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DISCUSSION PAPER

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Can Social Comparisons and Moral Appeals Increase Public Transport Ridership and Decrease Car Use?

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Can social comparisons and moral appeals increase public transport ridership and decrease car use?*

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Abstract

In a field experiment with 341 participants, we study whether social comparisons, either in isolation or in combination with a climate-related moral appeal, can change the use of public and car-related transportation. We do so in the context of a mobility budget offered to employees of a large German company as an alternative to a company car. The budget can be used to pay for both leisure and commuting trips, and for various modes of transport. Behavioral interventions in this setting are of particular interest, since companies are constrained to significantly alter financial benefits to employees yet strive to lower carbon emissions via a shift to low-emission transport modes. We find strong evidence for a reduction in car-related mobility in response to the combined treatment, driven by reduced expenditures for taxi and UBER rides. This is accompanied by substitution towards micromobility, but not towards public transport. Furthermore, we do not find any effects of the social comparison alone. Our results demonstrate that norm-based nudges are able to change transportation behavior, at least temporarily.

Keywords: mobility behavior, randomized experiment, nudging, descriptive norm, injunctive norm, social norms, moral appeal, habit formation

JEL-code: C93, D04, D91, L91

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1 Introduction

Reducing CO_2 emissions from car-related mobility is not only socially desirable but also the objective of many private companies that have adopted targets for their emissions or even pledged to become carbon-neutral. Emissions reductions in this area require a fundamental change in the way companies have been managing mobility options for their employees. In Europe, where tax provisions favor company cars that can be used for commuting and trips unrelated to work (Copenhagen Economics, 2010), many companies have been operating car fleets much larger than what would be needed for business purposes. Generous tax provisions for company cars are conducive to generating high CO_2 emissions because they distort modal choice towards driving, encourage the adoption of larger vehicles with high fuel consumption, and take away fuel conservation incentives as firms often reimburse up to 100 % of the fuel cost, even for private trips. Abolishing company cars as a fringe benefit could thus go a long way towards reducing corporate CO_2 emissions. Doing so unilaterally, however, might put the firm at a disadvantage in tight labor markets, because employees would have to be compensated for the higher total costs of private car ownership and, potentially, for the loss of status that a company car is associated with.

Against this background, firms have been looking for alternative mobility options that steer modal choice away from car use while preserving tax benefits. According to a survey by Kantar/Arval Mobility Observatory (2020), around 30 % of EU companies with company cars are considering to replace these cars with a so-called mobility budget, i.e., a monthly or annual budget that employees can flexibly spend on a broad variety of transport modes available on the market. Implementing a mobility budget for abatement purposes gives rise to a trade-off, however. On one hand, the benefit should provide mobility services at least equivalent to those of a company car. This means that car-based transportation such as car sharing, rental cars, and taxis, cannot be excluded from the menu of mobility options. On the other hand, emissions abatement hinges on employees using transportation modes other than cars, in particular public transportation. Solving this trade-off is not trivial, because restricting car use might drive employees to revert to the company car or even change employers. This setting thus provides a strong case for nudges that encourage the switch towards more climate-friendly modes of transport.

In this paper, we describe a randomized field experiment that tested the effectiveness of nudging subjects into more sustainable transport mode choices within a mobility budget scheme implemented at a large German company. Subjects in the treatment group received nudges in bi-weekly e-mail messages sent over an eight-week period while subjects in the control group received e-mails with very general information. We chose two nudges that promised to be effective at inducing substitution away from car-related mobility to public transportation, a social comparison and a moral appeal to reduce emissions from individual transportation choices. Social comparisons convey a *descriptive norm*, i.e., the behavior adopted by the majority, in a relevant peer group. This should be effective in the context of the mobility budget if participants benchmark their transportation choices against those of their co-workers. Moral appeals communicate information about *injunctive norms*, i.e., shared standards of acceptable group or societal behavior, and may change individual behavior if participants feel a need to comply with the communicated expectations of the peer group or have an intrinsic motivation to do something about the moral issue at hand, in our case mitigating climate change.

In the social comparison (SC) treatment, we informed participants of the mobility budget scheme about their own share of public transportation expenditures as compared to the respective share of a peer group. In the second treatment, the message additionally contained (i) information on the CO_2 emissions savings of public transportation relative to car use, (ii) information on the necessity to combat climate change, and (iii) a moral appeal to use public transportation (and other low-emissions transport modes) whenever possible in order to effectively combat climate change. Because of the additional moral appeal, we refer to this treatment as social comparison plus moral appeal (SC + MA) treatment.

We find that the combined treatment reduced the participants' expenditures for car-related mobility, such as car sharing, ride-sharing or ride-hailing services, by 38 %. Interestingly, this reduction was not accompanied by a substitution towards public transport, as measured by expenditures on this mode. This suggests that participants either substituted transportation modes other than public transport for car-related mobility services, or reduced their overall mobility. In line with the substitution channel, the combined treatment increased expenditures for bikes and electric scooters by 44 %, whereas total expenditures in the mobility budget did not change significantly in response to our treatments. The significant treatment effect was driven by reactions in the first half of the intervention period and vanished after the treatment had ended. This suggests that participants got used to the e-mail messages and dampened their reaction with recurrence, instead of forming new habits. By contrast, the social comparison alone had no significant effects on public transport and car-related mobility expenditures overall.

To shed light on potential channels explaining the observed effects, we estimate additional treatment effects (i) on the extensive margin (modal choice), (ii) on individual transport modes comprised in car-related and public transportation, and (iii) for relevant sub-groups within our sample. The upshot is that the reduction in car-related mobility expenditures caused by treatment SC + MA is driven by reductions along both the intensive and extensive margins, particularly by reductions in expenditures for ride-hailing and ride-sharing services, such as UBER and taxi rides, and by participants with high car-related expenditures pre-treatment.

Furthermore, we find evidence of heterogeneous effects for *both* treatments among participants who either used the corresponding transport mode a lot pre-treatment or who received a strong social comparison, in the sense that they received more messages with the information that their peer group used a larger share of their mobility expenditures for public transport. For the SC treatment, the observed null-effect can at least partly be explained by counteracting effects between individuals receiving a strong vs. a weak social comparison and between individuals with above- vs. below-median expenditures for car-related or public transportation: while subjects with a strong social comparison or with above-median expenditures significantly decreased their expenditures (for the corresponding transport mode), there was an increase in expenditures for the other individuals (though this effect is insignificant). Such "boomerang" effects have also been found in the previous literature (Schultz et al., 2007).

Our experimental setting within a corporate mobility budget is novel and highly policy relevant: Since mobility budgets are regarded as more flexible and more sustainable alternatives to company cars, their popularity is bound to increase in the future. However, academic research so far provides little guidance on how those budgets should be designed so as to steer participants towards sustainable mobility choices. By contributing the first causal evidence on the effectiveness of nudges in this setting, our paper takes an important first step towards filling this gap.

In terms of the broader behavioral economics literature, our contribution is to evaluate the interaction of social comparisons and moral appeals in the domain of mobility and transport. An advantage of our experimental setting is that we observe a large share of individual transport mode choices, including public transportation, car sharing, rental cars, and ride-hailing and ride-sharing services. This allows us to study substitution between different modes of transport and sets our paper apart from previous research in this domain which mostly used data on a single transport mode only (see, e.g., Kormos et al., 2014; Kristal and Whillans, 2020; Gravert and Collentine, 2021). In contrast to previous studies observing transportation behavior across multiple transport modes (Cellina et al., 2019; Hintermann et al., 2021), participants in our study are not aware that they participate in a field experiment.

The remainder of this paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the setup for the experiment and discusses potential mechanisms through which the two treatments could work. In Section 4, we analyze the effects of the e-mail messages on various outcome variables. Section 5 concludes.

2 Related literature

This paper draws on research in economics, transportation, psychology and behavioral sciences to analyze whether behavioral interventions in the form of nudges can help mitigate externalities from fossil fuel-based mobility. Nudges are often employed to counteract deviations from rational behavior, such as bounded rationality or cognitive biases (Thaler and Sunstein, 2009), and can then be referred to as "self-focused nudges" (Carlsson et al., 2021). In the transportation context, such nudges could target biases that have been shown to induce sub-optimal choices of transportation modes at the individual level (e.g., Innocenti et al., 2013; Larcom et al., 2017; Lattarulo et al., 2019; Moody and Zhao, 2019; Andor et al., 2020b).[1] Moreover, nudges are becoming increasingly popular as a behavioral substitute for regulation of traditional economic problems, such as environmental externalities, and can then be referred to as "green nudges" (Carlsson et al., 2021). Such nudges can be used to alter transportation choices that are *collectively* sub-optimal, which is the focus of this paper.

Nudges have been studied in countless field experiments across a broad range of settings. In this paper, we employ interventions using *social comparisons* and *moral appeals*. A social comparison communicates a descriptive norm (Cialdini et al., 1990), i.e., a characterization

[1] For comprehensive reviews on behavioral aspects in transportation, see Graham-Rowe et al. (2011), Avineri (2012), Metcalfe and Dolan (2012), Garcia-Sierra et al. (2015) and Semenescu et al. (2020).

of the factual behavior of a peer group. According to Cialdini et al. (1990), participants tend to conform to the behavior of their peers, either because they consider the observed behavior as a signal for individually optimal behavior in a given situation, or because they have a preference for conformity.[2] Social comparisons are the most frequently evaluated type of green nudge (Carlsson et al., 2021) and have proven effective at reinforcing pro-environmental behavior (Farrow et al., 2017), particularly in the area of energy and water conservation by households (e.g., Schultz et al., 2007; Nolan et al., 2008; Ferraro et al., 2011; Ferraro and Price, 2013; Allcott and Rogers, 2014; Allcott and Kessler, 2019; Andor et al., 2020a).[3]

In the field of transportation, social comparisons have been found to reduce self-reported car usage (Kormos et al., 2014), while having no effects on observed car-pooling decisions (Kristal and Whillans, 2020) or the observed use of public transportation (Gravert and Collentine, 2021). Given the stark difference in the performance of nudges in the transportation context as compared to other environmental domains, Gravert and Collentine (2021) conjecture that "switching transport options comes at a higher effort and even monetary cost than [...] reducing shower time by a couple of minutes", implying that individuals might stick more to the status quo (car-related mobility). We take this conjecture as a motivation for testing interventions that combine information about peer group behavior with a moral appeal to reduce transport-related CO_2 emissions. This should result in a stronger nudge, as moral appeals signal socially approved behavior. They have been shown to enhance energy and water conservation efforts (Ferraro et al., 2011; Ferraro and Price, 2013; Ito et al., 2018), and they also performed well in other domains (Bursztyn et al., 2019; Bott et al., 2020). Our study is closely related to Ferraro et al. (2011) and Ferraro and Price (2013) who experimentally evaluate a social comparison combined with a moral appeal in the context of water conservation. Ours is the first paper to test this "strong social norm treatment" on individual transportation choices.

Finally, several recent papers track the mobility behavior of participants using mobile applications (Cellina et al., 2019; Hintermann et al., 2021; Götz et al., 2022). Our study differs from these papers, as we conduct a natural field experiment using expenditure data. Furthermore, these papers focus on other research questions: Hintermann et al. (2021) analyze the effect of providing information about external costs of different mobility choices (and pricing of these costs). In contrast, we combine information on externalities with behavioral interventions. Cellina et al. (2019) focus on the effect of a mobile application combining a number of behavioral interventions, including a social comparison but no moral appeal. Götz et al. (2022) analyze the effect of providing participants with a mobile application that communicates a moral appeal to reduce CO_2 emissions from individual mobility choices. In this paper, the social comparison is one of many "gamification features" into which participants can select, whereas our study directly administers the moral appeal and the social comparison to *all* participants in the corresponding treatment groups.

[2]For a paper separating the influence of conformity and social learning, see, e.g., Götte and Tripodi (2020).

[3]While most of the literature focuses on the US, recent papers find much smaller effects in countries other than the US (Andor et al., 2020a).

3 Experimental setup

This section describes the experimental environment, the selection of the experimental sample, the randomization procedure, and the setup of the experiment.

3.1 The experimental environment

The present study was carried out in collaboration with a large company that has several business locations in Germany. The company offers a company car as a fringe benefit to approximately 50 % of its employees. It provides the vehicle and pays for insurance, maintenance, gasoline and/or electricity. Private car use is explicitly allowed in return for a monthly deduction from the pre-tax salary. Because of their benefits to employees and also employers, company car schemes have been adopted by many German firms, to the point that approximately a fifth of newly registered vehicles are company cars that may also be used privately (German Environmental Protection Agency, 2021).[4] Since companies own or lease these vehicles, their carbon emissions - be they work-related or not - count towards corporate carbon emissions targets.

In 2020, our partner company introduced a mobility budget as an alternative to the company car. After a pilot run at two business locations, the mobility budget program, which provides the framework for our experiment, was rolled out at a larger number of locations in April 2021, with a duration of 24 months. Employees eligible for a company car can choose to participate in the program and then receive an annual budget to cover their mobility expenses. The size of the budget is 2,400 euros for full-time employees and at least 1,400 euros for part-time employees. Any remaining budget at the end of the year is lost, but the company communicated at the beginning of the budgetary year that it would donate any remaining budget to a reforestation project.[5]

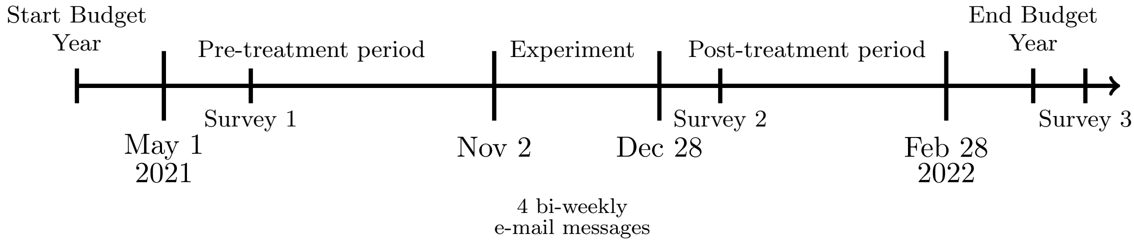
The mobility budget can be spent on commuting and leisure trips (expenses for business trips are reimbursed separately) and admits the use of a broad range of means of transportation (listed in the next paragraph). The program intends to provide attractive substitutes for the mobility services provided by a company car. It therefore allows that the budget be used on trips outside Germany, and it partly pays for mobility expenditures of the employee's family members. The budget is implemented as a reimbursement scheme whereby participants pay for expenditures out of their own pocket and subsequently claim reimbursement by entering the trip details (day and time of the trip, location where the trip was booked, trip fare, transport category) into the company's expense tool. For tax compliance purposes, employees are asked to hand in their tickets and receipts as soon as possible and not after the end of the calendar year.[6] Thanks to this documentation requirement, we observe most

[4]The deduction covers not only an imputed cost of ownership for private usage but also the employee's tax liability for the associated in-kind benefit in a lump-sum fashion. Therefore, an employee's tax savings from this scheme are increasing in kilometers driven, taxable income, and the value of the car. See Diekmann et al. (2011) for an economic analysis of company car taxation in Germany. The firm benefits in that the reduction in taxable wages lowers contributions to social security.

[5]The company emphasized the implied carbon sequestration, but also benefits to the local communities and to wildlife.

[6]Expenditures for all transport modes except for public transportation are taxed as non-cash benefits to the employee and thus must be handed in before the end of the corresponding calendar year. Participants

Figure 1: Timeline of the Experiment



of the participants' travel activity in terms of expenditures and mode choice, both for the commute to work and for leisure trips, including annual vacation trips.[7,8]

Eligible expenditures can be divided into three categories. *Public transportation (PT)* includes all short-distance ("local") and long-distance public transportation tickets for single and multiple rides, as well as monthly commutation tickets. While the program also reimburses annual commutation tickets, we do not include these expenditures in the PT category unless otherwise noted, as their period of validity does not match the timing of the interventions we describe below.[9] *Car-related transport (CT)* includes ride-hailing and ride-sharing services (e.g., taxis, UBER, etc.), car sharing and rental cars. Fuel expenditures for rental cars are not reimbursable though. *Micromobility (Micro)* is the residual category and comprises electric scooters, electric kick scooters, bike sharing, bike subscriptions and bike repairs.

3.2 Implementation

Timeline. Prior to the start of the program on April 1st, 2021, our partner company invited employees eligible for a company car to sign up for the mobility budget instead. Participation was voluntary but binding for a two-year period. All employees who expressed an interest in the program were enrolled. Of those 463 participants, roughly 80 % had not made use of the company car offer before. 21 subjects joined the program after April 1st (but prior to the treatment period) because they had not yet been eligible to join the program on the start date. Figure 1 displays the timeline for our interventions and data collection. The experiment lasted from November 2nd to December 28th (eight weeks) and was thus fully contained within the first budget year (April 1st, 2021 to March 30th, 2022). We conducted three voluntary surveys that elicited additional data from the participants.

were encouraged to also hand in expenditures for public transportation in time.

[7] We do not observe individual public transit rides that are covered by commutation tickets, rides with the private bike, and, of course, walking. Neither do we observe whether participants use other vehicles that are available to their household, such as private cars, motorbikes, or their partner's company car. In a survey among participants of the mobility budget, held at the end of the first program year, 45 % of respondents stated that they regularly use a private car or their partner's company car.

[8] The users of the mobility budget provide information on the transport mode used, the date of the transaction and the expenditures made. However, they do not report the distance, duration, point of departure and destination of their journeys. Thus, we are unable to estimate the CO_2 emissions implied by the transportation behavior.

[9] The budget can also be used for annual rail cards that provide a discount on train fares ("BahnCard25", "BahnCard50"). As these cards are booked using the same label as tickets for long-distance public transport, we are not able to separate them from the expenditure data.

The baseline survey took place at the end of June 2021. Midline and endline surveys were conducted shortly after the end of the interventions and of the first budget year, respectively. For the purposes of the analysis, we define the *pre-treatment period* to last from May 1st until November 1st, 2021, and the *post-treatment period* to last from December 28th, 2021 until February 28th, 2022. That is, we disregard behavior in the first and last month of the budget year, which is likely to be very atypical.[10]

Randomization. In mid-October 2021, the company provided us with data on spending by all 463 program participants between April 1st and September 30th of 2021. Based on this dataset, we randomly assigned participants into control and treatment groups in the last week of October 2021. To ensure that participants with differing expenditure levels and commuting options were equally represented across groups, we stratified the sample between urban vs. rural business locations and across quartiles of PT expenditures and total expenditures (excluding expenditures incurred by household members) during the pre-treatment period.[11]

Panel A of Table 2 shows the number of participants assigned to the different groups at the time of randomization (the full sample). For the analysis of the experiment, two participants were excluded from the sample upon request by our partner company. Additionally, we removed 33 inactive participants from our sample who had not used the mobility budget before November 2nd, 2021.[12] We excluded 87 subjects who bought an annual PT ticket at some point during the budget year, because a large share of PT use for this group is covered by their annual ticket and is hence unobservable to us. As can be seen in Table 2, both inactive and annual PT ticket holders are distributed evenly over the three treatment arms. This yields a sample of 341 employees for the main analysis, of which 110 are in the control group, 115 are in the social comparison (SC) treatment, and 116 are in the combined social comparison and moral appeal (SC + MA) treatment.

We are not concerned about attrition for the participants we removed from our experiment based on pre-treatment behavior. Attrition could be a concern for the removal of users who booked an annual PT ticket during the treatment period, as this choice could be driven by our treatments. However, only 6 out of the 87 annual PT ticket users booked their annual ticket during the treatment period. We re-include all annual PT ticket users as a robustness check. Before aggregating expenditure items for each participant at the monthly level,[13] we

[10] In April 2021, heterogeneity between new participants and those who had participated in the previous pilot program likely inflates variance, as new participants learn about the benefits and possibilities of the program during this month. In March 2022, participants knew how much of their budget remained unused and would thus be donated. Depending on their preferences, this might have induced participants to increase or decrease their spending in the last month. Our results are robust to the re-inclusion of these months, see Table 8 in Appendix C.

[11] In total we have 34 strata. Urban locations of work are those classified as densely populated areas according to Eurostat's "Degree of Urbanization" (DEGURBA) classification for "Local Administrative Units". Rural refers to intermediate density areas. Two additional strata based on the degree of urbanization were assigned only to those participants that had not handed in any expenditures prior to October 1st, 2021.

[12] At the time of randomization, it was unclear whether inactive subjects would hand in receipts at a later point in time. At the end of the budget year, we removed only those subjects who did not use the mobility budget at all before November 2nd. Only four of those subjects used the budget at a later point in time.

[13] As our treatment period does not fully coincide with the months of November and December 2021, we define a month by first aggregating expenditures for each week from Tuesday to Monday, then assigning these

drop expenditures made outside Germany (most likely incurred during vacation travel) and expenditures made by the employee's family members.

3.3 Descriptive statistics

Table 1 summarizes the monthly averages of individual expenditures and budgeted items, respectively, for CT and PT over the whole observation period, i.e., from May 1st, 2021 until February 28th, 2022. Monthly average expenditures over this period amount to 55.32 euros for PT and 40.39 euros for CT. Adding expenditures on micromobility, total expenditures amount to 104.39 euros. On average, participants submitted 2.60 expenditure items for PT and 1.10 for car-related mobility. Adding micromobility brings the total to four items in an average month. This appears to be low, but there is considerable variation across participants, and the maximum usage corresponds to about one expenditure item per day. When the treatment period began, the average participant had spent 43 % of their annual budget. It seems likely that this share would have been higher in the absence of the COVID-19 pandemic. The average participant spent only 1,516 euros during the entire year on all eligible items. This is less than two thirds of the full budget. Only 24 % of participants used their full budget.[14]

Table 1: Average Monthly Transportation Expenditures

	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Total Expenditures [EUR]	341	104.39	66.06	0.00	45.73	98.07	154.73	238.75
thereof PT Exp.	341	55.32	48.00	0.00	14.78	43.90	88.09	231.56
thereof CT Exp.	341	40.39	54.73	0.00	0.00	14.20	58.17	220.73
thereof Micro Exp.	341	8.67	18.80	0.00	0.00	0.00	10.93	178.90
Total Use Count	341	4.10	3.97	0.00	1.40	3.00	5.70	31.20
thereof PT Use Count	341	2.60	2.67	0.00	0.60	1.60	3.80	14.90
thereof CT Use Count	341	1.10	2.25	0.00	0.00	0.40	1.00	17.30
thereof Micro Use Count	341	0.41	1.44	0.00	0.00	0.00	0.30	20.90

Notes: The average monthly use is calculated by summing the expenditure items and expenditure item counts for a participant for the period May 1st, 2021 - February 28th, 2022. PT abbreviates public transport. CT abbreviates car-related transport, including, e.g., taxis or UBER rides, car sharing and rental cars. Micro abbbreviates micromobility, e.g. bike sharing, rental and repairs or shared e-scooters. We include only expenditure items within Germany and exclude expenditure items of family members. The maximum monthly averages can exceed 200 euros, as we exclude April 2021 and March 2022.

Figure 2 summarizes the participants' average propensity to use the three main transportation categories (Panel a) and their respective expenditure shares (Panel b) during the pre-treatment period. Almost all participants booked at least one PT ticket, about two thirds made use of car-related mobility, but less than half used micromobility options. Most of the budget was spent on public transport (52 %), followed by car-related mobility (39 %) and micromobility (8 %). Panel (c) plots the average monthly expenditures for a more disaggregate modal classification. With respect to public transportation, the average partic-

weekly observations to the corresponding Sunday in that week, and finally assigning these Sundays to their corresponding month.

[14] We consider full usage when less than 1 % of the budget remained by April 4th, when we received the final data. As eligible expenditure items bought during March 2022 could be handed in for reimbursement until April 30th, the share of participants that used the full budget might be slightly higher.

ipant spent 25.30 euros per month on local vs. 37.40 euros on long-distance transportation. Monthly expenditures on car-related mobility are split almost evenly between car sharing (16.30 euros), rental cars (17.20 euros) and taxis (13.40 euros, including ride-hailing services such as UBER and shuttle pooling). As expenditures for micromobility account for less than 10 % of overall pre-treatment expenditures and are mostly for bike sharing, bike rentals and repairs,[15] which is often not directly linked to mobility usage in terms of kilometers traveled, we are going to focus mostly on PT and CT in the subsequent analysis.

We assess the balance on time-invariant and pre-treatment covariates across the control and treatment groups in Panel B of Table 2. The differences between groups along the covariates of interest are not jointly significant. PT expenditures were slightly (but insignificantly) higher in the treatment groups as compared to the control group. In the econometric analysis, we control for such differences via employee fixed effects.

3.4 The interventions

The interventions consisted of a series of e-mail messages.[16] The messages were in English (the second company language besides German) and were sent to the participants' company e-mail addresses. Overall, every participant received four e-mails, in bi-weekly intervals between Tuesday, November 2nd, and Tuesday, December 14th, 2021. Both the control and the two treatment groups received e-mails. The subject line was the same for all groups and read "Information about *[name of the mobility budget program]*". Since the sender was the company's team managing the mobility budget, participants had strong incentives to read the e-mails, and hence we interpret the effects reported below as average treatment effects (ATEs) rather than intent-to-treat effects.[17] While the exact wording of all e-mail messages is relegated to Appendix A, we shall summarize below their most important contents and outline potential channels through which they could have altered behavior.

All e-mails were comprised of two paragraphs and were very similar in length. We sent an e-mail ("placebo e-mail") to the control group because the literature has shown that e-mails and other types of messages can serve as a reminder for feasible options that subjects have forgotten about (see, e.g., Allcott and Rogers, 2014; Sonntag and Zizzo, 2015; Castleman and Page, 2015; Karlan et al., 2016; Habla and Muller, 2021). The first paragraph of the placebo e-mail thanked the employees for participating in the mobility budget scheme and provided some information on the scheme itself, e.g., that the budget can be used to pay for different transport modes. It mentioned explicitly that this includes public transportation. The second paragraph provided further information about the program, unrelated to the participant's transport mode choice and use of the budget.

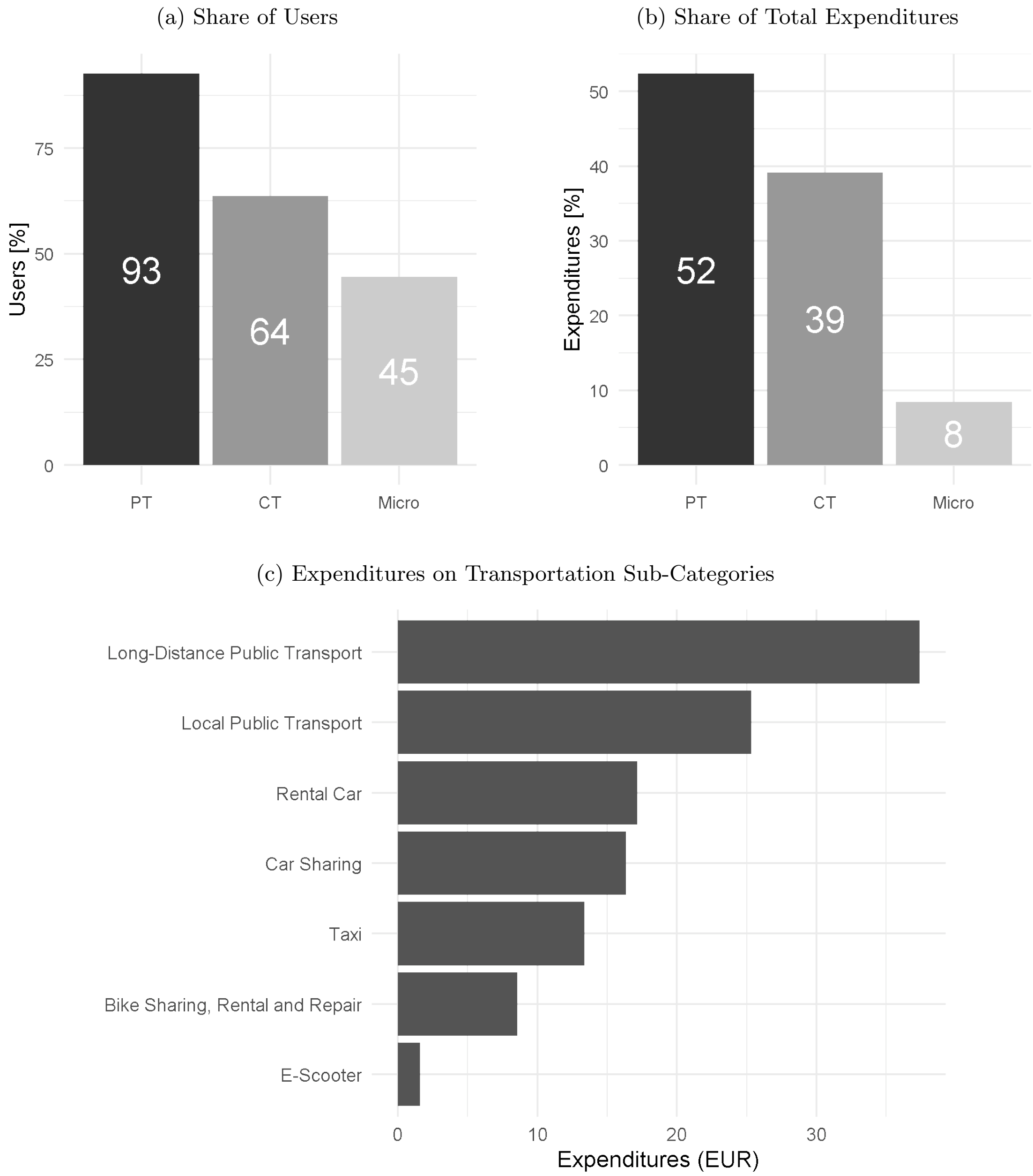
Treatment SC. Treatment group SC received an e-mail that compared, in the first paragraph,

[15]Expenditures for electric sccoters amount to 1.58 euros per month, in contrast to 8.55 euros for bike sharing, bike rentals and repairs.

[16]Subjects were not financially incentivized, but their choices have economic consequences in terms of time and effort costs, opportunity costs of using the budget, and environmental costs.

[17]In robustness tests included in Tables 3 - 6, we find no evidence for stronger treatment effects in a sub-sample of respondents who are likely to be more attentive, which corroborates our approach.

Figure 2: Pre-Treatment Usage of the Mobility Budget



Notes: Users [%] gives the share of participants who used the transport mode at least once during the pre-treatment period. Expenditures [%] gives the share of expenditures for one transport mode during the pre-treatment period, relative to the sum over the three transport modes included. Expenditures (EUR) gives the average monthly pre-treatment expenditures for the sub-categories making up the transport modes included in Panels (a) and (b). PT stands for public transportation, CT stands for car related transportation, and micro stands for micromobility. The average pre-treatment expenditures made by family members (15.30 euros) are excluded in Panel (c) and in the subsequent analysis.

Table 2: Time-Invariant Variables and Pre-Treatment Mobility

	Control		SC		(SC + MA)		
Panel A: Full Sample							
N	150		156		157		
thereof Inactive Users	11		12		12		
thereof Annual Ticket Holders	29		29		29		
Panel B: Sample for the Main Analysis							
Variable	Mean	SD	Mean	SD	Mean	SD	Test
Total Expenditures	113	91	123	90	123	84	F= 0.471
thereof PT Expenditures	56	58	66	61	66	56	F= 0.977
thereof CT Expenditures	46	79	48	76	47	69	F= 0.008
Total Use Count	4	4	5	6	5	4	F= 0.852
thereof PT Use Count	3	3	3	3	3	3	F= 1.863
thereof CT Use Count	0.9	2	2	4	1	3	F= 1.588
% PT Users	95%		91%		92%		$\chi^2 = 0.917$
% CT Users	61%		62%		68%		$\chi^2 = 1.533$
% Gender Male	55%		50%		62%		$\chi^2 = 3.705$
% Urban	45%		46%		41%		$\chi^2 = 0.869$
Annual Budget	2343	174	2351	190	2316	224	F= 1.014
Age	44	9	44	9	42	10	F= 1.413
% High Career Level	54%		49%		43%		$\chi^2 = 2.515$
N	110		115		116		

Statistical significance markers: * p<0.1; ** p<0.05; *** p< 0.01

Notes: The full sample corresponds to the sample included in the randomization. In the sample for the main analysis, inactive users and annual PT ticket users are removed. PT abbreviates public transportation (excluding annual public transportation tickets). Total expenditures exclude expenditures made by household members of the participant and expenditures made outside Germany. Expenditures give the monthly average expenditures for the corresponding transport mode for the time period May 1st - November 1st, 2021. Count gives the average monthly number of expenditure items in the corresponding category during this time. Users indicate whether an individual has used the corresponding transport mode at least once during this time. % Gender Male gives the share of male participants. % Urban gives the share of employees that work at a location classified as urban. Annual Budget gives the average annual mobility budget. Age gives the average age. % High Career Level gives the share of participants on a high career level (according to the company's career level specifications). To test whether the variable of interest varies significantly with the treatment group assigned, a χ^2-test is used for categorical, and an F-test for numerical variables.

1. the share of PT expenditures in the participant's cumulative reimbursements (spanning the time period April 1st, 2021, up to either October 1st for the first two e-mails, November 1st for the third e-mail, and December 1st, 2021, for the last e-mail), and
2. the average share of PT expenditures across participants at all business sites in either rural or urban areas, depending on whether the employee worked at a business location classified as urban or rural, so as to provide a valid reference point for the social comparison.[18]

The second paragraph was identical to the second paragraph of the placebo e-mail, so as to ensure similar total length.

This treatment could have influenced behavior through the following channels: First and foremost, it informed participants about a descriptive norm (Cialdini et al., 1990) for public transportation usage among relevant peers. In the context of a corporate benefit scheme, such as the mobility budget, the behavior displayed by co-workers may convey information about individually optimal behavior to the participant, given that co-workers have similar qualifications and interests. The social environment indeed matters for some participants. In our baseline survey, 42 % of respondents stated that they take the behavior of their social environment, e.g., their colleagues, into account when making decisions (and 43 % disagreed).[19] Furthermore, as Carlsson et al. (2021) point out, "norms can be particularly powerful in unfamiliar situations where decision makers might look to others to receive cues on how to behave" [p. 14]. This might be particularly true for participants in our study, since the majority had been using the mobility budget for only seven months prior to our intervention. Related to this, the social comparison could have contained new information, at least to some participants, on their individual share of PT expenditures, inducing them to re-optimize their transport mode choice. We expected that this channel would be irrelevant in our experiment, as participants could access information about their expenditures for different transport modes at any time online or in a mobile application. However, 38 % of respondents in our endline survey indicated that they would not have known their own PT expenditures without receiving the information provided in the intervention e-mails.[20]

Second, the social comparison could have worked because people care about their status and consumption relative to others (e.g., Solnick and Hemenway, 2005). Specifically, it has been suggested that many employees behave competitively and so "individual performance is positively influenced by feedback on one's relative position in the group" (Charness et al., 2014). If this holds true in our setting, our intervention - albeit anonymous - encourages

[18] In Germany, the degree of urbanization is an important determinant of the transport modes available at a certain place. In particular, access to public transportation is typically better in urban areas (Nobis and Herget, 2020). This inequality between urban and rural areas has frequently been subject to public debate (Vorholz, 2021; Brandau, 2021). Capturing a salient determinant of the size of the choice set for transportation by comparing participants working at business locations with a similar degree of urbanization should make the peer group comparison more relevant.

[19] The exact wording of the question was: *"Please indicate how strongly you agree with the following statement: I consider the behavior of my social environment (e.g. colleagues) when making my own decisions.*

[20] The exact wording of the question was: *"Do you agree with the following statement? Without receiving such information [as displayed in the previous survey question, which was the treatment message for treatment groups SC or SC + MA], I would not know how much I actually spend on public transportation in the mobility budget scheme."* [Yes or No].

public transit use by those participants who learn that they 'under-perform' compared to their peers in terms of the share of the budget spent on public transportation.

Treatment SC + MA. The second treatment group received an e-mail with the same social comparison text as sent to group SC in the first paragraph, but the second paragraph contained a moral appeal instead of the very general text that the control group and group SC received. The moral appeal was framed in the context of climate change and comprised three parts:[21]

1. information about the participant's ability to reduce her transport-related CO_2 emissions by changing transport modes (*"traveling one kilometer by public transportation causes only between 20 and 60 % of CO_2 emissions released when traveling the same distance by car"*),
2. a sentence highlighting the necessity and urgency of mitigating climate change (*"scientific evidence gathered by the United Nations emphasizes that immediate and large-scale efforts to mitigate climate change are needed"*), and
3. the actual moral appeal to use low-emissions transport modes like public transportation (*"in order to combat climate change, you should use public transportation or other low-emissions transport modes whenever possible"*).

In addition to the channels activated by the social comparison, behavior in group SC + MA could be affected via the following channels: First, the moral appeal informs participants about an injunctive norm, i.e., behavior that is socially approved (see, e.g., Cialdini et al., 1990). As compared to a descriptive norm, an injunctive norm illustrates what should be done (and not only what is being done by peers). According to Bicchieri (2005), the combination of a descriptive norm and an injunctive norm expresses a social norm. While compliance with a descriptive norm is "always dictated by self-interest" (Bicchieri, 2005), either because there are *intrinsic* gains from conformity or due to social learning, conformity to social norms can be induced even when compliance with them conflicts with self-interest. We might thus expect reactions to interventions involving social norms even when a purely descriptive norm does not alter behavior.

Second, the moral appeal was framed in the context of climate change. Thus, the utility from choosing low-emissions transport modes could be boosted by impure altruism (the "warm glow" from doing something good for the climate and hence for other people, see Andreoni, 1990). The baseline survey supports this channel in that there are pre-existing preferences for environmentally-friendly transportation decisions in the sample.[22] Given these

[21]Following the norm activation model by Schwartz (1977), the three elements outlined below are meant to increase awareness for a "state of need" for environmental protection, for "actions which could relieve the need" and the "own ability to provide some relief".

[22]80 % of survey respondents in the baseline survey indicated that environmental concerns play a role for their transport mode choice. The exact wording was: *"Please indicate how strongly you agree with the following statement: Environmental concerns play no role for my transport mode choice."* [5-point Likert scale: Totally Agree - Totally Disagree].

pre-existing preferences, communicating an injunctive norm for environmentally-friendly behavior without invoking some kind of warm-glow utility would not be possible, which is why we refrain from trying to separate the two channels.

Finally, note that treatment SC + MA does not provide new information to most participants; 95 % of respondents in our baseline survey stated that they believe that climate change is already happening, and 94 % correctly ranked cars and public transportation in terms of their CO_2 emissions.[23]

4 Results

In this section, we first inspect the development of the main outcome variables (CT and PT expenditures and use) over time, then introduce the regression framework and show the regression results. Finally, we interpret our results and estimate heterogeneous treatment effects.

4.1 Trends

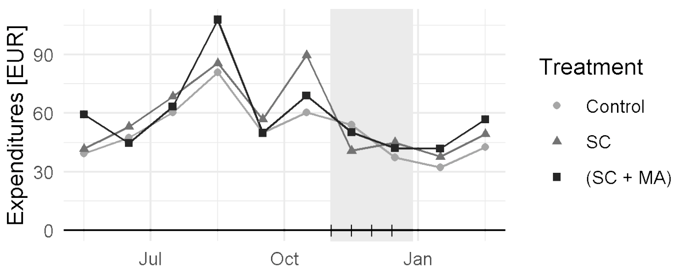
Figure 3 shows the average monthly PT and CT expenditures by treatment arm in Panels (a) and (b), and the shares of participants who used PT and CT at least once in a given month in Panels (c) and (d). The diagram reveals quite some variation in average expenditures and use for all groups. This variation can partly be explained by increased travel activity over the summer months and in autumn because of school holidays (which last approximately six weeks in the summer and between one and two weeks in the fall, depending on the federal state). Furthermore, travel activity in all groups decreased after October 2021 and remained low compared to the pre-treatment averages. These fluctuations are broadly aligned with the course of the COVID-19 pandemic, which severely affected Germany at the beginning of 2021 and again after October 2021 and led to full or partial lock-downs as well as travel restrictions. Fear of infection likely limited participants' disposition towards public transportation. Employees at our partner company were allowed to work from home during the whole observation period. Consequently, the pandemic likely affected travel behavior, which is why it is important to control for such impacts with a randomized control group.

For the pre-treatment period, we see that expenditures for PT and CT (as well as the respective user shares) follow similar trends. Differences between treatment and control groups are somewhat stronger in August and October, i.e., during holiday travel season. In our empirical strategy explained in the next subsection, we rely on a parallel-trends assumption. We corroborate this assumption by providing evidence for parallel pre-trends in Figure 8 in Appendix C. Furthermore, the distribution of individual expenditures during the

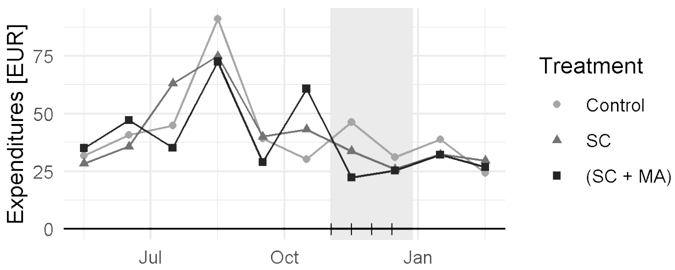
[23] The exact wording of the two related questions was: (i) *"Select the statement with which you agree most: Global climate change is already happening. Global climate change is not happening yet, but will be happening in the next few decades until 2050. Global climate change will not be happening in the next few decades until 2050, but afterwards. Global climate change will not be happening at all."*, (ii) *"Please rank the following means of transport according to their CO_2 emissions per passenger kilometer traveled, starting with the means of transport with the highest CO_2 emissions: Car with internal combustion engine (e.g. gasoline, diesel), (Pure) battery electric vehicle, Local public transport (e.g. bus, suburban train, tram), Long-distance public transport (e.g. train, long-distance coach), Plane."*

Figure 3: Trends in Mobility Expenditures Across Treatment Groups

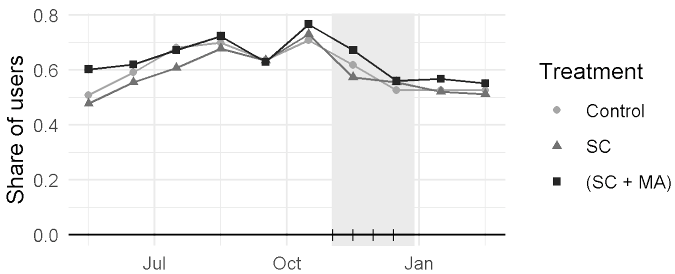
(a) Public Transportation Expenditures



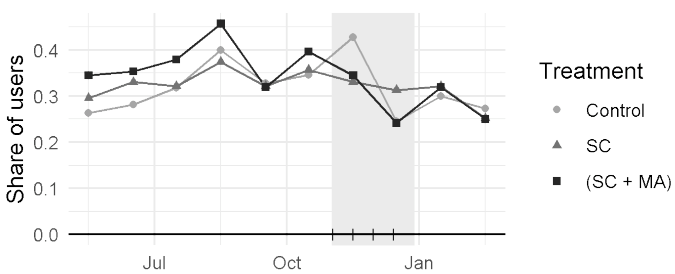
(b) Car-Related Mobility Expenditures



(c) Share of Public Transportation Users



(d) Share of Car-Related Mobility Users



Notes: Panels (a) and (b) depict the average expenditures for the transport mode in the corresponding treatment arm. Panels (c) and (d) illustrate the share of participants who used the transport mode at least once in a given month as a percentage of the size of the treatment arm. The gray area indicates the treatment period. The four marks on the x-axis indicate the dates on which the intervention e-mails were sent.

pre-treatment period in Figure 7 in Appendix B indicates that differences across groups may be driven by some exceptionally large expenditures, e.g., a booking of a rental car for the holidays or a relatively expensive long-distance train ticket. We seek to contain the impact of outliers in our empirical strategy described below.

During the treatment period, two different patterns emerge for CT and PT. PT expenditures of the treatment and control groups continue on similar paths, with a stronger decrease in treatment group expenditures in November being counteracted by a stronger decrease in control group expenditures in December. By contrast, CT expenditures fluctuate a lot more overall. Taking the average over both November and December (the point of intersection between the mark of treatment e-mail no. 3 and the time series), we see that expenditures in the control group increased, while expenditures in the treatment groups decreased compared to the previous two-month period. This could be explained by an increased use of CT when a new wave of the COVID-19 pandemic hit Germany, which is not observed for groups SC and SC + MA.

Panels (c) and (d) of Figure 3 show that the share of users for PT developed in a parallel fashion (Figure 3c) for all three groups, both during the pre-treatment and the treatment period. During the treatment period, we see a decline in the share of PT users, which coincides with the beginning of the COVID-19 wave at the end of October 2021. This decline is less pronounced for the share of CT users. The share of CT users increased in the control group during November 2021 and decreased in both treatment groups. This is offset by a strong decrease in the control group during December. Over the full treatment period, the share of CT users remained roughly constant for both the control group and group SC, while it decreased for group SC + MA.

Based on the inspection of Figure 3, one might anticipate treatment effects for CT expenditures but not necessarily for PT expenditures. The next section tests this conjecture using regression analysis.

4.2 Regression analysis

We employ regression analysis to formally identify potential causal treatment effects on outcome Y_{it} of employee i in month t. We estimate regression equations of the form

$$Y_{it} = \beta_1 \tau_t + \beta_2 \rho_t + \sum_{j \in \{SC,\, SC+MA\}} \left[\beta_3^j T_i^j \times \tau_t + \beta_4^j T_i^j \times \rho_t \right] + \omega_t + c_i + \epsilon_{it} \tag{1}$$

where τ_t and ρ_t are indicator variables for the treatment and post-treatment period, respectively, T_i^j is an indicator for subject i being in treatment arm $j \in \{SC, SC+MA\}$, and ϵ_{it} is an error term. We additionally control for month fixed effects w_t and employee fixed effects c_i. In a sensitivity analysis, we replace the employee fixed effect by individual-specific regressors X_i containing employee characteristics and pre-treatment use of the mobility budget.[24]

[24] X_i includes age, gender, a dummy for whether the location of work is predominantly urban, the size of the individual mobility budget, and the career position in the company, average pre-treatment expenditures and number of expenditure items, as well as the number of weeks a particular means of transport was used, per transport mode.

We estimate this equation for monthly PT and CT expenditures, which contain many zeros but also – particularly for the car-related mobility expenditures – some very large numbers. We thus apply the Inverse Hyperbolic Sine (IHS) transformation (see, e.g., Johnson, 1949; Burbidge et al., 1988) to both of these outcome variables.[25] Unlike continuous regressors, the coefficients from a dummy regressor in a model with an IHS-transformed outcome variable need to be transformed in order to display percentage changes. Following Bellemare and Wichman (2020) and van Garderen and Shah (2002), consistent estimates of the average percentage change in the IHS-transformed expenditures caused by discrete changes in the treatment dummies can be calculated using the following estimator:

$$\widehat{ATE}^{j}(Expenditures) = \exp\left(\hat{\beta}_3^j - 0.5\widehat{Var}(\hat{\beta}_3^j)\right) - 1 \tag{2}$$

The variance of this estimator is given by:

$$\widehat{Var}(\widehat{ATE}^{j}) = \exp(2\hat{\beta}_3^j)\left(\exp(-\widehat{Var}(\hat{\beta}_3^j)) - \exp(-2\widehat{Var}(\hat{\beta}_3^j))\right) \tag{3}$$

Moreover, we estimate eq. (1) for binary variables that indicate whether a given transport category was used at least once in a given month. This is implemented as a linear probability model.[26]

4.2.1 Baseline results

Expenditure shares. Table 3 shows the regression results for percentage changes in IHS-transformed monthly expenditures on public transportation (Panel A) and car-related transportation (Panel B). Model (1) displays our preferred specification from equation (1), a difference-in-differences (DiD) approach with employee fixed effects that control for unobserved heterogeneity. Identification relies on the assumption of parallel trends across the groups in the absence of treatment, which is untestable but highly plausible given randomization.[27]

We observe that the Average Treatment Effect (ATE) on PT expenditures is not significantly different from zero for both treatments during the intervention, which indicates that the e-mails were not successful at increasing PT expenditures. However, for CT expenditures, we do find a significant and sizable decrease of 38 % for treatment SC + MA (significant at the 1 %-level), which corresponds to a reduction by 17.48 euros per month if we take the average pre-treatment control group expenditures for CT as baseline.[28] By contrast, treatment SC did not have any significant effect on CT expenditures. These results imply

[25] For more details on the distribution of expenditures and IHS-transformed expenditures in the pre-treatment period, please refer to Appendix B.

[26] With a set of continuous covariates, this choice would be problematic, as this model can predict probabilities outside the [0,1] interval. However, as our covariates of interest are binary, we think the LPM is suitable due to its simplicity and ease of interpretation. We avoid the above issue by controlling for pre-treatment covariates and mobility patterns using only a small set of dummies (indicators for the quartile of the pre-treatment number of weeks in which the participant used car-related or public transportation).

[27] A plot showing that pre-trends are parallel is available in Figure 8 in Appendix C.

[28] To put this into perspective, this is equivalent to, e.g., the cost of renting a compact class car at a car sharing provider for slightly less than three hours.

Table 3: ATE on Monthly Expenditures

	%-Change Expenditures (Based on IHS-Transformation)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Public Transportation Expenditures					
SC × Treat. Period	−0.07	0.07	−0.04	−0.06	−0.12
	(0.20)	(0.22)	(0.25)	(0.19)	(0.20)
(SC + MA) × Treat. Period	−0.08	0.01	0.20	−0.08	−0.07
	(0.19)	(0.20)	(0.31)	(0.17)	(0.20)
SC × Post Treat. Period	0.02	0.18	0.05	−0.08	−0.01
	(0.22)	(0.26)	(0.29)	(0.19)	(0.24)
(SC + MA) × Post Treat. Period	−0.07	−0.01	0.20	−0.05	0.08
	(0.22)	(0.23)	(0.34)	(0.21)	(0.28)
Observations	3,410	3,410	3,410	4,280	3,140
F Statistic	0.10	263.87***	0.54	0.08	0.15
Panel B: Car Transportation Expenditures					
SC × Treat. Period	−0.17	−0.13	−0.12	−0.13	−0.04
	(0.19)	(0.18)	(0.23)	(0.17)	(0.22)
(SC + MA) × Treat. Period	−0.38***	−0.33**	−0.26	−0.31**	−0.33**
	(0.14)	(0.14)	(0.19)	(0.13)	(0.15)
SC × Post Treat. Period	−0.09	−0.06	−0.03	−0.25	−0.13
	(0.22)	(0.22)	(0.24)	(0.17)	(0.23)
(SC + MA) × Post Treat. Period	−0.20	−0.15	−0.03	−0.19	−0.22
	(0.21)	(0.21)	(0.24)	(0.19)	(0.21)
Observations	3,410	3,410	3,410	4,280	3,140
F Statistic	0.97	1,676.58***	0.35	1.21	0.84
Annual Ticket Users				X	
Survey Particip.					X
Covariates		X			
Individual FE	X			X	X
Month FE	X	X	X	X	X

Notes: Significance markers * p < 0.1, ** p < 0.05, *** p < 0.01. Expenditures are measured as the inverse hyperbolic sine of individual expenditures per month. Coefficients and standard errors are transformed into percentage changes following van Garderen and Shah (2002). SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Annual Ticket Users indicates that participants holding annual public transportation tickets were included. Survey Particip. indicates that only participants who took part in one of the post-treatment surveys were included. Covariates indicates whether the following covariates were included in the regression: participant age group, gender, size of the individual mobility budget, degree of urbanization of the participant's location of work, career level, average monthly pre-treatment expenditures, expenditure items count and number of weeks in which the participant used public transportation, car-based mobility and total mobility. Individual and month FE indicate that the corresponding fixed effects were included.

that the significant reduction in CT expenditures due to the combined treatment cannot be explained by substitution towards public transport. Furthermore, we do not observe any significant effects during the post-treatment period, which implies that even the significant reduction in car-related mobility expenditures is not persistent.

For the effect of treatment SC on PT expenditures in model (1) in Table 3, we can rule out treatment effects bigger than a 32.2 % increase or smaller than a 46.2 % decrease with 95 % confidence. For treatment SC + MA the 95 % confidence interval spans from -45.3 % to 29.2 %. Based on the estimated standard error for the coefficient in treatment SC + MA in model (1), our experiment had 80 % power to detect an effect larger than a change in PT expenditures by 53.2 % (Minimum Detectable Effect Size, MDES in short). For the effect of treatment SC on CT expenditures in model (1), the 95 % confidence interval excludes treatment effects larger than a 20.2 % increase and smaller than a 54.2 % decrease.

In columns (2) - (5) of Table 3, we analyze whether our results are sensitive to changes in the estimation equation and the sample. Model (2) controls for sociodemographic information and pre-treatment mobility use, while model (3) controls only for the treatment assignment. These models thus do not include individual fixed effects. Models (4) and (5) are equivalent to model (1) but consider different sets of participants to check whether our results are robust to the specification of the sample of interest. For model (4), participants who bought an annual PT ticket and thus were excluded from the outset, are added back to the sample. As riding PT has no opportunity costs with respect to their mobility budget, these participants might actually decrease car-related mobility by more than other participants. Finally, model (5) includes only participants who took part in our midline or our endline survey (or in both surveys). Those subjects appear more inclined to read their e-mails and might thus respond more strongly to our treatments. If we were to find stronger results for this group, this would suggest that the other participants actually paid less attention to the e-mails, and what we estimate in model (1) is in fact an intent-to-treat effect.

Across all five specifications, we do not find evidence for treatment effects on PT expenditures (Panel A). Furthermore, the insignificance of treatment effects in model (5), which is based on participants that are likely to be the most attentive towards our e-mails, suggests that this null-result is not driven by a lack of treatment uptake. The results for CT expenditures reported in Panel B show that the significant negative effect of treatment SC + MA is robust to all but one alternative specification. Only specification (3) - the difference-in-means estimator that fails to control for differences in pre-treatment mobility - yields a negative but statistically insignificant effect. As before, we do not observe any significant post-treatment effects for either treatment.

Modal choice. We measure extensive-margin responses to the interventions in terms of a change in the propensity to use PT and CT at least once in a given month, which we recover by estimating (1) as a linear probability model. Table 4 reports the results.

Across specifications, there are no statistically significant differences in the propensity to use PT (Panel A) between the control group and the treatment groups, neither during nor after the intervention. By contrast, Panel B shows that treatment SC + MA reduced the propensity to use CT during the treatment period by 10 % (significant at the 5 %-level). Also in line with the expenditure regressions above, we find no significant effect of treatment SC on the propensity to use CT, and no persistent effects of any treatment in post-treatment months. These findings are robust to alternative specifications analogous to those in Table 3.[29]

[29] The results for both PT and CT are not sensitive to the inclusion of annual ticket users (model (4)) or users who participated in at least one post-treatment survey (model (5)). Across all specifications controlling for pre-treatment mobility, the coefficients stay roughly the same size. For the significant effect of treatment SC + MA on CT, the significance level obtained stays below 10 %, as long as we control for pre-treatment mobility. Controlling only for month fixed effects in model (3), the size of the coefficient decreases, and the effect becomes insignificant.

Table 4: ATE on the Extensive Margin

	Use Indicator (Monthly)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Public Transportation Use					
SC × Treat. Period	0.02	0.02	−0.01	0.01	0.005
	(0.05)	(0.05)	(0.06)	(0.04)	(0.05)
(SC + MA) × Treat. Period	0.01	0.01	0.04	−0.001	0.02
	(0.04)	(0.05)	(0.06)	(0.04)	(0.05)
SC × Post Treat. Period	0.01	0.02	−0.01	0.0005	0.02
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
(SC + MA) × Post Treat. Period	0.001	−0.01	0.03	−0.01	0.03
	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)
Observations	3,410	3,410	3,410	4,280	3,140
R^2	0.0001	0.30	0.001	0.0000	0.0002
Panel B: Car Transportation Use					
SC × Treat. Period	−0.03	−0.04	−0.01	−0.01	0.02
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
(SC + MA) × Treat. Period	−0.10**	−0.08*	−0.04	−0.08**	−0.08*
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
SC × Post Treat. Period	−0.01	−0.03	0.001	−0.04	−0.01
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
(SC + MA) × Post Treat. Period	−0.05	−0.04	−0.002	−0.04	−0.06
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
Observations	3,410	3,410	3,410	4,280	3,140
R^2	0.002	0.31	0.16	0.002	0.002
Annual Ticket Users				*X*	
Survey Particip.					*X*
Covariates		*X*			
Individual FE	*X*			*X*	*X*
Month FE	*X*	*X*	*X*	*X*	*X*

Notes: Significance markers * p < 0.1, ** p < 0.05, *** p < 0.01. Use is an indicator for whether an individual used the corresponding transport mode in a given month. SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Annual Ticket Users indicates that participants holding annual public transportation tickets were included. Survey Particip. indicates that only participants who took part in one of the post-treatment surveys were included. Covariates indicates whether the following covariates were included in the regression: dummies for the quartile of the participants' pre-treatment car-related expenditures and dummies for the quartile of the participant's pre-treatment public transport expenditures. Individual and month FE indicate that the corresponding fixed effects were included.

Interestingly, the decrease in the propensity to use CT induced by treatment effect of SC + MA is not accompanied by a simultaneous increase in the propensity to use PT. This implies that participants either reduced their overall mobility or switched to transport modes other than PT. While we do not observe usage of privately owned cars or bikes, we can assess substitution by looking at the use of micromobility options in the mobility budget.

Substitution towards micromobility and overall expenditures. Panel A of Table 5 reports estimates of the ATE for micromobility expenditures, shedding light on one possible

Table 5: ATE on Micromobility and Total Expenditures

	%-Change Expenditures (Based on IHS-Transformation)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Micromobility Expenditures					
SC × Treat. Period	0.25	0.08	−0.11	0.18	0.12
	(0.16)	(0.12)	(0.12)	(0.14)	(0.15)
(SC + MA) × Treat. Period	0.44**	0.35**	0.26	0.35**	0.33*
	(0.21)	(0.17)	(0.19)	(0.16)	(0.20)
SC × Post Treat. Period	0.21	0.07	−0.14	0.17	0.12
	(0.18)	(0.14)	(0.12)	(0.16)	(0.17)
(SC + MA) × Post Treat. Period	0.07	0.01	−0.06	0.08	0.08
	(0.17)	(0.14)	(0.13)	(0.15)	(0.16)
Observations	3,410	3,410	3,410	4,280	3,140
F Statistic	3.27**	213.41***	2.14*	2.64**	1.46
Panel B: Total Expenditures					
SC × Treat. Period	−0.13	0.04	−0.11	−0.05	−0.04
	(0.22)	(0.24)	(0.25)	(0.22)	(0.25)
(SC + MA) × Treat. Period	−0.18	−0.06	0.07	−0.16	−0.14
	(0.20)	(0.21)	(0.28)	(0.18)	(0.21)
SC × Post Treat. Period	−0.04	0.16	−0.02	−0.11	−0.06
	(0.25)	(0.30)	(0.29)	(0.22)	(0.26)
(SC + MA) × Post Treat. Period	−0.10	−0.003	0.17	−0.02	0.08
	(0.24)	(0.26)	(0.34)	(0.24)	(0.30)
Observations	3,410	3,410	3,410	4,280	3,140
F Statistic	0.20	167.03***	0.37	0.30	0.25
Annual Ticket Users				*X*	
Survey Particip.					*X*
Covariates		*X*			
Individual FE	*X*			*X*	*X*
Month FE	*X*	*X*	*X*	*X*	*X*

Notes: Significance markers * p < 0.1, ** p < 0.05, *** p < 0.01. Expenditures are measured as the inverse hyperbolic sine of individual expenditures per month. Coefficients and standard errors of the regressions in Panel A are transformed into percentage changes following van Garderen and Shah (2002). SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral suasion treatment. Annual Ticket Users indicates that participants holding annual public transportation tickets were included. Survey Particip. indicates that only participants who took part in one of the post-treatment surveys were included. Covariates indicates whether the following covariates were included in the regression: participant age group, gender, size of the individual mobility budget, degree of urbanization of the participant's location of work, career level, average monthly pre-treatment expenditures, expenditure items count and number of weeks in which the participant used public transportation, car-based mobility and total mobility. Individual and month FE indicate that the corresponding fixed effects were included.

substitution channel between transport modes. In our preferred specification, model (1), micromobility expenditures increased in response to treatment SC + MA by 44 % during the treatment, roughly matching the size of the opposite effect found for CT expenditures in Table 3. We regard this as suggestive evidence that substitution away from CT towards micromobility can explain the negative effect observed for CT and the missing effect on PT. The reduction in expenditures for CT could also reflect a reduction in the overall expenditures in the mobility budget. The estimates obtained for total expenditures, reported in Panel B of Table 5, lack statistical significance, however. Thus, we cannot reject the hypothesis that the total mobility demand of the participants remained unchanged.[30]

Table 6: ATE on the Intensive Margin

	%-Change Expenditures (Based on IHS-Transformation)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Public Transportation Expenditures						
SC × Treat. Period	−0.24	−0.07	−0.10	−0.19	−0.23	−0.22
	(0.18)	(0.21)	(0.25)	(0.19)	(0.20)	(0.18)
(SC + MA) × Treat. Period	−0.09	0.03	0.22	−0.11	−0.05	−0.08
	(0.21)	(0.23)	(0.33)	(0.20)	(0.24)	(0.20)
SC × Post Treat. Period	−0.01	0.21	0.17	−0.13	−0.07	0.15
	(0.25)	(0.31)	(0.36)	(0.21)	(0.26)	(0.32)
(SC + MA) × Post Treat. Period	−0.10	−0.01	0.19	−0.12	−0.05	−0.02
	(0.23)	(0.26)	(0.37)	(0.22)	(0.28)	(0.27)
Observations	2,670	2,670	2,670	3,280	2,480	2,210
F Statistic	0.38	94.76***	0.66	0.27	0.25	0.44
Panel B: Car Transportation Expenditures						
SC × Treat. Period	−0.21	−0.18	0.09	−0.18	0.21	−0.05
	(0.30)	(0.29)	(0.46)	(0.28)	(0.47)	(0.35)
(SC + MA) × Treat. Period	−0.37*	−0.42**	−0.35	−0.34	−0.30	−0.47**
	(0.21)	(0.19)	(0.25)	(0.21)	(0.24)	(0.19)
SC × Post Treat. Period	−0.11	−0.12	0.26	−0.28	0.06	0.24
	(0.38)	(0.36)	(0.52)	(0.29)	(0.47)	(0.61)
(SC + MA) × Post Treat. Period	−0.28	−0.35	−0.24	−0.13	−0.17	−0.25
	(0.29)	(0.25)	(0.30)	(0.31)	(0.34)	(0.37)
Observations	1,420	1,420	1,420	1,720	1,320	1,050
F Statistic	0.36	159.97***	0.97	0.44	0.51	0.69
Annual Ticket Users				X		
Survey Particip.					X	
Treatment Period Users						X
Covariates		X				
Individual FE	X			X	X	X
Month FE	X	X	X	X	X	X

Notes: Significance markers * p < 0.1, ** p < 0.05, *** p < 0.01. Regressions include only individuals who used the corresponding transport mode during the period September 13th - November 1st, 2022. Expenditures are measured as the inverse hyperbolic sine of individual expenditures per month. Coefficients and standard errors are transformed into percentage changes following van Garderen and Shah (2002). SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Annual Ticket Users indicates that participants holding annual public transportation tickets were included. Survey Particip. indicates that only participants who took part in one of the post-treatment surveys were included. Treatment Period Users indicates that only subjects who used the corresponding transport mode during the treatment period were included. Covariates indicates whether the following covariates were included in the regression: participant age group, gender, size of the individual mobility budget, degree of urbanization of the participants' location of work, career level, average monthly pre-treatment expenditures, expenditure items count and number of weeks in which the participant used public transportation, car-based mobility and total mobility. Individual and month FE indicate that the corresponding fixed effects were included.

[30]We analyze the sensitivity of our results in Table 5 using the same specifications as in Tables 3 and 4. For the effects on expenditures for micromobility, the significant effects found for treatment SC + MA are robust as long as we control for pre-treatment mobility. The insignificance of the effect of both treatments on total monthly expenditures (Panel B) is robust across all specifications.

Intensive-margin response. To evaluate intensive-margin reactions in detail, we analyze how expenditures for the transport mode changed among those participants who used the corresponding transport mode between mid-September (the end of the summer travel period) and the beginning of the treatment period. The results for intensive-margin reactions in Table 6 are not very different from the overall reactions reported in Table 3. There are no significant effects for PT expenditures, and for CT, there is no significant effect of treatment SC. The ATE of treatment SC + MA is again negative and of similar magnitude as in Table 3. However, the effect is estimated with less precision and significant only at the 10 %-level, as the intensive-margin sample contains only 142 "active" CT users during that period vs. a total of 341 users in Table 3. Again, we do not find any significant differences between the treatment groups and the control group during the post-treatment period. In model (6), we estimate the same specification as in model (1), but include only participants who actively used CT both *before* and *during* the treatment period. This specification more narrowly identifies intensive-margin reactions. The effect of SC + MA is increased by 10 percentage points and significance is boosted to the 5 %-level, suggesting that the intensive-margin reaction to treatment SC + MA is strong.

4.2.2 Further robustness checks

This subsection summarizes the main insights obtained from a number of additional analyses that we ran to further assess the robustness of our main results. The reader is referred to Appendix C for more details.

First, we re-estimate all regressions using data on the full observation period, including the months of April 2021 and March 2022 which were omitted in the main analysis. The estimated treatment effects, reported in Tables 7 - 9 in Appendix C, are similar in magnitude, and the significance of the coefficients is robust to the inclusion of the two months.

Second, we investigate whether our interventions also had an impact on the number of booked expenditure items. Since this is count data, we estimate a Poisson Maximum-Likelihood model with fixed effects using the FIXEST package in R (Bergé, 2018) with otherwise identical specifications as for expenditures. The results are reported in Table 10 in Appendix C. We observe that for PT, there are again no significant effects of both interventions during the treatment period. For CT, we now estimate significant (at the 5 %-level) and large effects in the treatment period for *both* treatments (and not only for treatment SC + MA as before), while there are again no significant effects in the post-treatment period. As expected, reductions in the number of booked car-related mobility items were larger for treatment SC + MA than for treatment SC alone, amounting to up to 63 %, which corresponds to less than one additional CT expenditure item, based on the pre-treatment average monthly CT use of the control group (Table 2).

For reference, Table 11 in Appendix C reports the results for the IHS-transformed monthly expenditures in levels, i.e., before transforming the coefficient estimates and standard errors into the estimators for percentage changes used in our main results in Table 3. The results are qualitatively and quantitatively very similar. The estimated effect of treatment SC + MA remains significant at the 5 %-level in our preferred specification.

4.3 Summary and interpretation of results

Altogether, we do not find any significant effects of the two treatments on the use of PT. A plausible reason for this is that participants do not have much scope to further increase their use of PT, probably because they had been using PT for suitable trips already quite frequently before the intervention and cannot switch to PT for their other trips. In addition, participants might have been reluctant to use PT more frequently due to the course of the COVID-19 pandemic in Germany, where cases surged in late October 2021.

By contrast, we find robust evidence that combining a moral appeal with a social comparison significantly reduces car-related mobility expenditures by 38 %. Compared to prior findings on social comparisons in the transportation domain (Kristal and Whillans, 2020; Gravert and Collentine, 2021; Götz et al., 2022), this effect is big. The large effect size is credible in our setting for three reasons. First, in contrast to previous studies in the transportation domain, our intervention combined a social comparison with a moral appeal.[31] Since we find that the social comparison alone is not sufficient to change transportation behavior, our results for treatment SC + MA are not directly comparable to those previous studies. Previous research on water conservation by Ferraro and Price (2013) also finds much larger effects for an intervention combining a social comparison with a moral appeal than earlier studies using a social comparison in isolation. Second, transportation decisions in the mobility budget are more flexible in the short term, as there are no lock-in effects: while transport mode choices are typically determined by long-term decisions such as the purchase of a car or an annual public transportation ticket, participants in a mobility budget can more flexibly decide between transport modes on a day-to-day basis. Third, the treatment SC + MA is effective in our setting as it links subjects' transportation behavior back to a pre-existing injunctive norm among large parts of the sample: In the baseline survey, 44 % of respondents expressed the belief that their social environment (e.g., colleagues) expects them to act environmentally friendly.[32]

The observed effect is explained by adjustments both at the intensive (how much participants using the transport mode spent) and extensive margins (how many participants used the transport mode). However, the effects disappear in the post-treatment period. This suggests that an insistent message with an injunctive norm can indeed have a short-term effect and reduce car-related transportation in our sample. This result is in line with a recent meta-analysis on the effectiveness of behavioral interventions in reducing car use (Semenescu et al., 2020), which finds that interventions targeting social, cultural and moral norms are the

[31] As the moral appeal was sent by the participants' employer, messenger effects (Dolan et al., 2012) could also play a role: If the messages had been sent by another source, participants might have reacted differently. However, in the endline survey, 93 % of respondents stated that the fact that the messages were sent by their employer did not alter their reactions. The moral appeal could also have worked through guilt aversion (Battigalli and Dufwenberg, 2009; Balafoutas and Sutter, 2017) if employees felt obliged to use public transportation or other climate-friendly modes of transport more frequently because they believe that their employer expects them to do so (which is related to messenger effects). Given the size of the company (several thousands of employees), it seems unlikely that this is the case, the more so because the mobility budget is managed by a separate entity in the company and individual behavior is thus not observed by the immediate superior (and this would be known by almost every participant).

[32] The exact wording was: *"My social environment (e.g. colleagues) expects me to act environmentally friendly. [5-point Likert scale: Totally agree - Do not agree at all]"* (44 % agreed, 30 % disagreed).

most effective. Although participants in treatment group SC + MA use car-related transportation less, we do not observe the anticipated substitution towards public transportation. One potential reason for this could be that it is relatively easy for participants to forego car-related transport or even avoid the whole trip. Another explanation is that the replaced trips are now made with transport modes outside of the mobility budget, such as a private car or a private bike, or transport modes counted as micromobility within the mobility budget. We find some evidence that there was substitution towards the use of micromobility within the mobility budget, but do not find evidence for reduced overall expenditures.

4.4 Heterogeneous treatment effects

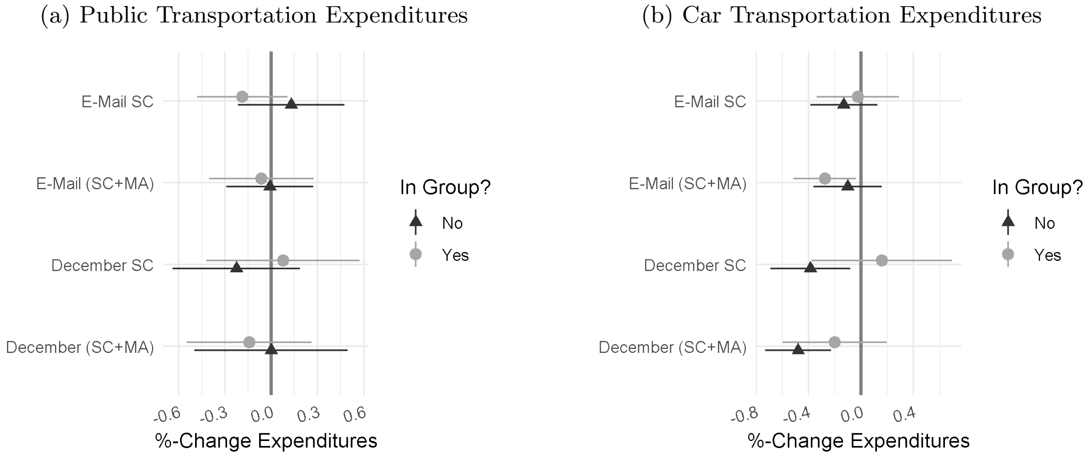
In this subsection, we examine whether there are heterogeneous treatment effects across time (during the intervention), for different groups of users, and for the individual transport modes included in public and car-related transportation.

Temporal heterogeneity. We begin by examining the time dimension of our treatment within our regression framework. We distinguish between (i) weeks in which the e-mails were sent and weeks in which no e-mails were sent, and (ii) the treatment month (November vs. December).

Table 12 in Appendix C as well as Figure 4 report the results for these two regressions. As can be seen in Panel A of Figure 4, the two treatments did not significantly change PT expenditures for any of the time periods considered. For car-related transportation, Panel B reveals that the significant effect observed for treatment SC + MA for the whole treatment period is driven by the reaction during the first month of the treatment period. During November, participants in group SC + MA reduced their CT expenditures by 47.9 % (significant at the 5 %-level). Furthermore, the difference between treatment effects in November vs. December is statistically significant (5 %-level), and the treatment effect vanishes completely in December. We interpret this as participants habituating to our e-mail messages. With recurrence, the participants seem to get used to the interventions received and react less. Also, the treatment effects are not very persistent and disappear after a month. This lack of persistence is further supported by the results for weeks in which an e-mail was sent. Treatment SC + MA had a significant (5 %-level) effect during weeks in which an e-mail was sent but not during subsequent weeks without e-mails. This is a clear pattern of "action and backsliding" (Allcott and Rogers, 2014), whereby participants react to an intervention immediately, but go back to their previous behavior after a short period of time, in our case after one week.

Heterogeneity in individual characteristics/behavior. The impact of the treatments may vary with employee characteristics and mobility behavior. We investigate (i) heterogeneity between urban and rural business sites, (ii) heterogeneity between individuals with below- and above-median expenditures on a given transportation mode in the pre-treatment period, and (iii) whether a participant received a "strong" or a "weak" social comparison. To this end, we define a measure of treatment intensity below.

Figure 4: Heterogeneous Treatment Effects Over Time



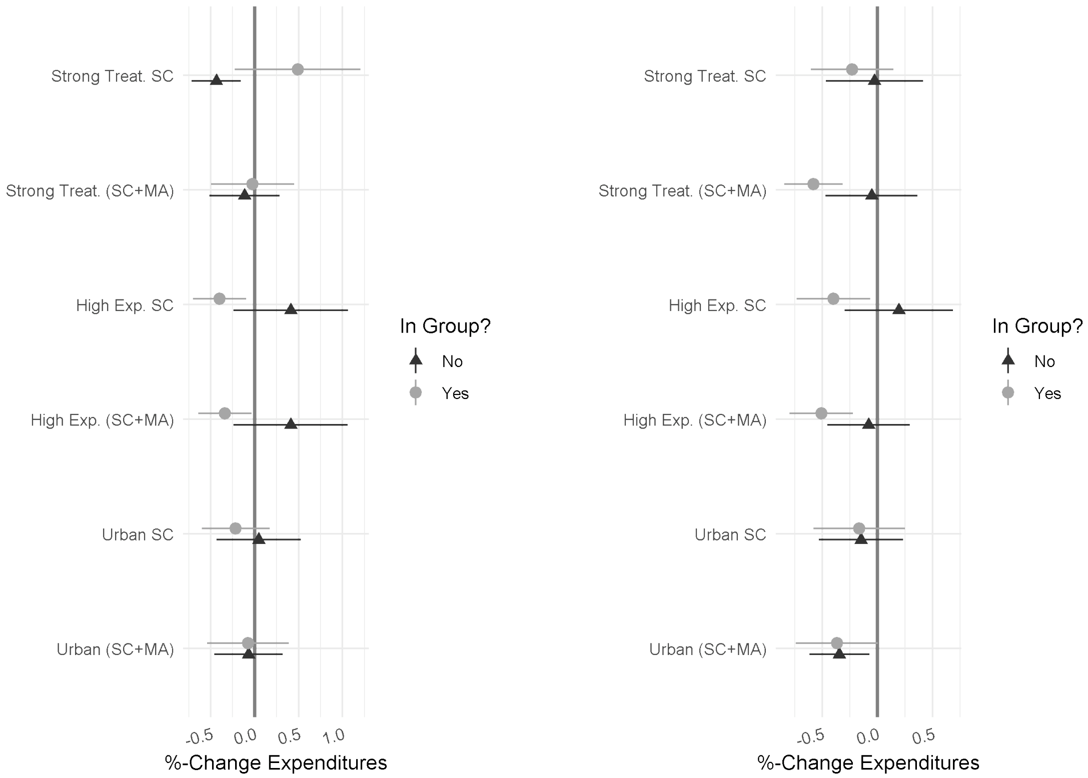
Notes: Treatment effects are estimated according to our main specification for the IHS-transformed expenditures outlined in Section 4.2, but adding an interaction between the treatment dummy and the covariate of interest. The coefficients and standard errors are transformed to percentage changes following van Garderen and Shah (2002). E-Mail is an identifier for expenditures which were made during a week in which an intervention e-mail was sent, aggregated on the monthly level. December is an identifier that expenditures were made during the month December. Coefficient estimates and 95 % confidence intervals are displayed.

Table 13 in Appendix C summarizes the results for the treatment effect heterogeneity, and Figure 5 displays the 95 % confidence intervals for the different groups. Starting from the bottom of Figure 5, we see that differences between participants working at urban vs. rural business locations do not seem to influence the effects of our treatments. Notice that the sub-group effects of treatment SC + MA on CT expenditures in Panel B are of almost the same size as the main effect in Table 3. The irrelevance of the participant's location of work is somewhat surprising, since one would expect that the two groups have very different access to various transport modes. Given the rather coarse classification of rural and urban, it seems likely that access to public transportation varies more with the participants' place of *residence* than with their place of *work*. Unfortunately, we do not observe this distinction in the available data.

The middle part of Figure 5 shows that subjects with above-median expenditures (titled "High Exp.") in the pre-treatment period reduced their expenditures on PT and CT significantly in response to both treatments. The sub-group effects for participants with below- and above-median pre-treatment expenditures are significantly different from each other (at the 1 %-level for PT and at the 5 %-level for CT, see Table 13 in the appendix). Combined with the insignificant positive coefficients in Panel A of Table 13 for PT expenditures for participants with below-median expenditures, these findings suggest counteracting effects. This points to the presence of a so-called "boomerang effect" (Schultz et al., 2007); participants using PT more than the median during the pre-treatment period are discouraged, while participants using PT less than the median are encouraged to use public transport more often. Interestingly, for PT we see boomerang effects for both treatments in Panel (a) of Figure 5. In previous studies, these effects typically vanished after an injunctive message (as in treatment SC + MA) was added. This is not the case in the present study.

Figure 5: Treatment Effect Heterogeneity Across Sub-Groups

(a) Public Transportation Expenditures (b) Car Transportation Expenditures



Notes: Treatment effects are estimated according to our main specification for the IHS-transformed expenditures outlined in Section 4.2, but adding an interaction between the treatment dummy and the covariate of interest. The coefficients and standard errors are transformed to percentage changes following van Garderen and Shah (2002). Strong Treat. is an identifier for participants who received 3 or more e-mails with a social comparison stating that they had spent a smaller share of their expenditures on public transportation than their peer group. High Exp. is an identifier for participants with pre-treatment expenditures for the corresponding transport mode larger than the pre-treatment median. Urban is an identifier for participants working at a business location in an urban area. Coefficient estimates and 95 % confidence intervals are displayed.

This sub-group analysis focuses on absolute expenditures but does not reflect the intensity of the social comparison, which was getting at PT expenditure *shares* relative to the peer group. For example, consider a participant who spends 600 euros on PT and 400 euros on CT in the pre-treatment period. Given these expenditures, this participant would fall in the high expenditures group for both transport modes. However, the participant will receive a "weak" social comparison in the sense that she will be told that her PT expenditure share is already higher than the average in her peer group.[33] Therefore, we construct a measure of treatment intensity based on how often a participant gets such "weak" social comparisons. In particular, we define a "weak treatment" as receiving a weak comparison at least three out of four times (note that every participant received four e-mails). Conversely, the group with a "strong treatment" comprises subjects that received a weak comparison at most once.

[33]The average PT expenditures shares were 59 % (urban business location) vs. 58 % (rural business location) in the last e-mail.

For this distinction to work, we drop 13 subjects that received two weak comparisons.[34]

In the upper part of Figure 5, we analyze sub-group effects for participants receiving strong vs. weak social comparisons. In Panel B, we observe that the significant effect of treatment SC + MA on CT is driven by participants receiving a strong treatment. We observe a significant reduction (5 %-level) in expenditures for the strong treatment group (-57.8 %), but not for the weak treatment group. This is in line with expectations, as those participants are repeatedly made aware that their environmental performance is worse than the performance of their peer group, and should thus react the strongest to the norm-based intervention. We do not observe any significant sub-group effects for treatment SC in Panel B. In Panel A, we again observe a boomerang effect of treatment SC on PT expenditures among participants receiving a weak treatment (-43.7 %, significant at the 5 %-level). We observe an insignificant coefficient with opposite sign for treatment SC, implying that counteracting effects could explain part of the observed null-effect for this treatment in Table 3 in the appendix. For treatment SC + MA, we do not observe any significant sub-group effects on PT in Panel A of Figure 5.

Heterogeneity between transport modes. Third, we analyze treatment effects for the individual transport modes included in the categories public and car-related transportation. Tables 14 and 15 in Appendix C present the results for the different transport modes, and Figure 6 displays the corresponding 95 % confidence intervals for the estimated percentage change in expenditures. For PT the treatment effects in Panel (a) of Figure 6 remain insignificant, no matter whether we consider long-distance PT or local PT. For car-related transport, treatment SC + MA has significant treatment effects only for the category "Taxi", which contains taxi rides, UBER rides and the use of other ride-hailing and ride-sharing services. The effect has the same sign and roughly the same magnitude as the effect for total CT expenditures (treatment SC + MA reduced expenditures for taxis by 28.1 %). This indicates that the treatment effect observed for total CT expenditures is driven by reductions in expenditures in the category Taxi. This finding is in line with expectations, as we would expect stronger treatment effects for the transport modes summarized in this category, since the typical taxi ride might have closer (and more) substitutes than, e.g., a rental car.

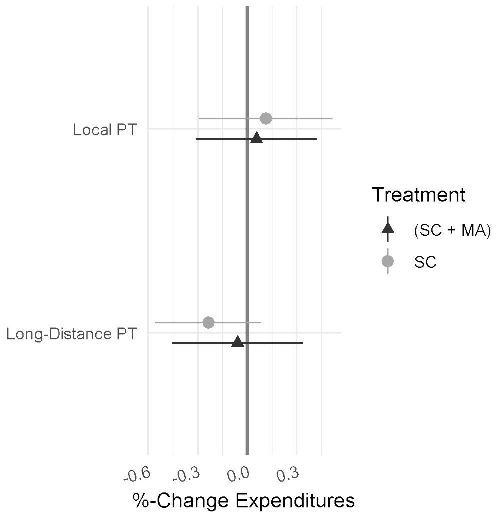
5 Conclusion

Using a randomized field experiment, we find that a social comparison alone does not lead to a significant change in travel behavior within the mobility budget scheme. This stands in stark contrast to results obtained by studies in areas other than transportation, where social comparisons did have persistent effects (Ferraro et al., 2011; Allcott and Rogers, 2014).

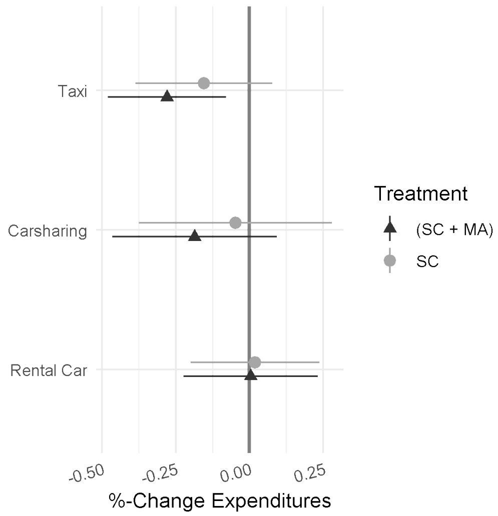
[34]Note that the constructed measure is partly endogenous, since whether participants get treated with above- or below-average comparisons can be partly influenced, at least from the second e-mail onward. For the first treatment message, we had, by mistake, not included expenditures for long-distance trains in the calculated expenditure share for public transportation. This mistake was corrected from the second e-mail onward. Thus, one change in the treatment intensity can be expected for some participants. 96 out of 341 participants changed their treatment intensity once. Only 13 participants changed their treatment intensity twice.

Figure 6: Treatment Effects for Transport Mode Sub-Categories

(a) Public Transportation Expenditures



(b) Car Transportation Expenditures



Notes: Treatment effects are estimated according to our main specification for the IHS-transformed expenditures outlined in Section 4.2, but adding an interaction between the treatment dummy and the covariate of interest. The coefficients and standard errors are transformed to percentage changes following van Garderen and Shah (2002). Local PT is an identifier for monthly expenditures for local public transport tickets. Long-Distance PT is an identifier for monthly expenditures for long-distance public transport tickets. Taxi is an identifier for monthly expenditures for taxis, shuttle pooling, ride-sharing or ride-hailing services. Carsharing is an identifier for monthly expenditures made for car-sharing services. Rental Car is an identifier for monthly expenditures for rental cars. Coefficient estimates and 95 % confidence intervals are displayed.

Explanations for why social comparisons fail to achieve the desired effects in our setting include (i) boomerang effects (for which we also find some evidence) that lead to counteracting effects for different parts of the sample, (ii) disregard of how other people, in particular colleagues, travel, (iii) strong habits that are difficult to change, and (iv) the lack of appropriate adjustment margins in our specific setting (as are present, e.g., in the context of energy conservation where one-off investments can increase energy efficiency permanently).

By contrast, we do find evidence that combining a social comparison with a moral appeal, framed in the context of climate change, significantly altered mobility behavior within the mobility budget. Specifically, it decreased car-related mobility expenditures and frequency of use, particularly mostly for taxis and other ride-hailing and ride-sharing services. It increased expenditures on micromobility but not on public transport. Total expenditures did not change significantly, meaning that our interventions would not be suitable if the goal were to reduce the costs of the mobility budget.

The lack of a substitution towards public transit is a striking result. From a policy perspective, it is important to know whether this generalizes to other settings. We believe that this is not necessarily the case because, in our field experiment, several factors coincided which were conducive to finding a null-result. First, the onset of a new wave of the COVID-19 pandemic during the treatment phase may have deterred subjects from using public transit in order to minimize infection risks. Second, many participants already used public transport frequently before the intervention and thus had little scope to use this mode of transport more often. Third, for participants not included in the previous category, public transport options may have been either unavailable or poor substitutes for car-related mobility. Future research will show how influential these external factors are for our results.

Our finding that a moral appeal can drive mobility choices away from car-related mobility is highly policy relevant as those mobility options are the most harmful in terms of CO_2 emissions, a fact that is known to participants in our experiment. The upside of this is that participants pondered their mobility options and were aware that they can contribute to reducing greenhouse gas emissions by forgoing car-based trips. The downside is that those changes were short-lived. The treatment effects we observe were driven by reactions in the first treatment month and in the week of an intervention e-mail. Thus, for participants to change their mobility habits, the experimenter would probably have to repeat moral appeals over longer time periods, or even indefinitely. We leave this as a topic for future research.

An important question is whether the moral appeal is effective also when it is not accompanied by a social comparison. While our heterogeneity analysis provides clues that this might be the case, we could not analyze this directly due to the limited sample size. This question is thus also left as a topic for future research.

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Appendix A: Details on the E-Mail Messages

The subject line for all treatment arms (including the control group) read "Information about *[name of the program]*". The e-mails were sent by the company's team managing the program. This part of the appendix documents the exact wording of the e-mails.
For the social comparison treatment (SC), the e-mail read:

> *Dear* [participant's first name] *,*
> *Thank you for participating in the program* [name of the program] *.*
>
> *We thought you might be interested in the following information:*
> *Until ⟨October 1st, November 1st, December 1st⟩, you have spent* [individual share] *% of your expenditures on public transportation. The average participant at our business sites in predominantly ⟨urban/rural⟩ areas has spent* [average share] *% on public transportation.*
>
> *Judging from your feedback so far, the* [name] *program is a success: The majority of participants in the survey we ran in June 2021 stated that they were satisfied with the program and that they would recommend it to a colleague. We are happy that many of you participated in this survey, as your feedback allows us to further improve the program.*
>
> *We hope you are enjoying the benefits of the program.*
> *Your* [name of the company's team managing the mobility budget]

For the combined social comparison and moral appeal treatment (SC + MA), the e-mail read:

> *Dear* [participant's first name] *,*
> *Thank you for participating in the program* [name of the program] *.*
>
> *We thought you might be interested in the following information:*
> *Until ⟨October 1st, November 1st, December 1st⟩, you have spent* [individual share] *% of your expenditures on public transportation. The average participant at our business sites in predominantly ⟨urban/rural⟩ areas has spent* [average share] *% on public transportation.*
>
> *The German Environmental Protection Agency estimates that traveling one kilometer by public transportation causes only between 20 and 60 % of CO_2 emissions released when traveling the same distance by car (see Umweltbundesamt, 2019). Scientific evidence gathered by the United Nations emphasizes that immediate and large-scale efforts to mitigate climate change are needed (see UN, 2021). To combat climate change, you*

should use public transportation or other low-emissions transport modes[35] *whenever possible.*

We hope you are enjoying the benefits of the program.
Your [name of the company's team managing the mobility budget]

Additionally, either treatment message contained a postscript:
P.S.:

Public transportation expenditures are defined as the sum over all expenditures in the following categories: "Local Passenger Traffic (ÖPNV, e.g. Bus, S-Bahn, RB etc.)", "Train local traffic (IRE, RE, RB, S-Bahn)", "Train long-distance traffic (IC, ICE, EC, Bahncard 25 & 50)", "Long-Dist. Traffic: Ways Home-Work (Single or Monthly Tickets)", "Local Passenger Traffic Annual Tickets (ÖPNV, e.g. Bus, S-Bahn)", "Long-Distance Coach", "Long-Dist. Traffic: Ways Home-Work (Annual Tickets)".

Expenditures of "Eligible Family Members" are excluded when calculating total expenditures.

Zero public transportation expenditure shares are also displayed for participants who did not hand in any expenditures before December 1st.

Thus, the two messages differed in the second paragraph. Particularly treatment SC + MA was intended to increase the use of public transport (and other climate-friendly alternatives) and decrease the use of car-related mobility, respectively.

The control group received the following two e-mails. The first e-mail was sent in the first three treatment rounds. The e-mail was updated for the last round after the company's unit in charge of the mobility budget scheme received complaints by employees that they get the same e-mail repeatedly. When the placebo message was updated, the second paragraph of the message for treatment group SC was updated, as well.

Dear [participant's first name] ,
Thank you for participating in the program [name of the program] .

We thought you might be interested in the following information:
We offer a mobility budget to employees at our business locations in Germany, both in urban and more rural areas. You can use the budget to pay for different transport modes, including public transportation.

[35]The words "other low-emissions transport modes" were added from the second e-mail onwards because some participants in the program had complained internally that they used to ride bikes, which is also an environmentally-friendly mode of transport.

As you know, [name of the company] *implemented a mobility budget to provide employees with the flexibility to choose between different transport modes. The centerpiece for a mobility budget is a mobile application for invoicing and reimbursing the costs incurred.* [some information on the success of the application that is used for the reimbursement process] *.*

We hope you are enjoying the benefits of the program.
Your [name of the company's team managing the mobility budget]

Dear [participant's first name] *,*
Thank you for participating in the program [name of the program] *.*

We thought you might be interested in the following information:
At [name of the company] *, we believe that our colleagues know best which transport mode best suits their needs. With* [name of the company] *'s mobility budget, you can pay for different transport modes, including public transportation and many more.*

Judging from your feedback so far, the [name] *program is a success: The majority of participants in the survey we ran in June 2021 stated that they were satisfied with the program and that they would recommend it to a colleague. We are happy that many of you participated in this survey, as your feedback allows us to further improve the program.*

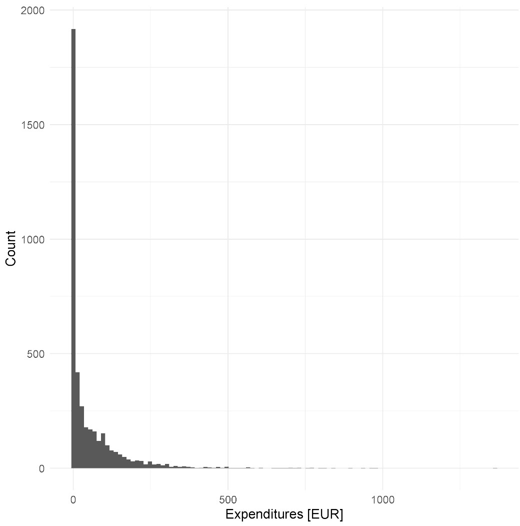
We hope you are enjoying the benefits of the program.
Your [name of the company's team managing the mobility budget]

By providing information on the popularity and the success of the program (or the application used for the reimbursement process outside of the company) in the second paragraph, behavior could be altered, as well. For the effect of the social comparison, however, this cannot play a role, as the message to group SC also contained this paragraph. We find it unlikely that being informed about the success of the program would encourage participants to use the budget more frequently or switch to certain modes of transport.

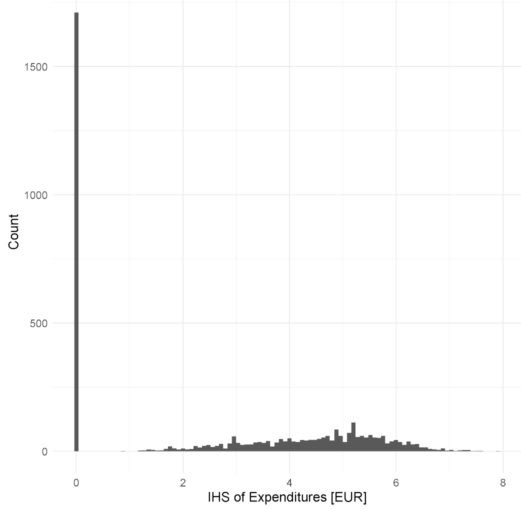
Appendix B: Details on Expenditures per Participant and Month

Figure 7: Individual × Month Expenditures During the Pre-Treatment Period

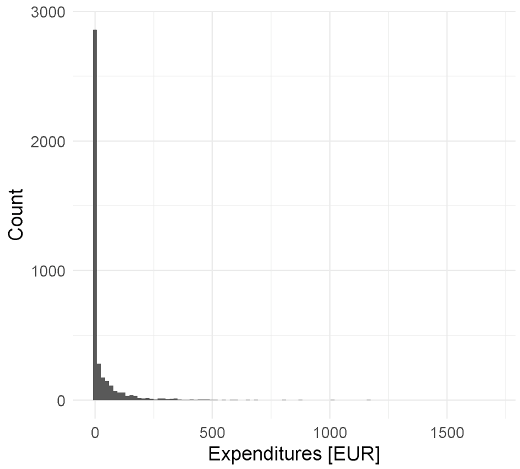
(a) Expenditures Public Transportation



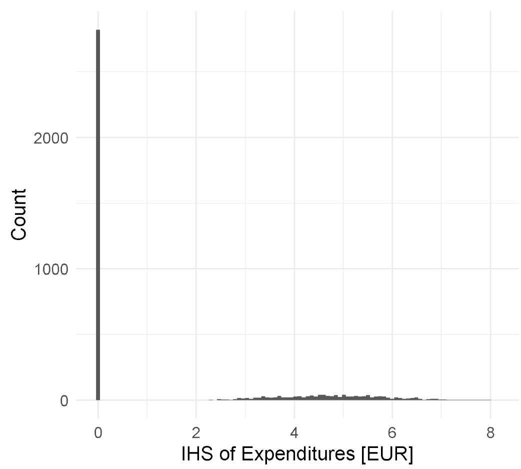
(b) IHS-Transformed Exp. Public Transp.



(c) Expenditures Car-Related Transportation



(d) IHS-Transformed Exp. Car Transp.



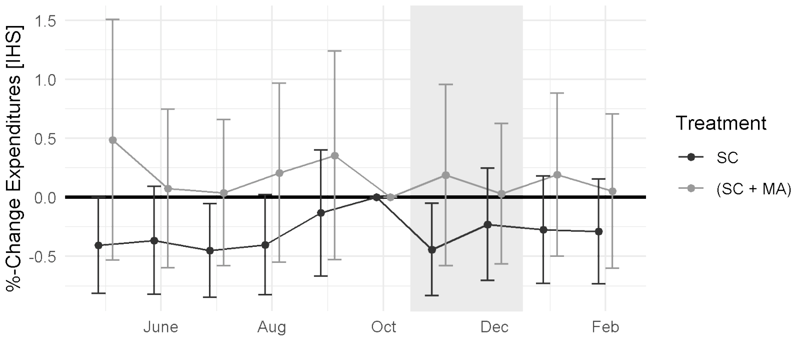
Notes: Panels (a) and (c) show histograms of all monthly expenditures for the corresponding transport modes made by the 341 participants in the sample, whereas Panels (b) and (d) show histograms of the IHS-transformed monthly expenditures.

The individual × month observations for the outcomes public and car-related transportation expenditures are created by aggregating all expenditure items within a week (as the treatment was assigned as bi-weekly e-mails) and then aggregating these weekly observations to a month. We observe 13132 expenditure items for PT and 6177 expenditure items for car-related transportation for our main sample. After removing expenditure items booked outside Germany, we are left with 11951 expenditure items for PT and 5087 expenditure items for car-related transportation. As can be seen in Panels (a) and (c) in Figure 7, these expenditure items display a very right-skewed distribution, with many small expenditure items and very few very large expenditure items. These very large expenditure items could drive the results of the experiment. The largest expenditure item for car-related transportation is 2204.80 euros, which is almost half as large as the average monthly pre-treatment car-related expenditures for the entire control group ($43 * 139 = 5977$ euros). To reduce the potential impact of very large expenditure items, and to estimate proportional effects, we apply an inverse hyperbolic sine (IHS) transformation to the expenditure outcomes. For completeness, the histograms for the IHS-transformed outcomes are displayed in Panels (b) and (d) of Figure 7.

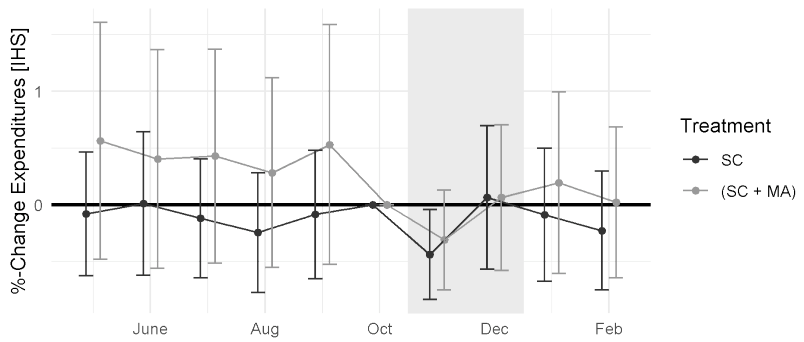
Appendix C: Additional Graphs and Tables

Figure 8: Event Study Graph for Differences in Expenditures

(a) Expenditures (IHS-Transformed) Public Transportation



(b) Expenditures (IHS-Transformed) Car-Related Transportation



Notes: Event study plots showing coefficients + confidence intervals of a regression of the IHS-transformed expenditures for the corresponding transport modes on interaction of dummies for the treatment groups with dummies for all months during our observation period. October 2021 (the last month pre-treatment) is the left-out category. Regressions include individual and time fixed effects. Standard errors are clustered by individual. Coefficients and standard errors are transformed into percentage changes following van Garderen and Shah (2002).

Table 7: ATE on Monthly Use, Including the First and Last Month of the Budget Year

	Use Indicator (Monthly)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Public Transportation Use					
SC × Treat. Period	0.03	0.02	−0.01	0.01	0.01
	(0.05)	(0.05)	(0.06)	(0.04)	(0.05)
(SC + MA) × Treat. Period	0.01	0.01	0.04	−0.01	0.01
	(0.04)	(0.05)	(0.06)	(0.04)	(0.05)
SC × Post Treat. Period	0.04	0.03	0.004	0.02	0.03
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
(SC + MA) × Post Treat. Period	−0.004	−0.01	0.03	−0.02	0.01
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	4,092	4,092	4,092	5,136	3,768
R^2	0.001	0.27	0.0005	0.0004	0.0003
Panel B: Car Transportation Use					
SC × Treat. Period	−0.03	−0.04	−0.01	−0.01	0.01
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
(SC + MA) × Treat. Period	−0.10**	−0.07*	−0.04	−0.09**	−0.09*
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
SC × Post Treat. Period	−0.02	−0.03	−0.01	−0.04	−0.01
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
(SC + MA) × Post Treat. Period	−0.07	−0.05	−0.01	−0.06	−0.08
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
Observations	4,092	4,092	4,092	5,136	3,768
R^2	0.003	0.28	0.0003	0.002	0.003
Annual Ticket Users				*X*	
Survey Particip.					*X*
Covariates		*X*			
Individual FE	*X*			*X*	*X*
Month FE	*X*	*X*	*X*	*X*	*X*

Notes: Significance markers * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Use is an indicator whether an individual used the corresponding transport mode in a given month. SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Annual Ticket Users indicates that participants holding annual public transportation tickets were included. Survey Particip. indicates that only participants who took part in one of the post-treatment surveys were included. Covariates indicates whether the following covariates were included in the regression: dummies for the quartile of the participants pre-treatment car-related expenditures and dummies for the quartile of the participants pre-treatment public transport expenditures. Individual and month FE indicate that the corresponding fixed effects were included.

Table 8: ATE on Monthly Expenditures, Including the First and Last Month of the Budget Year

	%-Change Expenditures (Based on IHS-Transformation)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Public Transportation Expenditures					
SC × Treat. Period	0.003	0.08	−0.04	−0.04	−0.11
	(0.21)	(0.22)	(0.25)	(0.19)	(0.20)
(SC + MA) × Treat. Period	−0.07	0.02	0.20	−0.13	−0.14
	(0.19)	(0.21)	(0.31)	(0.16)	(0.19)
SC × Post Treat. Period	0.07	0.17	0.03	−0.06	−0.01
	(0.24)	(0.25)	(0.27)	(0.19)	(0.23)
(SC + MA) × Post Treat. Period	−0.16	−0.11	0.09	−0.17	−0.08
	(0.20)	(0.20)	(0.28)	(0.18)	(0.23)
Observations	4,092	4,092	4,092	5,136	3,768
F Statistic	0.46	251.27***	0.38	0.37	0.16
Panel B: Car Transportation Expenditures					
SC × Treat. Period	−0.16	−0.14	−0.12	−0.14	−0.07
	(0.19)	(0.18)	(0.23)	(0.17)	(0.21)
(SC + MA) × Treat. Period	−0.40***	−0.32**	−0.26	−0.34***	−0.35**
	(0.14)	(0.14)	(0.19)	(0.13)	(0.15)
SC × Post Treat. Period	−0.09	−0.07	−0.04	−0.21	−0.11
	(0.21)	(0.19)	(0.21)	(0.17)	(0.21)
(SC + MA) × Post Treat. Period	−0.23	−0.16	−0.05	−0.22	−0.28
	(0.19)	(0.18)	(0.21)	(0.17)	(0.19)
Observations	4,092	4,092	4,092	5,136	3,768
F Statistic	1.21	1,568.19***	0.38	1.38	1.15
Annual Ticket Users				*X*	
Survey Particip.					*X*
Covariates		*X*			
Individual FE	*X*			*X*	*X*
Month FE	*X*	*X*	*X*	*X*	*X*

Notes: Significance markers * p < 0.1, ** p < 0.05, *** p < 0.01. Expenditures are measured as the inverse hyperbolic sine of individual expenditures per month. Coefficients and standard errors are are transformed into percentage changes following van Garderen and Shah (2002). SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Annual Ticket Users indicates that participants holding annual public transportation tickets were included. Survey Particip. indicates that only participants who took part in one of the post-treatment surveys were included. Covariates indicates whether the following covariates were included in the regression: participant age group, gender, size of the individual mobility budget, degree of urbanization of the participant's location of work, career level, average monthly pre-treatment expenditures, expenditure items count and number of weeks in which the participant used public transportation, car-based mobility and total mobility. Individual and month FE indicate that the corresponding fixed effects were included.

Table 9: ATE on the Intensive Margin, Including the First and Last Month of the Budget Year

	%-Change Expenditures (Based on IHS-Transformation)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Public Transportation Expenditures						
SC × Treat. Period	−0.20	−0.06	−0.10	−0.17	−0.21	−0.20
	(0.19)	(0.22)	(0.25)	(0.19)	(0.20)	(0.19)
(SC + MA) × Treat. Period	−0.08	0.03	0.22	−0.16	−0.11	−0.09
	(0.21)	(0.23)	(0.33)	(0.19)	(0.22)	(0.20)
SC × Post Treat. Period	0.07	0.27	0.21	−0.05	0.05	0.15
	(0.28)	(0.32)	(0.35)	(0.23)	(0.28)	(0.34)
(SC + MA) × Post Treat. Period	−0.20	−0.12	0.07	−0.24	−0.14	−0.17
	(0.21)	(0.23)	(0.31)	(0.19)	(0.24)	(0.24)
Observations	3,204	3,204	3,204	3,936	2,976	2,652
F Statistic	0.80	91.51***	0.73	0.61	0.48	0.88
Panel B: Car Transportation Expenditures						
SC × Treat. Period	−0.27	−0.18	0.09	−0.24	0.10	−0.20
	(0.28)	(0.29)	(0.46)	(0.26)	(0.42)	(0.29)
(SC + MA) × Treat. Period	−0.41**	−0.41**	−0.35	−0.39**	−0.34	−0.53***
	(0.20)	(0.19)	(0.25)	(0.19)	(0.22)	(0.17)
SC × Post Treat. Period	−0.31	−0.27	0.06	−0.39*	−0.14	−0.12
	(0.27)	(0.28)	(0.39)	(0.23)	(0.36)	(0.42)
(SC + MA) × Post Treat. Period	−0.39*	−0.40**	−0.31	−0.26	−0.29	−0.33
	(0.22)	(0.20)	(0.24)	(0.24)	(0.26)	(0.30)
Observations	1,704	1,704	1,704	2,064	1,584	1,260
F Statistic	0.67	206.89***	0.94	0.81	0.57	0.55
Annual Ticket Users				*X*		
Survey Particip.					*X*	
Treatment Period Users						*X*
Covariates		*X*				
Individual FE	*X*			*X*	*X*	*X*
Month FE	*X*	*X*	*X*	*X*	*X*	*X*

Notes: Significance markers * p < 0.1, ** p < 0.05, *** p < 0.01. Regressions include only individuals who used the corresponding transport mode during the period September 13th - November 1st, 2022. Expenditures are measured as the inverse hyperbolic sine of individual expenditures per month. Coefficients and standard errors are transformed into percentage changes following van Garderen and Shah (2002). SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Annual Ticket Users indicates that participants holding annual public transportation tickets were included. Survey Particip. indicates that only participants who took part in one of the post-treatment surveys were included. Treatment Period Users indicates that only subjects who used the corresponding transport mode during the treatment period were included. Covariates indicates whether the following covariates were included in the regression: participant age group, gender, size of the individual mobility budget, degree of urbanization of the participant's location of work, career level, average monthly pre-treatment expenditures, expenditure items count and number of weeks in which the participant used public transportation, car-based mobility and total mobility. Individual and month FE indicate that the corresponding fixed effects were included.

Table 10: ATE on the Monthly Count of Expenditure Items

	Expenditure Items (Poisson Pseudo-MLE)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Public Transportation Expenditure Items					
SC × Treatment Period	−0.05	0.00	−0.06	−0.04	−0.08
	(0.14)	(0.14)	(0.18)	(0.13)	(0.15)
(SC + MA) × Treatment Period	−0.13	−0.07	0.08	−0.20	−0.24
	(0.13)	(0.13)	(0.17)	(0.15)	(0.18)
SC × Post Treatment Period	−0.17	−0.11	−0.19	-0.28^{*}	-0.32^{*}
	(0.16)	(0.16)	(0.21)	(0.15)	(0.17)
(SC + MA) × Post Treatment Period	−0.25	−0.22	−0.04	-0.30^{*}	−0.33
	(0.16)	(0.16)	(0.20)	(0.17)	(0.20)
Observations	3410	3410	3410	4280	3140
Panel B: Car Transportation Expenditure Items					
SC × Treatment Period	-0.54^{**}	-0.35^{*}	0.03	-0.40^{**}	−0.20
	(0.21)	(0.19)	(0.29)	(0.19)	(0.21)
(SC + MA) × Treatment Period	-0.63^{**}	-0.42^{**}	−0.31	-0.54^{**}	−0.36
	(0.26)	(0.20)	(0.28)	(0.26)	(0.26)
SC × Post Treatment Period	−0.18	−0.08	0.39	−0.17	−0.19
	(0.31)	(0.31)	(0.30)	(0.29)	(0.33)
(SC + MA) × Post Treatment Period	0.00	0.20	0.32	0.10	0.06
	(0.36)	(0.33)	(0.32)	(0.31)	(0.36)
Observations	3410	3410	3410	4280	3140
Annual Ticket Users				*X*	
Survey Particip.					*X*
Covariates		*X*			
Individual FE	*X*			*X*	*X*
Month FE	*X*	*X*	*X*	*X*	*X*

Notes: Significance markers * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Expenditure items are the number of purchase acts per individual and month. SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Annual Ticket Users indicates that participants holding annual public transportation tickets were included. Survey Particip. indicates that only participants who took part in one of the post-treatment surveys were included. Covariates indicates whether the following covariates were included in the regression: participant age group, gender, size of the individual mobility budget, degree of urbanization of the participants location of work, career level, average two-monthly pre-treatment expenditures, expenditure items count and number of weeks in which the participant used public transportation, car-based mobility and total mobility. Individual and month FE indicate that the corresponding fixed effects were included. Standard errors are clustered by individual.

Table 11: IHS-Transformed Outcome, Coefficients not Transformed into Percentage Changes

	Expenditures (IHS-Transformed)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Public Transportation Expenditures					
SC $\times$ Treat. Period	-0.05	0.09	-0.003	-0.05	-0.10
	$p = 0.84$	$p = 0.67$	$p = 1.00$	$p = 0.82$	$p = 0.66$
(SC + MA) $\times$ Treat. Period	-0.06	0.03	0.22	-0.07	-0.05
	$p = 0.79$	$p = 0.90$	$p = 0.42$	$p = 0.73$	$p = 0.82$
SC $\times$ Post Treat. Period	0.04	0.19	0.09	-0.06	0.02
	$p = 0.85$	$p = 0.40$	$p = 0.76$	$p = 0.78$	$p = 0.95$
(SC + MA) $\times$ Post Treat. Period	-0.05	0.01	0.23	-0.03	0.11
	$p = 0.85$	$p = 0.96$	$p = 0.44$	$p = 0.90$	$p = 0.67$
Observations	3,410	3,410	3,410	4,280	3,140
F Statistic	0.08	81.04***	0.57	0.05	0.16
Panel B: Car Transportation Expenditures					
SC $\times$ Treat. Period	-0.15	-0.12	-0.09	-0.12	-0.01
	$p = 0.51$	$p = 0.57$	$p = 0.73$	$p = 0.56$	$p = 0.96$
(SC + MA) $\times$ Treat. Period	-0.45**	-0.38*	-0.27	-0.36*	-0.37
	$p = 0.05$	$p = 0.07$	$p = 0.31$	$p = 0.07$	$p = 0.12$
SC $\times$ Post Treat. Period	-0.06	-0.04	-0.002	-0.27	-0.10
	$p = 0.81$	$p = 0.88$	$p = 1.00$	$p = 0.26$	$p = 0.71$
(SC + MA) $\times$ Post Treat. Period	-0.18	-0.13	0.001	-0.18	-0.21
	$p = 0.50$	$p = 0.59$	$p = 1.00$	$p = 0.45$	$p = 0.46$
Observations	3,410	3,410	3,410	4,280	3,140
F Statistic	1.34	81.03***	0.38	1.54	1.07
Annual Ticket Users				*X*	
Survey Particip.					*X*
Covariates		*X*			
Individual FE	*X*			*X*	*X*
Month FE	*X*	*X*	*X*	*X*	*X*

Notes: Significance markers * p < 0.1, ** p < 0.05, *** p < 0.01. Expenditures are measured as the inverse hyperbolic sine of individual expenditures per month. SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Annual Ticket Users indicates that participants holding annual public transportation tickets were included. Survey Particip. indicates that only participants who took part in one of the post-treatment surveys were included. Covariates indicates whether the following covariates were included in the regression: participant age group, gender, size of the individual mobility budget, degree of urbanization of the participant's location of work, career level, average monthly pre-treatment expenditures, expenditure items count and number of weeks in which the participant used public transportation, car-based mobility and total mobility. Individual and month FE indicate that the corresponding fixed effects were included.

Table 12: Temporal Treatment Effect Heterogeneity

	December	E-Mail
	(1)	(2)
Panel A: Public Transportation Expenditures		
SC	−0.22	0.13
	(0.28)	(0.16)
(SC + MA)	0.03	0.002
	(0.26)	(0.15)
SC × Time 1	0.32	−0.32
	(0.34)	(0.28)
(SC + MA) × Time 1	−0.15	−0.05
	(0.33)	(0.28)
Linearcomb. SC	0.1	−0.19
	(0.25)	(0.19)
Linearcomb. (SC + MA)	−0.12	−0.05
	(0.25)	(0.19)
Observations	3,410	6,820
Panel B: Car Transportation Expenditures		
SC	−0.46*	−0.13
	(0.26)	(0.15)
(SC + MA)	−0.62**	−0.10
	(0.25)	(0.15)
SC × Time 1	0.63**	0.12
	(0.29)	(0.25)
(SC + MA) × Time 1	0.43	−0.21
	(0.30)	(0.24)
Linearcomb. SC	0.18	−0.01
	(0.24)	(0.17)
Linearcomb. (SC + MA)	−0.19	−0.31*
	(0.26)	(0.16)
Observations	3,410	6,820

Notes: Significance markers * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Expenditures are measured as the inverse hyperbolic sine of individual expenditures per month. SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Time 1 is an indicator for the month December in column 1 and for weeks in which an e-mail was sent to the participants in column 2.

Table 13: Treatment Effect Heterogeneity Across Sub-Groups

	(1)	(2)	(3)
Panel A: Public Transportation Expenditures			
SC	0.07	0.37	-0.54^{**}
	(0.24)	(0.24)	(0.26)
(SC + MA)	-0.05	0.37	-0.09
	(0.22)	(0.24)	(0.23)
SC × Group 1	-0.28	-0.85^{***}	0.97^{***}
	(0.30)	(0.28)	(0.29)
(SC + MA) × Group 1	0.01	-0.76^{***}	0.11
	(0.29)	(0.27)	(0.29)
Linearcomb. SC	-0.21	-0.48^{**}	$0.43*$
	(0.26)	(0.24)	(0.23)
Linearcomb. (SC + MA)	-0.04	$-0.38*$	0.01
	(0.27)	(0.23)	(0.26)
Observations	3,410	3,410	3,280
Panel B: Car Transportation Expenditures			
SC	-0.13	0.20	0.0003
	(0.23)	(0.21)	(0.23)
(SC + MA)	-0.40^{*}	-0.06	-0.03
	(0.21)	(0.21)	(0.23)
SC × Group 1	-0.01	-0.67^{**}	-0.23
	(0.28)	(0.26)	(0.27)
(SC + MA) × Group 1	-0.02	-0.62^{**}	-0.80^{***}
	(0.29)	(0.25)	(0.27)
Linearcomb. SC	-0.15	$-0.47*$	-0.23
	(0.26)	(0.27)	(0.25)
Linearcomb. (SC + MA)	-0.42	-0.68^{***}	-0.83^{***}
	(0.29)	(0.26)	(0.25)
Observations	3,410	3,410	3,280

Notes: Significance markers * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Expenditures are measured as the inverse hyperbolic sine of individual expenditures per month. SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Group 1 is an indicator for working in an urban business location in column 1, for above-median expenses for the corresponding transport mode in column 2 and for a high treatment intensity for the social comparison in column 3. A high treatment intensity is defined as receiving a message stating that the peer group used a larger share of their budget for public transportation in at least 3 out of 4 treatment messages, the opposite is a low treatment intensity, where participants were below average in less than one message.

Table 14: ATE for Public Transportation

	Expenditures (IHS-Transformed)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Long-Distance Public Transportation Expenditures					
SC × Treat. Period	−0.24	−0.21	−0.14	−0.22	−0.37
	(0.22)	(0.21)	(0.22)	(0.21)	(0.23)
(SC + MA) × Treat. Period	−0.04	0.09	0.28	−0.08	−0.16
	(0.22)	(0.21)	(0.23)	(0.20)	(0.23)
SC × Post Treat. Period	0.06	0.08	0.16	−0.07	−0.04
	(0.19)	(0.19)	(0.21)	(0.19)	(0.21)
(SC + MA) × Post Treat. Period	0.16	0.27	0.48**	0.17	0.21
	(0.23)	(0.22)	(0.23)	(0.21)	(0.26)
Observations	3,410	3,410	3,410	4,280	3,140
F Statistic	0.55	32.84***	2.29*	0.72	1.05
Panel B: Local Public Transportation Expenditures					
SC × Treat. Period	0.12	0.21	0.05	0.05	0.09
	(0.19)	(0.19)	(0.24)	(0.17)	(0.20)
(SC + MA) × Treat. Period	0.07	0.02	0.16	0.01	0.03
	(0.18)	(0.18)	(0.23)	(0.17)	(0.19)
SC × Post Treat. Period	0.02	0.12	−0.05	−0.01	0.02
	(0.19)	(0.21)	(0.26)	(0.17)	(0.20)
(SC + MA) × Post Treat. Period	−0.12	−0.19	−0.04	−0.13	−0.03
	(0.19)	(0.21)	(0.25)	(0.18)	(0.21)
Observations	3,410	3,410	3,410	4,280	3,140
F Statistic	0.42	80.10***	0.19	0.28	0.09
Annual Ticket Users				*X*	
Survey Particip.					*X*
Covariates		*X*			
Individual FE	*X*			*X*	*X*
Month FE	*X*	*X*	*X*	*X*	*X*

Notes: Significance markers * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Expenditures are measured as the inverse hyperbolic sine of individual expenditures per month. SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Annual Ticket Users indicates that participants holding annual public transportation tickets were included. Survey Particip. indicates that only participants who took part in one of the post-treatment surveys were included. Covariates indicates whether the following covariates were included in the regression: participant age group, gender, size of the individual mobility budget, degree of urbanization of the participant's location of work, career level, average monthly pre-treatment expenditures, expenditure items count and number of weeks in which the participant used public transportation, car-based mobility and total mobility. Individual and month FE indicate that the corresponding fixed effects were included.

Table 15: ATE for Car-Related Transportation

	Expenditures (IHS-Transformed)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Expenditures for Rental Cars					
SC × Treat. Period	0.02	0.05	0.02	−0.01	−0.10
	(0.11)	(0.11)	(0.10)	(0.09)	(0.10)
(SC + MA) × Treat. Period	0.01	0.06	0.05	−0.001	−0.07
	(0.12)	(0.11)	(0.11)	(0.09)	(0.12)
SC × Post Treat. Period	0.02	0.05	0.01	−0.09	−0.05
	(0.13)	(0.12)	(0.11)	(0.11)	(0.13)
(SC + MA) × Post Treat. Period	−0.01	0.04	0.03	−0.07	−0.04
	(0.14)	(0.12)	(0.12)	(0.12)	(0.14)
Observations	3,410	3,410	3,410	4,280	3,140
F Statistic	0.02	9.61***	0.07	0.21	0.18
Panel B: Expenditures for Car Sharing					
SC × Treat. Period	−0.03	−0.10	−0.13	−0.11	−0.12
	(0.18)	(0.18)	(0.20)	(0.15)	(0.18)
(SC + MA) × Treat. Period	−0.19	−0.16	−0.14	−0.14	−0.25
	(0.18)	(0.18)	(0.19)	(0.15)	(0.19)
SC × Post Treat. Period	0.10	0.03	0.01	−0.08	0.05
	(0.17)	(0.18)	(0.18)	(0.16)	(0.19)
(SC + MA) × Post Treat. Period	−0.12	−0.10	−0.08	−0.13	−0.08
	(0.19)	(0.18)	(0.18)	(0.17)	(0.20)
Observations	3,410	3,410	3,410	4,280	3,140
F Statistic	1.10	38.16***	0.34	0.56	0.97
Panel C: Expenditures for Taxis					
SC × Treat. Period	−0.16	−0.06	0.07	−0.02	0.19
	(0.14)	(0.16)	(0.22)	(0.13)	(0.14)
(SC + MA) × Treat. Period	−0.32**	−0.25	−0.13	−0.26**	−0.11
	(0.14)	(0.16)	(0.20)	(0.13)	(0.15)
SC × Post Treat. Period	−0.23	−0.15	−0.01	−0.16	−0.15
	(0.18)	(0.18)	(0.20)	(0.17)	(0.19)
(SC + MA) × Post Treat. Period	−0.12	−0.07	0.06	−0.02	−0.10
	(0.19)	(0.18)	(0.20)	(0.17)	(0.20)
Observations	3,410	3,410	3,410	4,280	3,140
F Statistic	1.77	74.71***	0.43	1.94	1.49
Annual Ticket Users				*X*	
Survey Particip.					*X*
Covariates		*X*			
Individual FE	*X*			*X*	*X*
Month FE	*X*	*X*	*X*	*X*	*X*

Notes: Significance markers * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Expenditures are measured as the inverse hyperbolic sine of individual expenditures per month. SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Annual Ticket Users indicates that participants holding annual public transportation tickets were included. Survey Particip. indicates that only participants who took part in one of the post-treatment surveys were included. Covariates indicates whether the following covariates were included in the regression: participant age group, gender, size of the individual mobility budget, degree of urbanization of the participant's location of work, career level, average monthly pre-treatment expenditures, expenditure items count and number of weeks in which the participant used public transportation, car-based mobility and total mobility. Individual and month FE indicate that the corresponding fixed effects were included.

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