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

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

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Abstract

The issue of transportation is of primary importance in our societies. A large share of greenhouse gases is generated by the transport sector, and road casualties are one among the most common causes of death. In the present work, we study commuter choice between alternative transport modes using an evolutionary-game model, wherein commuters can choose between using their private car or taking the bus. We examine the possible dynamics that can emerge in a homogeneous urban population, where agents are boundedly rational and imitate the others. 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 the society towards more sustainable transportation patterns.

Keywords: Commuter choices; Transportation; Evolutionary dynamics; Environmental policy.

JEL Classification: C73; R4; D6.

1 Introduction

The issue of transportation is of primary importance in our societies, as it affects many facets of our lives and has a wealth of 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 2011, the transport sector accounted for 22% of the global energy-related CO_2 emissions, 75% of which derive from road transport (International Energy Agency, 2013). 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 1.24 million in 2013, and it is expected to become the fifth leading cause of death by 2030 (World Health Organization, 2014).

The transport sector currently accounts for 90% of total oil demand and half of total oil consumption (International Energy Agency, 2012), and the number of cars is expected to double by

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2035, when their total number will reach 1.7 billions. 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 countries. In addition, the expected increase in urbanization 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. Other issues are related to human health: air pollution can cause and worsen respiratory diseases, 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 most of these problems. For these reasons, a growing and compelling need of defining a more sustainable pattern of transportation has been acknowledged by public institutions of many countries, which have been implementing different policies aimed at reducing car use and encouraging modal switch. These measures are addressed 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, within the more general issue of people transportation, we focus on commuter-mode choice. We study an evolutionary-game model (Vega-Redondo, 1996), where commuters living in a homogeneous urban population can choose between using their private car or taking the bus. As it is customary in this literature, we assume that agents are boundedly rational and imitate the others.

We suggest that this theoretical approach is appropriate for the subject of our study for two reasons (Antoci et al., 2012). 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 means of transportation they prefer to commute with, and 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 limits 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 optimization 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. 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.

This work improves upon existing commuter-mode choice studies by examining not only the damages suffered by the whole population due to the widespread diffusion of cars, but also the negative effects on bus riders deriving from overcrowded buses. Furthermore, we perform simulation 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 proper policy measures that can be devised to lead the society towards more sustainable transportation patterns.

The paper is structured as follows. In the Section 2 we review the existing literature on commuter transport choice, distinguishing between theoretical and empirical models. Section 3 presents the model. In Section 4 we discuss the results of the model in terms of type and number of possible equilibria, and we perform comparative-welfare analyses. In Section 5 we employ numerical simulations 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 Related Literature

A large number of empirical and theoretical contributions has addressed the issue of transport-mode choice.

On the empirical side, a wealth of econometric techniques have been employed to study the determinants of transportation 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, multinomial logit models are typically used (Ben-Akiva and Bierlaire, 1999). Controlling for both trip-related and socio-economic variables, 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 transportation or travel time reduction (Williams, 1978; Fillone et al., 2007; Nurdden et al., 2007; Vedagiri and Arasan, 2009).

Additional empirical studies using SP data suggest that factors such as time of travel and its variability significantly affect the choice between public transport and private car (Van Vugt et al., 1996), and that infrastructure and facilities, such as bike parking and showers at workplaces may encourage the choice of alternative transport modes (Buehler, 2012). In addition, gender issues have been shown to affect transport choices, with women being generally less willing to commute by bicycle (Dickinson et al., 2003). More generally, Mackett (2003) argues that the main reasons for choosing the private car instead of alternative transport modes are carrying heavy goods, giving lifts, and time saving. More recent studies also underline the relevance of attitudes and perceptions in transport-mode choices (Spears et al., 2013; Eriksson and Forward, 2011).

From a theoretical perspective, three main approaches have been employed to tackle the issue of transport-mode choices. First, models based on Random Utility Theory (RUT) (Bhat, 2002) have been attempting to evaluate the effectiveness of policy interventions aimed at solving traffic-related problems. For example, Basso et al. (2011) tackle the issue of congestion-pricing mechanisms, and propose a theoretical model in which agents can choose between using the car, the bus or the bicycle. The utility of different transport modes is modeled as dependent on specific features of the means of transport (e.g. cost, travel time, parking cost) and some socioeconomic characteristics of the individual (e.g. income, number of people in the household). The model allows optimization for bus frequency, fleet size and other variables concluding that dedicated bus lanes are a better stand-alone policy than congestion pricing or public transport subsidization. A RUT framework can also accommodate heterogeneity among individual travellers. This can be done using either a mixed-logit approach (Bhat, 2000) or a latent-class model (Ben-Akiva and Bierlaire, 1999). In particular, the latent-class approach allows the inclusion of non-observable variables such as individual latent attitudes concerning safety or pollution (Greene and Hensher, 2003; Hess et al., 2013).

Second, game-theoretical setups have been used to describe several transportation-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 transportation. 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, respectively, beyond the congestion faced by each transport mean. 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.

Third, 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 modeling framework, we focus on bus use as a specific alternative to the use of a personal car. Second, whereas Antoci et al. (2012) studies 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. Third, we try to provide a deeper interpretation of payoff parameters in terms of real-world forces and factors that can shape them. Fourth, we carry out extensive simulation 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 feel 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 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:

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

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

where $a, b, c, e \in (-\infty, +\infty)$, 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.

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).

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.

Table 1: *Interpretation of the parameters of the model*

Parameter	Meaning	Influencing factors	References
a	Net benefit of car use	Journey time Flexibility Effort minimisation Personal space and privacy Perceived monetary costs Control over the surrounding environment Non-instrumental motives	Steg (2005) Tertoolen et al. (1998) Gardner and Abraham (2007)
b	Negative externality on car users caused by cars	Congestion Stress and aggression Air pollution Health risks	Arnott and Small (1994) Lajunen et al. (1999) Beatty and Shimshack (2011) World Health Organization (2014)
c	Net benefit of bus use	Frequency Punctuality and reliability Fares Journey time Physical and social environment	Commission for Integrated Transport (2008) Guiver (2007) Steg (2005) Dell'Olio et al. (2010) Wall and McDonald (2007)
d	Externality on bus users caused by the diffusion of bus use	Crowded buses Safety	Guiver (2007) Stradling et al. (2007)
e	Externality on bus users caused by the diffusion of car use	Congestion Safety and health risks	Guiver (2007) Stradling et al. (2007)

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:

$$\dot{x} = x(1-x)[\Pi_A - \Pi_B] \tag{3}$$

where $\dot{x}$ is the time derivative of $x(t)$. The payoff difference can be re-written as:

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

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

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

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. Notice 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 equation (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 bus; and (*ii*) $d < g$ (i.e. $b > d + e$), in which the opposite applies.

4.1 Scenario $d > g$

In this first scenario, the term $(d - g)$ is positive, thus the curve representing the payoff difference is convex. Since the following conditions hold:

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

the dynamic regimes under equation (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 (Figure 1). These three conditions, respectively, imply that the payoff difference when $x = 0$ is positive; the payoff difference when $x = 1$ is positive; and the numerator of the ordinate of the vertex of the parabola representing the payoff difference is also positive[1]. This last assumption is essential for ensuring that the system ends up in the steady state where everyone uses the car, as it excludes the existence of multiple equilibria.

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 intersect the horizontal axis in two points, i.e. there will be two values of $\bar{x} \in (0, 1)$ such that $\Pi_{A-B} = 0$ (Figure 2). This outcome is confirmed

[1] The payoff difference can be rewritten as: $\Pi_{A-B} = x^2 - \frac{2d}{d-g}x + \frac{f+d}{d-g}$. Being the y-coordinate of a parabola equal to $y = -\frac{\triangle}{4a}$, in our case this value will be equal to $y = -\frac{1}{4}\left(\left(\frac{2d}{d-g}\right)^2 - 4\frac{f+d}{d-g}\right)$. This last equation can be rewritten as $\frac{df-dg-fg}{(d-g)^2}$, and as the denominator is always positive, the only condition needed for determining the sign of the whole fraction is the sign of the numerator.

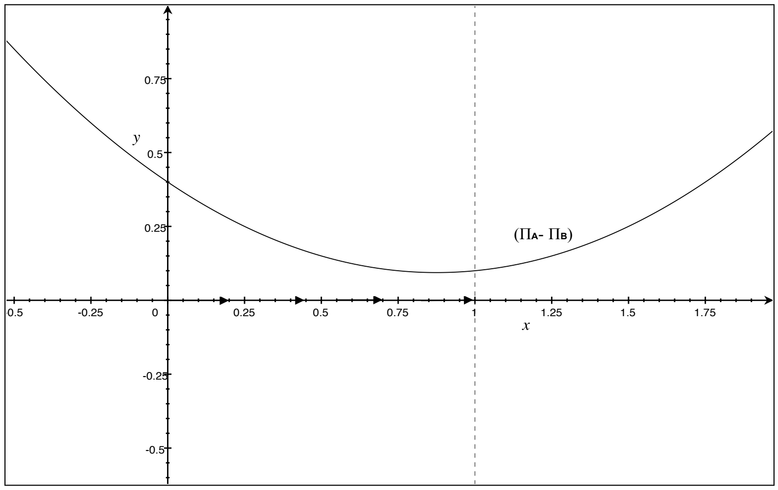

Figure 1: *Scenario $d > g$, Case (1).*

by the fact that, if $d > 0$, the x-coordinate of the vertex is positive[2].

The equilibrium which lays at a value closer to zero is an attractive one (x_1), while the other one 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 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.

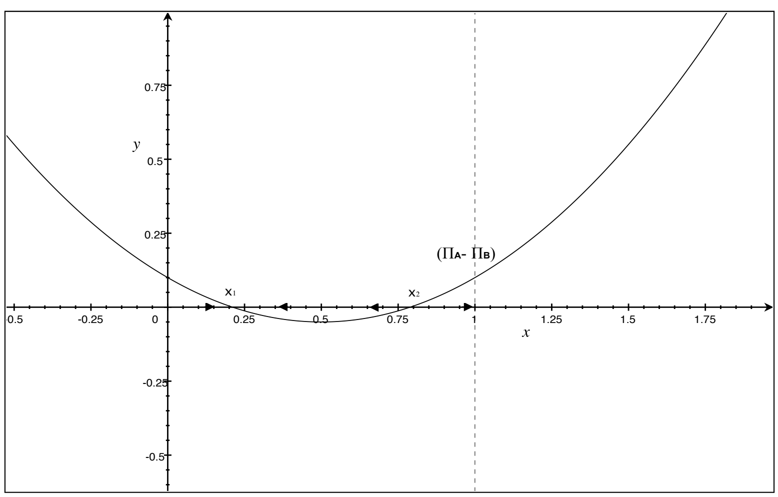

Figure 2: *Scenario $d > g$, Case (2).*

Case (3) If $f < -d$, $f < g$ and (consequently) $(df - dg - fg) < 0$ then, whatever the initial

[2] In fact, since the abscissa of the vertex of the parabola is equal to $\frac{d}{d-g}$, and 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, the two inner equilibria coincide and the resulting equilibrium is a saddle point

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 eventually converge to the stationary state $x = 0$, where the whole population chooses B (Figure 3).

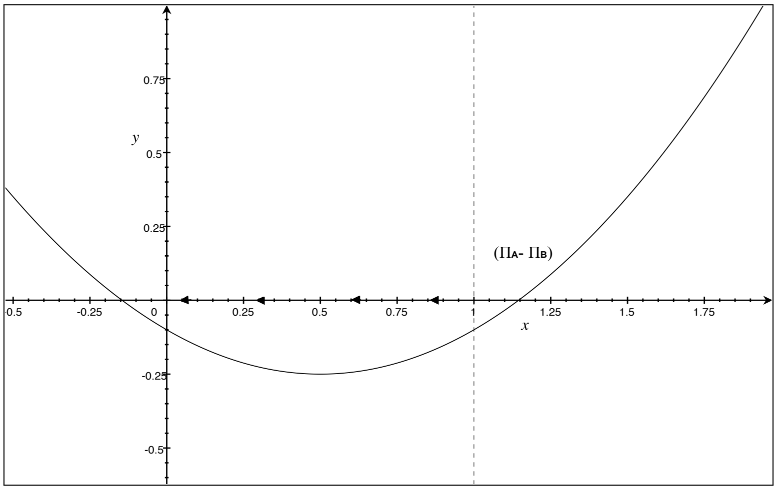

Figure 3: *Scenario $d > g$, Case (3).*

Case (4) 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 have one attractive equilibrium for $x \in (0,1)$ (Figure 4).

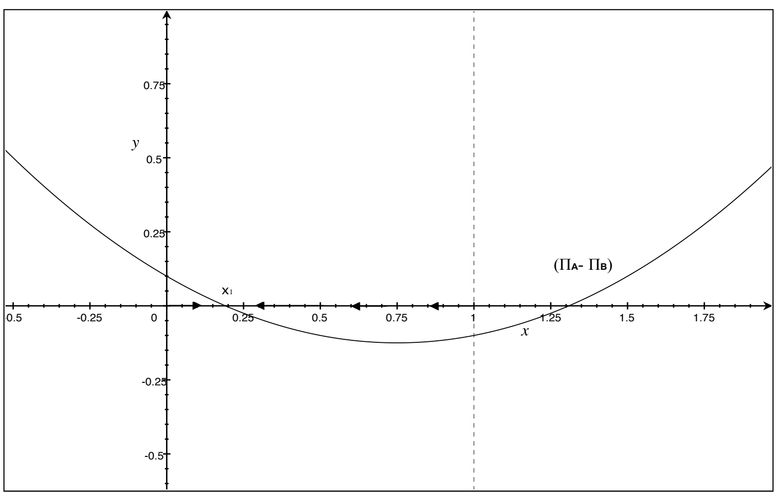

Figure 4: *Scenario $d > g$, Case (4).*

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 (Figure 5). 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.

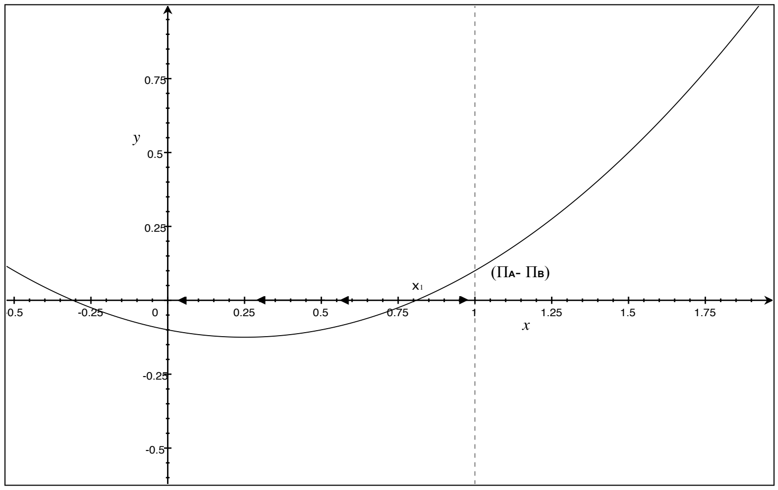

Figure 5: *Scenario $d > g$, Case (5).*

The outcomes of the model in first scenario are summarized in Table 2.[3]

No. of equilibria	Inner or extreme	Equilibria	Type of equilibria
1	extreme	$x = 1$ $x = 0$	attractive
1	inner	$x_1 \in (0, 1)$	attractive or repulsive
2	inner	$x_1 \in (0, 1)$ $x_2 \in (0, 1)$	one attractive, one repulsive

Table 2: *Model outcomes in the Scenario $d > g$ (payoff difference is convex).*

4.2 Scenario $d < g$

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

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

Similarly to the first scenario, the dynamic regimes under equation (3) can be classified as follows:

[3]Notice that the combination of the three conditions on the parameters taken into account could potentially give rise to 8 possible cases. For each scenario, however, we describe only the cases in which the three conditions can simultaneously be met, excluding those cases in which they are not compatible.

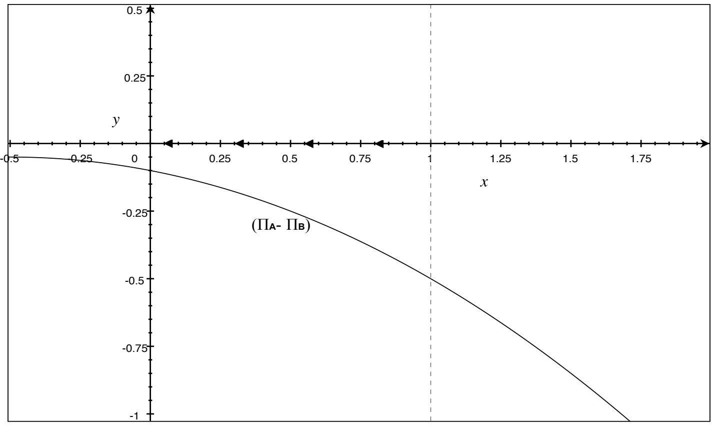

Figure 6: *Scenario $d < g$, Case (1).*

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 Figure 6).

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 (Figure 7).

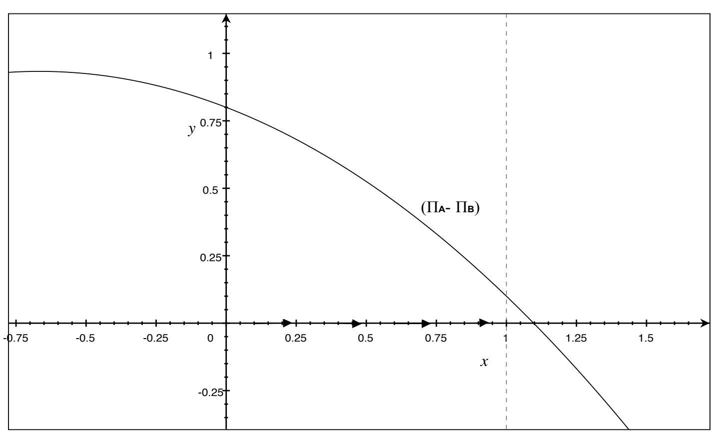

Figure 7: *Scenario $d < g$, Case (2).*

Case (3) If $f > -d$ and $f < g$ and (consequently) $(df - dg - fg) > 0$, then whatever the initial distribution of strategies $x(0) \in (0, 1)$, the system will have one attractive equilibrium for $x \in (0, 1)$ (Figure 8).

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

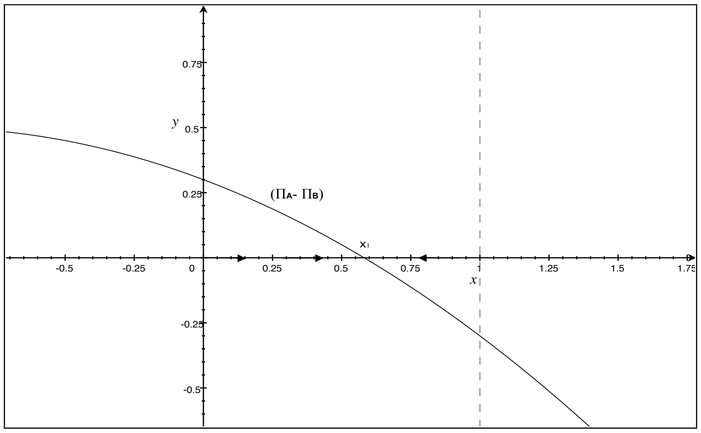

Figure 8: *Scenario $d < g$, Case (3).*

No. of equilibria	Inner or extreme	Equilibria	Type of equilibria
1	extreme	$x = 1$ $x = 0$	attractive
1	inner	$x_1 \in (0, 1)$	attractive

Table 3: *Model outcomes in the Scenario $d < g$ (payoff difference is concave).*

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.

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 $(d - b)$. If this is the case, the economy will move along a welfare-reducing path in the case described in Figure 1, while it will move along a Pareto-improving trajectory in Figure 3.

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. Figure 2 and Figure 4), whereas a welfare increase will occur if the economy moves in the opposite direction (as in Figure 5).

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 Figure 2. If we substitute the numerical values used in Figure 2[4] in equations 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 Figure 2) will be welfare improving, whereas a shift from x_1 to the extreme equilibrium $x = 1$ (cf. Figure 2) will be welfare reducing.

5 Simulation results and policy implications

Having determined the results of our model, 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

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

parameters change?

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. [5]

To perform our first comparative-statics exercise, we carry out a numerical simulation 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 the value of parameter a could occur, for example, if a higher tax on fuel is introduced. 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 simulation results. The solid line is the initial situation, i.e. the one presented in Figure 1, 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 Figure 9).

The same 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

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

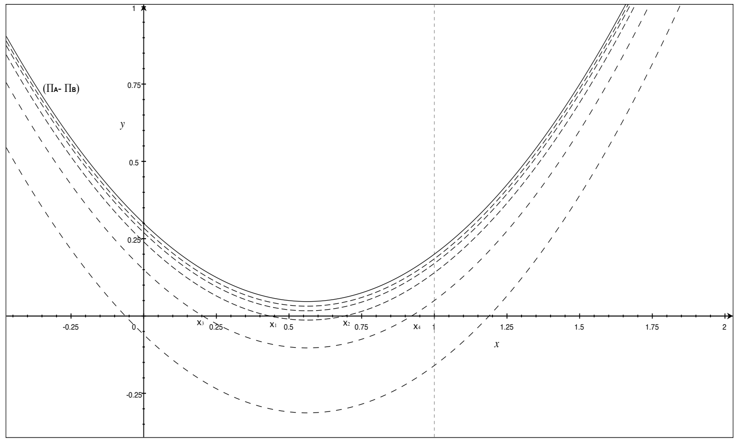

Figure 9: *The effect of a decrease in parameter a in scenario $d > g$, Case 1. The payoff-difference parabola shifts downward as a is reduced with respect to the baseline case ($a = 0.3$) by 5%, 10%, 20%, 50%, 120%. Other parameters: $b = 0.05$; $c = 0.45$; $d = 0.45$; $e = 0.4$; $f = -0.15$*

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 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 Figure 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[6]. 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

[6] 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.

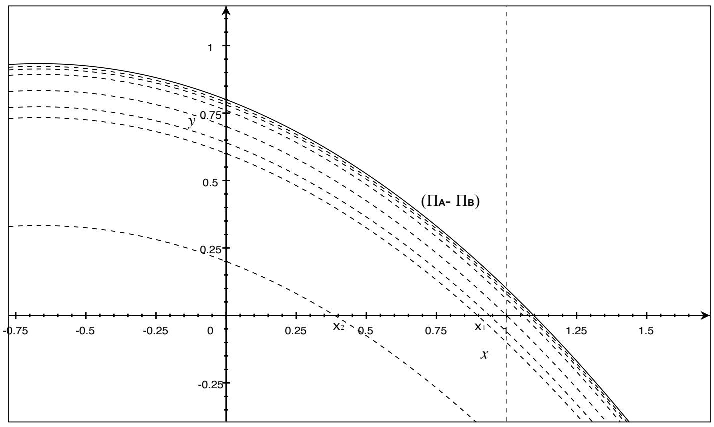

Figure 10: The effect of an increase in parameter c in Scenario $d < g$, Case 2. The payoff-difference parabola shifts to the left as c is increased with respect to the baseline case ($c = 0.2$) by 5%, 10%, 20%, 50%, 80%, 300%. Other parameters: $a = 0.8$; $b = 0.7$; $d = 0.2$; $e = 0.2$; $f = 0.6$.

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&Ride bus stop facilities or increase in service frequency.

5.1 Comparative Welfare Analysis

The welfare analysis introduced earlier can be applied to our simulation exercise in order to observe how changes in the value of parameters affect social welfare. In the comparative statics exercise illustrated in Figure 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 equation (6), the average payoffs in the four different equilibria is 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 Figure 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 simulation, 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, five and three 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 in 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 simulation 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 disincentive 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.

Finally, 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.

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