Soft and Timely Monetary Incentives to Shift Commuters' Modal Choices

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Abstract

Reducing greenhouse gas emissions through a modal shift from private cars to public transportation is commonly approached from either an economic or a psychological perspective. The present paper draws on both frameworks' strengths while addressing their respective shortcomings to propose an innovative experimental framework which tests interventions aimed at achieving an effective and durable modal shift in commuters at a relatively low cost. These interventions incentivise – or disincentivise – certain choices without disrupting the apparent incentive structure nor its underlying hierarchy between options. The influence of timeliness on their effectiveness is also investigated. Participants make repeated commute-relevant decisions under constraints designed to reflect the ecological perceptual characteristics of the decision problem commuters face. Negatively framed interventions display substantial and consistent effectiveness regardless of the occurrence of a timely event, increasing the number of public transport choices by up to 120%, while positive and combined frames' effectiveness are contingent on their respective interaction with the occurrence of a synchronous timely event. The uncovered results provide a promising perspective to transform travel behaviours while reinforcing the importance of context-specific tailoring of interventions.

Keywords: Public Transport, Behaviour, Experiment, Modal shift, Commute, Policy

1 Introduction

Greenhouses gas emissions, and CO_2 especially, are central drivers of climate change. The latest available data from the IEA (2023) establishes the transport sector as being responsible for about 21% of worldwide CO_2 energy combustion emissions in 2022. In France in particular, private cars alone are responsible for 18% of national greenhouse gas emissions, thus accounting for 53% of the transport sector's emissions (Ministère de la Transition Écologique, 2025). As mitigating climate change and its current and future consequences is of growing importance to populations and policy-makers, changing travel practices appears essential. Cars are associated with several other negative externalities, such as intensive metal and rare metal use, road accidents, congestion, and noise. Moreover, car use is correlated with higher stress and negative mood levels than public transport use (Wener & Evans, 2011), but also with a higher risk of obesity, higher blood pressure, and poorer physical health (Hoehner et al., 2012), for which an explanation lies in the greater amount of incidental physical activity typically accumulated by public transport users (Wener & Evans, 2007). As public transport is significantly less polluting than cars, notably due to emission sharing between a large number of passengers, one avenue to reduce the aforementioned negative externalities is to encourage the expansion of public transport systems and, where they are available, to support behavioural changes in favour of public transport mode choices.

To achieve such an objective, the economic literature has devised a set of tools such as taxes, subsidies, and emissions trading schemes, which tend to be effective (Salihou et al., 2023) but may become burdensome for public finances and political careers while also being generally perceived as unfair by the general public. In contrast, literature from the behavioural sciences offers a wide range of interventions which are associated with high public acceptability as well as low or contained costs, but display heterogeneous or inconclusive findings, with reported effects ranging from non-existent (Arnott et al., 2014) to modest (Semenescu et al., 2020; Mertens et al., 2022), alongside motivated suspicions of a sizeable publication bias (Hummel & Maedche, 2019; Kristal & Whillans, 2020).

The present paper devises so-called "soft monetary incentives" which consist in small sums of money given to or taken from travellers depending on their choices. They effectively provide additional monetary incentives to guide choices without coercion but, critically, do not modify the apparent incentive structure nor the underlying incentive structure' hierarchy between options. These characteristics are key differentiators between the proposed incentives and more traditional economic incentives. The underlying idea is that monetarily "nudging" travellers may prove more efficient than nudging them without the monetary component, as it allows for the nudge to be aligned with the underlying economic incentives (Lorko et al., 2025).

Additionally, there exists an ongoing debate in the literature regarding whether intervening at "timely" moments, *i.e.* moments of exogenous change in individual's lives, holds potential for effectively breaking habits and modifying behaviours durably (see the review by Department for Transport, 2025). As of yet, the evidence is limited and contrasted. The present paper provides an attempt at experimentally generating such a moment, and tests whether its interaction with soft monetary incentives yields promising results.

Thus, the nature of the effects of timely soft monetary incentives on commuter's modal choices is here investigated. The paper puts a marked emphasis on the originality of the conceived experimental design's incentive scheme by acknowledging the limitations of considering travellers as rational agents who perfectly perceive the characteristics of the decision problems they face, and accounting for these biased perceptions explicitly.

2 Background and Related Work

In most cases, commuting requires the use of a motorised vehicle, may it be a private one such as a car, or a public one, such as a bus or a train. For simplicity's sake, the discussion will hereafter be centred around a categorical dichotomy between single-occupancy vehicles and public transport. Other travelling modes, such as walking or cycling, and multimodal travel will not be considered. Henceforth, the term *car* will be assumed to refer to single-occupancy vehicles, and the term *public transport* will be assumed to refer to all forms of public transport including, but not limited to, buses, metros, trains, and trams.

2.1 Choice Criteria for Transport Modes

The choice between one mode or another does not merely consist in the resolution of a rational utility maximisation problem, but is rather a product of a breadth of internal processes and considerations which are largely considered to be normatively irrelevant (Mattauch et al., 2016). In other words, car use does not only fulfil instrumental functions, *i.e.* getting from a point to another, but also symbolic and affective functions (Steg, 2005). Mokhtarian et al. (2015) separate extrinsic and intrinsic motivations for travelling. The former refers to instrumental, utilitarian, and functional motives, while the latter refers to autotelic, hedonic, and experiential motives. They argue that both types of motivations should be taken into account when considering transportation issues. It thus appears that cars' perceived value does not only come from functionality and use but also from non-use, *i.e.* mere ownership (Moody et al., 2021) or qualities such as freedom, autonomy, and status associated with car ownership (Haustein, 2021).

Work has also been done to identify the criteria influencing transport mode choices. Most of the literature interests itself with urban populations as they are larger, more accessible for research, and benefit from denser public transport networks that facilitate mode shifts from cars to public transport. In French urban populations, a discrepancy exists between the reported importance of choice criteria and their actual impact on use (Union des Transports Publics et Ferroviaires, 2023). For instance, even though the top three self-reported choice criteria are safety, speed, and cost, the authors relate that perceptions of safety and cost are found to have no influence on behaviour. The perceptions which do have an influence on public transport use are in fact related to fluidity and regularity of the service. In contrast, French rural and semi-urban populations are typically limited in their ability to use public transport due to the insufficient provision of public transport services in these areas (Coldefy et al., 2025). Scheiblhofer et al. (2022) identified that the most impactful attribute on public transport choice for these populations was price, with travel time and reliability only having a limited effect. Overall, the literature linking individuals' residential setting and the discrepancies between self-reported choice criteria and their actual impact on behaviour is hindered by the limited availability of data accounting for all residential settings.

The influence of perceptions on the choice criteria for choosing a transport mode or another constitutes a developing branch of the scientific literature. An important part of perception is the discrepancy between one's subjective impression of a situation and the objective underlying facts. The ways this discrepancy manifests itself in transport mode choices is detailed in the following section.

2.2 Passenger's Biases and Heuristics

As in all other aspects of their lives, travellers reason and make decisions based on a plethora of biases and heuristics, which are well studied in the literature. Travel choices are affected by long-term choices as well as short-term ones, as reviewed by Garcia-Sierra et al. (2015). Long-term choices include residential and employment location, getting a driving license, and owning a car. Short-term choices include the trip's destination, departure time, mode choice, and route choice if applicable. Each choice category is associated with specific biases and heuristics. Within the transport mode choice category, a further distinction influencing the kind of behavioural processes at work is the frequency of a given mode's use (Behavioural Insights Team, 2017).

In spite of these documented effects of psychological processes on transportation mode choices, transport economists customarily rely on axiomatic models which typically assume rational behaviour (Hörcher & Tirachini, 2021). This limits the ability of their results to extend beyond the restricted framework they set up. Perhaps due to the relative cutting-edge nature of the literature on behavioural and perceptual characteristics of travellers, models and experimental designs pertaining to transport mode choices largely lack proper accounts of such factors. The present paper constitutes an initial attempt at remedying this issue. A list of biases and heuristics most relevant for transportation mode choices, which are typically not accounted for in transportation mode choice tasks despite their crucial role in real-life decisions, are presented hereafter in order to later account for them in the experimental design and data analysis.

2.2.1 Biased Perception of True Transport Mode Costs

Aside from other kinds of valuations of transportation modes detailed above, there is an asymmetry between the perception of monetary costs associated with cars and with public transport. Public transport typically exhibits salient pricing in that the full cost which the passenger has to bear is usually either paid per trip, or as some form of salient periodic subscription. In contrast, the costs of car ownership and use are numerous and associated with different degrees of saliency. Andor et al. (2020) report that expenditures related to fuel are typically nearly perfectly estimated by car owners but other expenditures including depreciation, repairs, taxes, and insurance, are drastically underestimated. This leads to the true costs of car ownership being under-perceived. This finding is corroborated by Gössling et al. (2022) who present that motorists underestimate the full private costs of car ownership, thereby creating complexities in the perception of transport modes' costs. Grison et al. (2023) replicate these findings and provide evidence of a parallel overestimation of train costs. This set of evidence demonstrates that false beliefs exist in travellers that they are better off by preferring to use their car rather than public transport, when they may in fact maximise their utility by preferring to use the latter instead of the former.

Another important dimension of travel mode choices is the presence of sunk costs associated with each transport mode. Sunk costs are non-recoverable costs which have priorly been incurred or to which decision-makers are priorly committed (Dijkstra & Hong, 2019). Surprisingly, despite being a well-known effect amongst economists and psychologists alike, it is, to the best of the author's knowledge, not implemented nor studied within modal choice tasks. However, as posited by Axhausen et al. (2000), any model of daily travel should include travellers' pre-commitments. As Wong & Kwong (2007) state, commitment escalates as a function of responsibility for initiating a previous decision and anticipated regret. In the context of sunk costs, this translates respectively to the responsibility for the sunk cost and the anticipated regret of not profiting enough from the good or service for which a cost is sunk. For public transport, the sunk cost corresponds to the subscription to the service or the previously bought tickets. For cars, the sunk costs are the purchase or leasing of a car and its maintenance fees. Indeed, once car costs are sunk, the cost of driving an additional distance is perceived as low (Krämer, 2017). Moreover, travellers may try to justify their large sunk costs by intensifying usage of the associated mode, especially if they suffer from a high level of cognitive dissonance (Chung & Cheng, 2018) due to their purchase choices. This is also linked with loss aversion: given a reference point fixed prior to the purchase, travellers may choose to invest more in car-related expenses despite a negative expected return value so that the sunk cost is not perceived as a loss. Interestingly, the behavioural biases linked to sunk costs, *i.e.* over-use of a good or service given a sunk cost, are attenuated over time (Roth et al., 2015). This is an important insight for transport stakeholders looking to transform travel behaviours as it opens a temporal perspective for successful interventions.

To the best of the authors' knowledge, previous experimental investigations have not acknowledged these insights, even though they appear essential if researchers are to create frameworks that elicit behaviours akin to real-life actions.

2.2.2 Habits and Inertia

Habits are regarded as one of the strongest predictors of car use (Osman Idris et al., 2015; Hoffmann et al., 2017; Lanzini & Khan, 2017; Müller-Eie et al., 2019; Ramos et al., 2020; Van Brecht et al., 2022; Haustein & Kroesen, 2022). The literature proposes several conceptualisations of transport habits, all quite close but nevertheless distinguishable. In Triandis' (1977) theory of interpersonal behaviour, habits are explained by the destitution of behavioural intentions as the main predictor of a given behaviour which occurs after individuals frequently perform said behaviour in response to a specific goal (such as commuting), a finding consistent with that of Aarts et al. (1997) who report that habits reduce the elaborateness of information use in judgements of daily travel mode use. Chorus (2014) considers travel choice inertia as a learning-based lock-in effect emerging in contexts of uncertainty regarding travel options. Maréchal (2016) enriches the previous approaches and conceptualises transport habits as being path-dependent, meaning that the modality of a habit's emergence influences its essence and the firmness of the grip it holds. Habits are thus seen as differentiated propensities to behave in a certain manner.

Experimental evidence supports the prevalence of transport habits. Kenyon & Lyons (2003) show that the majority of travellers do not consider their modal choice for most of their journeys, making these choices automatic and habitual. Congruently, Innocenti et al. (2013) demonstrate experimentally that individuals exhibit travel mode stickiness, meaning they are inclined to confirm their first mode choice in subsequent choices. Of relevance to note is that inertia is also found in departure times (Thorhauge et al., 2020), such that it is a widespread behavioural phenomenon across decisions, not one limited to mode choices. Consequently, it appears necessary to properly account for inertial behaviour when designing and implementing transport-related policies.

2.2.3 Methodological Considerations

Transportation mode choice studies involving laboratory – or online – settings and using experimental economics methods, i.e. investigating consequential and incentivised choices, are relatively few (Dixit et al., 2017). Notable examples include works by Denant-Boèmont & Petiot (2003), Innocenti et al. (2013), Chidambaram et al. (2014), and Gagnepain et al. (2024). Laboratory and, to a lesser degree, online settings are valuable in that they offer controlled environments in which clean elicitation and isolation of behaviours is possible. Their main shortcoming lies in their intrinsic lack of ecological validity, as real-world decisions are taken based on a wider breadth of variables and at a slower, more discontinuous pace. While there is no real alternative to field experiments to compensate for this limitation, the issue may be mitigated by creating a set of incentives which closely replicate those which participants perceive in real life. None of the mentioned articles assume such a posture and instead fix incentives that aim to reflect the underlying costs and benefits of choices. In other words, rather than focusing on perceived incentives, they focus on objective incentives. The present paper adopts the former approach and explicitly considers the main behavioural and perceptual characteristics of travellers in an effort to increase the ecological validity of the study and, *in fine*, to offer insights which are as credible and actionable as possible.

2.3 Policy Interventions

In order to influence transport mode choices, different categories of interventions have been devised. While some of them are derived from economic theory, others stem from psychological insights such as the ones described above. A non-exhaustive account of these interventions is made below.

2.3.1 Theory

Policy interventions can be categorised as either using persuasion to increase public transport use - *pull* measures - or as using dissuasion to reduce car use - *push* measures (see Batty et al., 2015 for a review). Traditionally, a distinction exists between interventions and incentives derived from economics and those derived from psychology to promote mode shifting. Salihou et al. (2023) provide an exhaustive review of these interventions and highlight their respective strengths and limitations. Essentially, economic interventions are divided between price regulations, which comprise taxes and subsidies and modify the monetary incentive structure to make certain options more or less attractive, and quantity regulations which regulate the authorised amount of supply of a good or service which can be provided in an economy. Another possible way to classify economic interventions is to distinguish between command-and-control policies (i.e. regulation), incentive-based policies, and fiscal instruments (Santos et al., 2010). When correctly implemented, these interventions are effective in shifting mode choices, but often pose a public acceptability problem (Schade & Schlag, 2003). However, as described by Mattauch et al. (2016), the orthodox approach of only internalising externalities is insufficient. The authors argue that transport demand modelling should instead consider behavioural effects explicitly.

Traditional psychological interventions are based on theories such as Ajzen's (1991) theory of planned behaviour or Triandis' (1977) theory of interpersonal behaviour, manipulating concepts such as norms, attitudes, intentions, or travellers' perception of control. More recently, Kormos et al. (2021) have proposed that all behavioural interventions, which are interventions based on insights from psychology but also behavioural economics, can be categorised into three broad categories. First, communication-based approaches strategically utilise information provision, goal-setting, and framing. Second, bias-busting approaches focus on interventions which either leverage or counteract specific biases, such as habits, anticipated preferences, or emotions. Third, technology-based approaches make use of gamification or personalised feedback. These measures are typically not coercive and do not generate social discontent, but often lack the desired effectiveness.

Policy-makers and scholars have traditionally used these frameworks in isolation from the others. While isolating effects are necessary for initial theorising and testing, recent literature has highlighted that combining intervention types appears to be a promising avenue to increase interventions' effectiveness (Lattarulo et al., 2019; Xiao et al., 2022; Salihou et al., 2023). Additionally, it is essential to consider the socio-demographic group(s) of the population(s) under study (Geng et al., 2016), as well as contextual factors and user profiles (Grison et al., 2016; Redman et al., 2013) if significant change is to be brought about. Finally and importantly, policy instruments perceived as effective, fair, and nonintrusive achieve higher levels of public support (Huber et al., 2020), such that these attributes are sought-after in policy interventions.

2.3.2 Practice

Numerous attempts have been made to generate a significant transport mode shift. Overall and as outlined in section 1, so-called behavioural approaches have not been conclusive for shifting traveller's choice of transportation mode (Batty et al., 2015). For instance, Gravert & Collentine (2021) compare the effectiveness of social norms against economic incentives and find a "tightly estimated zero" effect for the former, but a significant effect for the latter. This is coherent with Mertens et al.'s (2022) review which finds that acting on behavioural intentions is consistently less effective than acting on the presentation of information, which itself is consistently less effective than acting on the decision structure. Nudges can even have counter-productive, undesirable effects. Yang et al. (2022) report that choices of and between public transport options are subject to the information paradox, which states that more information may be detrimental and increase travel costs and travel times, which shows the importance of carefully designing interventions. This heterogeneity in uncovered results from behavioural interventions is not uniquely associated with transport choices, but is a larger issue affecting the climate change mitigation literature as a whole (Vlasceanu et al., 2024).

Economic interventions have so far proven to be better suited to the task of shifting transport mode choices. This is supported by a set of successful attempts, as reviewed by Whillans et al. (2021). For example, in one experiment, offering rebates for each day of not using the parking facilities led to a reduction in parking demand (Tang et al., 2016). Both Bueno et al. (2017) and Ghimire & Lancelin (2019) present results showing a positive effect of public transportation subsidies on public transport use among firm employees, alongside a negative effect of parking benefits on public transport use. Of importance to note is that these successes were achieved in different areas across the United States, where public transport systems are significantly less developed and efficient than in Europe, and where the cultural *status quo* is to take the car for most journeys. Regarding European contexts, Hilton et al. (2014) show that a standard scheme taxing polluting modes and subsidising greener ones significantly shifts transport mode choices, though too high an incentive-to-price ratio may backfire. Economic incentives are also found to be effective in the context of vehicle acquisition choices (Santarromana et al., 2020).

It comes from the attempts at designing effective interventions to stimulate modal change that inertia is a particularly difficult behavioural regularity to influence and change, in accordance with its importance in determining transport choices. One tentative pre-requisite to do so is to intervene at timely moments, typically when other important changes are occurring in the life of travellers (Thøgersen, 2012), such as work or home relocation, marriage, childbirth, *etc.* This is congruent with Verplanken et al.'s (2008) habit discontinuity hypothesis, which states that when a context change disrupts individuals' habits, a window opens in which behaviour is more likely to be deliberately considered. Empirical evidence supporting this hypothesis is however mixed. Walker et al. (2015) point towards the existence a time period after residential relocations during which habits may weaken and change. However, Adjei & Behrens (2023) suggest that the trigger for deliberation and information-seeking leading to habit change may instead lie around two months before the timely event, when the decision-maker is consolidating his plan of action, meaning that the window may be missed by targeting interventions around the time of the event rather than in the planning phase. A meta-analysis conducted by Semenescu et al. (2020) suggests that residential relocation does not significantly moderate mode change following behavioural interventions. Moreover, switching one's mode after a habit-disrupting event may repose on a myriad of factors (Fatmi & Habib, 2017), thus rendering the habit discontinuity hypothesis insufficient to properly approach the issue. For instance, post-relocation mode choices may be more determined by inherent incentives embedded in the infrastructure's constraints (Zarabi & Lord, 2019; Pfertner et al., 2022) rather than supplementary incentives from interventions.

In light of the state of the literature, some recommendations and promising avenues are emerging to increase behavioural interventions' effectiveness. Beshears et al. (2021) present that nudges should avoid being forward-looking as this creates a lack of urgency which can counter-balance behaviour against the nudge, and may work better by being framed as fresh starts. Ceceli et al. (2020) show that a combination of feedback on performance and monetary incentives stops automated decision-making and restores goal-directed control, *i.e.* makes people contemplate their choices unlike when they act under habitual behaviour. This insight is promising in that feedback on performance after a transport mode decision is endogenously existent and salient, such that coupling incentives may lead to desirable outcomes. Kristal & Whillans (2020) conduct a set of field experiments in which they test the effectiveness of typical nudges which have been found to work in other frameworks, such as informational nudges, non-cash incentives, or personalised travel plans. Their well-powered interventions do not yield statistically significant effects, but insightful lessons are drawn from them. The authors propose a threefold explanation behind this lack of significance: the lack of monetary incentives, the convenience and lack of friction associated with the *status quo*, and the intrinsic stickiness of habits which altogether suggest that the behavioural approach may not be the most appropriate one. Their recommendations for more effective future interventions include leaning towards interventions which display the characteristics of economic ones and intervening in a timely fashion.

2.4 Research Question

The present papers draws on this literature and devises a novel experimental framework which explicitly accounts for major transport-related behavioural phenomena, namely the biased perception of transport modes' costs and inertia, in order to increase the relevance of participants' behaviours and the validity of any uncovered results. Innovative interventions called "soft monetary incentives" and lying at the crossroads of economic and psychological insights, that direct choices without coercion while not modifying the apparent incentive structure nor the underlying incentive structure's hierarchy between options, are tested. By implementing the latter characteristic, this paper investigates incentives which deviate from purely economic interventions while nevertheless maintaining a monetary incentive component, but, through the former characteristic, go beyond this aspect by explicitly accounting for participants' perception of the problem they face. It also explores the effect of introducing a timely "critical" moment of exogenous change on the proposed interventions.

As such, the present paper explores whether introducing soft monetary incentives at timely moments in commuters' lives can successfully stimulate a modal shift from cars to public transport. Two sets of hypotheses are formulated. The first set is about behavioural inertia and built upon the literature presented in section 2.2.2 and section 2.3.2.

H1.1 Participants initially implement exploration strategies to try out options and exhibit variability in their choices, but then develop inertia and engage in exploitation strategies, *i.e.* develop habits.

H1.2 The occurrence of a critical moment of change leads to a rebound in exploration, before a subsequent return to inertial exploitation.

The second set of hypotheses concerns the effectiveness of soft monetary incentives depending on the occurrence of a synchronous critical moment of change.

H2.1 Without a critical moment of change, soft monetary incentives are effective in shifting mode choices from the car to public transport.

H2.2 Associated with a critical moment of change, soft monetary incentives are effective to a greater extent than without such a moment in shifting mode choices from the car to public transport.

H2.3 In both cases, gain-framed incentives are less effective than loss-framed incentives, which are themselves less effective than incentives combining both frames.

3 Experimental Methods

3.1 Participants

Two hundred and thirty-four French car-commuters were recruited through Prolific, a commercial recruitment platform. Due to the specificity of the required sample and despite the authors' best efforts, the number of recruited participants is slightly below the desired level. They voluntarily took part in the experiment knowing they would receive, upon completion, monetary compensation consisting of a fixed fee and a performance-dependent fee. The sample displays satisfying representations of urban (41.77%), semi-urban (33.76%) and rural populations (24.47%). This observation also applies for participants' reported access to public transport stations, with 47.00% having walking access in under ten minutes, 22.22% having vehicular access in under ten minutes, and 30.77% not having any access. A detailed description of the sample's characteristics is available in appendix A.

3.2 Material

The experiment was programmed using oTree (Chen et al, 2016) and conducted online. The visuals used were adapted from the SNCF's internal image database.

3.2.1 Framework

The main task of the experiment consists in a set of commute-related transport choices which is repeated over forty rounds, not including three initial training rounds. This number of repetitions was selected in light of existing literature (Denant-Boèmont & Petiot, 2003; Hartman, 2007; Anderson et al., 2008; Chidambaram et al., 2014; Dechenaux et al., 2014; Janusch et al., 2015; Gagnepain et al., 2024) to allow for the identification of relevant effects without overburdening participants. The experiment is framed as a fictional context in which, at each repetition, participants must commute to work with the objective of arriving at work at exactly nine o'clock in the morning. Each repetition is called a day i, with five days making a week j. Thus, the forty days correspond to a total of eight experimental weeks. Combinations of i and j are hereafter denoted $t \in \{1, 2, \ldots, 40\}$. This framing is implemented to facilitate participants' ability to represent themselves in the experimental context.

3.2.2 Decisions

During each repetition, participants attempt to achieve their daily objective by selecting a transport mode, either car or public transport, as well as a departure time, given a set of incentives described in the following subsections.

Before being autorised to select a given transport mode, participants must pay a mode-specific fixed fee which grants access to the associated mode for five experimental days, *i.e.* one experimental week. Each transport mode is associated with a unique and unchanging fixed fee. Once a fixed fee is paid, the associated transport mode becomes available for selection and the option to pay that mode's fixed fee is disabled for five repetitions. At each repetition, participants are exposed to information regarding the number of remaining repetitions during which they may use the mode. The fixed fee for any transport mode may be paid at any repetition, provided that no payment for the selected mode has been in made during the preceding four repetitions. Furthermore, it must be that participants maintain access to at least one transport mode throughout the task, as they cannot proceed with the experiment otherwise. Payments for different modes' fixed fee are allowed, but not forced, to occur simultaneously.

Once access to the desired number of transport modes is obtained by paying the applicable fixed fee(s), participants must select the transport mode with which they want to commute on that experimental day. The generic term "public transport" is preferred to more precise descriptions so as not to disrupt participants' internal representations of what using public transports means. Let M_t denote one's modal choice at repetition t, PT a public transport choice, and C a car choice, then:

$$M_t \in \{PT, C\} \tag{1}$$

After selecting a transport mode, participants must choose a departure time at which they will leave for work on that experimental day. Cars are associated with a set of options ranging from 8:00 am to 8:40 am discretised at the one minute level, while public transport is associated with three departure time options: 8:00 am, 8:15 am, and 8:30 am. This discrepancy is implemented to account for the greater freedom associated with taking the former with respect to the latter. Let $D_t(M_t)$ denote one's departure time choice at repetition t given modal choice M_t for that same repetition, then:

$$D_t(M_t) = \begin{cases} \{8{:}00 \text{ am}, 8{:}15 \text{ am}, 8{:}30 \text{ am}\} & \text{if } M_t = PT \\ \{8{:}00 \text{ am}, 8{:}01 \text{ am}, \ldots, 8{:}39 \text{ am}, 8{:}40 \text{ am}\} & \text{if } M_t = C \end{cases} \tag{2}$$

These decisions are mandatory as participants cannot move forward with the experiment unless a transport mode and a departure time are selected.

3.2.3 Disruptions

Each transport mode is assigned a fixed set of probabilities of a binary disruption λ_t occurring on a given repetition t. These probabilities are dependent on the chosen mode M_t and its associated departure time $D_t(M_t)$. Participants know that these probabilities exist, are fixed, and are differentiated, but do not know what the probabilities are exactly or how the underlying logic is constructed. The disruption encompasses any and all reasons why the trip might be longer than usual, such as weather conditions, accidents, congestion, roadworks, etc. Most transport mode choice experiments model congestion as an endogenous phenomenon. They typically use simplified frameworks in which a small subset of participants (often ten) plays together and whether congestion occurs for the repetition is determined by the share of participants who choose the same transport mode. This method does not consider that playing in such small subsets gives an unrealistically heavy weight to a single decision on the congestion outcome. It is uncertain whether these over-weighting and over-salience characteristics reflect real-life thought processes. Though indeed endogenous to each individual commuter's modal decision, congestion may usually be perceived as an exogenous process which does not depend on one's own behaviour, but only on the behaviour of others. Thus, it is here assumed that is not necessary to endogenise congestion. Consequently, congestion is exogenised. The unique probabilities of disruption $P(\lambda_t = 1 \mid M_t, D_t(M_t))$ associated with each combination of travel mode M_t and departure time $D_t^{M_t}$ follow stylised convex distributions specified below.

$$P(\lambda_t = 1 \mid M_t = C, D_t(C)) = \begin{cases} 0.20 & \text{if } D_t(C) \in \{8{:}00 \text{ am}, \dots, 8{:}04 \text{ am}\} \\ 0.2075 & \text{if } D_t(C) \in \{8{:}05 \text{ am}, \dots, 8{:}09 \text{ am}\} \\ 0.225 & \text{if } D_t(C) \in \{8{:}10 \text{ am}, \dots, 8{:}14 \text{ am}\} \\ 0.255 & \text{if } D_t(C) \in \{8{:}15 \text{ am}, \dots, 8{:}19 \text{ am}\} \\ 0.305 & \text{if } D_t(C) \in \{8{:}20 \text{ am}, \dots, 8{:}24 \text{ am}\} \\ 0.355 & \text{if } D_t(C) \in \{8{:}25 \text{ am}, \dots, 8{:}29 \text{ am}\} \\ 0.455 & \text{if } D_t(C) \in \{8{:}30 \text{ am}, \dots, 8{:}34 \text{ am}\} \\ 0.605 & \text{if } D_t(C) \in \{8{:}35 \text{ am}, \dots, 8{:}39 \text{ am}\} \\ 0.805 & \text{if } D_t(C) = 8{:}40 \text{ am} \end{cases} \tag{3}$$

$$P(\lambda_t = 1 \mid M_t = PT, D_t(PT)) = \begin{cases} 0.10 & \text{if } D_t(PT) = 8{:}00 \text{ am} \\ 0.135 & \text{if } D_t(PT) = 8{:}15 \text{ am} \\ 0.22 & \text{if } D_t(PT) = 8{:}30 \text{ am} \end{cases} \tag{4}$$

These distributions are designed to replicate two empirical phenomena. First, the more numerous empirical disruptions and congestion observed in car traffic as compared with public transport traffic, which is captured by the systematically higher probability of disruption of the car mode for any given departure time. Second, the higher risk of a disruption occurring when more people use a mode, as during rush hour, which is assumed to intensify as departure times approach the latest possible option to arrive on time.

3.2.4 Travel Times

Travel time for a given repetition is dependent on the chosen transport mode and on whether or not a disruption occurs. Denote $n_t^{M_t,\lambda_t}$ the number of minutes spent in a given transport mode M_t at repetition t given an absence of disruption $\lambda_t = 0$ or presence thereof $\lambda_t = 1$. We have:

$$n_t^{M_t,\lambda_t} = \begin{cases} 20 & \text{if } M_t = C,\ \lambda_t = 0 \\ 40 & \text{if } M_t = C,\ \lambda_t = 1 \\ 30 & \text{if } M_t = PT,\ \lambda_t = 0 \\ 60 & \text{if } M_t = PT,\ \lambda_t = 1 \end{cases} \tag{5}$$

These times are not experienced. This travel time structure models the fact that taking the car is typically faster than using public transit when there are no disruptions, and that a disruption in public transport may lead to significantly more delay than that in car traffic. The values allow for the incentives to be appropriately structured.

3.2.5 Incentives

On top of a fixed completion fee, a performance-dependent monetary reward scheme is implemented. Participants earn performance-dependent points during each repetition, and one experimental week is randomly selected for payment at the end of the experiment, at what time the points are converted to currency at a pre-determined rate.

Each repetition affords an opportunity to earn points. The punctuality with which participants arrive at work determines the attributed number of points for a given repetition. Let G_t^a denote the gain, expressed in points, obtained on repetition t and associated with arrival time a, then:

$$G_t^a = \begin{cases} 12 & \text{if } a \in \{\text{8:20 am}, \ldots, \text{8:24 am}\} \\ 12.5 & \text{if } a \in \{\text{8:25 am}, \ldots, \text{8:29 am}\} \\ 13 & \text{if } a \in \{\text{8:30 am}, \ldots, \text{8:34 am}\} \\ 14 & \text{if } a \in \{\text{8:35 am}, \ldots, \text{8:39 am}\} \\ 15 & \text{if } a \in \{\text{8:40 am}, \ldots, \text{8:44 am}\} \\ 16.5 & \text{if } a \in \{\text{8:45 am}, \ldots, \text{8:49 am}\} \\ 18 & \text{if } a \in \{\text{8:50 am}, \ldots, \text{8:54 am}\} \\ 20 & \text{if } a \in \{\text{8:55 am}, \ldots, \text{8:59 am}\} \\ 22 & \text{if } a = \text{9:00 am} \\ 19.5 & \text{if } a \in \{\text{9:01 am}, \ldots, \text{9:04 am}\} \\ 17 & \text{if } a \in \{\text{9:05 am}, \ldots, \text{9:09 am}\} \\ 15 & \text{if } a \in \{\text{9:10 am}, \ldots, \text{9:14 am}\} \\ 13.5 & \text{if } a \in \{\text{9:15 am}, \ldots, \text{9:19 am}\} \\ 12.5 & \text{if } a \in \{\text{9:20 am}, \ldots, \text{9:24 am}\} \\ 12 & \text{if } a \in \{\text{9:25 am}, \ldots, \text{9:30 am}\} \end{cases} \tag{6}$$

The underlying logic for these values is, first, that arriving closer to the objective yields more utility, and second, for a deviation of equivalent magnitude from the optimal time of arrival, being late leads to a lesser payoff. The hierarchy of gains is designed to encapsulate the utility costs associated with arrival time, notably in terms of time spent and psychological comfort. Arriving on time is assumed to make one feel good about oneself, showcasing punctuality, appropriate planning, and trip optimisation. Arriving early is hypothesised to be associated with the psychological safety of certainty, but also with "wasted" time which could have been devoted to other activities, such as sleeping or spending time with one's family. Arriving late is presumed to be associated with the discomfort and social sanction of tardiness, which can hinder one's mood or generate stress. This is an imperfect approximation, as individual differences undoubtedly exist on the matter, but is posited to represent the general case well.

Participants must also take into account two sources of costs when making their decisions. First, to use a given transport mode, one has to pay a fixed fee which allows to use the mode for five experimental days. Denoting the fixed fee $FC_t^{M_t}$ paid on repetition t with M_t the associated transport mode, we have:

$$FC_t^{M_t} = \begin{cases} 6 & \text{if } M_t = C \\ 4 & \text{if } M_t = PT \\ 10 & \text{if } M_t = C + PT \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

This novel feature is introduced to account for the sunk cost phenomenon whereby most or all of a transport mode's costs is typically incurred priorly to individual trips. It replaces the daily fixed fee commonly used in experimental modal choice tasks. Two mechanisms underlie this fixed fee design. First, having to pay a relatively large lump sum only periodically allows for having sets of four repetitions during which the true cost of participants mode choices is not salient. Second, when participants choose to pay for a fixed fee, the corresponding number of points is deducted instantaneously and no further mention is made of this transaction. Consequently the feedback page (see section 3.2.6) does not include any information regarding fixed fees. The fixed fees in the experiment may correspond to acquisition and maintenance costs for cars and periodic subscription for the public transport service. The car fixed fee is set higher than the alternative to capture the fact that car use requires a higher initial payment than public transport use. In this way, ecological validity is increased and participants' thought processes and decisions are proximal to those under real-life conditions.

The other cost corresponds to a variable fee $VC_t^{M_t}$ which depends on the chosen transport mode M_t on a given repetition t and is charged for every minute spent on a given transport mode. The fees are the following:

$$VC_t^{M_t} = \begin{cases} 0.07 & \text{if } M_t = C \\ 0.12 & \text{if } M_t = PT \end{cases} \tag{8}$$

This variable fee structure is designed to account for the fact that cars are typically perceived as costing less than public transport, though they factually cost more. Given the simplified experimental setting, making the variable fee of public transport less than that of the car, as is the case in real life, would make the task a trivial one: choosing the public transport option would be perceived as a strictly dominating strategy with respect to the car option.

Thus, the payoff π_t of participants at repetition t is:

$$\pi_t = G_t^a - FC_t^{M_t} - VC_t^{M_t} \times n_t^{M_t, \lambda_t} \tag{9}$$

Overall, the above model sets up a behaviourally-informed setting which, rather than giving participants objective information which does not mimic real-life perceptions, provides information congruent with participants' real-life perceptions. This allows them to reason and make decisions which are close to the ones they would in their life. Specifically, the model is calibrated such that participants perceive the car alternative as being more rewarding than its public transport counterpart – at least initially for more sophisticated participants, even though choosing the public transport option with the departure time associated with a punctual arrival under normal circumstances is associated with the highest expected reward.

3.2.6 Feedback

For each repetition, after participants have taken their decisions, they are exposed to feedback reminding them of their choices, informing them whether a disruption occurred on that repetition, and summarising their gains. The fixed fee expenditure is purposefully not included in the gain summary in order to simulate the psychological implications of sunk costs, as explained in section 3.2.5. Furthermore, this allows not to bias choices following the first repetition which would necessarily be associated with a subpar gain, likely leading to a negative stereotype of the initially selected transport mode.

3.2.7 Treatments

A $2 \times 2 \times 2$ factorial design is employed, making eight randomly assigned experimental conditions. The first factor corresponds to a gain-framed corporate intervention which is enforced starting from the day following the treatment message display. Specifically, participants are informed that from there on, their employer would give them an additional two points for every time they choose the public transport option for their commute. The accumulated points are paid in a single instalment at the end of the session following the same random week selection payment rule as for the rest of the incentives, such that no further mention is made of this new policy until the final payment. Apart from the initial explanation of the policy, an effort is made to minimise the salience of the intervention, as such an intervention in the real-world would likely take the form of a monthly or yearly payment, as opposed to a daily one. Moreover, this allows to keep the apparent incentive structure intact during the remainder of the experiment.

The second factor corresponds to a loss-framed corporate intervention. It consists in the employer deducting two points from participants for every time they choose to commute by car in the following repetitions. The treatment is otherwise identical to the previous one. Critically, the first and second factors do not modify the incentive hierarchy between transport mode options, they merely provide additional monetary incentives without altering the options' standing relative to one another.

The third factor corresponds to the introduction of a so-called critical moment of change in the experimental life of participants. Participants are told that they have moved houses and that they must consequently arrive at work by 9:15 am from that moment on, instead of the initial 9:00 am. They are also informed that there exists a non-zero probability that the disruption probabilities have changed. The probability that the disruption probabilities change is one percent. This is done to encourage choice exploration by disrupting habits, as may occur after a real-life move. The departure time options are all moved forward fifteen minutes accordingly. Additionally, the visual framework changes to some extent when a critical moment occurs (see section 3.2.9).

In the case where all factors are equal to zero, a noise message is displayed in the same manner as those described in section 3.2.8. Participants are exposed to one of eight possible combinations of these three factors.

3.2.8 Noise

Once per experimental week, a character representing one's company conveys a random noise message. This message is displayed after one of the randomly selected experimental weekdays' feedback page. All messages are designed to be neutral and irrelevant to the tasks so as not to bias subsequent decisions. They are introduced to somewhat reduce the drudgery of the task and lessen the salience of the treatment information provided halfway through the task. There are six messages in total, one for each experimental week except the fifth one, during which the treatment is provided, and the last one. The former omission is aimed at avoiding a cognitive overload for the week which might reduce the effectiveness of the interventions. The latter omission is due to the noise messages having served their use and no longer being needed so close to the end of the experiment. The presented messages are taken from a battery of eight possible messages. The list of messages is available in appendix B.

3.2.9 Visual Framework

Throughout the experiment, participants are helped to visualise the setting by a set of drawings, which can all be found in appendix C. On the choice page figures a drawing of a house located either on the bottom-left side or the bottom-right side of the screen (with the side randomly assigned at the beginning of the session) and a building representing the company located at the centre of the page. Between them lies a road with a few houses and trees, and an arrow going from the house to the company building, indicating what the trip to be made is. On the feedback page, visuals depict a car or a train (depending on choice) positioned next to the company building, indicating arrival at work.

Noise messages and treatments providing point-incentives take the form of a character with a text bubble above him in which the relevant message is inscribed. Regarding the critical moment treatment, a box provides information on the house move and the associated consequences. Under that box, the house displayed on choice pages is shown by an arrow to move to the other side of the screen. For all following repetitions, the house and associated visuals are correspondingly flipped to the other side of the screen.

3.2.10 Comprehension and Control Questions

To make sure participants understand the choice context they are placed in during the experiment, comprehension questions are asked following the provision of important incentive-relevant information. First, after the initial instructions, participants are prompted to answer a series of three questions (see appendix E). Correct answers lead to being allowed to proceed with the rest of the experiment, while incorrect answers require participants to further their search for relevant information in the instructions. The comprehension questions are non-trivial and require some degree of thought and computations, but no limit is imposed on the number of mistakes they can make. Second, right after being exposed to the treatment information, participants are asked a set of questions to test their comprehension of the treatment information in the same manner as after the initial instructions. The implications of correct and wrong answers are identical to those of the post-instructions questions.

At the end of the experiment, participants answer a set of control questions. First, risk preferences are controlled for by means of a simple question asking participants to self-assess their general risk attitude on a scale ranging from one to ten. It is derived from Falk et al. (2018) and preferred over more complex elicitation methods for two reasons. The first is that it is short and allows to minimise participant fatigue and maximise their willingness to finish the study, given the relative tediousness of the main task. The second is that it typically performs well when used as a mere control variable as it is straightforward. Second, motility, *i.e.* the ability to be mobile, is controlled for by means of a short version of the motility questionnaire as links between motility and mobility behaviours have been established by its authors (Bernier et al., 2019). Finally, participants are asked to provide some demographic information comprising age, gender, highest achieved educational level, socio-professional category, residency (urban, semi-urban, rural), car possession, car use for commuting, public transport access (within ten minutes) for commuting, and their habits and work-provided leeway in terms of punctuality.

3.3 Procedure

After providing their informed consent, participants read the instructions (available in appendix D) for the experiment. After successfully answering the comprehension questions, participants proceed to complete three training repetitions of the main task. When these are done, a message indicating the end of the training session and the resetting of repetitions to one and of points to zero is displayed.

Participants complete the first twenty repetitions of the task at their desired pace. After the twentieth repetition, *i.e.* after experimental day five of experimental week four, participants are randomly exposed to one of the eight possible treatments. They are then prompted to complete the post-treatment comprehension questions. After they have provided correct answers, the tasks proceeds where it left off and participants complete the remaining twenty repetitions with the appropriate contextual modifications depending on assigned condition.

Once all repetitions are completed, participants proceed to answer the set of control questions. After this is done, participants are shown which experimental week has been selected for payment, alongside a breakdown of their earnings for each associated experimental day. If applicable, they are informed of the provision or deduction of points due to the incentive treatments. Finally, the monetary payoff corresponding to their total number of earned points is displayed and they are thanked and paid for their contribution.

4 Results

4.1 Data Analysis

A distinction is established between sets of repetitions. Repetitions are categorised according to whether they occur in the pre- or post-treatment phase. Within each of these categories, a further distinction is made between so-called exploration and exploitation repetitions. Exploration repetitions are assumed to consist in the first ten repetitions of each phase, thus comprising repetitions one to ten as well as repetitions twenty-one to thirty. They leave enough time for participants to try out each transport mode, thus affording opportunities to explore options by paying for each fixed fee at least once without overlap between modes. Exploitation repetitions are assumed to consist in the remaining ones, eleven to twenty and thirty-one to forty, during which participants, having had a chance to try out strategies, stick with their preferred choice. These sets of repetitions are denoted S_p^{set} with $set \in \{explore, exploit, full\}$ the possible repetition categories and

$p \in \{prior, post\}$ the phase of the experiment with respect to the treatment interventions.

To test the first set of hypotheses – the one pertaining to inertial behaviour – two complementary analyses are conducted. On the one hand, the proportion of participants who choose the same mode "most of the time" during exploitation phases is explored. A necessarily arbitrary definition of "most of the time" is used and characterises the frequency as "more than seventy-five percent of the time", meaning that participants need to choose the same mode for at least eight out of the ten exploitation repetitions to be qualified as exhibiting inertia under this approach. This criterion is relatively conservative, but more liberal ones do not lead to drastically dissimilar statistics (see appendix F). On the other hand, the variability of these participants' transport mode choices is investigated. The mean standard deviations of these choices are aggregated into four groups: initial exploration $S^{explore}_{prior}$, initial exploitation $S^{exploit}_{prior}$, post-treatment exploration $S^{explore}_{post}$, and post-treatment exploitation $S^{exploit}_{post}$. A set of Fligner-Killeen tests are conducted to determine whether statistical differences exist in choice variability between these sets of repetitions, as well as between groups who were exposed to a critical moment of change and groups who were not.

The second set of hypotheses – the one relating to the effectiveness of the treatment interventions – is tested by means of a set of negative binomial regressions following a Differences-in-Differences methodology. This kind of regression model is employed as the objective of this paper is to estimate whether the interventions affect the number of times participants choose the public transport option, rather than their effect on the likelihood of choosing this mode. The difference between the two is subtle but nevertheless important, as count data helps provide clear and actionable insights about actual choices and variations therein, not propensities to make these choices. Since the count data displays systematic overdispersion, negative binomial regression models are preferred over Poisson models. Thus, the regressed models are chiefly interested in the interaction effect between a binary temporal variable capturing whether a choice is made before or after the provision of the treatments and a factorial variable capturing which soft monetary incentive, if any, is provided. Not all collected control variables are included in the final regression models. The exclusions are motivated by comparisons made between different model specifications' Akaike Information Criterion.

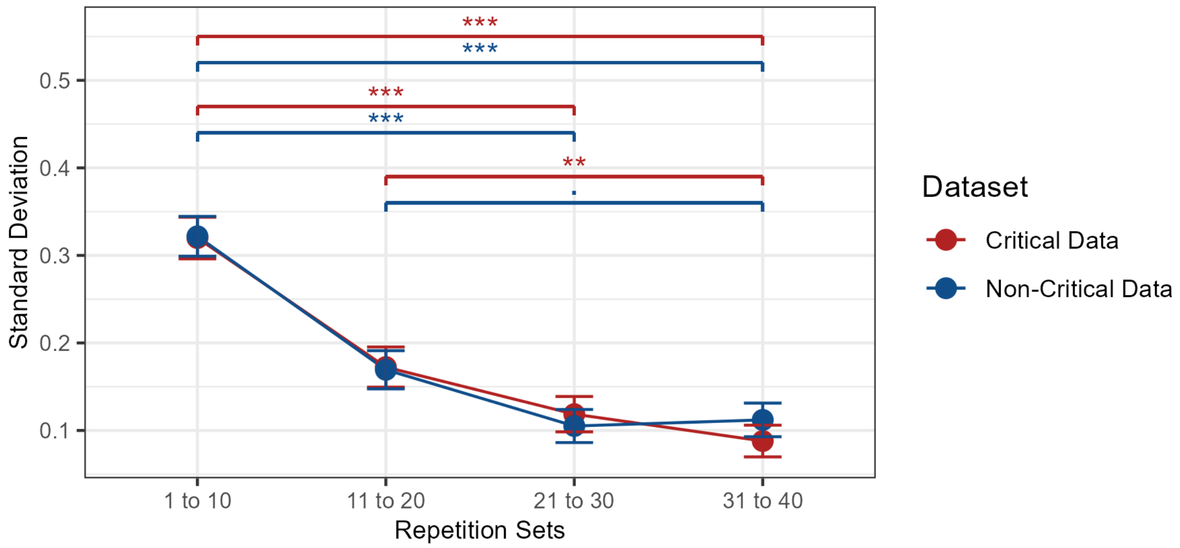
4.2 Inertia

Table 1 exposes the proportion of participants who, following the definition proposed in section 4.1, can be qualified as making habitual choices during the exploitation phases before and after the treatment provision. Summing over both transport modes, it comes that inertia is found in around 57.15% to 83.87% of participants' transport mode choices prior to the treatment provision, depending on experimental condition. This range moves to 75.86% to 89.28% after the treatment provision. These rates confirm the preponderance of habitual choices and the reinforcement thereof as the experiment moves on, which is congruent with existing literature. Another finding which can be extracted from the table is that, pre-treatment, the proportion of participants exhibiting inertia towards the car mode is systematically greater than that for the public transport mode, while post-treatment, this observation holds for both conditions where no soft monetary incentive is provided, but is reversed for all those where at least one form of soft monetary incentive is provided. Although this constitutes a descriptive account rather than a formal statistical analysis, it aligns closely with the more rigorous findings of section 4.3.

Exploitation Phase	Pre-Treatment		Post-Treatment	
Mode	Public Transport	Car	Public Transport	Car
Control	14.29	42.86	28.57	60.71
Loss	30	46.67	76.67	6.67
Gain	28.57	39.29	78.57	7.14
Interaction	37.04	40.74	70.37	11.11
BL Control	24.14	44.83	31.03	44.83
BL Loss	25.81	32.26	77.42	6.45
BL Gain	32.26	51.61	58.06	22.58
BL Interaction	30	40	76.67	6.67

Note: The remainder consists of the proportion of participants alternating between modes.

Table 1: Proportion of Participants Making Habitual (> 75%) Transport Mode Choices



*Note: .p<0.1; **p<0.01; ***p<0.001*

Figure 1: Mean Variability in Transport Mode Choices by Round Set and Dataset.

The data regarding the variability of transport mode choices is visualised in figure 1. Participants exhibit a high rate of variability in their transport mode choices during the opening phase $S^{explore}_{prior}$, meaning that they try out the two mode options which allows them to sample and compare a set of mentally representative consequences associated with each option. This rate is statistically significantly higher at all relevant levels than both post-treatment phases $S^{explore}_{post}$ and $S^{exploit}_{post}$, indicating lower variability in mode choices during the second half of the experiment. No rebound in exploration is observed during the second exploratory phase $S^{explore}_{post}$, such that participants did not further their exploration of options after the introduction of the treatment interventions. Instead, what is observed is that the initial exploitation phase $S^{exploit}_{prior}$ sees a sizeable reduction in transport mode choice variability with respect to the first set of repetitions, and that choice variability subsequently stabilises itself at a low level in the post-treatment phases $S^{explore}_{post}$ and $S^{exploit}_{post}$, which attests to the emergence of habitual behaviour within the experimental setup.

4.3 Treatment Effectiveness

The following two subsections are centred around the comparison of the number of public transport mode choices before and after the time of treatment provision, first using the full sample S^{full}, *i.e.* comparing S^{full}_{prior} to S^{full}_{post}, and second using a restricted sample composed only of exploitation rounds $S^{exploit}$, *i.e.* comparing $S^{exploit}_{prior}$ to $S^{exploit}_{post}$. Descriptive Differences-in-Differences plots of the data are available in appendix G.

4.3.1 Full Sample S^{full}

The regression results regarding the effectiveness of the treatment interventions under the full sample S^{full} are presented in table 2. The main effect variables ending in "Treatment" in the table are levels of the regression's factorial variable for treatment, which takes on eight levels, one for each experimental condition. Its reference level is the so-called "control" condition which includes no soft monetary incentive but does include a critical moment of change. The same factorial logic applies to the interaction effects. Within the controls section, variables pertaining to public transportation access are also levels of a factorial variable, the reference level of which being having walking access to public transportation.

The Differences-in-Differences analysis focuses on the interaction effects between time (before or after the treatment interventions) and the treatments associated with each experimental condition. Regarding the conditions which include a critical moment of change, gain-framed and loss-framed soft monetary incentives respectively lead to statistically significant increases of 81.68% ($p \approx 0.005$) and 84.09% ($p \approx 0.005$) in the expected number of public transport mode choices during S^{full}_{post}, with respect to the counterfactual outcome trajectory inferred from the control condition's trend. The interaction condition, where both soft monetary incentives are implemented alongside a critical moment of change, displays a slightly less robust but nevertheless statistically significant increase in expected public transport mode choice counts of approximately 68.35% ($p \approx 0.012$). To properly analyse the effects of soft monetary incentives when no critical moment of change occurs, *i.e.* under the baseline (denoted "BL" in the regression table) conditions, a set of linear hypothesis tests are conducted to account for the necessary combination of baseline treatment groups' effects with that of the baseline control group. This yields that, on their own, gain-framed, loss-framed, and interactional soft monetary incentives respectively lead to statistically significant increases in expected number of public transport mode choices during S^{full}_{post} of 58.86% ($\chi^2(1) \approx 9.24$, $p \approx 0.002$), 75.69% ($\chi^2(1) \approx 15.97$, $p < 0.000$), and 84.21% ($\chi^2(1) \approx 15.08$, $p < 0.000$), with respect to the inferred counterfactual.

To assess whether critical moments of change alone influence choices, further linear hypothesis tests are conducted. For the control conditions, which are not associated with any soft monetary incentive, the effect of a critical moment of change on the expected number of public transport mode choices is not statistically significant at any relevant level ($\chi^2(1) \approx 0.04$, $p = 0.85$). Controlling for identical soft monetary incentives, critical moments of change show no statistically significant effects on expected public transport

	Dependent variable:
	Public Transport Choice Count
Intercept	1.471^{***}
	(0.201)
Main Effects	
Time	-0.047
	(0.174)
Gain Treatment	0.399^{*}
	(0.177)
Loss Treatment	0.437^{*}
	(0.177)
Interaction Treatment	0.441^{*}
	(0.189)
Baseline Control Treatment	0.319.
	(0.191)
Baseline Gain Treatment	0.385.
	(0.199)
Baseline Loss Treatment	0.441^{*}
	(0.177)
Baseline Interaction Treatment	0.368^{*}
	(0.182)
Controls	
Age	0.007.
	(0.004)
Risk Attitude	0.028^{*}
	(0.014)
Car Use (5 a week)	-0.211^{**}
	(0.075)
Vehicule Access to Public Transportation	0.093
	(0.082)
No Access to Public Transportation	0.256^{**}
	(0.085)
Interaction Effects	
Time x Gain Treatment	0.597^{**}
	(0.212)
Time x Loss Treatment	0.610^{**}
	(0.218)
Time x Interaction Treatment	0.521^{*}
	(0.208)
Time x BL Control Treatment	-0.040
	(0.214)
Time x BL Gain Treatment	0.503^{*}
	(0.217)
Time x BL Loss Treatment	0.604^{**}
	(0.203)
Time x BL Interaction Treatment	0.651^{**}
	(0.217)
Observations	468
Log Likelihood	-1,587.628
θ	2.102^{***} (0.196)
Akaike Inf. Crit.	3,217.255
Note:	.$p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 2: Regression Results (All Rounds) with Individual-Level Clustered Standard Errors

mode choice counts across the gain-framed ($\chi^2(1) \approx 0.28$, $p \approx 0.597$), loss-framed ($\chi^2(1) \approx 0.00$, $p \approx 0.970$), and interactional ($\chi^2(1) \approx 0.58$, $p \approx 0.448$) conditions.

Three control variables significantly moderate expected transport mode choices. First, each unit increase in risk attitude leads to a 2.81% ($p \approx 0.046$) decrease in the expected count of public transport choices. Second, using one's car five times a week or more is associated with an approximate 19.06% ($p \approx 0.005$) lesser expected count. Third, having no access to public transportation approximately leads to a 29.21% ($p \approx 0.003$) increase in the expected count.

4.3.2 Exploitation Rounds $S^{exploit}$

The regression presented hereafter is structured in exactly the same way as the one featured in the previous subsection 4.3.1. However, here, only exploitation repetitions $S^{exploit}$ are included in the dataset. This is done in order to evaluate whether effects emerge when studying stabilised choices which are assumed not to capture the variability associated with exploration repetitions $S^{explore}$. In other words, the objective here is to see whether consolidated habits are significantly changed by the interventions. The regression results are available in table 3.

As before, the interaction effects are the main variables of interest as they provide information on the treatments' effectiveness, as compared with a counterfactual inferred from the control group's trajectory. For the conditions which include a critical moment of change, it is uncovered that gain-framed soft monetary incentives approximately led to a 102.24% ($p \approx 0.010$) statistically significant increase in the expected count of stabilised public transport mode choices, loss-framed soft monetary incentives led to a statistically significant 117.54% ($p \approx 0.008$) approximate rise therein, but interactional ones do not modify behaviour at a relevant statistical significance level ($p \approx 0.052$). Mirroring the analysis on the full sample, linear hypothesis tests are conducted to examine the effects of soft monetary incentives in the absence of a critical moment of change on the expected number of public transport choices made during $S^{exploit}_{post}$. The results show that, in this context, gain-framed soft monetary incentives have no significant effect ($\chi^2(1) \approx 2.12$, $p = 0.145$), but loss-framed and interactional soft monetary incentives display statistically significant approximate increases of 120.22% ($\chi^2(1) \approx 6.29$, $p \approx 0.012$) and 117.92% ($\chi^2(1) \approx 5.28$, $p \approx 0.022$), respectively.

Regarding the influence of critical moments of change on mode choices, linear hypothesis tests are again conducted. Similarly to the analysis on the full sample, holding type and provision of soft monetary incentive constant yields no statistically significant effect of the critical moments of change on expected public transport mode choice counts for the control ($\chi^2(1) \approx 0.07$, $p \approx 0.786$), gain-framed ($\chi^2(1) \approx 0.88$, $p \approx 0.349$), loss-framed ($\chi^2(1) \approx 0.08$, $p \approx 0.781$), and interactional ($\chi^2(1) \approx 0.46$, $p \approx 0.496$) conditions.

Three control variables are found to significantly moderate the expected number of public transport mode choices during the exploitation phases $S^{exploit}$. The first one is age, with each additional year of age being associated with a 0.99% ($p \approx 0.044$) increase in the expected number of public transport mode choices. The second one is using one's car five times or more per week, which is negatively related to public transport choices through an approximate 22.24% ($p \approx 0.008$) expected decrease in their count. The third significant control variable is having no access to public transportation, with an approximate 36.69% associated rise in expected number of public transport mode choices.

	Dependent variable:
	Public Transport Choice Count
Intercept	0.617*
	(0.269)
Main Effects	
Time	−0.044
	(0.219)
Gain Treatment	0.376
	(0.243)
Loss Treatment	0.347
	(0.254)
Interaction Treatment	0.498*
	(0.245)
Baseline Control Treatment	0.279
	(0.264)
Baseline Gain Treatment	0.384
	(0.261)
Baseline Loss Treatment	0.439.
	(0.231)
Baseline Interaction Treatment	0.370
	(0.244)
Controls	
Age	0.010*
	(0.005)
Risk Attitude	0.028
	(0.019)
Car Use (5 a week)	−0.252**
	(0.095)
Vehicule Access to Public Transportation	0.102
	(0.108)
No Access to Public Transportation	0.313**
	(0.106)
Interaction Effects	
Time x Gain Treatment	0.704*
	(0.274)
Time x Loss Treatment	0.777**
	(0.294)
Time x Interaction Treatment	0.533.
	(0.274)
Time x BL Control Treatment	0.081
	(0.297)
Time x BL Gain Treatment	0.475.
	(0.283)
Time x BL Loss Treatment	0.709**
	(0.264)
Time x BL Interaction Treatment	0.698*
	(0.282)
Observations	468
Log Likelihood	-1,291.027
θ	1.152*** (0.121)
Akaike Inf. Crit.	2,624.053
Note:	.p<0.1; *p<0.05; **p<0.01; ***p<0.001

Table 3: Regression Results (Exploitation Rounds), with Individual-Level Clustered Standard Errors

5 Discussion

The present study offers a threefold contribution that addresses important gaps in the existing literature. Firstly, a novel experimental framework for transport mode choice models that explicitly incorporates key behavioural regularities shaping real-life transport decisions is proposed. Secondly, a set of innovative interventions, called soft monetary incentives, are built on insights from both economics and psychology and tested within the experimental framework. Thirdly, an attempt is made at generating a critical moment of change within the experimental framework, and its interaction with the proposed incentives is investigated.

In line with the literature described in section 2.2.2, inertia is found to be prominent in the transport mode choices participants made. This is attested by the high share of participants sticking with one mode or the other at any given time of the experiment, and by the rapid and significant reduction in mode choice variability as well as its stabilisation at a low level. Thus, hypothesis H1.1 is not rejected, but hypothesis H1.2 is, as no rebound in exploration is observed after treatment provision. These insights not only add additional evidence to the rich body of work suggesting the importance of habits, but also show that even with a relatively complex set of incentives designed to reflect real-life incentives, participants exhibit inertia in their choices and develop habits.

The average treatment effects of the treated are systematically statistically significant at satisfying levels when using the full data S^{full}. This is an interesting preliminary results as, overall, it hints that soft monetary incentives are successful in changing transport mode choices. Moreover, the magnitudes of the changes are high, indicating potential to bring about large-scale behavioural changes. It must be kept in mind that the associated numbers stem from a limited number of repetitions such that percentages may easily become spectacular. This is not to say that the observed behavioural changes are not of important magnitude, but that caution is warranted when mobilising such numbers in isolation from their underlying context. In any case, these results are insufficient to properly grasp the effects of the interventions, due to the habitual nature of transport mode choices.

As such, a complementary analysis using only those choices that were made during exploitation phases $S^{exploit}$ was carried out. It reveals encouraging, but more contrasted, findings. Indeed, the gain-framed soft monetary incentive displays a substantial and significant effect on transport mode choices only when it interacts with a critical moment of change. In contrast, the loss-framed soft monetary incentive displays a consistently large and significant effect, regardless of the occurrence of a critical moment of change. When simultaneously providing both soft monetary incentive frames, a sizeable and significant effect is only found when no critical moment of change occurs. This suggests that, when solely considering stabilised and habitual choices, the interventions exhibit more complex effects but are nevertheless overall satisfyingly effective and hold potential to stimulate an important modal shift from cars to public transport. One element of explanation for the effectiveness of soft monetary incentives is that they are aligned with the underlying economic incentives (Lorko et al., 2025). Indeed, even though transport-related cost perceptions are biased, as described in subsection 2.1.1, taking the car is an economically dominated strategy in cases where a viable public transport option exists, and the provided soft monetary incentives introduce payoff-altering signals congruent with the underlying economic incentives, thus partly correcting the discrepancy between perceived and real incentives and allowing for optimal choices. These results are also in line with the policy mix recommendations of Lattarulo et al. (2019), Xiao et al. (2022), and Salihou et al. (2023). Soft monetary incentives are constructed to intrinsically lie at the intersection of economic and psychologic incentives and include a rewarding as well as a punitive component.

Nevertheless, the described heterogeneity in effectiveness warrants a deeper analysis. A likely reason behind loss-framed interventions' consistent effectiveness lies in loss aversion (Kahneman & Tversky, 1979; Oprea, 2024), whereby the prospect of suffering a loss, though small in size, may orient strategies away from the choices associated with it. This may also help explain why gain-framed interventions lacked effectiveness when no critical moment of change occurred. Indeed, as gains are felt less intensely than losses, participants may have been relatively indifferent to the prospect of small additional gains and preferred to stick with their habitual car choice. However, when this incentive interacted with a critical moment of change, participants significantly chose the public transport option more, which suggests that gain-framed incentives are effective only when an exogenous disruptive moment occurs, *i.e.* when participants' habits are otherwise disrupted. Thus, the gain-framed soft monetary incentive influences behaviour accordingly with the hypothesis expressed by Thøgersen (2012). Contrastingly, interactional interventions only have a significant effect when no critical moment of change arises. One possible explanation for this lies in a potential cognitive overload as, despite controlling for participants' comprehension of the new incentives they were exposed to, the condition where both soft monetary incentives were provided alongside the occurrence of a critical moment of change displayed more information than all other conditions, such that the information volume may have been too high and its content therefore diluted or not properly taken into account. This may signify that during critical moments of change, providing an overwhelming amount of information and/or incentives is detrimental to the behaviour change objective, but further work is needed to elucidate this aspect. A starting point could consist in implementing a control measure for cognitive load. This finding also suggests that when implementing either both soft monetary incentive framings simultaneously or only the loss-framed one in isolation, timeliness needs not be sought, thus easing the introduction of such a policy. This is an especially important finding since these two interventions are arguably the most economically efficient, as they may generate a surplus or, in the former case, at least finance part of the cost on policy-makers or firms of providing the gain-framed incentive. The interaction between soft monetary incentives and timeliness is compelling in that it provides much needed initial evidence (Department for Transport, 2025) that intervening during critical moments of change may prove effective, but requires careful considerations as to the characteristics of the provided interventions, as the consequent results may prove heterogenous. This evidence is notably valuable in that it accompanies the finding that critical moments of change on their own do not modify transport mode choices. With respect to the initial hypotheses, H2.1 and H2.2 are only partially rejected due to effectiveness being differentially dependent on soft monetary incentives' interaction with timeliness. H2.3 is rejected, as the evidence suggests that a loss frame in isolation is effective in more contexts than both other frames.

Regarding the significant effects among the control variables, the fact that intense car use is associated with less public transport choices is entirely logical and attests once more to the importance of habits. More interestingly, having no access to public transport within ten minutes on foot or by vehicle was associated in both samples with higher expected counts of public transport mode choice. This may be explained by several reasons, such as a desire to try out an otherwise inaccessible mode, an underlying preference for public transport hindered by a lack of access, or perhaps lucidity regarding the true costs of using the car.

The experimental design distinguishes itself from those existing in the literature on several aspects. One of them is the way the incentive structure is constructed. Instead of reflecting the underlying costs and benefits of empirical options, as is standard practice, it instead attempts at reflecting travellers' perceptions thereof by translating recent findings related to the biased perception of transport modes' costs (Grison et al., 2023) and transport-related sunk costs (Krämer, 2017) into the monetary incentives presented to participants. Indeed, the interaction between the known costs of each transport mode and the unknown distribution of disruption probabilities associated with each combination between mode and departure time allows participants' perception to be congruent with that in empirical conditions, *i.e.* the car being perceived as less costly than public transport, even though the expected payoff is maximised when choosing to take the public transport option and departing at the time associated with punctual arrival under normal circumstances. One limitation of this incentive structure is that for it to function as intended, participants must realise that choosing to depart with the public transport option at earlier times constitutes dominated options. While the authors acknowledge that this may seem to be a strong requirement, they argue that it is largely mitigated by two elements. First, the net and expected payoffs associated with these options are comparatively smaller than most options. Second, the disruption probabilities for public transport are drastically lower than those for the car, such that participants are able to quickly perceive that choosing the latest possible option is a relatively safe option. Moreover, while departing earlier to account for a risk of tardiness is an understandable initial strategy, it becomes difficult to justify once low disruption probabilities are observed. Consequently to these arguments, participants who choose the public transport option at other departure times than the latest one utilise dominated strategies. They may however be qualified as behaving "reasonably" in that they satisfy their objective without optimising their strategy (Madsen et al., 2024). In that case, the fact that they do not satisfy the required condition for the incentive structure to function as intended is of little incidence, as these participants likely would not have aimed to further optimise their strategy.

Furthermore, regarding the implementation of sunk costs, they were introduced as being weekly even though monthly or even yearly commitments are likely more ecological. The decision to make sunk costs a weekly issue is based on the desire for commitments to a mode not to be so constraining that participants would never explore their options or switch modes if they so desired. Additionally, it may have been too salient that obtaining access to both transport modes was a systematically dominated option which lowered participants' payoff, such that participants used to having the freedom to take the mode they desire on a daily basis may have not have felt they truly had an incentive to do so. Future work may consider mitigating this latter issue by introducing different and/or differentiated temporalities for modes' sunk costs, as well as forcing some initial sunk costs upon participants, especially for the car mode.

Another aspect of the experimental design which deviates from standard practice is the exogenous quality of disruptions. Indeed, most mode choice experiments make congestion – a subset of disruptions – endogenous to participants' decisions (see section 3.2.3), which is justified by the importance of this phenomenon for car travel. Aside from the fact that endogenous applications are typically performed with a small subset of participants, thus creating artificial biases in the way congestion arises and is perceived, congestion may in fact be perceived as exogenous by travellers even though the underlying process is intrinsically endogenous. As car commuters engage in car travel at regular times on a regular basis, they observe repeated and numerous states of the world regarding congestion. Thereby, they may develop mental representations of what the likelihood of a congestion arising during a given commute is. Thence, removing themselves from the mental equation may be a byproduct of apprehending congestion as an exogenous phenomenon which follows a law which, though unknown, they have developed a satisfying approximation for. These considerations motivate the decision to assume that congestion is captured by the general exogenous disruption probabilities, which are moreover designed to capture that as more people tend to take a mode, *i.e.* as departure times move closer to the ideal departure time under no disruption to arrive on time, the likelihood of a disruption occurring increases.

A final discussion point which the authors would like to address is the seemingly arbitrary nature of the travel times which participants had to consider. Indeed, it is uncertain whether participants experiencing commutes which last for varied and differentiated amounts of time behaved accordingly to real-life in the experimental setting. Future work may benefit from controlling for this aspect of participants' travelling habits, or, more ambitiously, from adapting the experimental travel times to decrease the potential discrepancy between empirically and experimentally experienced travel times.

6 Conclusion and Avenues for Future Research

An innovative experimental framework to assess commuters' transport mode choice behaviours is herein presented. It notably distinguishes itself from existing frameworks by explicitly incorporating cognitive and behavioural insights regarding the determinants and reasoning behind commuters' decisions. Within this framework, a set of novel "soft monetary incentives" are tested for their effectiveness with an emphasis on their interaction with an experimental implementation of a critical moment of change in the life of commuters.

The present paper not only provides evidence that soft monetary incentives are generally effective in significantly and considerably shifting commuters' transport mode choices from the car towards public transport, but also that, depending on their framing, coupling them with a critical moment of change may better or worsen their effectiveness. Consequently, the authors insist on the importance of tailoring interventions to specific situations and contexts.

Future work may build upon the present contribution by studying whether the generated behavioural changes last when soft monetary incentives are extinguished. Identifying an optimal level for these incentives may also be of interest, especially for researchers looking to provide precise actionable insights to policy-makers or firms. Future work could also consider modulating the temporal delay of soft monetary incentives, to investigate whether such a dimension plays a role. Generally improving upon the experimental framework may also prove valuable. For instance, enriching the disruption system by increasing the number of disruption levels, perhaps adding a disruption with intermediate probabilities and consequences, could be considered.

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Due to the strategic nature of the data, it must remain confidential and cannot be shared.

CRediT Authorship Contribution Statement

Dorian Deeks: Conceptualisation, Methodology, Software, Investigation, Formal analysis, Validation, Visualisation, Data Curation, Writing - Original Draft. **Elise Grison:** Conceptualisation, Methodology, Writing - Review & Editing, Supervision. **Simone Morgagni:** Conceptualisation, Methodology, Writing - Review & Editing, Supervision.

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Appendices

Appendix A: Participant Sample Characteristics

Table A.1: Sample Characteristics

Characteristic	Mean	Share	Median	Std. Dev.
Demographics				
Age (years)	32.61		31	8.50
Gender				
Female		39.32%		
Male		59.40%		
Not Disclosed		1.28%		
Socioeconomic Variables				
Education Level				
8 Years of Post-High School Education		3.85%		
5 Years of Post-High School Education		51.28%		
4 Years of Post-High School Education		5.13%		
3 Years of Post-High School Education		17.52%		
2 Years of Post-High School Education		11.97%		
High School (General Track)		5.56%		
High School (Professional Track)		2.56%		
Middle School		2.14%		
Residency				
Urban		41.45%		
Semi-Urban		33.76%		
Rural		24.79%		
Socio-Demographic Category				
Executive and Superior Intellectual Profession		35.04%		
Craftsman, Retailer, Business Owner		6.41%		
Intermediate Professions		9.83%		
Farmer		0.43%		
Employee		39.32%		
Worker		2.99%		
Student		5.56%		
Other Person with No Professional Activity		0.43%		
Car Possession		96.15%		
Car Use				
Five Days or More		40.60%		
Four Days		11.54%		
Three Days		22.65%		
Two Days		13.68%		
One Day or Less		11.53%		
Access to Public Transport				
On Foot		47.00%		
By Vehicle		22.22%		
No Access		30.77%		
Attitudinal Variables / Constraints				
Risk Attitude (1–10)	5.08		4	2.38
General Punctuality Tendency				
Early		50.00%		
On Time		40.60%		
Late		9.40%		
Punctual Arrival at Work Tendency (yes)	2.8	3	1.4	
Workplace Flexibility on Punctuality (yes)		61.54%		
Motility				
Competence (1-7)	6.30		6.5	0.72
Aspiration (1-7)	5.35		5.5	1.00

Note: Due to rounding, percentages may not amount to precisely 100%.

Appendix B: Noise Messages

List of noise messages:

- Your company has repainted the walls of the stairwells in its premises.
  French original: *Votre entreprise a repeint les murs des escaliers de ses locaux.*
- A new colleague has started their employment contract.
  French original: *Un nouveau collègue a commencé son contrat de travail.*
- Your company has installed a new coffee machine.
  French original: *Votre entreprise a installé une nouvelle machine à café.*
- Your company has received a paper delivery.
  French original: *Votre entreprise a reçu une livraison de papier.*
- All employees have received your company's annual newsletter.
  French original: *Tous les employés ont reçu la lettre d'information annuelle de votre entreprise.*
- Your company's old water cooler has been replaced with a new one.
  French original: *L'ancienne fontaine à eau de votre entreprise a été remplacée par une nouvelle.*
- The company logo on the building has been cleaned.
  French original: *Le logo de l'entreprise figurant sur le bâtiment a été nettoyé.*
- The stock of hand sanitiser has been replenished.
  French original: *Le stock de gel hydroalcoolique a été réapprovisionné.*

Appendix C: Visual Framework

Figure C.1: Choice Page (Initial Disposition).

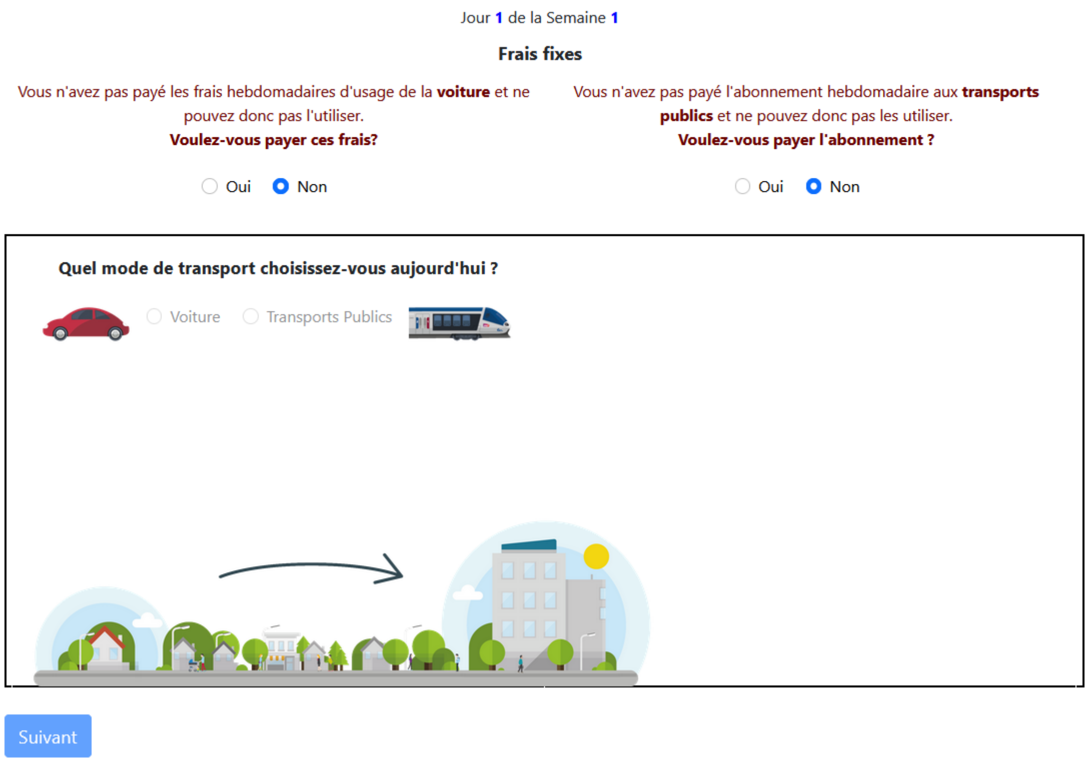


Figure C.2: Choice Page (Confirmation Pop-Up).

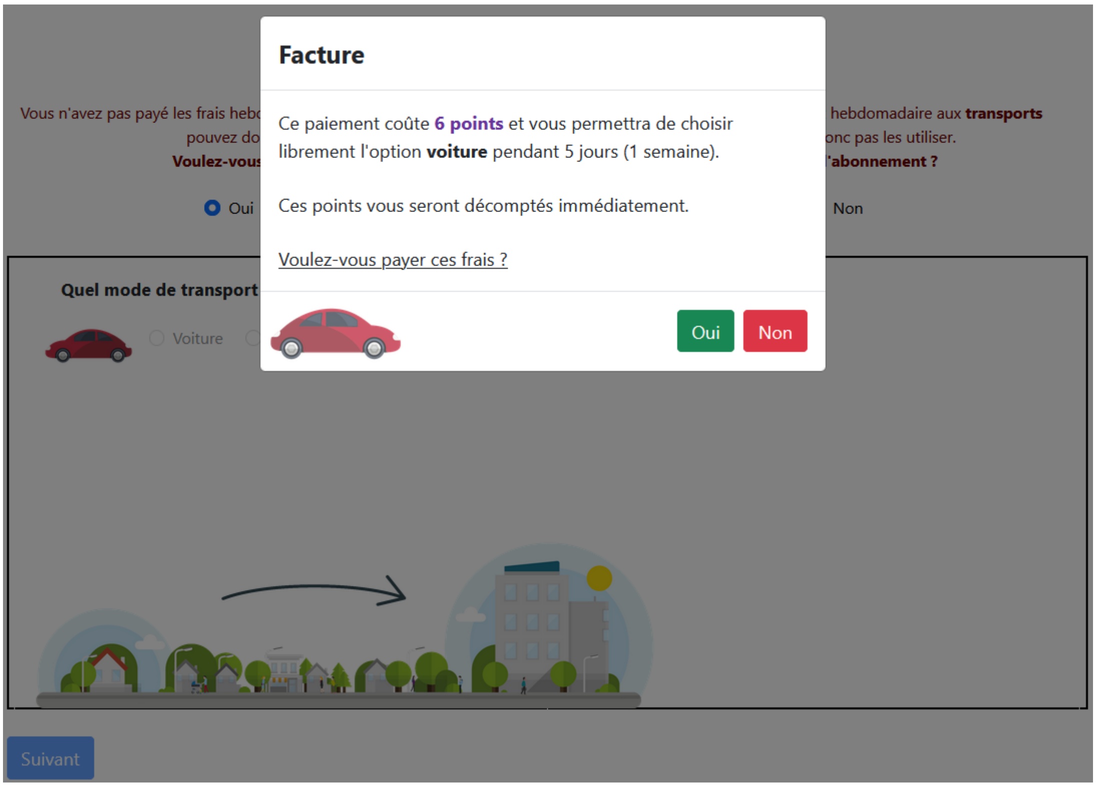


Figure C.3: Choice Page (Paid Car Fixed Fee).

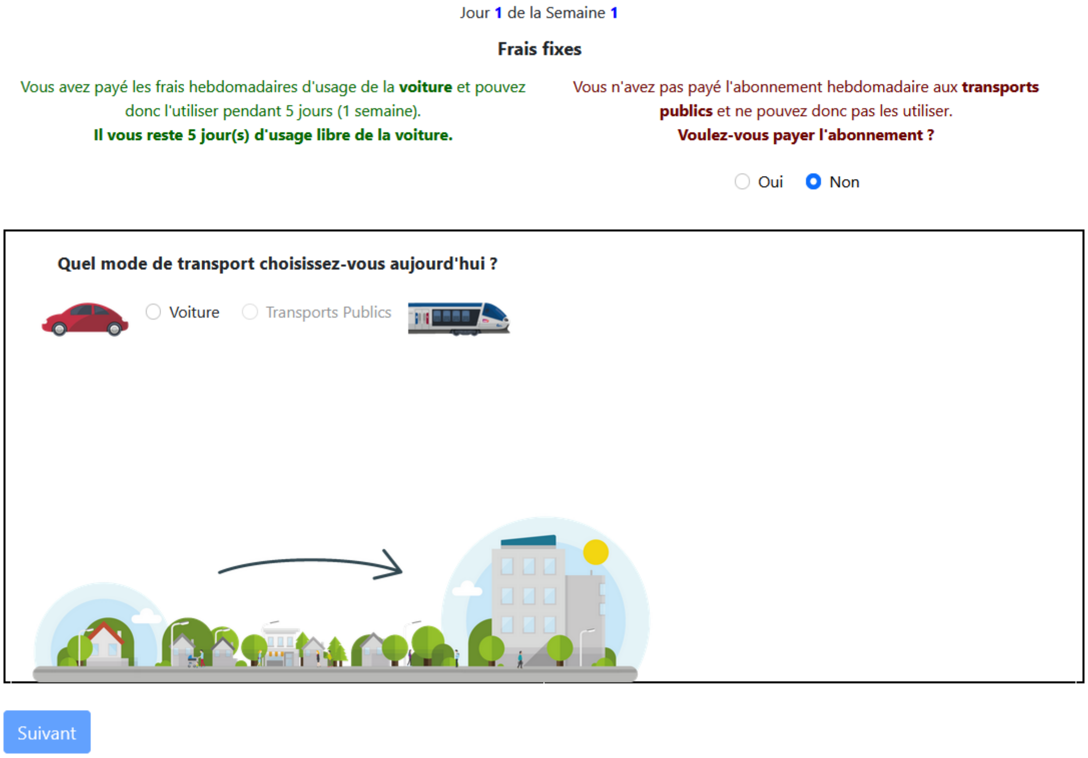


Figure C.4: Choice Page (Car Mode Selected).

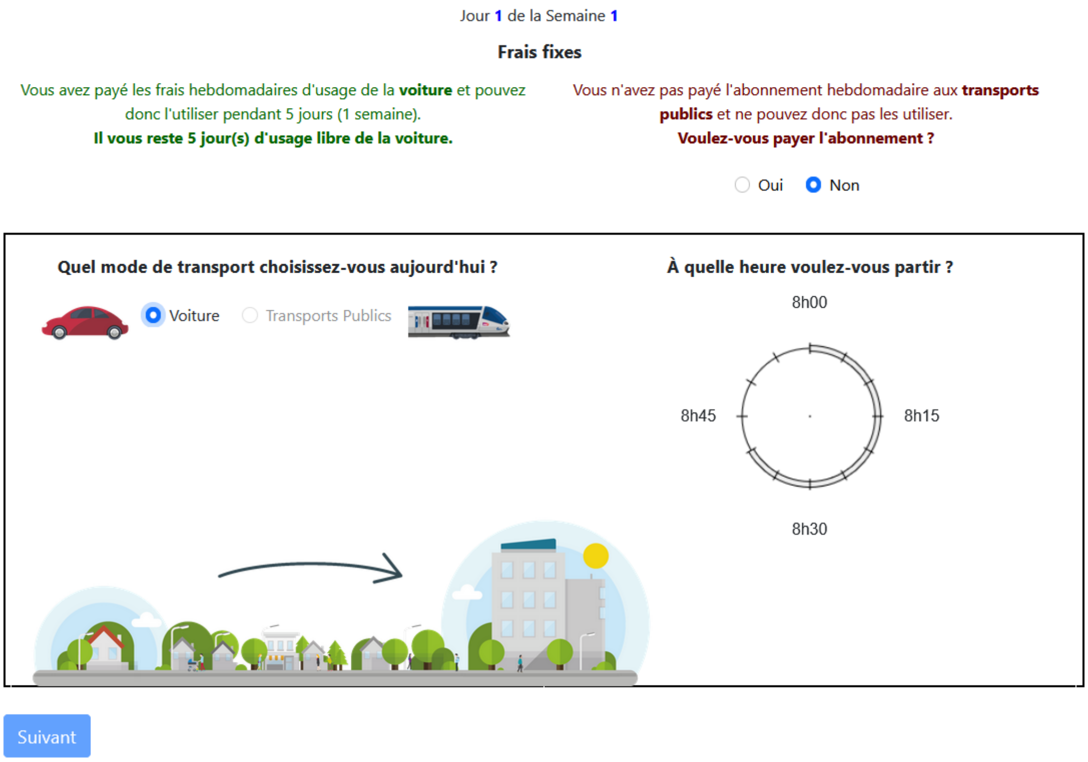


Figure C.5: Choice Page (Departure Time Selected).

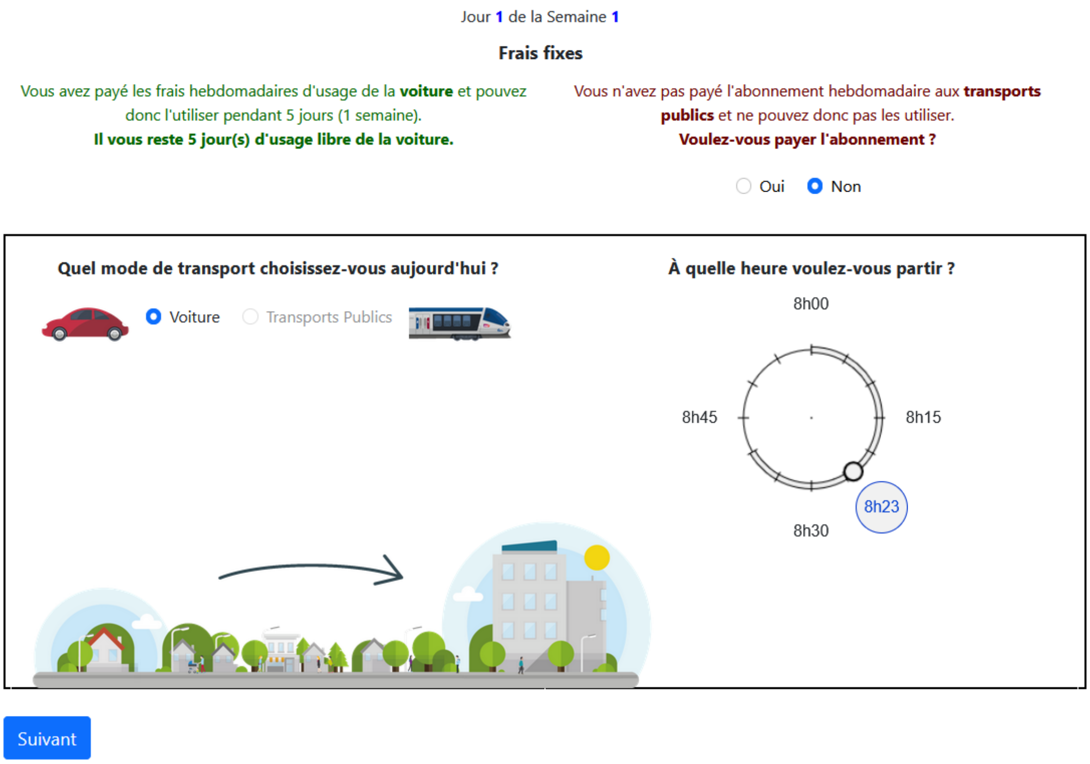


Figure C.6: Feedback Page.

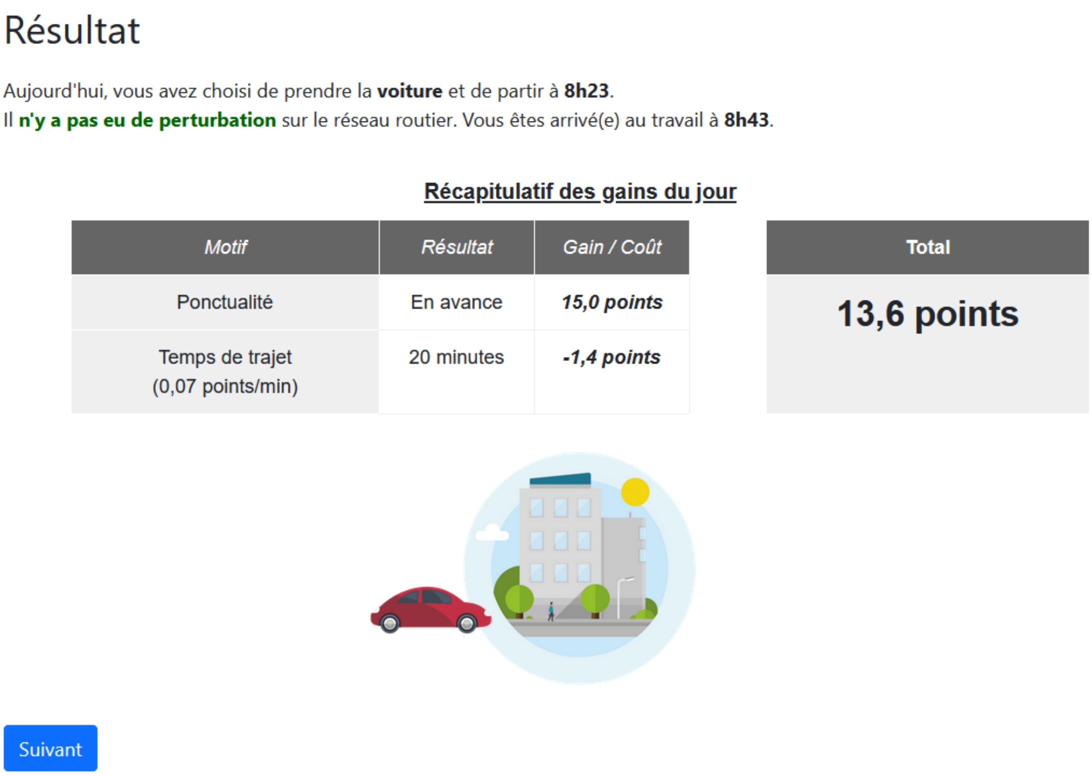


Figure C.7: Gain-Framed Soft Monetary Incentive Treatment.

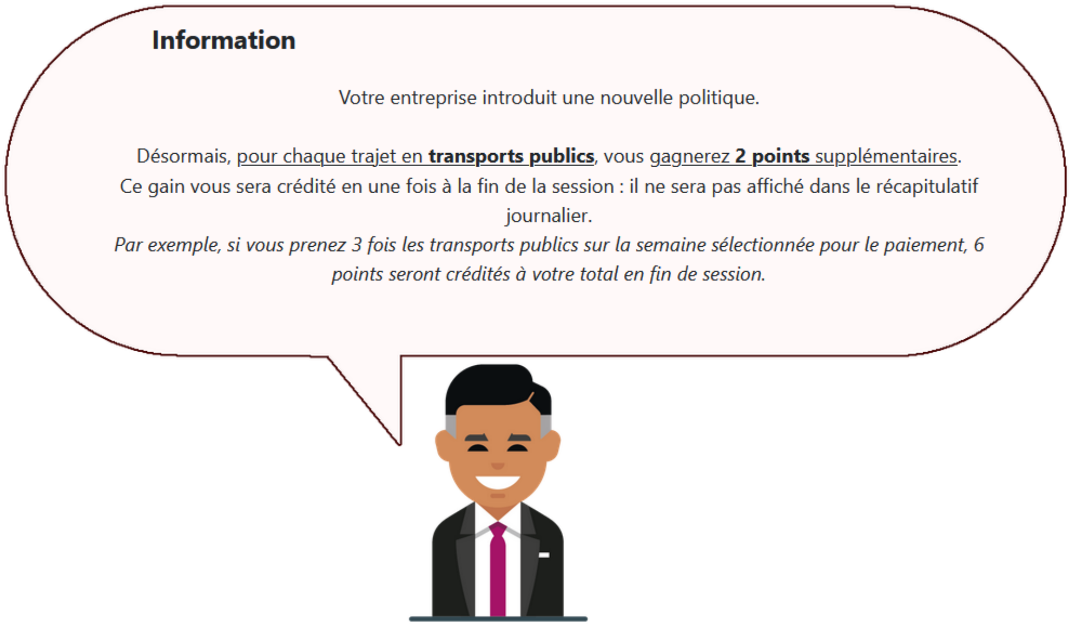


Figure C.8: Loss-Framed Soft Monetary Incentive Treatment.

Figure C.9: Critical Moment of Change Treatment.

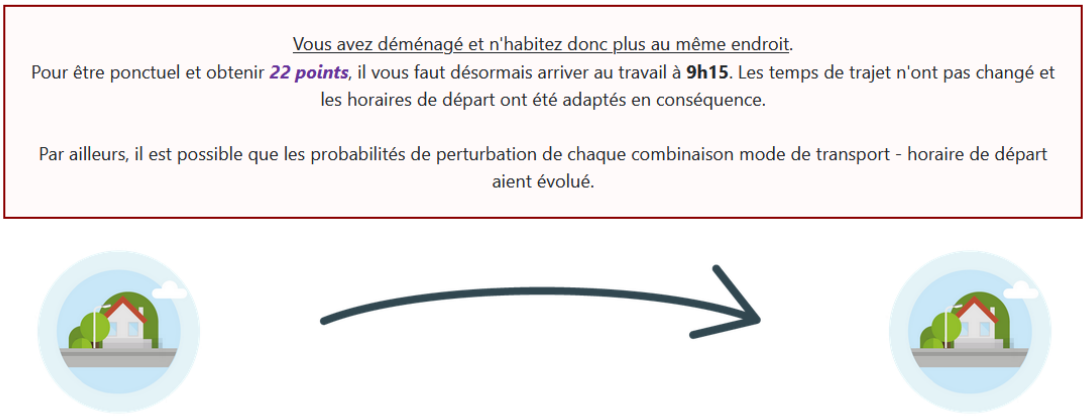
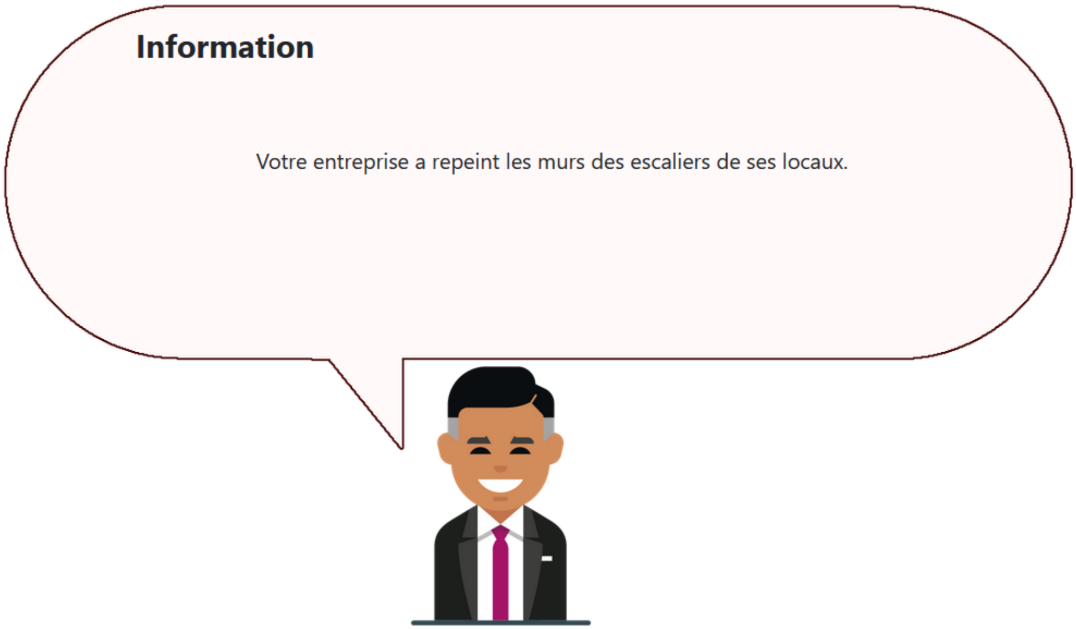


Figure C.10: Noise Message Example.



Appendix D: Instructions

Figure D.1: Instructions (Part 1).

Instructions

Dans cette expérience, vous allez faire des choix qui détermineront le montant final de votre rémunération.

En fonction de votre performance, vous gagnerez un certain nombre de ***points*** durant l'expérience, qui seront convertis en fin de session en livres (£) au taux de ***10 points*** = **0.2 £**.

Vous recevrez également un montant forfaitaire de **2.5 £** pour votre complétion de l'expérience.

Rémunération = **2.5 £** (fixe) + **X £** (variable)

Votre objectif dans cette expérience est d'obtenir le plus grand nombre de ***points*** à chaque répétition.

Suivant

Figure D.2: Instructions (Part 2).

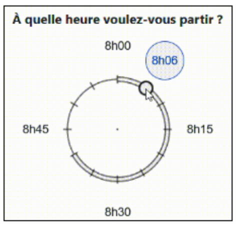
Instructions

Vous allez faire une tâche dans un contexte fictif composé de 40 répétitions, appelées "jours". Cinq jours forment une "semaine".
Par exemple, la sixième répétition de la tâche est appelée le "premier jour de la deuxième semaine".
Chaque jour, vous devrez vous rendre sur votre lieu de travail fictif en partant de votre domicile fictif, avec l'**objectif** d'y arriver à 9h précises.

Vous aurez trois choix (en gras ci-dessous, avec les options soulignées) à faire chaque jour :

- Le choix de **payer ou non le coût forfaitaire** permettant d'utiliser un mode de transport pendant 5 jours (soit une semaine).
  - *Si celui-ci a déjà été payé il y a moins de 5 jours, il n'est pas nécessaire (ni possible) de le payer à nouveau.*
- Le choix du **mode de transport** :
  - Voiture.
  - Transports Publics.
- Le choix de votre **horaire de départ** associé au mode de transport choisi :
  - Voiture : tout horaire entre 8h00 et 8h40 (8h00, 8h01, 8h02, 8h03, [...], 8h38, 8h39, 8h40).
  - Transports Publics : 8h00, 8h15, ou 8h30.

Pour sélectionner l'horaire, il vous faudra cliquer sur la bande glissante suivante pour faire apparaître le bouton à l'endroit désiré puis faire glisser le bouton pour ajuster votre choix. Par exemple pour un départ en voiture à 8h06 :



Précédent

Suivant

Figure D.3: Instructions (Part 3).

Instructions

Pour chaque mode de transport utilisé à un certain horaire, il est possible qu'une **perturbation** vienne allonger le temps de trajet du jour. Chaque combinaison entre mode de transport et horaire de départ a une probabilité fixe qu'une perturbation survienne.

Par exemple, si vous prenez les transports publics à 8h00, la probabilité de perturbation associée est différente de celle associée au choix de prendre les transports publics à 8h30. Le raisonnement est le même pour la voiture.
D'autre part, pour un horaire donné, par exemple 8h15, la probabilité de perturbation associée à la voiture et celle associée aux transports publics peuvent être différentes.

Ainsi, certaines options sont plus avantageuses que d'autres.

Le **temps de trajet** d'un mode de transport dépend uniquement de la survenance ou non d'une perturbation. Ce temps de trajet est fictif et vous n'aurez pas à le vivre :

- Pas de perturbation :
  - Voiture : 20 minutes
  - Transports Publics : 30 minutes.
- Perturbation :
  - Voiture : 40 minutes
  - Transports Publics : 60 minutes.

Précédent Suivant

Figure D.4: Instructions (Part 4).

Instructions

Chaque jour, le **gain de points** est déterminé principalement par la ponctualité avec laquelle vous arrivez au travail. Ainsi, vous maximisez vos gains en arrivant précisément à 9h00, et vous réduisez vos gains potentiels à mesure que vous vous éloignez de l'horaire objectif.
Veuillez prendre connaissance du détail de vos gains potentiels de points suivant :

Points														
12	12.5	13	14	15	16.5	18	20	**22**	19.5	17	15	13.5	12.5	12
Plage d'heures d'arrivée														
8h20 à 8h24	8h25 à 8h29	8h30 à 8h34	8h35 à 8h39	8h40 à 8h44	8h45 à 8h49	8h50 à 8h54	8h55 à 8h59	**9h00**	9h01 à 9h04	9h05 à 9h09	9h10 à 9h14	9h15 à 9h19	9h20 à 9h24	9h25 à 9h30

Chaque jour, il y aura deux sources de coûts qui pourront réduire votre gain de points.
D'une part, le **coût forfaitaire** associé à chaque mode de transport qui ne sera facturé que le jour de l'achat :

- Voiture : *6 points*.
- Transports Publics : *4 points*.

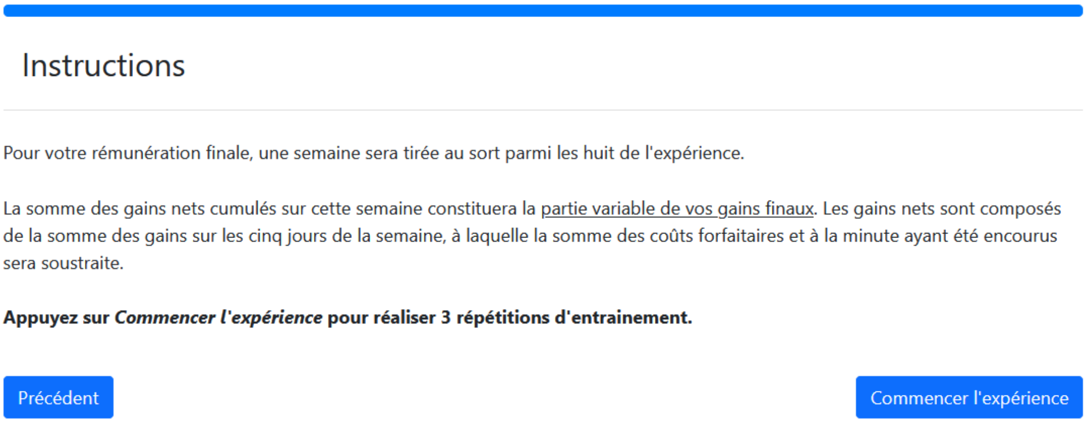
D'autre part, un **coût à la minute** vous sera facturé pour chaque minute (fictive) passée dans un mode de transport :

- Voiture : *0.07 points / minute*.
- Transports Publics : *0.12 points / minute*.

Après chaque jour, vous aurez accès à un récapitulatif détaillé de vos gains pour la journée. Veuillez noter qu'il est impossible d'avoir un nombre de points négatif.

Précédent Suivant

Figure D.5: Instructions (Part 5).



Instructions

Pour votre rémunération finale, une semaine sera tirée au sort parmi les huit de l'expérience.

La somme des gains nets cumulés sur cette semaine constituera la partie variable de vos gains finaux. Les gains nets sont composés de la somme des gains sur les cinq jours de la semaine, à laquelle la somme des coûts forfaitaires et à la minute ayant été encourus sera soustraite.

Appuyez sur *Commencer l'expérience* pour réaliser 3 répétitions d'entrainement.

Précédent | Commencer l'expérience

English transcript

In this experiment, you will make choices that will determine the final amount of your remuneration.

Depending on your performance, you will earn a certain number of *points* during the experiment, which will be converted at the end of the session into pounds (£) at the rate of *10 points* = **£0.2**.

You will also receive a flat amount of **£2.5** for your completion of the experiment.

Remuneration = **£2.5** (fixed) + **£X** (variable)

Your objective in this experiment is to obtain the highest number of *points* at each repetition.

You will perform a task in a fictional context composed of 40 repetitions, called "days". Five days form a "week".
For example, the sixth repetition of the task is called the "first day of the second week".
Each day, you will need to travel to your fictional workplace from your fictional home, with the **objective** of arriving there at precisely 9:00 am.

You will have three choices (in bold below, with the options underlined) to make each day:

- The choice of **paying or not the fixed fee** allowing to use a transport mode during 5 days (one week).
  - *If it has already been paid less than 5 days ago, it is not necessary (nor possible) to pay it again.*
- The choice of **transport mode**:
  - Car.
  - Public Transport.

- The choice of your **departure time** associated with the chosen transport mode:
  - Car: any time between 8:00 am and 8:40 am (8:00 am, 8:01 am, 8:02 am, 8:03 am, [...], 8:38 am, 8:39 am, 8:40 am).
  - Public Transport: 8:00 am, 8:15 am, or 8:30 am.

To select the time, you will have to click on the following sliding strip to make the button appear at the desired place then slide the the button to adjust your choice. Fox example for a departure by car at 8:06 am: [GIF illustration]

For each transport mode used at a given time, it is possible that a **disruption** extends the travel time of the day. Each combination between transport mode and departure time has a fixed probability that a disruption occurs.

For example, if you take public transport at 8:00 am the associated disruption likelihood is different than that associated with the choice of taking public transport at 8:30 am. The reasoning is the same for the car.
Furthermore, for a given time, for instance 8:15 am, the disruption likelihood associated with the car and the one associated with public transport may be different.

Thus, certain options are more advantageous than others.

The **travel time** of a transport mode depends only on whether or not a disruption occurs. This travel time is fictional and you will not have to experience it:

- No disruption:
  - Car: 20 minutes
  - Public Transport: 30 minutes.
- Disruption:
  - Car: 40 minutes
  - Public Transport: 60 minutes.

Every day, the **earned points** are primarily determined by the punctuality with which you arrive at work. Thus, you maximise your earnings by arriving precisely at 9:00 am, and you reduce your potential earnings as you move away from the time objective.
Please review the following details of your potential earnings: [table]

Every day, there will be two sources of costs which may reduce your point earnings.
On the one hand, the **flat fee** associated with each transport mode which will only be charged on the day of purchase:

- Car: *6 points.*
- Public Transport: *4 points.*

On the other hand, a per-minute fee will be charged for each (fictional) minute spent in a transport mode:

- Car: *0.07 points / minute.*
- Public Transport: *0.12 points / minute.*

After each day, you will have access to a detailed summary of your earnings for the day. Please note it is impossible to have a negative number of points.

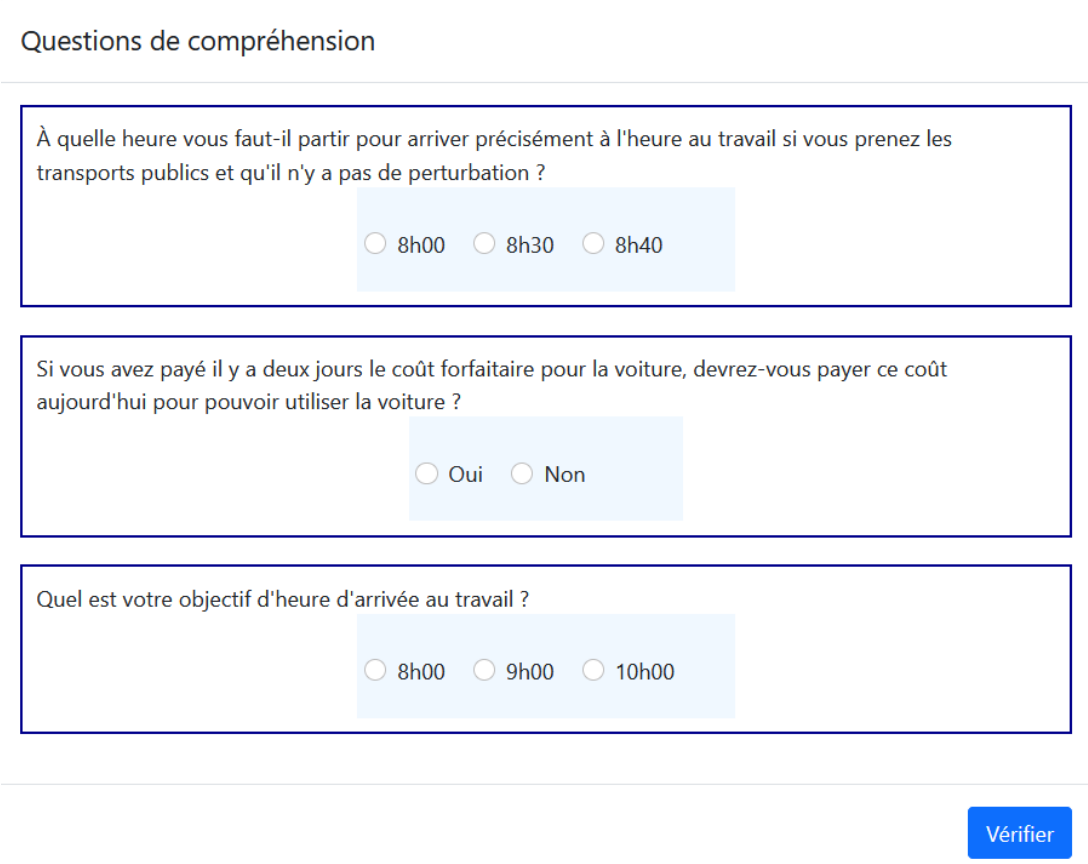
For your final remuneration, one week will be randomly selected among the eight of the experiment.

The sum of cumulative net earnings of that week will constitute the variable part of your final remuneration. The net earnings are composed of the sum of the earnings over the five days of the week, to which the sum of flat and per-minute fees that have been incurred will be deducted.

Press *Start experiment* to carry out 3 training repetitions.

Appendix E: Comprehension Questions

Figure E.1: Post-Instructions Comprehension Questions.


Questions de compréhension

À quelle heure vous faut-il partir pour arriver précisément à l'heure au travail si vous prenez les transports publics et qu'il n'y a pas de perturbation ?

8h00 8h30 8h40

Si vous avez payé il y a deux jours le coût forfaitaire pour la voiture, devrez-vous payer ce coût aujourd'hui pour pouvoir utiliser la voiture ?

Oui Non

Quel est votre objectif d'heure d'arrivée au travail ?

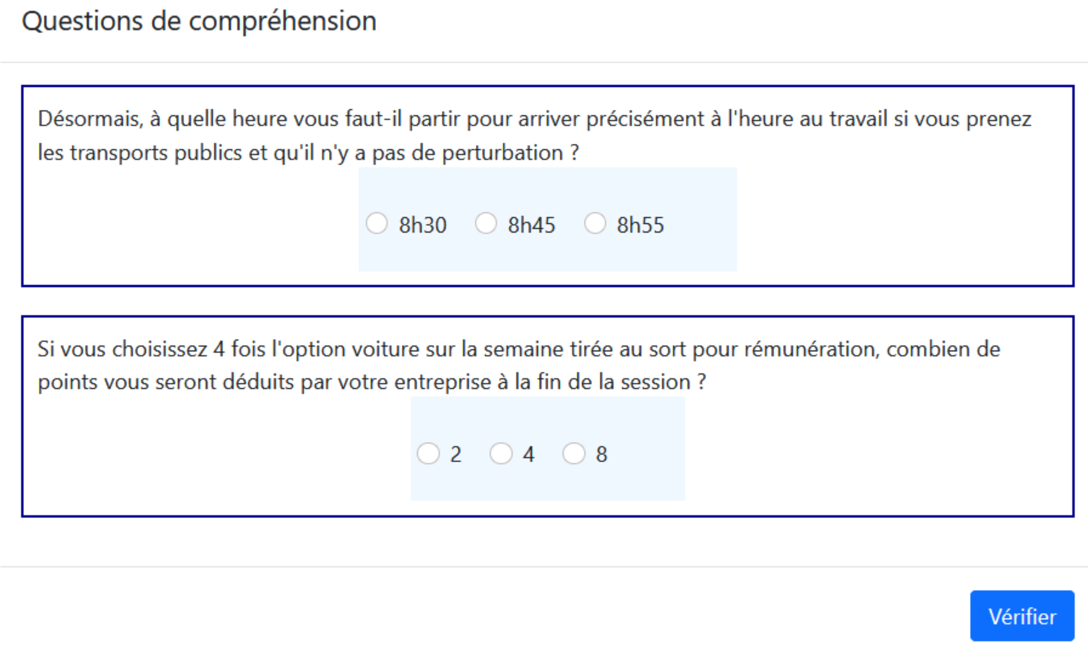
8h00 9h00 10h00

Vérifier

English transcript

- At what time must you leave to precisely arrive at work on time if you take public transport and there is no disruption?
- If you've paid the flat fee for the car two days ago, must you pay this cost today to be able to use your car?
- What is your target arrival time at work?

Figure E.2: Post-Treatment Provision Comprehension Questions (Example for Loss-Framed Soft Monetary Incentives with a Critical Moment).


Questions de compréhension

Désormais, à quelle heure vous faut-il partir pour arriver précisément à l'heure au travail si vous prenez les transports publics et qu'il n'y a pas de perturbation ?

8h30 8h45 8h55

Si vous choisissez 4 fois l'option voiture sur la semaine tirée au sort pour rémunération, combien de points vous seront déduits par votre entreprise à la fin de la session ?

2 4 8

Vérifier

English transcript

- From now on, at what time must you leave to arrive at work precisely on time if you take public transport and there is no disruption?
- If you choose the car option 4 times during the week selected for remuneration, how many points will be deducted by your company at the end of the session?

Appendix F: Habitual Transport Mode Choices Under a Liberal Criterion

Exploitation Phase	Pre-Treatment		Post-Treatment	
Mode	Public Transport	Car	Public Transport	Car
Control	17.86	42.86	28.57	60.71
Loss	33.33	46.67	80	6.67
Gain	32.14	39.29	78.57	7.14
Interaction	40.74	40.74	74.07	11.11
BL Control	27.59	44.83	31.03	44.83
BL Loss	25.81	32.26	80.65	6.45
BL Gain	41.94	51.61	61.29	22.58
BL Interaction	30	40	76.67	6.67

Note: The remainder consists of the proportion of participants alternating between modes.

Table F.1: Proportion of Participants Making Habitual ($> 55\%$) Transport Mode Choices

Appendix G: Descriptive Differences-In-Differences Plots

Figure G.1: Differences-in-Differences Plot (Exploitation Data): Gain vs. Control.

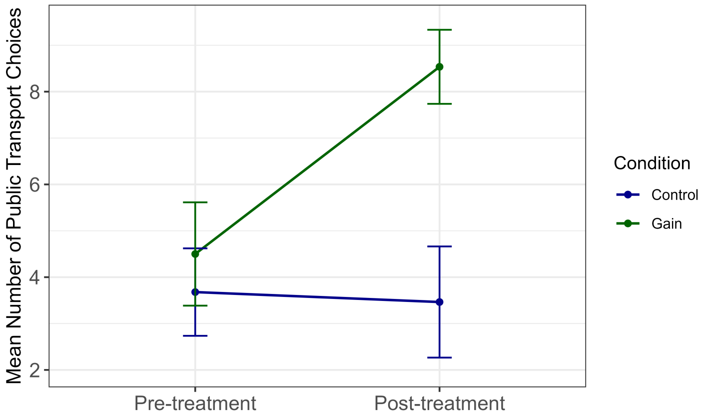


Figure G.2: Differences-in-Differences Plot (Exploitation Data): Loss vs. Control.

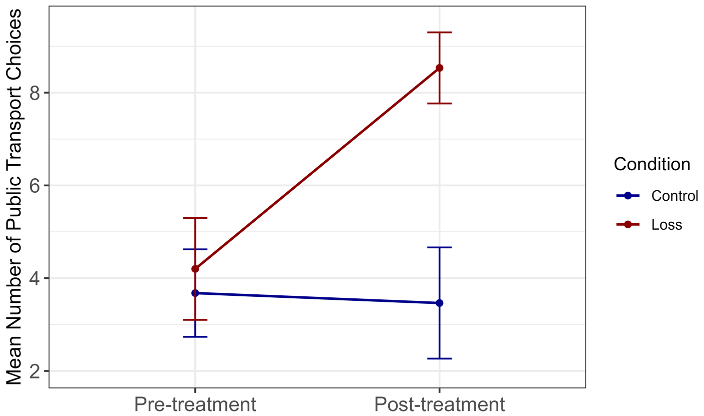


Figure G.3: Differences-in-Differences Plot (Exploitation Data): Interaction vs. Control.

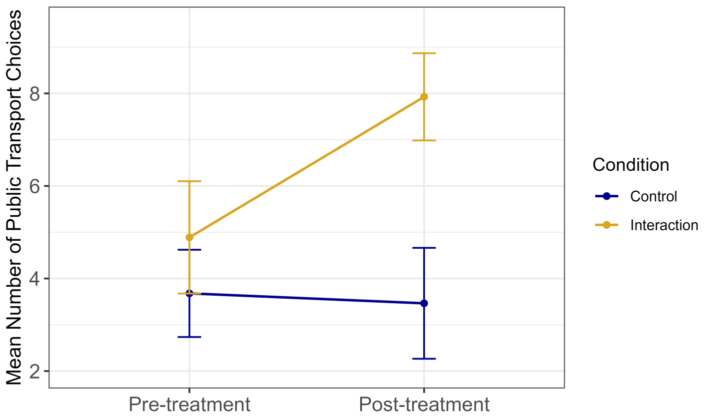


Figure G.4: Differences-in-Differences Plot (Exploitation Data): Baseline Gain vs. Baseline Control.

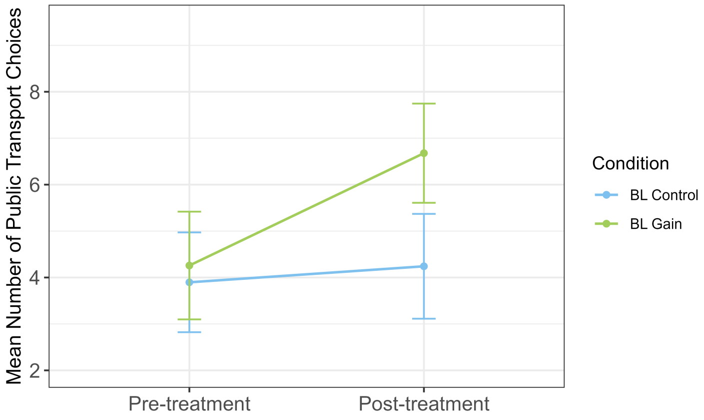


Figure G.5: Differences-in-Differences Plot (Exploitation Data): Baseline Loss vs. Baseline Control.

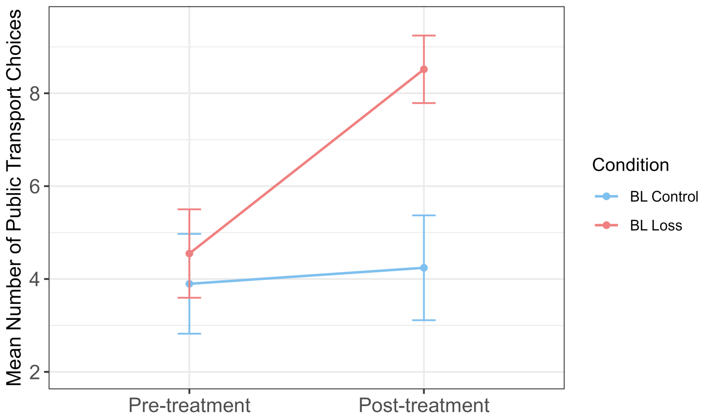


Figure G.6: Differences-in-Differences Plot (Exploitation Data): Baseline Interaction vs. Baseline Control.

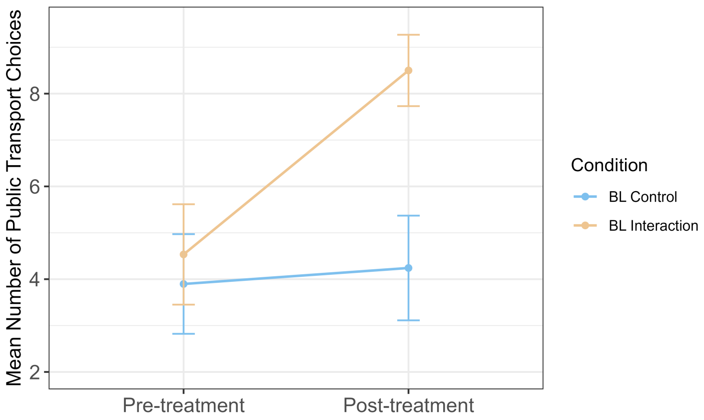


Figure G.7: Differences-in-Differences Plot (Exploitation Data): Gain vs. Baseline Gain.

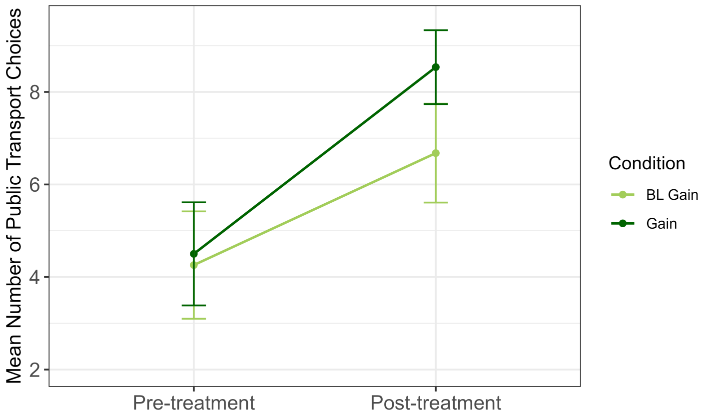


Figure G.8: Differences-in-Differences Plot (Exploitation Data): Loss vs. Baseline Loss.

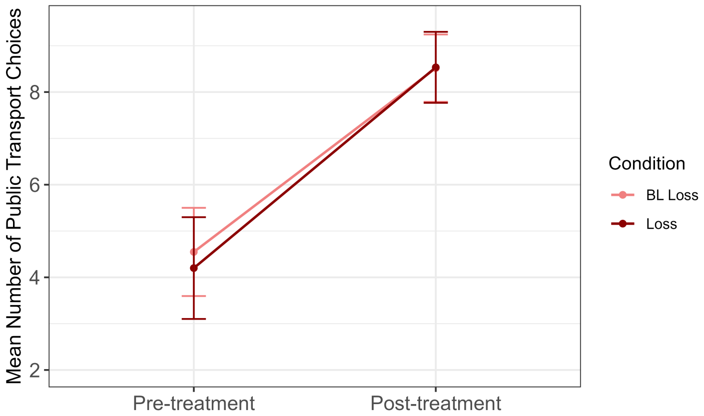


Figure G.9: Differences-in-Differences Plot (Exploitation Data): Interaction vs. Baseline Interaction.

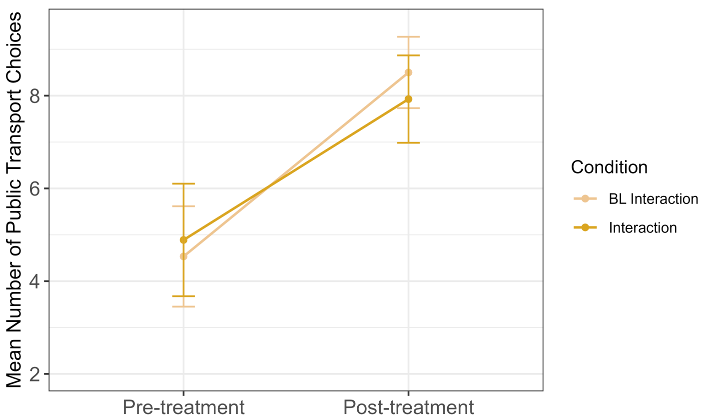


Figure G.10: Differences-in-Differences Plot (Full Data): Gain vs. Control.

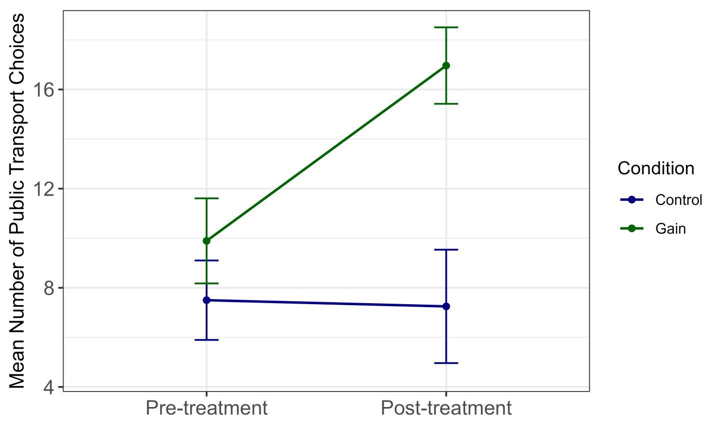


Figure G.11: Differences-in-Differences Plot (Full Data): Loss vs. Control.

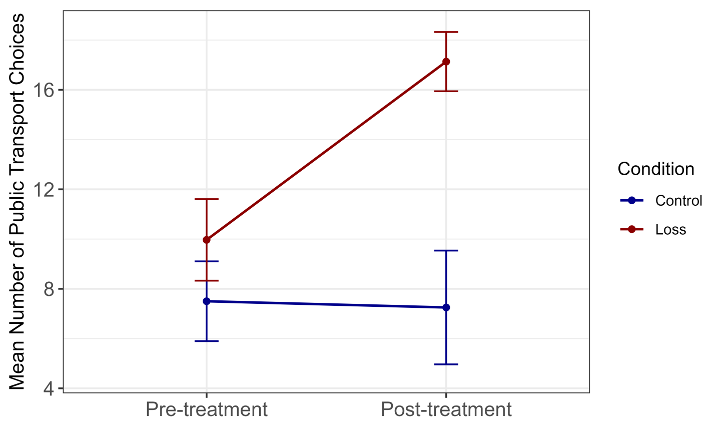


Figure G.12: Differences-in-Differences Plot (Full Data): Interaction vs. Control.

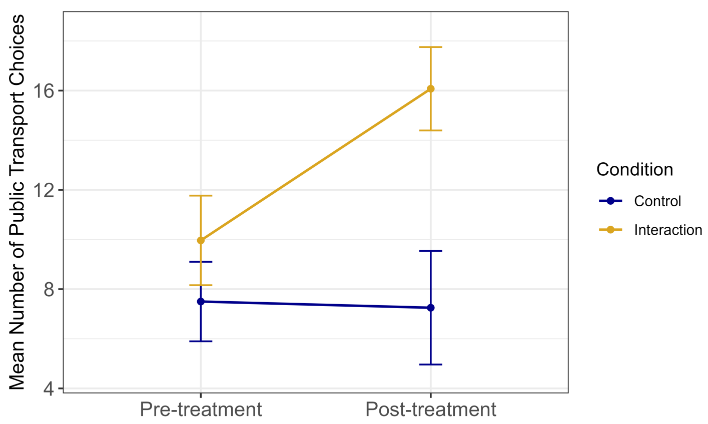


Figure G.13: Differences-in-Differences Plot (Full Data): Baseline Gain vs. Baseline Control.

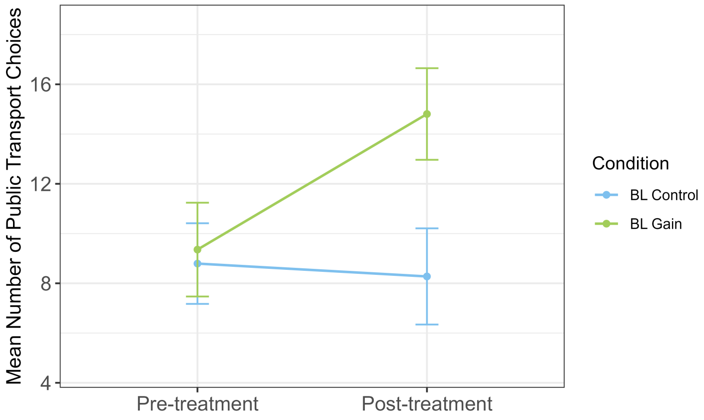


Figure G.14: Differences-in-Differences Plot (Full Data): Baseline Loss vs. Baseline Control.

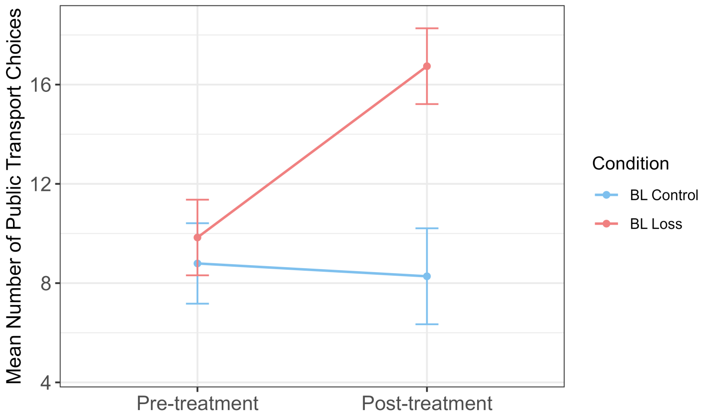


Figure G.15: Differences-in-Differences Plot (Full Data): Baseline Interaction vs. Baseline Control.

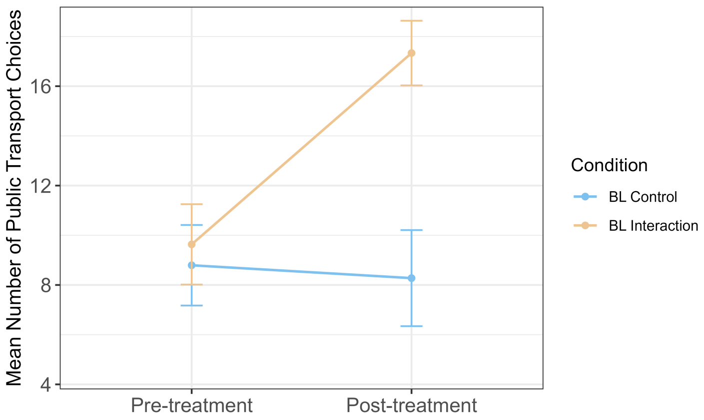


Figure G.16: Differences-in-Differences Plot (Full Data): Gain vs. Baseline Gain.

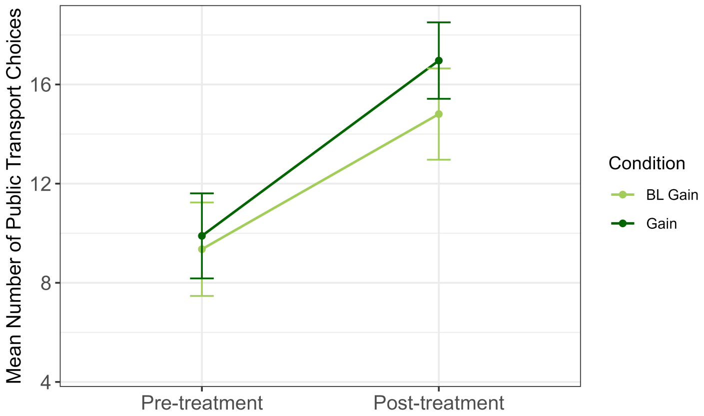


Figure G.17: Differences-in-Differences Plot (Full Data): Loss vs. Baseline Loss.

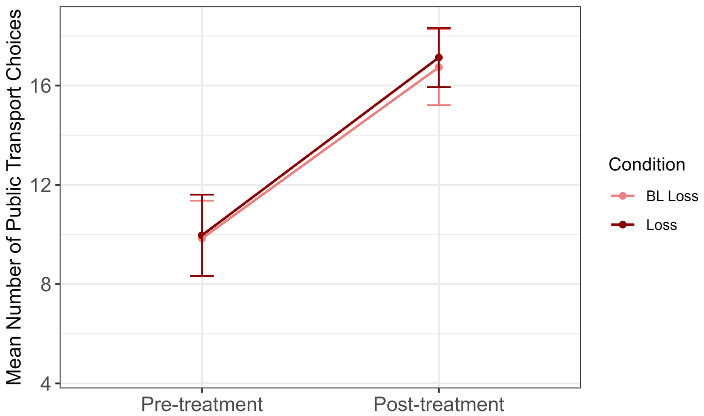


Figure G.18: Differences-in-Differences Plot (Full Data): Interaction vs. Baseline Interaction.

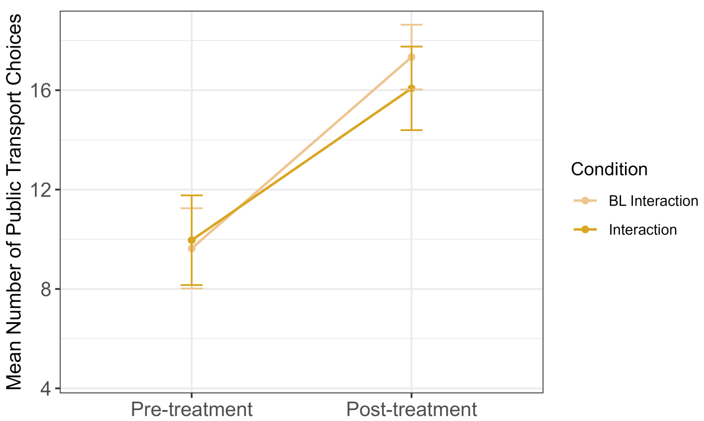


Figure G.19: Differences-in-Differences Plot (Exploitation Data): Control vs. Baseline Control.

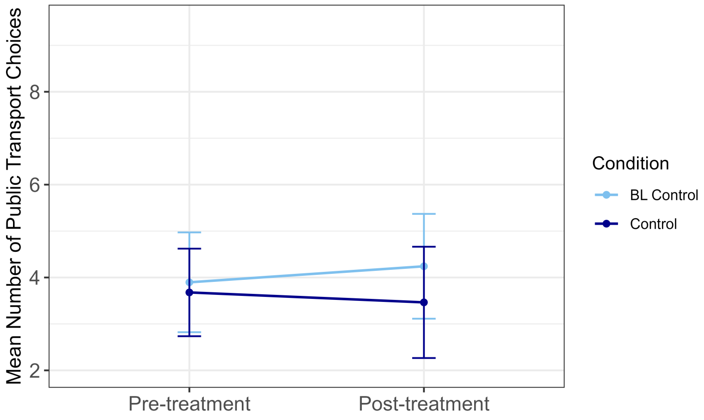


Figure G.20: Differences-in-Differences Plot (Full Data): Control vs. Baseline Control.