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# Nudging employees for greener mobility. A field experiment

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# Abstract

The central issue of this paper is to understand how policy makers can design instruments to create incentives towards green mobility. With this in mind, we ran a field experiment in 89 French firms (both public and private organizations) over 54 weeks to investigate how nudges and financial incentives can decrease the use of polluting vehicles by employees during their commute to work each week. Based on data including 845 employees, our study highlights several results related to three important attributes of policy design: the type of instrument, the timing and the targeting. We find that individuals exposed to the nudges "Moral Appeal", "Risk of Loss", and a combination of these two, significantly decrease their use of polluting vehicles in their daily commute to work. We find no treatment effect, either for the other nudges or for the impact of financial incentives. Our findings also reveal a persistent effect in time of the three successful nudges on the transport behavior of employees. Using a causal forest method to evaluate the heterogeneous treatment effects of these three nudges, we demonstrate that distance from work and pro-environmental behavior are the strongest predictors of treatment effects. We find that the further the employees reside from their workplace, the lower the treatment effect estimates. It suggests that selective targeting can improve the efficiency of the nudging policy.



**Keywords:** Nudge; field experiment; green mobility; transport mode.

**JEL:** C93; D91; Q5; R4.

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# Nudging employees for greener mobility

# A field experiment

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**Abstract**

The central issue of this paper is to understand how policy makers can design instruments to create incentives towards green mobility. With this in mind, we ran a field experiment in 89 French firms (both public and private organizations) over 54 weeks to investigate how nudges and financial incentives can decrease the use of polluting vehicles by employees during their commute to work each week. Based on data including 845 employees, our study highlights several results related to three important attributes of policy design: the type of instrument, the timing and the targeting. We find that individuals exposed to the nudges "Moral Appeal", "Risk of Loss", and a combination of these two, significantly decrease their use of polluting vehicles in their daily commute to work. We find no treatment effect, either for the other nudges or for the impact of financial incentives. Our findings also reveal a persistent effect in time of the three successful nudges on the transport behavior of employees. Using a causal forest method to evaluate the heterogeneous treatment effects of these three nudges, we demonstrate that distance from work and pro-environmental behavior are the strongest predictors of treatment effects. We find that the further the employees reside from their workplace, the lower the treatment effect estimates. It suggests that selective targeting can improve the efficiency of the nudging policy.

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# 1 Introduction

According to IPCC data published on 4 April 2022, transport is the largest emitter of greenhouse gases (GHG) in France (31%) and is responsible for a quarter of global emissions, which constitutes a threat to both climate and health. Even if the majority of European governments have increased their investments in sustainable transport infrastructures, the car remains the primary mode of transport in these countries (Eurostat, 2021). For instance, in France, car journeys represent 65% of transport mobility, while public transport only accounts for 8%, a total of 3.15 journeys per day. This highlights that without behavioral changes in individual mobility these investments will not be sufficient. In this context, the central issue is how policy makers can design instruments to create incentives and encourage environmentally friendly transport behavior.

In the environmental economics literature, the effectiveness of monetary instruments such as taxes or subsidies to drive environmental behavior has long been recognized (Gollier, 2019). In theory, these instruments can guide individual actions through appropriate 'price signals'. The effectiveness of financial incentives is explained by the postulate that economic agents are individuals with perfect rationality seeking to maximize private interest without taking into account other elements such as social influence, peer pressure, etc. However, in practice, many governments have failed to implement monetary instruments such as carbon tax due to a lack of public acceptability of these policies (Carattini et al., 2019). Moreover, the development of behavioral economics has profoundly questioned the effectiveness of these instruments. For example, by highlighting the crowding-out effect of financial incentives, Frey (1997) suggests, on the one hand, that financial incentives may not have the expected effects and, on the other hand, that a more complex individual rationality (as opposed to the traditional one) must be studied. Indeed, if individuals have an intrinsic motivation to make certain decisions beyond purely financial and individualistic considerations, this means that other elements such as social, psychological and cognitive factors (e.g., the behavior of others, social norms, moral considerations, limited cognitive abilities, etc.) influence individual behavior (Rege and Telle, 2004; Brekke et al., 2003).

In this context, several scholars preconized (Thaler and Sunstein, 2009; Benartzi et al., 2017; Carlsson et al., 2021) non-monetary instruments as behavioral instruments to encourage environmentally friendly behavior. These behavioral tool, also known as nudges (Thaler and Sunstein, 2009), are considered as an alternative public instrument, given that they are easier to implement and less intrusive than conventional tools such as taxes and regulations (Benartzi et al., 2017). As per the definition in Thaler and Sunstein (2009) (p.6):"A nudge, as we will use the term, is any aspect of the choice architecture that alters people's behavior in a predictable way without denying any other options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid. Nudges are not mandates. Putting fruit at eye level counts as a nudge. Banning junk food does not." In other words, the nudge represents a soft incentive instrument encouraging individuals to change their behavior by affecting their cognitive bias without penalties. For instance, a nudge could consist of modifying the default option applied to a given choice, and thus relies on the inertia that typically characterizes individual behavior to guide individuals towards a particular option. Another type of nudge could simply include information (e.g., of a scientific nature) to correct possible mis-perceptions, or to help individuals become aware of the real issues behind their decision. A nudge can also aim to activate social norms of behavior. For instance, by informing individuals of what most other individuals choose in the same situation (descriptive norm). It could also be a way of communicating to individuals what the majority approve or disapprove of (injunctive norm). Thaler and Sunstein (2009) recommend the use of 'private nudges', in various contexts. This is why several fields of application have explored the effectiveness of nudges.

In the electricity consumption of (usually American) households, many scholars have studied the effectiveness of nudges (Darby, 2006; Allcott, 2011; Ayres et al., 2013; Houde et al., 2013; Costa and Kahn, 2013; Allcott and Rogers, 2014; Holladay et al., 2019; Fowlie et al., 2021). Asensio and Delmas (2015) argue for the implementation of "behavioral strategies" to reduce energy consumption. The landmark study by Allcott (2011), based on a large-scale experiment conducted in partnership with the American company Opower, demonstrated that the impact of a social comparison nudge is equivalent to those obtained by increasing the price of electricity between 11 and 20% (via a tax, for example). In a different context, Holladay et al. (2019) highlight no effect of different information (social comparison) on subscription to Home Energy Assessments and subsequently the installation of energy-efficient sustainable goods. Moreover, given that employees do not pay the energy bill of the structure where they are employed, they could react to different incentives affecting electricity consumption. Indeed households pay their energy bills and know (or can access information on) the consumption of their individual household, while employees do not pay the energy bill of the structure where they are employed and do not know *a priori* its consumption levels. They therefore have no financial incentive to reduce their energy bills. In this context, Charlier et al. (2021) analyzed the effect of nudges on electricity consumption in companies. They conducted an experiment to examine the effect of three different types of nudges (moral appeal, social comparison and stickers) on employees' energy consumption. They show that the moral appeal and social comparison nudges combined with the stickers significantly affected employees' energy consumption.

In the transport field, even if many articles and policy reports suggest the use of behavioral measures in the public transport sector (Planning and Team, 2018; Metcalfe and Dolan, 2012; Garcia-Sierra et al., 2015), very few scholars talk explicitly about nudges. Indeed, in their literature review of nudges in the transport, Ortmann et al. (2017) identify, on the Web of Science platform, 28 articles mentioning behavioral economics instruments with only one dealing with nudges. However, they pointed out that several studies examine behavioral instruments that can be categorized as nudges. For example, theoretical and empirical papers discuss the importance of activation of social norms in mobility decision. Garcia-Sierra et al. (2015) test the use of descriptive norms to emphasize information messages in the promotion of public transport. The authors suggest that environmental behavior is guided by social norms. This means, although driving a car is harmful to society, it can be optimal for the individuals if it is socially accepted. Therefore, emphasizing the social norm of public transport use may affect beliefs about conditional co-operators. In that case, free riding could be considered as a violation of the norm. Also, if public transport is the social norm in terms of mobility, we should strive to discourage free riding. In the same way, the study by Sunitiyoso et al. (2011a) details lab experiments observing the effect of social norms. They highlight that individuals reinforce their behaviors when group members behave in a similar and majority way. In their previous research, Sunitiyoso et al. (2011b) also show that more complete 'social' information about other participants' choices increases cooperative behavior compared to more limited information. Moreover, the social norm also appears to affect the choice of cycling use (Bartle et al., 2013; Dill and Voros, 2007). Gravert and Olsson Collentine (2021) also analyse the effect of social norms and economic incentives on the use of public transportation relying on a large-scale natural experiment including more than 14,000 individuals in Sweden. Their results reveal that their social norm message fails to increase response rates to the free public transport offer. The authors conclude that the nudge was inefficient, while economic incentives such as a two-week free travel card were so. Furthermore, they show that a longer trial period allows to significantly increase long-term behavior changes.

Other articles study the issue of the activation of positively and negatively-framed social norms. In their paper, Avineri and Waygood (2011; 2013) theoretically explore the effect of negative framing in terms of the cost transport and environmental pollution. They study the framing effect of perceived differences in the amount of $CO_2$ emissions between the different alternatives. The information provided represents either a positive framing (the potential of a mode of transport to provide environmental benefits) or a negative framing (the potential of a travel mode to reduce environmental loss). They advocate the use of negatively framed social norms to change people's travel patterns. For instance, individuals might be more sensitive to losing 10 minutes on a journey than gaining 10 minutes, and the same is true for paying for a journey. Thus, reference points matter in people's preferences. The study of Kristal and Whillans (2020) test a positive framing by analyzing the financial benefits of carpooling. The results do not support a change in employee travel behavior.

In addition, few authors question the cognitive bias of the individual gap between intention and actual behavior. O'Donoghue and Rabin (1999) highlight that although individuals are willing to change their behavior, they are hesitant and tend to postpone decisions with a longer term visibility. To reduce this gap between intention and action, scholars point out the importance of defining a concrete plan of action (called implementation intentions) (Milkman et al., 2011). Kristal and Whillans (2020) tested the impact of personalized travel plans on reducing car use. These plans provided each employee with personalized information on routes, transit schedules, travel discounts and carpooling connections that best met their needs. The authors find no effect on travel behavior.

Nevertheless, despite these empirical and theoretical insights, there are several shortcomings in the literature. Firstly, most of the studies analyzing the mobility decision use surveys. Surveys report declared intention and it has been demonstrated in the behavioral literature that there is a gap between declared intentions and actions (Sheeran and Webb, 2016). Therefore, inquiring into individuals' intentions to modify their transport mobility in the future in response to a public policy could be a poor proxy of their future transport choice. Secondly, there is no robust empirical evidence at present of the effectiveness of nudges in the transport field (Ortmann et al., 2017). Indeed, most of the studies do not sufficiently control for the multiple contextual effect to isolate the marginal effect of the nudge. Furthermore, they do not use sufficient experimental controls such as the "availability of relevant data or period of trial", the only exception being the analysis of Gravert and Olsson Collentine (2021). Thirdly, none of the studies analyze more specifically the mobility decisions of home to work commute, even though they represented 38% of the total mobility in France in 2019.[1] Fourthly, the existing studies focus on the modal change from the car to a single mode of transport, rather than on all possible alternatives (walking, scooters, cycling, tramways, buses, trains, carpooling, two-wheelers, and combinations). However, analyzing the effect of policy on each alternative is essential as the impact could be different between each mode of transport.

To fill these gaps, we conducted an original field experiment to examine the causal effect of monetary and non-monetary incentives in changing the transport habits of individuals. We ran this experiment on 845 employees from 89 French firms (both public and private organizations) in the Hauts-de-France (HdF)

[1] According to the French "Commissariat général au développement durable".

region over 54 weeks. Six interventions were made involving these employees, enabling the creation of six different treatment groups. The first intervention aimed at activating a social norm using comparison with others (social comparison nudge). The second intervention consisted of a change in presentation regarding availability of transport infrastructure (Change nudge). The third intervention aimed to emphasize the risks in terms of health, time or money, associated with a continuation in individuals' transport behavior (Risk of loss nudge). The fourth intervention consisted of activating moral norms by highlighting the negative effects of the use of polluting vehicles on global warming (Moral appeal nudge), while the fifth intervention featured a combination of the Risk of loss and moral appeal nudges (policy mix). Finally, the last intervention involved the use of a financial incentive that characterized by a financial reward in cases where cars were not used to get to work during the week.

We assess the causal effects of these different interventions using both parametric (difference-in-differences) and non-parametric (causal forest) methods. Our empirical results show that only three interventions have significantly altered employees' transport behavior, namely risk of loss, moral appeal and the combination of these two. More precisely, the group targeted by the risk of loss nudge have reduced the share of polluting vehicles in their weekly trips to work by 12 percentage points, while the average treatment effect is -0.085 and -0,090 for the groups targeted by the moral appeal and combination nudges, respectively. Our results also reveal that employees have mainly substituted the use of polluting vehicles for the use of cycling and that these changes are persistent. Furthermore, a timing analysis also indicates that the risk of loss nudge and the policy mix treatment have a significant effect in the very short run (2 weeks) on transport mode choice of employees, while the effects of the moral appeal nudge take longer to materialize (8 weeks). However, the effect of the three nudges is reinforced during the experiment period. Furthermore, we estimate that these changes in transport mode behaviour have allowed to reduce particulate matter in the air by 165g, nitrogen oxides by 2.746kg and carbon dioxide by 1.435 tons per week. We also estimate the heterogeneous treatment effects of the different interventions for each employee using the recently developed causal forest algorithm (Wager and Athey, 2018; Athey et al., 2019). We demonstrate that distance from work is the main observable characteristic explaining the differences in treatment effects of the different interventions.

The contribution of this paper is manifold. Firstly, we test the effectiveness of monetary and non-monetary incentives in changing the transport behavior of individuals through a field experiment. Indeed, while the literature is full of field experiments using nudges on electricity consumption (Darby, 2006; Allcott, 2011; Ayres et al., 2013; Houde et al., 2013; Allcott and Rogers, 2014; Holladay et al., 2019; Murakami et al., 2022; Andor et al., 2022), by contrast, studies focusing on transport mode decisions are very scarce. As mentioned earlier, most papers in the transport literature rely on surveys to evaluate mobility which creates bias in identifying causal effects. The only exception being the paper from Gravert and Olsson Collentine (2021), which relies on a large-scale experiment to investigate the effect of social norms on public transport usage. However, this analyse only focuses on public transportation and a particular nudge (social norm), while omitting other transport alternatives and other type of nudges. Our paper, thus, enriches the existing literature on transport mode decisions by estimating a causal effect through a difference-in-differences analysis for different interventions and transport modes. Secondly, it analysis six different interventions and compares the effectiveness of both monetary and non-monetary incentives. It goes beyond the standard social norm and social comparison nudges by examining for instance a nudge linked to the risk of loss and a policy mix. Thirdly, we can also highlight the effect of these instruments over time by analyzing short and long run effects. This enables us to observe the optimal length of the experiment and the possible persistence of the changes in transport mode behavior. Fourthly, our study attempts to compare the heterogeneity of the different interventions using recent machine learning techniques, which allow us to shed light on the importance of taking into account individual heterogeneity in order to increase the policy's efficiency through targeting.

The remainder of this article is organized as follows. Section 2 describes the experimental design, treatment and data. Section 3 presents the empirical strategy. Section 4 displays results of the parametric estimation of the average treatment effect. Section 5 investigates the heterogeneity of the estimated effects using the causal forest algorithm. Finally, Section 6 discusses the implications of our results and concludes.

# 2 Experimental Design, Treatment, and Data

## 2.1 Study setting

The field experiment was conducted between October 2020 and October 2021 (54 weeks) in the Hauts-de-France region. 99 firms have been selected to participate to the field experiment after signing a convention with the University[2]. A mobile application, allowing to record daily transport to work commute, has been created and proposed to each employee of the selected firms. In each firm, a referring person was identified to promote the study, explain the use of the mobile application and try to involve as many employees as possible. These referrers, specific to each selected company, were trained over several weeks. They were provided materials such as information to give to employees and a video explaining how the phone application

[2] Université Polytechnique Hauts-de-France.

works. They knew about the name of the experiment (IMPULCE) and they had access to a website, using a specific code, which provided all information about the experiment. Usually they were the direct supervisors of the employees and got used to communicate with them. No pressure was put on employees to download the application and fill in the survey about their modes of transport. Each referrer has organized a launch meeting in his firm in order to explain to employees that the firm was participating to a research project about transport mobility lead by researchers from the "Université Polytechnique Hauts-de-France" and to explain the use of the phone application. Employees only knew about the name of the phone application ($BLOB^{Lab}$).

Thus, the targeted employees had no idea that they were part of the field experiment[3] and only knew that they would have to complete a survey about their travels to work every week during a year. The information was provided as follows: "By participating in this study, you contribute to French research. The researchers' objective is to analyse the factors that determine your mobility choices. They have no preference for a particular mode of transport and do not consider one mode to be better than another. They observe that existing studies, often cited by policymakers, come from countries with different customs and habits. Thus, this study will help to understand the reasons that influence choice of one mode of transportation over another of French people. They just want to examine and understand which infrastructure would be necessary for French people to use some transportation and to examine the following questions: does seasonality impact French employees' mobility behavior ? Do other external factors also influence it?" Furthermore, each referrer insisted that staff should provide an accurate picture of reality, explaining that considering all types of users are important. At no point referrers mentioned that the main objective of the experiment was to initiate a change in employees' mobility. They were prohibited from mentioning that. Referrers just insisted that there are no good or bad behaviours and that the survey was only informative, i.e. to describe the determinants of transport mode choices, in order to reduce a potential reporting bias.

In the end, 1088 individuals have downloaded the application in order to be part of the filed experiment. It is important to notice that the download of the application is made on a voluntary basis as in most clinical trials. Thus, in the case that an employee from a selected firm do not download the application, no information on this specific employee is available.

[3] The word "experiment" has never been used by referrers in their communication with employees. They only have talked about a "research project".

## 2.2 Sampling

The region Hauts-de-France comprises 5 different departments. Out of the 99 firms selected, 61 are located in the "Nord" department, 30 in the "Oise" department, 5 in the "Somme", and 3 in the other departments of the region. Firms were randomly selected into different groups based on three criteria. (i) the firm's environmental commitment, (ii) the geographical area (department) where the firm is located, and (iii) the size of the firm. For the environmental commitment, a score ranging from 0 to 4 was given according to the different actions undertaken by the firm, from the total absence of an environmental approach (0) to the completion of all the different steps (4), i.e. the commitment to a Corporate Social Responsability (CSR) approach, the implementation of a Mobility Plan, the carrying out of a diagnosis of the mobility practices, and the publication of firm's carbon balance. Regarding the geographical area, and in order to ensure that all the departments in the different groups were representative, a score of 1 to 4 was given according to the department in which the firm is located (1 for the "Nord" department, 2 for the "Oise", 3 for the "Somme", and 4 for other departments). Finally, regarding the size of the firms, four categories were defined by taking the quartiles of the distribution of the firms' number of employees. The random sampling was therefore carried out according to these three criteria, respecting quotas by treatment group.

The 99 firms in the sample were randomly divided into a "Social Comparison" (SC) group (15 firms and 173 employees), a "Change of presentation" (Change) group (14 firms and 280 employees), a "Risk of Loss" (RL) group (17 firms and 233 employees), a "Moral Appeal" (MA) group (14 firms and 61 employees), a combination of "Moral Appeal" and "Risk of Loss" (MA-RL) group (16 firms and 189 employees), a financial incentive (FinInc.) group (9 firms and 85 employees) and a pure control group (14 firms and 67 employees), stratified by department, size, and an environmental commitment score.

Nevertheless, 2 firms (representing 41 employees) selected and randomly assigned to intervention groups (Change and RL) enter during the experiment (after the fifth week) and are thus excluded from the analysis. Furthermore one employee have deleted the application during the treatment period. Thus, we end up with a sample of 97 firms and 1046 employees.

Finally, out of the 1046 employees for which we have information about their daily work commuting, only 845 (representing 89 firms) filled an *ex ante* survey regarding their individual characteristics such as age, distance to work, education level, etc. Thus, in the heterogeneity analysis in Section 5, we can only use information about these 845 employees.

## 2.3 Experimental Design and Timeline

As the philosophy of these nudges was presented in the introduction, we present below the technical characteristics retained in our experimentation.

## 2.4 Treatments

Four nudges were tested in our field experiment: a 'Social Comparison' nudge that communicates a descriptive norm, a 'Change of presentation' nudge that makes the proposed option fun; a 'Risk of Loss' nudge that highlights the loss the individual risks if they do not change their behavior; and finally, a 'Moral Appeal' nudge that communicates an injunctive norm to employees.

### 2.4.1 The 'Social Comparison' nudge treatment

The first treatment, 'clash of blob', corresponds to the 'social comparison' nudge. This instrument aims at activating a social norm that can be used to induce individuals to act in the direction desired by the regulator. In particular, it involves highlighting a behavior performed by the majority of individuals in the environment. Our nudge is based on a game where each week an employee could challenge a colleague, within their intra-institution, to use soft mode of transport. At the end of week, each participant received their own ranking compared to their colleagues. The social comparison is 100% on the application, even though a poster (see Figure OA1 in the online Appendix) and a pop-up reminded them every week over 40 weeks that they could challenge each other.

### 2.4.2 The 'Risk of Loss' nudge treatment

The third treatment, called "risk of loss", highlights the loss that the individual risks incurring if they do not change their behavior. This loss may be in terms of money, time, health, etc. Loss aversion is a cognitive bias that describes the tendency to value a loss more than an equivalent gain. We distributed posters presenting loss aversion messages via the application every Monday over 40 weeks. And example and the full set of messages used in the experiment are shown in the online Appendix (see Figure OA2 and Table OA1).

### 2.4.3 The "Change of presentation" nudge treatment

The second treatment, 'change of presentation', uses graphic visual installations that aim to modify their bias perception on different dimensions of their move such as the availability of infrastructure, journey timing by mode, etc. As shown in the online Appendix (see Figure OA3), this can range from a simple reminder of the direction of public transport to a more complex map showing the walking or cycling distance to various key points around the facility.

#### 2.4.4 The 'Moral Appeal' nudge treatment

The fourth treatment, known as "moral appeal", refers to the activation of moral norms. This reflects people's feelings of moral obligation to do something and their feelings of being obliged to adopt environmental friendly behavior. Through posters, we emphasized the negative effect of car use on global warming, and on the environment more generally. These messages were sent every Monday over 40 weeks. An example and the full set of texts provided in this treatment are displayed in the online Appendix (see Figure OA4 and Table OA2).

#### 2.4.5 Policy-mix treatment

This is the previous two nudges combined. Thus, over 40 weeks employees received 'risk of loss' messages on their application every Monday, and were sent the 'moral appeal' messages every Thursday.

#### 2.4.6 Financial incentive treatment

The sixth treatment, the financial incentive, is a financial reward. The reward works like a competition. Every week over 40 weeks, one person per establishment is entered into a draw to win a shopping card worth 20€. Only employees who have not used their own car can be entered. Note that it is the improvement with regard to the reference week (before the treatment) that is rewarded. Thus, an employee that already uses alternative modes of transport before the implementation of the treatment cannot be rewarded. The same person can be drawn several times. Given the limited budget, we were not able to reward responsible behavior among all participants every week for the duration of the experiment. We therefore opted for a financial incentive in the form of a lottery. A poster (see Figure OA5 in the online Appendix) and a pop-up reminded them every week over 40 weeks that they could win shopping cards.

#### 2.4.7 Implementation of the field experiment

The 97 sites of the experiment were randomly allocated to the different treatments. Table 1 below presents a quantitative description of the allocation of sites to the different treatments (number of sites per group, number of employees concerned) for the whole sample and for the sample of employees that answered the *ex ante* survey.

Table 1: Description of the groups

| | Total sample | | Sample (ex ante) | | Period | | |
|---|---|---|---|---|---|---|---|
| Group | No. of companies | No. of employees | No. of companies | No. of employees | Control period | Treatment period | Period after treatment |
| Control | 13 | 65 | 12 | 55 | 54 weeks | - | - |
| Moral Appeal (MA) | 14 | 58 | 12 | 44 | 4 weeks | 40 weeks | 10 weeks |
| Risk of Loss (RL) | 17 | 228 | 17 | 190 | 4 weeks | 40 weeks | 10 weeks |
| MA-RP | 16 | 180 | 16 | 155 | 4 weeks | 40 weeks | 10 weeks |
| Social comparison (SC) | 15 | 162 | 13 | 121 | 4 weeks | 40 weeks | 10 weeks |
| Change of presentation | 13 | 272 | 11 | 215 | 4 weeks | 40 weeks | 10 weeks |
| Financial incentive | 9 | 81 | 8 | 65 | 4 weeks | 40 weeks | 10 weeks |
| Total | 97 | 1046 | 89 | 845 | | | |

The firms that make up the control group do not receive any particular treatment and are unaware that they are participating in an experiment. The experiment is carried out over a period of 40 weeks (see the timeline in Figure OA6 in the online Appendix). We start the experiment after 4 weeks of pre-treatment. This period serves to collect information on their habits mobility. After this step, during the 40-week period, each instrument described above is implemented. This phase enables us to measure the effectiveness of the tested instruments. The 10-week post-treatment period is used to assess whether the change in behavior persists over time. We completed the design of the experiment with two anonymous surveys. The first survey, administrated before treatment, identifies the social characteristics of the employees, as well as their mobility habits, and their environmental preferences. The second survey, implemented after the treatment period, once again inquired about the employees' habits.

## 2.5 Data

### 2.5.1 Summary statistics

This experimental design enables us to collect several data. Every day, each employee records the transport mode he used in his commute. These modes of transport included: car or motorcycle, cycling, bus, subway, train, scooter, walk, or carpool. We also have information concerning teleworking days and non-working days. Then, we create five categories of modes of transport. The first category incorporates polluting vehicles (car and motorcycle), the second category includes only cycling, the third category incorporates all modes of public transport (bus, subway, train), the fourth category includes the other modes of transport (scooter, carpool, walking) and the last category includes teleworking. Finally, for each employee $i$ of firm $e$, we calculate the share of each transport mode category $k$ in weekly trips $t$ as follows:

$$y_{iet}^{k} = \frac{N_{ie}^{k}}{7} \tag{1}$$

Where $N_{ie}^{k}$ represents the number of times (days) that an employee $i$ of a given firm $e$ has used a particular mode of transport $k$ ($k \in$ {Polluting vehicles, cycling, public transportation, other transport modes, teleworking}) during a given week.[4]

Table 2 displays descriptive statistics on the share of transport mode category $k$ in weekly trips for each group of employees for the sample of respondents of the *ex ante* survey. The same statistics for the total sample of 1046 employees are available in Table B1. We can observe that employees from the control group frequently use more polluting vehicles for their trips to work during the weeks prior to the implementation of the field experiment than MA, SC, RL and Financial incentive groups. Indeed, on average, 51.2% of weekly trips to work are made using polluting vehicles by employees from the control group, whereas the figure is just 40% for individuals from the other four groups. For transport using cycling, it seems that, at a 5% level of confidence, there is no significant difference between the decision of the control group and other nudged groups.[5] A similar pattern emerges for public transportation, with the exception of the nudged group "Change in presentation" which exhibits a significantly lower share of public transportation in their weekly trips. Table B1 exhibits a very similar pattern for the total sample. Note that for the rest of the analysis, we disregard the category "other transportation", as it always represents 0% of weekly trips of the control group, which makes it difficult to verify the common trend assumption.

#### 2.5.2 Attrition

The study ran for 54 weeks, but employees could obviously leave the study for some reasons. However, to avoid attrition due to the time required to enter daily travel information by the employees of the experiment, an option has been added to the mobile application. This mechanism allows employees to record automatically, in one click, the previous week declared as the current one, if they do not have changed their daily transport mode. As discussed earlier, one individual from the group RL, have leaved the experiment and deleted the mobile application, before the end of the treatment period (at week 27). This is very low and strongly attenuates a potential attrition bias.

[4] Note that during non-working days no transport mode is recorded. Consequently, $\sum_k y_{iket} \neq 1$. To obtain 1, one must incorporate the share of non-working days.

[5] For these groups, cycling represents between 4% and 11% of weekly trips to work.

Table 2: Descriptive statistics on pre-treatment period

| | Control | MA | SC | Change | Fin. incent. | RL | MA-RL |
|---|---|---|---|---|---|---|---|
| Share polluting | 0.512 | 0.400 | 0.412 | 0.537 | 0.410 | 0.372 | 0.489 |
| *p-value* | | *0.004* | *0.001* | *0.354* | *0.004* | *0.000* | *0.423* |
| Share cycling | 0.069 | 0.111 | 0.049 | 0.041 | 0.089 | 0.068 | 0.041 |
| *p-value* | | 0.084 | 0.255 | 0.085 | 0.355 | 0.961 | 0.096 |
| Share CT | 0.098 | 0.119 | 0.106 | 0.033 | 0.107 | 0.108 | 0.066 |
| *p-value* | | *0.453* | *0.712* | *0.001* | *0.721* | *0.630* | *0.121* |
| Share other | 0.000 | 0.044 | 0.045 | 0.043 | 0.063 | 0.055 | 0.046 |
| *p-value* | | *0.001* | *0.000* | *0.000* | *0.000* | *0.000* | *0.000* |
| Share teleworking | 0.058 | 0.067 | 0.107 | 0.076 | 0.045 | 0.095 | 0.057 |
| *p-value* | | *0.559* | *0.000* | *0.088* | *0.310* | *0.001* | *0.914* |

*Note:* The column gives averages for employees in the control, moral appeal, social comparison, change in presentation, financial incentive, risk of loss and combined moral appeal and risk of loss group. P-values from t-tests on mean equality between each group and the control group are presented in italics.

# 3 Empirical strategy

**Difference-in-Difference.** In order to evaluate the causal impact of each nudge and the financial incentive on employees' mode of transport, we run difference-in-differences (DID) regressions. Even though a before-after analysis could be helpful, it may also be biased if external factors drive changes in individual transport mode decisions during the period under scrutiny. Thus, for each nudge $n$ and each transport mode category $k$, we estimate the following DID model:

$$y^k_{iet} = \alpha + \gamma(period_1 * group^n_i) + \lambda_i + \eta_t + \theta_e + \epsilon_{iet} \tag{2}$$

Where $period_1$ is a dummy variable that equals 1 from week 5 to week 44 and 0 otherwise, $group^n_i$ is a dummy variable that equals 1 for individuals $i$ treated by a particular nudge $n$ ($n \in \{$MA, SC, Change in presentation, Financial incentive, RL, MA-RL$\}$ and 0 for individuals in the control group. $\lambda_i$ denotes individual-specific fixed effects which captures initial differences in the share of each transport mode category. $\eta_t$ represents week-specific fixed effects that captures unobserved weekly heterogeneity (seasonal variations are thus captured here). Finally, firm fixed effects $\theta_e$ are introduced to capture characteristics of the firm that could influence initial differences in the outcome variable. The variable ($period_1 * group_n$) indicates whether an observation belongs to the group treated by a particular nudge $n$ during the treatment period. Thus, coefficient $\gamma$ represents the Average Treatment Effect (ATE) of a particular nudge $n$ on the share of a given transport mode category $k$ in weekly trips. Note that this DID model is estimated only on pre-treatment and treatment periods (from week 1 to week 44) to capture short-run effects of the different nudges.

Note that standard errors are clustered at the firm-level, which is our unit of randomization. Even if conventional cluster standard errors can be extremely conservative, clustering is still relevant in our case, as individuals that belong to the same cluster (firm) have benefited from the same treatment assignment (Abadie et al., 2022). In Section 4.4, we test the sensitivity of our results to another level of clustering, namely the individual level and also implement a randomization inference procedure following Heß (2017).

Two critical assumptions have to be verified in order for the DID estimation to deliver unbiased results.

**Counterfactual validity.** The first assumption implies that the control group is a valid counterfactual in the sense that any exogeneous events during the experiment (such as the two different lockdowns for example) affected employees in treated and control groups in similar ways (Kurz, 2018). If weekly-specific fixed effects allow to capture these exogeneous shocks, it does not imply that individuals forming the different groups react similarly to these events. However, the study of individual characteristics of the employees of each group and of firms selected for the field experiment is a way to validate the control group.

First, in Table 3, we report summary statistics of individual characteristics of workers among the different groups and the results of the balance check after randomization. All this information is extracted from an ex ante (i.e., prior to the treatment) survey completed by the participants of the field experiment.[6] In Table 3, distance represents the distance in kilometers between home and location of work, the NEP scale stands for New Ecological Paradigm scale, which is a measure of endorsement of a "pro-ecological" world view, number of cars, bicycles and motorcycles and represents the number of each mode of transport per household. Age category is a categorical variable evaluating age of the employee,[7] Socioprofessional category is a categorical variable evaluating the occupation of employee,[8] Education represents the level of education of each individual[9] and Gender is a binary variable that equals one for male and zero otherwise.

Together with summary statistics results, Panel (a) reports results from t-tests on mean equality, and shows the absence of significant differences between the control group and the different nudged groups. Consequently, individuals from the control group seem to display similar ecological values and live at a relatively similar distance from their work to nudged groups. In Panel (b) and (c), we compare categorical and binary variables between the control group and the different nudged groups. Mann-Whitney and Fisher's exact tests allow us to confirm that there is no significant differences among groups. Therefore, the populations

[6]Unfortunately, only 845 employees among the total of 1046 used in the field experiment filled in the document and answered the different questions in the survey.

[7]Values are {1=15-29 years; 2=20-44 years; 3=45-59 years; 4= >= 60 years}.

[8]Values are {1=agricultural workers; 2=craftspeople, traders and business executives; 3=blue collar workers; 4=employees; 5= white collar workers; 6=technicians and associate professionals; 7=Students}.

[9]Values are {1=below Baccalaureate; 2=Baccalaureate; 3=Two years after Baccalaureate; 4=Bachelor; 4= Master; 5= PhD}.

Table 3: Statistics on individual characteristics and randomization check

| | Control (N= 55) | MA (N= 44) | SC (N= 121) | Change (N=215) | Fin. incent. (N=65) | RL (N=190) | MA-RL (N=155) |
|---|---|---|---|---|---|---|---|
| *Panel (a)* | | | | | | | |
| Distance (in km) | 28,614 | 54,539 | 34,467 | 28,632 | 20,934 | 34,600 | 37,353 |
| *p-value* | | *0,121* | *0,550* | *0,998* | *0,289* | *0,452* | *0,389* |
| NEP scale | 1,070 | 1,05 | 0,972 | 1,095 | 1,114 | 1,113 | 0,971 |
| *p-value* | | *0,803* | *0,123* | *0,665* | *0,522* | *0,472* | *0,097* |
| Number of cars | 1,455 | 1,500 | 1,471 | 1,516 | 1,554 | 1,593 | 1,625 |
| *p-value* | | *0,772* | *0,906* | *0,635* | *0,500* | *0,298* | *0,203* |
| Number of bicycles | 1,527 | 1,704 | 1,670 | 1,525 | 1,781 | 1,693 | 1,619 |
| *p-value* | | *0,560* | *0,560* | *0,993* | *0,374* | *0,465* | *0,689* |
| Number of motorcycles | 0,091 | 0,116 | 0,099 | 0,126 | 0,154 | 0,238 | 0,077 |
| *p-value* | | *0,688* | *0,867* | *0,459* | *0,351* | *0,050* | *0,768* |
| *Panel (b)* | | | | | | | |
| Age category | 2,164 | 2,182 | 2,099 | 2,088 | 2,046 | 2,121 | 2,155 |
| *p-value* | | *0,913* | *0,629* | *0,576* | *0,496* | *0,817* | *0,990* |
| Min-Max | (1-4) | (1-4) | (1-4) | (1-4) | (1-3) | (1-4) | (1-4) |
| Socioprofessional category | 3,764 | 3,454 | 3,670 | 3,781 | 3,692 | 3,616 | 3,703 |
| *p-value* | | *0,791* | *0,524* | *0,234* | *0,592* | *0,924* | *0,655* |
| Min-Max | (1-6) | (1-6) | (1-6) | (1-6) | (1-6) | (1-6) | (1-6) |
| Education | 3,763 | 3,954 | 3,835 | 3,702 | 3,831 | 4,016 | 3,871 |
| *p-value* | | *0,614* | *0,772* | *0,796* | *0,959* | *0,295* | *0,696* |
| Min-Max | (1-7) | (1-7) | (2-7) | (1-7) | (1-7) | (2-7) | (1-7) |
| *Panel (c)* | | | | | | | |
| Gender | 0,436 | 0,454 | 0,529 | 0,479 | 0,492 | 0,432 | 0,413 |
| *p-value* | | *0,982* | *0,329* | *0,678* | *0,668* | *0,927* | *0,886* |
| Min-Max | (0-1) | (0-1) | (0-1) | (0-1) | (0-1) | (0-1) | (0-1) |

*Note:* The column gives averages for employees in the control, moral appeal, social comparison, change in presentation, financial incentive, risk of loss and combined moral appeal and risk of loss group. P-values from t-tests on mean equality between each group and the control group are presented in italics in Panel (a). P-values from Mann-Whitney tests are reported for cardinal variables in Panel (b). P-values from Fisher's exact tests are reported for the binary variable gender in Panel (c).

of the different groups are similar with respect to age structure, educational attainment, socioprofessional category and gender distribution. Consequently, results of balancing tests displayed in Table 3 reveal that the likelihood that individuals from control and nudged groups react to exogeneous events in similar ways is relatively high. The study of firm characteristics also increases this probability. Indeed, firms selected in the field experiment have on average a similar size and operate in the same industrial sectors.

**Parallel trend assumption.** The second assumption, the parallel trend assumption (PTA) is also crucial in order to obtain unbiased results. It implies that in the absence of treatment, the trend in the dependent variable must be the same in all groups. There is no formal test to verify if the PTA holds because it is impossible to observe the trend of the dependent variable in the absence of treatment. However, there exists several ways to ensure that the PTA holds. Firstly, a graphical representation of outcomes before the implementation of the field experiment represents a visual diagnostic of this assumption. In Figure A1a in the Appendix, we plot the mean of the share of polluting vehicles in weekly trips of the different groups under scrutiny. It appears that control and nudged individuals followed the same trend before the treatment. The same observation emerges for the use of public transportation and teleworking (see appendix Figures A1c and A1d). However, for cycling (see Appendix Figure A1b) it is harder to tell, as some groups seem to exhibit different trends during the pre-treatment period (RL group, for instance). Another way to ensure the validity of the PTA is to estimate a linear-trend model, i.e., to include variables representing time trends before and after the treatment for control and particular nudge groups, and to perform a test to evaluate if the trajectories are parallel. If we cannot reject the null hypothesis that the difference in linear trends prior to treatment is zero using a F-test, the linear pre-treatment trends are parallel. Otherwise, identification of the ATE may be biased. In Tables 4, 5, and 6, we report p-values of this test for each transport mode (polluting vehicles, cycling and public transportation) and each nudged group. We can observe that for almost all models, we cannot reject the null hypothesis of parallel linear trends at the 5% level. The only exception concerns the RL group for the use of cycling. Finally, another common test to check the validity of the PTA is to compare changes in outcomes for the two groups repeatedly before the treatment, by changing the date for the introduction of the different treatments (Giaccherini et al., 2021; Chiappini et al., 2022). Consequently, we use the period before the implementation of the different nudges and exclude data at the date and after the beginning of the treatment period. We assign two weeks before the (real) treatment and estimate the DID models. Table OC1 in the online Appendix summarizes the estimation results. We find no significant effect of the "placebo" nudge on the share of polluting vehicles or the share in public transportation on weekly trips, regardless of the group under scrutiny. This provides strong evidence that the PTA holds. However, confirming our previous test, we find a significant estimate for the share of cycling in weekly trips of the RL group. Consequently, this is the only estimation that may be questionable in the following DID results.

# 4 Results

## 4.1 Effect of the nudges

Table 4 shows the effect of the different nudges on the share of polluting vehicles in weekly trips of individuals. Note that DID models are estimated only for individuals that have responded to the ex ante survey[10] and for pre-treatment and treatment periods.[11] Column (1) gives the ATE for the "Moral Appeal" (MA) group, while columns (2), (3), (4), (5) and (6) describe the ATE for the Social Comparison (SC), Change of presentation (Change), Financial Incentive (Fin. incen.), "Risk of Loss" (RL) and combined "Moral Appeal" and "Risk of Loss" (MA-RL) groups. We find that the MA nudge has entailed a significant decrease of 8.5 percentage points in the share of polluting vehicles used in weekly trips after its implementation. A close treatment effect is found for the combined nudge "Moral Appeal + Risk of Loss" (9 percentage points). It seems that the nudge "Risk of Loss" has the highest effect on the share of polluting vehicles in weekly trips (12.2 percentage points). On the contrary, we do not find any significant effect of the "Social comparison" nudge on the use of polluting vehicles. This result is puzzling: in the empirical literature on energy conservation, this nudge is always efficient in changing households' behavior in terms of energy consumption (Allcott and Kessler, 2019) except in cases where individuals do not pay energy bills, like at their workplace (Myers and Souza, 2020). This result could be explained by the role of social distancing inside establishments during the Covid period. Indeed, the social comparison aims to activate a social norm by highlighting a behavior performed by the majority of individuals and thus requires a high degree of interaction between individuals to be effective.

Our results also highlight that the nudge 'Change in presentation' seems to have entailed an increase in the use of polluting vehicles. However, as described in Section 4.4, this result is not robust to sensitivity tests. Consequently, giving individuals information about travel possibilities and infrastructure available within the establishments does not seem sufficient to change their behavior in terms of transport mode. This

[10]Results for the whole sample (1,046 individuals) are available in Table B2 in the Appendix. Results are quantitatively similar to those of Table 4.

[11]We consider the post-treatment period to estimate persistent effects in the following subsection.

is not surprising as most individuals already have access to this kind of information.

Our results also show that the financial incentive did not significantly reduce the share of polluting vehicles used in weekly trips. This result can be explained by the uncertainty of the reward. Indeed, in our experiment the financial incentive consisted of drawing one person per site per week to win a 20€shopping card. As shown by Kazunori and Yasuhiro (2010) people were more likely to engage in environmental behavior when the reward was certain, rather than when the reward was uncertain.

Table 4: Effect of the nudges on the share of polluting vehicles in weekly trips

| | (1) MA | (2) SC | (3) Change | (4) Fin. incen. | (5) RL | (6) MA-RL |
|---|---|---|---|---|---|---|
| $period_1 * group_i^n$ | -0.0877** | 0.0110 | 0.0165** | 0.0191 | -0.122*** | -0.0904*** |
| | (0.0348) | (0.00989) | (0.00709) | (0.0176) | (0.0167) | (0.0161) |
| Intercept | 0.440*** | 0.420*** | 0.507*** | 0.437*** | 0.383*** | 0.475*** |
| | (0.0140) | (0.00618) | (0.00513) | (0.00867) | (0.0118) | (0.0108) |
| Observations | 4,356 | 7,744 | 11,880 | 5,280 | 10,780 | 9,240 |
| R-squared | 0.964 | 0.955 | 0.943 | 0.953 | 0.895 | 0.915 |
| F-test for PTA | 0.789 | 0.314 | 0.359 | 0.479 | 0.0801 | 1.303 |
| p-value | 0.384 | 0.580 | 0.555 | 0.497 | 0.779 | 0.264 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values $< 0.10$, 0.05, 0.01 represented by *, **, ***, respectively.

Table 5 reports DID results for the share of cycling in weekly trips. As for polluting vehicles, we find that only the MA, RL and MA+RL nudges have significantly increased the use of cycling for weekly trips.

For public transport, the results are less conclusive as displayed in Table 6. Indeed, only the "Risk of loss" nudge seems to have had a significant and positive effect on the use of public transport (an increase of 6.7 percentage points). Finally for teleworking, none of the treatments have had a significant effect.[12] Indeed, teleworking seems to have been only affected by the two lockdowns as shown in Figure A1d.

To summarize, only three nudges led to a change in individual transport behavior: the "Moral Appeal" nudge, the "Risk of loss" nudge and the "Moral appeal + Risk of Loss" nudge. These three nudges led to a significant decrease in the use of polluting vehicles, mainly in favor of cycling. To a lesser extent, the "Risk of loss" nudge also led to an increase in the use of public transportation. In contrast, the other nudges did not have any significant effect.

[12] See Table OF1 in the online Appendix.

Table 5: Effect of the nudges on the share of cycling in weekly trips

| | (1) MA | (2) SC | (3) Change | (4) Fin. incen. | (5) RL | (6) MA-RL |
|---|---|---|---|---|---|---|
| $period_1 * group_i^n$ | 0.0396** | 0.000685 | -0.00526 | 0.00713 | 0.0523*** | 0.0748*** |
| | (0.0158) | (0.00485) | (0.00322) | (0.00568) | (0.0107) | (0.0116) |
| Intercept | 0.0854*** | 0.0526*** | 0.0434*** | 0.0800*** | 0.0651*** | 0.0464*** |
| | (0.00637) | (0.00303) | (0.00233) | (0.00280) | (0.00752) | (0.00779) |
| Observations | 4,356 | 7,744 | 11,880 | 5,280 | 10,780 | 9,240 |
| R-squared | 0.968 | 0.960 | 0.956 | 0.980 | 0.886 | 0.943 |
| F-test for PTA | 3.404 | 1.732 | 5.190 | 1.309 | 4.406 | 1.604 |
| p-value | 0.0780 | 0.201 | 0.0328 | 0.267 | 0.0450 | 0.216 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values < 0.10, 0.05, 0.01 represented by *, **, ***, respectively.

Table 6: Effect of the nudges on the share of public transportation in weekly trips

| | (1) MA | (2) SC | (3) Change | (4) Fin. incen. | (5) RL | (6) MA-RL |
|---|---|---|---|---|---|---|
| $period_1 * group_i^n$ | 0.0241 | -0.00332 | -0.00141 | -0.0126 | 0.0668*** | 0.0101 |
| | (0.0185) | (0.00589) | (0.00424) | (0.0104) | (0.0190) | (0.00743) |
| Intercept | 0.106*** | 0.101*** | 0.0463*** | 0.102*** | 0.104*** | 0.0737*** |
| | (0.00746) | (0.00368) | (0.00307) | (0.00510) | (0.0134) | (0.00499) |
| Observations | 4,356 | 7,744 | 11,880 | 5,280 | 10,780 | 9,240 |
| R-squared | 0.969 | 0.958 | 0.954 | 0.967 | 0.931 | 0.947 |
| F-test for PTA | 0.124 | 0.502 | 0.00278 | 0.852 | 0.263 | 0.102 |
| p-value | 0.728 | 0.486 | 0.958 | 0.368 | 0.612 | 0.751 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |

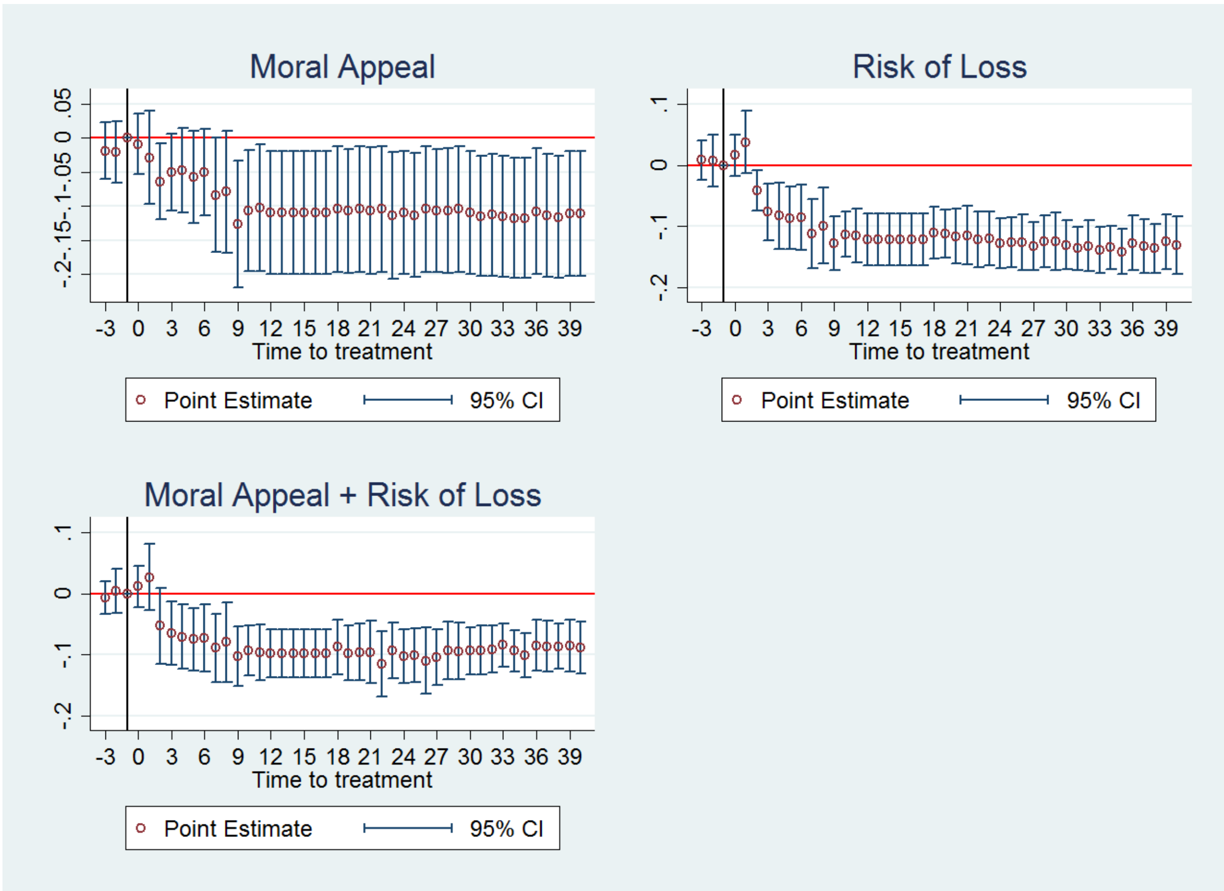
*Note:* Standard errors clustered at the firm level in parentheses, p-values < 0.10, 0.05, 0.01 represented by *, **, ***, respectively.

## 4.2 Effect of the nudges over time

To analyze the development of the treatment effect over time, we first apply a panel event study that allows for dynamic leads and lags to the starting date of the field experiment, while controlling for individual, firm and week fixed effects. In the following regressions, we only focus on successful nudges. Results of the estimations for polluting vehicles are depicted in Figure 1, while Figures C1 and C2, in the Appendix, presents estimation results for share of cycling and common transportation, respectively.

It reveals that only the nudges "Risk of Loss" and "Risk of Loss + Moral Appeal" have an immediate

Figure 1: Leads and lags of the effect of the different nudges on the share of polluting vehicles in weekly trips




*Note:* The Figure shows the dynamics of the share of polluting vehicles in weekly trips to work before and after the beginning of the interventions for treated individuals in comparison with the control group. Standard errors are clustered at the firm-level. Confidence intervals are defined at 5%. The estimated equations has individual, firm and week fixed effects.

effect on the use of polluting vehicles. Indeed, we can remark that two weeks after the implementation of the "Moral Appeal" nudge, no significant impact is found on the use of polluting vehicles. This nudge takes more time to be effective and to change individuals' behavior. Furthermore, we remark that the effect of the three nudges is reinforced through time and but that after 9 weeks after the beginning the interventions it starts to be very stable. The same pattern can be observed for the share of cycling and public transportation in weekly trips (see Figures C1 and C2). It suggests that ten weeks are sufficient to change individuals' behavior in terms of work commuting. In Tables OF2 and OF3 in the online Appendix, we select three different time frames: 2 weeks after the treatment, 8 weeks after the treatment and 20 weeks after the treatment. Results summarized in these Tables confirm our previous conclusion.

In a second analysis, we investigate whether the effect of the three successful nudges is persistent. In order to do so, we exploit the post-treatment period, and create a dummy variable that equals 1 for this period (from week 45 to week 54) and zero otherwise and interact it with the variables capturing the different groups. We then estimate all the DID models including this interaction term. Table 7 summarizes estimation results for the different successful nudges and the different transport modes. It reveals that the change occurring during the treatment period is persistent. The effect of the nudges is still significant in the post-treatment period and even significantly higher for some transport modes.

Table 7: Persistent effect of the successful nudges

| | Polluting vehicles | | | Cycling | | | Public transportation | | |
|---|---|---|---|---|---|---|---|---|---|
| | MA | RL | MA-RL | MA | RL | MA-RL | MA | RL | MA-RL |
| $period_1 * group_i^n$ | -0.0877** | -0.122*** | -0.0904*** | 0.0396** | 0.0523*** | 0.0748*** | 0.0241 | 0.0668*** | 0.0101 |
| | (0.0348) | (0.0167) | (0.0161) | (0.0158) | (0.0107) | (0.0116) | (0.0185) | (0.0190) | (0.00743) |
| $period_2 * group_i^n$ | -0.106** | -0.144*** | -0.0942*** | 0.0393* | 0.0654*** | 0.0768*** | 0.0300 | 0.0784*** | 0.0191 |
| | (0.0386) | (0.0180) | (0.0139) | (0.0200) | (0.0120) | (0.0124) | (0.0202) | (0.0216) | (0.0124) |
| Intercept | 0.441*** | 0.384*** | 0.476*** | 0.0861*** | 0.0658*** | 0.0471*** | 0.106*** | 0.104*** | 0.0742*** |
| | (0.0146) | (0.0121) | (0.0105) | (0.00679) | (0.00774) | (0.00798) | (0.00773) | (0.0140) | (0.00567) |
| Observations | 5,346 | 13,230 | 11,340 | 5,375 | 13,255 | 11,340 | 5,375 | 13,255 | 11,340 |
| R-squared | 0.968 | 0.904 | 0.923 | 0.971 | 0.899 | 0.950 | 0.973 | 0.938 | 0.946 |
| treated*period1= treated*period2 | 6.625 | 14.88 | 0.308 | 0.00194 | 7.528 | 0.290 | 2.450 | 9.031 | 2.095 |
| p-value | 0.0170 | 0.000 | 0.583 | 0.965 | 0.0105 | 0.595 | 0.131 | 0.00555 | 0.159 |
| Individual FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values $<$ 0.10, 0.05, 0.01 represented by *, **, ***, respectively.

## 4.3 Effect of the nudges on air pollution

If the three successful nudges have significantly decreased the use of polluting vehicles in weekly trips to work of individuals, it is also important to evaluate how they have impacted air pollution. Three major pollutants come from the use of thermal cars and motorcycles: particulate matter with a diameter of 10 microns or less ($PM_{10}$), which is a mixture of many chemical species, carbon dioxide ($CO_2$), emitted when car fuel is burned, and nitrogen oxides ($NO_x$), which are also produced when fuel burns[13]. Using few assumptions, we can perform a back-of-the-envelope computation of the impact of the three successful nudges on the emissions of these three air pollutants.

In this perspective, we use information regarding the daily transport mode of each employee and the distance between home to work of each of these individuals. We focus here on emissions due to the use of the different transport modes rather that on the emissions due to the life-cycle of each transport mode. We

[13] Unlike $NO_x$ and $PM_{10}$, $CO_2$ is not considered a direct atmospheric pollutant. Moreover, $NO_x$ and $PM_{10}$ not only impact the environment but also health, particularly the respiratory system.

rely on two different sources to compute emissions. First, we rely on the emission calculator provided by Airparif[14] which allows to compute emissions of both $PM_{10}$ and $NO_x$ for car, bus, motorcycle, subway or train, cycling and walking journeys for a given distance. For car use, the calculator allows distinguishing between diesel, gasoline and electric cars. However, we do not have this information concerning our sample of employees. Thus, we use a weighted average[15] of the emissions due to diesel and gasoline cars. We also assume that cars have a *Crit'Air* 2 sticker[16]. Second, for $CO_2$ emissions, we rely on the *Agence de l'environnement et de la maîtrise de l'énergie* (ADEME)'s calculator of emissions[17]. It is less detailed than the one of Airparif, but allows to get $CO_2$ emissions of thermal car, bus, cycling, two-wheeler, subway or walking journeys for a given distance. For instance, a 10km trip implies 2.2kg of $CO_2$ using a thermal car, 1.1kg using a bus, and 0 using cycling or walking. Note that every distances used in the analysis corresponds to the round trip from home to work of each individual.

These two calculators allow us to get data on air pollution for each transport mode used daily by each employee from the field experiment. Then, we aggregate data on a weekly basis in order to obtain total air pollution emitted by each employee, each week during the field experiment. Restring our analysis to week 4 (before the implementation of the interventions) and week 44 (the end of the treatment period), we estimate the DID model described in Eq. 2. Estimation results summarized in Table 8, confirm that the three successful nudges have entailed a significant decrease of air pollution.

For instance, the nudge RL has allowed an average decrease of 10.1 grams (g) of $NO_x$, of 0.596 grams of $PM_{10}$ and of 5.426 kilograms (kg) of $CO_2$. Overall, if we multiply the average effects by the number of employees in each group and sum up the effect of the three groups, it reveals that the three interventions has allowed to reduce particulate matter in the air by 165g, nitrogen oxides by 2.746kg and carbon dioxide by 1.435 tons. As changes seem to be persistent, it represents a weekly reduction. Descriptive statistics on air pollution in Table OF4, in the online Appendix, illustrate these effects. Indeed, we can remark that air pollution have slightly increased in the control group between week 4 and week 44, while it has strongly decreased in the three other groups.

[14]The link to the calculator is the following: https://www.airparif.asso.fr/calculateur-emissions/.

[15]We weight each transport mode emissions following the national statistics of the French *Ministère de la Transition Ecologique et de la Cohésion des Territoires*: https://www.statistiques.developpement-durable.gouv.fr/387-millions-de-voitures-en-circulation-en-france-au-1er-janvier-2022#:~:text=1er%20janvier%202022-,38%2C7%20millions%20de%20voitures%20en%20circulation,France%20au%201er%20janvier%202022&text=Au%201er%20janvier%202022%2C%2038,diminue%20mais%20reste%20cependant%20majoritaire. Thus, we apply 0.432 for gasoline cars and 0.568 for diesel cars.

[16]The Crit'Air sticker (air quality certificate) classifies vehicles according to their polluting emissions of fine particles and nitrogen oxides. In France, according to the French *Ministère de la Transition Ecologique et de la Cohésion des Territoires*, 37% of cars are concerned by this sticker, which represents the major part.

[17]The link to the calculator is the following: https://agirpourlatransition.ademe.fr/particuliers/bureau/deplacements/calculer-emissions-carbone-trajets.

Table 8: Effect of the successful nudges on air pollution

| | MA | | | RL | | | MA-RL | | |
|---|---|---|---|---|---|---|---|---|---|
| | $NO_x$ | $PM_{10}$ | $CO_2$ | $NO_x$ | $PM_{10}$ | $CO_2$ | $NO_x$ | $PM_{10}$ | $CO_2$ |
| ATE | -4.180* | -0.313* | -2.200* | -10.09*** | -0.596*** | -5.426*** | -4.166*** | -0.249*** | -1.985** |
| | (2.177) | (0.167) | (1.193) | (2.239) | (0.140) | (1.292) | (1.356) | (0.0857) | (0.720) |
| Intercept | 80.87*** | 7.430*** | 49.24*** | 62.87*** | 5.732*** | 37.30*** | 88.73*** | 7.704*** | 52.51*** |
| | (0.484) | (0.0371) | (0.265) | (0.868) | (0.0541) | (0.501) | (0.500) | (0.0316) | (0.266) |
| Observations | 198 | 198 | 198 | 490 | 490 | 490 | 420 | 420 | 420 |
| R-squared | 0.999 | 0.999 | 0.999 | 0.977 | 0.979 | 0.975 | 0.997 | 0.997 | 0.997 |
| Individual FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values $<$ 0.10, 0.05, 0.01 represented by *, **, ***, respectively.

## 4.4 Robustness checks

**Daily data.** To test the sensitivity of our results, we first rely on daily data concerning the mobility choices of individuals traveling to work and their choice of transport mode. We use a linear probability model to estimate the probability of using a particular mode of transport to go to work at the individual level. In the online Appendix, Table OB1 confirms the significant decreasing impact of the three successful nudges on the probability of using polluting vehicles for daily trips. In the online Appendix, Table OB2 , we re-estimate the LPM excluding non-working days from the sample. Results are slightly higher but confirms our previous conclusions on the effectiveness of the nudges “Moral Appeal”, “Risk of Loss” and combined “Moral Appeal + Risk of Loss”.

**Randomization inference.** In this field experiment, treatment assignments are implemented at the firm level rather than at the individual level. There are 89 firm selected in total[18]. This implies that classical inference methods might not be valid. Thus, we perform randomization inference to test the robustness of our main results. This test allows to get proper inference in case of small samples or clustered treatment assignments (Heß, 2017). In case of random treatment assignment, randomization inference provides an exact test of the sharp hypotheses no matter the sample size (Young, 2019). We follow the methodology proposed by Heß (2017) and randomly permute the treatment indicator 1,000 times within strata (size class of firm, environmental commitment score, department), while taking into account the clustered design of the field experiment. In Table OB3 in the online Appendix, we report p-values computed using this method as well as p-values resulting from a clustering at the firm-level and those resulting from a clustering at the individual level. Table OB3 reveals that across all regressions, results that were significant remain significant

[18]See Table 1 for a detailed description of the allocation of firms to the different treatments.

at the 5% level. The only notable exceptions being the ATE of the nudge 'Change in presentation' that becomes highly insignificant.

**Departure from PTA.** Even if both placebo and difference in linear trend prior to the treatment tests suggest that our data do not violate the PTA in most cases, there is still one estimation, linking the nudge RL to the share of cycling, for which the PTA does not seem to hold. To test the sensitivity of our results to deviations from the PTA, we perform two robustness checks. First, we include an interaction between a group-specific linear trend and the treatment dummy variable ($group_i^n$) in Eq. 2. The idea is to assess whether and how treatment effects are affected by the inclusion of group-specific linear trends. If results remain stable, it will be a sign that they are not driven by smooth mechanical changes in trends between treatment and control groups. Estimation results summarized in Table OC2 in the online Appendix reveal that although estimated ATEs of the three successfully nudges are slightly lower than those reported in Tables 4, 5 and 6, they remain statistically significant. In particular, these results confirm the significant positive impact of the RL nudge on the share of cycling. Second, to prob the robustness of our results, we apply the recent approach developed by Rambachan and Roth (2023). The main idea behind their methodology is to simulate how estimates of ATEs are affected by deviations from the PTA. Their method allows the post-treatment violation of the PTA but imposes restrictions on the possible differences in trends between treated and control groups. It imposes that the slope of the pre-trend can change by no more than $M$ across consecutive periods. In the specific case where $M = 0$, the difference in trends between treated and control groups is exactly linear, while larger values for $M$ allow for more non-linearity. Then, the method allows to provide robust confidence intervals given the restrictions imposed on $M$. Therefore, this approach permits to test the sensitivity of estimated ATEs at each post-period $k$ under alternative restrictions on how the trends can deviate from the PTA. Figure OC1, OC2, and OC3 in the online Appendix, plot the fixed-length confidence intervals (FLCI) for various values of $M$[19]. They provide evidence that the higher the maximum deviation from the linear trend ($M$), the wider the confidence intervals around the estimates. Furthermore, as long as $M < 0.04$, meaning that that we allow for the linear extrapolation across consecutive periods to be off by more than 0.04 percentage points, allowing for some non-linear violations of the PTA still provides significant and negative impact of the three successful nudges on the share of polluting vehicles. For the impact of the nudge RL on the share of cycling in weekly trips to work, it is positive and significant as long as $M < 0.05$. Overall, this tends to prove that our results are robust to some violations in the PTA.

[19]Note that it gives confidence intervals for the treatment at week 44, compared to results in previous tables that provide the average effects on all the treatment period (from week 5 to week 44).

# 5 Heterogeneous analysis

While it's important to note that some nudges had the desired effect of encouraging a change in individual behavior towards more environmentally friendly transport modes, there may exist response heterogeneity to the treatment among groups, linked to individual observable characteristics.

## 5.1 Exploratory analysis

We explore how individual characteristics affect the size of the treatment effect using interactions in Table 9. We select several observable attributes relying on the *ex-ante* survey: distance (in km) between home and work, NEP scale, number of cars, motorcycles, and cycling (continuous variables in Panel A of Table 9), and five dummies capturing whether the individual is male, has to make at least on stop during their commute to work (for example to drop kids off at school), is over 60 years old, is a highly skilled worker,[20] has an estimated mobility budget over 300 € per month (binary variables in Panel B of Table 9). Note that for this heterogeneous analysis, we only focus on successful nudges.[21] Our results reveal that distance affects the effectiveness of all successful nudges. Indeed, we can remark that the coefficient associated with the interacted variable with the logarithm of the geographical distance is significant and positive. This means that the greater the distance from home to work, the more the beneficial effect of the nudge decreases. Thus, distance appears to be a major brake on the effectiveness of nudges. This result seems instinctive. Indeed, beyond a certain distance, it becomes too "expensive" to use an alternative means of transport to polluting vehicles, such as cycling for instance. Moreover, it seems that nudges have not entailed a significant decrease of the use of polluting vehicles for individuals aged over 60. This result could be explained by the fact that for older individuals the cost of changing their transport mode is higher (due to their physical condition) than for younger ones. Other characteristics do not seem to affect the size of the ATE. Results are very similar when we consider the effect of the nudges on cycling decisions, as we find that distance also strongly affects the effectiveness of the different nudges (see Table OD1 in the online Appendix). Results concerning common transportation are different. Indeed, we find that the effectiveness of the RL nudge is mainly affected by age of individuals, but not by distance between employees' homes and their workplace (see Table OD2 in the online Appendix).

[20] It reflects the fact that the individual has at least a Master's degree.
[21] For other nudges, both ATE and interactions are not significant.

Table 9: ATE by individual characteristics (Share of polluting vehicles)

| | MA | MA | MA | MA | MA | RL | RL | RL | RL | RL | MA-RL | MA-RL | MA-RL | MA-RL | MA-RL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A* | | | | | | | | | | | | | | | |
| $ATE$ | -0.242** | -0.0952* | -0.102** | -0.177** | -0.0923** | -0.219*** | -0.175*** | -0.109*** | -0.131*** | -0.120*** | -0.325*** | -0.130** | -0.0786*** | -0.0705** | -0.0954*** |
| | (0.0935) | (0.0482) | (0.0393) | (0.0801) | (0.0388) | (0.0303) | (0.0402) | (0.0282) | (0.0416) | (0.0188) | (0.0525) | (0.0503) | (0.0181) | (0.0293) | (0.0170) |
| $ATE$*ln(Dist.) | 0.0505** | | | | | 0.0344*** | | | | | 0.0801*** | | | | |
| | (0.0227) | | | | | (0.0119) | | | | | (0.0127) | | | | |
| $ATE$*NEP scale | | 0.00716 | | | | | 0.0480* | | | | | 0.0405 | | | |
| | | (0.0241) | | | | | (0.0274) | | | | | (0.0456) | | | |
| $ATE$*Nbr bicycles | | | 0.00838 | | | | | -0.00732 | | | | | -0.00724 | | |
| | | | (0.00831) | | | | | (0.0108) | | | | | (0.00481) | | |
| $ATE$*Nbr cars | | | | 0.0599 | | | | | 0.00365 | | | | | -0.0122 | |
| | | | | (0.0403) | | | | | (0.0186) | | | | | (0.0147) | |
| $ATE$*Nbr moto. | | | | | 0.0519 | | | | | -0.00582 | | | | | 0.0646** |
| | | | | | (0.0486) | | | | | (0.0235) | | | | | (0.0238) |
| Obs. | 4,356 | 4,356 | 4,356 | 4,356 | 4,312 | 10,780 | 10,780 | 10,736 | 10,736 | 10,736 | 9,240 | 9,240 | 9,240 | 9,240 | 9,240 |
| R-squared | 0.965 | 0.964 | 0.964 | 0.965 | 0.964 | 0.897 | 0.896 | 0.896 | 0.897 | 0.896 | 0.920 | 0.915 | 0.915 | 0.915 | 0.915 |
| Individual FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| | MA | MA | MA | MA | MA | RL | RL | RL | RL | RL | MA-RL | MA-RL | MA-RL | MA-RL | MA-RL |
| *Panel B* | | | | | | | | | | | | | | | |
| $ATE$ | -0.0413* | -0.0880** | -0.0925** | -0.0961** | -0.0845** | -0.131*** | -0.112*** | -0.126*** | -0.135*** | -0.116*** | -0.107*** | -0.0933*** | -0.0881*** | -0.0899*** | -0.0947*** |
| | (0.0224) | (0.0368) | (0.0349) | (0.0393) | (0.0389) | (0.0261) | (0.0227) | (0.0170) | (0.0237) | (0.0199) | (0.0180) | (0.0216) | (0.0157) | (0.0178) | (0.0154) |
| $ATE$*Male | -0.102 | | | | | 0.0210 | | | | | 0.0392 | | | | |
| | (0.0607) | | | | | (0.0292) | | | | | (0.0363) | | | | |
| $ATE$*One stop | | 0.00066 | | | | | -0.0174 | | | | | 0.00497 | | | |
| | | (0.0420) | | | | | (0.0239) | | | | | (0.0287) | | | |
| $ATE$*Age over 60 | | | 0.105*** | | | | | 0.210*** | | | | | -0.0584 | | |
| | | | (0.0354) | | | | | (0.0699) | | | | | (0.128) | | |
| $ATE$*High skilled | | | | 0.0169 | | | | | 0.0240 | | | | | -0.000893 | |
| | | | | (0.0345) | | | | | (0.0346) | | | | | (0.0136) | |
| $ATE$*High budget | | | | | -0.0232 | | | | | -0.0588 | | | | | 0.0417 |
| | | | | | (0.0451) | | | | | (0.0556) | | | | | (0.0355) |
| Obs. | 4,356 | 4,356 | 4,356 | 4,356 | 4,356 | 10,780 | 10,780 | 10,780 | 10,780 | 10,780 | 9,240 | 9,240 | 9,240 | 9,240 | 9,240 |
| R-squared | 0.965 | 0.964 | 0.964 | 0.964 | 0.964 | 0.896 | 0.896 | 0.896 | 0.896 | 0.896 | 0.915 | 0.915 | 0.915 | 0.915 | 0.915 |
| Individual FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values < 0.10, 0.05, 0.01 represented by *, **, ***, respectively. Intercept included in estimations but not reported to save space.

## 5.2 Causal forest

Even if informative, the preliminary heterogeneous analysis is based on linear regressions and therefore excludes the possibility of non-linear heterogeneity unless more interactions with polynomials are included. Furthermore, dividing the sample into different selected subgroups may lead to significant but spurious heterogeneous patterns (Athey and Imbens, 2016; Wager and Athey, 2018). Wager and Athey (2018) and Athey et al. (2019) propose a powerful non parametric approach, called causal forest (CF), to evaluate heterogeneous treatment effects and address the issues raised by the use of interactions. Recently, the CF algorithm has been widely used in the empirical literature to evaluate heterogeneous effects of different treatments. Areas covered by these studies are numerous and include, for instance, the evaluation of U.S. youth employment programs (Davis and Heller, 2020), the impact of programs to reduce household energy use (Knittel and Stolper, 2021), the effect of information campaigns for residential energy conservation (Andor et al., 2022), the effect of nudges and rebates on electricity conservation (Murakami et al., 2022), and the adoption of soft commitment devices to limit smartphone use (Hoong, 2021).

The CF is a machine-learning technique that extends the Random Forest (RF) algorithm introduced by Breiman (2001) and allows for valid statistical inference and a tractable asymptotic theory for heterogeneous treatment effect estimation (Wager and Athey, 2018). The main purpose of this method is to find neighborhoods in the covariate space (X) and estimate conditional average treatment effects (CATE). However, contrary to RF which are based on decision trees, CF is built from causal trees. Each tree grows by first recursively splitting the data until it have been partitioned into a set of leaves (subgroups) based on covariates and effects are estimated within the resulting leaves. The splitting criterion optimizes for the identification of splits associated with treatment heterogeneity. The procedure is repeated and averaged over $B$ trees, which leads to a causal forest that can be used to estimate CATE at the leaves of the trees instead of predicting the outcome variable as in a random forest. A causal forest is a collection of trees, where the trees differ due to subsampling. An important feature of causal forests is called “honesty”. To ensure the accuracy of the estimation and to enable statistical inference, Athey et al. (2019) have introduced the notion of *honest trees*. A tree is honest if the training data is split into two subsamples: a splitting subsample and an estimating subsample. The first one is used to implement the splits and grow the tree, while the second one is used to make the predictions. Such a condition ensures that the estimates are asymptotically consistent and normal and allow for valid confidence intervals (Wager and Athey, 2018).

It is important to note that the causal forest algorithm is not well suited for panel data. However, some possible solutions have been implemented in the literature to deal with a panel data structure (Murakami et al., 2022; Jens et al., 2022) and Stefan Wager himself provides useful recommendations in order to apply causal forest using panel data.[22] Consequently, in order to take into account the panel data structure in our analysis, we implement three different steps as per the recommendations of Stefan Wager and the approach adopted by Murakami et al. (2022). Firstly, we regress our outcome and treatment variables on individual fixed effects. Secondly, to control for time fixed effects, we include a weekly trend in our set of covariates. Thirdly, we apply the causal forest algorithm on the residuals of variables obtained in the first step and use the "cluster" command to cluster individuals. Indeed, Athey and Wager (2019) has shown that an analysis that ignores clusters can lead to very different estimation results. We select 14 covariates (individual characteristics) taken from the *ex ante* survey[23] and choose to determine the tuning parameters through cross-validation as suggested in Athey et al. (2019). We also perform an 'omnibus' test for overall heterogeneity following "the best linear predictor" method of Chernozhukov et al. (2018). To implement the heterogeneous treatment effect analysis, we rely on the R package *grf*.

Table 10 reports results of both estimated ATEs using CF and omnibus test for heterogeneity. Results confirm our previous conclusions. Indeed, the CF algorithm reveals that only three nudges have successfully changed workers' transport behavior. Indeed, the ATE is not significant for the social comparison, change in presentation and financial incentive nudges. Furthermore, the estimated ATEs by the CF are very close to those estimated by the DID model (see Table 4), which illustrates the robustness of our estimations. Two other statistics are presented in Table 10. The first one (mean forest prediction) is a measure of the quality of the prediction of the forest and a coefficient of 1 suggests a correct prediction. The second one (difference forest prediction) is a measure of the quality of estimates of treatment heterogeneity, and a coefficient of 1 suggests that the treatment heterogeneity estimates are well calibrated. In most cases, the coefficient associated with the mean forest prediction is significant and around one, which reveals that the outcome is accurately predicted by the CF model. Regarding the test of the null of treatment effect heterogeneity, we find that for the MA, RL, and MA+RL nudges, the null hypothesis of heterogeneity cannot be rejected at the 5% level, suggesting that for these three nudges the treatment is heterogeneous. In Table OE2, we explore the hypothesis of heterogeneity of the effect of the successful nudges on cycling and common transportation. Firstly, as previously mentioned for polluting vehicles, we find very similar results regarding the estimation of ATEs; the only exception being the ATE of the nudge MA+RL on public transport that is significant using the CF algorithm. Secondly, the omnibus test suggests that the effects of the three nudges on the share of

[22] See the comments of Stefan Wager in the *grf* repository: `https://github.com/grf-labs/grf/issues/310` and `https://github.com/grf-labs/grf/issues/973`.

[23] See the detailed list in Table OE1.

cycling in weekly trips is heterogeneous, while for common transportation, only the RL nudge seems to have an heterogeneous impact on individuals' behavior. Overall, our results corroborate our previous conclusions but also indicate that there exists a certain heterogeneity in the impacts of the different nudges.

Table 10: ATE calculated using causal forest and heterogeneity test (Share of polluting vehicles)

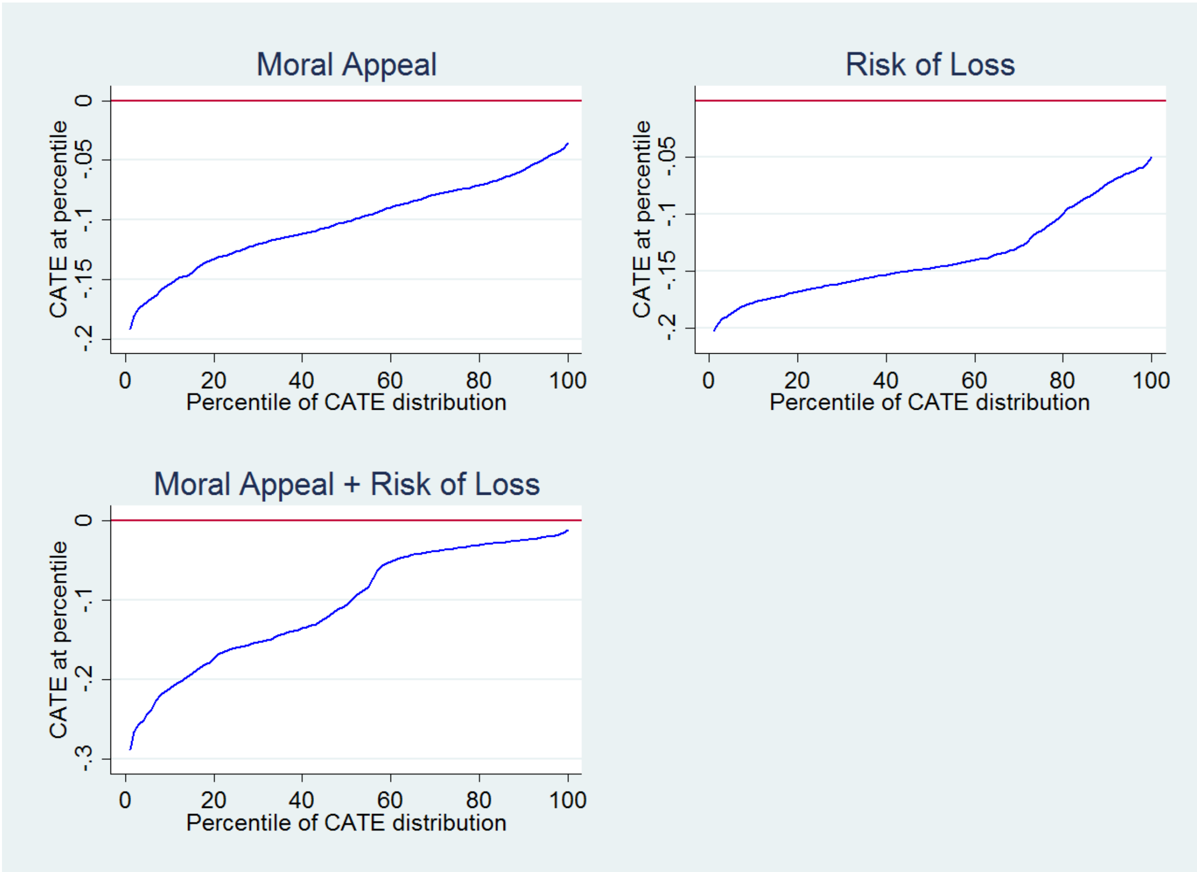
| | MA | SC | Change | Fin. Incen. | RL | MA-RL |
|---|---|---|---|---|---|---|
| ATE | -0.106*** | 0.00060 | 0.0090 | 0.00264 | -0.138*** | -0.1095*** |
| | (0.0254) | (0.00823) | (0.00638) | (0.0148) | (0.0113) | (0.0118) |
| Mean forest prediction | 1.0864*** | -4.9384 | 0.8790 | 0,7177 | 1.00754*** | 1.0605*** |
| Difference forest prediction | 1.5847** | -2.0707 | 1.0523*** | -2.9520 | 1.1736*** | 1.2282*** |

*Note:* ATE estimated using the causal forest algorithm allowing for 3,000 trees. The omnibus test calculates two synthetic predictors. The first one (mean forest prediction) is a measure of the quality of the prediction of the forest and a coefficient of 1 suggests a correct prediction. The second one (difference forest prediction) is a measure of the quality of estimates of treatment heterogeneity, and a coefficient of 1 suggests that the treatment heterogeneity estimates are well calibrated. The p-value of the 'difference prediction' coefficient also acts as a test for the null of no heterogeneity. Standard errors in parentheses, p-values < 0.10, 0.05, 0.01 represented by *, **, ***, respectively.

Figure 2 plots the CATE estimates sorted by the CATE percentile for the three successful nudges (MA, RL and MA+RL). It confirms what is suggested by the result of the omnibus test for the different nudges, as we observe treatment heterogeneity for the three different nudges. Our results reveal that about 40% and 30% of workers targeted by the nudges RL and MA+RL nudges, respectively, reduce the share of polluting vehicles used in their weekly trips by more than 15 percentage points. We can also observe that CATE estimates are always negative for the three different nudges. The results also indicate that the nudge RL has entailed higher effects, as around 80% of workers have decreased the share of polluting vehicles in their weekly trips by 10 percentage points in this group, compared to only 50% for the groups MA+RL and MA.

In Figure 3, we report the 10 variables with the highest variable importance in growing trees, i.e., the fraction of times a worker's characteristic is used for splits. A high importance reflect that the variable is an essential determinant of treatment heterogeneity (Murakami et al., 2022). Figure 3 indicates that distance from work is the main characteristic determining heterogeneity of treatment. This is true for the three successful nudges under scrutiny. The environmental implication of workers, reflected by the NEP scale, ranks second for the three nudges. Finally, the presence of work and round trips in the typical week of workers, the level of education, the socioprofessional category, the age category of workers or the number of bicycles in the household are also determining characteristics, but far behind distance from work. For cycling and common transportation, conclusions regarding variance importance in growing trees are very similar. Indeed, distance from work largely represents the first characteristic determining heterogeneity of

Figure 2: CATE estimated using grf package in R sorted by CATE percentile




*Note:* The Figure depicts CATE estimates, sorted by CATE percentile for the share of polluting vehicles. ATE estimated using the causal forest algorithm allowing for 3,000 trees.

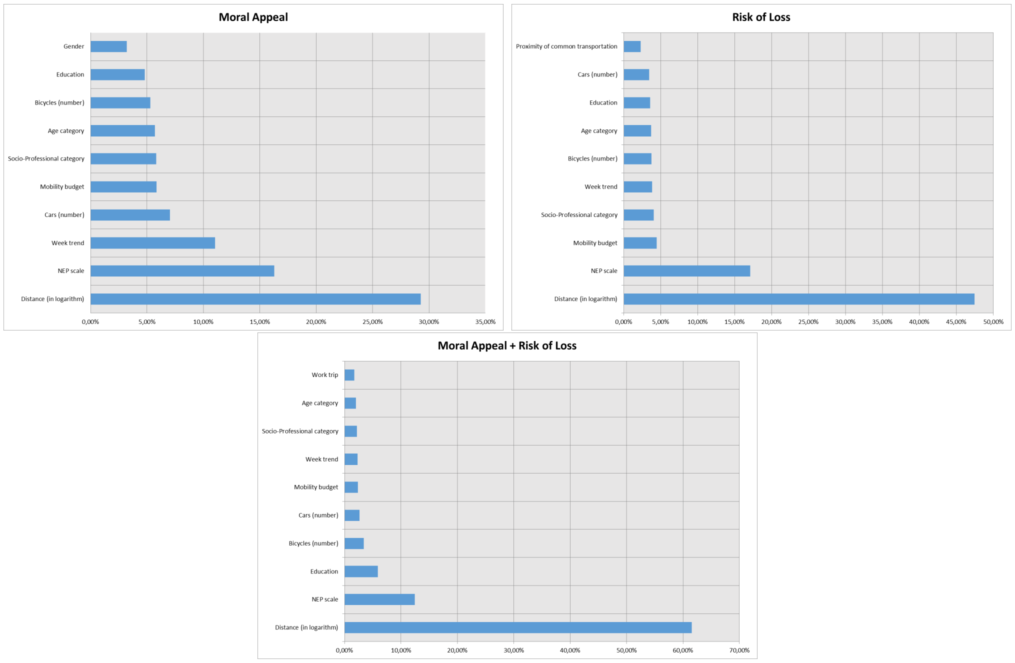
treatment.[24]

Figure 4 illustrates the non-linearity of the relationship between the treatment effect and employees' distances from work (in logarithm) and reveals the potential for improved outcomes using nudges through selective targeting based on employees' individual characteristics. Indeed, we can observe that the treatment effect of the three successful nudges decreases with the distance between the employees' home and their work location. Setting the threshold for nudge inclusion to around 12.2 kilometers[25], for instance, will be a way of avoiding a boomerang effect and improve the treatment effects. We find very similar outputs when referring to the heterogeneity of the effects of the nudges on cycling decisions (see Figure OE1). For the heterogeneous

[24]For cycling: 25% for the nudge MA, 47% for the nudge RL, and 65% for the nudge MA-RL. For common transportation: 27% for the nudge RL. We do not report variable importance in growing trees for other nudges, as the omnibus test has rejected the presence of heterogeneity of the effect of these nudges on the use of common transportation.

[25]We use exp(2.5), as distance is expressed in logarithm in Appendix, Figure 4.

Figure 3: Variable importance in growing trees (Share of polluting vehicles)



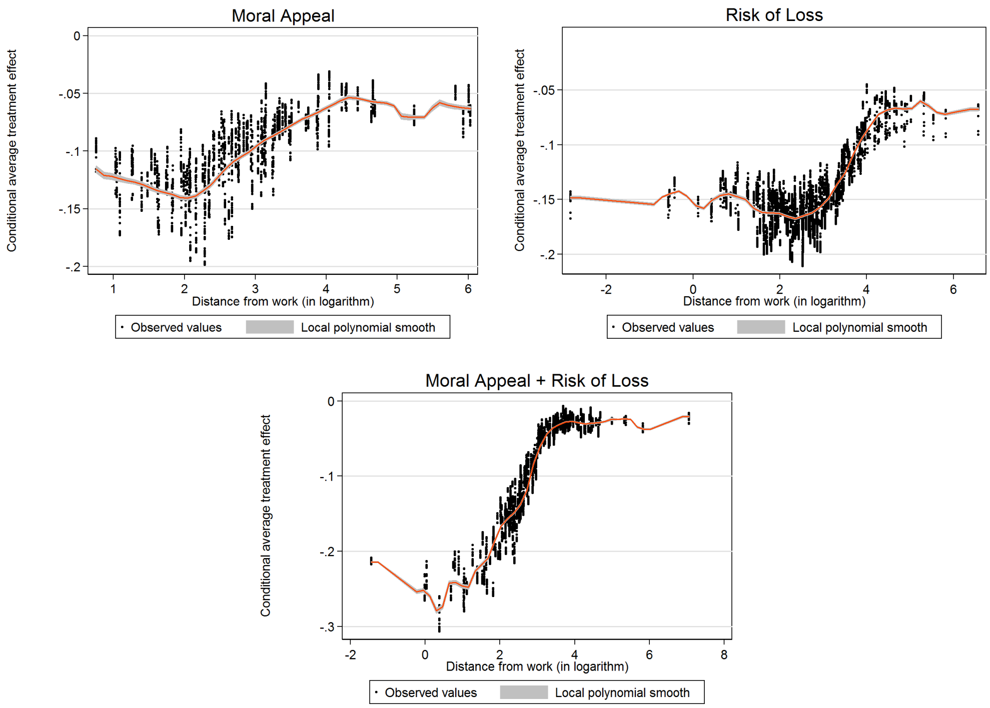

*Note:* This Figure represents the 10 variables with the highest variable importance in growing trees, i.e., the fraction of times a worker's characteristic is used for splits in the causal forest algorithm.

effect of the nudge RL on the decision to use common transportation, conclusions are somehow different. Indeed, if Figure 4 highlights the heterogeneity of the ATE regarding distance from work, it seems that the effect reaches its highest level when the distance from work is between 12 and 54 kilometers.[26] This has interesting implications, as the RL nudge has a greater effect on the use of cycling among individuals living near their workplace, while it has greater effect on the use of public transport for individuals located the furthest from their workplace.

In the Appendix, Figure OE3 indicates that heterogeneity in the treatment effects of nudges regarding employees' environmental preferences is less pronounced. However, it highlights the fact that endorsement of a "pro-ecological" world view is not necessary to change individuals' habits in terms of modes of transport used to commute to work. Indeed, even among the population of employees with a very low level of the NEP scale, we identify strong treatment effects of nudges.

[26]Exp(2.5) and exp(4).

Figure 4: Distance from work and treatment effects (Share of polluting vehicles)




*Note:* The Figure shows the impact of the three different nudges on the share of polluting vehicles regarding the distance between individuals' home and work. The x-axis measures the distance (in logarithm), while the y-axis measures the treatment effect predicted by the causal forest algorithm. The red line depicts the local smoothed polynomial relationship between ATE and distance.

## 5.3 Robustness check

As previously noted, the causal forest algorithm is not well suited to panel datasets. In order to test the sensitivity of our results, we follow previous works such as Knittel and Stolper (2021) or Andor et al. (2022) and transform the outcome variable to first difference. In order to do so, we take the difference between the share of polluting vehicles in weekly trips at the end of the treatment period (week 44) and the corresponding value just before the treatment occurs (week 4). Then, we apply the causal forest algorithm and perform the 'omnibus' test for overall heterogeneity. The estimation results are summarized in Table OE3. We can observe that estimation results are very similar to those found in Table 10, which supports our previous conclusions regarding the heterogeneity effect of the different nudges.

# 6 Conclusions

The central issue of this paper is to understand how policy makers can design instruments to create incentives towards green mobility. In this perspective, our field experiment allows testing the causal impact of non-monetary and monetary incentives on the change in transport mode behavior of workers (from polluting vehicles to green commuting).

The main results of our study enable us to provide policy recommendations related to three important attributes of policy design: the type of instrument, the timing and the targeting.

Firstly, we show that 3 out of 6 incentives, namely MA, RL, MA-RL, have a positive effect on changing travel behavior. Among the successful nudges, the RL nudge seems to be the most effective instrument. Indeed, it decreases the share of polluting vehicles in trips, working in favor of cycling and public transport, while the other successful nudges (MA, MA-RL) increase only the cycling mode. Furthermore, it has changed transport behavior among a larger share of targeted individuals than the other two nudges. Consequently, it seems important for policymakers to pay particular attention to using nudges that stimulate loss aversion especially if they want to promote several modal alternatives such as public transportation and cycling. In addition, the weaker positive effect of the policy mix instrument (MA-RL) suggests that it is not necessary to combine two types of messages to change individual travel behavior. In other words, it seems that providing more information to individuals does not reinforce average effect, suggesting that the two instruments are not complementary.

Secondly, regarding the timing of the interventions, two important results stand out. In the first place, the effect of RL and MA-RL immediately affect (i.e., after 2 weeks) the use of polluting vehicles, while MA takes more time to be effective (8 weeks). Furthermore, the magnitude of the effect is reinforced through time during the treatment period. This finding has important policy implications by highlighting that exposure to these kind of nudges has to be sufficiently long in order to maximize their effects and affect as many people as possible. In addition, behavioral changes, due to the three successful nudges that occurred during the treatment period, are persistent. This result is congruent with the hypothesis that behavioral incentives change individual preferences and thus have an impact on in-depth behaviors. Therefore, this gives strong support for policymakers to use nudges for green mobility rather than only relying on monetary incentives in other to affect behavior in the long run.

Thirdly, we conduct a heterogeneity analysis to identify individuals' characteristics that may affect the effectiveness of nudges and thus provide policy recommendations on the targeting strategy. Our results reveal that the heterogeneity of individuals' characteristics impacts the treatment effect of nudges. The most important aspect of the heterogeneity is explained by distance from work. The benefits of the different nudges seems to strongly diminish when the distance from home to work reaches 12 kilometers. This result highlights that beyond a certain distance threshold, the effect of the nudge decreases. This suggests that it is important for policymakers to identify this threshold in order to be cost-effective. For example, in our experimental area (North of France), the threshold is around of 12 km. Moreover, the average distance between employees' homes and workplaces in France is 13.3 km. Thus, the successful nudges identified in this paper, can affect a significant part of the French population, but they are not sufficient to change the travel behavior of all French workers. Above this threshold, other complementary instruments should be considered. As recommended in the transport literature, in order to change the transport mode behavior of workers, policymakers should promote more efficient infrastructure. This implies improving the proximity, availability, frequency and transfer point of public transport. They can also create more incentives for carpooling, for example by developing platforms.

As with any scientific research, this paper presents limits. First, this experiment was conducted during the post lockdown period, in a context where people, still fearful of the coronavirus (Covid-19), limited their social interaction. That's why the results concerning social comparison should be taken with precaution. Indeed, as explained in the results section, the analysis of their effect is limited by the context of lockdown and lack of social interaction. Therefore, it would be interesting to repeat the experiment in a context without social distancing in order to confirm our result.

Secondly, although the scientific literature shows the effectiveness of financial instruments, the financial instrument tested in this paper, a financial reward, did not reduce the share of polluting vehicles in weekly trips. However, this conclusion must be qualified. Given the limited budget to test the effectiveness of a traditional financial incentive, we tested an uncertain financial reward. That's why it would be relevant to test a traditional financial incentive in future research and compare its effectiveness with nudges.

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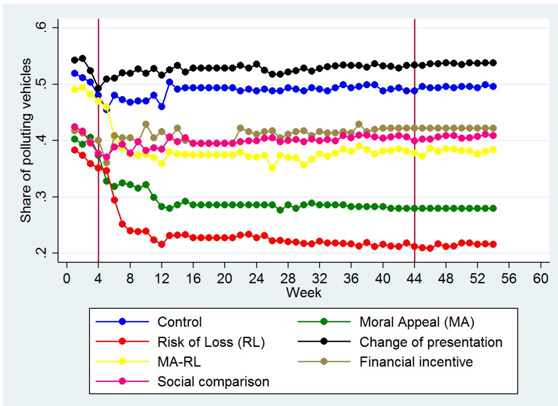
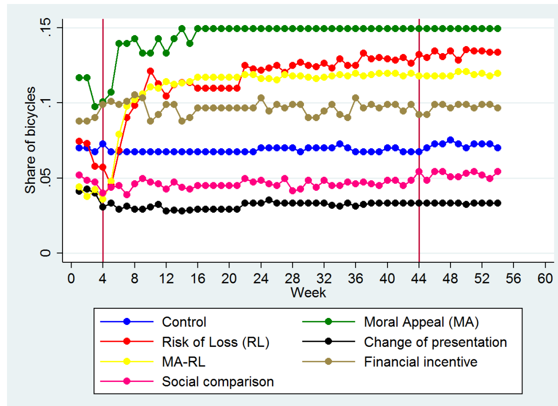
# Appendix

## Appendix A: Descriptive statistics

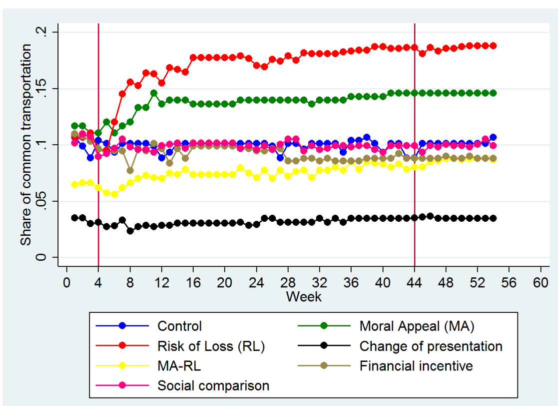
Figure A1: Share of transport modes in weekly trips by treatment status



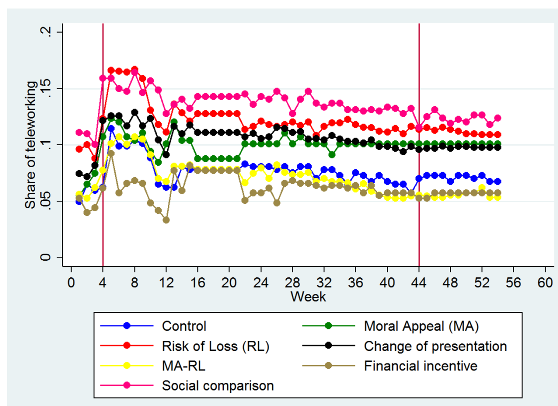

(a) Share of polluting vehicles in weekly trips by treatment status




(b) Share of cycling in weekly trips by treatment status




(c) Share of common transportation in weekly trips by treatment status




(d) Share of teleworking by week and by treatment status

## Appendix B: Results for the whole sample (1046 individuals)

Table B1: Descriptive statistics on pre-treatment period (Total sample)

| | Control | MA | SC | Change | Fin. incent. | RL | MA-RL |
|---|---|---|---|---|---|---|---|
| Share polluting | 0.519 | 0.403 | 0.403 | 0.553 | 0.400 | 0.384 | 0.498 |
| | | *0.000* | 0.000 | *0.177* | *0.000* | *0.000* | *0.401* |
| Share cycling | 0.070 | 0.0911 | 0.073 | 0.035 | 0.092 | 0.069 | 0.040 |
| | | *0.304* | *0.817* | *0.022* | *0.253* | *0.966* | *0.059* |
| Share CT | 0.093 | 0.010 | 0.010 | 0.038 | 0.125 | 0.1063 | 0.071 |
| | | *0.793* | *0.742* | *0.002* | *0.175* | *0.494* | *0.241* |
| Share other | 0 .002 | 0.074 | 0.040 | 0.040 | 0.059 | 0.0512 | 0.040 |
| | | *0.000* | *0.000* | *0.000* | *0.000* | *0.000* | *0.000* |
| Share teleworking | 0.053 | 0.066 | 0.105 | 0.075 | 0.057 | 0.092 | 0.052 |
| | | *0.332* | *0.000* | *0.020* | *0.762* | *0.000* | *0.841* |

*Note:* The column gives averages for employees in the control, moral appeal, social comparison, change in presentation, financial incentive, risk of loss and combined moral appeal and risk of loss group. P-values from t-tests on mean equality between each group and the control group are presented in italics.

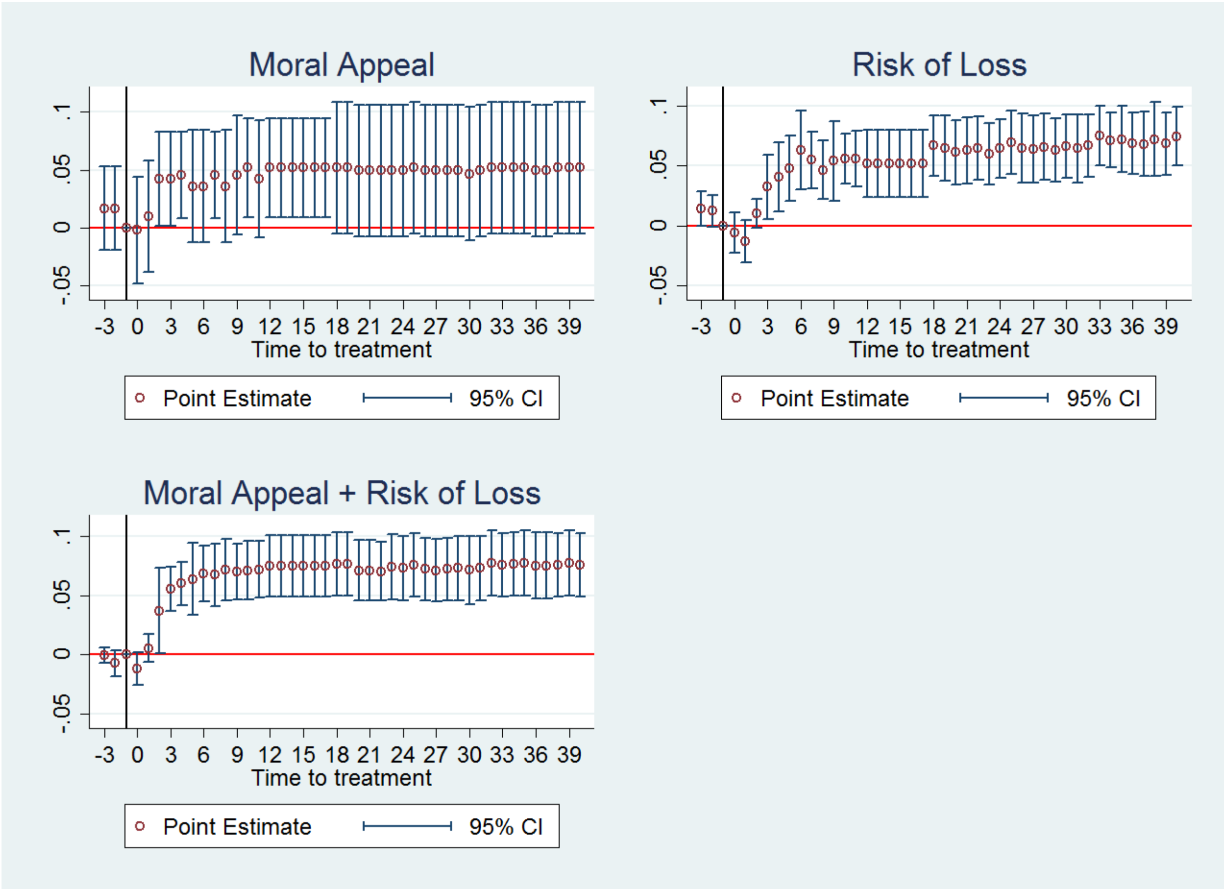
Table B2: Effects of the nudges (total sample)

| | MA | SC | Change | Fin. Incen. | RL | MA-RL |
|---|---|---|---|---|---|---|
| $period_1 * group_i^n$ | -0.0885** | 0.0134 | 0.0168** | 0.0213 | -0.126*** | -0.0907*** |
| | (0.0338) | (0.00802) | (0.00614) | (0.0154) | (0.0174) | (0.0160) |
| Intercept | 0.445*** | 0.416*** | 0.524*** | 0.434*** | 0.394*** | 0.485*** |
| | (0.0145) | (0.00520) | (0.00450) | (0.00774) | (0.0123) | (0.0107) |
| Observations | 5,412 | 9,988 | 14,828 | 6,424 | 12,892 | 10,780 |
| R-squared | 0.958 | 0.963 | 0.953 | 0.956 | 0.903 | 0.919 |
| F-test for PTA | 0.149 | 0.247 | 0.710 | 0.0281 | 0.225 | 0.0163 |
| p-value | 0.702 | 0.623 | 0.408 | 0.869 | 0.638 | 0.899 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |
| | | | Cycling | | | |
| | MA | SC | Change | Fin. Incen. | RL | MA-RL |
| $period_1 * group_i^n$ | 0.0514*** | 0.000392 | -0.00406 | 0.00557 | 0.0536*** | 0.0706*** |
| | (0.0178) | (0.00383) | (0.00244) | (0.00452) | (0.0105) | (0.0128) |
| Intercept | 0.0780*** | 0.0695*** | 0.0390*** | 0.0821*** | 0.0662*** | 0.0461*** |
| | (0.00762) | (0.00248) | (0.00179) | (0.00228) | (0.00742) | (0.00855) |
| Observations | 5,412 | 9,988 | 14,828 | 6,424 | 12,892 | 10,780 |
| R-squared | 0.955 | 0.970 | 0.963 | 0.978 | 0.897 | 0.947 |
| F-test for PTA | 3.073 | 1.843 | 5.637 | 1.260 | 3.788 | 1.451 |
| p-value | 0.091 | 0.186 | 0.025 | 0.274 | 0.061 | 0.238 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |
| | | | Common transportation | | | |
| | MA | SC | Change | Fin. Incen. | RL | MA-RL |
| $period_1 * group_i^n$ | 0.0216 | -0.00764 | -0.00386 | -0.0129 | 0.0654*** | 0.0113 |
| | (0.0189) | (0.00570) | (0.00442) | (0.00835) | (0.0162) | (0.00942) |
| Intercept | 0.0973*** | 0.0974*** | 0.0508*** | 0.111*** | 0.104*** | 0.0782*** |
| | (0.00810) | (0.00370) | (0.00325) | (0.00421) | (0.0114) | (0.00629) |
| Observations | 5,412 | 9,988 | 14,828 | 6,424 | 12,892 | 10,780 |
| R-squared | 0.964 | 0.962 | 0.962 | 0.970 | 0.933 | 0.950 |
| F-test for PTA | 0.640 | 0.235 | 0.974 | 0.140 | 0.448 | 0.991 |
| p-value | 0.431 | 0.632 | 0.333 | 0.712 | 0.509 | 0.328 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values $< 0.10, 0.05, 0.01$ represented by *, **, ***, respectively.

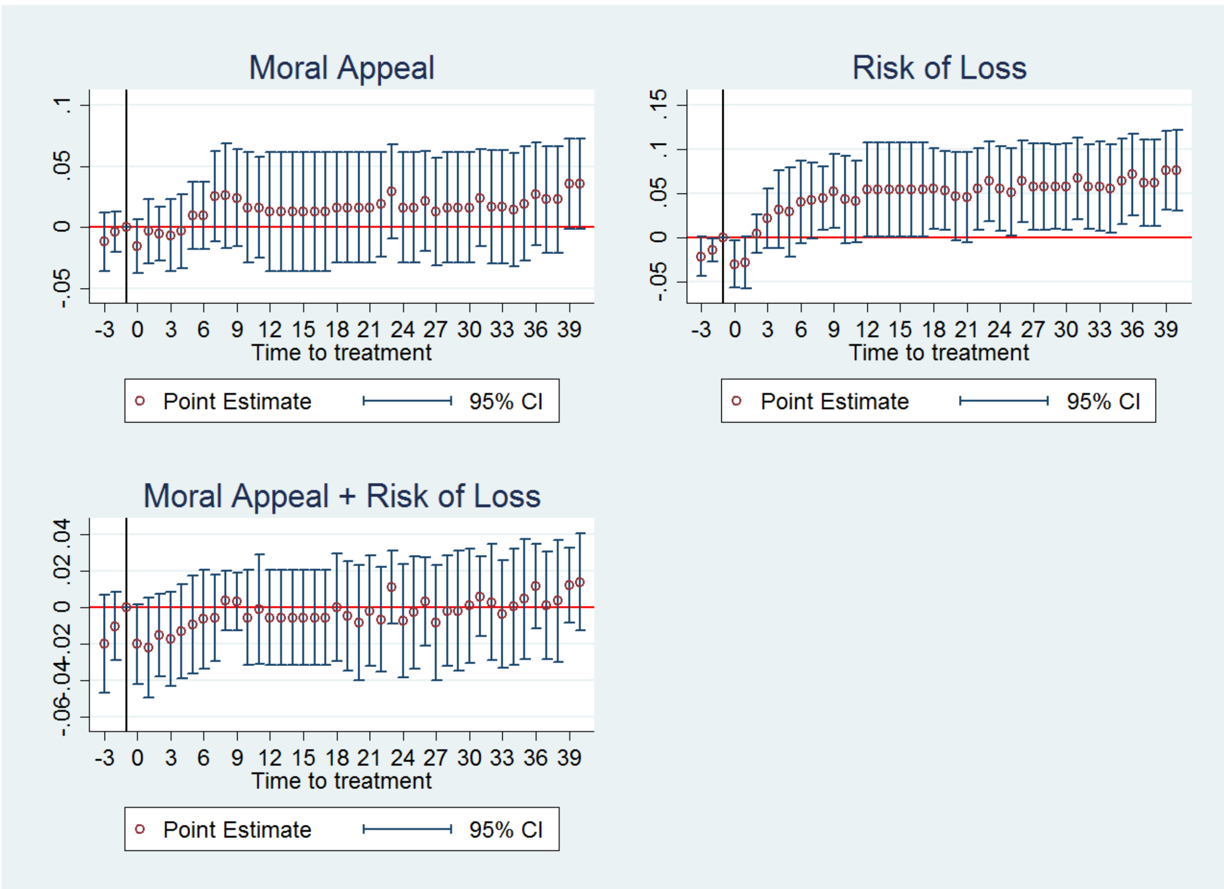
## Appendix C: Additional results

Figure C1: Leads and lags of the effect of the different nudges on the share of cycling in weekly trips




*Note:* The Figure shows the dynamics of the share of cycling in weekly trips to work before and after the beginning of the interventions, for treated individuals in comparison with the control group. Standard errors are clustered at the firm-level. Confidence intervals are defined at 5%. The estimated equations has individual, firm and week fixed effects.

Figure C2: Leads and lags of the effect of the different nudges on the share of cycling in weekly trips




*Note:* The Figure shows the dynamics of the share of common transportation in weekly trips to work before and after the beginning of the interventions, for treated individuals in comparison with the control group. Standard errors are clustered at the firm-level. Confidence intervals are defined at 5%. The estimated equations has individual, firm and week fixed effects.

# Online Appendix

## Online Appendix A: Description of the nudges and timing


Figure OA1: 'Social comparison' poster


Figure OA2: Example of 'Risk of Loss' nudge


Figure OA3: Example of the 'Change of presentation' nudge


Figure OA4: Example of 'Moral Appeal' nudge


Figure OA5: 'Financial incentive' poster

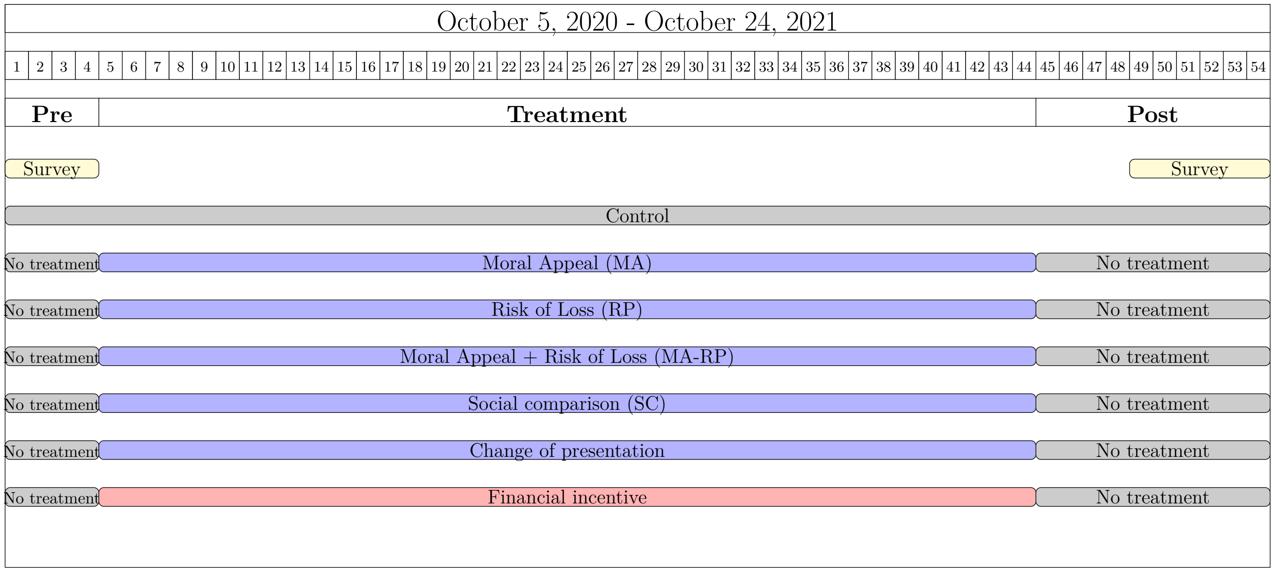
Table OA1: Texts communicated in the 'Risk of Loss' nudge

| Week | Text |
|---|---|
| 2020 - 45 | A simple endurance activity such as a walk can increase the volume of the hippocampus and thus help prevent brain aging. |
| 2020 - 46 | The use of a private car costs €500/month, share the costs, carpool! |
| 2020 - 47 | Stuck by strikes? Here is the solution: the scooter. |
| 2020 - 48 | Want to see your grandchildren grow up? Daily cycling increases life expectancy: +8 years according to the WHO. |
| 2020 - 49 | Walking saves you from having to pay for car insurance and from knowing about this great thing called the insurance report. |
| 2020 - 50 | Taking public transport means having time to learn a new language. |
| 2020 - 51 | Want to enjoy your retirement? Cycling reduces cardiovascular risks by 45%. |
| 2020 - 52 | Increasing your purchasing power also means opting for a public transport season ticket that is 50% reimbursable by your employer. |
| 2021 - 01 | Carpooling means using your travel time to meet people. |
| 2021 - 02 | Fed up with depriving yourself? A bag of mayo fries = 20 minutes on the scooter. |
| 2021 - 03 | A full tank of petrol = 6 cinema tickets. |
| 2021 - 04 | Stress is weighing you down? Cycling to work reduces stress by 40%. |
| 2021 - 05 | The anti-clogging solution: walking! |
| 2021 - 06 | Tired of paying fines? Switch to a scooter. |
| 2021 - 07 | Fed up with depriving yourself? One welsh (a culinary specialty of northern France) = 1 hour of cycling. |
| 2021 - 08 | The night is too short? Think of public transport to recover the sleep you're missing. |
| 2021 - 09 | 12 km by car = €17.64. 12 km by bike = €0.8. |
| 2021 - 10 | A sedentary lifestyle doubles the risk of cardiovascular disease. |
| 2021 - 11 | 114h = 14 full nights or the time spent in traffic jams in Lille each year. |
| 2021 - 12 | Using a scooter saves you money on insurance and petrol. |
| 2021 - 13 | Moderate physical activity makes the immune system more active and therefore more effective in fighting infections. |
| 2021 - 14 | Taking public transport is like letting someone else drive while you read. |
| 2021 - 15 | A full tank of gas = a good restaurant for two. |
| 2021 - 16 | Physical activity has a positive effect on children's brain development, so get them walking! |
| 2021 - 17 | 114 hours = 456 stories told to your children or the average time spent in traffic jams per year. |
| 2021 - 18 | Did you know that your public transport pass could be used for leisure activities? |
| 2021 - 19 | A sedentary lifestyle doubles the risk of obesity, so get moving and try a scooter! |
| 2021 - 20 | 20 minutes on a bike = 20 minutes less in the gym. |
| 2021 - 21 | Can't afford to go to the gym? Let the gym come to you and pedal. |
| 2021 - 22 | Stressed? Walking to work reduces your stress by 40%. |
| 2021 - 23 | With the scooter, no time to look for a parking space! |
| 2021 - 24 | With the bike, you don't need change for the parking meter. |
| 2021 - 25 | Your endorphin level is 4 times higher after 20 minutes of sport, the peptide that reduces stress. Ride your bike and arrive at work relaxed! |
| 2021 - 26 | Tired of being flashed (radar)? Think of public transport. |
| 2021 - 27 | 50% of journeys of less than 3 km are made by car, but a 3 km journey by bike takes less than 15 minutes. Shall we have a race? |
| 2021 - 28 | Physical activity halves the risk of obesity, so switch to the scooter. |
| 2021 - 29 | Using public transport means only paying for your subscription: no insurance, no fines, no maintenance! |
| 2021 - 30 | With the bike, you don't need time to look for a parking space! |
| 2021 - 31 | Only millionaires really save time by car. The others only transfer between work and transport time. |
| 2021 - 32 | A sedentary lifestyle kills 2 million people every year, so get moving, switch to a bicycle! |

Table OA2: Texts communicated in the "Moral Appeal" nudge

| Week | Text |
|---|---|
| 2020 - 45 | Through your commute, you are contributing to climate change, which is increasing the rise of the oceans. |
| 2020 - 46 | Motorized modes of transport such as driving pollute, walking does not. Be sporty and switch to walking. |
| 2020 - 47 | Even in the middle of traffic, the air you breathe is healthier than the polluted and harmful air in your car. Drop your children off by bike to avoid poisoning them. |
| 2020 - 48 | Some things can't wait, think of others, switch to carpooling, don't create traffic jams. |
| 2020 - 49 | By driving your car, you contribute to the nauseating odors emitted by the exhaust fumes, leave it in the garage more often and think about the planet you will leave to your children... |
| 2020 - 50 | Through your commute, you contribute to the climate change that threatens coral reefs. |
| 2020 - 51 | Motorized modes of transport such as the car pollute, but scooters do not. Be sporty and switch to a scooter. |
| 2020 - 52 | The car turns you into a potential road killer. What if you switched to walking? |
| 2021 - 01 | It took more than a century to build the church of St Eustache in Paris, it takes less than 10 years for pollution to blacken it. Reduce public spending, pedal. |
| 2021 - 02 | 0 deaths on public transport in 2020. It's time to be transported. |
| 2021 - 03 | Through your travel, you contribute to climate change. |
| 2021 - 04 | Motorized modes of transport like the car pollute. Play it collective, carpool. |
| 2021 - 05 | The scooter does not poison your children, unlike the car, whose interior air is polluted and harmful to passengers. What if you dropped your children off on a scooter? |
| 2021 - 06 | The construction of the Pantheon cost the same as its renovation due to pollution. Preserve our heritage, switch to a bicycle. |
| 2021 - 07 | Through your travels, you contribute to climate change. |
| 2021 - 08 | In Hauts-de-France, 6,500 deaths due to air pollution could be avoided. Switch to non-polluting modes of transport. |
| 2021 - 09 | Children are the direct victims of the polluting fumes from cars, motorbikes and scooters that pass in the street next to their school. Drop them off on foot instead. |
| 2021 - 10 | 1 km travelled by car costs €0.15 on the French budget, reduce public spending, switch to cycling. |
| 2021 - 11 | Through your travels, you contribute to climate change and increased rainfall. |
| 2021 - 12 | By driving or riding a motorbike, you contribute to noise pollution. The scooter is quieter. |
| 2021 - 13 | AIDS: 770,000 deaths/year, car accidents: 1,500,000 deaths/year worldwide. Switch to cycling. |
| 2021 - 14 | Some things can't wait, think of the others, switch to walking and don't create traffic jams. |
| 2021 - 15 | Through your commute, you contribute to climate change, which results in a climate shift every second. |
| 2021 - 16 | Motorized modes of transport such as the car pollute, but cycling does not. Be sporty, switch to a bike. |
| 2021 - 17 | Ebola: 5,500 deaths/year, car accidents: 1,500,000 deaths/year worldwide. Switch to scooters. |
| 2021 - 18 | Some things can't wait, think of others, think of others, go by metro, don't create traffic jams (114 hours of traffic jams in the Lille metropolis per year). |
| 2021 - 19 | By using your car, you contribute to visual pollution. 50% of urban public space is dedicated to cars. |
| 2021 - 20 | By using your car or motorbike, you contribute to noise pollution. Walking is less noisy. |
| 2021 - 21 | The leading cause of accidents at work is the car. You don't work to die at the end of the road. |
| 2021 - 22 | The cost of a cycle path is 200 times less than an urban motorway for the same number of users, reduce public expenditure, switch to cycling. |
| 2021 - 23 | Through your commute, you contribute to climate change, which leads to the disappearance of one sixth of animal species. The golden toad has disappeared since 1989. |
| 2021 - 24 | 11 to 16 months of life expectancy can be gained by reducing pollution. Switch to non-polluting modes of transport. |
| 2021 - 25 | Walking doesn't poison your children, unlike the car, whose indoor air is polluted and harmful to passengers. What if you dropped your children off while walking? |
| 2021 - 26 | Some things can't wait, think of the others, switch to a bicycle and don't create traffic jams. |
| 2021 - 27 | In Hauts-de-France, road travel produces 45% of the nitrogen oxides released into the air. Let's change our mobility. |
| 2021 - 28 | Through your travel, you contribute to climate change, which encourages the emergence of new viruses. |
| 2021 - 29 | By driving or riding a motorbike, you contribute to noise pollution. I am the bike |
| 2021 - 30 | A sedentary lifestyle costs the social security system 14 billion euros. What if you filled the social security hole by walking, cycling or scooting? |
| 2021 - 31 | Through your movements, you contribute to climate change, which threatens global food security. |
| 2021 - 32 | 48,000 deaths per year, that's the cost of polluting emissions from car travel. Think of your children, switch to a bicycle! |

Figure OA6: Experimental design



## Online Appendix B: Robustness checks

Table OB1: Robustness check: Estimation of the LPM on polluting vehicles

| | MA | SC | Change | Fin. incen. | RL | MA-RL |
|---|---|---|---|---|---|---|
| $period_1 * group_i^n$ | -0.0877*** | 0.0110 | 0.0165** | 0.0191 | -0.122*** | -0.0904*** |
| | (0.0348) | (0.009890) | (0.00703) | (0.0176) | (0.0167) | (0.0161) |
| Constant | 0.440*** | 0.420*** | 0.507*** | 0.437*** | 0.383*** | 0.475*** |
| | (0.0140) | (0.00618) | (0.00513) | (0.00867) | (0.0118) | (0.0108) |
| Observations | 30,492 | 54,208 | 83,160 | 36,960 | 75,460 | 64,680 |
| R-squared | 0.633 | 0.588 | 0.632 | 0.645 | 0.487 | 0.570 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Day-week FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values < 0.10, 0.05, 0.01 represented by *, **, ***, respectively.

Table OB2: Robustness check: Estimation of the LPM on polluting vehicles excluding non-working days

| | MA | SC | Change | Fin. incen. | RL | MA-RL |
|---|---|---|---|---|---|---|
| $period_1 * group_i^n$ | -0.120** | 0.00577 | 0.0119 | 0.0129 | -0.188*** | -0.137*** |
| | (0.0505) | (0.0142) | (0.0117) | (0.0265) | (0.0236) | (0.0239) |
| Constant | 0.602*** | 0.585*** | 0.694*** | 0.608*** | 0.548*** | 0.674*** |
| | (0.0203) | (0.00885) | (0.00852) | (0.0130) | (0.0166) | (0.0158) |
| Observations | 22,290 | 39,352 | 61,443 | 26,864 | 53,958 | 45,911 |
| R-squared | 0.746 | 0.693 | 0.693 | 0.797 | 0.593 | 0.653 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Day-week FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values < 0.10, 0.05, 0.01 represented by *, **, ***, respectively.

Table OB3: Randomization inference p-values

| | MA | SC | Change | Fin | RL | MA-RL |
|---|---|---|---|---|---|---|
| *Panel A: Polluting vehicles* | | | | | | |
| Unadjusted p-value (clustered at the firm-level) | 0.019 | 0.279 | 0.030 | 0.292 | 0.000 | 0.000 |
| Unadjusted p-value (clustered at the individual-level) | 0.002 | 0.323 | 0.094 | 0.241 | 0.000 | 0.000 |
| RI adjusted p-value | 0.013 | 0.785 | 0.7130 | 0.582 | 0.004 | 0.070 |
| *Panel B: Cycling* | | | | | | |
| Unadjusted p-value (clustered at the firm-level) | 0.020 | 0.889 | 0.117 | 0.224 | 0.000 | 0.000 |
| Unadjusted p-value (clustered at the individual-level) | 0.032 | 0.897 | 0.167 | 0.262 | 0.000 | 0.000 |
| RI adjusted p-value | 0.041 | 0.959 | 0.797 | 0.714 | 0.001 | 0.003 |
| *Panel C: Common transportation* | | | | | | |
| Unadjusted p-value (clustered at the firm-level) | 0.205 | 0.578 | 0.742 | 0.240 | 0.002 | 0.184 |
| Unadjusted p-value (clustered at the individual-level) | 0.151 | 0.708 | 0.775 | 0.144 | 0.000 | 0.129 |
| RI adjusted p-value | 0.125 | 0.885 | 0.915 | 0.723 | 0.019 | 0.468 |

*Note:* Randomization inference p-values obtained using the 'ritest' command developed by Heß (2017).

## Online Appendix C: Testing the PTA

Table OC1: Placebo test on pre-treatment period

| | Polluting vehicles | | | | | |
|---|---|---|---|---|---|---|
| | MA | SC | Change | Fin. Incen. | RL | MA-RL |
| $period_1 * group_i^n$ | 0.0153 | -0.0109 | -0.0125 | 0.00689 | 6.84e-05 | 0.00725 |
| | (0.0139) | (0.0143) | (0.0170) | (0.0165) | (0.0132) | (0.0109) |
| Intercept | 0.452*** | 0.438*** | 0.527*** | 0.450*** | 0.397*** | 0.487*** |
| | (0.00310) | (0.00493) | (0.00677) | (0.00448) | (0.00514) | (0.00403) |
| Observations | 396 | 704 | 1,080 | 480 | 980 | 840 |
| R-squared | 0.958 | 0.935 | 0.905 | 0.943 | 0.913 | 0.929 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |
| | Teleworking | | | | | |
| | MA | SC | Change | Fin. Incen. | RL | MA-RL |
| $period_1 * group_i^n$ | 0.0269** | 0.0156* | 0.0247 | 0.00270 | 0.00362 | 0.0113 |
| | (0.0112) | (0.00869) | (0.0144) | (0.0189) | (0.0130) | (0.00902) |
| Constant | 0.0604*** | 0.0957*** | 0.0718*** | 0.0531*** | 0.0909*** | 0.0571*** |
| | (0.00258) | (0.00299) | (0.00572) | (0.00511) | (0.00502) | (0.00333) |
| Observations | 396 | 704 | 1,080 | 480 | 980 | 840 |
| R-squared | 0.805 | 0.712 | 0.707 | 0.753 | 0.701 | 0.825 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |
| | Cycling | | | | | |
| | MA | SC | Change | Fin. Incen. | RL | MA-RL |
| $period_1 * group_i^n$ | -0.0179* | -0.00649 | -0.00664* | 0.00659 | -0.0162** | -0.00184 |
| | (0.0104) | (0.00578) | (0.00338) | (0.00468) | (0.00692) | (0.00387) |
| Constant | 0.0909*** | 0.0564*** | 0.0476*** | 0.0798*** | 0.0729*** | 0.0486*** |
| | (0.00230) | (0.00199) | (0.00135) | (0.00127) | (0.00268) | (0.00143) |
| Observations | 396 | 704 | 1,080 | 480 | 980 | 840 |
| R-squared | 0.960 | 0.951 | 0.916 | 0.987 | 0.901 | 0.966 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |
| | Public transportation | | | | | |
| | MA | SC | Change | Fin. Incen. | RL | MA-RL |
| $period_1 * group_i^n$ | -0.00000 | -0.000590 | 0.00184 | -0.00230 | 0.00273 | 0.00511 |
| | (0.00602) | (0.00534) | (0.00555) | (0.00595) | (0.00489) | (0.00783) |
| Constant | 0.106*** | 0.101*** | 0.0457*** | 0.103*** | 0.103*** | 0.0719*** |
| | (0.00134) | (0.00184) | (0.00220) | (0.00161) | (0.00190) | (0.00289) |
| Observations | 396 | 704 | 1,080 | 480 | 980 | 840 |
| R-squared | 0.978 | 0.939 | 0.950 | 0.974 | 0.965 | 0.961 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values $<$ 0.10, 0.05, 0.01 represented by *, **, ***, respectively.

Table OC2: Robustness check: Adding a group-specific linear trend

| | | | | | | |
|---|---|---|---|---|---|---|
| Share of polluting vehicles | | | | | | |
| | MA | SC | Change | Fin. Inc. | RL | MA-RL |
| $period_1 * group_i^n$ | -0.0577** | 0.0105 | 0.0201* | 0.0166 | -0.0820*** | -0.0735*** |
| | (0.0268) | (0.0158) | (0.0100) | (0.0196) | (0.0168) | (0.0189) |
| $Trend * group_i^n$ | -0.00137** | 0.0000 | -0.000166 | 0.000111 | -0.00180*** | -0.000765* |
| | (0.000656) | (0.000371) | (0.000267) | (0.000268) | (0.000264) | (0.000397) |
| Constant | 0.442*** | 0.420*** | 0.507*** | 0.437*** | 0.386*** | 0.476*** |
| | (0.0146) | (0.00586) | (0.00506) | (0.00860) | (0.0118) | (0.0107) |
| Observations | 4,356 | 7,744 | 11,880 | 5,280 | 10,780 | 9,240 |
| R-squared | 0.964 | 0.955 | 0.943 | 0.953 | 0.896 | 0.915 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |
| Share of cycling | | | | | | |
| | MA | SC | Change | Fin. Inc. | RL | MA-RL |
| $period_1 * group_i^n$ | 0.0316** | -0.000162 | -0.00655* | 0.00910 | 0.0288*** | 0.0616*** |
| | (0.0114) | (0.00457) | (0.00374) | (0.00676) | (0.0104) | (0.0103) |
| $Trend * group_i^n$ | 0.000363 | 3.85e-05 | 5.90e-05 | -8.95e-05 | 0.00107*** | 0.000599*** |
| | (0.000512) | (8.96e-05) | (0.000106) | (9.92e-05) | (0.000231) | (0.000108) |
| Constant | 0.0850*** | 0.0526*** | 0.0433*** | 0.0801*** | 0.0630*** | 0.0453*** |
| | (0.00678) | (0.00309) | (0.00237) | (0.00275) | (0.00766) | (0.00792) |
| Observations | 4,356 | 7,744 | 11,880 | 5,280 | 10,780 | 9,240 |
| R-squared | 0.968 | 0.960 | 0.956 | 0.980 | 0.886 | 0.943 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |
| Share of common transportation | | | | | | |
| | MA | SC | Change | Fin. Inc. | RL | MA-RL |
| $period_1 * group_i^n$ | 0.0127 | -0.00412 | -0.00650 | -0.00857 | 0.0399** | -0.000354 |
| | (0.0129) | (0.00885) | (0.00578) | (0.00854) | (0.0154) | (0.00569) |
| $Trend * group_i^n$ | 0.000518 | 3.64e-05 | 0.000231* | -0.000181 | 0.00122*** | 0.000477** |
| | (0.000345) | (0.000173) | (0.000151) | (0.000184) | (0.000270) | (0.000201) |
| Constant | 0.105*** | 0.101*** | 0.0459*** | 0.102*** | 0.101*** | 0.0728*** |
| | (0.00779) | (0.00349) | (0.00303) | (0.00525) | (0.0138) | (0.00523) |
| Observations | 4,356 | 7,744 | 11,880 | 5,280 | 10,780 | 9,240 |
| R-squared | 0.969 | 0.958 | 0.954 | 0.967 | 0.932 | 0.947 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values $< 0.10, 0.05, 0.01$ represented by *, **, ***, respectively.

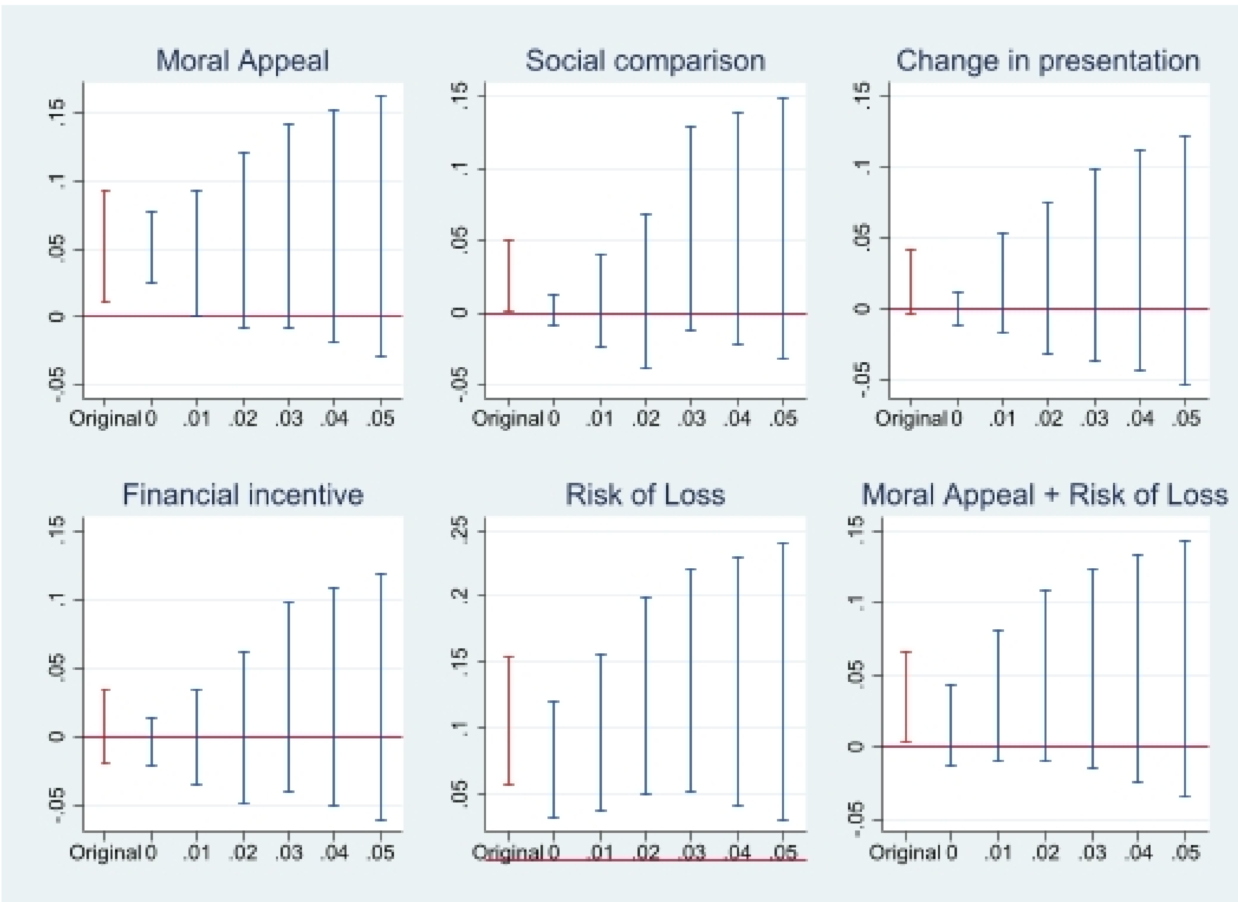
Figure OC1: Sensitivity estimates on share of polluting vehicles (at week 44) based on Rambachan and Roth (2023)


*Note:* The Figure indicates the sensitivity of the confidence interval around different estimates for the impact of the different nudges on the share of polluting vehicles to potential violations of the parallel trends assumption. In red, the original confidence interval is plotted, assuming parallel trends. In blue, Fixed-Length Confidence Intervals (FLCI) developed by Rambachan and Roth (2023) are plotted. The parameter M in the x-axis represents the maximal bound on the amount by which the underlying time trend can vary between consecutive periods. For $M = 0$, the difference in trends between treated and control groups is exactly linear. $M > 0$ allows for increasingly more varied nonlinear trends

Figure OC2: Sensitivity estimates on share of cycling (at week 44) based on Rambachan and Roth (2023)


*Note:* The Figure indicates the sensitivity of the confidence interval around different estimates for the impact of the different nudges on the share of cycling to potential violations of the parallel trends assumption. In red, the original confidence interval is plotted, assuming parallel trends. In blue, Fixed-Length Confidence Intervals (FLCI) developed by Rambachan and Roth (2023) are plotted. The parameter M in the x-axis represents the maximal bound on the amount by which the underlying time trend can vary between consecutive periods. For $M = 0$, the difference in trends between treated and control groups is exactly linear. $M > 0$ allows for increasingly more varied nonlinear trends

Figure OC3: Sensitivity estimates on share of common transportation (at week 44) based on Rambachan and Roth (2023)




*Note:* The Figure indicates the sensitivity of the confidence interval around different estimates for the impact of the different nudges on the share of common transportation to potential violations of the parallel trends assumption. In red, the original confidence interval is plotted, assuming parallel trends. In blue, Fixed-Length Confidence Intervals (FLCI) developed by Rambachan and Roth (2023) are plotted. The parameter M in the x-axis represents the maximal bound on the amount by which the underlying time trend can vary between consecutive periods. For $M = 0$, the difference in trends between treated and control groups is exactly linear. $M > 0$ allows for increasingly more varied nonlinear trends

## Online Appendix D: Linear heterogeneity analysis

Table OD1: ATE by individual characteristics (Share of cycling)

| | MA | MA | MA | MA | MA | RL | RL | RL | RL | RL | MA-RL | MA-RL | MA-RL | MA-RL | MA-RL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A* | | | | | | | | | | | | | | | |
| $ATE$ | 0.0691 | 0.0475 | 0.0346** | 0.0862** | 0.0456** | 0.134*** | 0.0788** | 0.0407* | 0.0606 | 0.0466*** | 0.195*** | 0.0786** | 0.0722*** | 0.0846*** | 0.0776*** |
| | (0.0676) | (0.0497) | (0.0124) | (0.0342) | (0.0194) | (0.0195) | (0.0168) | (0.0215) | (0.0364) | (0.0117) | (0.0468) | (0.0352) | (0.0195) | (0.0239) | (0.0132) |
| $ATE$*Ln (Dist.) | -0.00963 | | | | | -0.0290*** | | | | | -0.0408*** | | | | |
| | (0.0177) | | | | | (0.00577) | | | | | (0.0117) | | | | |
| $ATE$*NEP scale | | -0.00749 | | | | | -0.0238 | | | | | -0.00394 | | | |
| | | (0.0375) | | | | | (0.0174) | | | | | (0.0316) | | | |
| $ATE$*Nbr bicycles | | | 0.00293 | | | | | 0.00702 | | | | | 0.00161 | | |
| | | | (0.0116) | | | | | (0.0105) | | | | | (0.00744) | | |
| $ATE$*Nbr cars | | | | -0.0310 | | | | | -0.00368 | | | | | -0.00607 | |
| | | | | (0.0222) | | | | | (0.0216) | | | | | (0.0109) | |
| $ATE$*Nbr moto. | | | | | -0.0439** | | | | | 0.0252 | | | | | -0.0370 |
| | | | | | (0.0193) | | | | | (0.0188) | | | | | (0.0273) |
| Observations | 4,356 | 4,356 | 4,356 | 4,356 | 4,312 | 10,780 | 10,780 | 10,736 | 10,736 | 10,736 | 9,240 | 9,240 | 9,240 | 9,240 | 9,240 |
| R-squared | 0.968 | 0.968 | 0.968 | 0.969 | 0.968 | 0.888 | 0.886 | 0.886 | 0.888 | 0.886 | 0.946 | 0.943 | 0.943 | 0.943 | 0.943 |
| Individual FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| | MA | MA | MA | MA | MA | RL | RL | RL | RL | RL | MA-RL | MA-RL | MA-RL | MA-RL | MA-RL |
| *Panel B* | | | | | | | | | | | | | | | |
| $ATE$ | 0.0149 | 0.0345 | 0.0377* | 0.0408 | 0.0381** | 0.0539*** | 0.0567*** | 0.0534*** | 0.0759*** | 0.0495*** | 0.0934*** | 0.0784*** | 0.0707*** | 0.0816*** | 0.0814*** |
| | (0.0101) | (0.0348) | (0.0186) | (0.0299) | (0.0175) | (0.0131) | (0.0191) | (0.0110) | (0.0225) | (0.00953) | (0.0193) | (0.0143) | (0.00962) | (0.0154) | (0.0129) |
| $ATE$*Male | 0.0543 | | | | | -0.00361 | | | | | -0.0450** | | | | |
| | (0.0451) | | | | | (0.0208) | | | | | (0.0193) | | | | |
| $ATE$*One stop | | 0.00972 | | | | | -0.00769 | | | | | -0.00609 | | | |
| | | (0.0497) | | | | | (0.0295) | | | | | (0.0107) | | | |
| $ATE$*Age over 60 | | | 0.0407 | | | | | -0.0517*** | | | | | 0.105 | | |
| | | | (0.0670) | | | | | (0.0109) | | | | | (0.123) | | |
| $ATE$*High skilled | | | | -0.00244 | | | | | -0.0430 | | | | | -0.0140 | |
| | | | | (0.0303) | | | | | (0.0272) | | | | | (0.0123) | |
| $ATE$*High budget | | | | | 0.0112 | | | | | 0.0295 | | | | | -0.0646*** |
| | | | | | (0.0186) | | | | | (0.0280) | | | | | (0.0185) |
| Observations | 4,356 | 4,356 | 4,356 | 4,356 | 4,356 | 10,780 | 10,780 | 10,780 | 10,780 | 10,780 | 9,240 | 9,240 | 9,240 | 9,240 | 9,240 |
| R-squared | 0.969 | 0.968 | 0.968 | 0.968 | 0.968 | 0.886 | 0.886 | 0.886 | 0.886 | 0.886 | 0.944 | 0.943 | 0.944 | 0.943 | 0.944 |
| Individual FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values $< 0.10$, 0.05, 0.01 represented by *, **, ***, respectively.

Table OD2: ATE by individual characteristics (Share of common transportation)

| | MA | MA | MA | MA | MA | RL | RL | RL | RL | RL | MA-RL | MA-RL | MA-RL | MA-RL | MA-RL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A | | | | | | | | | | | | | | | |
| *ATE* | 0.0270 | -0.00781 | 0.0407*** | 0.0905*** | 0.0171 | 0.0379*** | 0.108*** | 0.0844*** | 0.0915*** | 0.0696*** | -0.00159 | 0.00221 | 0.00487 | 0.00577 | 0.00978 |
| | (0.0405) | (0.0241) | (0.00963) | (0.0280) | (0.0157) | (0.00776) | (0.0385) | (0.0262) | (0.0318) | (0.0201) | (0.0116) | (0.0176) | (0.0116) | (0.0111) | (0.00811) |
| *ATE** Ln (Dist.) | -0.000945 | | | | | 0.0102 | | | | | 0.00421 | | | | |
| | (0.00776) | | | | | (0.00726) | | | | | (0.00349) | | | | |
| *ATE**NEP scale | | 0.0304 | | | | | -0.0367 | | | | | 0.00815 | | | |
| | | (0.0364) | | | | | (0.0285) | | | | | (0.0160) | | | |
| *ATE**Nbr. bicycles | | | -0.00977 | | | | | -0.0107* | | | | | 0.00325 | | |
| | | | (0.0119) | | | | | (0.00619) | | | | | (0.00297) | | |
| *ATE**Nbr. cars | | | | -0.0443 | | | | | -0.0155 | | | | | 0.00268 | |
| | | | | (0.0274) | | | | | (0.0105) | | | | | (0.00391) | |
| *ATE**Nbr. moto. | | | | | 0.0316 | | | | | -0.0141* | | | | | 0.00448 |
| | | | | | (0.0389) | | | | | (0.00816) | | | | | (0.0167) |
| Observations | 4,356 | 4,356 | 4,356 | 4,356 | 4,312 | 10,780 | 10,780 | 10,736 | 10,736 | 10,736 | 9,240 | 9,240 | 9,240 | 9,240 | 9,240 |
| R-squared | 0.969 | 0.969 | 0.969 | 0.970 | 0.970 | 0.931 | 0.931 | 0.932 | 0.931 | 0.932 | 0.947 | 0.947 | 0.947 | 0.947 | 0.947 |
| Individual FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| | MA | MA | MA | MA | MA | RL | RL | RL | RL | RL | MA-RL | MA-RL | MA-RL | MA-RL | MA-RL |
| Panel B | | | | | | | | | | | | | | | |
| ATE | 0.0323 | 0.0231 | 0.0221 | 0.0235 | 0.0386*** | 0.0726*** | 0.0581*** | 0.0682*** | 0.0650*** | 0.0679*** | 0.0116** | 0.000924 | 0.0105 | 0.00999 | 0.00943 |
| | (0.0257) | (0.0178) | (0.0194) | (0.0272) | (0.0137) | (0.0225) | (0.0186) | (0.0191) | (0.0235) | (0.0200) | (0.00536) | (0.00733) | (0.00761) | (0.00934) | (0.00893) |
| *ATE**Male | -0.0180 | | | | | -0.0135 | | | | | -0.00363 | | | | |
| | (0.0298) | | | | | (0.0161) | | | | | (0.00872) | | | | |
| *ATE**One stop | | 0.00189 | | | | | 0.0154 | | | | | 0.0155* | | | |
| | | (0.0224) | | | | | (0.0199) | | | | | (0.00798) | | | |
| *ATE**Age over 60 | | | 0.0441 | | | | | -0.0681*** | | | | | -0.0104 | | |
| | | | (0.0559) | | | | | (0.0188) | | | | | (0.00687) | | |
| *ATE**High skilled | | | | 0.00114 | | | | | 0.00323 | | | | | 0.000295 | |
| | | | | (0.0216) | | | | | (0.0247) | | | | | (0.00679) | |
| *ATE**High budget | | | | | -0.106*** | | | | | -0.0116 | | | | | 0.00677 |
| | | | | | (0.0200) | | | | | (0.0213) | | | | | (0.0189) |
| Observations | 4,356 | 4,356 | 4,356 | 4,356 | 4,356 | 10,780 | 10,780 | 10,780 | 10,780 | 10,780 | 9,240 | 9,240 | 9,240 | 9,240 | 9,240 |
| R-squared | 0.969 | 0.969 | 0.969 | 0.969 | 0.970 | 0.931 | 0.931 | 0.931 | 0.931 | 0.931 | 0.947 | 0.947 | 0.947 | 0.947 | 0.947 |
| Individual FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values $< 0.10$, 0.05, 0.01 represented by *, **, ***, respectively.

## Online Appendix E: Causal forest and robustness checks

Table OE1: List of covariates used in Causal Forest (from ex ante survey)

| Name | Definition |
|---|---|
| Ln (Dist.) | Distance from work in kilometers (in logarithm) |
| NEP scale | New Ecological Paradigm (NEP) scale |
| Nbr. cars | Number of cars in individuals' household |
| Nbr. moto. | Number of motorcycles in individuals' household |
| Nbr. bicycles | Number of bicycles in individuals' household |
| Prox. CT | Dummy variable that equals one if individual makes a stop near their home and/or their work, and zero otherwise |
| Age Category | Categorical variable and values are {1=15-29 years; 2=20-44 years; 3=45-59 years; 4= >= 60 years} |
| Socioprofessional category | Categorical variable evaluating the occupation of employee. Values are {1=agricultural workers; 2=craftspeople, traders and business executive; 3=blue collar workers; 4=employees; 5= white collar workers; 6=technicians and associate professionals; 7=Students} |
| Education | Categorical variable evaluating the level education of the employee. Values are {1=below Baccalaureate; 2=Baccalaureate; 3=Two years after Baccalaureate; 4=Bachelor; 4= Master; 5= PhD} |
| Gender | Dummy variable that equals one for male and zero otherwise |
| Round trip | Dummy that equals one if the employee has to make at least on stop during their trip to work |
| Work trip | Dummy that equals one if the employee has to make at least one journey for work during working hours |
| Mobility budget | Categorical variable evaluating the monthly budget for journey from home to work. Values are {1=€0; 2=Less than €100; 3=Between €100 and €200; 4=Between €200 and €300; 5=Between €300 and €400; 6= Between €400 and €500; 7=Over €500} |
| Weekly trend | Weekly trend to capture time fixed effects |

Table OE2: ATE computed using causal forest algorithm and heterogeneity test (cycling and public transport)

| | MA | | RL | | MA-RL | |
|---|---|---|---|---|---|---|
| | cycling | CT | cycling | CT | cycling | CT |
| ATE | 0.0384** | 0.0242 | 0.0579*** | 0.06934*** | 0.07904*** | 0.00995** |
| | (0.0187) | (0.0168) | (0.00923) | (0.00901) | (0.00865) | (0.00401) |
| Mean.prediction | 1.17709*** | 0.87818 | 1.11886*** | 1.04402*** | 1.09971*** | 0.99026** |
| Difference. Prediction | -4.27566 | -5.80891 | 1.01455** | 0.78806* | 1.11427*** | -3.78963 |

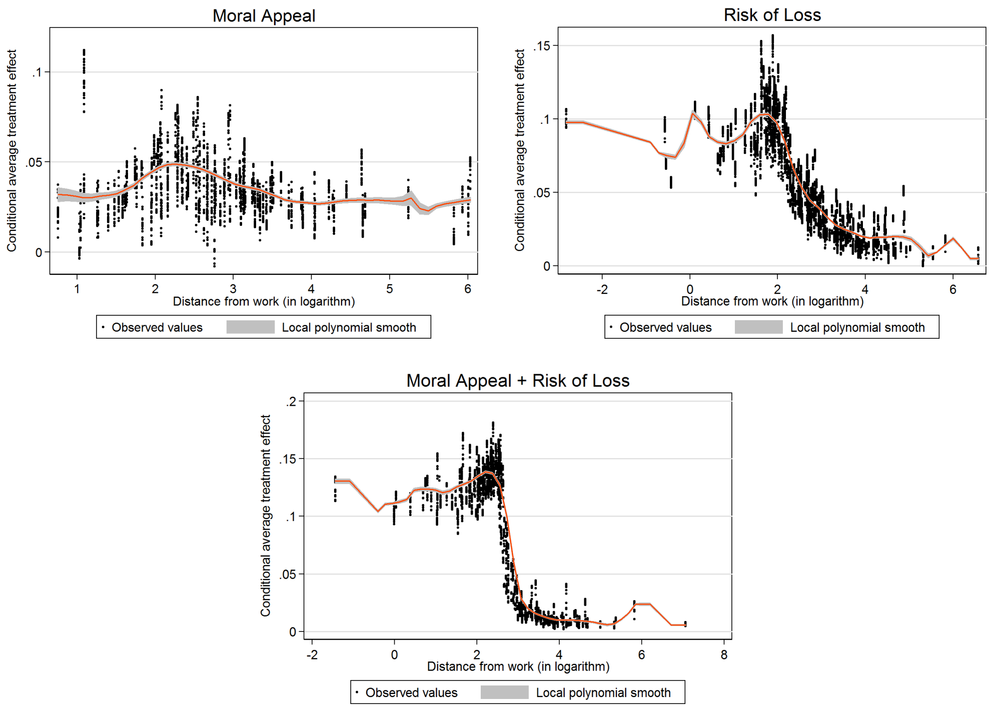
*Note:* ATE estimated using the causal forest algorithm. The omnibus test calculates two synthetic predictors. The first one (mean forest prediction) is a measure of the quality of the prediction of the forest and a coefficient of 1 suggests a correct prediction. The second one (difference forest prediction) is a measure of the quality of estimates of treatment heterogeneity, and a coefficient of 1 suggests that the treatment heterogeneity estimates are well calibrated. The p-value of the 'difference prediction' coefficient also acts as a test for the null of no heterogeneity. Standard errors in parentheses, p-values < 0.10, 0.05, 0.01 represented by *, **, ***, respectively.

Table OE3: ATE computed using causal forest and heterogeneity test (using difference in outcome variable between week 44 and week 4)

| | MA | SC | Change | Fin. Incen. | RL | MA-RL |
|---|---|---|---|---|---|---|
| ATE | -0.106*** | 0.0112 | 0.0307 | 0.0178 | -0.1323*** | -0.1029*** |
| | (0,030) | (0.0198) | (0.0191) | (0.0238) | (0.0262) | (0.0256) |
| Mean forest prediction | 0,99169*** | 1,4851* | 0,96103*** | 0,97381 | 1,0035*** | 1,0456*** |
| Difference forest prediction | 1,13746 | -23,6201 | -0,48045 | -15,067 | 0,7556* | 1,31803*** |

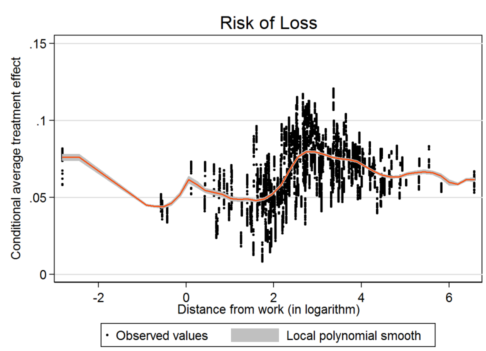
*Note:* ATE estimated using the causal forest algorithm. The omnibus test computes two synthetic predictors. The first one (mean forest prediction) is a measure of the quality of the prediction of the forest and a coefficient of 1 suggests a correct prediction. The second one (difference forest prediction) is a measure of the quality of estimates of treatment heterogeneity, and a coefficient of 1 suggests that the treatment heterogeneity estimates are well calibrated. The p-value of the 'difference prediction' coefficient also acts as a test for the null of no heterogeneity. Standard errors in parentheses, p-values $<$ 0.10, 0.05, 0.01 represented by *, **, ***, respectively.

Figure OE1: Distance from work and treatment effects (Share of cycling in weekly trips)



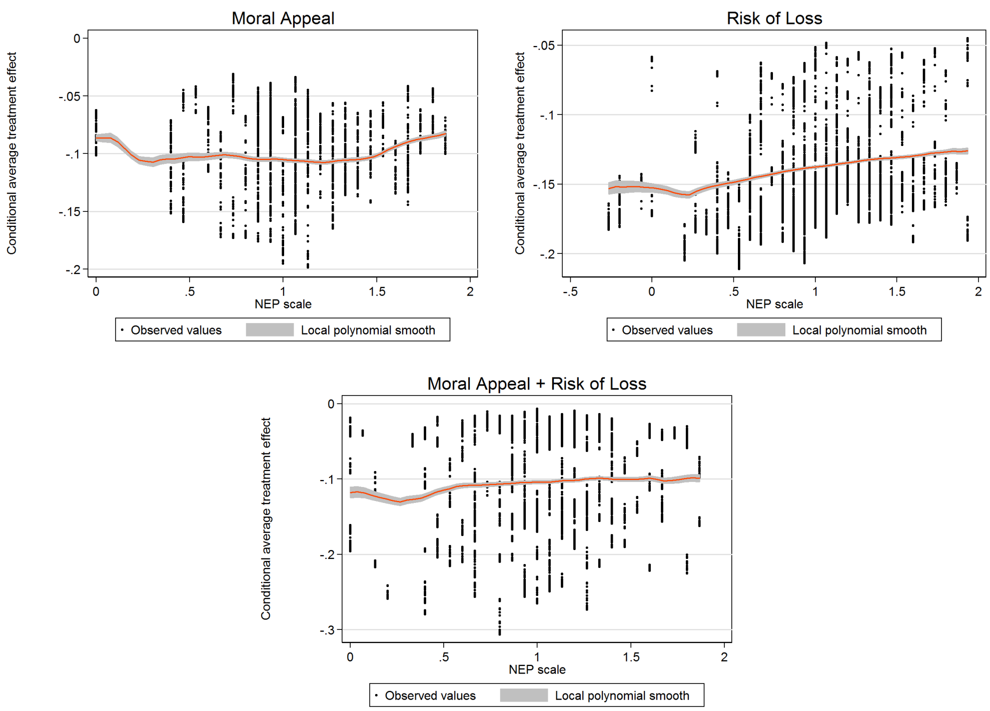

*Note:* The Figure shows the impact of the three different nudges on the share of cycling regarding the distance between individuals' home and work. The x-axis measures the distance (in logarithm), while the y-axis measures the treatment effect predicted by the causal forest algorithm. The red line depicts the local smoothed polynomial relationship between ATE and distance.

Figure OE2: Distance from work and treatment effects (Share of common transportation in weekly trips)




*Note:* The Figure shows the impact of the nudge RL on the share of common transportation regarding the distance between individuals' home and work. The x-axis measures the distance (in logarithm), while the y-axis measures the treatment effect predicted by the causal forest algorithm. The red line depicts the local smoothed polynomial relationship between ATE and distance.

Figure OE3: NEP scale and treatment effects (Share of polluting vehicles in weekly trips)




*Note:* The Figure shows the impact of the three different nudges on the share of polluting vehicles regarding the individuals' environmental preferences (NEP scale). The x-axis measures the distance (in logarithm), while the y-axis measures the treatment effect predicted by the causal forest algorithm. The red line depicts the local smoothed polynomial relationship between ATE and NEP scale.

## Online Appendix F: Additional content

Table OF1: Effects of the nudges on teleworking

| | MA | SC | Change | Fin. Incen. | RL | MA-RL |
|---|---|---|---|---|---|---|
| $period_1 * group_i^n$ | 0.00617 | 0.000384 | 0.00245 | -0.00509 | 0.00451 | -0.00627 |
| | (0.0137) | (0.0141) | (0.0147) | (0.0176) | (0.0132) | (0.0129) |
| Intercept | 0.0835*** | 0.118*** | 0.0987*** | 0.0710*** | 0.109*** | 0.0783*** |
| | (0.00555) | (0.00881) | (0.0106) | (0.00865) | (0.00927) | (0.00864) |
| Observations | 4,356 | 7,744 | 11,880 | 5,280 | 10,780 | 9,240 |
| R-squared | 0.875 | 0.835 | 0.835 | 0.769 | 0.790 | 0.812 |
| Individual FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values < 0.10, 0.05, 0.01 represented by *, **, ***, respectively.

Table OF2: Effect of the nudges over time - Share of polluting vehicles

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | MA | | | RL | | | MA-RL | | |
| | 2 weeks | 8 weeks | 20 weeks | 2 weeks | 8 weeks | 20 weeks | 2 weeks | 8 weeks | 20 weeks |
| $period_1 * group_i^n$ | -0.0354 | -0.0532* | -0.0774** | -0.0347** | -0.0827*** | -0.107*** | -0.0326 | -0.0666*** | -0.0846*** |
| | (0.0226) | (0.0260) | (0.0316) | (0.0152) | (0.0175) | (0.0167) | (0.0199) | (0.0189) | (0.0165) |
| Intercept | 0.440*** | 0.434*** | 0.438*** | 0.383*** | 0.376*** | 0.381*** | 0.474*** | 0.468*** | 0.473*** |
| | (0.00430) | (0.00799) | (0.0118) | (0.00506) | (0.00938) | (0.0109) | (0.00628) | (0.00965) | (0.0102) |
| Observations | 693 | 1,287 | 2,475 | 1,715 | 3,185 | 6,125 | 1,470 | 2,730 | 5,250 |
| R-squared | 0.929 | 0.929 | 0.947 | 0.875 | 0.845 | 0.871 | 0.885 | 0.863 | 0.893 |
| Individual FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values < 0.10, 0.05, 0.01 represented by *, **, ***, respectively.

Table OF3: Effects of the nudges over time - Share of cycling and common transportation

| | Cycling | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | MA | | | RL | | | MA-RL | | |
| | 2 weeks | 7 weeks | 20 weeks | 2 weeks | 7 weeks | 20 weeks | 2 weeks | 7 weeks | 20 weeks |
| $period_1 * group_i^n$ | 0.0234* | 0.0296** | 0.0371*** | 0.00492 | 0.0324*** | 0.0433*** | 0.0375*** | 0.0603*** | 0.0708*** |
| | (0.0119) | (0.0126) | (0.0128) | (0.00881) | (0.0104) | (0.0104) | (0.00958) | (0.0105) | (0.0112) |
| Intercept | 0.0858*** | 0.0851*** | 0.0850*** | 0.0655*** | 0.0648*** | 0.0646*** | 0.0468*** | 0.0462*** | 0.0460*** |
| | (0.00227) | (0.00389) | (0.00479) | (0.00293) | (0.00560) | (0.00680) | (0.00303) | (0.00535) | (0.00692) |
| Observations | 693 | 1,287 | 2,475 | 1,715 | 3,185 | 6,125 | 1,470 | 2,730 | 5,250 |
| R-squared | 0.938 | 0.950 | 0.959 | 0.794 | 0.798 | 0.849 | 0.889 | 0.876 | 0.914 |
| Individual FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| | Common transportation | | | | | | | | |
| | MA | | | RL | | | MA-RL | | |
| | 2 weeks | 7 weeks | 20 weeks | 2 weeks | 7 weeks | 20 weeks | 2 weeks | 7 weeks | 20 weeks |
| $period_1 * group_i^n$ | 0.00281 | 0.0163 | 0.0198 | 0.0157* | 0.0429*** | 0.0567*** | -0.00573 | 0.00344 | 0.00606 |
| | (0.00964) | (0.0105) | (0.0167) | (0.00827) | (0.0141) | (0.0179) | (0.00577) | (0.00497) | (0.00648) |
| Intercept | 0.105*** | 0.105*** | 0.106*** | 0.104*** | 0.103*** | 0.104*** | 0.0735*** | 0.0728*** | 0.0742*** |
| | (0.00184) | (0.00324) | (0.00623) | (0.00275) | (0.00755) | (0.0117) | (0.00182) | (0.00254) | (0.00402) |
| Observations | 693 | 1,287 | 2,475 | 1,715 | 3,185 | 6,125 | 1,470 | 2,730 | 5,250 |
| R-squared | 0.968 | 0.958 | 0.963 | 0.926 | 0.899 | 0.914 | 0.942 | 0.948 | 0.954 |
| Individual FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |

*Note:* Standard errors clustered at the firm level in parentheses, p-values < 0.10, 0.05, 0.01 represented by *, **, ***, respectively.

Table OF4: Descriptive statistics on estimated air pollution of the different groups

| | | Week 4 | | Week 44 | | Difference | |
|---|---|---|---|---|---|---|---|
| | | Mean | Total | Mean | Total | Mean | Total |
| | NOX (in grams) | 36,963 | 2032,963 | 37,261 | 2049,343 | 0,298 | 16,380 |
| Control | PM10 (in grams) | 3.280 | 180.406 | 3.298 | 181.378 | 0.018 | 0.971 |
| | CO2 (in kilograms) | 22226 | 1222461 | 22297 | 1226357 | 70.840 | 3896 |
| | NOX (in grams) | 44.437 | 1955 | 42.644 | 1876 | -1.792 | -78.859 |
| AM | PM10 (in grams) | 4.239 | 186.527 | 4.100 | 180.428 | -0.139 | -6.099 |
| | CO2 (in kilograms) | 27532 | 1211429 | 26503 | 1166152 | -1029 | -45276 |
| | NOX (in grams) | 29.641 | 5631 | 24.892 | 4729 | -4.749 | -902,3 |
| RP | PM10 (in grams) | 2.735 | 519.6 | 2.455 | 466.4 | -0.280 | -53.258 |
| | CO2 (in kilograms) | 17568 | 3338051 | 14926 | 2836044 | -2642 | -502007 |
| | NOX (in grams) | 46.793 | 7252.92 | 45.007 | 6976 | -1.786 | -276,72 |
| AMRP | PM10 (in grams) | 4.043 | 626.6 | 3.936 | 610.1 | -0.107 | -16.594 |
| | CO2 (in kilograms) | 27635 | 4283436 | 26713 | 4140608 | -921 | -142828 |

*Note:* This Table displays emissions of $PM_{10}$, $CO_2$, and $NO_x$, for the control group, the group AM, the group RL, and the group AM-RL before the start of the interventions (week 4) and at the end of the treatment period (week 44). $Mean$ corresponds to the average emissions of each group, while $Total$ corresponds to the total emissions of each group.

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# Derniers numéros – Last issues



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