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How do people choose their commuting mode? An evolutionary approach to travel choices

Chiara Calastri[1] · Simone Borghesi[2,3] · Giorgio Fagiolo[4]

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Abstract A considerable amount of studies in the transport literature is aimed at understanding the behavioural processes underlying travel choices, like mode and destination choices. In the present work, we propose the use of evolutionary game theory as a framework to study commuter mode choice. Evolutionary game models work under the assumptions that agents are boundedly rational and imitate others' behaviour. We examine the possible dynamics that can emerge in a homogeneous urban population where commuters can choose between two modes, private car or public transport. We obtain a different number of equilibria depending on the values of the parameters of the model. We carry out comparative-static exercises and examine possible policy measures that can be implemented in order to modify the agents' payoff, and consequently the equilibria of the system, leading society towards more sustainable transportation patterns.

Keywords Commuter choices · Transportation · Travel behaviour · Evolutionary dynamics · Evolutionary game theory · Bounded rationality · Environmental policy

✉ Chiara Calastri
c.calastri@leeds.ac.uk

Simone Borghesi
simone.borghesi@unisi.it

Giorgio Fagiolo
giorgio.fagiolo@sssup.it

1 Institute for Transport Studies and Choice Modelling Centre, University of Leeds, Leeds, UK

2 Dipartimento di Scienze Politiche e Internazionali, Università di Siena, Siena, Italy

3 Florence School of Regulation Climate, European University Institute, Florence, Italy

4 Istituto di Economia, Scuola Superiore Sant'Anna, Pisa, Italy

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1 Introduction

The transition towards a more sustainable transportation system is an important and pressing theme of discussion in the policy agenda of many countries, as the way we travel affects many facets of our lives and has multiple consequences on our future. Recent studies estimate that a large percentage of air pollutants which are responsible for global warming is generated by the transport sector. In 2015, the transport sector accounted for 24% of the global energy-related CO_2 emissions, 75% of which derive from road transport (International Energy Agency 2017a). Road injuries are among the top 10 causes of death in the world. The number of fatal accidents has increased slightly, but more than proportionately, with the world population, from 1 million in the year 2000 to 1.25 million in 2015, and it is expected to become the fifth leading cause of death by 2030 (World Health Organization 2017).

The transport sector currently accounts for approximately 65% of total oil consumption (International Energy Agency 2017b), and the number of cars is expected to double by 2030, when their total number will reach 2 billions (Sperling and Gordon 2008). This rise is mainly related to the development of emerging economies like China, India and the Middle East. The boost in oil demand predicted for these countries will more than outweigh the reduction in oil consumption of the OECD (Organisation for Economic Co-operation and Development) countries. In addition, the expected increase in urbanisation is likely to cause serious congestion problems in the next decades in most cities all over the world.

The rising number of people travelling by car is a concern for a number of reasons. Among the most cited ones are congestion in urban areas, environmental damages caused by pollution and reliance on exhaustible resources. Indeed, motor vehicles contribute to approximately 14% of global carbon dioxide emissions from fossil fuel burning, being the first single source of atmospheric pollution (World Carfree Network 2017). Other issues are related to human health. The United Nations has estimated that over than 600 million people in the world suffer from dangerously high levels of air pollution from traffic (Cacciola et al. 2002).

Air pollutants can cause and worsen respiratory diseases (Khreis et al. 2016), and the increasing car dependence of households is held responsible for obesity and lack of physical exercise, which in turn can cause severe health problems.

Switching to more sustainable transport modes, less polluting and less congesting, is likely to be an effective solution to at least some of these problems. For these reasons, a growing and compelling need to define a more sustainable pattern of transportation has been acknowledged by public institutions in many countries, which have implemented different policies aimed at reducing car use and encouraging modal shift. These measures are aimed both at making alternative transport modes cheaper, more comfortable and attractive, and at mitigating the influence of psychological factors that determine personal attachment to cars.

In this paper, we suggest the application of a game-theoretic framework to model commuter-mode choice. We implement an evolutionary game model (Vega-

Redondo 1996), where commuters living in a homogeneous urban population can choose between using their private car or travelling by bus. The choice of these two modes serves demonstration purposes, and the model can be applied to other modes as well. As it is customary in the literature, we assume that agents are boundedly rational and, as fundamentally assumed in game theory, that their choices are affected by the behaviour of other agents. As we will explain in greater detail below, agents in our framework imitate others.

We suggest that this theoretical approach is appropriate for the subject of our study for two reasons. First, evolutionary game theory is generally used to explain phenomena involving a population in which agents meet continuously, and where the payoff of an agent making a certain choice is influenced by what the rest of the population does. This framework can be a valid approximation of certain urban populations of commuters who face similar transport problems: they can choose the modes of transport they prefer to commute with, but at the same time they observe what other people in the population choose, and they can decide to adjust their choice because of it, as they all are affected by the positive or negative externalities due to others' behavior.

Second, evolutionary approaches represent an attempt to overcome one of the main limitations of traditional game theory, as they allow to relax the assumption of perfect rationality. As a matter of fact, traditional game theory assumes fully informed, far-sighted agents which make their choices by solving a constrained optimisation problem. On the contrary, evolutionary game theory assumes that players adaptively adjust their choices, as they are assumed to hold limited information about the consequences of their actions.[1] A framework in which people are backward looking and update their beliefs looking at the past and imitate the others seems therefore to be a better approximation of real-world dynamics.

It is important to note that, in principle, an agent who is forward-looking and fully informed would make his/her choices on the basis of expectations on city planning, fuel cost and other observable and expected factors, but in our case agents do not have perfect information and are backward looking, therefore they use past information to inform their future choices. In the present context, for instance, agents can revise their decisions on the preferred transport mode looking at their past investments and experience. For example, if an agent invested a substantial amount of money in a new car in the past and now finds him/herself always stuck in traffic, while public transport users experienced lower commuting time, he/she might decide to change his/her decision and imitate public transport users.

This work contributes to the existing commuter-mode choice literature in several ways. First of all, we advocate the use of different behavioural models to represent mode choice behaviour, contributing to the discussion about introducing bounded rationality and social influence in models of travel choice.

In addition, our analysis is not limited to accounting for the damages suffered by car users by the widespread diffusion of cars (resulting in congestion and pollution), but also

[1] Standard evolutionary theory, as well as replicator dynamics, when applied to biology, assume that agents meet a sufficiently high number of times, either deterministically or stochastically. This interpretation is not suitable for our specific application. Therefore, we rely on the alternative "behavioral" interpretation of the theory, according to which agents hold limited information and therefore make choices by reacting to what they observe in the population (Vega-Redondo 1996).

the negative effects on bus riders deriving from overcrowded buses. Furthermore, we perform numerical evaluation analyses to understand how different equilibria emerge as the payoff parameters change in the model. We also discuss how model parameters can be affected by real-world forces and factors, and suggest policy measures that can be devised to lead society towards more sustainable transportation patterns.

The current work presents elements of novelty with respect to previous work in this field. Differently from Antoci et al. (2012), on which the present work relies for the core modelling structure, we focus on a specific alternative to the use of private car and its potential negative externalities (as opposed to a generic alternative). This allows us to provide a deeper interpretation of the model parameters, also when, differently from Antoci et al. (2012), we carry out numerical evaluation analyses. More details about the differences between the two approaches are reported in the next section.

Our approach also departs from other efforts focused on a similar research question, such as David and Foucart (2014). The latter represents the choice between car and a generic public transport option using game theoretical approach but without making use of evolutionary game theory, which takes into account the dynamics of the population over time. Moreover, that paper does not only focus on the share of users adopting a specific mode, but looks also at the level of traffic separation between the two, which is not among the objectives of the present paper.

This paper also has implications for policy making. By performing comparative-static exercises, we show how, following changes in the model parameters, the equilibria of the model change. For example, we show that if the net benefit of commuting by bus increases, this can bring the system from an equilibrium where everyone uses car to one where an increasing number of people commute by bus. The extent of the policy effort needed to achieve this change will depend on the initial position of the system, but measures such as an improvement in the fleet and in the quality of the service can contribute to such shift, as it will be shown in Sect. 5 in further detail.

The paper is structured as follows. In Sect. 2 we provide an overview on the framework applied to the study of commuter mode choice, both from the theoretical and the practical perspective. Section 3 presents the model. In Sect. 4 we discuss the results of the model in terms of type and number of possible equilibria, and we perform comparative-welfare analyses. In Sect. 5 we employ numerical evaluations to perform comparative-static exercises aimed at examining how the equilibria of the model can be modified by changing some key parameter values, and we also discuss possible policy interventions affecting such parameters. We conclude with a discussion on policy recommendations and possible directions for further research.

2 Overview of the literature

Understanding the determinants of travel mode choice as well as developing methods to influence it to achieve more sustainable mobility has been the object of a large number of theoretical and empirical contributions. In particular, efforts in different fields ranging from sociology to economics have attempted to incorporate the role of other agents in travel decision making in different ways.

Sociological theories as the Theory of Planned Behaviour (Ajzen 1991) have been applied to account for the role of attitudes, norms and perceived behavioural control on choices. As an example, Bamberg et al. (2003) applied it to predict mode choice following the introduction of a pre-paid bus ticket. The influence of others was captured by asking respondents to anticipate the reaction of their close social circle.

Empirical studies based on Random Utility Theory (RUT) constitute a large share of the existing literature on the topic of modal choice. A wealth of econometric techniques have been employed to study the determinants of transport choices, using data on stated preferences (SP) or revealed preferences (RP). In presence of several transport-mode alternatives, and when the aim of the researcher is to forecast the probabilities with which each one will be chosen, discrete choice models are typically used (Ben-Akiva and Bierlaire 1999).

These models can account for both deterministic and random heterogeneity across decision makers (Bhat 2000; Ben-Akiva and Bierlaire 1999). While controlling for both attributes of choice alternatives and socio-economic characteristics of the decision maker, several studies find an increased probability of switching from private car to other alternatives in presence of auto-use disincentives, improved level of service of public transport or travel time reduction (Williams 1978; Fillone et al. 2007; Nurdden et al. 2007; Vedagiri and Arasan 2009).

Recent studies have underlined the relevance for travel behaviour of the so-called “soft factors”, like latent attitudes and perceptions (Spears et al. 2013; Eriksson and Forward 2011) and social networks. As explained by Dugundji and Walker (2005), the impact of the social environment on decision making has been incorporated in empirical models in different ways, for example by means of *field variables*, “allowing the systematic utility to be a function of the proportion of a given decision-makers reference entities who have made this choice” or dummy variables to account for the belonging of an individual to a certain group or community. The traffic behaviour literature also incorporates effects of other drivers, for example assuming that the behaviour of a car driver may depend on the leader’s speed or spacing (Toledo 2007).

Game-theoretical setups have been used to describe several transport-related problems, although with a limited attention to individual transport-mode choices. As argued in Zhang et al. (2010), applications range from macro- to micro-policy analysis. In the macro case, games between travellers and authorities, among authorities and among travellers, have been developed in order to study optimal road tolls to improve efficiency. In the micro case, the focus has been on games between authorities and travellers, and among travellers. One of the few game-theoretical contributions concerning modal choices is David and Foucart (2014), who study a simultaneous game in which commuters can rationally choose between using the car or public transport. The two equations that represent the utility of choosing the car or public transport include the fixed costs of car use and the waiting time for the public transport and the congestion faced by each mode. Heterogeneity is modelled via a parameter representing the strength of commuter preference for the car or the bus. Despite its simplicity, the model allows to draw several conclusions about the existence and multiplicity of equilibria. David and Foucart (2014) claim that, if multiple equilibria exist, the one involving the highest use of public transport Pareto-dominates the others.

Finally, evolutionary game theory has been applied to model agent learning mechanisms in presence of congestion pricing (Dimitriou and Tsekeris 2009) and traffic dynamics (Yang et al. 2005). Furthermore, Antoci et al. (2012) have examined agent choice between using a private car or an alternative transport mode (walking, cycling, and public transport). Using an evolutionary game model in which the payoff of each choice is affected by traffic congestion due to car use, they show the existence of suboptimal Nash equilibria characterized by the widespread diffusion of cars. Our model builds upon Antoci et al. (2012) but differs from it in several respects. First, although we share its general modelling framework, we focus on bus use as a specific alternative to the use of a personal car. Second, while Antoci et al. (2012) study the negative effects deriving from the increasing diffusion of cars and the consequent increase in congestion and pollution, we assume here that also an increased number of bus commuters may harm bus users, as a consequence of bus overcrowding. In our view, this is particularly important since high levels of crowding is often reported as one of the main reasons not to use public transports (e.g. Mazzulla and Eboli 2006), which can induce commuters to travel by car, although this increases traffic congestion and thus further worsens traffic problems.

Third, we try to provide a deeper interpretation of payoff parameters in terms of real-world forces and factors that can shape them. This is possible in our case as we assume the choice between car and a specific type of public transport (bus) instead of a generic alternative. Relying on the existing literature, we explicitly enumerate all the possible sources of benefit from car/bus use as well as the externalities from excessive spread of one or the other option in the population. These are captured by the parameters of the model, as we will explain in the following section. Fourth, we carry out numerical evaluation analyses to better understand how changes in the payoff parameters affect the dynamics and equilibria of the model. This allows us to get a better understanding of the potential effects of policy interventions.

3 The model

We model individual transport-mode choices in a large population of identical commuters endowed with the same strategy set and payoffs. At each time t, each commuter chooses between driving a car or traveling by bus. In order to make comparisons easier, we follow Antoci et al. (2012)' s notation[2] and denote with A the choice of the agent who uses the car, and with B the choice of the agent who decides to take the bus. Let $x(t)$ be the share of the population choosing A.

The payoffs of the two strategies can be written as follows:

[2] As pointed out above, the current model is a generalisation and extension of this model.

$$\Pi_A = a - bx^2 \tag{1}$$

$$\Pi_B = c - d(1-x)^2 - ex^2 \tag{2}$$

where a and $c \in (-\infty, +\infty)$, $b \geq 0$, $e \geq 0$ and $d \geq 0$.

Parameters a and c measure the net benefit, respectively, of choosing the car or the bus. The value of the net benefit of traveling by car (a) may depend on factors such as the flexibility in choosing when to depart and how many stops to make along the route, or on non-instrumental factors such as symbolic and affective motives, i.e. the value that a person may attribute to owning a big and fashionable car which may improve her reputation or image. Analogously, parameter c (i.e. net benefit of commuting by bus) may vary depending on buses frequency, punctuality, reliability and journey time. Other factors that can influence this parameter are the level of fares and the availability and quality of information, such as timetables. Just as for parameter a, factors which are more difficult to measure, such as the physical and social environment, may have an influence on modal decisions. As argued above, the existence of negative externality associated with bus transport makes the present model depart from Antoci et al. (2012) that do not account for this possibility. A similar assumption, instead, is made by David and Foucart (2014).

Parameters b, d, and e control instead for all different types of externalities that we consider in the model. More specifically, b governs the negative externality on car users caused by other cars, including congestion effects, stress, air pollution and health risks. Instead, d tunes externality effects on bus users due to a higher share of the population choosing the bus as a transport mode (e.g., crowded buses and safety concerns).

Finally, parameter e models the cross-externality on bus riders caused by the diffusion of car users (e.g. road congestion, safety and health risks).

Despite our assumption $d \geq 0$, it would be reasonable to allow the possibility that crowding in buses may potentially also generate a positive externality on bus users. For example, an increase in the number of bus users may generate a reduction in the price of tickets, and improvements in bus frequency or an improvement in the feeling of safety during the night. This would motivate an assumption of $d \in (-\infty, +\infty)$. Nevertheless, given the theoretical nature of our analysis, and to limit the number of possible cases that we will present in the following sections of our paper, we decided to limit ourselves to the case $d \geq 0$, leaving the case $d \in (-\infty, +\infty)$ as a possible extension of the present work.

Table 1 provides a detailed summary of the possible interpretation underlying each parameter and of the related studies which have proposed and/or examined such interpretations in the literature.

We model the process of choosing among the two strategies by means of replicator dynamics (RD, cf. Hofbauer and Sigmund 1998), wherein the growth rate of the share of people playing a certain strategy is assumed to be proportional to the difference between the current payoffs of the two strategies. This means that only strategies that grant a higher payoff with respect to the average payoff spread in the population.

The RD equation can be written as follows:

Table 1 Interpretation of the parameters of the model

Parameter	Meaning	Influencing factors	References
a	Net benefit of car use	Journey time	Steg (2005)
		Flexibility	Tertoolen et al. (1998)
		Effort minimisation	Gardner and Abraham (2007)
		Personal space and privacy	
		Perceived monetary costs	
		Control over the surrounding environment	
		Non-instrumental motives	
b	Negative externality on car users caused by cars	Congestion	Arnott and Small (1994)
		Stress and aggression	Lajunen et al. (1999)
		Air pollution	Beatty and Shimshack (2011)
		Health risks	World Health Organization (2017)
c	Net benefit of bus use	Frequency	Commission for Integrated Transport (2008)
		Punctuality and reliability	Guiver (2007)
		Fares	Steg (2005)
		Journey time	Dell'Olio et al. (2010)
		Physical and social environment	Wall and McDonald (2007)
d	Externality on bus users caused by the diffusion of bus use	Crowded buses	Guiver (2007)
		Safety	Stradling et al. (2007)
e	Externality on bus users caused by the diffusion of car use	Congestion	Guiver (2007)
		Safety and health risks	Stradling et al. (2007)

$$\dot{x} = x(1-x)[\Pi_A - \Pi_B] = [\Pi_A - x\Pi_A - (1-x)\Pi_B)]x = [\Pi_A - \overline{\Pi}]x, \qquad (3)$$

where $\overline{\Pi}$ is the average payoff and $\dot{x}$ is the time derivative of $x(t)$.[3] From Eq. (3) it follows that the per capita growth rate of the strategy's frequency is equal to the difference between strategy A pay-off and the average payoff in the population. Accordingly, strategy A will spread or shrink depending on whether it does better or worse than the average payoff.

The payoff difference can be re-written as:

$$\begin{aligned}\Pi_{A-B} := \Pi_A - \Pi_B = a - bx^2 - c + d(1-x)^2 \\ + ex^2 = (a-c+d) - 2dx + (d+e-b)x^2.\end{aligned} \qquad (4)$$

In order to simplify our analysis, we re-parametrize the payoff difference Π_{A-B} as follows:

$$\Pi_{A-B} = (f+d) - 2dx + (d-g)x^2, \qquad (5)$$

where $f = a - c$, i.e. the difference between the net benefits of the two means of transport; and $g = b - e$, i.e. the difference between the negative effects caused by the diffusion of A on car users and on bus users. This leaves us with three parameters instead of five. Note that the payoff difference Π_{A-B} is a convex parabola if the term $d - g$ is positive, and a concave parabola if it is negative.

4 Evolutionary dynamics

As we can clearly see from Eq. (3), the two equilibria of the model where all agents make the same choice, i.e. $x = 0$ and $x = 1$, are stationary states for the replicator dynamics because when x takes one of these two values, it yields $\dot{x} = 0$. Any other value $\bar{x} \in (0, 1)$ is a stationary state if and only if $\Pi_{A-B} = 0$, i.e. if the payoffs of the two strategies are equal, and no one will have the incentive to revise her choice.

We will analyze the outcomes of the model in two scenarios: (*i*) $d < g$ (i.e. $b > d + e$) wherein the total negative effects are more severe for individuals who choose to commute by car; and (*ii*) $d > g$ (i.e. $b < d + e$), in which the opposite applies.

As it will emerge from the analysis that follows, the model admits 2, 3 or 4 stationary states (as summarized in Tables 2 and 3 below) and is highly path-dependent, converging to inner or extreme equilibria, depending on the initial share of car users in the population. We will then compare the welfare of the population at different steady states and discuss under which conditions the population is better off at equilibria characterised by the presence of fewer or no cars.

[3] In the one-dimensional context of the model, every sign preserving adoption dynamics (i.e. for which the sign of the time derivative $\dot{x}$ and the one of the payoff differential $\Pi_A - \Pi_B$ is the same (Weibull 1995) generates the same trajectories of replicator dynamics in the interval (0, 1).

Table 2 Equilibria in the scenario $d < g$ (payoff difference is concave)

Case	No. of equilibria	Attractors
1	2	$x = 0$
2	2	$x = 1$
3	3	$0 < x_1 < 1$

Table 3 Equilibria in scenario $d > g$ (payoff difference is convex)

Case	No. of equilibria	Attractors
1	2	$x = 1$
2	4	$0 < x_1 < 1, x = 1$
3	2	$x = 0$
4	3	$0 < x_1 < 1$
5	3	$x = 0, x = 1$

4.1 Scenario $d < g$

In this first scenario, the term $d - g$ is negative, thus the parabola representing the payoff difference is concave. The following conditions hold:

$$\Pi_A(0) - \Pi_B(0) = f + d > 0 \quad \text{iff} \quad \mathrm{f} > -\mathrm{d}$$
$$\Pi_A(1) - \Pi_B(1) = f - g < 0 \quad \text{iff} \quad \mathrm{f} < \mathrm{g}.$$

The dynamic regimes under Eq. (3) can be classified as follows:

Case (1) If $f < -d$, $f < g$ and $df - dg - fg < 0$ then, whatever the initial distribution of strategies $x(0) \in (0, 1)$, the payoff of B will be higher than the payoff of A for any x, and thus the system will converge to the stationary state $x = 0$, where the whole population chooses B (see Fig. 1). These three conditions, respectively, imply that the payoff difference when $x = 0$ is negative; the payoff difference when $x = 1$ is negative; and the ordinate of the vertex of the parabola representing the payoff difference is positive.[4] This last assumption is essential for ensuring that the system ends up in the steady state where everyone uses the bus, as it excludes the existence of multiple equilibria.

Case (2) If $f > -d$, $f > g$ and $df - dg - fg < 0$ then, whatever the initial distribution of strategies $x(0) \in (0, 1)$, the payoff of A will be higher than the payoff of B for any x, and thus the system will converge to the stationary state $x = 1$, where the whole population chooses A (Fig. 2).

Case (3) If $f > -d$ and $f < g$ and $df - dg - fg < 0$, then whatever the initial distribution of strategies $x(0) \in (0, 1)$, the system will have one attractive equilibrium for $x \in (0, 1)$ (Fig. 3). This implies that if the initial distribution of

[4] The payoff difference can be rewritten as: $\Pi_{A-B} = (d - g)\left(x^2 - \frac{2d}{d-g}x + \frac{f+d}{d-g}\right)$. Being the y-coordinate of a parabola equal to $y = -\frac{\triangle}{4a}$, in our case this value will be equal to $y = \frac{df-dg-fg}{d-g}$. In the current case $(d < g)$, the denominator is always negative, therefore the only condition needed for determining the sign of the whole fraction is the sign of the numerator.

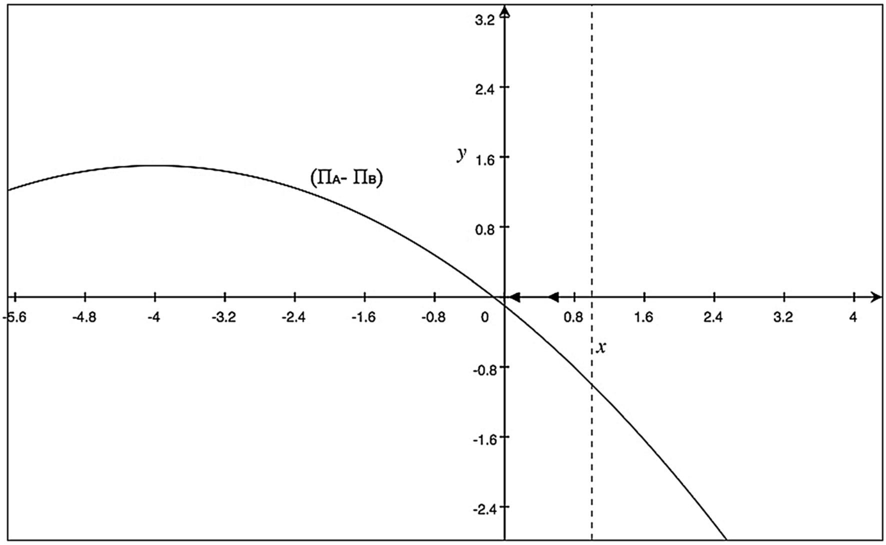

Fig. 1 Scenario $d < g$, Case (1)

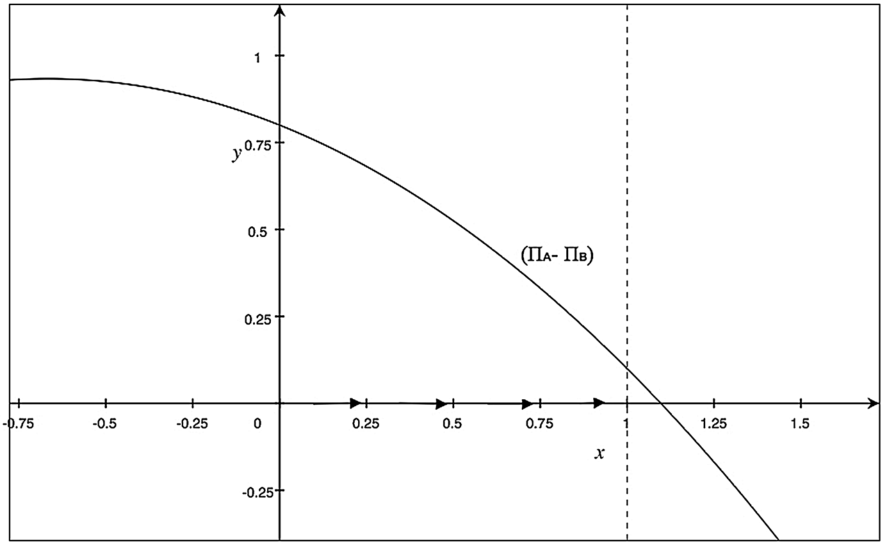

Fig. 2 Scenario $d < g$, Case (2)

strategies $x(0) \in (0, 1)$ either lays in the interval $(0, x_1)$ or in the interval $(x_1, 1)$, the dynamics will lead the system to the equilibrium x_1. The "pure" equilibria $x = 0$ and $x = 1$ can only be reached if the initial distribution of strategies x(0) coincides with one of these points.

The outcomes of the model in the first scenario are summarized in Table 2.

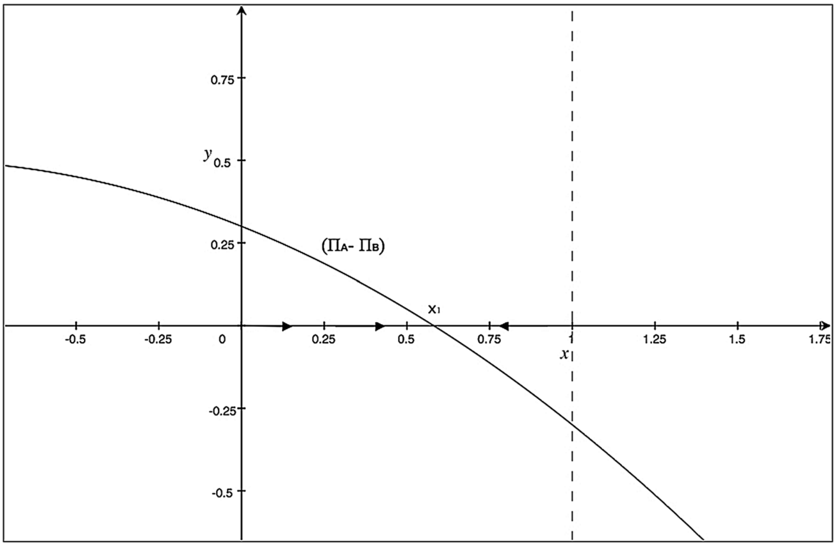

Fig. 3 Scenario $d < g$, Case (3)

4.2 Scenario $d > g$

In this second scenario, the term $d - g$ is positive, thus the curve representing the payoff difference is convex. The conditions on the extreme values reported for the Scenario $d < g$ also hold in this case and the dynamic regimes under Eq. (3) can be classified as follows:

Case (1) If $f > -d$, $f > g$ and $df - dg - fg > 0$ then, whatever the initial distribution of strategies $x(0) \in (0, 1)$, the payoff of A will always be higher than the payoff of B for any x, and thus the system will eventually converge to the stationary state $x = 1$, where the whole population chooses A (Fig. 4).

Case (2) If $f > -d, f > g$, and $df - dg - fg < 0$ then the payoff difference when $x = 0$ and when $x = 1$ is positive, but the ordinate of the vertex of the parabola representing the payoff difference is negative, thus the curve intersects the horizontal axis in two points, i.e. there will be two values of $\bar{x} \in (0, 1)$ such that $\Pi_{A-B} = 0$ (Fig. 5). This outcome is confirmed by the fact that, if $d > 0$, the x-coordinate of the vertex is positive.[5] The equilibrium which lays at a value closer to zero is an attractive one (x_1), while the other one (x_2) is repulsive. This means that if the initial distribution of strategies $x(0) \in (0, 1)$ either lays in the interval $(0, x_1)$ or in the interval (x_1, x_2), the dynamics will lead the system to the equilibrium x_1; while if the initial distribution of strategies $x(0) \in (0, 1)$ lays to the right of point x_2, the system will converge to the "pure" equilibrium $x = 1$ in

[5] In fact, since the abscissa of the vertex of the parabola is equal to $\frac{d}{d-g}$, recalling that $d \geq 0$ and that in the present scenario $d > g$, we can conclude that if $d > 0$ the entire fraction is positive. Notice that if $d = 0$ (i.e. bus users are not harmed by overcrowded buses), the abscissa of the vertex is zero; if so, $\dot{x} \in (0, 1)$ is the one-dimensional analogous of the saddle-node point in a two-dimensional space.

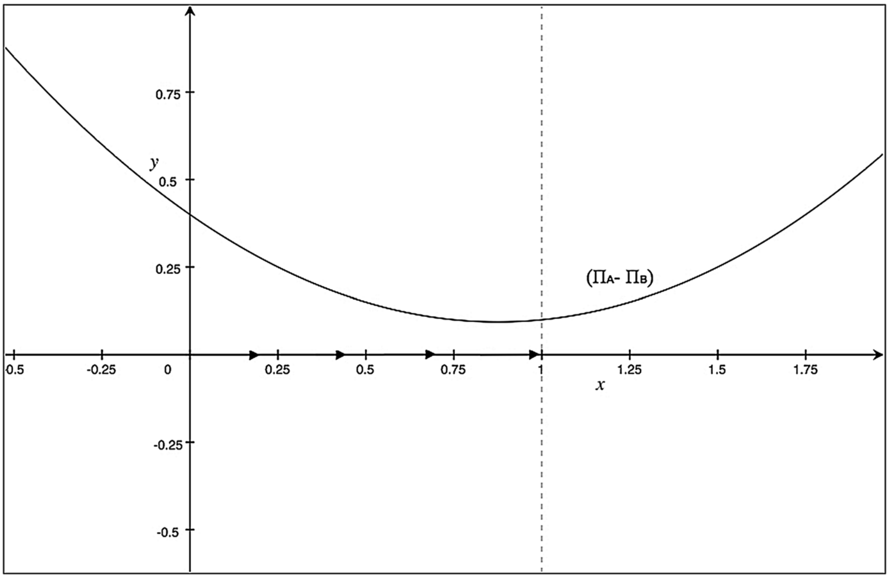

Fig. 4 Scenario $d > g$, Case (1)

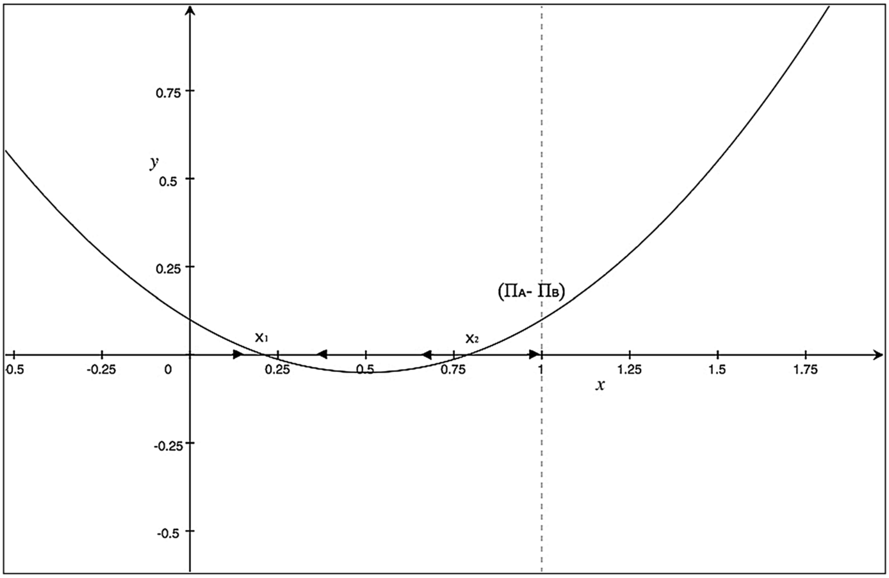

Fig. 5 Scenario $d > g$, Case (2)

which everyone uses the car. The equilibria $x = 0$ and $x = x_2$ can only be reached if the initial distribution of strategies $x(0)$ coincides with one of these points.
Case (3) If $f < -d, f < g$ and (consequently) $df - dg - fg < 0$ then, whatever the initial distribution of strategies $x(0) \in (0, 1)$, the payoff of B will be higher than

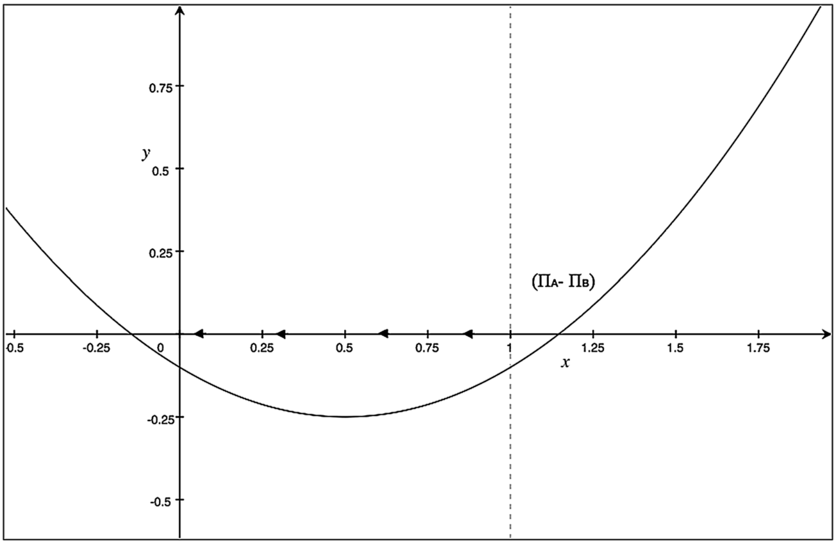

Fig. 6 Scenario $d > g$, Case (3)

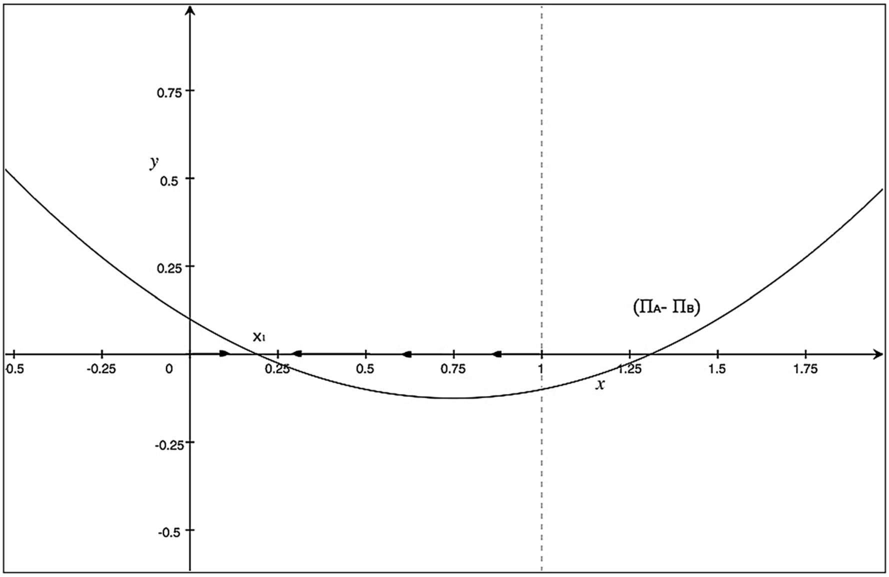

Fig. 7 Scenario $d > g$, Case (4)

the payoff of A for any x, and thus the system will eventually converge to the stationary state $x = 0$, where the whole population chooses B (Fig. 6).
Case (4) If $f > -d, f < g$ and (consequently) $df - dg - fg < 0$, then, the system admits an internal equilibrium x_1 , which is globally attractive in the interval (0, 1) (Fig. 7).

Case (5) If $f < -d$, $f > g$ and (consequently) $df - dg - fg < 0$, then, whatever the initial distribution of strategies $x(0) \in (0, 1)$, the system will exhibit one equilibrium for $x \in (0, 1)$, which is repulsive (Fig. 8). Therefore, if the initial distribution of strategies $x(0)$ lays to the left of the intersection, the dynamics will lead the system to the 'pure' equilibrium $x = 0$, while if it lays to the right of it, the system will end up in the steady state $x = 1$. The equilibrium x_1 can be maintained only if it corresponds to the initial distribution of strategies.

The outcomes of the model in the second scenario are summarised in Table 3.

4.3 Comparative welfare analysis

Let us now turn to compute the average payoff of the population at each equilibrium point. This may allow one to compare the equilibria in terms of the corresponding welfare levels and help to identify the stationary states which are desirable by the population as a whole.

Notice that the population we refer to is the one of the commuters only, and the present welfare analysis focuses specifically on their payoffs, therefore it cannot be regarded as a social welfare analysis. Indeed, the present analysis does not consider the implications of different commuting modes on the profits of the automobile industry and of the bus companies, nor it accounts for the payoffs of the workers who are employed in these sectors. Moreover, the current welfare analysis does not account for the costs that Public Administration and tax-payers have to bear for the implementation of different policies.

The average payoff equation is:

$$\bar{\Pi}(x) := x\Pi_A(x) + (1 - x)\Pi_B(x). \tag{6}$$

Applying this to the cases of the two extreme equilibria ($x = 0$ and $x = 1$) and to the inner equilibrium $x = x_1$ we get:

$$\bar{\Pi}(0) = \Pi_B(0) = c - d \tag{7}$$

$$\bar{\Pi}(1) = \Pi_A(1) = a - b \tag{8}$$

$$\bar{\Pi}(x_1) = \Pi_A(x_1) = \Pi_B(x_1) = a - b(x_1)^2 = c - d(1 - x_1)^2 - e(x_1)^2. \tag{9}$$

The stationary state $x = 1$ is Pareto-dominated by the stationary state $x = 0$, i.e. $\bar{\Pi}(0) > \bar{\Pi}(1)$, if $c - d > a - b$ or, equivalently, if $c - a > d - b$. In other words, the whole population is better off when everybody uses the bus rather than the car if the difference between the net benefits of the two mean of transport $(c - a)$ is higher than the difference between the negative externalities provoked by the users of each mean on the other users of the same mean $(d - b)$.

Stated differently, what the condition suggests is that even if everybody uses the bus (so that the bus congestion problem is potentially maximum and the car congestion problem is minimum), using the bus can still be the preferable choice. This is true as long as the positive gap in terms of net benefits from using the bus

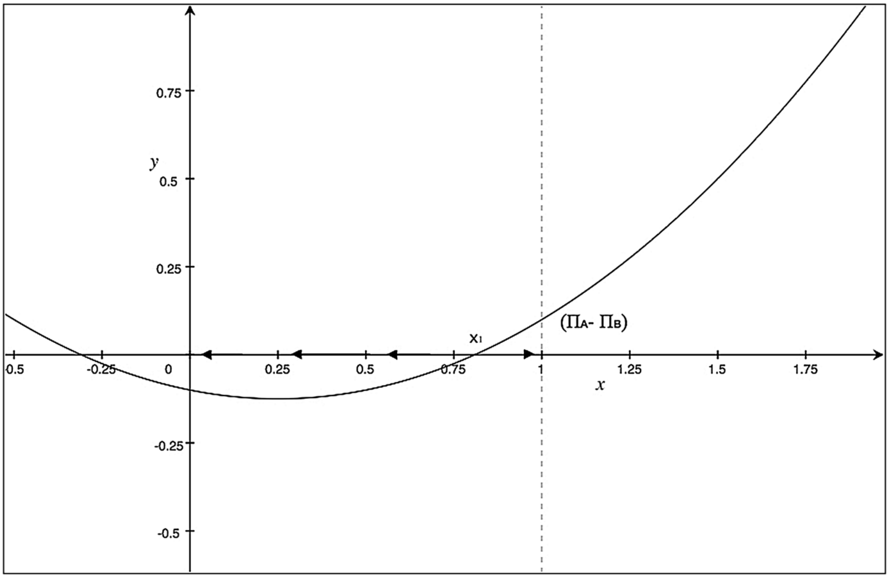

Fig. 8 Scenario $d > g$, Case (5)

rather than the car is much higher than the negative gap in terms of negative externality between the two choices. This condition could be satisfied, for instance, if more frequent and comfortable buses are warranted to bus commuters, which minimizes the negative externality they suffer from overcrowded buses. Similarly, the condition could also be satisfied by imposing fees on car drivers (e.g. in the form of congestion charging) and using the revenues to offer season ticket discounts to bus users. This would increase (decrease) the net benefit of using the bus (car), thus enlarging the gap in terms of net benefits between the two alternative choices.

If this is the case, the economy will move along a welfare-reducing path in the case described in Fig. 4 , while it will move along a Pareto-improving trajectory in Fig. 6.

An inner equilibrium x_1 is Pareto-dominated by the extreme state $x = 0$ if $c - d > c - d(1 - x_1)^2 - ex_1^2$ or, equivalently, if $-(d + e)x_1^2 + 2dx_1 < 0$. If bus users suffer negative externalities from both bus congestion ($d > 0$) and traffic congestion ($e > 0$), the condition above is equivalent to $x_1 > 2d/(d + e)$. This suggests that if the share of car users at equilibrium is sufficiently high (that is, x_1 is above a given threshold level) then the correspondent average payoff is lower than in the case without cars. In this case the whole population is better off if everybody commutes by bus ($x = 0$) than in the inner equilibrium in which the two strategies coexist ($x = x_1$). It follows that—under these conditions—a shift from $x = 0$ towards $x = x_1$ will reduce the overall population welfare (cf. Figs. 5, 7), whereas a welfare increase will occur if the economy moves in the opposite direction (as in Fig. 8).

If two inner equilibria x_1 and x_2 exist, then $\bar{\Pi}(x_1) > \bar{\Pi}(x_2)$ if $a - bx_1^2 > a - bx_2^2$. Since $x_1 < x_2$, if $b > 0$ this is always the case. Put it differently, if an agent's car use causes a negative externality on the other car users, people are better-off in the equilibrium with less cars.

To illustrate this point consider, for instance, the case described in Fig. 5. If we substitute the numerical values used in Fig. 5[6] in Eqs. 7–9, we can observe that in this case the average payoff in the two extreme equilibria coincides ($\bar{\Pi}(0) = \bar{\Pi}(1) = 0.1$) and turns out to be lower than in the two inner equilibria, being respectively $\bar{\Pi}(x_1) = 0.19$ and $\bar{\Pi}(x_2) = 0.14$. In this case, therefore, the attractive equilibrium x_1 provides the highest welfare level to the population, consistently with our previous considerations on the sign of b (being here strictly positive). Any movement towards x_1 (as the ones shown in Fig. 5) will be welfare improving, whereas a shift from x_2 to the extreme equilibrium $x = 1$ (cf. Fig. 5) will be welfare reducing.

5 Evaluation results and policy implications

As it emerges from the previous analysis, multiple equilibria can arise from the model. Coordination failures among agents' decisions can therefore make the economy depart from a preferable equilibrium (i.e. a Pareto-dominant outcome in which all agents are better-off) and move along a welfare-reducing path. Public policies can play a crucial role in this case to overcome such coordination failures and lead the economy towards a welfare-increasing equilibrium.

We now carry out a few comparative-static exercises and discuss possible policy interventions that can be implemented in order to modify the value of agent' payoffs—and consequently the equilibria of the system—bringing the society to more sustainable transportation patterns. In other words, we aim here at answering the following question: what happens to the number and type of equilibria when the values of the model parameters change? As shown below, a change in the net benefits of using the car or the bus can generate multiple equilibria and the population can be better-off at inner equilibria (in which some people use the car, others the bus) than at extreme equilibria (where everybody uses either the bus or the car). The calibrations performed, however, show that a large increase (decrease) in the net benefit of using the bus (car) is needed to remarkably reduce the share of drivers in the population.

5.1 Change in the net benefit of car and bus

To address this issue we consider percentage changes in the net benefits of the two means of transport, i.e. we first investigate the effects on the model of a growing percentage increase/decrease, respectively, in c and a, independently of the kind of policy interventions that can produce them.

Since our work is concerned with reaching more sustainable pattern of transportation, in what follows we will focus on parameter changes that produce

[6] There the values of the parameters are: $a = 0.2$, $b = 0.1$, $c = 0.4$, $d = 0.3$, $e = 0.4$; and the payoff difference equation is equal to $(\Pi_A - \Pi_B) = 0.1 - 0.6x + 0.6x^2$.

a reduction of car use or an increase in bus use. A quantification of the effects that specific policy interventions can have on single parameter values is at present very difficult and goes beyond the scope of the present analysis. However, below we will speculate on possible policy interventions that can produce a change in the net benefit of car drivers and bus users.

To perform our first comparative-statics exercise, we carry out a numerical evaluation aimed at showing the changes in the payoff difference curve in response to a change in parameter a, i.e. the net benefit of using the car.

A reduction in parameter a may be obtained by implementing a policy that affects the benefit of travelling by car, as discussed in Sect. 3. This could be obtained, for example, by means of a higher tax on fuel, on parking, or by the introduction of congestion charging.

Parameter a enters the payoff difference through the term $f = a - c$. Thus if a lowers, f lowers as well. The constant term of the equation of the parabola representing the payoff difference is $f + d$. Thus a lower value of a will lower the value of $f + d$, shifting the parabola downwards.

Let us suppose we are in Case (1) of Scenario $d > g$, i.e. the only attractive equilibrium of the system is $x = 1$, where the whole population chooses to commute by car. If parameter a gets sufficiently low (i.e. enough to produce at least one intersection between the curve and the x-axis), this will alternatively produce one attractive equilibrium, one repulsive equilibrium or two equilibria, depending on the initial value of the other parameters of the curve.

Figure 9 illustrates the latter case, specifying the parameter values underlying the evaluation results. The solid line is the initial situation, i.e. the one presented in Fig. 4, while the dotted lines represent the curve after increasing percentage reductions in a. Starting from a situation like the one represented by the initial setting, if the authorities want commuters to revise their choice, a must decrease by at least 20% of its initial value. In this case, two equilibria x_1 (attractive) and x_2 (repulsive) emerge, and the final allocation will depend on the initial value of x. When the percentage change increases, the distance between the two equilibria increases, possibly up to the point in which the only equilibrium will be $x = 0$ and no one will find it advantageous to commute by car (see the 120% decrease in a in Fig. 9).

The opposite reasoning applies when the value of a increases, with the obvious difference that in this case the parabola would move upwards.

In a similar vein, we can observe the effects of an increase in the net benefit of commuting by bus. Figure 10 shows the shifts of the payoff curve when the value of parameter c increases, ceteris paribus. The solid curve represents the initial payoff difference, while the new curves laying to its left correspond to increases of the value of c ranging from 5 to 300% of its initial value. This time, being the initial situation different in terms of parameter values, substantial changes like 50% change produce no effect on equilibria. In our experiment, the curve representing the first intersection with the horizontal axis (which is in any case very close to one, with $x_1 = 0.9$) is the one obtained through an 80% change in c. The curve that intersects the x-axis determining a share of drivers lower than that of bus riders ($x_2 = 0.39$) corresponds to a 300% increase of the value of c. This relative difficulty

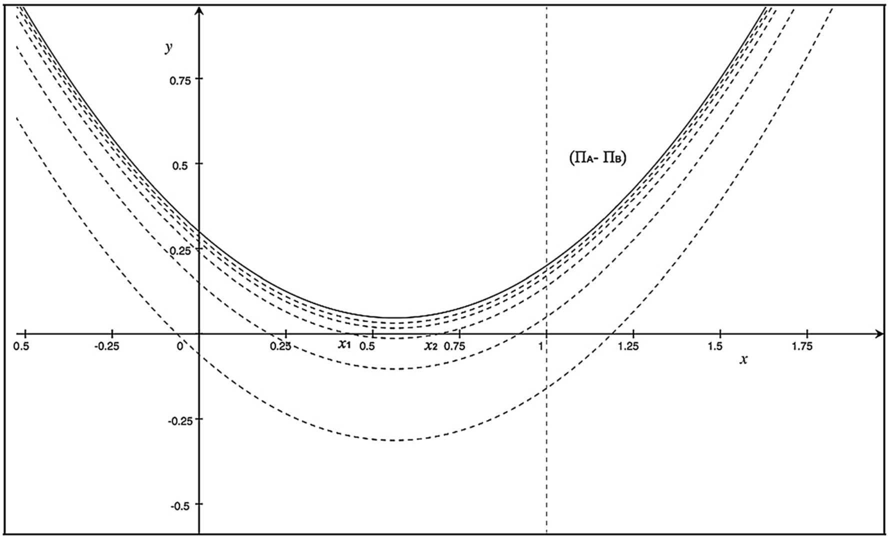

Fig. 9 The effect of a decrease in parameter a in scenario $d > g$, Case 1. The payoff-difference parabola shifts downward as a is reduced with respect to the baseline case ($a = 0.3$) by 5, 10, 20, 50, 120%. Other parameters: $b = 0.05$; $c = 0.45$; $d = 0.45$; $e = 0.4$; $f = -0.15$

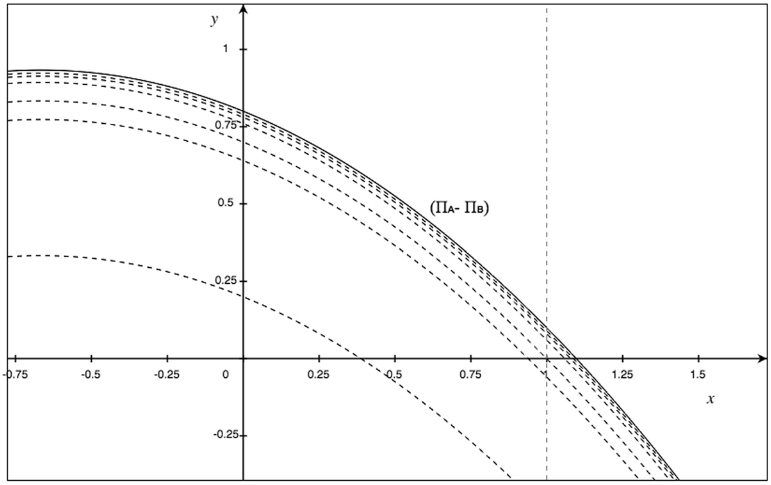

Fig. 10 The effect of an increase in parameter c in Scenario $d<g$, Case 2. The payoff-difference parabola shifts to the left as c is increased with respect to the baseline case ($c = 0.2$) by 5, 10, 20, 50, 80, 300%. Other parameters: $a = 0.8$; $b = 0.7$; $d = 0.2$; $e = 0.2$; $f = 0.6$

in changing the equilibrium pattern obviously depends on the initial position of the curve, i.e. on the values of the parameters of the model. If the system is in a situation similar to that depicted in Fig. 10, a huge effort in terms of policy is needed in order to produce changes in equilibria. This result stresses the importance of the implementation of joint policies aimed at inducing people to start to commute by bus, and highlights the fact that small changes in service quality, for example adding a new vehicle to the fleet or reducing fares without improving frequency or reliability, can end up being costly but having no effect on modal switch. This is coherent with the literature arguing that joint implementation of several policies aimed at providing an overall better service are generally successful.

One can provide several examples of appropriate policies that can modify the net benefit of using the car and/or the bus (i.e. a and/or c). Fuel taxes are certainly among the most important and most widely implemented car use reduction policies.[7] Another example is congestion charging (CC), i.e. schemes that generally imply that car users have to pay to enter "charging zones" (commonly city centres). London's CC scheme has been estimated to have impacted transport modal choice by 30%, i.e. one third of those that were previously commuting by car changed their transport mode (Transport for London 2008). Examples of non-economic measures might be strictly enforced speed limitations, traffic calming of residential zones, turn restrictions for cars but not for transit and bicycles and priority to transit and bicycles. Examples of policies more precisely directed at increasing bus use by commuters can also be economic measures, such as fare reductions or subsidies (Kain and Liu 1999) or non-economic measures related to improvements in the service quality of infrastructures, for example Park and Ride bus stop facilities or increase in service frequency.

5.2 Change in other parameters

It is of course possible that, as a result of different policy interventions, other parameters of the model will also change. As a purely illustrative example, we will show the results of changing policy measures that result in a change of parameters e and d.

Parameter e represents the externality on bus users caused by the diffusion of car use. In the presence of policies that reduce the interference of cars with an effective activity of buses, the value of this parameter will be reduced. For example, bus lanes could be introduced, or even when previously present, further regulations could be introduced so that buses only have the right to use these and cars that travel along them can be heavily fined. Regulations to reduce congestions and air pollution can also reduce externalities on public transport users and therefore result in a decreased value of the e parameter. The effect of these interventions is shown in Fig. 11. Starting from a situation where everyone travels by car, a progressive reduction of e moves the system to equilibria where the private travel mode is used by fewer and fewer commuters.

[7] Fuel taxes are generally seen as an effective measure, but some studies question their effectiveness. For example, Storchmann (2001) recognizes that an increase in fuel taxes potentially implies a "triple dividend", i.e. a regulative, modal-shift effect, a fiscal effect and a positive effect on the public transport sector, represented by a decrease in deficit. But the author argues that the first two effects are rarely jointly achievable: in fact, if demand for car use is inelastic (i.e. people will not give up their car when the tax is imposed) the fiscal effect will prevail, while if it is elastic the regulative one will, with negative consequences for public revenue.

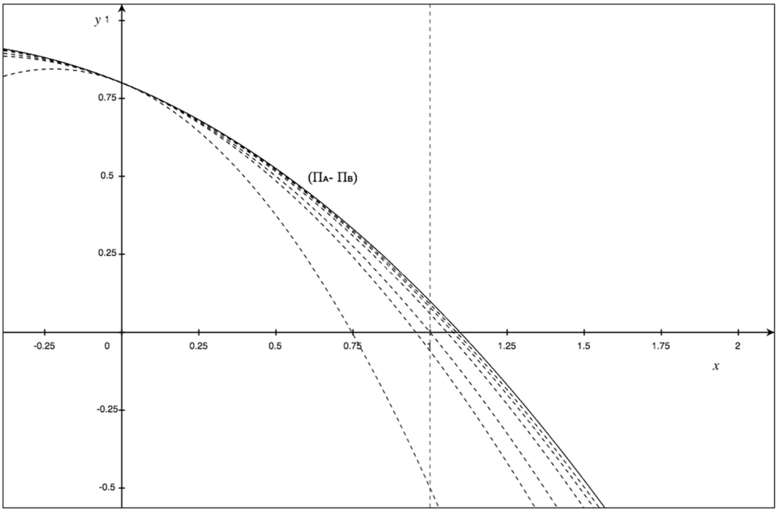

Fig. 11 The effect of a decrease in parameter e in Scenario $d < g$, Case 2. The payoff-difference parabola shifts to the left as e decreases with respect to the baseline case ($e = 0.2$) by 5, 10, 20, 50, 80, 300%. Other parameters: $a = 0.8$; $b = 0.7$; $c = 0.2$; $d = 0.2$; $f = 0.6$

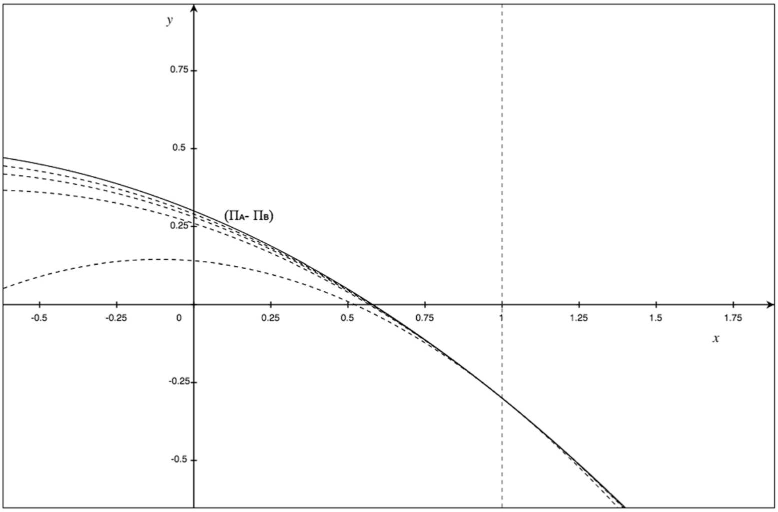

Fig. 12 The effect of a decrease in parameter d in Scenario $d < g$, Case 3. The payoff-difference parabola rotates as d decreases with respect to the baseline case ($d = 0.2$) by 5, 10, 20, 80%. Other parameters: $a = 0.4$; $b = 0.7$; $c = 0.3$; $e = 0.3$; $f = 0.1$

Parameter d represents the externality on bus users caused by the diffusion of bus use, as discussed above. This parameter will decrease if policies aimed at reducing overcrowding on buses are implemented, e.g. adding further buses to the existing fleet. The effect on the parabola of a change in this parameter is less straightforward than in the cases seen so far, as d enters all the different terms of the equation. Figure 12 shows the effect of a decrease in this parameter. As it can be noted, in the cases reported in this figure the curve rotates so that the new equilibria are located to the left of the initial one, indicating that a higher number of commuters choose to travel by bus.

It is important to note that this result can change depending on the entity of the change in the value of the parameter, the values of the other parameters and the initial condition, and ad-hoc analyses of changes need to be carried out to explore the expected effects of policy measures.

5.3 Comparative welfare analysis

The welfare analysis introduced earlier can be applied to our evaluation exercise in order to observe how changes in the value of parameters affect social welfare. In the comparative statics exercise illustrated in Fig. 9 we start from the situation showed by the solid line, in which the only two equilibria are $x = 0$ and $x = 1$, the former being repulsive and the latter attractive. In this case, it can easily be shown that $\bar{\Pi}(0) = 0$ and $\bar{\Pi}(1) = 0.25$ so that the equilibrium which ensures the maximum well-being for the population is the one in which no-one commutes by bus. When the value of parameter a decreases by 50%, the system has four different equilibria, represented by:

$$x = 0,$$

$$x = 1,$$

$$x_{1,2} = \frac{\frac{2d}{d-g} \pm \sqrt{\left(\frac{2d}{d-g}\right)^2 - 4\left(\frac{f+d}{d-g}\right)}}{2}.$$

Substituting the values of the parameters and the equilibrium values in Eq. (6), the average payoffs in the four different equilibria are equal to $\bar{\Pi}(0) = 0$, $\bar{\Pi}(1) = 0.25$, $\bar{\Pi}(x_1) = 0.29$, $\bar{\Pi}(x_2) = 0.25$. In this case, the equilibrium $x = 0$ is Pareto-dominated by all the others, the welfare level in $x = 1$ is equal to that in the repulsive equilibrium x_2, and the best stationary state is the attractive inner equilibrium x_1, where only one fifth of the population commutes by car.

Similar results are obtained when analyzing the exercise illustrated in Fig. 10. In the initial situation we have $\bar{\Pi}(0) = 0$, $\bar{\Pi}(1) = 0.1$. When c increases by 80% the average payoff corresponding to the inner equilibrium x_1 is $\bar{\Pi}(x_1) = 0.24$ and when c is increased by 300%, the average payoff of x_2 equals 0.7, i.e. in both cases the new equilibria grants a welfare level which is higher than the one provided by the two extreme equilibria.

We can therefore observe that, with the specific parameter values chosen in our evaluation, when there are exclusively extreme equilibria, the one where everybody commutes by car seems to grant a higher average payoff, but when inner solutions are also present, these are strongly better in terms of social welfare than the extreme equilibria.

6 Conclusions

In the present work, we have studied a very simple evolutionary game model to address modal choices in terms of transportation for daily commuting and the possibility to induce people to change their habits promoting sustainable and environmentally friendly transportation.

Our model improves upon previous studies in several directions. In particular, we describe agents' payoffs taking into account not only the negative effects due to the diffusion of cars, but also the inconvenience caused by overcrowded buses, which can be a discouraging factor for potential and actual bus commuters.

We have analyzed the outcomes of the model in two scenarios, each of which features, respectively, three and five different cases, depending on the values of parameters. Each of these cases corresponds to an equilibrium setting. We observe extreme equilibria (were the whole population chooses the same mean of transport) as well as inner ones, in which people are divided into two groups, car and bus users. The observed equilibria are path dependent, so the initial share of people choosing one alternative or the other is very important for the model dynamics and the final equilibria that will be reached. Our evaluation exercises, featuring an increase/decrease in the value of key parameters by different percentages, suggests the size of the changes that are needed to induce different equilibria, shifting the system from one case to the other.

Although the model is admittedly oversimplified in many respects (e.g., it focuses only on two alternative transport modes), it suggests that transport authorities could reach more desirable patterns of transportation through the enforcement of policies that make car driving less convenient and attractive, and alternative transport modes particularly appealing. As it stems from the analysis, in fact, policy interventions that change the value of the parameters may produce new equilibria in the model, in which a higher share of people chooses the alternative transport mode rather than their car.

In this regard, the literature provides several examples of economic as well as non-economic transport policies that can shift the system towards more sustainable outcomes. For instance, taxes or subsidies can disincentivize car use, although it is important to gather as much information as possible about demand elasticity (Storchmann 2001). As far as bus policies are concerned, temporary economic incentives, such as free passes, are generally effective in producing an immediate switch in modal choices, and to some extent determine a change in habits (Fujii and Kitamura 2003). In the case of commuting, these policies seem to be more likely to succeed, as evidence shows that people are generally willing to re-organize these trips, differently from other purpose trips. The same holds for measures implemented at workplaces, such as subsidies to alternative modes or parking restrictions (Su and Zhou 2012). Most studies argue that re-investment of the revenues from these measures in interventions aimed at enhancing public transportation will entail higher levels of acceptance and effectiveness.

Non-economic measures, such as parking management and traffic calming are important as they limit one of the major advantages of driving, i.e. travel times (Herrstedt 1992). At the same time, public transport attractiveness can rise if service improvements are undertaken. Examples are upgrades such as switches to rapid bus transit, interchange facilities and in general all actions suggesting a change in the quality of service.

Although the present study provides some interesting insights on commuter-transport choices, it should be interpreted as a preliminary analysis of this issue and can be therefore extended in several directions in the future. First, the model allows commuters to choose between car and bus only, but other alternatives, like rail, cycling and walking could be considered. This would imply the definition of the payoffs associated to the new commuting alternatives, and new results in terms of model equilibrium dynamics, producing further and possibly more detailed policy recommendations.

Second, instead of examining binary choices (i.e. car vs. bus), multiple transport alternatives could be simultaneously taken into account. This could be implemented, for instance, by dividing the population in three fractions x, y and z, representing the share of users of each mode of transport, and examining the correspondent replicator dynamics and system equilibria.

Another possible way of expanding the present work consists in introducing heterogeneity among commuters, i.e. distributing commuters in a number of different populations. This may allow one to embody heterogeneous beliefs and latent attitudes in the type of commuter belonging to each specific population, beliefs and attitudes which proved to be quite hard to modify for most people.

Moreover, in this study we have attributed arbitrary values to the parameters of the model. Conversely, following e.g. Abrantes and Wardman (2011), who have recently proposed different methods to attribute a value to time for the different transport mode users, future research could attempt to pursue a more realistic estimation or calibration of model parameters.

Finally, an interesting extension of our work could be considering a stochastic version of the model, where agents can make mistakes or experiment with a small probability. In this way, one might better understand whether, in presence of multiple equilibria, some of them resist to temporary or persistent small shocks. This becomes crucial to better evaluate policy implications and the role of policy makers.

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