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Commuters' mode choice as a coordination problem: A framed field experiment on traffic policy in Hyderabad, India

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ABSTRACT

All major Indian cities face a severe transport crisis, with the number of cars on the road increasing every day. Policy makers are trying to keep pace with this growth by supplying more roads, largely neglecting demand-side policy measures. We have developed an economic experiment to investigate behavioral responses of citizens to such measures. Drawing on a sample of 204 white-collar commuters from Hyderabad, India, we model mode choice as a coordination problem and analyze how bus subsidies, increased parking costs, and public information on preferential car use can affect mode choice. We find that pecuniary treatments are effective for shifting behavior towards socially more desirable outcomes and increasing total benefits. Mode choice is relatively unaffected by socio-economic variables like gender, education or income but is significantly affected by actual traffic behavior. We discuss limitations of the applied sampling, conclude with a critical evaluation of the strengths and weaknesses of economic experiments in transportation research, and offer an outlook on how further experimentation could enrich the policy debate.

1. Introduction

India's economic growth is being fueled by the development of its cities, as the rapidly growing service sector has created many jobs in the urban centers of the sub-continent. Rising incomes have led to an expanding middle class and, in combination with population growth, to a tremendous increase in the number of cars in Indian cities. Especially in the megacities of Mumbai, Delhi, and Kolkata and the emerging megacities of Bangalore, Chennai, and Hyderabad, this has led to a "transport crisis." Authorities face the challenge of how to limit the growth of individualized traffic, find adequate ways of promoting public transport, and, more generally, develop a sustainable transport system (Pucher et al., 2005).

In attempting to confront this crisis, policy makers have largely focused on supply-side measures. With limited success, the dominant paradigm has been to increase supply of roads (Chidambaram, 2011) or focus on promotion of large-scale infrastructure projects, such as metro-rails (Mohan, 2008; Ramachandraiah, 2007). On the other hand, demand-side measures have not been adequately addressed in the policy debate on this issue (Chidambaram, 2011; Pucher et al., 2005). We believe that, to evaluate the scope of such measures, it is important to understand the preferences and actual decision-making processes of traffic participants, which can however be difficult and costly to do in practice. Stated preferences

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methods such as choice experiments have been widely applied in transport economics (cf. Ben-Akiva and Lerman, 1985; Ortúzar and Willumsen, 2011), and traffic psychologists have used survey research to investigate the role of attitudes in mode choice (Gardner and Abraham, 2007). Yet, these studies have not usually addressed the interdependence of individual choices and subsequent dynamics, which game theory and experimental economics explicitly do take into account. Furthermore, subjects in such settings are motivated by payoffs which, in principle, should largely determine their decision-making (Smith, 1976).

In transport modeling, various theoretical approaches have attempted to address the interdependence of travelers in mode or route choice (Hollander and Prashker, 2006). From the perspective of game theory, choosing between public and private transport can be understood as a coordination problem, because using a car appears to be more attractive when the number of cars is small, whereas public transport seems more attractive during periods of heavy traffic (Vugt et al., 1995).

In spite of their great potential, empirical applications building on game theory and using the empirical toolkit of experimental economics are still relatively rare in transportation research (de Jong, 2012). Also, focus has typically been on market modeling (de Jong, 2012), with only a few studies analyzing individual choices (e.g. Gabuthy et al., 2006; Hartman, 2012; Selten et al., 2007). As far as we are aware, no economic experiment has yet used traffic framing to study behavioral effects of demand-side policy measures in a developing country. Drawing on middle-class white-collar commuters from Hyderabad as a subject pool, we develop here an economic experiment to test behavioral response to three popular measures that have been discussed in the policy debate on demand-side policies (Wootton, 1999), namely, increasing parking costs, subsidizing bus fares, and providing information to enhance coordination. All three of these measures can be implemented by urban authorities, as opposed to fuel taxes, for instance, which would require policies on the state or central government levels. In the experiment, we investigate the effects of these measures on solving the coordination problem while analyzing the socio-economic determinants of mode choice and the role interdependence plays for individual choices.

In the next section, we provide background information on the transport policy debate and the neglected role of demand-side measures in urban India, focusing on Hyderabad. The third section introduces some key theoretical concepts, describes our empirical approach, and lays out the key research hypotheses. Sections four and five present the results and discuss our findings with regard to the policy debate. The concluding section assesses our approach and offers an outlook on how further experimentation could enrich the policy debate.

2. Hyderabad's transport crisis and the role of demand-side policy measures

According to a recent report on Hyderabad's traffic challenges, the city faces a severe mobility crisis (CSE, 2011). Every day, more than 600 vehicles are being added to the existing population of about three million vehicles. In fact, vehicle growth is faster than population growth by a factor of four, which is seen as one reason for the steady decline of travel speed over the last two decades (CSE, 2011). Frequent violation of traffic rules further adds to the problem (Dandona et al., 2005). Air pollution from traffic, especially from trucks, regularly reaches unacceptable levels and has contributed to an increase in respiratory disease and eye irritation (CSE, 2011; Sharma et al., 2010).

In spite of the ambitiously set targets for increasing the share of public transport to 80% in the City Development Plan (GHMC, 2006), the actual share of public transport has been constantly declining and is projected to drop from the current 35% to only 12% by 2031 (CSE, 2011). It will be important for the authorities to embrace more realistic planning goals in the future. Currently, the share of car trips is around 20% (CSE, 2011, p. 24). Under the Jawaharlal Nehru National Urban Renewal Mission (GoI, 2005) – a national funding scheme for urban infrastructure development – Hyderabad has received a tremendous amount of funding for investing in infrastructure (HPEC, 2011), the vast majority of which has been spent on constructing new roads and flyovers (CSE, 2011). However, these major public works have not led to substantial relief of the city's tense traffic situation. One of the key reasons for this is that road expansion has not been combined with the promotion of public and non-motorized transport (CSE, 2011). Also, the bus transport system has not been improved; instead, a costly and risky large-scale metro-rail is being planned. In the metro-rail planning process, citizens' preferences and attitudes have been widely neglected (Mohan, 2008; Ramachandraiah, 2007).

According to a recent study, more than 90% of surveyed citizens in Hyderabad perceive frequent congestion as a major problem for the city; there is great discontent with the public transport system, which is rated as "good" by only 16% of the population, as compared to 40% which describe it as "poor"; the majority of people believes that there is insufficient space for the use of bicycles and walking; and congestion caused by illegal parking is seen as a severe problem by about 92% (CSE, 2011). It would seem to follow from this that, from a citizen's perspective, parking costs and parking restrictions, subsidized and improved public transport, and restricted car use should be the most relevant demand-side measures to consider for Hyderabad. It is claimed that complementing supply-side measures with policies to manage demand can help in solving the problem of traffic congestion in cities (Bull, 2003; Ferguson, 1990). However, the question remains concerning what the chances of success for demand-side measures could be in an arena dominated by strong desires for technical solutions and monumental constructions as symbols of development.

Generally speaking, reducing the use of cars has not often been achieved voluntarily. Instead, demand-side management must use "carrots and sticks" to control travel behavior (Meyer, 1999), including measures such as parking costs, parking prohibitions, vehicle use restrictions, road pricing, provision of traffic information or subsidies for public transport (Bull, 2003; Ison and Rye, 2008). Pricing or coercive restrictions all have their particular merits and demerits, which have been extensively discussed in the literature (cf. Gärling and Schuitema, 2007; Schade and Schlag, 2003). In the Indian context, both India's National Urban Transport Policy and the Jawaharlal Nehru National Urban Renewal Mission have highlighted the importance of demand-side measures, such as funds for subsidized bus fares (GoI, 2006). However, implementation has been slow, with only three Indian cities – Jaipur, Delhi and Mumbai – having yet achieved some implementation of bus subsidies (Cropper and Bhattacharya, 2007; Tiwari and Jain, 2012). Until now, discouraging or restricting the use of cars has not been considered as an option by India's metropolitan authorities. Most likely, such measures are seen as being rather unpopular among the newly emerging middle and upper classes, so the underlying urban political economy is preventing their effective implementation.

Based on the policy debate just outlined, we have developed an economic experiment aimed at shedding some light on the effects three demand-side measures – bus subsidies, parking costs, and externally provided information – might have on individual behavior. More importantly, this experiment allows us to explore the socio-economic determinants of behavioral factors and to analyze the interdependence of individual choices.

3. The experiment

Different methods exist for studying traffic behavior, a variety of which are summarized in the following table in terms of some of their particular strengths and weaknesses. It also includes examples of recently published studies from this journal.

Table 1 shows that various tradeoffs exist when choosing a method, notably between different kinds of experiments.[1] Controlled lab and framed field experiments and agent-based modeling allow the study of interacting agents and emergent properties in dynamic systems. They are well-suited for testing general behavioral hypotheses, but it is sometimes difficult to extrapolate their results to the actual world. Survey methods offer a better fit in this regard and allow for rich data collection on many different aspects of actual transport behavior. However, it is often difficult to understand interaction between respondents. Case study research provides in-depth insights which cannot be obtained by any other method. However, it is more prone to response bias, and it is more difficult to establish causal theoretical links from such studies. In the end, we agree that pluralism and application of mixed-method designs will be important for helping us to understand complex phenomena from diverse methodological perspectives (see Poteete et al., 2010).

3.1. Behavioral game theory in transportation research

A variety of theoretical models exist for studying the interdependent behavior of individuals in transport research using game theory (Hollander and Prashker, 2006).[2] With respect to mode choice, "commuting by car is more attractive" when "fewer individuals choose to go by car because of a lower probability of time delays caused by traffic jams and/or parking problems. However, when the number of other people commuting by car exceeds a certain limit, the choice for public transportation may yield greater outcomes for oneself because congestion can be avoided" (Vugt et al., 1995).[3] Expectations about the behavior of others, hence, become critical for determining choice and subsequent utility and payoffs.

Coordination problems have been widely studied under lab conditions in macroeconomics or in so-called market entry games (see, for example, Cooper, 1999 and Erev and Rapoport, 1998 for reviews). Lab applications in transportation research are, however, still rare (de Jong, 2012). Table 2 summarizes some key experimental studies in relation to our own.

As Tables 1 and 2 show, in spite of their growing popularity, "framed field experiments" have not yet been applied in transportation research. According to Harrison and List (2004), economic field experiments can be categorized by the nature of the subject pool, available information, the commodity traded, trading rules, the stakes, and the environment subjects are placed in. Using a non-student subject pool and a contextual framing, our experiment would qualify as a framed field experiment.

[1] Experiments in which subjects undertake a task in their natural environment and typically do not know that they are part of an experimental study are called "natural field experiments" within the taxonomy of Harrison and List (2004). An example of such an experiment in the transport realm would be Knockaert et al. (2012). In this study, participants were sampled through noting down license plates of frequent commuters on the Dutch highway A12 and contacting them by mail. In addition, snowball sampling was used. Participants then received rewards for avoiding morning rush-hour traffic. Subjects knew they were part of an experimental study, but their behavior was observed in a natural context which is sufficient for qualifying as a "natural field experiment" within the Harrison and List (2004) taxonomy. In a developing-country context, such experiments can be logistically very demanding, however. It is a particular strength of "framed field experiments" that they can be carried out more easily. They can also be more directly related to economic theory, whereas "natural field experiments" have the great advantage of higher external validity. For a critical review on the relationship of the two, see Harrison (2013).

[2] Most empirical experimental applications focus on coordination problems. When the focus is on environmental externalities, the underlying game resembles a social dilemma (Vugt et al., 1995). There is an emerging literature (Chidambaram, 2011; Frischmann, 2012) which is trying to integrate the economics of infrastructure with the literature on common-pool resources, under the assumption that car drivers, by "subtracting road space," may create a "tragedy of the commons" (Hardin, 1968), with each car user reducing the utility of infrastructure use for everyone else.

[3] Note that this relationship holds only if public transport is unaffected or less affected by congestion. Such coordination problems also exist for route choice or the starting time of a journey (Selten et al., 2007).

Coordination games are also largely absent from the growing body of "lab-to-the-field" experiments (Viceisza, 2012). Thus, our study differs from previous experiments in the transport realm in at least three important aspects. Firstly, by altering payoffs and framing, we have studied the effect of policy measures on behavior. Secondly, we have conducted the first lab-to-the-field experiments with non-student subjects in transportation research. Thirdly, we have conducted the first experiment on traffic behavior in a developing-country context.

In addition to context-related framing and nonstandard subject pools, experimental research on the collective management of natural resources has often gained additional insights from employing post-experimental surveys to gather socio-demographic information on experimental subjects and using this data in econometric models (Hayo and Vollan, 2012; Vollan, 2008; Werthmann, 2011). We have taken up this approach, as it allows us to identify individual characteristics which may affect mode choice in an experimental context.

3.2. Experimental design and hypotheses

Our experiment was a coordination game with n (=6) players who each make a choice to use a bus ($x = 0$) or car ($x = 1$) for commuting. The payoff for the individual player depends on their own decisions and those of the other players, as depicted in Table 3.[4] Payoffs are inversely U-shaped and follow Greenshields' (1935) speed-flow model.[5] The social optimum is to have one car and five participants riding the bus. Note that the individual in the car will have a higher payoff in the social optimum. Therefore, the social optimum is unstable. If players are selfish and rational, and expect that others are too, they will chose the car if they expect there are zero, one or two other participants choosing it. If participants expect three or four other participants to choose the car, choosing the bus leads to better earnings. The participant is indifferent if she expects all others to choose the car. Hence, there are various Nash equilibria, dependent on the expectations of the participants.

Participants' payoffs include operating costs as well as travel time. The latter depends on the choices of the other players, since both cars and buses use road space. In spite of low car ownership, the streets of Hyderabad are already heavily congested, so already at low fractions of car use in the experiment (e.g. when going from one to two car users out of six), congestion is taken into account by a reduction in payoffs for both, car users and bus users. If more persons will use the car, congestion will get worse and the payoffs for both modes will be further reduced.[6]

The instructions of the experiment were framed as a traffic mode-choice decision situation: White-collar participants ($n = 204$, grouped in 34 experiments) were asked to picture a situation where every morning they would decide to take either a bus or car to commute to their offices. Individual payoffs depended on the decisions of five other commuters who also face the same binary choice. If many participants chose the car, travel times would increase and, hence, the expected benefit from car travel would decrease. As in actual traffic behavior, the choices of other players are known only after a particular round and only in aggregation (i.e. the total number of car drivers and bus passengers). A table depicting payoffs, based on each player's own choices combined with those of the other five subjects, was handed out to each participant on paper (see section two in Supplementary material).

Based on the policy debate outlined in Section 2, the following hypotheses were formulated.

H1. Increasing the attractiveness of taking a bus versus a car by changing the payoff structure through a bus subsidy or parking cost will lead to a higher proportion of participants choosing the bus.

H2. Coordination improves when participants do not have to rely solely on self-coordination. By providing them with a model of how to behave when facing an ill-defined problem, the sum of payoffs can be increased.

To test these hypotheses, we designed the following treatments: A baseline scenario was combined with three treatments in a mixed within- and between-subjects design, which is summarized in the following table.[7]

Table 4 shows that each of the 204 subjects needed to make 18 binary decisions. Groups were randomly assigned to either the bus subsidy or the parking cost group. Both treatments modified payoffs by either adding or subtracting three tokens to/from the baseline payoffs, providing pecuniary incentives to change behavior.[8] The psychological effects of the framing might have induced loss aversion in the parking cost treatment, whereas the bus subsidy may have been perceived as a gain (Tversky and Kahneman, 1991).

[4] The payoffs in the table are presented in "tokens." One token is equal to one Rupee paid to the subject after the game.

[5] For more details on how the payoffs were calculated, see the Supplementary material below.

[6] Note that, in another game, one could assume separate bus lanes. This would result in a lower decrease in payoffs for choosing the bus. Travel time would stay constant independent of cars, and comfort would be slightly reduced (crowding in the bus). The specific design of payoffs will then depend on commuters' preferences for travel time and comfort.

[7] Our rationale for choosing this design was based on several pre-tests run by the authors with German graduate students. The results of this testing are not published and were only used to improve the instructions and questionnaire. In principle, within-subject designs allow for more powerful statistical testing, as all fixed effects such as gender are effectively controlled for within subjects. On the other hand, within-designs are more prone to demand, learning, ordering effects and fatigue. A recent discussion on the topic can be found in Charness et al. (2012).

[8] Note that there are other important transport policies which are beyond the scope of this paper. These include, for instance, the promotion of shorter and fewer trips, higher car-occupancy ratios, and non-motorized transport.

Table 1
Schematic methodical literature review with empirical examples in relation to this study. *Source:* own formulation.

Method	Strengths	Weaknesses	Recent TR-A example
Lab experiments	Behavioral control (Monetary) incentives Interaction of agents	Artificiality Design limitations, with only a few factors which can be studied	Sunitiyoso et al. (2011)
Framed field experiments	Behavioral control (Monetary) incentives Interaction of agents	Artificiality Design limitations, with only a few factors which can be studied	This study
Natural field experiments and field trials	Some behavioral control Behavior under real world incentives	Design limitations, with only a few factors which can be studied Relatively low control, survey information often hard to obtain High costs	Schuitema et al. (2010)
Agent-based Modeling	Study of interaction and dynamics in complex systems over long periods of simulation Large combinations of factors and their interaction can be studied	Artificiality Empirical calibration often difficult	Guo et al. (2013)
Survey-based stated and revealed preferences methods	Random sampling and subsequent statistical generalization Detailed quantitative information on respondents and preferences	No interaction No incentives In some cases of stated preferences "hypothetical bias"Sometimes "social desirability bias"	Beck et al. (2013)
Participatory methods and case study research	Allows complex narratives In-depth understanding of motivations	Often very context-specific Difficult to establish causal relationships Difficult to measure effects	Wahl (2013)

In the public coordination treatment (testing H2) players were informed that, to enhance coordination and increase social benefits, a "central planner" would announce one player who would be allowed to take the car in one particular round and that every player would be allowed to do so exactly once.[9] There was to be no enforcement or sanctioning implemented regarding this restriction – a condition which was also explained to the subjects. Thus, each participant was still free in her or his decisions, meaning that it was possible to choose the car when it was "someone else's turn" or to take the bus when one's car-taking turn was announced. Assuming a "purely economic" approach to rule violation[10] (Becker, 1968), observed treatment effects would, thus, not result from a change in the payoff structure but rather from a change of expectations regarding the behavior of others or from "moral discomfort."

Aggregate payoffs were maximized if only one subject chose the car. In the two treatments which modified payoffs, group payoffs were also maximized if everyone went by bus, although with different distributional effects. Individual strategies deviated from the social optimum, as Nash best responses depend on subjects' expectations of what others will do. In the baseline and public coordination treatments, it was individually rational to choose the car if a player expected two or less other players to also take it. Players were indifferent when three other cars were expected. When treatments were implemented, this changed. Here subjects were able to increase their payoffs by taking the car only if not more than one other player chose it as well. Thus, in all treatments, the Nash best response clashed with the social optimum, defined as the combination of choices which maximizes aggregate payoffs.

3.3. Sampling and practical conduct of the experiment

The experiment was run with 204 subjects in 34 groups on 21 days in August and September 2012 in Hyderabad. Subjects were recruited according to their familiarity with the task, because it is not necessarily the case "that abstract, context-free experiments provide more general findings if the context itself is relevant to the performance of subjects" (Harrison and List, 2004). In other words, subjects should have experience with *both* car and bus use. In Hyderabad, white-collar workers commuting to their offices fulfill these conditions best, and participants were recruited from offices throughout the city, including employees from private companies, government bureaucrats and universities. Some of the organizations were known to the authors, others were contacted by telephone from the telephone directory. Break rooms or conference rooms of respective buildings where participants worked were used to run the experiment, and in most cases participants knew each other. Results were announced to all players after each round, though maintaining the anonymity of their choices. Subjects were not allowed to talk, and they were seated in a way that they could not directly see each other. A short general introduction was given by a facilitator. After questions from players were answered, subjects then received written instructions for the first exercise. After completion, instructions for the next exercise were distributed. Following the experiment, a brief survey

[9] This was done by announcing the ID Code of the player, which was only known by the respective player, not by the others.
[10] Here we refer to the rule that a player is "allowed" to take the car only in one out of six rounds. However, no monetary consequences resulted from violating this rule.

Table 2
Schematic empirical literature review in relation to this study. *Source:* own formulation.

Reference	Description and results	Subject pool and mode of conduct
Gabuthy et al. (2006)	Route choice as a coordination problem Predicted Nash equilibrium is not reached; behavior is sensitive to tolling regime	96 Management students from Lyon, France Computer-based lab experiment
Hartman (2012)	Route choice as a coordination problem under an efficient toll (external travel cost added to others is internalized through the toll) Travel time is substantially reduced by the toll, and the outcome under the toll is close to efficiency	180 subjects (not further specified) Computer-based lab experiment
Iida et al. (1992)	Route choice as a coordination problem No equilibrium reached and substantial fluctuations until the end	40 civil engineering students from Kyoto, Japan Computer-based lab experiment
Schneider and Weimann (2004)	Congestion externalities as a social dilemma Treatment which allows subjects to play with more than one car increases efficiency (externality is partly internalized)	40 economics students from Magdeburg, Germany Computer-based lab experiment
Selten et al. (2007)	Route choice behavior as a coordination problem Fluctuations persist; no convergence to Nash equilibrium; subjects who switch a lot earn less	216 economics students from Bonn, Germany Computer-based lab experiment
Sunitiyoso et al. (2011)	Mode choice as a social dilemma (public good game); treatments with communication and feedback/information on contributions in other groups No statistically significant effect of the treatments on contributions to the public good	15 post-graduate students from the University of West England, Bristol, UK Computer-based lab experiment without financial incentives
Vugt et al. (1995)	Mode choice between coordination problem (travel time) and social dilemma (environmental concerns) with a psychological focus on attitudes/social values Social-value orientations can explain mode choice	56 citizens of Maastricht, the Netherlands, recruited through newspaper advertisement Computer-based lab experiment
Ziegelmeyer et al. (2008)	Departure time as a coordination problem Congestion occurs according to prediction; information, number of drivers and costs of delay have no effect on behavior	128 students from Strasbourg, France Computer-based lab experiment
This study	Mode choice as a coordination problem Treatments of different policy measures	204 commuters from Hyderabad, India Pen-and-paper field experiment

Table 3
Payoffs for baseline rounds. *Source:* own formulation.

Players' aggregate choices (number of cars/number of bus users)	0/6	1/5	2/4	3/3	4/2	5/1	6/0
Individual payoffs if car	–	23	18	14	9	4	0
Individual payoffs if bus	15	14	13	12	9	0	–
Summed payoffs	90	93	88	78	54	20	0

was conducted which contained questions on the socio-economic background of participants, their everyday traffic behavior and their attitudes regarding different policy measures and traffic-related problems.

A typical session lasted about one and a half hours. Subjects received a show-up fee of 200 Rupees (about four US Dollars) plus their variable experimental earnings.[11] We provide a description and summary statistics of the variables used in the analysis in Table 5.

The table shows that only eleven percent of the participants actually own a car.[12] On the other hand, half the participants use a car at least once a month. It should be noted that the Indian situation is very different from that in Western countries. Cheap labor allows even middle-class people to have drivers. Especially in Hyderabad, "travel agencies" offering relatively cheap car rental are prevalent and it is not uncommon to rent cars with drivers on a daily basis. Often only professional drivers have licenses; thus, the use of data on driving licenses is not very informative regarding people who make the decision to use cars. Sampling more "upper class" participants might have resulted in a sample with higher car ownership. On the other hand, this subject pool would very likely have problems relating to the option of taking a public bus. Indeed, about a fifth of the sample

[11] Median, mean, standard deviation, minimum, and maximum of the variable earnings were 234, 237, 28.55, 146, and 322 Rupees, respectively. For our sample, the mean earnings are approximately equal to half of a daily wage. One survey item asked about the degree of agreement with the statement "I could understand the instructions of exercise 1," to which more than 90% of the subjects chose "strongly agree" or "agree" on a five-point Likert scale. About half of the sampled subjects were using a car at least once a month. This gives us some evidence for claiming that the instructions were clear enough for subjects and that familiarity with the task was likely among our selected sample.

[12] Exact figures on car ownership of private households are not available for Hyderabad. There are about 300,000 cars registered – including all vehicles which are used for commercial purposes – in the city (CSE 2011, p. 25). With a total population of about eight million people, these figures give us some indication that car ownership is above the average in our sample. In the game, the situation was described as "using your own car." This may be a small drawback in the framing of the instructions, as there are several ways to use a car without owning one in Hyderabad. On the other hand, for most middle class participants owning a car is within reach, at least in the medium term. The game abstracted from this point, ownership of driver licenses, and having more than one person in a car, which could all be important points to explore in further research.

Table 4
Overview of the experimental design. *Source:* own formulation.

	Exercise 1 (6 rounds)	Exercise 2 (6 rounds)	Exercise 3 (6 rounds)
Bus subsidy group, 17 groups of six players, 102 subjects	Baseline treatment	Bus subsidy treatment (+3 tokens for taking the bus)	Public coordination
Parking cost group, 17 groups of six players, 102 subjects	Baseline treatment	Parking cost treatment (−3 tokens for taking the car)	Public coordination

was not using buses at all at the time of the experiment. After careful assessment of the pros and cons of sampling different subject pools, we decided to look for a target population for whom deciding between bus and car was really an option.

Compared to the general population of Hyderabad, our sample is apparently biased towards males with high income. On the other hand, we believe it is more representative of the commuting white-collar population, because it includes many subjects who qualify as part of the new emerging middle class of India, for whom car ownership is becoming an attainable goal.

4. Results

4.1. Analyzing treatment effects

In the baseline condition, we see an increase of car usage over the rounds. Initially, about two of the participants chose a car on average. These figures increase to about three in round 6 as can be seen from the following figure.

Introduction of the bus subsidy or parking fee initially has a positive effect on the group, but over time we see an increase of choosing the car. The same happens when we move to the public coordination treatment. It can also be seen that, on average, players choose the car "too often." In all rounds there is more than one car on average, suggesting inferior outcomes for most groups. Recall that in the baseline rounds and in the public coordination treatment it is individually rational to choose the car only when two or less other players use one. On average, players stayed within the limit of having three or less cars in total in these rounds. In the two pecuniary treatments, it is individually rational to choose the car if one expects not more than one other player to use one. However, on average, choosing the car was fairly above the 33% which would have been individually rational.

Fig. 2 depicts the average proportion of subjects choosing the car during the various exercises across the two different versions of the game.

As can be seen from the figure, introducing the treatments reduces the number of cars relative to the baseline. The pecuniary treatments demonstrate a larger decrease in the number of cars chosen as compared to the public coordination condition. With the new treatment in round seven, we observe a sharp drop in cars chosen (see Fig. 1).[13] Compared to the first six rounds, the number of cars is slightly lower in rounds 7–12, but, on average, this effect is not very large. Introduction of the public coordination treatment (in round 13) prompts a small difference. Aggregated across all six rounds, the bus subsidy treatment reduced the proportion of cars from 47.9% to 39.4% compared to the baseline treatment. Formal hypothesis testing by comparing the first round of each treatment reveals that the difference is not statistically significant at the five-percent level (McNemar's test $\chi^2 = 3.10$; $p = 0.0782$). If we compare rounds six and seven, however, the difference in the drop – more than 20% – becomes highly significant (McNemar's test $\chi^2 = 11.52$; $p = 0.0007$).

The parking cost treatment reduced the proportion of cars from 41.3% to 37.4%. Testing for the difference between subjects' decisions in rounds one and seven reveals, however, that this difference is only a small one and statistically not significant (McNemar's test $\chi^2 = 0.27$; $p = 0.6015$). The proportion of cars drops from 45% to 30% when comparing rounds six and seven, however, and this reduction is statistically significant (McNemar's test $\chi^2 = 5.44$; $p = 0.0196$).

Compared to the baseline scenario, introducing public coordination reduces the proportion of cars from 44.6% to 41.8% (McNemar's test for first round decisions $\chi^2 = 0.00$; $p = 1.0000$). The difference between the bus subsidy and the parking cost treatment is small, with proportions of 39.4% and 37.4%, respectively. Testing these proportions between subjects for the decisions made in round seven reveals that this difference is not statistically significant (Two-sample test of proportions $z = -0.15$; $p = 0.8795$). The difference between rounds 12 and 13, that is, the pecuniary treatments and the public coordination treatment, is also not significant (McNemar's test for the increase in the parking cost treatment $\chi^2 = 1.60$; $p = 0.2059$ and for the decrease in the bus subsidy treatment $\chi^2 = 0.11$; $p = 0.7456$). However, aggregated earnings of players are higher in the public coordination treatment (79.73 Rupees) as compared to the baseline scenario (75.94 Rupees). This difference of about five percent is statistically highly significant (Paired t-test $t = -4.0543$; $p = 0.0001$).

[13] This might be explained by a "restart effect." In that case, the introduction of a new treatment acts as a new opportunity for coordination. What happens later in a particular treatment may also be influenced by results of earlier rounds. We have, thus, compared the *first* rounds of each treatment and *neighboring* rounds across treatments with each other.

Table 5
Description and summary statistics of independent variables. *Source:* own calculations, based on field data.

Variable name	Description	Obs.	Mean	SD	Min	Max
MALE	=1 if subject is male	204	0.71	0.45	0	1
AGE	Age in years	203	31.00	9.95	17	60
MARRIED	=1 if married	202	0.49	0.50	0	1
INCOME1	=1 if income below 5000 Rupees per month	172	0.08	0.27	0	1
INCOME2	=1 if income between 5000 and 15,000 Rupees per month	172	0.22	0.42	0	1
INCOME3	=1 if income between 15,000 and 50,000 Rupees per month	172	0.49	0.50	0	1
INCOME4	=1 if income between 50,000 and 100,000 Rupees per month	172	0.16	0.37	0	1
INCOME5	=1 if income above 100,000 Rupees per month	172	0.05	0.21	0	1
OWNSCAR	=1 if households owns a car	204	0.11	0.32	0	1
OWNSBIKE	=1 if households owns a motorbike	204	0.50	0.50	0	1
CARFREQ1	=1 if respondent is never using the car	203	0.50	0.50	0	1
CARFREQ2	=1 if respondent is using the car up to ten times a month	203	0.33	0.47	0	1
CARFREQ3	=1 if respondent is using the car up between ten and 20 times a month	203	0.08	0.27	0	1
CARFREQ4	=1 if respondent is using the car more than 20 times a month	203	0.09	0.28	0	1
BUSFREQ1	=1 if respondent is never using the bus	202	0.20	0.40	0	1
BUSFREQ2	=1 if respondent is using the bus up to ten times a month	202	0.31	0.46	0	1
BUSFREQ3	=1 if respondent is using the bus up between ten and 20 times a month	202	0.17	0.38	0	1
BUSFREQ4	=1 if respondent is using the bus more than 20 times a month	202	0.33	0.47	0	1

Summing up, the pecuniary treatments moderately reduce the number of cars on average. This effect is small, however, and is statistically significant only when comparing rounds 6 and 7, not when comparing the first rounds of the treatments. Also, the reduction of cars induced by the public coordination treatment is relatively small. Yet it did help players to achieve significantly higher earnings in the public coordination condition.

Another way to evaluate the monetary demand-side policy measures used is from the perspective of total social benefits created and efficiency,[14] including for the "transport authority." Table 6 below depicts aggregated earnings and choices by treatments.

This table presents calculations taking into account the costs and benefits of the policy treatments. As can be seen, both policies increase total benefits over the particular rounds. But the parking cost policy generating earnings for the transport authority in the game and the bus subsidy introducing a cost are factors that should also be carefully considered. The net benefit increases by 52 Rupees in the bus subsidy condition (from the second to the third column in the last row of the table) and by 621 Rupees in the parking cost condition (from column 4 to column 5 in the last row of the table). Under the bus subsidy condition, players' earnings are raised by 1165 Rupees in total. However, this comes at a high cost of almost the same size for subsidizing bus rides (1113 Rupees). Note that in the parking cost condition player earnings are reduced by only 66 Rupees while, at the same time, the parking fees generate an income of 687 Rupees for the transport authority. It can thus be said that, in our game, the parking cost measure appears to have been more efficient.

4.2. Analyzing the socio-economic determinants of mode choice

Table 7 presents six specifications of binary logistic regression models on subjects' mode choices in the experiment (0 = bus, 1 = car). The first five columns pool the data. The sixth column presents coefficient and standard error estimates of a random effects model. To study the effect of socio-economic characteristics on mode choice, we have included the independent variables described in Table 5 to models (3) to (6). The first model uses only the dummy variables on the treatment. The second model includes other variables from the game. The third model (3) tests for learning effects by including the round as an independent variable.[15] In model (4), we have included dummy variables on the treatments (PARKCOST, BUSSUB, and PUBCOORD), and in the fifth column (5) we have also included variables for the number of cars in the previous round (of a treatment) to test for changes in expectations based on what others have done in the previous round.[16] We use dummy variables to capture expected non-linearity in the effect (from the game design and the underlying coordination problem). Models

[14] This is also very often done in social dilemma experiments with punishment or communication. Typically, subjects – when given a choice – opt for sanctioning institutions (Gürerk et al., 2006). Cooperation typically increases with communication (Sally, 1995) and (costly) punishment (Fehr and Gächter, 2000). However, it has also been shown that efficiency is not always increased when punishment is costly. Gains from increased cooperation are sometimes outweighed by punishment costs (Ohtsuki et al., 2009; Bochet et al., 2006).

[15] Due to multicollinearity – with the highest estimated variance inflation factors (VIF) being 12.30 in a linear probability model – specifications including both the round and the treatment dummy variables are not presented here. Estimation results of the respective linear probability models are presented in the Supplementary material. A VIF indicates the degree of uncertainty with respect to a coefficient's standard error estimate in a linear regression. The square root of a VIF indicates how much larger a standard error estimate is due to correlation of the independent variables. Such bias in standard error estimates will also affect test statistics and p-values which ultimately may result in erroneous conclusions. Note that coefficient estimates are not affected by collinearity.

[16] In these two dynamic models, observations of the first round of a treatment (i.e. rounds 1, 7, and 13) have been excluded, which explains the smaller number of observations. In these models (columns 2, 5, and 6 in the table), 1CAR is a dummy variable taking the value of 1 for round t if there has been in total *one* player in round $t-1$ choosing the car; 2CARS takes the value of 1 if *two* players in the previous round have chosen the car, and so on. The reference category for this variable is "no cars," i.e. all players have chosen the bus.

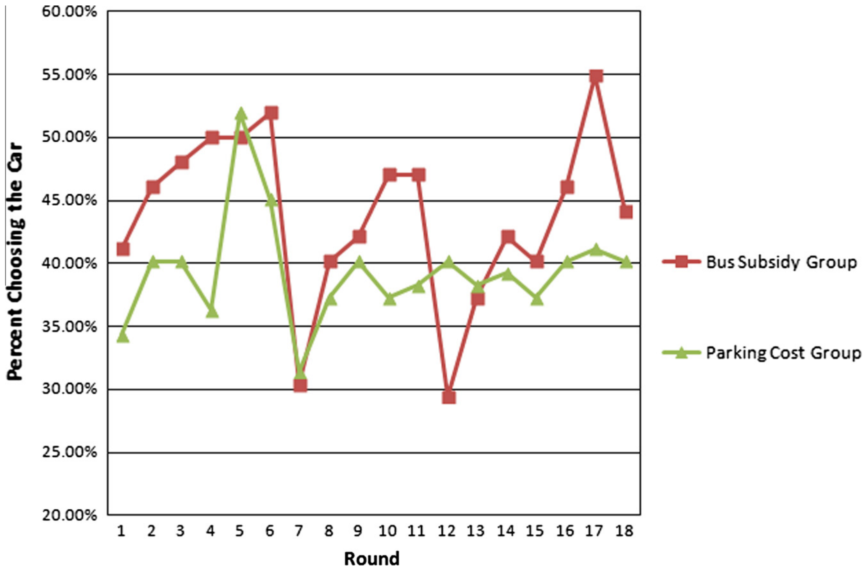

Fig. 1. Relative frequency of choosing the car by rounds and between-subject treatments. *Source:* own design, based on field data.

(2), (4), and (5) also include the variable CARPREVROUND, indicating whether a player has chosen the car in the previous round, and the variable ALLOWED, a dummy variable indicating whether a particular player was the one who was "allowed" to take the car in a particular round of the public coordination treatment.[17] Model (6) uses the same data as (5), but with a random effects model for estimation to address the serial correlation of the 18 choices observed per subject.

In all models, coefficients for the MALE variable are negative, indicating that women are more likely to choose the car. This is in line with our expectations, as women in India are usually more sensitive to security issues on public transport, such as harassment in buses. However, the coefficients are not very large and also not statistically significant at the five percent level. Coefficients of age and marital status are also relatively small and not statistically significant.

The effects of income are fairly small in the estimations. Especially respondents in the second-lowest income category are somewhat less likely to choose the car, when compared to the lowest income category. All other income categories are very similar to the lowest, as indicated by the coefficient estimates, which are close to zero. Our interpretation here is that the poorest participants in our sample may want to demonstrate their ambition for "upward mobility" by choosing the car more often, whereas the rich are more used to choosing the car. Overall these effects are fairly small, however.

It is a bit surprising that owning a car does not increase the propensity to choose one in the experiment. Three out of four estimated coefficients even have a negative sign, indicating a possible opposite effect. However, as pointed out earlier, owning a car may not be critical for the decision to use one. Looking at the coefficient estimates of the CARFREQ variables reveals that actually using a car has the expected positive effect on choices in the game. However, both the OWNSCAR and the CARFREQ variables are statistically not significant. The same applies to the coefficient of OWNSBIKE, which is small and statistically not significant.

The frequency of using the bus has the expected negative sign, and coefficients are comparatively large and statistically significant. It is notable that the effect can largely be attributed to the step from "not using the bus at all" (BUSFREQ1, the reference category) to one of the other categories, as coefficients of BUSFREQ2, BUSFREQ3, and BUSFREQ4 are fairly close to each other. The treatment dummy variables are jointly significant, with the two pecuniary treatments being a little less effective than the public coordination treatment. The effect of ROUND is virtually zero in model (3), indicating no substantial change of choices over time.

The coefficients of the variables added in models (3) to (5) show that the players change their behavior – only to a limited extent, however – depending on what others do in the game and depending on the particular treatment. The high and significant coefficient of CARPREVROUND in models (2), (4), and (5) suggests that players tend to repeat their choices, but the random effects model which addresses the serial correlation within subjects almost eliminates this effect. Thus, the overall effect can be assumed to be zero. Coefficients of the ALLOWED variable are large and statistically significant in all three models. This indicates that, when subjects are encouraged to choose the car in a particular round of the public coordination treatment, they are relatively likely to use this opportunity. The high coefficient estimates of the dummy variables of the number of cars in the previous round suggest that, even when many others choose the car, the likeliness of a particular player choosing the car remains relatively high. Taken together, the increase in the χ^2-value from (4) to (5) is relatively small, however. A

[17] Likelihood ratio tests for the categorical variables with more than one category are presented in the Supplementary material.

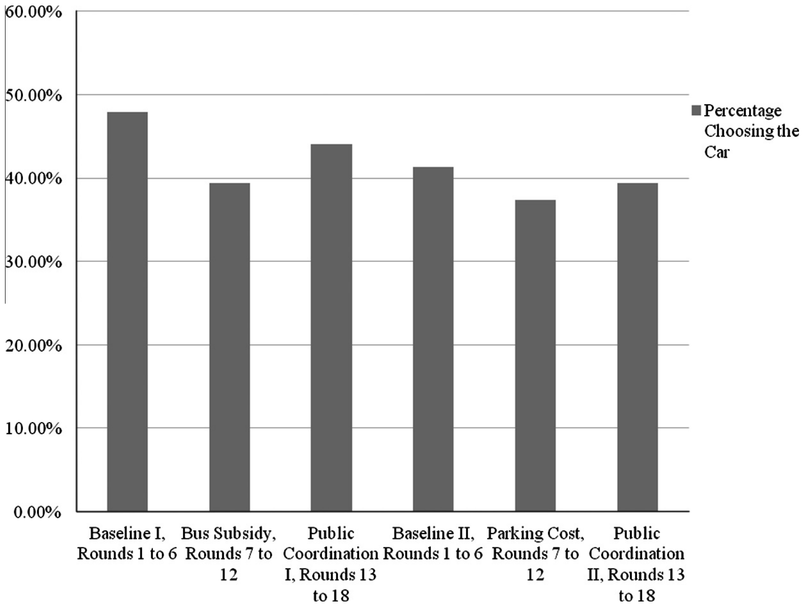

Fig. 2. Proportion of car users for each exercises. *Source:* own design, based on field data.

likelihood ratio test shows that the two models are equivalents.[18] Coefficients of the included dummies are relatively close to each other. This indicates that most of the increase in explanatory power can be attributed to the large difference between those cases where there are no cars (the reference category) to any other scenario. In other words, when no one chooses the bus in round t, the likeliness of a player choosing the car in round $t + 1$ is substantially higher. If one or more players choose the car in round t, the effect on choices in round $t + 1$ was relatively small.

5. Discussion

Our results show that the introduced treatments induce a modest increase in choosing the bus in the game. Increasing the parking costs or subsidizing the bus in the game has a positive effect, although in some cases these changes are statistically not significant. When also taking into account the costs and benefits for the "transport authority," our results show that both policies produce net benefits, although with a substantially higher degree of efficiency under the parking-cost condition. In this treatment, players' total earnings are reduced by less than 1%, whereas the raised income from parking fees represents more than 9% of all players' earnings in the baseline condition.

The non-pecuniary treatment is a little less effective in reducing the number of cars, yet significantly increases participants' earnings because of enhanced coordination. A larger sample and playing for more rounds – perhaps in a computerized version of the game – would certainly allow more reliable statistical tests. Previous work on coordination has shown that, after playing 50 rounds and more of a coordination game, no equilibrium emerges, even if additional information on others' behavior is provided to participants (cf. Schneider and Weimann, 2004; Selten et al., 2007; Ziegelmeyer et al., 2008).

Our experiment also shows that people tend to choose the car, even if such behavior is to their own disadvantage. One reason may be that boundedly rational subjects use diverse and imperfect models to predict what others will do. In some instances, this may result in socially inferior outcomes and impede the quick emergence of stable equilibria. Another interpretation could be that participants get the impression that other players take the car "too often," thereby benefitting from their own "bus choice." By also choosing the car, they may give up some of their payoff, but also reduce the payoff of others, as a form of strategic behavior – similar to costly punishment often observed in social dilemma experiments (Fehr and Gächter, 2000) – to influence other players' choices in subsequent rounds. Anecdotal evidence from the pretests with university students supports this interpretation. In those tests, choosing the car was very often motivated by a feeling of envy, the desire to punish and the objective of making others choose the bus in the game. It may be that in real life people support policies aimed at reducing the number of cars without necessarily feeling that this should have real consequences for their own behavior. Economic experiments are well-suited for detecting and exploring such cases where stated preferences and actual behavior diverge, because they link behavior to monetary incentives.

Controlling for observed socio-economic characteristics, the regression models have shown that age, gender, or income are rather unimportant for explaining the experimental behavior observed, whereas the introduced treatments had

[18] The fairly stable Akaike Information Criterion shows that not much additional explanatory power is achieved by controlling for socio-economic heterogeneity. Choices are to a large extent the result of introduced treatments.

Table 6
Evaluating the efficiency of monetary policy measures. *Source:* own calculations, based on field data.

	Baseline I (rounds 1 to 6)	Treatment I (Bus subsidy, rounds 7 to 12)	Baseline II (rounds 1 to 6)	Treatment II (Parking costs, rounds 7 to 12)
Frequency of choosing the bus	319 (52.12%)	371 (60.62%)	359 (58.66%)	383 (62.58%)
Frequency of choosing the car	293 (47.88%)	241 (39.38%)	253 (41.34%)	229 (37.42%)
Earnings of all players in tokens	7920	9085	7572	7506
Total costs/income of the "transport authority" in tokens	None	Costs for subsidizing 371 bus rides × 3 = 1113	None	Income from 229 times the parking fee × 3 = 687
Net benefits, including "transport authority" in tokens	7920	7972	7572	8193

Table 7
Binary logistic regressions on mode choice in the games. *Source:* own calculations.

	(1) Pooled data	(2) Pooled data	(3) Pooled data	(4) Pooled data	(5) Pooled data	(6) Random effects
MALE			−0.2721 (0.1680)	−0.1984 (0.1464)	−0.1884 (0.1485)	−0.3185 (0.2349)
AGE			−0.0081 (0.0103)	−0.0084 (0.0092)	−0.0082 (0.0092)	−0.0107 (0.0153)
MARRIED			0.1183 (0.2035)	0.1912 (0.1783)	0.1865 (0.1784)	0.2624 (0.2866)
INCOME2			−0.4037 (0.3529)	−0.4412 (0.3222)	−0.4372 (0.3227)	−0.6001 (0.4228)
INCOME3			−0.0075 (0.3494)	−0.0556 (0.3169)	−0.0409 (0.3185)	−0.0163 (0.4050)
INCOME4			−0.1410 (0.3810)	−0.1328 (0.3458)	−0.0982 (0.3483)	−0.1398 (0.4748)
INCOME5			−0.0539 (0.4244)	−0.0020 (0.3960)	0.0323 (0.4003)	0.0364 (0.6191)
OWNSCAR			−0.0564 (0.2786)	0.0103 (0.2489)	−0.0090 (0.2540)	−0.0248 (0.3874)
OWNSBIKE			0.1592 (0.1900)	0.1062 (0.1663)	0.0935 (0.1686)	0.1528 (0.2411)
CARFREQ2			−0.0356 (0.1989)	−0.0703 (0.1762)	−0.0780 (0.1779)	−0.1149 (0.2458)
CARFREQ3			0.4485 (0.3315)	0.2617 (0.2994)	0.2536 (0.2955)	0.3831 (0.4395)
CARFREQ4			0.3126 (0.2951)	0.1338 (0.2578)	0.1422 (0.2607)	0.3044 (0.4048)
BUSFREQ2			−0.5822** (0.2364)	−0.4126** (0.2054)	−0.4007* (0.2062)	−0.5942* (0.3066)
BUSFREQ3			−0.4470 (0.2965)	−0.3562 (0.2561)	−0.3582 (0.2589)	−0.5119 (0.3599)
BUSFREQ4			−0.6678*** (0.2485)	−0.5176** (0.2142)	−0.5068** (0.2163)	−0.7706** (0.3182)
ROUND			−0.0028 (0.0068)			
PARKCOST	−0.2978** (0.1198)	−0.2741** (0.1109)		−0.1557 (0.1153)	−0.1924 (0.1181)	−0.2417 (0.1478)
BUSSUB	−0.2149* (0.1157)	−0.2023** (0.1026)		−0.2062* (0.1205)	−0.2259* (0.1202)	−0.3513** (0.1497)
PUBCOORD	−0.1166 (0.0757)	−0.3080*** (0.0839)		−0.3340*** (0.0946)	−0.3347*** (0.0942)	−0.4241*** (0.1203)
CARPREVROUND		0.8851*** (0.1257)		0.8210*** (0.1260)	0.7987*** (0.1336)	0.0193 (0.1188)
ALLOWED		1.0701*** (0.1837)		1.1425*** (0.2046)	1.1413*** (0.2041)	1.3699*** (0.2211)
1CAR		0.3590* (0.2044)			0.4282** (0.2168)	0.4381* (0.2650)
2CARS		0.4348** (0.2118)			0.5102** (0.2256)	0.6340** (0.2566)
3CARS		(0.2182)			0.4076* (0.2336)	0.4553* (0.2629)
4CARS		0.2362 (0.2373)			0.2653 (0.2640)	0.3042 (0.2900)
5CARS		0.6003** (0.2865)			0.5809* (0.3258)	0.7345** (0.3375)
6CARS		0.5844 (0.4913)			0.6097 (0.4937)	0.5007 (0.5182)
Constant	−0.2165*** (0.0811)	−0.9172*** (0.2117)	0.5120 (0.4225)	0.1944 (0.3814)	−0.2231 (0.4148)	0.3015 (0.6576)
N	3672	3060	2988	2490	2490	2340
Pseudo R^2	0.002	0.048	0.023	0.058	0.060	
Akaike Information Criterion	1.357	1.308	1.334	1.301	1.303	
σ_u^2						1.1321 (0.0994)
ρ						0.2803 (0.0354)
Log likelihood	−2487.8615	−1989.9046	−1975.2767	−1599.3429	−1595.2083	−1463.6772
χ^2	10.36**	104.3256***	23.9937***	104.7039***	114.8549***	68.4975***

Standard errors (clustered for individuals in models 1–3) in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

significant behavioral effects. The low level of statistical significance of observed socio-economic heterogeneity may be explained by the relatively homogeneous sample. The importance of treatment effects is indicated by the increase in explanatory power in the respective likelihood ratio test. Further, some unobserved characteristics, such as political and environmental attitudes or perceived comfort and social status of cars and buses, may have influenced decision-making in the game. In the end, it is very important to understand how participants form expectations regarding the behavior of others, as this is critical for their payoffs and thus for mode choice in the game. Future research could pick up on these points to take a more detailed examination of these relationships by extending the sample to other target populations, gathering more data on attitudes, perceptions, and the formation of expectations about others' behavior, with regard to mode choice. Specifically, it will be important to take into account the low level of car use and ownership of private vehicles in our data. Few people in our sample own a car and only about half of the respondents regularly use one. This may have introduced bias in favor of the bus choice.

More interestingly from our perspective, the regressions suggest that some of participants' actual traffic behavior is – to some extent – "carried over" to the game. For instance, we found that participants who use buses in real life also have a higher propensity to choose this option in the game. Differences are particularly clear between the category of people who never use the bus and all remaining categories. Traffic measures affecting the use of either option may start virtuous or vicious feedback cycles. Impeding the use of cars can break the vicious cycle of having more cars on the road in our game. It is notable that the frequency of using the car has smaller coefficients in the regressions than the coefficients of bus frequency. Of course, the number of bus and car trips is not independent of each other. Yet, our experimental results give some indication that, *ceteris paribus*, encouraging people to use the bus may be a better strategy than decreasing the number of car trips.

The high coefficients of the ALLOWED variable indicate that people may take up a suggested model for coordination. The treatment effects show that this does not lead to an increase in the use of cars in the game. This finding indicates that the roles of policy and the public are important. Authorities of some cities, such as Shanghai, have experimented with an odd–even number license plates system during periods of heavy congestion, with drivers only being allowed to use certain main roads on alternate days, depending on their plates. The mechanism in our game works in a similar way, without monitoring or enforcement. It just provides players with a model to better predict what others may do. How such policies can actually work in practice and what the roles of monitoring and enforcement of such rules may be needs to be further clarified through more detailed analysis.

6. Conclusion

In this paper we have presented a framed field experiment on mode choice, run with commuters in Hyderabad, India. The results show that participants made their own decisions based on the expected decisions of others. In a given round, the more participants in an experimental group chose the car, the more likely it became that even more participants would choose the car in the following round. Subjects also became habituated, as indicated by a positive probability to stick with a choice from a previous round. We find that participants chose the car less frequently when we introduced monetary incentives for using public transport or avoiding the car. We have also shown that providing information to facilitate coordination helped subjects to improve their earnings. This effect works in two ways. Firstly, as shown in the regression analysis, when it is "their turn," players were more likely to choose the car. Secondly, as indicated by the higher average payoffs, players exhibited a greater willingness not to take the car when it was "someone else's turn."

We acknowledge that generalization of the results to directly dictate traffic policies is neither possible nor desirable. The main goal of such experiments is rather to test more general hypotheses and advance our theoretical understanding of human decisions (Guala, 1999; Guala and Mittone, 2005; Schram, 2005). In addition, games like the one discussed in this paper might be particularly useful for participatory traffic planning that moves beyond one-dimensional surveys or qualitative methods (cf. Bickerstaff and Walker, 2001; Fouracre et al., 2006). It might be very costly to disentangle complex causal relationships by testing traffic policies in the field under controlled conditions. It might also be very difficult to quantitatively assess and understand interactions and subsequent dynamics of traffic behavior. In such a situation, framed field experiments like the one presented in this paper can provide rich sources of information on behavioral factors under different policy options, which may also guide further research such as surveys (cf. Mahmassani and Jou, 2000), although the limited sample may be a drawback, as only half of the people use the car on a regular base.

Experimental research in transportation economics could generate further interesting insights for demand-side measure policy debates and enrich the current discourses therein. For example, it would seem particularly relevant to combine policy measures and test whether the resulting change is more or less than the sum of its parts. The research presented in this paper was developed following such a logic and can hopefully lead the way towards experimenting with such an approach. Moreover, the possibility of soft policy measures, such as awareness-raising campaigns, could be further explored in experimental settings so as to assess their potential contributions to achieving more sustainable transport systems. Just how far attitudes affect behavior and how these attitudes interact with experience and learning in a game constitute additional challenging questions for further research. Economic experiments on transport could also be useful in exploring the models people use for predicting the behavior of others and using such models for simulation. Another important issue to take up in the future is the number of motorbikes, which is growing at an even faster rate than the number of cars, in Indian cities. The positive – albeit small and statistically not significant – effect of OWNSBIKE may be a first indicator of a negative effect. In this context, it will also be important to look at policies which promote non-motorized transport (walking and bicycles) or which aim at reducing distances or frequency of motorized trips.

At this stage, our results suggest that soft policies alone might not be very effective. This finding, however, does not rule out the reasonable possibility of such policies functioning as multipliers in conjunction with other demand- or supply-side measures. Developing context-dependent games for different economic strata of the Indian society, e.g. a mode choice game on walking vs. taking the bus for the poor or games on using the car individually vs. using it jointly with others for the affluent, are promising extensions of the game developed in this paper. Sampling participants who can relate to the particular task at hand will be critical for the successful conduct of such experiments in the future. Again, investigating combinations of policy measures in games and then using these games as a starting point for discussion and gaining deeper insights into behavioral factors can be seen as a promising way ahead for a sector that, especially in the developing world, appears to be largely trapped in a vicious circle: more roads lead to more traffic which, in turn, fuels even more supply of infrastructure.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.tra.2014.03.014.

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