The Effect of Public Transport Pricing Policy: Experimental Evidence

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Abstract

We investigate the impact of different public transport pricing schemes on daily commuting habits. Psychological inertia, car stickiness, complexity aversion, or skewed perception of prices are expected to influence decisions. We build a controlled experiment, where participants make transport decisions and face various public transport tariffs. Our findings indicate that players are rational as they reach the Nash predictions of our model, but cognitive biases inherent to users are also present. Peak/off-peak and two-part tariffs prove to be more successful in encouraging public transit use than flat fare subscriptions, possibly due to a preference for flexibility and the ability to take past experiences into account (congestion and incident) in future travel choices. Thus, this paper suggests that well designed pricing strategies are useful tools to promote public transit use and reduce road congestion.

JEL codes: R41, R48, C91.

Keywords: Public transport pricing; private car; congestion; experiment;

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1 Introduction

Transportation contributes to around 25% of CO2 emissions and 14% of annual overall emissions on the world scale (Gao et al., 2020). In France, transport is the only sector whose emissions have increased since 1990, particularly due to the increase in road traffic, which today represents 94% of these emissions. As a consequence, reducing car use is an important challenge that involves a modal shift from cars to less polluting transportation modes such as public transportation, particularly for daily commuting.

In practice, the promotion of modal shift toward public transportation is a complex task, in particular because commuters face a structural absence of suitable infrastructure for public transportation, and because car stickiness is an important concern. The economic literature has discussed several policy measures that could help facilitating modal shift, both from a theoretical and an empirical perspective. On the one hand, policies aimed at restricting car usage can be mostly classified as price- or quantity-based. Quantity-based policies entail driving restrictions in urban areas depending on the distance or the type of vehicle driven. Price-based strategies are usually designed as urban tolls and have shown to be much more difficult to implement (Rivera (2021), Fageda et al. (2022)).

On the other hand, policies aimed at promoting public transport mostly rely on public transport pricing and are traditionally motivated by the production of positive externalities. Since Vickrey's work in the 1960s, it is well accepted that transport fares should be based on real travel costs and should also take into account externalities such as congestion or pollution (Vickrey, 1963). Moreover, price differentiation with respect to time, distance traveled, or specific socio-demographic criteria, such as income or age, can be implemented in order to increase commercial revenue or promote travel equity. While the theory of optimal public transport pricing has been debated to a large extend by the economic literature, attempts to test empirically the impact of *good* pricing policies on public transport usage have been however much more scarce (De Borger and Proost, 2001, 2015).

Our paper aims at filling the gap in this direction and tries to identify the causal impact of different pricing policies on the habit of urban commuters. In particular, our main question of interest is whether public transport pricing can be used as an efficient tool to convince drivers to switch transportation mode and to reduce congestion on the road. We depart from the popular assumption that commuters are fully rational and are expected to maximize their individual utility subject to time and budget constraints. We assume instead that the presence of users' cognitive biases, which are generic, or specific to choices in transport services and are linked to errors of judgment, risk aversion, strong consumption habits or aversion to tariff complexity, are likely. In this context, a more behavioral approach based on the seminal work of Tversky and Kahneman (1974) may prove fruitful when shedding light on how psychological, social and behavioral factors can affect individuals' travel choices and blur the effectiveness of optimal pricing (Gómez Pajares et al., 2015). In particular, a well-known pattern is the so-called psychological inertia, which triggers automatism in the sense that economic agents tend to repeat the same choice regardless of the circumstances: car users are well-known for their reluctance to switch to public transport as they exhibit strong car reliance (Innocenti et al., 2013; González et al., 2017). In a context of entrenched habits, commuters tend to ignore new information about the price changes or travel conditions (Aarts et al., 1997).

To conduct our empirical test, we rely on a lab experiment which is particularly well suited for our purpose. The experiment allows a group of individuals to interact with each other in a controlled environment. The incentives to choose specific actions are designed in such a way that we are able to investigate the evolution of certain psychological patterns at individual and collective level. A lab experiment is also a very useful tool for studying the important question of how economic agents learn and react in highly repetitive situations, a key characteristic of the travel activity of the daily commuter.

To test empirically how commuters respond to different pricing schemes in public transport, we construct a setting where participants choose between two possible transportation modes, namely private car and public transport. They are told to arrive at the same point at a given hour, and they can then choose their time of departure. The travel time for each mode of transportation is uncertain as the initial expected travel time may be extended due to random incidents and congestion that can occur both on the road and in public transportation. Congestion is endogenously formed in the sense that it depends on the number of participants choosing either the car or the public transport option at the same time. Participants repeat the same non-cooperative game several times, and they are given information about the consequences of their own decisions at each stage. Different public transport fares serve as different treatments along the procedure. We consider a single fare ticket, a transit pass, a peak/off-peak scheme, and a two-part tariff. Our objective is to shed light on whether different treatments entail distinct participant decisions in a context where potential cognitive biases on the part of the participants could distort the perception and acceptance of these fares.

Our experiment produces several interesting results. First, the theoretical predictions of our behavioral setting are in line with the decisions made by our lab participants. They usually play the Nash equilibria of the game and thus prove to be able to act rationally and make good inferences about the others' choices. Second, our results also suggest that public transport pricing schemes have a significant impact on commuters' habits. In particular, Peak/off-peak and two-part tariffs increase the demand for public transport services compared to the transit pass and the single fare ticket. We interpret this outcome as a symptom that participants prefer tariff flexibility and are reluctant to commit to fixed fees over several periods. Moreover, our experiment shows that these effects are persistent, even if behavioral inertia is present and affects participants' choices. Thus, users' cognitive effort is certainly higher than what a simple inertia model would predict. We also highlight the fact that recent (instead of long-run) experiences of congestion and incidents on the public transport network and on the road are important drivers of modal choice.

Finally, our empirical results show that an increase in the public transport usage allows reducing congestion on the road. First, this suggests that participants learn to coordinate their decisions and take into account the information provided about the decisions of the others. Second, this is an potential contribution to the on-going debate on whether the development of public transport infrastructure allows reducing traffic congestion. As suggested by Downs (1998), a reduction of congestion also attracts additional automobile trips that were previously not undertaken. This so-called induced demand effect might outweigh the initial substitution effect between public transport and private car usage. Recent studies have shown that the global effect (induced demand plus substitution effect) of the extension of public transport networks could be a reduction of congestion (Yang et al. (2018) and Beaudoin and Lawell (2018)). Our experimental framework makes another contribution on this front.

The paper is organized as follows: Section 2 provides a literature review. Section 3 presents our experimental protocol and the theoretical predictions of our setting. Section 4 then presents our empirical model and discusses our results. Section 5 provides a summary and some concluding remarks.

2 Public transport pricing and irrational commuters

A pricing policy in public transport usually aims at achieving several objectives, namely, to finance the cost of producing the service, to help users to learn about its quality or value, to promote equity, to provide travelers with incentives to substitute public transport for their private vehicles, to save energy, to reduce air pollution, or to counterbalance the under-taxation of private vehicle use. Given that some of these objectives are in conflict with each other, economists usually evaluate the effect of public transport fare changes through the prism of economic efficiency (De Borger and Proost, 2012).

As the increase in congestion and pollution levels in urban areas has widened the gap between private and social costs of urban traffic over the last decades, the economic prescription is that transport users should bear the social marginal costs of their consumption. Thus, a user should pay (in addition to the time invested) a price equal to the marginal cost of service production plus the additional cost imposed on all other users. As public transport is a common good, the presence of a greater number of users increases the costs borne by other users, especially when congestion-related problems arise due to usage and comfort conditions. In this case, the socially optimal price should be above the marginal production costs.[5] Researchers then suggest charging distinct prices to different user groups. The so-called *Ramsey pricing* involves proposing higher prices (and consequently deviating more from the social marginal cost) for consumers whose demand elasticity is lower, particularly for users who value time the most. It is then important to understand how the demand for public transport is distributed among user groups based on their characteristics (for

[5] Efficient pricing at the social marginal cost does not necessarily guarantee coverage of the total costs incurred by the public transport operator. The conflict between efficiency and economic viability is then resolved through subsidies. If the public sector has sufficient resources, the first possible alternative is to maintain the rule of efficient pricing at the social marginal cost (or even below if universal service rules mandate the implementation of low fares to ensure mobility for all citizens, including those with lower income) and to offset the deficit with subsidies.

instance, income, age, or gender), travel characteristics, or service characteristics (express or local, peak or off-peak hours, bus or rail).

In practice, the most popular fares in public transportation are fourfold.[6] First, a single fare consists of a constant price regardless of the length of the trip or the time of the day. This is the simplest tool for transit regulators and users, but it may also generate inequalities (Cervero, 1981). Those who pay disproportionately high fares in relation to the cost of the services are, in this case, short-distance travelers, the unemployed, families without a private vehicle at their disposal, and unconstrained travellers. Single fares force users with lower incomes to subsidize the travel of those with higher incomes, and they discourage short-distance and off-peak transit travel. Second, a zonal tariff sets a higher rate for users traveling longer distances. This pricing strategy allows charging more for a more costly transportation service, but it fails to account for the impact of each user on the consumption of other users, as described by Turvey and Mohring (1975). To internalize congestion within public transport vehicles, one could envision that the price paid by users increases with the vehicle's occupancy rate. Third, pricing can also be based on peak and off-peak hours throughout the day. The fare is higher during peak hours and aims at shifting travelers from peak hours to off-peak hours thereby (Glaister, 1974; Kilani et al., 2014). Finally, the flat-rate subscription, or transit pass, allows for an unlimited number of trips over a specified period, regardless of the length of the journey. As a result, transit passes encourage subscribers to use public transport instead of active modes, which can lead to decreased comfort and increased congestion.

Given the variety of tariffs available and their theoretical efficiency properties, it becomes important to empirically assess how commuters react. Behavioral economics has proven especially useful in this context, as it challenges and expands upon the classical economic assumption that individuals always make rational, self-interested decisions based on complete information (Kahneman and Tversky, 1974). Introducing various psychological, emotional, and social factors into economic analysis, behavioral approaches show that human

[6] It is important to note that the success of any tariff reform depends to a large extent on a broader consideration of prices in other competing transport sectors. Indeed, as long as the taxation of private vehicle use remains undervalued, public transport tariff policies may prove ineffective (Mayeres et al., 1996). Significant tolls at city entrances and substantial parking fees for private vehicles can have a significant impact on the demand for public transportation.

decision-making often deviates from what would be predicted by models of rational behavior due to bias, limited cognitive resources, and the influence of social norms, among other factors.

On the one hand, when choices are complex or under limited computational ability, individuals may rely on mental shortcuts (heuristics) that lead them to make errors of judgment. They have a limited capacity to process all the available information and tend to prefer simplicity over complexity when it comes to pricing, as in other sectors (Hobman et al., 2016; Mayol and Staropoli, 2021). The so-called "flat rate bias", which refers to consumers' intrinsic preference for flat-rate payment over pay-per-use, even if the subscription's break-even point is not reached, is thus a relevant concern (Wirtz et al., 2015). The zero marginal cost of a flat-rate subscription potentially provides users with a sense of freedom and allows a lower cognitive effort (Hörcher and Graham, 2020). Instead, complexity is better dealt with when the tariff follows an "obvious" logic based on time of use, such as peak/off-peak pricing (Taylor and Bonsall, 2017).

On the other hand, behavioral economics suggests that user habits are also an important driver of transport mode choice and contribute to the temporal inconsistency of preferences. Most journeys are habitual, even automatic, and involve minimal consideration of new information (Verplanken et al., 1994). Commuters do not always respond to a rational mental process, which requires a cognitive process of deliberation enabling preferences to be formed, all information to be taken into account, and a choice to be made based on these preferences (Gärling et al., 2001).

Hence, with limited rationality (Simon, 1956) and in the presence of uncertainties regarding traffic conditions, commuters cannot predict these conditions accurately over a given period of time without error (Traverso et al., 2012) and their ability to adapt their behaviors. As shown by Denant-Boèmont and Hammiche (2008), providing participants in a lab experiment with more information or travel choice options may thus not be enough to have them make optimal decisions. They value more flexibility independently of price or information and are thus potentially less sensitive to the cost-reflective tariffs discussed previously in this section. Lindsey et al. (2014) examines how pre-trip information affects route choices under unpredictable travel conditions, finding that such information can paradoxically increase total expected travel costs when route capacities are correlated, but decrease costs when capacities vary independently.

Our objective in this paper is to challenge these behavioral predictions in the lab. We show that, although cognitive biases are a relevant concern, well-designed public transport pricing policies successfully manage to influence commuters' decisions. In the next section, we present the detail of our experimental protocol.

3 The experiment

Our goal is to test in the lab the impact of the implementation of various public transport pricing schemes on commuters' modal choices. We consider four types of fare structures, namely a single ticket, a peak/off-peak tariff, a transit pass, and a two-part tariff, which serve as four different treatments in the experiment. We follow a between-subjects procedure in which participants are randomly assigned to treatments, and the results across treatments are compared to assess the effects of a set of explanatory variables on the probability of choosing a particular transportation mode, public transport, or private car. Hence, participants do not have the option of choosing the fare themselves. Participants are incentivized to coordinate in order to avoid congestion, which arises when a given number of participants choose the same mode of transportation at the same departure time. Simultaneously, incidents can occur randomly and increase, together with congestion, travel time. In this section, We present our experimental protocol in further detail and our theoretical predictions. The precise instructions given to the participants are listed in the Appendix.

3.1 Experimental protocol

We design a lab experiment where participants (also referred to as commuters) must travel from point A to point B, and their common objective is to arrive on time (9 a.m.). They choose a mode of transportation, public transport or private car, and a departure time that depends on the chosen mode of transportation. The choice is repeated 40 times for each participant. At the end of the process, participants are required to respond to a survey and provide information on their socio-demographic characteristics.

The cost of the journey includes the cost of using the chosen transport mode and the cost of travel time. The usage cost is fixed and known in advance, while the travel time is contingent upon the existence of congestion and the occurrence of an incident. Moreover, the cost of time is specific to each transport mode: 0.25 euros per minute for car-use and 0.16 euros per minute for public transport. This difference reflects a lower opportunity cost for public transport users, who can engage in various activities (reading, working, listening to music, watching movies, etc.), whereas a car user is assumed to remain focused on driving. At the end of each period, participants receive their payoff, which is 15 euros if they arrive on time, 10 euros if they arrive early, and 5 euros if they arrive late.

Two transportation modes are considered: On the one hand, public transport can be affected by incidents and/or congestion, which generates an additional time cost on top of the base fare, which is treatment-specific. On the other hand, private cars are affected as well by the possibility of incidents or congestion, and this also creates additional time cost on top of a fixed base cost. Public transport passengers and car drivers use distinct infrastructures, resulting in the fact that neither of the two transportation modes generates negative traffic externalities for the other. Multiple departure time options are suggested to offer participants greater flexibility and assess their capacity to coordinate effectively, thereby reducing congestion and maximizing their payoff, as will be defined subsequently. For the car, there are three possible departure times (8 a.m., 8:20 a.m., and 8:40 a.m.), and there are two departure times for public transport (8 a.m. and 8:30 a.m.). Thus, private cars offer more flexibility to the commuter than public transport, even if the number of departure slots has deliberately been reduced here to facilitate the occurrence of congestion.

The travel time for each transport mode is uncertain. In the absence of any adverse event (congestion and incident), the expected travel time is 20 minutes for the car option, and 30 minutes for public transport. Random incidents and congestion resulting from participants' choices affect the travel time of both modes. Incidents occur with a probability of 0.2 for the car option and 0.05 for public transport, while congestion is endogenous, and depends on the number of participants choosing either the car or public transport at the same time.

In our setting, car congestion mirrors the standard traffic jams observed in reality when too many users choose to drive simultaneously. Public transport congestion, on the other hand, depicts saturation in transport vehicles when too many passengers are on board, which complicates on-board and off-board movements, and delays the schedule. With the intention of parallelism with reality, car incidents include accidents or delays due to weather or technical issues, while an incident in public transport is seen as a mechanical breakdown or train cancellation. Congestion in the lab allows us to test the ability of the participants to coordinate, i.e., to distribute themselves across each mode of transportation and departure times to limit congestion and trip duration. Coordination is not explicit since participants are unable to communicate with each other during the experiment. Instead, the information communicated to them at the end of each stage allows them to update their beliefs on what the other players do and to coordinate tacitly. In our experiment, the congestion threshold depends on each mode of transportation: Car congestion occurs when at least two participants choose the car option in the same time slot, while public transport congestion happens when at least four participants choose public transport in the same time slot.

Finally, we assume that the impact of congestion and incidents on travel duration varies across the two transport modes: Car congestion doubles the initial travel duration, while an incident increases it by 50%. Public transport congestion increases the initial travel duration by 50%, while a random event doubles the initial travel duration. The total duration and associated costs are summarized in Table 1 below.

Table 1: Trip length and cost

		Car		PT	
		No cong.	Cong.	No cong.	Cong.
Trip length (in min)	No Inc.	20	40	30	45
	Inc.	30	50	60	75
Trip cost (in Euros)	No inc.	5	10	4.8	7.2
	Inc.	7.5	12.5	9.6	12

Note: Unit cost is 0, 25€/min (car) and 0, 16€/min (public transport). "Inc." and "Cong." refers respectively to incident and congestion

3.2 Tariffs treatments

Four different tariffs are considered while the cost of the car journey remains the same for the four treatments: 1.5 euros. The tariffs are designed as follows.

- Treat-1: Single ticket, priced at 1.5 euros per trip.
- Treat-2: Peak/off-peak fare, priced at 1.5 euros on peak hours at 8:30 AM, and 0.75 euros off-peak, at 8:00 AM.
- Treat-3: Transit pass priced at 2 euros and valid for a maximum of four consecutive periods depending on when the subscription is activated[7].
- Treat-4: Two-part tariff, with a fixed part of 1 euro valid for a maximum of four consecutive periods on the same principle as for Treat-3 plus a variable part of 0.75 euros per trip.

Thus, for each treatment, every group of ten participants engages in the congestion game 40 times consecutively. The experiment is based on a partner design where the same participants play the 40 periods in the same group of 10. Table 2 below provides a summary of the different prices and the average cost per trip under each treatment. Under Treat-3 and Treat-4, the user commits to 4 periods and has an incentive to make as many trips as possible (i.e., 4) with public transportation to benefit from the lowest possible unit cost (0.50€/trip for Treat-3 and 1.00€/trip for Treat-4).

At the end of each period, participants are informed about of the monetary consequences of their choices through both the cost components (mode use and time) and the gain components (the initial endowment and the gain depending on their arrival time). The emergence of congestion on their route (mode and departure time) as well as the occurrence of an incident for the period are also clearly notified.

[7] In practical terms, if the participants choose public transportation during periods 1, 5, 9, 13, 17, 21, 25, 29, 33, and 37, their subscription can be used for four consecutive periods. If they choose the car during these periods and public transportation during periods 2, 6, 10, 14, 18, 22, 26, 30, 34, and 38, they can only use their subscription for a maximum of 3 consecutive periods, and so on.

Table 2: tariffs applicable in each treatment

Type of tariff	Value	Average tariff per trip	
Treat-1	Single ticket	1.5	1.5
Treat-2	Peak/off-peak	1.5/0.75	1.5/0.75
Treat-3	Transit pass	Fixed part: 2 Variable part: 0	4 trips: 0.5 3 trips: 0.67 2 trips: 1 1 trip: 2
Treat-4	Two-part	Fixed part: 1 Variable part: 0.75	4 trips: 1 3 trips: 1.08 2 trips: 1.25 1 trip: 1.75

Note: Values and costs are in euros.

3.3 Theoretical predictions

Participants are randomly assigned to a group of ten at the beginning of the experiment. Within the group, congestion can occur both on the road and in public transport. Following Arnott et al. (1993) and Ziegelmeyer et al. (2008), we consider a setting where congestion on the road (in public transport resp.) is seen as a bottleneck in the infrastructure (in public transport vehicles resp.) with a maximum flow capacity which is measured as the maximal number of drivers (public transport users resp.) that can travel without congestion. In a given time slot, if the number of commuters increases beyond that capacity, a queue develops. In what follows, we present the congestion model as a normal-form game played by participants, and we define the Nash equilibria in pure strategies and the social optimum.

Our experiment entails a game with $n = 10$ players, so-called commuters. A pure strategy for commuter i is an alternative which combines a departure time and a transportation mode $a_i \in A = \left\{a^{car.d_1}, a^{car.d_2}, a^{car.d_3}, a^{train.d_4}, a^{train.d_5}\right\}$, where $\{d_1, d_2, d_3\} = \{8.00, 8.20, 8.40\}$, and $\{d_4, d_5\} = \{8.00, 8.30\}$. Hence, a pure-strategy profile is a vector of alternatives $\mathbf{a} = (a_1, ..., a_{10}) \in A^{10}$. As indicated above, each player participates in the commuting game 40 times, conditional on a particular tariff treatment t, $t = \{\text{Treat-1}, \text{Treat-2}, \text{Treat-3}, \text{Treat-4}\}$. In each round, every commuter receives an initial endowment of 10 euros. Each one of them also receives an additional gain $F\left(a_i|\mathbf{a}_{-i}\right) = \{15, 10, 5\}$, depending on the arrival time (on time, early, or late, respectively). Moreover, we denote as $C(a|\mathbf{a}_{-i})$ the individual cost per trip for each commuter, which depends on whether a congestion and an incident occur, as defined in Table 1 above. Finally, under each treatment, each commuter using public transport pays a tariff $T(t)$, as shown in Table 2. Thus, the pay-off $\pi(a_i|\mathbf{a}_{-i})$ received by a player i in each round is

$$\pi(a_i|\mathbf{a}_{-i}) = 10 + F(a_i|\mathbf{a}_{-i}) - C(a_i|\mathbf{a}_{-i}) - T(t). \tag{1}$$

Hence, in each round, a pure strategy Nash equilibrium of the congestion game is a profile of alternatives $\mathbf{a} = (a_1, ..., a_{10}) \in A^{10}$, such that, given the other players' choices, no single commuter i can increase their pay-off by choosing another alternative $a_i' \in A$. This translates into the following condition:

$$\pi(a_i'|\mathbf{a}_{-i}) \leq \pi(a_i|\mathbf{a}_{-i}), \; i \in \{1, ..., 10\}, a_i' \in A. \tag{2}$$

A socially optimal strategy profile can be defined as a profile of alternatives that maximize the aggregated pay-offs of all players in one round. In other words, $\mathbf{a} = (a_1, ..., a_{10}) \in A^{10}$ is a socially optimal profile if, for any alternative profile $\mathbf{a}' = (a_1', ..., a_{10}') \in A^{10}$, the following inequality holds:

$$\sum_i \pi(a_i'|\mathbf{a}'_{-i}) \leq \sum_i \pi(a_i|\mathbf{a}_{-i}), \; i \in \{1, ..., 10\}. \tag{3}$$

These characteristics delineate the anticipated result of the static game, wherein each of the 10 players endeavors to make an optimal conjecture about the decisions of others and respond accordingly. It is a commonly acknowledged fact that, despite the rationality of players, they may encounter difficulty in accurately predicting the choices of others, thus complicating the convergence towards a Nash equilibrium. Our experiment entails repeating the same static game 40 times (under each treatment), which could improve players' predictions as information is provided to them at the end of each round. Ziegelmeyer et al. (2008) suggest that information in the form of an aggregate statistic of past actions might help players to reach an equilibrium in the game, as it gives them the ability to best-reply much more efficiently. On the one hand, in the absence of information about others' decisions, players can adapt their decisions only according to their own past pay-offs. In this case, a natural learning process entails that a player chooses an alternative more frequently, which has given them a relatively larger pay-off than other alternatives in the past. On the other hand, if information about other players is provided, a natural learning process involves assuming that, in each round, each player chooses the best response to the historical frequency of play, which could facilitate convergence toward equilibrium.

From Equation 1, we compute the pay-offs of the players, conditional on the tariff treatment and whether or not congestion occurs in the route. As random incidents may also occur during the trip, we compute the expected pay-offs. Table 3 below provides a summary of the different outcomes. As the different treatments impact public transport tariffs only, pay-offs for car users depend only on whether congestion occurs or not. The highest possible pay-off for car users is obtained in the absence of congestion with a departure at 8:40, which allows them to arrive on time if they do not undergo any incident. Leaving at 8:00 or 8:20 results in the same payoff since commuters typically arrive early, regardless. If there is a congestion, the worst decision for car users is leaving at 8:40 as commuters arrive late, with or without any incident. Leaving at 8:20 allows car users to arrive on time in the absence of an incident.

The pay-off for the commuters who choose to travel with public transport is obviously affected by the type of treatment considered. Treat-1 consists of a flat tariff of 1.5 euro per trip. Treat-2 corresponds to a 50 percent discount compared to Treat-1 for commuters leaving at 8:00 instead of 8:30, which is considered the peak hour. In both cases, the highest pay-off possible is obtained in the absence of congestion by commuters leaving at 8:30; those who do not face any incident arrive on time. However, congestion implies that a departure at 8:30 is the worst possible decision. Leaving at 8:00 usually allows commuters to arrive on time or early, with or without congestion, in the absence of any incident. The interpretation of Treat-3 and Treat-4 is trickier since, as suggested in Table 2, the lump-sum payment included in both tariffs has an ambiguous effect. Frequent use of public transport decreases the average fare paid by commuters, whereas sporadic use increases it. To present our findings, we examine the two extreme scenarios that represent the least and most intensive use of public transport.

As in the previous two treatments, the 8:30 departure slot is the most appealing one in the absence of congestion, and the outcome is reversed if congestion occurs.

As there are 10 players participating in the game and 5 possible alternatives, and since

Table 3: Participants expected pay-offs

	PT tariff	Congestion	Alternatives				
			$a^{car.d_1}$	$a^{car.d_2}$	$a^{car.d_3}$	$a^{train.d_4}$	$a^{train.d_5}$
Treat-1	1.5	No	13.0	13.0	16.0	13.7	18.0
		Yes	8.0	11.0	3.0	10.8	6.1
Treat-2	1.5/0.75	No	13.0	13.0	16.0	14.5	18.0
		Yes	8.0	11.0	3.0	11.6	6.1
Treat-3	2	No	13.0	13.0	16.0	13.2	17.5
		Yes	8.0	11.0	3.0	10.3	5.6
	0.5	No	13.0	13.0	16.0	14.7	19.0
		Yes	8.0	11.0	3.0	11.8	7.1
Treat-4	1.75	No	13.0	13.0	16.0	13.5	17.7
		Yes	8.0	11.0	3.0	10.6	5.8
	1	No	13.0	13.0	16.0	14.2	18.5
		Yes	8.0	11.0	3.0	11.3	6.6

Note: All values are in euros.

congestion occurs on the road as soon as two car drivers choose the same departure slot, congestion cannot be avoided. As illustrated in Table 3, an interesting observation is that, when congestion occurs, the order of preference of the two alternatives $a^{car.d_2}$ and $a^{train.d_4}$ depends on the treatment considered. Indeed, in the case of a high public transport tariff, as in Treat-1, $\pi\left(a^{car.d_2}|.\right) > \pi\left(a^{train.d_4}|.\right)$. On the contrary, a discount in the public transport tariff, as in Treat-2, entails $\pi\left(a^{train.d_4}|.\right) > \pi\left(a^{car.d_2}|.\right)$. This particular feature has a direct impact on the Nash equilibrium of the game in pure strategies. As shown in Table 4, there is only one Nash equilibrium in Treat-1 and in Treat-2: When the public transport tariff is higher, as in Treat-1, the number of drivers increases, and congestion occurs on the road at 8:20. Conversely, with a lower public transport tariff, as in Treat-2, the number of public transport users increases, and congestion occurs in public transport at 8:00. There are however two Nash equilibria in pure strategies in Treat-3 and in Treat-4, and it depends in both cases on the perception that the commuter may have of the price of the transport pass when they purchase it. If the commuter expects to use their pass intensively (occasionally resp.), the average public transport tariff is perceived as cheaper (more expensive resp.), and congestion is thus moved into the public transport network (the road, resp.). The cut-off value for the public transport tariff is estimated to be 1.31

euros; if the public transport tariff is perceived by the commuter to be lower than this cut-off, congestion is shifted to the public transport, and vice versa.

Table 4: Theoretical predictions of the static game

			Alternatives				
			$a^{car.d_1}$	$a^{car.d_2}$	$a^{car.d_3}$	$a^{train.d_4}$	$a^{train.d_5}$
		PT tariff	# of commuters				
Pure strategy Eq.	Treat-1	1.5	1	2	1	3	3
	Treat-2	1.5/0.75	1	1	1	4	3
	Treat-3	2	1	2	1	3	3
		0.5	1	1	1	4	3
	Treat-4	1.75	1	2	1	3	3
		1	1	1	1	4	3
Social optimum	Any treatment		1	2	1	3	3

We note that the social optimum is independent of the type of treatment applied and implies congestion on the road. We thus note that higher public transport tariffs in our framework always entail the same Nash equilibrium is in pure strategies, and this equilibrium is socially efficient. As a consequence, the theoretical prediction is that the magnitude of the public transport tariff has a direct impact on modal choices and switches congestion to one mode or the other. We empirically test this result in the lab.

4 The empirical model

We first present the characteristics of the participants of our experiment. We then explore with a simple discrete choice model how the different tariff treatments impact the transport mode choice of the participants, and we illustrate how potential cognitive biases shape the decision process.

4.1 Data

We conducted both on-site and online experiments. The on-site experiments took place between November 2022 and May 2023 at the Laboratory of Experimental Economics in Paris (LEEP), while the online sessions were organized with the support of the S2cH platform of the Online Laboratory of Experimental Economics in Paris (LEEL).

To avoid substantial participant selection biases, we account for potential differences in participant characteristics. A large share of participants originate from the Ile-de-France region, as shown in the descriptive statistics below. We also use the subject pools from other partner experimental labs located in Strasbourg, Nancy, and Nice to recruit participants. A total of 680 individuals took part in the experiment.

Table 5: Geograhical origin of the participants

On site	%	Online	%
Paris	46	Bas-Rhin	38
Seine Saint Denis	13	Alpes Maritimes	30
Val de Marne	13	Moselle	8
Hauts de Seine	8	Gard	6
Val d'Oise	7	Pas de Calais	5
Essonne	4	Loire Atlantique	3
Yvelines	4	Var	3
Seine et Marne	3	Seine Maritime	2
Others	2	Haut-Rhin	2
		Bouches du Rhone	2
		Others	1
TOTAL	100		100

Table 5 and 6 above provide a more detailed description of the geographical origins of the on-site and online participants. We note that 98% of on-site participants originate from the Ile-de-France region, which has a population of over 12 million inhabitants, with a large fraction of people living in the Paris urban area. 60% of them are women, 50.4% are between 18 and 29 years old, and 40.42% hold an undergraduate degree. The on-site participants are thus primarily residents of the Ile-de-France region with a relatively high level of education. On the other hand, the socio-demographic distribution of online participants is quite different, as a larger fraction of them are from the Bas-Rhin (38%) and the Alpes Maritimes (30%). A smaller fraction of individuals come from other *departements* (French districts). 66% of them are women, while 88.2% are between 18 and 29 years old, and 37.14% have obtained their hold an undergraduate degree. The online participants are thus relatively younger than those on-site.

As suggested in Tables 7 and 8 below, there is also a difference between the two groups in terms of commuting habits: On-site participants are more intensive users of public

Table 6: Socio-demographic characteristics

	On site (%)	Online (%)
	Age	
18-29	50,4	88,3
30-49	26,6	8,3
50-64	13,0	1,7
65+	10,0	1,7
	Gender	
Male	60	65
Female	40	35
	Education	
Until High School	29.6	30.8
Undergraduate	40.4	37.1
Master and PhD	29.8	32
	Socio-professional category	
Retired	11.0	0.3
Unemployed	6.8	6.0
Workers	35.1	20.0
Students	41.5	71.4
Others	5.5	2.3

transport as 84.22% use it on a daily basis. As a direct consequence, 84.23% of them have a public transport Pass (annual, monthly, or weekly), compared to 68.58% for online participants. We observe a difference in the use between online and on-site. While close to 80% of the on-site-subjects use public transport for vital or social activities, only 68% of the online-subjects use public transportation for this. These differences explain why we control whether the experiment was on-site or online.

Table 8: Comparison of public transport use for Different Activities: Online vs. On site

	On site (%)	Online (%)
Public transport use for work	80.8	81.4
Public transport use for vital activities	80.0	67.1
Public transport use for social activities	79.1	68.9
Public transport use for sport/leisure on weekdays	73.8	57.1
Public transport use for sport/leisure on weekends	70.8	58.6

Table 7: PT habits

	On site (%)	**Online (%)**
Annual pass	52.7	34.3
Monthly pass	31.6	34.3
Weekly pass	1.1	0.0
Pack of 10 tickets	8.5	13.7
Individual ticket	4.5	15.4
Other	1.7	2.3
Frequency of PT use		
Daily	84.2	64.6
Occasional	14.9	32.0
Never	0.8	3.4

4.2 The empirical model

We see each participant in our experiment as a random utility maximizing commuter who chooses a transportation mode m among a set of available types, namely $\Omega = \{CAR, PT\}$, where CAR and PT stands for car and public transport, respectively. The random utility function of each commuter is defined as $\widetilde{u}^m = u^m + \omega^m$, where u^m is the mean utility level of the commuter associated with transport mode m and ω^m is an error term.

As shown by McFadden (1981), the maximization of the random utility over the choice set generates a probabilistic choice system, which is conditional on the characteristics of choice alternatives and individuals through the following mapping:

$$\Pr(m|\Omega) = \Pr\left(\widetilde{u}^m \geq \widetilde{u}^{m'}\right), m \neq m', (m, m') \in \Omega^2. \tag{4}$$

Thus, the solution of the maximization program of the commuter translates into the choice probabilities of the choice of a mode of transportation among two options, namely CAR or PT. Assuming a logistic distribution, it is rewritten as

$$\Pr(m|\Omega) = \frac{\exp(u^m)}{\exp(u^m) + \exp(u^{m'})} = \frac{\exp\left(u^m - u^{m'}\right)}{1 + \exp(u^m - u^{m'})}. \tag{5}$$

Assuming that $u^m - u^{m'} = X\beta$, we can express the probability of choice of one particular transportation mode as a function of a vector X that includes a set of variables that capture the characteristics of the participants in the experiments, as well as the type of fare structure used. In other words, we estimate the probability that a commuter travels with public transportation as

$$\Pr\left(PT|\Omega\right) = \frac{\exp\left(X\beta\right)}{1+\exp\left(X\beta\right)}, \tag{6}$$

where X includes the following variables: A counter which indicates the current period number from 1 to 40 ($Trend$), the type of public transport tariff treatment, *t={Treat-1, Treat-2, Treat-3, Treat-4}*, the average congestion level in PT in all previous periods ($Cong\ PT - All$), the average congestion level on the road in all previous periods ($Cong\ Car - All$), the average number of incidents in public transport in all previous periods ($Inc\ PT - All$), the average number of incidents on the road in all previous periods ($Inc\ Car - All$), and the frequency of public transport usage for all previous periods ($Use\ PT - all$). We then construct the same variables for the previous four periods only: $Cong\,PT-4$, $Cong\,Car-4$, $Inc\,PT-4$, $Inc\,Car-4$, and $Use\,PT-4$. Additionally, the following indicators are also included and are equal to 1 (0 otherwise) if there is, in the previous period, congestion in PT ($Cong\,PT-1$), congestion on the road ($Cong\,Car-1$), an incident in PT ($Inc\ PT-1$), an incident on the road ($Inc\,Car-1$), or if the chosen mode in the previous period is PT ($Use\ PT-1$).

We also include several variables that account for the socio-demographic categories of the participants (age, gender, professional activity, marital status, level of education, and ownership status), as well as commuting habits (# of vehicles owned, public transport usage, type of public transport subscription). Finally, LAB takes value 1 if the experiment is conducted in the lab, and 0 otherwise. Our logit specification is estimated with individual random effects to account for the panel structure of our dataset. We cluster the regressions on the group identification variable.

4.3 Results

We now discuss the main results of our empirical model. We compare first our theoretical Nash predictions with the empirical probabilities of choice of each one of the alternatives. We then model the choice of a transport mode and comment on the main results of our discrete choice analysis.

4.3.1 Nash equilibria

We first test whether participants behave as described by our Nash predictions. To do so, we compare the empirical probability of each alternative in each treatment, $\widehat{\Pr}(a)$, with the theoretical one, $\Pr^N(a)$, as predicted by the Nash equilibrium. We provide average statistics for all the 40 rounds, and we also disentangle the information across each round in order to shed light on whether the information provided in past decisions could influence the participants and help them to reach the equilibrium.

Table 9 shows the results. The Nash predictions $\Pr^N(a)$ are those discussed in Section 3.3, while the empirical probabilities $\widehat{\Pr}(a)$ are computed over 40 rounds. A first interesting result is that $\widehat{\Pr}(a)$ is usually close to $\Pr^N(a)$, which suggests that the participants make average decisions that are rational and that they seem to have a good understanding of each other's strategies. Second, $\widehat{\Pr}(a)$ is quite stable across treatments for $a = \left\{a^{car.d_1}, a^{car.d_3}, a^{train.d_5}\right\}$. These decisions can be seen as *extreme* in the sense that they entail leaving very early $(a^{car.d_1})$ or very late $(a^{car.d_3}, a^{train.d_5})$. Participants who have a preference for these particular decisions do not seem to be sensitive to changes in public transport tariffs. On the other hand, as suggested previously by the Nash predictions, changes in public transport tariffs mostly impact commuters who have a preference for $a^{car.d_2}$ and $a^{train.d_4}$, i.e., those who anticipate potential delays due to congestion and/or incidents. Whether the preferences of these three types of commuters (early departure; normal departure; late departure) can be directly linked to their attitude toward risk remains to be tested and is out of the scope of this paper. Our results however suggest that a change in public transport tariffs could have a limited impact on commuters who are very risk-averse (those departing very early) and those who have a limited risk-aversion (those departing late).

Finally, we have noted already that there are two possible Nash equilibria in Treat-3 and Treat-4, depending on whether commuters who hold a transit pass or pay a two-part tariff discount the fixed cost over several periods or not. In Treat-3, $\widehat{\Pr}\left(a^{car.d_2}\right)$=0.16, which is closer to $\Pr^N\left(a^{car.d_2}\right) = 0.2$, a Nash prediction for commuters who do not discount the cost of the transit pass at all. At the same time, $\widehat{\Pr}\left(a^{train.d_4}\right)$=0.36, which is closer to $\Pr^N\left(a^{train.d_4}\right) = 0.4$, a Nash prediction for commuters who fully discount the cost of the Transit Pass over future periods. Thus, participants who (do not resp.) discount the cost of public transport over future periods have a preference for public transport (their private car resp.) over their private car (public transport resp.). The same type of outcome is obtained in Treat-4.

We now investigate in further details the difference between the empirical $\widehat{\Pr}(a)$ and the predicted $\Pr^N(a)$ over time. To do so, in each treatment, we measure for each alternative $a = \left\{a^{car.d_1}, a^{car.d_2}, a^{car.d_3}, a^{train.d_4}, a^{train.d_5}\right\}$, and for each period t, the distance between $\widehat{\Pr}(a)$ and $\Pr^N(a)$:

$$Distance\left(a_t\right) = \left[\widehat{\Pr}\left(a_t\right) - \Pr^N\left(a\right)\right]^2. \tag{7}$$

We then run the following simple regression for each alternative a_t:

$$Distance\left(a_t\right) = \alpha_0 + \alpha_1 Trend_t + \epsilon_t, \tag{8}$$

where ϵ_t is an error term. A negative α_1 suggests that $\widehat{\Pr}\left(a_t\right) \rightarrow \Pr\left(a^N\right)$ over time, which is interpreted as a signal that participants use the information provided on past periods to make optimal decisions as described by the Nash equilibrium. The results are provided in Table 9: The estimated $\widehat{\alpha}_1$ is usually negative and highly significant, which indicates that the gap between $\widehat{\Pr}(a)$ and $\Pr^N(a)$ closes over time. Interestingly, the magnitude of the effect is strongest when $a = a^{train.d_5}$, which suggests that, at the beginning of the game, participants find it more difficult to make a good prediction regarding this alternative.

Figure 1 and 2 below also provide interesting insights on aggregate outcomes. First, participants systematically prefer public transport over private car. Second, the probability of choosing public transport increases over time, regardless of the treatment considered. Unsurprisingly, public transport is less popular when the unit fare is applied as it is more expensive in this case. Third, total congestion in public transport and on the road decreases over time, regardless of the treatment considered. This probably suggests that participants learn to coordinate their decisions and take into account the information provided about

Table 9: Nash equilibria in theory and in practice

	tariff	Pr (.)	$a^{car.d_1}$	$a^{car.d_2}$	$a^{car.d_3}$	$a^{train.d_4}$	$a^{train.d_5}$
		Nash	0.1	0.2	0.1	0.3	0.3
Treat-1	1.5	Empirical[1]	0.08	0.24	0.094	0.28	0.29
		$\widehat{\alpha}_1$	0.78***	-0.16	-0.55***	-0.37	-0.85***
		Nash	0.1	0.1	0.1	0.4	0.3
Treat-2	1.5/0.75	Empirical[1]	0.09	0.18	0.09	0.35	0.29
		$\widehat{\alpha}_1$	-0.20	-0.50***	-0.64***	-0.27	-0.96***
	2	Nash 1	0.1	0.2	0.1	0.3	0.3
Treat-3	0.5	Nash 2	0.1	0.1	0.1	0.4	0.3
	2/0.5	Empirical[1]	0.1	0.16	0.09	0.36	0.29
		$\widehat{\alpha}_1$	-0.75***	0.36	-0.22	-0.36	-1.01***
	1.75	Nash	0.1	0.2	0.1	0.3	0.3
Treat-4	1	Nash	0.1	0.1	0.1	0.4	0.3
	1.75/1	Empirical[1]	0.1	0.16	0.08	0.37	0.29
		$\widehat{\alpha}_1$	-0.13	0.20	-0.38*	-0.35	-0.94***

Note: *** Significant at 1%, ** Significant at 5%, * Significant at 10%. .
[1] Average computed over 40 rounds
* $\widehat{\alpha}_1$ is obtained from the estimation of $Distance\,(a_t) = \alpha_0 + \alpha_1 Trend_t + \epsilon_t$.
In Treat-3 and Treat-4, we consider the closest $\Pr^N(a)$ to the average $\widehat{\Pr}(a)$.

the decisions of the others at the end of each period of the experiment.

4.3.2 Estimation results

To refine the analysis of the impact of the tariff treatment on the probability of choosing public transport, it is useful to conduct an binary choice analysis that quantifies the relationship between the fare type and the modal choice while controlling for other relevant determinants. The estimation results are presented in Table 10 and 11 below. The explained variable is the probability $\Pr(PT = 1) = \frac{\exp(X\beta)}{1+\exp(X\beta)}$. The set of explanatory variables included in each of the four specifications depends on several experimental designs and tested hypotheses. Several interesting results are worth emphasizing:

First, peak/off-peak (Treat-2) and two-part tariffs (Treat-4) strongly increase public transport usage, as opposed to single ticket (Treat-1) and transit pass (Treat-3). This outcome may illustrate commuters' preference for flexibility and absence of commitment. In other words, commuters express aversion towards significant fixed costs which commit them over

Figure 1: Share of public transport choice over the 40 periods

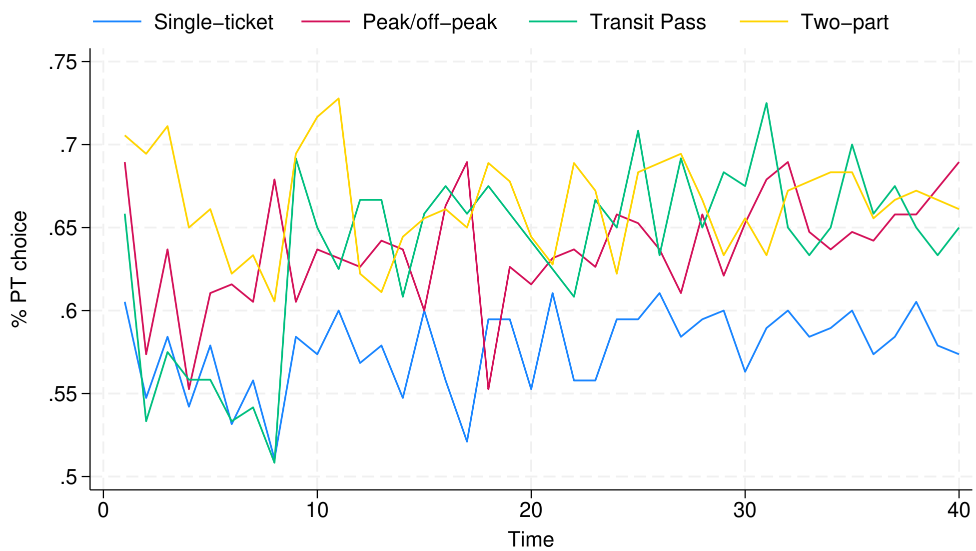
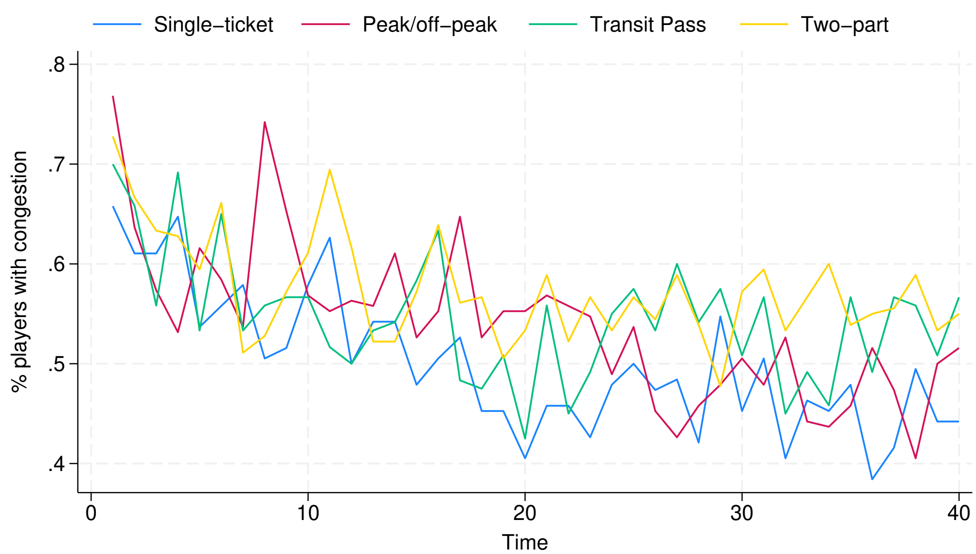


Figure 2: Share of congested trips over the 40 periods



four periods and do not allow them to internalize the information obtained in each period regarding congestion or incidents.

Second, we aim at highlighting the role of past transit experience as an explanatory factor in the decision making of commuters regarding mode choice. More specifically, we investigate the effect of experience as the impact of past levels of congestion or incidents faced by the commuter, and we also test whether there is some form of inertia regarding the choice of transportation mode. In the lab, we distinguish between short-run and long-run experience, i.e., the average congestion (frequency of incidents resp.) over all the previous periods, the last four periods only, or we just introduce an indicator of whether or not the commuter has experienced congestion (an incident resp.) in the previous period.

Our results suggest that the demand for public transport decreases (increases resp.) if the commuter has experienced more congestion in public transport (on the road resp.) in the past. Short-run events (those that are more recent) seem to have a stronger impact compared to long-run ones. This outcome is in line with other decision-making settings discussed in the behavioral literature such as risk perception, evaluation of gains and losses, intertemporal choices, or emotional judgments. We also notice that there is a difference in the intensity of the two effects, in the sense that the impact of road congestion on the probability of choosing public transport is weaker than that of congestion in public transport. This probably suggests a stronger inertia effect among commuters who have a preference for the car. In a similar fashion, incidents in public transport (on the road resp.) decrease (increase resp.) the demand for public transport. Again, the closest events in time seem to have a stronger impact. A noticeable difference however is that the intensity of the effect of incidents on the road on the probability of choosing public transport is stronger than that of incidents in public transport. A possible interpretation then is that drivers express a higher degree of aversion to random events (incidents) compared to those that are thought to be predictable (congestion).

Third, choice inertia is an important driver of transportation mode choice. Users are more likely to use public transport (private car resp.) today if they have used it more frequently in the past. Interestingly, the magnitude of the inertia effect is much higher than that of congestion or incidents. We have also suggested in the previous section that the probability

Table 10: Estimation results (part 1)

	(1)	(2)
	ChoicePT_avgt1	ChoicePT_avgt4
Peak	0.620***	0.626***
	(3.88)	(4.03)
Pass	0.457*	0.481*
	(2.05)	(2.23)
2part	0.971***	0.969***
	(4.55)	(4.55)
$Cong\,TP - All$	-1.533***	
	(-15.86)	
$Inc\,TP - All$	-0.424*	
	(-2.08)	
$Cong\,Road - All$	1.139***	
	(8.79)	
$Inc\,Road - All$	0.589***	
	(5.80)	
$Use\,TP - All$	3.653***	
	(19.21)	
$Cong\,TP - 4$		-2.075***
		(-15.94)
$Inc\,TP - 4$		-0.679**
		(-2.63)
$Cong\,Road - 4$		1.205***
		(7.52)
$Inc\,Road - 4$		0.959***
		(6.75)
$Use\,TP - 4$		4.360***
		(17.89)
$Trend$	0.00884***	0.00737**
	(4.08)	(3.28)
$Online$	0.376	0.328
	(1.73)	(1.51)
Socio-dem var.	Yes	Yes
N	26520	26520

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Estimation results (part 2)

	(1)	(2)
	ChoicePT_lagPT	ChoicePT_lagCAR
Peak	0.598***	0.554***
	(3.67)	(3.45)
Pass	0.379*	0.343
	(1.68)	(1.59)
2part	0.952***	0.905***
	(4.45)	(4.47)
(a) $Cong\,TP-1$	-0.109	
	(-0.49)	
(b) $Inc\,TP-1$	-0.935***	
	(-10.99)	
$(a)\times(b)$	-1.309***	
	(-7.02)	
(c) $Cong\,Road-1$		0.350***
		(2.60)
(d) $Inc\,Road-1$		0.824***
		(7.36)
$(c)\times(d)$		1.045***
		(8.25)
$Use\,TP-1$	1.874***	
	(16.18)	
$Use\,Road-1$		-1.935***
		(-13.85)
$Trend$	0.00837***	0.0110***
	(4.09)	(5.53)
$Online$	0.423	0.501*
	(1.89)	(2.35)
Socio-dem var.	Yes	Yes
N	26520	26520

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

of choosing public transport increases from one period to another, all else being equal.

Finally, we compare the impact of tariff structures and mode of transport choice on earnings. Table 12 presents a linear regression model with individual random effects explaining the individual gains of players. We note that the average gain for each participant at the end of the experiment amounts to 19.15 euros. As expected, final gains decrease with congestion and incidents, both in public transport and on the road. Final gains can be higher when public transport is the chosen alternative, but it depends on the fare treatment: -1.40€ if single ticket, -0.179€ if peak/off-peak, +0.91€ if transit pass, and +0.28€ if two-part. Hence, public transport provides a higher pay-off to public transport users only if a transit pass or a two part tariff is implemented. This suggests that a preference for flexibility (peak/off peak or two-part tariff) does not necessarily translate into a higher pay-off for the participant. This is consistent with the previous experiments about flexibility and pricing in transportation, as shown for instance by Denant-Boèmont and Hammiche (2008).

5 Conclusion

This paper provides valuable insights into public policy design by constructing pricing schemes that encourage public transportation usage. While tariffs offering greater flexibility to users increase the likelihood of choosing public transport, fixed annual subscriptions seem to be rather inefficient in this respect. This contribution thus opens a window of opportunity for offering flexible pricing structures that facilitate modal shifts in demand.

Our findings also reveal potential inertia in transportation choice in the form of habits and long term persistence of the impact of negative past experiences. That said, users are also shown to be quite rational and able to predict others' decisions as their behavior tends to align with our theoretical predictions based on Nash equilibrium calculations.

This article also has several potential limitations. First, the pricing scheme could also incorporate more variations between fixed and variable components. Second, our discussion could be better connected to the ongoing debates initiated by Dixit and Denant-Boemont (2014) regarding theoretical predictions derived from congestion game models. Here, we

Table 12: Player gains estimation

	(1)
	Player_Gain
PT	-1.415***
	(-5.92)
Peak	-0.423
	(-1.65)
Pass	-1.085***
	(-3.51)
2part	-0.801**
	(-3.10)
PT*Peak	1.290***
	(3.91)
PT*Pass	2.481***
	(6.51)
PT*2part	1.667***
	(5.19)
Congestion	-6.372***
	(-74.96)
Incident	-8.481***
	(-59.23)
Trend	-0.00397
	(-1.50)
Socio-demographic	Yes
N	27,200

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

adopt a model with a pure strategy equilibrium, though other forms are possible and could affect the outcomes. Third, the way we provide information to users could also be challenged. As Lindsey et al. (2014) shows, real-time information can influence user choices. We provide feedback only for the previous period and solely for the user's chosen mode of transportation and time slot (i.e., the participant knows whether there was congestion or an incident in the previous round for their selected option). Altering informational parameters could provide valuable insights into whether participants converge more rapidly towards a Nash equilibrium.

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Appendix: Lab instructions and results

- This is an experiment on transportation mode choices.
- You will receive a fixed gratification of €5.00 for agreeing to participate in this experiment, in addition to the gain you will obtain through your own decisions in the game that will be explained to you in the subsequent instructions.
- Your choices and gains are not known to other players.
- At the beginning of the experiment, you will be divided into groups of ten people. The composition of the groups will remain the same throughout the experiment.
- All participants must complete a journey from point A to point B. All participants start from the same point A, the distance they have to cover is the same, and they follow the same route. Additionally, you must arrive at point B by 9 a.m. During the experiment, you will repeat this same journey 40 times. Therefore, the experiment consists of 40 periods.
- Each participant chooses a mode of transportation independently of the choices made by other participants. There are two possibilities: Public transport (a bus or a train which operates in a dedicated infrastructure) or private car. You can change your mode of transportation at each period.
- In each period, you receive an initial endowment of €10. The cost of the journey will be deducted from this sum. In each period, the cost of your journey depends on your choices, as well as the choices made by other participants in your group. At the end of the experiment, one period will be randomly chosen to determine your final gain.
- In each period, your objective is to arrive at point B by 9 a.m. If you arrive on time, you receive €15; if you arrive early, your gain is €10; if you arrive late, it amounts to €5.
- Your arrival time at point B will depend on the choice of departure time and the travel time. You need to choose a departure time based on the mode of transportation. For the car, you have the option to choose between 3 departure times (8:00 am, 8:20 am, 8:40 am). For public transportation, you have the option to choose between two departure times (8:00 am, 8:30 am).
- The estimated travel time between A and B depends on the chosen mode of transportation: Driving takes 20 minutes and public transportation takes 30 minutes. This estimated time may be extended depending on traffic conditions. Two events may occur:
  - Congestion. For the car option, congestion occurs as soon as two or more participants leave at the same time. In public transportation, congestion occurs as soon as four or more participants leave at the same time.
  - An incident. The incident is random: it can be linked to a breakdown of a vehicle (public transportation or car). For the car option, an incident occurs on average once every five times. In public transportation, an incident occurs on average once every twenty times. In both cases, this extends the estimated travel time and delays the scheduled arrival time, which has an impact on the journey's gain.
- The cost of the journey depends on the time spent in transportation and the usage cost specific to each mode. Cost of time spent: The travel time for each mode may vary during each period depending on congestion and any slowdown due to an incident. The usage cost depends on the mode of transportation, it is fixed and known in advance.
  - The usage cost of the car is 1.5 euros per trip.
- The usage cost of public transportation depends on the current pricing method:
  - TREATMENT 1: The usage cost of transportation is 1.5 euros per trip in the form of a single ticket.
  - TREATMENT 2: The cost of the ticket for public transportation depends on the departure time. At 8:00 am, the ticket costs 0.75 euro. At 8:30 am, the ticket costs 1.5 euros.
  - - TREATMENT 3: In this scenario, the fare works as a flat-rate subscription for 4 periods if you subscribe during periods 1, 5, 9, 13, 17, 21, 25, 29, 33, and 37. The subscription price is 2 euros, and you incur no additional cost each time you take public transportation. The subscription price remains the same whether you use it for 4, 3, 2, or 1 trip. You can also choose to subscribe during periods 2, 6, 10, 14, 18, 22, 26, 30, 34, and 38 after choosing the car in the previous period. In this case, your subscription will only be valid for the next three periods, and you pay no additional cost if you choose to use public transportation. Similarly, if you choose to subscribe during periods 3, 7, 11, 15, 19, 23, 27, 31, 35, and 39, your subscription will only be valid for the next two periods, and you pay no additional cost if you choose to use public transportation. Finally, if you choose to subscribe during periods 4, 8, 12, 16, 20, 24, 28, 32, 36, and 40, your subscription will only be valid for the current period.
  - TREATMENT 4: Here, the fare operates as a flat-rate subscription for 4 periods. The subscription price is 1 euro. Each time you use public transportation, you must pay an amount of 0.75 euro. You are offered to subscribe during periods 1, 5, 9, 13, 17, 21, 25, 29, 33, and 37. You can also choose to subscribe during periods 2, 6, 10, 14, 18, 22, 26, 30, 34, and 38 after choosing the car in the previous period. In this case, your subscription will only be valid for the next three periods, and you pay no additional cost if you choose to use public transportation. Similarly, if you choose to subscribe during periods 3, 7, 11, 15, 19, 23, 27, 31, 35, and 39, your subscription will only be valid for the next two periods, and you pay no additional cost if you choose to use public transportation. Finally, if you choose to subscribe during periods 4, 8, 12, 16, 20, 24, 28, 32, 36, and 40, your subscription will only be valid for the current period. Please note that the subscription price remains the same whether you use it for 4, 3, 2, or 1 trip.
- At the end of the experiment, one of the forty periods is randomly selected. The final gain of the experiment is that of the period that is drawn randomly.