ of the work relative to the seminal work of Bass from the marketing literature. We further explore, through a fairly extensive case study, the sensitivity of the dynamic effects of the model to assumed values of the input parameters. In the absence of data to calibrate our model, our objective is to illustrate the potential importance of considering trend effects for transport policy, and so our focus is on exploring qualitative features of the model. In Section 5, we discuss the potential policy impacts and issues for calibration that arise from adopting such a modelling approach. Finally, Section 6 concludes the paper by discussing its contribution as well as shortcomings, and identifies paths for further research.

## **2. Mass effects: Evidence and Potential Modelling Approaches**

### **2.1. The evidence for positive mass effects within real-life transportation systems**

Although the present paper is concerned with modelling approaches, we begin our review not with models but with real-life transportation systems, and ask the questions: do mass effects really exist, and if so what kinds of mass effect are there?

Certainly transportation planners are familiar with the *negative* effects of mass transportation, and these are routinely evaluated. That is to say, the well-understood, aggregate effects of individual mode, departure time and route decisions are routinely modelled through impact models to represent on-street congestion, public transport crowding, pollution, etc. These effects are negative in the sense that increased use of a mode by the 'mass' will tend to decrease its attractiveness. Our interest, on the other hand, is for the potential for significant *positive* mass effects to exist, whereby increased use of a mode by the 'mass' will generally increase its attractiveness for future travellers.

We imagine a situation such as the following: A transport planner might set up a scheme, such as car-sharing, and encourage its usage through communicative measures. This might then persuade some to initially join. Through the experience of these few, others might be persuaded to join. For minor services, such as car-sharing, this might then allow the service to be improved by, for example, providing further vehicles at additional locations. The service might hence become more attractive to additional users, eventually creating a positive cyclic effect. In summary, initial investments and possibly communicative measures to a selected group will be the trigger for a desirable trend effect as envisaged by mobility management.

This small example is in line with the main argument of a simulation study by Sunitiyoso et al (2011a), who also argue that a minority can significantly influence a majority to change their behaviour. It shows that there are several kinds of positive mass effect that may exist, and here we shall identify these different types in order to 'position' the present paper in the existing literature and to clearly distinguish which kinds of mass effect are the particular focus of this contribution. Broadly, a classification of positive mass effects may be made as follows:

*Real mass effects:* Evidence for such effects exists across a variety of modes. An increase in car use may increase congestion and thereby reduce speeds, thereby leading to negative travel time impacts but positive safety impacts for the car-mode, since lower speeds are associated with lower accident frequency and severity (McCarthy, 2001). In cities where bicycles are little-used the vehicular traffic dominates, but as cycling use increases so there may be a real effect of 'safety in numbers', in terms of a reduced accident risk per cyclist (Jacobsen, 2003). This effect has been

seen to extend to pedestrians (Leden, 2002), implying that there is also a real positive effect of increased use of modes involving a walk stage.

*Perceived mass effects:* Walking in a relatively empty or low density part of a city can give a feeling of insecurity beyond the actual safety risks (Cho et al, 2009). Increasing use of walk-related modes can therefore have a significant positive effect on perceptions of safety. This ‘perceptual’ effect is potentially in addition to any real mass effects; it may be highlighted by linking it to improvements in the aesthetic environment (a kind of link to the ‘consequential’ effects mentioned below).

*Consequential mass effects:* Travellers are not the only actors making decisions in a transportation system, though often models and modellers assume this to be the case. If the decisions of other actors are included, then a variety of positive mass effects may exist as a consequence of the decisions of other actors. Increased use of public transport may lead to economies of scale that may be passed on to travellers by public transport operators in terms of reduced bus fares or increased frequencies (Mohring, 1972). In planning a staged implementation of a mode-specific scheme over time, the actual implementation of future stages may be contingent on the public support gained from the success of earlier stages in encouraging increased use of that mode (Ngoduy et al, 2013), thus giving rise to what is in effect another form of positive mass effect.

*Information mass effects:* Conventional demand modelling assumes that individuals have both perfect and complete knowledge of the options available. While random disturbance terms are often used to capture traveller heterogeneity and/or the inability of the modeller to observe all the factors that motivate traveller decisions, a quite different dimension is the level of incompleteness and misinformation that travellers may possess. This is particularly the case for alternatives that have been never or rarely used by some individuals, i.e. previously non-chosen modes. The greater use of a mode will in turn mean a greater penetration in the travelling population of those with experience in using a mode, and thereby a great chance of a non-user to have a social connection with a user of that mode (Blickstein & Hanson, 2001; Páez & Scott, 2007; Arentze & Timmermans, 2008). In automated information gathering (e.g. intelligent transport systems), then vehicles may be used as probes, and a greater use of the mode gives potential for a greater sample rate, wider coverage and therefore improved information (Shladover et al, 2007; Herrera et al, 2010).

The above grouping might be said to classify mass effects according to their “mode of action”. Through this proposed classification of mass effects, we wish to emphasise that mass effects are possibly significant in transport or mobility decisions of individuals not just through social interaction. However, this latter kind of mass effect, which in the above classification is an example of an *information mass effect*, has possibly received most attention in recent literature and is reviewed in more detail in the following section. Sunitiyoso et al (2011a) summarise some of the empirical findings and classify types of social interactions into further subcategories based on their directness of interaction (interdependent situation, observation and communication.)

It seems likely that much of the information travellers derive about their transport options, especially for non-chosen modes, will be from word-of-mouth, and may follow (and reinforce) the general negative or positive perceptions of a mode within an individual’s social group (Bartle, 2011; Sutinyoso et al, 2011b). While interactions between household members are considered in activity-based approaches, we are in this paper more interested in the wider influences across social groups and households which we believe are not yet well represented in existing modelling approaches, despite various studies confirming their importance for travel decisions. For example the U.K.’s Department for Transport recently published their “behavioural insights toolkit” in which they also stress that transport choices by individuals are influenced directly by various norms, which, in our categorisation, might be seen as one important aspect of the “information mass effect” (Department for Transport, 2011). The report further provides a summary of the main underlying theories that can explain how behaviour is influenced by norms. One important social psychological model with several transport applications is the Theory of Planned Behaviour (Ajzen, 1991), which proposes that subjective norms are an important determinant of behavioural intentions. As well as describing theories of behavioural changes, this has also inspired the above-mentioned travel feedback programmes. This report, as well as that of Abou-Zeid et al (in press), describes the role of norms on mobility decisions in more detail.

There are furthermore a number of recent examples with real data that appear noteworthy: Goetzke and Rave (2011) explain differences in bicycle usage in German cities with social network effects that could be due to any of the above modes of action. They use the aggregate bicycle modal split as an instrumental variable to estimate an individual’s probability of choosing to use



the bicycle mode. Taking aggregate bicycle modal split as a proxy for the social network effect, they find that this is indeed a significant factor for mode choice for shopping and recreational trips. Walker et al (2011) discuss the problem of endogeneity in the estimation of social network effects (or field effects) in more detail, and suggest a different correction method. With mode choice data from the Netherlands they also find significant field effects for the mode choice for work trips. Weinberger and Goetzke (2011) aim to control for the above mentioned endogeneity by accounting for average behaviour in peer groups. They then show that the percentage of households without cars in a neighbourhood can explain ownership decisions. Their results suggest that social network effects or “peer pressure” reduce the effect of income, education and household size. In fact, they find a negative sign for income when taking into account peer pressure, and suggest that a likely explanation is that cars play a more significant role as a status symbol in poorer families.

These examples illustrate the importance of positive mass effects. As argued by the authors they suggest these are based on social networks, i.e. information mass effects. However, as the discussion on endogeneity effects shows, such effects are difficult to distinguish from other mass effects that are also possibly at work at the same time, in particular consequential mass effects. Furthermore, the approaches in the above study are used to explain and quantify the importance of mass effects, but do not treat the dynamic process explicitly and are therefore probably less suitable as a basis to forecast the development of future demand.

## **2.2. Modelling mass effects**

In some fields of transportation, there is already a growing body of work on modelling the dynamics of mass transportation. One such field is dynamic traffic network modelling, which focuses on day-to-day dynamic models to represent the effects of congestion and user learning of the choice attributes (Cascetta and Cantarella, 1995). Although the focus of such approaches has been exclusively on negative mass effects, it is not inconceivable that such approaches might be adapted to represent positive mass effects in the future, perhaps building on some of the ideas we discuss later (Section 5). The key question we must answer, though, is: how might we represent positive mass effects in a model?

If we turn attention to the marketing literature, then we see that (in contrast) trend and word-of-mouth effects are well-known. In a rather widely-known paper from this field, Bass (1969) observed that the uptake of new products such as washing machines and dish washers can be explained through a model with two population groups, referred to as “innovators” and “imitators”. The innovators are typically imagined to be a small population group who are willing to invest in the new product. After time, “imitators” follow by also purchasing these products, creating significant sales until market satisfaction is reached. Bass’s model suggests that the number of persons owning a product at any one time is a significant factor in the decision of imitators to purchase the product at that time.

The model has been highly influential in the field of modelling sales trends and has been widely used in practice. Bass states that first-time product sales follow an S-shaped curve described by the following relationship:

$$f(\tau) / (1-F(\tau)) = p + qF(\tau) \tag{1}$$

where  $f(\tau)$  is the likelihood for any randomly selected individual to purchase at time  $\tau$ , and  $F(\tau)$  is the market saturation at time  $\tau$ .  $p$  is the “innovation coefficient” and  $q$  is the “imitation coefficient”. The latter two parameters are, in later literature, also referred to as the coefficients of external and internal influence (Mahajan et al, 1990). A large  $p$  reflects a market with a large number of “innovators” who are not influenced by others, whereas “imitators” buy the product partly because of the social pressure to adapt. Analysing (1), it can be found that the introduction of imitators creates a characteristic curve with a slow start of sales, followed by a rapid increase in sales leading to a peak, before sales drop due to market penetration. The pressure on imitators to buy at any time  $\tau$  increases with  $F(\tau)$ , the proportion of the population already owning the new product at time  $\tau$ .

Though Bass does not discuss in detail the mechanism of *how* imitators will be attracted, his model implicitly suggests that communication in social networks plays an important role. Such communication might promote the usefulness or “utility” of products, as well as trigger the perception that new or expensive products are seen as “positional goods” (Frank, 2005).

These communication effects within social networks might at first seem to be uncontrollable, but they are formally exploited by marketing through various forms, in particular the internet. For example, Sparks and Browning (2011) discuss the importance of online reviews for hotel bookings, while Jalilvand et al (2011) discuss the extent to which electronic communication has overcome some limitations of conventional word-of-mouth effects, the latter being constrained to occur typically between persons who know each other.

From this literature, we can conclude that there is agreement that social network or trend effects are important to be considered for decision-making in general, and for consumer purchases in particular. A great deal of work in economics and evolutionary game theory has hence studied various sorts of dynamic models incorporating network effects. The dynamic models describe the long-run process of social interactions through which agents revise their behaviour over time. They can be distinguished depending on the specifications of agents' revision procedures, termed their *revision protocol* by Sandholm (2011). Some of the most commonly-studied dynamics are replicator, (perturbed) best response, Brown - von Neumann - Nash imitation and mutator dynamics, which correspond to different behavioural assumptions about agents' decision procedures (see Hofbauer and Sigmund, 2003; Sandholm, 2011). Although the main focus of the literature seems to be on an evolutionary justification of equilibria in games, such as Nash equilibrium, the modelling approaches have been applied to the study of social network effects in various fields, so as to capture diffusion processes of certain types of behaviours or technologies in population. This has included applications to considerate smoking behaviour (Nyborg and Rege, 2003), common-pool resource uses (Sethi and Somanathan, 1996), market share of products (Cantner et al, 2010), and innovation and technological change (Safarzynska, van den Bergh, 2011). However, there are few applications within the transportation research field, Yang and Zhang (2009) being one of the exceptions in introducing evolutionary dynamic games to the modelling of traffic flow patterns.

The dynamics to be studied later in the present paper correspond to a version of *logit dynamics* in the evolutionary game theory literature. The logit dynamics approach, which was introduced by Fudenberg and Levine (1998) and Hofbauer and Sandholm (2002; 2007), is formulated by assuming the logit model as each individual's behavioural principal. Although the logit model has

been theoretically justified and also extensively used in empirical work, this form of dynamics has been rarely applied to model diffusion of behaviour, and not (to our knowledge) travel behaviour.

Although our approach therefore has links to evolutionary game theory, we shall focus more on its emergence from a body of literature related to system analysis in physics. Here, we see an overlap between the above, evolutionary game literature, and the physics literature utilising the so-called quasi-mean value equations of the *master equation approach*. Nakayama and Nakayama (2004) note that 'statistical physics can provide powerful methods for studying social phenomena with interaction'. Similar to the work we shall present, Nakayama and Nakayama utilise the logit model for describing transition probabilities based on perceived utilities of choice, with these utilities including both attraction and repulsion elements towards a choice, depending on how many people have already adopted this option. They investigate time evolution as well as system bifurcation points for different parameter settings. In contrast to the work we shall present, they do not distinguish different population groups nor do they distinguish congestion and mass effects.

Our model development is in parts influenced by ideas described in the book "Sociodynamics" by Weidlich (2000). In his book he describes approaches for quantitative analysis of stochastic phenomena originally developed to describe natural phenomena. In particular, our analysis is inspired by the migration problem described in Chapter 4.3 of Weidlich (2000), but with some important differences in the model specification, as we shall describe in the following section.

### **3. Problem description**

#### **3.1. General notation**

It is first useful to clarify the kind of transportation situation we are envisaging with our model. Specifically we are considering a long term decision such as, for example, whether to join a car sharing scheme, whether to buy an eco-friendly car, or whether to start using a bicycle. This may be distinguished from the emphasis of mode choice models, for example, where the question is whether individuals in a specific transport situation will choose a particular mode for that situation.

Rather than mode *choice*, then, our focus will be on mode *uptake* (as in Watling, 2010), or in even more general terms the choice of *mobility lifestyle*.

Although we believe our approach can be readily applied to the choice between any number of mobility lifestyles, for any number of ‘population groups’ (as defined below), in order to communicate the key ideas we shall in this paper restrict attention to the simplest case, of the choice between two mobility lifestyles, for two population groups. We shall denote the two mobility lifestyles by  $c$  and  $t$  and the two population groups by  $\lambda$  and  $\varphi$ . Broadly, since we are in fact imagining a policy situation in which the objective is to promote more sustainable transport modes, then we may think that  $c$  stands for car and  $t$  for transit, but one might more generally consider  $c$  as the prevailing unsustainable mode and  $t$  as the new sustainable mode. Similarly,  $\lambda$  stands for the “leading” population group and  $\varphi$  for the “following”, but one might more generally interpret  $\lambda$  as innovators as in the Bass model; that is to say, those who are more willing or find it easier to experiment with new forms of mobility, and are possibly convinced by persuasive policy measures. Followers are more likely to be influenced by the decisions of others and often make up the mass of the population. Alternatively, one might interpret  $\lambda$  and  $\varphi$  simply as two different population groups with different utility functions, with the members within the two groups influenced to different degrees by persons from their own group and the other group. Our question will be primarily to understand at what stage a large amount of the population will be likely to consider switching to the mode promoted by the policy-makers, i.e. mode  $t$ .

Though we discuss the meaning of further variables throughout our paper, we provide the reader here with an overview of all the notation used for easier reference:

$A: \{ \lambda, \varphi \}$ :	Set of population groups, $\lambda$ : leading, trendsetting group, $\varphi$ : following group
$\Lambda, \Phi$ :	Size of population groups $\lambda$ and $\varphi$ respectively
$L: \{ t, c \}$ :	Set of possible mobility lifestyles, $t$ : transit oriented, $c$ : car oriented
$n_i^\alpha(\tau)$ :	Expected number of persons in group $\alpha$ with mobility life style $i$ in time interval $\tau$
$u_i^\alpha(\tau)$	Utility of mobility lifestyle $i$ for group $\alpha$ in time interval $\tau$

$\zeta_i^\alpha$	Intrinsic utility of mobility lifestyle $i$ for subgroup $\alpha$
$\nu_{ji}^\alpha$	General possibility to move from mobility lifestyle $i$ to $j$ for population subgroup $\alpha$
$p_{ji}^\alpha(\tau)$	Proportion of population type $\alpha$ that moves from mobility lifestyle $i$ to $j$ in time interval $\tau$
$w_{ji}^\alpha(\tau)$	Expected number of people from population type $\alpha$ that move from mobility lifestyle $i$ to $j$ in time interval $\tau$

We note that  $p_{ji}^\alpha(\tau)$  and  $w_{ji}^\alpha(\tau)$  could alternatively have been defined as individual and aggregate transition *probabilities* respectively, leading to a stochastic process model formulation, in which we would model the time-evolution of the probabilistic distribution of the states in the dynamic process. In our work, however, we interpret  $p_{ji}^\alpha$  and  $w_{ji}^\alpha$  as proportions rather than probabilities, leading to a deterministic process model; effectively, it can be interpreted that we assume that the dynamics may be captured approximately by the time-evolution of the expected values, assuming a uni-modal probability distribution of the stochastic process and invoking a ‘law of large numbers’ argument. Weidlich (2000) describes this as the assumption that “taking the weighted mean over the hopping processes of a bundle of stochastic trajectories from a given point  $(n_{t_0}^\lambda, n_{t_0}^\varphi)$  ... leads to the equations for the preferential mean direction and mean velocity by which the trajectory-bundle proceeds” (p. 62).

From the notation it follows that the state of the population is described by  $\{n_t^\lambda(\tau), n_c^\lambda(\tau), n_t^\varphi(\tau), n_c^\varphi(\tau)\}$ . Since

$$n_c^\lambda(\tau) = \Lambda - n_t^\lambda(\tau) \quad (2)$$

$$n_c^\varphi(\tau) = \Phi - n_t^\varphi(\tau) \quad (3)$$

then these four state variables could in principle be fully described with only *two* unknown variables  $n_t^\lambda(\tau)$  and  $n_t^\varphi(\tau)$ ; however, we have retained reference to all four variables in our model definition below, as this seems a clearer way of explaining the model. We are interested in the evolution of these variables over time.

### 3.2. Utilities for mobility lifestyle decisions

We assume that each mobility lifestyle has its intrinsic, possibly population-specific, utility  $\zeta_i^\alpha$ . Further, in line with our motivation, we consider that the utility of a mode,  $u_i^\alpha$ , will be directly a function of  $n_i^\alpha(\tau)$ , in two particular ways. Firstly, there are congestion effects meaning that the utility of lifestyle  $i$  decreases with the total number of people adopting this lifestyle. To reflect the negative external effects of cars one might expect that the utility of lifestyle  $c$  decreases faster with more users taking up this lifestyle compared to the decrease in utility of lifestyle  $t$  when more people take it up. For lifestyle  $t$ , on the contrary, one might even consider positive long term “congestion” effects, considering that the service attractiveness of minor (uncongested) modes might increase if more users take it up due to, e.g. more demand-responsive buses or more car-sharing stations spreading throughout a city (what we termed ‘consequential mass effects’ in section 2.1). Though these congestion and service improvement effects will be similar for both population groups, we consider these as possibly group-specific to reflect a possible differing evaluation in the effects, for example group  $\lambda$  might be more sensitive to congestion effects than group  $\varphi$ .

Finally, we consider the trend or conformity effects to measure the influence an individual perceives by adapting the same mobility lifestyle as others. In general one would expect the effect to be larger if the characteristics or circumstances of the influencing person are in some way similar to the one being influenced as found in the psychological literature on provincial descriptive social norms (Goldstein et al, 2008). Further, given our definition of one group as “leading” and the other as “following”, we define the effect of group  $\lambda$  on group  $\varphi$  to be larger than vice versa.

In summary, considering all these effects leads to our general assumption on  $u_i^\alpha$  as in Eq. (4), where the specific functional forms are to be specified. We note that in Eq. (4) and in the following we omit time dependency whenever the function itself is not time dependent but only *evaluated* at a time  $\tau$ .  $g_i^\alpha$  specifies the congestion or service improvement effects due to the sum of people taking up lifestyle  $i$ . As these might be perceived differently by our two population groups, we define these two functions as  $\alpha$ -specific.  $h_\lambda^\alpha$  and  $h_\varphi^\alpha$  specify the trend effects, due to following

people in group  $\lambda$  and  $\varphi$  respectively. With this notation it follows also that  $h_\beta^\alpha$  specifies the trend effects due to following people in “my group” when  $\alpha = \beta$  and “the other group” when  $\alpha \neq \beta$  respectively. We emphasise that this trend effect is not mode-specific, it simply tends to reinforce the decision of the majority. Function  $f^\alpha$  then combines the group-specific and mode-specific effects while considering the intrinsic utility  $\zeta_i^\alpha$ . Note that the migration problem as set out in Weidlich also includes an intrinsic utility and trend effect, but does not include anything analogous to our mode-specific effect (which in his migration model would have been a location-specific effect, i.e.  $g_i^\alpha$  in our terms is omitted from Weidlich’s model). Weidlich further assumes linear-in-parameter functions for  $f^\alpha$ ,  $g_i^\alpha$ ,  $h_\alpha^\alpha$  and  $h_\beta^\alpha$ . For transport applications this linearity assumption might seldom be appropriate, as we discuss later, and so provide a more general notation which also permits non-linear forms.

$$u_i^\alpha(n_i^\lambda, n_i^\varphi) = f^\alpha\left(\zeta_i^\alpha, g_i^\alpha(n_i^\lambda + n_i^\varphi), h_\lambda^\alpha(n_i^\lambda), h_\varphi^\alpha(n_i^\varphi)\right) \quad \text{for } \alpha = \{\lambda, \varphi\}; i = \{c, t\} \quad (4)$$

### 3.3. Transitions during one time interval

To reflect the general likelihood of changing the mobility status (within a certain time period) we further introduce parameters  $v_{ji}^\alpha$ . We might expect such parameters to be, for example, dependent on income, as we might assume that a higher income will tend to allow people to more easily adopt and adapt to a different lifestyle. With these definitions, the one-step transition proportions between mobility lifestyles can be defined. Weidlich assumes an exponential form of transition proportions from  $i$  to  $j$  as

$$p_{ji}^\alpha(n_c^\lambda, n_t^\varphi, n_c^\lambda, n_t^\varphi) = v_{ji}^\alpha \exp\left(u_j^\alpha(n_j^\alpha + 1, n_j^\beta) - u_i^\alpha(n_i^\alpha, n_i^\beta)\right) \\ \text{for } \alpha, \beta = \{\lambda, \varphi\}; i, j = \{c, t\} \text{ with } i \neq j \quad (5)$$

While this form ensures positiveness of transition proportions, it does not guarantee that they are less than or equal to 1, though this can be avoided by assuming relatively small values for the parameters  $v_{ji}^\alpha$ . The form chosen by Weidlich further assumes “intelligent” individuals in that they



consider the utility of mode  $j$  *after* they have moved into this state i.e.  $u_j^\alpha(n_j^\alpha + 1, n_j^\beta)$ , but otherwise the formulation does not seem to be behaviourally justified. In the current contribution, however, we shall instead use transition proportions based on the logit model, as there is a stronger theoretical justification (see e.g. Ben-Akiva and Lerman, 1985). Furthermore, we assume that individuals only consider the *present* conditions of both lifestyles in their choice, i.e. decision makers are myopic in that they do not foresee the impact of their decision. This leads to the following functional form for our transition proportions:

$$p_{ji}^\alpha(n_c^\lambda, n_t^\varphi, n_c^\lambda, n_t^\varphi) = \frac{v_{ji}^\alpha \exp(u_j^\alpha(n_j^\lambda, n_j^\varphi))}{\exp(u_j^\alpha(n_j^\lambda, n_j^\varphi)) + \exp(u_i^\alpha(n_i^\lambda, n_i^\varphi))} = \frac{v_{ji}^\alpha}{1 + \exp(u_i^\alpha(n_i^\lambda, n_i^\varphi) - u_j^\alpha(n_j^\lambda, n_j^\varphi))}$$

for  $\alpha = \{\lambda, \varphi\}; i, j = \{c, t\}$  with  $i \neq j$  (6)

We note that (6) is a form of the dogit model. Bordley (1990) describes the dogit model as a way of modelling customer choice in which customers are to some extent loyal to the previous product they bought. For travel behavioural decisions loyalty might rather be explained with habitual behaviour and the difficulties associated with fitting changes into daily schedules with various constraints. Therefore, it is reasonable to assume that a fraction  $(1 - v_{ji}^\alpha)$  of travellers are “loyal” to their previous lifestyle, and a fraction  $v_{ji}^\alpha$  consider a change in lifestyle. That this functional form is a reasonable assumption is given some support by Whelan (2007). Whelan modelled car ownership developments in the U.K. and found that the dogit model in general provides good model fits.

We emphasise that in (6) changes from lifestyle  $c$  to  $t$  and vice versa are both possible, i.e. both  $p_{tc}^\alpha(\tau)$  and  $p_{ct}^\alpha(\tau)$  can be nonzero. In contrast to the original approach by Bass (1969), this might hence be described as “two Bass models in tandem”. Setting  $v_{tc}^\alpha$  or  $v_{ct}^\alpha$  to zero reduces our approach to one similar to the original Bass model.

The group proportions can now be used to define the aggregate transition rates or expected number of transitions within each group,  $w_{ji}^\alpha$ , by considering that there are  $n_i^\alpha(\tau)$  persons within each population group that could make a transition from  $i$  to  $j$ :

$$w_{ji}^\alpha(\tau) = n_i^\alpha(\tau) \cdot p_{ji}^\alpha \left( n_c^\lambda(\tau), n_t^\varphi(\tau), n_c^\lambda(\tau), n_t^\varphi(\tau) \right) \text{ for } \alpha = \{\lambda, \varphi\}; i, j = \{c, t\} \text{ with } i \neq j \quad (7)$$

In our case there are hence the  $|A| \cdot |L| = 4$  possible state transitions  $\{w_{tc}^\lambda(\tau), w_{ct}^\lambda(\tau), w_{tc}^\varphi(\tau), w_{ct}^\varphi(\tau)\}$ . For example a transition from an initial state  $(n_t^\lambda = \frac{\Lambda}{2}; n_t^\varphi)$  to  $(n_t^\lambda = \frac{\Lambda}{2} + 1; n_t^\varphi)$  has an aggregate transition probability of  $w_{tc}^\lambda = p_{tc}^\lambda \frac{\Lambda}{2}$  and the inverse transition back to the initial state can be executed by an additional individual so that  $w_{ct}^\lambda = p_{ct}^\lambda \left(\frac{\Lambda}{2} + 1\right)$ .

### 3.4. Transition Dynamics

Equation (8) follows from (7) and our model set up as a deterministic one. It describes the expected change in the mobility lifestyles by subtracting the aggregated outflow from each mobility lifestyle from the aggregated inflow.

$$\frac{dn_j^\alpha(\tau)}{d\tau} = w_{ji}^\alpha(\tau) - w_{ij}^\alpha(\tau) \text{ for } \alpha = \{\lambda, \varphi\}; i, j = \{c, t\} \text{ with } i \neq j \quad (8)$$

Assuming the special case of symmetric transition proportions in (6) i.e.  $v^\alpha = v_{tc}^\alpha = v_{ct}^\alpha$  the expected change in persons from population group  $\alpha$  with mobility lifestyle  $t$  can also be written as Eq. (9). This formulation is equivalent to the perturbed best response dynamics used in evolutionary game theory, and since it is derived by assuming Eq. 6 it also illustrates a connection to the logit model commonly used in transport demand modelling.

$$\begin{aligned} \frac{dn_t^\alpha(\tau)}{d\tau} = v^\lambda \left[ \frac{\Lambda}{1 + \exp(u_t^\alpha(n_c^\lambda(\tau), n_c^\varphi(\tau)) - u_t^\alpha(n_t^\lambda(\tau), n_t^\varphi(\tau)))} - n_t^\lambda(\tau) \right] = \\ v^\lambda \left[ \frac{\Lambda \exp(u_t^\alpha(n_c^\lambda(\tau), n_t^\varphi(\tau)))}{\exp(u_t^\alpha(n_t^\lambda(\tau), n_t^\varphi(\tau))) + \exp(u_t^\alpha(n_c^\lambda(\tau), n_c^\varphi(\tau)))} - n_t^\lambda(\tau) \right] \text{ for } \alpha = \{\lambda, \varphi\} \end{aligned} \quad (9)$$

If we make a discretisation in time of the above model, then, in line with (8), we obtain the following difference equation for the change in the population state over time.

$$n_j^\alpha(\tau + 1) = n_j^\alpha(\tau) + w_{ji}^\alpha(\tau) - w_{ij}^\alpha(\tau) \text{ for } \alpha = \{\lambda, \varphi\}; i, j = \{c, t\} \text{ with } i \neq j \quad (10)$$

## 4. Illustrative Example

### 4.1. Limiting cases

As shown in our literature review, dynamic evolutionary processes have been prominent in various disciplines, but especially the deterministic Bass model is a seminal work that has been applied to model user uptake of new products. To clarify the scope of our model in this section we illustrate similarities to and differences from the deterministic Bass model. We take parameter settings from those typically reported in Bass (1969) noting that these might not be realistic for travel behavioural decisions. In this section our focus is limited to a comparison of the general shape of the functional form obtained and possible interpretation of the variables.

The models cannot be mathematically derived from each other, even assuming limiting cases, which can be seen by comparing Eq. (1) with Eqs (6) and (8). Whereas the Bass model is based on a linear relationship between probability of purchase (change in mobility lifestyle) and number of previous buyers, our model is based on the assumption that each traveller changes his/her lifestyle according to a logit function based on the choice utilities.

In order to draw this comparison we translate product sales from the Bass model into transit uptake in our transportation system. To ignore the “tandem model” of returning to the previous car-dependent mobility lifestyle we set  $v_{ct}^\lambda = v_{ct}^\phi = 0$ . The Bass model further has only three variables. The first such variable is  $m$ , which relates to market size and total sales. We set  $m = \Lambda + \Phi$ . Secondly,  $p$ , the innovative factor, or probability of an initial purchase at  $\tau = 0$ . We set  $p = 0.02$  in line with common values reported in Bass (1969) reflecting the innovation potential in the population, i.e. the population who purchases new products without influence of any internal pressure. Translated into our model we set  $n_t^\lambda(0) = 2$  and  $\Lambda = 2$  meaning that all “leaders” change their lifestyle immediately. This illustrates one property of our model in that it can assume that leaders can also change their behaviour over time. The final parameter in the Bass model is the imitation factor  $q$ . In our model this factor should be reflected with the function  $g_i^\alpha(n_i^\lambda + n_i^\phi)$  not with the mass effect functions  $h_\lambda^\alpha(n_i^\lambda)$  and  $h_\phi^\alpha(n_i^\phi)$ . This is because the  $h^\alpha$  functions encourage trends towards both the car and transit similar to social norms, i.e. significant

$h^\alpha$  functions in a system with few transit- but many car-users will prevent a move towards transit. This again illustrates a difference between the two models. In our model the  $h^\alpha$  functions enforce social norms whereas in the Bass model the parameter  $q$  describes imitation (to purchase), regardless of the attraction to the current situation (of being in a state of not having the product). Following again studies reported in Bass (1969) we set  $q = 0.3$  and “equivalently” assume a linear  $g_i^\alpha$ -function as in (20) with  $\eta_t^\varphi = 0.3$  and  $\eta_c^\varphi = \eta_t^\lambda = \eta_c^\lambda = 0$ .

With  $h_\lambda^\alpha = h_\varphi^\alpha = \zeta^\alpha = 0$  for  $\alpha = \{\lambda, \varphi\}$  and  $f^\alpha(\cdot) = (\cdot)$  our utility function (4) reduces to  $u_i^\alpha(n_i^\lambda, n_i^\varphi) = g_i^\alpha$ .

$$g_t^\varphi(n_i^\lambda + n_i^\varphi) = \eta_i^\alpha(n_i^\lambda + n_i^\varphi) \text{ for } \alpha = \{\lambda, \varphi\} \quad (11)$$

Finally, we note that our dogit parameter  $v_{ji}^\alpha$  has no equivalence in the Bass model. By setting it to 0.1 we obtain the graphs below, which illustrate that there are differences in the models but that also with our models we can obtain the characteristic S-shaped curves observed by Bass for many product sales. The Bass model achieves this with far less parameters, though. While a low-parameter model would generally be favoured for prediction, the additional parameters in our model allow the potential to link to important policy factors, by describing the interaction between leaders and followers, by distinguishing imitation from normative effects, and by controlling the speed of the purchase/ mode change.

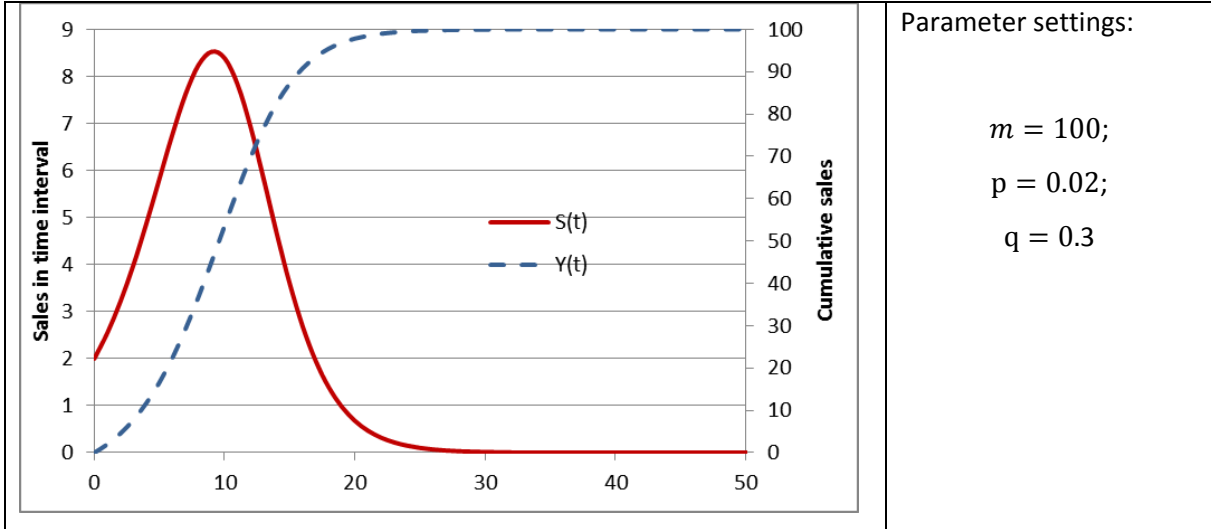


Figure 1 Illustration of deterministic Bass model

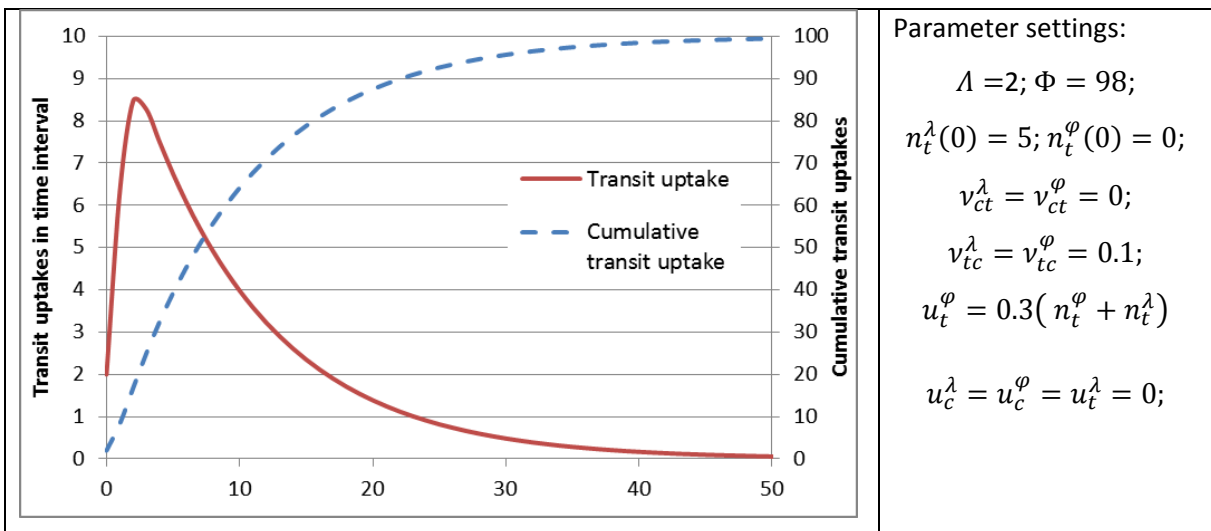


Figure 2 Application of model with parameters similar to Bass model

#### 4.2. Scenarios

While our example is artificial, we aim to create it so as to illustrate some plausible features that might be observed in reality. With this in mind, our first task is to consider the relative size of the trend-setting and following groups. In our example, we suppose that  $\Lambda < \Phi$ , which we believe to be a reasonable assumptions for our interest of promoting a new mobility lifestyle or an initially less-used mode through “a few leaders”. Leaders might, for example, denote those in the

population that are directly influenced by soft transport policy measures such as “mobility management”. We assume in the following a ratio of 4 followers per leader though it might often be larger unless mass media are utilised for the promotion of the sustainable mode. For brevity we do not report case studies with other population compositions but remark that the ratio of the two groups does have an impact on the final population state, if negative and/or positive feedback is considered.

In line with our objective to describe the potential impact of trends for long-range transport planning, let us assume a time interval duration of one year. We further assume  $v_{ji}^\alpha = 0.01$  for both population groups and transition in both directions, in other words this means, given  $u_j^\alpha = u_i^\alpha$ , we expect 0.5% of the population to change their mobility status within one time interval. Though this percentage might appear low, we would argue that a larger value is unrealistic. In a metropolitan city of a developed country where arguably the benefits of having a car for many are similar to not having a car, this would mean that 50 out of 1000 households per year change their status from having a car to having none or vice versa. Obviously a lower bound for this parameter is  $v_{ji}^\alpha = 0$ , corresponding to a fixed, unchangeable mobility status of the population.

We now consider various hypothetical scenarios in order to further illustrate our modelling approach, these scenarios successively building on one another. Let us assume a neighbourhood with 1000 peak time daily commuters to the CBD who are required to travel during the peak hour, and who if choosing the car mode would each use their own car. We assume there is one road connection available from this neighbourhood to the CBD with a bottleneck capacity  $z = 800$  veh/h. The free flow travel time by car is  $y = 30$  min, but delay due to congestion (real mass effects) might occur according to the standard BPR function, so that our car-usage related part of the utility function takes the following form:

$$g_c^\alpha(n_c^\lambda + n_c^\varphi) = -y * \left(1 + 0.15 * \frac{n_c^\lambda + n_c^\varphi}{z}\right)^4 \quad \text{for } \alpha = \{\lambda, \varphi\} \quad (12)$$

We now consider that a new mode is introduced such as a BRT service to the CBD. The BRT travel time is assumed to be identical to the uncongested car travel time, and the travel time is demand-

independent. Using BRT requires, however, some additional time  $x$  for access, boarding and egress which we set to 10min. In line with our discussion on “consequential mass effects” we assume though that the service might improve over time through more frequent services and more stops if more users can be gained. We therefore assume that for the transit mode usage related part of the utility function:

$$g_t^\alpha(n_t^\lambda n_t^\varphi) = -\frac{x}{(1+\eta_t(n_t^\lambda+n_t^\varphi))} - y \quad \text{for } \alpha = \{\lambda, \varphi\} \quad (13)$$

The parameter  $\eta_t^\alpha$  describes the sensitivity of the function to the demand. In case of  $\eta_t^\alpha > 0$  the additional time required for the new mode is a decreasing function of  $\eta_t^\alpha$ , with large demand meaning that eventually the travel time reduces to the undelayed travel time of the car. We further assume that the intrinsic utility of the new mode is higher for leaders to express that they are more likely to use the new mode and set  $\zeta_t^\lambda = 8$ ;  $\zeta_t^\varphi = 6$ . The intrinsic utility for car is set to 10 units for both population groups. We assume a simple addition of intrinsic utility, travel times and mass effect so that the car has a small perceived advantage of the equivalent of 2min and 4min for leaders and followers respectively if all mass effects are ignored. Regarding the informational mass effect we make the assumption that

$$h_\beta^\alpha(n_i^\beta) = \kappa^{\alpha\beta} n_i^\beta \quad \text{for } \alpha, \beta = \{\lambda, \varphi\} \quad (14)$$

where  $\kappa^{\alpha\beta}$  is a trend parameter describing the tendency to assimilate/follow the commuting decisions of persons from subgroup  $\beta$  for people from subgroup  $\alpha$ .

In the following tests, we report the findings from using the parameter settings shown in Table 1, abbreviated as Scenarios 1 to 7. We illustrate our scenarios with Figures 3 to 9. On the x-axis we illustrate the dynamics for  $n_t^\lambda(\tau)$  and on the y-axis that for  $n_t^\varphi(\tau)$ . In the figures we show the results of Eq. (10) solved for mode uptake  $t$  for different initial states of the population: each trend line is a plot of the evolution of the  $(n_t^\lambda(\tau), n_t^\varphi(\tau))$  pair over time steps  $\tau = 0, 1, 2, \dots$ , from different starting points  $(n_t^\lambda(0), n_t^\varphi(0))$ , the trajectory illustrated as a continuous line. We plot 1000 time steps for each trend line, at which point all had converged to a fixed point (but not necessarily all trend lines to the same fixed point). If each time step were to represent 1 year, then

obviously the stable points might not be reached within the typical planning horizons considered for transport policies, meaning that the trajectories are possibly as important as the convergent points. As that trajectory which emerges from an initial state with no/few transit users is most interesting for our case, this trendline is highlighted. If the other trendlines converge all to the same point, this would provide numerical evidence indicative of global stability of the solution, whereby the same solution is reached independent of the initial population state.

**Table 1** Parameter Settings in the scenarios

Fixed	$v_{tc}^\lambda = v_{ct}^\lambda = v_{tc}^\varphi = v_{ct}^\varphi = 0.01$						
	$\zeta_t^\lambda = 8; \zeta_t^\varphi = 6$						
	$\kappa^{\lambda\varphi} = \kappa^{\lambda\varphi} = 0$						
	<b>S1</b>	<b>S2</b>	<b>S3</b>	<b>S4</b>	<b>S5</b>	<b>S6</b>	<b>S7</b>
$\zeta_c^\lambda = \zeta_c^\varphi$	10				8		
$\eta_t$	0	0.1					
$\kappa^{\varphi\lambda}$	0		0.05				
$\kappa^{\varphi\varphi}$	0			0.005		0.01	0.02

In the base scenario S1 (Figure 3) we assume that the car has a higher intrinsic utility of  $\zeta_c^\lambda = \zeta_c^\varphi = 10$ , and that there are no consequential or informational mass effects. Congestion reduces the utility for the car but we find that not many commuters are likely to change mode as we find a stable situation at  $(n_t^\lambda = 18.8; n_t^\varphi = 11.1)$ . At this point the BRT travel time is 40 minutes compared to 39.7 minutes for the car. Considering intrinsic utilities  $\zeta_t^\alpha$  this means that the car utility is 2.3 units higher for leaders and 4.3 units higher for followers at the stable point. We remark that our stable dynamic solution does not have to be a Wardrop equilibrium solution. Rather a dynamic stable solution means that (8) equals zero.)

In a second scenario illustrated in Figure 4 we consider that consequential mass effects occur in the form of a reduction in the additional time required for using BRT per unit of demand, and set  $\eta_t = 0.1$  in Eq. (22). This leads to a stable point at  $(n_t^\lambda = 128, n_t^\varphi = 155)$ . Interestingly, following the highlighted trajectory from  $(n_t^\lambda(0) = 0; n_t^\varphi(0) = 0)$ , we see first an increase in usage from



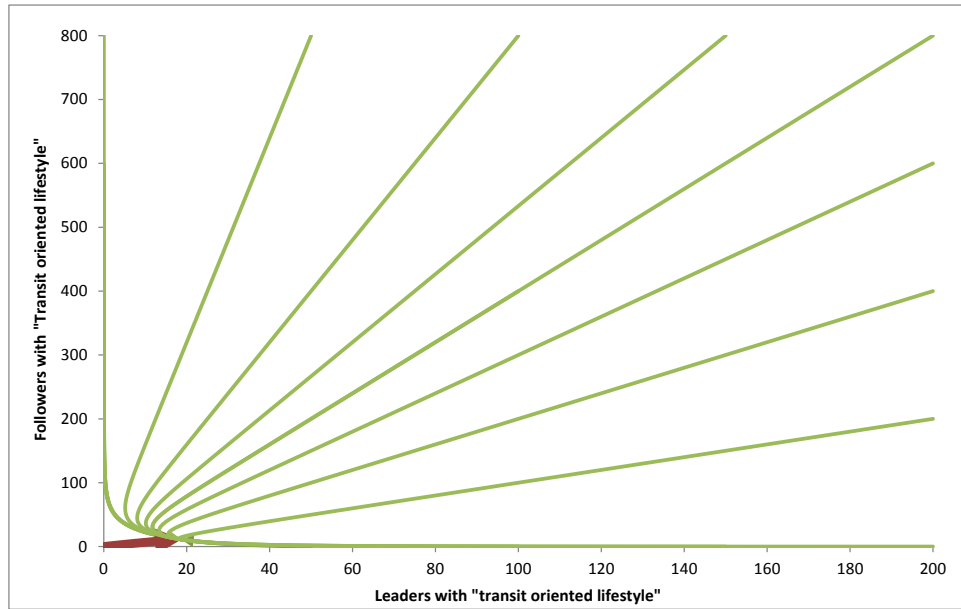
both leaders and followers, but after time a slight reduction in usage by the followers as a majority of the leaders start using the BRT.

In a third scenario we add an ‘information mass effect’ in the form of  $\kappa^{\varphi\lambda} = 0.05$  (Figure 5). This means that for every 20 leaders taking a mode, the followers perceive this as equivalent to an increase in utility of 1 minute. Compared to Figure 4 this leads to some change in the final stable point obtained ( $n_t^\lambda = 108, n_t^\varphi = 204$ ), with now more followers using the BRT; this is due to the fact that the majority of leaders choose BRT, which in turn attracts followers to also swap mode. However, possibly more importantly, the trajectory until this solution is obtained is very different from the previous scenario. In the current case we find that at first only leaders take up transit, but once a “critical mass” starts using BRT, then also followers are likely to consider using the new mode.

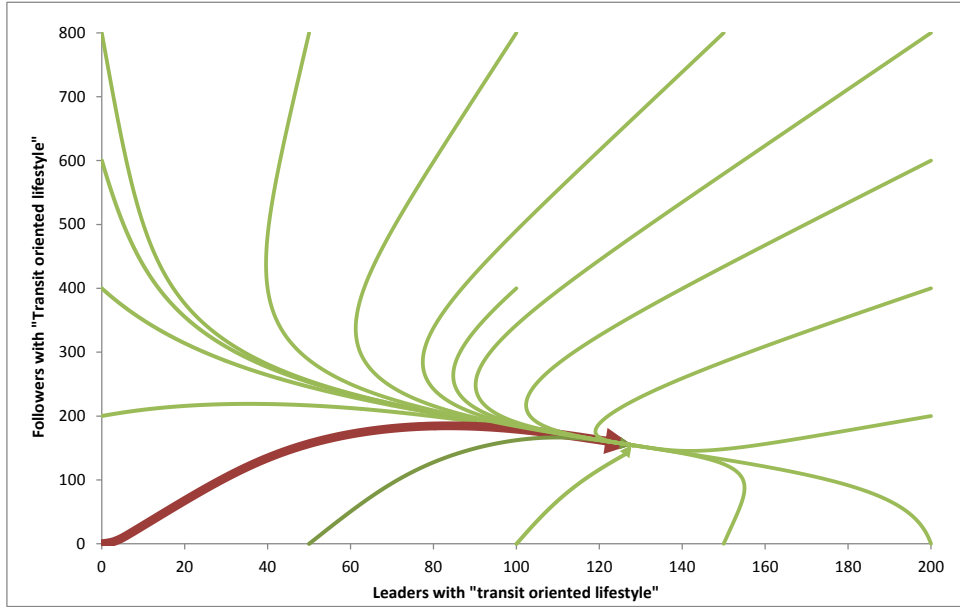
In S4, illustrated in Figure 6, we modify the scenario above to consider the case with  $\kappa^{\varphi\varphi} = 0.005$ . We set this parameter lower in the present scenario to reflect the fact that there are more followers, and therefore a single follower might not have as much an impact as a leader. The stable point moves to ( $n_t^\lambda = 125, n_t^\varphi = 161$ ) and the negative effect on the followers can be explained with the mass of followers taking car. We further observe that followers take up BRT even later: until the point at which around 100 leaders take BRT, almost no follower can be convinced.

In Figure 7 we consider the introduction of a TDM measure, such as road pricing or a petrol tax increase, aimed at reducing the utility of the car. We model this with a deduction in the intrinsic car utility for both population groups from 10 to 8 units (equivalent to 2 minutes). This has a significant effect on the followers as our stable point now moves to ( $n_t^\lambda = 115, n_t^\varphi = 426$ ). We note that the system takes a much longer time to settle down. Furthermore, we find that in this system state – where the utility between the two modes is very similar – the system becomes very sensitive to information mass effects. Removal of information mass effects leads to a significantly lower proportion of followers using the new mode (not illustrated due to space limitations). Doubling  $\kappa^{\varphi\varphi}$  to 0.01 leads to all followers using the new mode (Figure 8). A further increase leads to unstable solutions as illustrated in Figure 9 with  $\kappa^{\varphi\varphi} = 0.02$ . Depending on the starting point

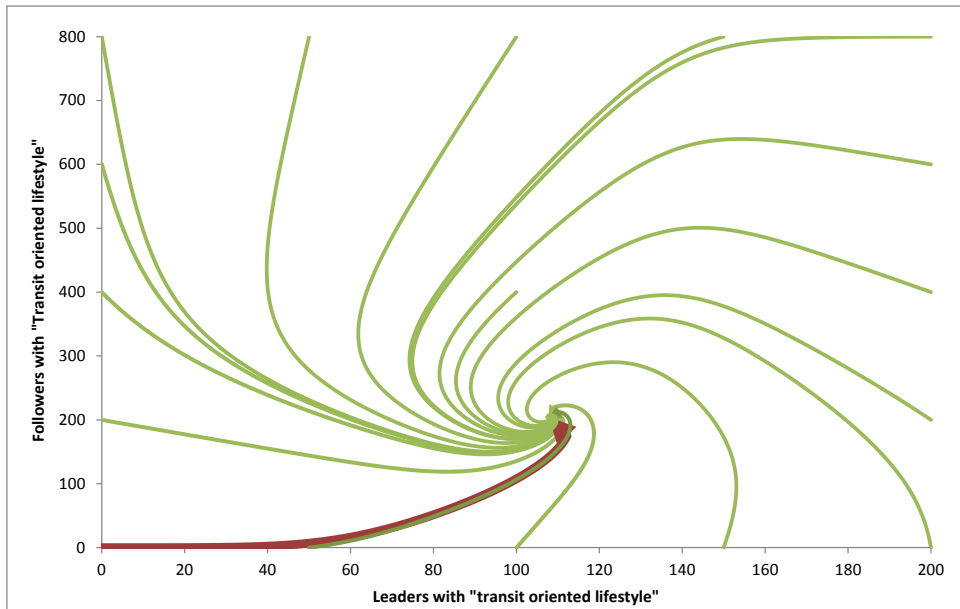
different stable points are reached. Starting from a no user situation, the point ( $n_t^\lambda = 196, n_t^\phi = 13$ ) is most likely to be reached. For a new mode it means that it might be very difficult to obtain significant market shares, as it is virtually only innovators that will change to BRT.



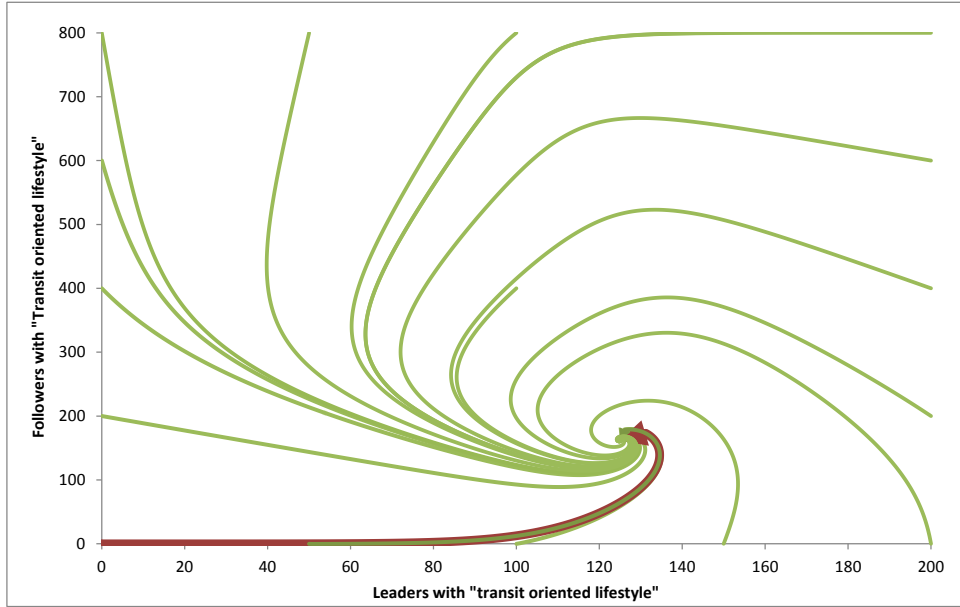
**Figure 3** Base Scenario (S1)



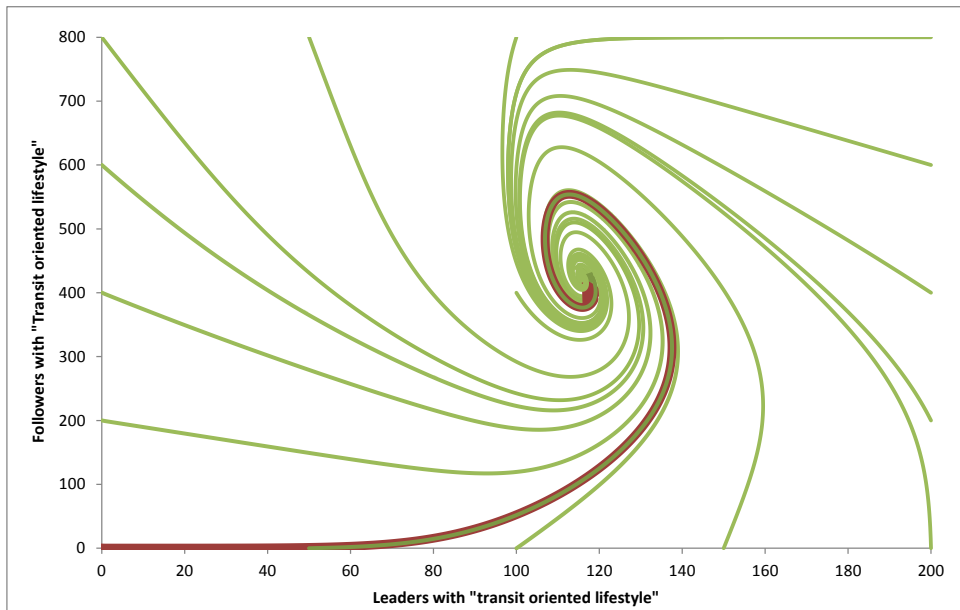
**Figure 4** S1+ service improvements effects (S2)



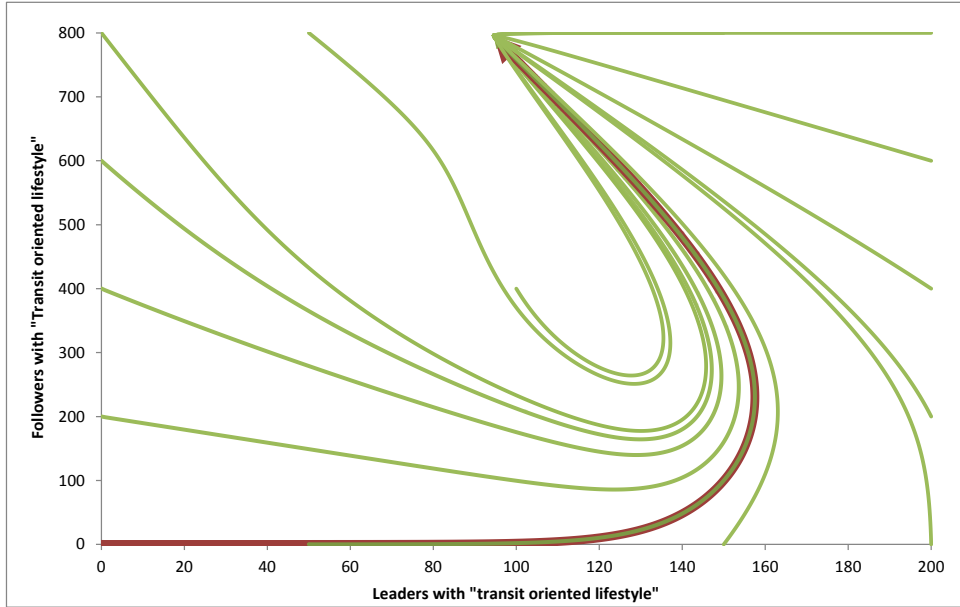
**Figure 5** S2 + Leader Trend effect (S3)



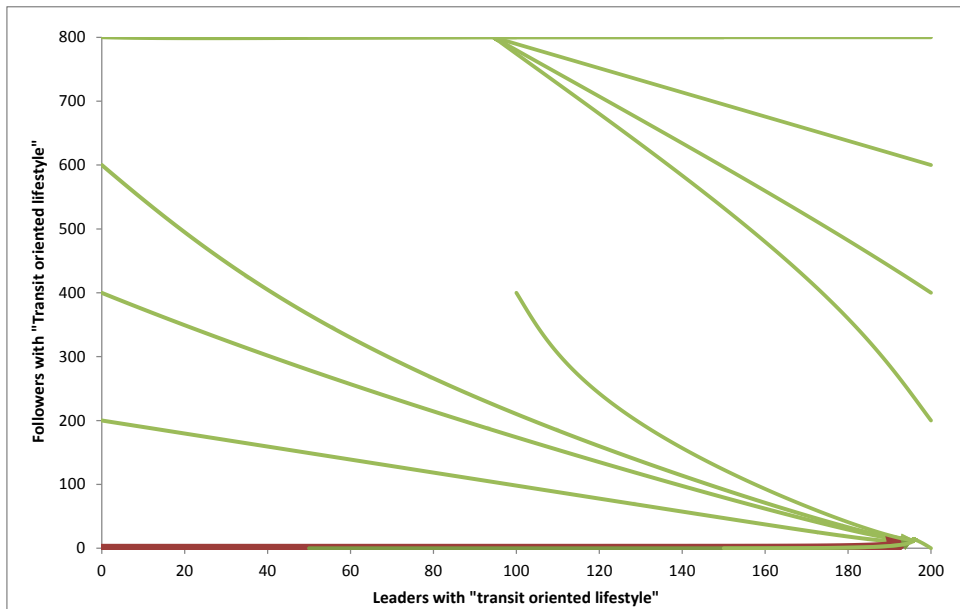
**Figure 6** S3 + Mass Trend effect (S4)



**Figure 7** S4 + TDM measure (S5)



**Figure 8** S5 + Mass Trend Effect increased to  $\kappa^{\varphi\varphi} = 0.01$  (S6)



**Figure 9** S6 + Mass Trend Effect increased to  $\kappa^{\varphi\varphi} = 0.02$  (S7)

## **5. Policy Implications and Calibration Issues**

### **5.1 Policy Implications**

The findings that were obtained from the numerical examples reported in Section 4 cannot be directly applied to practical situations and policy making, since the parameter values, functional forms and scenarios assumed were entirely fictitious. However, we believe that these results do provide some important indicative implications that could be taken into consideration when developing future policy measures to promote the shift toward a new travel mode. Firstly, our examples show that policy measures have an impact on the trajectory of population dynamics as well as the final state to which the trajectory converges. Trajectories are especially important to consider for transport planning with long term effects, since convergent states might never be obtained. Secondly, the case study with a series of scenarios highlights the influence of political externalities, where the effects of different measures are mutually interrelated. In particular, as indicated in the result of scenario S6, the introduction of a communicative measure encouraging interdependence among followers was seen to lead to an unexpected result, subverting the effects of other measures such as road pricing and service improvements. Thirdly, the current examples illustrate that the effects of a policy measure targeting one group may not be limited to that group, and can spill over to affect other groups. In our experiments we found that strengthening follower mass trends (S4, S6, S7) or leader mass trends (S3) could have a positive or negative impact on the other group. The overall results suggest that in order to use ‘mass effects’ as a tool to achieve a significant modal shift, a good combination and coordination of different policy measures is needed, with a better understanding of policy effects on the dynamics of the process, especially policy externalities and spillover effects to non-targeted groups. From our experiments we have shown that such a combination of measures might include a communicative measure with pricing and service improvements.

### **5.2 Calibration Issues**

The purpose of the present paper has been to set out a possible approach by which the dynamics of mass effects may be represented in transportation systems, and to explore the implications of

following such an approach. The assumptions, functional forms and examples we have considered have been hypothetical; our aim has been to set out one *candidate* approach, which could in the future be tested against alternative specifications, given the availability of suitable ‘tools’ for empirical analysis (by which we include survey methods, data sources and calibration techniques). The question then arises as to whether such tools already exist, or at least whether there is cause to believe they could be developed in the future. In aiming to answer such a question, we will consider the wider (as yet undefined) class of models that might be defined in the future to represent mass effects, and will draw on parallels in other fields.

As explained in section 2.1, our use of the term ‘mass effects’ covers a wide range of possible phenomena, and it seems that quite different approaches to modelling (and hence model calibration) may be appropriate in the different contexts. In a situation in which we only have what we have termed ‘real mass effects’, then it seems that an ‘engineering solution’ may be possible. In this case the conformity effects (as described in section 3.2) would not be so important, and so such terms may be neglected, and our interest may be solely on the extent to which the utility  $u_i^\alpha$  depends directly on  $n_i^\alpha$ . This function itself may be time-independent, and so standard transferable relationships might be developed for different phenomena; the dynamics then arise from the feedback of the collective effects of the individual travel decisions.

This is strongly analogous to the way in which time independent relationships representing traffic network congestion have been embedded within dynamic process models of decision-making (e.g. Cantarella & Cascetta, 1995), whereby travellers ‘learn’ of the collective impacts through direct experience, and the impacts motivate their subsequent choices. . The main difference is that here we are looking for positive rather than negative “network effects”. Thus the function  $g_i^\alpha(.)$  in the utility expression (4) might, for example, reflect the observed relationships between increased motor vehicle use and decreased accident risk per person (Smeed 1949; Adams, 1987, McCarthy, 2001) or the analogous relationships seen for walking and cycling (Jacobsen, 2003; Robinson, 2005).

Turning attention to the category that we termed ‘perceived mass effects’ in section 2.1, it would seem that in some cases these could be treated by an extension of the approach described above for ‘real mass effects’. For example, if we could assume that perception meant a subjective or mis-

perception of a real effect, then we might extend the interpretation of the function  $g_i^\alpha(\cdot)$  given above to suggest that it is a composite function reflecting not only the real effect, but also the valuation of that effect by an individual from the group in question. Such a valuation could be estimated by conventional means (e.g. revealed or stated preference) since it only reflects the individual's valuation, all the mass effect is wrapped up in the engineering function which represents the real effect. However, our argument that individual valuation might be separated from mass effects will only hold in some cases. On the contrary, for long range planning one might consider that valuations should be social context specific. In this spirit, Manrai and Manrai (1995) show that values of time differ between cultures and that migrants can adapt. Similarly, people who experience significant improvements in their transport system might start valuing transport system aspects such as congestion differently over time. In such cases we cannot consider individual valuation as distinct from the mass effect, and more likely for calibration we will have to turn to the kinds of theories discussed below under 'information mass effects'.

There are other cases which seem even less simple than this. For example, the aesthetics of some street environment may well both affect and be affected by the number of individuals choosing a mode to travel through that environment, yet there is probably no equivalent notion of a 'real effect' that can be quantitatively estimated through engineering functions. On the other hand, if it is possible to suggest relationships between broad levels of mode use and qualitative descriptors of the aesthetics, then again it may be possible to compose this with the valuation of the aesthetic qualities. While this is not such a common use of the survey methods used in transport, there is still certainly a significant amount of potentially relevant literature on the valuation of aesthetics (e.g. Ewing, 2001; Garrod et al, 2002; Ewing et al, 2005; Cao et al, 2009; Broach et al, 2012; Wahlgren and Schantz, 2012), several of which also relate modal volumes to such valuations.

Turning to the third category identified in section 2.1, namely consequential mass effects, we may again think of  $g_i^\alpha(\cdot)$  as a composite function with individual valuation of the factors (as above), but in this case combined with a function representing the actions of some other agent. Such an agent may, for example, be a public transport operator which is able to adjust frequencies and fares in response to patronage (e.g. Cantarella et al, 2012). There is considerable evidence of suitable functions to represent economies of scale in public transport provision (Berechman and Giuliano,



1985; Farsi et al, 2007; Di Giacomo and Ottoz, 2010), which if provided by a public, welfare-maximising operator (or strongly-regulated private company) might be passed on as benefits to travellers, and this chain of causes might be reflected in the function  $g_i^\alpha(\cdot)$ .

Finally, turning attention to the class of ‘information mass effects’, this class is distinctive in being highly dependent on the conformity or social effects in (4), rather than on the mass effects as reflected only through  $g_i^\alpha(\cdot)$ . This is the area in which our model is perhaps most tentative, as quantitative approaches to such effects are still in their infancy. Nevertheless several theoretical approaches which admit statistical estimation have been proposed in the literature, and a number of these have been applied and functional forms estimated (though not in the present transportation context). Brock and Durlauf (2001) proposed an extension to the conventional random utility model by including an additional, additive function to the usual individual utility and random component, which they called the ‘social utility’. They proposed several parametric forms for the social utility function, and explored the theoretical implications for equilibrium and stability. Fukuda and Morichi (2007) subsequently applied this approach in an econometric analysis of illegal bicycle parking in Tokyo.

Topa (2001), on the other hand, proposed a discrete-time markov process model for representing the exchange of information across social networks. An estimation procedure was proposed and a model estimated based on data concerned with the spread of information about job openings in a social network. Nakajima (2007), in a study which our approach perhaps most closely resembles, also followed a markov process approach, developed from a definition of utility which included an additive conformity effect. Statistical estimation procedures were proposed, and the resulting dynamic model estimated in application to data on peer effects in the decision to take up smoking. In addition to these reported applications, strong theoretical frameworks for analysing social interactions are emerging, and in this respect we would especially point to the works of Manski (2004) and Maccheroni et al (2012), both of which would seem to have considerable potential for future exploitation within the context considered in the present paper, and each of which provide formal frameworks in which we may specify and estimate models, given the availability of suitable data.

## 6. Conclusions

In this paper we discussed the potential importance of mass effects for travel demand forecasting. Based on previous literature, we have assumed that various mass effects might lead to positive or negative trends that could significantly influence travel demand over time (such as the uptake of sustainable modes). We describe the mobility decisions of individuals in this paper hence as a dynamic process, considering positive and negative feedback from other travellers as well as the transport system itself. We have proposed that such mass effects may be particularly relevant to demand forecasting applications over longer time-scales, and in the context of promoting presently little-used or new travel modes.

In order to illustrate and examine this approach, we have presented a hypothetical model in which individuals belonging to one of two population groups, termed “leader” and “follower”, have the choice between two lifestyle options, referred to as car-oriented and transit-oriented. Though our model is clearly too simple for direct applications, we believe that already with such a simple model our case study illustrates and raises the profile of some important aspects that are known and have been discussed in the literature, but, to our knowledge, have not been included in travel demand modelling approaches.

We illustrate with our case study that despite lower intrinsic utility for transit, significant changes towards transit can be achieved by considering congestion, service improvements and trend effects. We further illustrate that mass effects do not always have to be positive. Unsustainable mass effects, such as the perception of the car as a status symbol might be difficult to be overcome and can make it difficult for new (attractive) modes to obtain significant market shares. This result is also in line with findings by Sunitiyoso et al (2011b) who show with a simulation study that social learning can lead to positive or negative effects. Our study considers not only information mass effects but also consequential mass effects, in the form of transit service improvements. This illustrates that the combination of mass effects together with service improvements might be the formula to achieve the best results.

There are several functional forms and parameters in our model that would need calibration in order to apply this method to real-life case studies, and in Section 5.2 we have reviewed and

discussed the potential for calibrating such approaches. Several parameters might further be described as policy variables. In particular  $\eta_i^\alpha$  might be interpreted as being related to TDM measures; in such an interpretation,  $\eta_c^\alpha$  might be related to usage-based charging of non-sustainable modes, such as petrol taxes, and  $\eta_t^\alpha$  might be related to the service improvement of a sustainable mode in line with an increasing demand for that mode.

Our work clearly could be extended in various directions. A number of model simplifications in our case study are apparent and might need to be addressed depending on the application. An obvious extension would be to consider more than two choices and, possibly more importantly, more than two population groups. We also did not consider any geographical considerations or discuss particular forms of social networks. Furthermore, mass effect functions are not necessarily constant over time as we noted in our discussion on calibration of perceived mass effects.

Even with this simplified model some modifications could be tested though and theoretical advances made. The current analysis does not include a theoretical stability analysis; such an analysis in the future might explore the sensitivity of the stability to the parameter settings as well as the probability distribution of different (stable or unstable) population states. Achieving the latter is the aim of the “master equation approach”. Initial tests suggests that in our analysis most solutions are stable though a mathematical proof appears difficult to achieve with our logit formulation of transition probabilities. Connected to this, and possibly even more important to know for transport planners, are possible system bifurcation points as presented in the “fashion model” by Nakayama and Nakayama (2004) for a simplified utility function where the population is not divided into groups. We leave this also open for further work.

Finally, regarding our presumed choice behaviour, we assume a logit model for transition probabilities and showed this is equivalent to the perturbed best response used in the evolutionary game theory literature. Alternative assumptions on agent behaviour are possible, and we believe that in particular replicator dynamics might be an alternative worthy of further exploration. Replicator dynamics assume that an agent either sticks to the current choice or changes (with some probability) to the choice of an agent (s)he meets. Therefore replicator dynamics do not assume knowledge of non-chosen alternatives, which might be particularly

appropriate for modelling the uptake of new transport schemes with which the modelled population has not yet had much experience.

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