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Can Social Comparisons and Moral Appeals Induce a Modal Shift Towards Low-Emission Transport Modes?

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Can social comparisons and moral appeals induce a modal shift towards low-emission transport modes?*

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Abstract

Under pressure to reduce CO_2 emissions, companies are beginning to replace subsidized company car schemes with so-called mobility budgets that employees can spend on leisure and commuting trips, using a broad range of transport modes. Given their novelty, little is known about how mobility budgets should be designed to encourage sustainable choices. Since prices play a limited role in this subsidized setting, our study focuses on behavioral interventions. In a field experiment with 341 employees of a large German company, we test whether social comparisons, either in isolation or in combination with a climate-related moral appeal, can change the use of different means of transportation. We find strong evidence for a reduction in car-related mobility in response to the combined treatment, which is driven by changes in taxi and ride-sharing services. This is accompanied by substitution towards micromobility, i.e., transport modes such as shared e-scooters or bikes, but not towards public transport. We do not find any effects of the social comparison alone. Our results demonstrate that small, norm-based nudges can change transportation behavior, albeit for a limited time.

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 to reduce 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. Low taxes on company cars thwart CO_2 reduction targets at several levels: 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 CO_2 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.[1] For a period of eight weeks, subjects received bi-weekly e-mail messages containing either a nudge (treatment) or general information about the mobility budget (control). Treated subjects were nudged via a social comparison and an additional moral appeal to reduce emissions from individual transportation choices. Both treatments promise to induce substitution away from car-related mobility: 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

[1] A previous version of this paper was made publicly available as a ZEW Discussion Paper (Gessner et al., 2023).

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 this 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' propensity to use car-related mobility, such as car sharing, ride-sharing or ride-hailing services, by 10 %-points (in terms of the probability to use this mode of transport at least once per month). This reduction was not accompanied by a substitution towards public transport, suggesting that participants either substituted transportation modes other than public transport for car-related mobility, or reduced their overall mobility. In line with the first explanation (substitution), the combined treatment increased the propensity to use micromobility by 10 %-points. Overall use of transportation services in the mobility budget did not change significantly in response to our treatments. The social comparison alone had no significant effects on the propensity to use public and car-related transport (or overall mobility), and effects of this treatment on micromobility were not robust to alternative specifications. Furthermore, we do not find any statistically significant effects on expenditures for the various transport modes above, owing to strong variability in expenditures (and corresponding large standard errors) across subjects. Almost all effects we do observe disappear in the two-month post-treatment period, suggesting that mobility habits are difficult to change.

To shed light on potential channels explaining the observed effects, we estimate additional treatment effects (i) for different time periods during treatment, (ii) on individual transport modes, and (iii) for relevant sub-groups within our sample. The first exercise reveals that the significant treatment effect was driven by reactions in the first half of the intervention period. This suggests that participants got used to the e-mail messages and dampened their reaction with recurrence, instead of forming new habits. Regarding (ii), we find that the significant effects of the combined treatment are driven by reductions in the use of ride-hailing and ride-sharing services, such as UBER and taxi rides, whereas the significant effects for micromobility are driven by an increase in the use of e-scooters. This suggests that the combined treatment led to a modal shift mainly from ride-hailing and ride-sharing services to e-scooter rides. Finally, with respect to point (iii), we do not find differential treatment effects for participants working at urban vs. rural locations of work. We do find, however, that participants who received messages with the information that they had spent less on public transport as compared to their peer group, reacted more strongly on *both* treatments. Compared to the average treatment effect over the full sample, the treatment effect for participants receiving such a strong social comparison is larger in magnitude across both treatments for (almost) all transport modes, implying that the relative position within the peer group matters both for the social comparison both in isolation and in combination with a moral appeal.

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; Götz et al., 2022), 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 the use of the three transport mode categories. In Section 5, we present evidence on different mechanisms underlying our results from accompanying surveys. Section 6 concludes.

2 Related literature

Nudges are often employed to counteract deviations from rational behavior, such as bounded rationality or cognitive biases (Thaler and Sunstein, 2009). 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).[2] In addition, nudges are becoming increasingly popular as a behavioral substitute for regulation of traditional economic problems, such as environmental externalities. These so-called "green nudges" (Carlsson et al., 2021) can be used to alter transportation choices that are *collectively* sub-optimal. In this paper, we draw on research in economics, transportation, psychology and

[2]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).

behavioral sciences to analyze whether particular "green nudges" can help mitigate externalities from fossil fuel-based mobility.

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 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. 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). 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).

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 weak performance of nudges in the transportation context compared to other environmental domains, Gravert and Collentine (2021) conjecture that "switching transport options comes at a higher effort and even monetary cost", implying that individuals might stick more to the status quo, i.e., 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. In fact, moral appeals have been shown to enhance energy and water conservation efforts (Ferraro et al., 2011; Ferraro and Price, 2013; Ito et al., 2018), and to be effective in domains other than conservation (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 the effects of such a "strong social norm treatment" on individual transportation choices.

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, in that we conduct a natural field experiment using expenditure and usage data, and because these papers focus on other research questions: Hintermann et al. (2021) analyze the effect of providing information about external costs of different mobility choices. 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 their paper, the social comparison is one of many "gamification features" that participants can select, whereas our study directly administers the moral appeal and the social comparison to *all* participants in the corresponding treatment groups.

Finally, the paper contributes to the literature on interventions to improve environmental outcomes in a corporate setting. For instance, Egebark and Ekström (2016) evaluate, among others, a moral appeal message sent to university employees to cut back on printing and paper use. They do not find any effect of this message. Further papers in this line of research include, e.g., Gosnell et al. (2020), Hoffmann and Thommes (2020) and Fanghella et al. (2022).

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, fuel and/or electricity. Private car use is explicitly allowed in exchange for monthly deductions from the pre-tax salary. Because they financially benefit both employees and employers, company car schemes have been adopted by many German firms, to the point that approximately one fifth of newly registered vehicles are company cars (German Environmental Protection Agency, 2021).[3] Since companies own or lease these vehicles, their carbon emissions - be they work-related or not - count towards corporate carbon emissions.

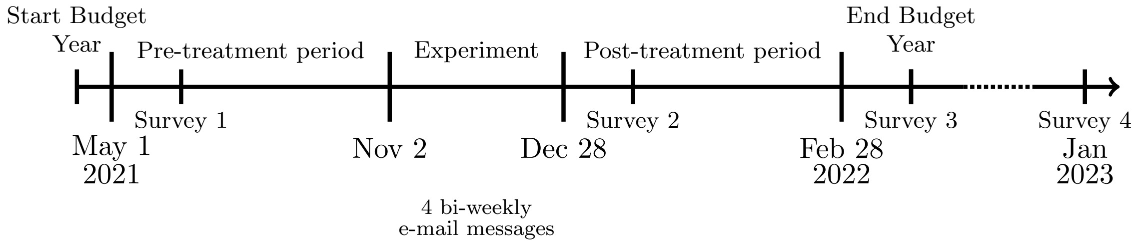
In 2020, our partner company introduced a mobility budget as an alternative to the company car. After a pilot run at two business locations, the mobility budget program, which provides the framework for our experiment, was rolled out at a larger number of locations in April 2021, with a duration of 24 months. Employees eligible for a company car could 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 for full-time employees and at least €1,400 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.[4]

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

[3]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 also benefits in that the reduction in taxable wages lowers contributions to social security.

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

Figure 1: Timeline of the Experiment



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.[5] Thanks to this documentation requirement, we observe most 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.[6,7]

Eligible expenditures can be subdivided 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.[8] *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 (MT)* is the residual category and comprises electric scooters and electric kick scooters (henceforth referred to as e-scooters), bike sharing, bike subscriptions and bike repairs.

3.2 Implementation

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

[6]We do not observe individual public transit rides covered by commutation tickets, rides with the private bike, and walking. Neither do we observe participants' use of other vehicles, such as private cars or motorbikes. In a survey among participants of the mobility budget 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.

[7]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.

[8]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 PT, we are not able to separate them from the expenditure data.

Timeline. Prior to the start of the program on April 1st, 2021, our partner company invited employees that were eligible for a new 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 31st, 2022). We conducted four voluntary surveys that elicited additional data from the participants. 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. A final survey was conducted one year after the experiment, in January 2023. For the purpose 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 first budget year, which is likely to be very atypical.[9]

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.[10]

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.[11] 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.[12] As can be seen in Table 2, both

[9]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 Tables C.2 - C.3.

[10]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.

[11]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.

[12]A potential concern with removing those users is that their decision to buy an annual PT ticket could

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.

Before aggregating expenditure items for each participant at the monthly level,[13] we drop expenditures made outside Germany (most likely incurred during vacation travel) and expenditures made by the employee's family members. We also re-include expenditures outside Germany as a robustness check.

3.3 Descriptive statistics

Table 1 summarizes the monthly averages of individual expenditures and budgeted items, respectively, for CT, PT and MT 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 for PT and €40.39 for CT. Adding expenditures on MT, total expenditures amount to €104.39. On average, participants submitted 2.60 expenditure items for PT and 1.10 for car-related mobility. Adding MT brings the total to four items in an average month. Despite the low average, there is considerable variation across participants, with the maximum usage amounting 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 might have been higher in the absence of the COVID-19 pandemic. The average participant spent only €1,516 during the entire year. This is less than two thirds of the full budget. Only 24 % of participants used their full budget.[14]

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 CT, but less than half used MT 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 participant spent €25.30 per month on local vs. €37.40 on long-distance transportation. Monthly expenditures on car-related mobility are split almost evenly between car sharing (€16.30), rental cars (€17.20) and taxis (€13.40, including ride-hailing services such as UBER and shuttle pooling). Note that expenditures for micromobility account for less than 10 % of overall pre-treatment expenditures. Micromobility expenditures are mostly made for bike sharing, bike rentals and repairs, which is the more costly category per expenditure item.[15]

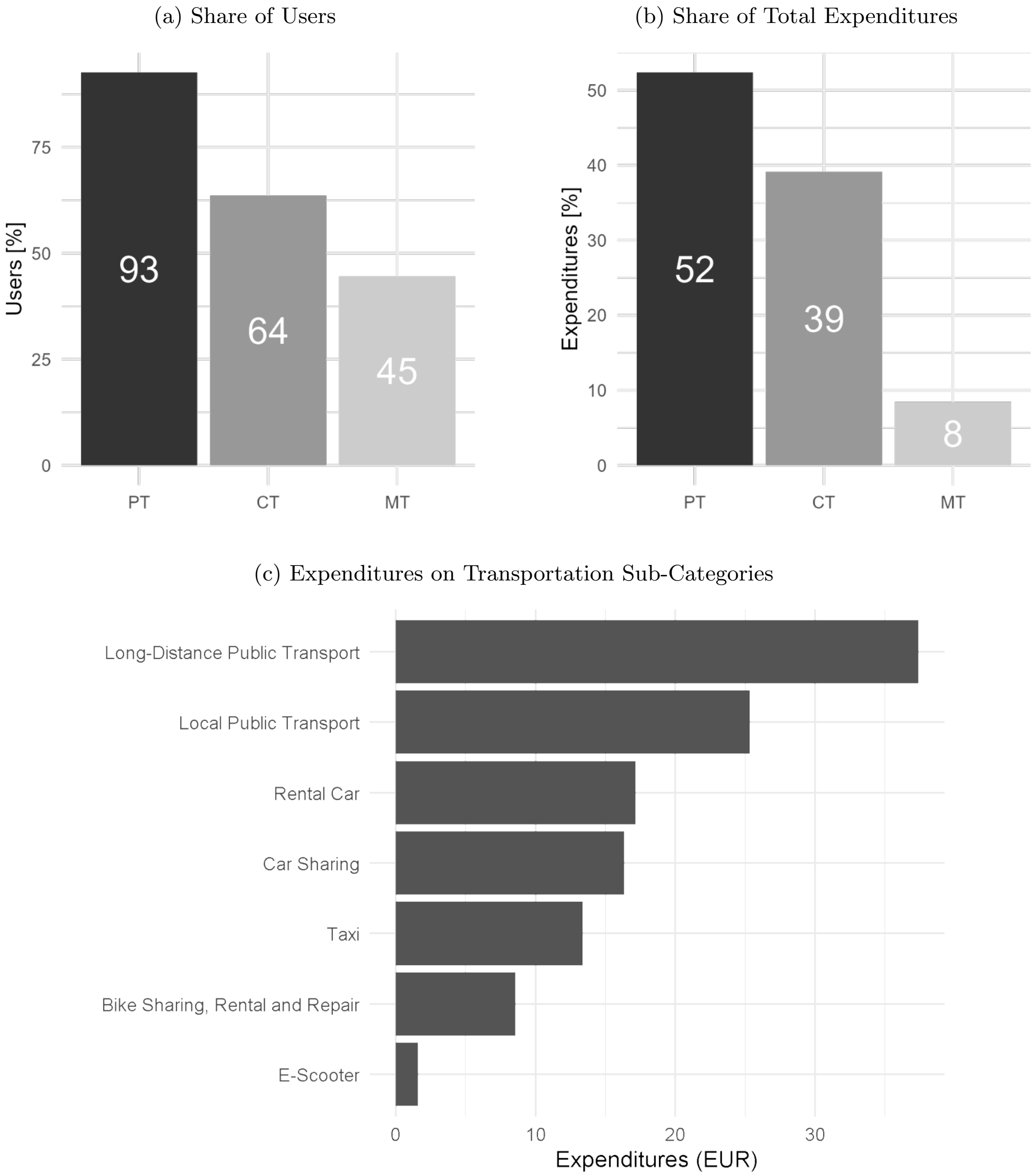
be driven by our treatments. However, only 6 out of 87 annual PT ticket users booked their annual ticket during the treatment period. In robustness checks, we include all annual PT ticket users.

[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 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.

[15] Expenditures for electric scooters amount to €1.58 per month, in contrast to €8.55 for bike sharing,

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 MT stands for micromobility. The average pre-treatment expenditures made by family members (€15.30) are excluded in Panel (c) and in the subsequent analysis.

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 MT 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 MT 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. MT abbreviates 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, as we exclude April 2021 and March 2022.

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 at the 5 %-level. Only the differences in the share of MT users are jointly significant at the 10 %-level.[16] 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.

Only employees eligible for a company car can select into the mobility budget. Therefore, it is interesting to compare the sample of participants in the mobility budget with the population of employees that would be eligible for the mobility budget and thus also for a company car. Table C.1 shows various characteristics of eligible employees holding a company car, eligible employees not holding a company car, and eligible employees participating in the mobility budget. We observe that users of the flexible mobility budget are on average younger, rather live in urban areas, and are less likely to live in households with access to a car than the population of employees eligible for a company car.

3.4 The interventions

The interventions consisted of a series of e-mail messages.[17] Messages were written in English (the second company language besides German) and 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 treated and control subjects 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

bike rentals and repairs.

[16]MT was included into the main analysis upon request by a reviewer in an earlier submission, and was thus not included in balance assessments at the time of randomization.

[17]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.

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		
	Mean	SD	Mean	SD	Mean	SD	Test
Panel B: Experiment Sample							
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
thereof MT Expenditures	10	20	9	26	11	22	F= 0.102
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 Car Use Count	0.9	2	2	4	1	3	F= 1.588
thereof MT Use Count	0.6	2	0.5	3	0.5	1	F= 0.069
% PT Users	95%		91%		92%		$\chi^2 = 0.917$
% CT Users	61%		62%		68%		$\chi^2 = 1.533$
% MT Users	50%		37%		47%		$\chi^2 = 4.708^*$
% 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	43	11	43	12	41	12	F= 0.906
% 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), CT stands for car-related transportation and MT for micromobility. 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.

hence we interpret the effects reported below as average treatment effects rather than intent-to-treat effects.[18] 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,

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.[19]

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 %

[18]In robustness tests included in Tables 3 - 5, 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.

[19]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.

disagreed).[20] 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.[21]

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 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. Following the norm activation model by Schwartz (1977), the moral appeal comprised three parts, which 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":

1. 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"*),

2. 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"*), and

3. the 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"*).

[20] 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.*

[21] 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].

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). According to Bicchieri (2005), the combination of a descriptive norm (communicated in the social comparison) 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, impure altruism could reinforce the effect of an injunctive norm as it works in the same direction in this climate change context. Participants could derive a "warm-glow" utility from choosing low-emissions transport modes (Andreoni, 1990). The baseline survey supports this additional channel in that there are pre-existing preferences for environmentally-friendly transportation decisions in the sample.[22] Given these pre-existing preferences, communicating an injunctive norm for environmentally-friendly behavior without invoking some kind of warm-glow utility would not be possible, a well-known issue in the literature on norm-based appeals (Ferraro et al., 2011; Bursztyn et al., 2020). Resolving it would require a much larger sample size (see, e.g., Bursztyn et al., 2020), so we refrain from empirically separating those mechanisms.

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.[23,24]

4 Results

In this section, we first inspect the development of the main outcome variables (expenditures and use of CT, PT and MT) over time, then introduce the regression framework and show

[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].

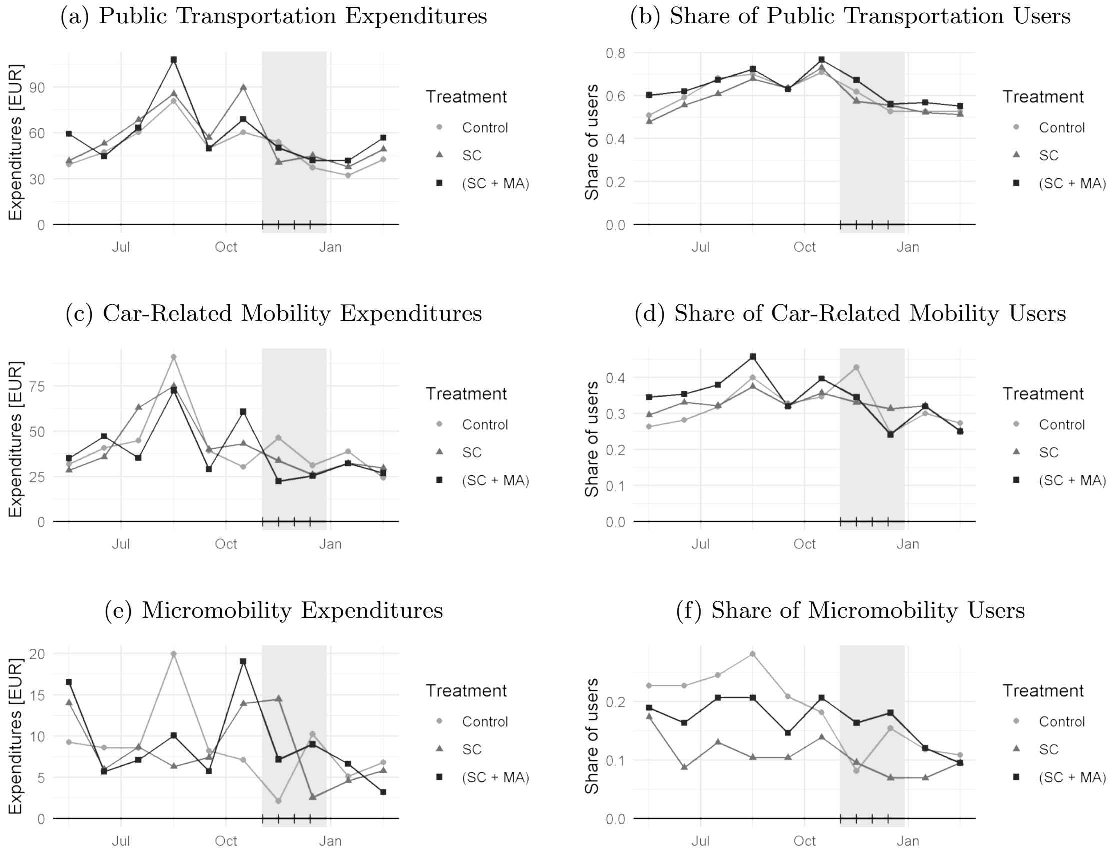
[23] The exact wording of the two related questions was: (i) *"Select the statement with which you agree most: Global climate change is already happening. Global climate change is not happening yet, but will be happening in the next few decades until 2050. Global climate change will not be happening 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."*

[24] 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 regression results. Finally, we interpret our results and estimate heterogeneous treatment effects.

4.1 Trends

Figure 3: Trends in Mobility Expenditures Across Treatment Groups



Notes: Panels (a), (c) and (e) depict the average monthly expenditures for the transport mode in the corresponding treatment arm. Panels (b), (d) and (f) 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 e-mails were sent.

Figure 3 shows the average monthly expenditures and shares of participants who used a certain transport mode at least once in a given month, by treatment arm. Panels (a) and (b) display the corresponding time series for PT, Panels (c) and (d) for CT and Panels (e) and (f) for MT. The diagram reveals quite some variation in average expenditures and use for all transport modes and 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, both the pandemic and seasonal variation in preferences for different transport modes[25] most likely affected travel behavior, which is why it is important to control for time trends with a randomized control group. Interactions between seasonal patterns and our treatments, however, cannot be ruled out.[26]

For the pre-treatment period, we see that expenditures for PT, CT and MT (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 C.1. Furthermore, the distribution of individual expenditures during the pre-treatment period in Figure B.1 indicates that differences across groups may be driven by a few 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, as described below.

During the treatment period, different patterns emerge for the three transport modes. 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. Expenditures for MT fluctuate the most, as can be seen in Panel (e) of Figure 3.

Panel (b) shows that the share of users for PT developed in a parallel fashion for all three groups, both during the pre-treatment and the treatment period. During the latter, 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 in Panel (d). 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. For MT in Panel (f), we see that the share of users evolves in parallel over the pre-treatment period and drops in the beginning of the treatment period. This drop is most pronounced for the control group, where the share of users drops by roughly 10 %-points in November, but almost fully recovers in December. While the share of users remains constant over the treatment period in group SC + MA, it decreases for the control group and group SC.

[25] Hudde (2023) shows that preferences for cycling vary by season, especially in Germany.

[26] To better address interactions between our treatments and the COVID-19 pandemic, we tried to leverage differences in the course of the pandemic at different business locations of the company. Unfortunately, the pandemic hit the two largest business locations at the same time and developed in a parallel fashion.

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

4.2 Regression analysis

We employ regression analysis to formally identify causal treatment effects on outcome Y_{it} of employee i in month t. We estimate the following equation as a linear probability model (LPM) to recover extensive-margin reactions to our treatment.

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

In this specification, Y_{it} is an indicator for whether participant i has used the corresponding transport mode in month t, 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 effects by time-invariant regressors Z_i containing employee characteristics and pre-treatment use of the mobility budget.[27]

To assess the combined effect along both the intensive and the extensive margins, we estimate the following equation for $\tilde{Y}_{it}$, the monthly expenditures per transport mode,

$$\tilde{Y}_{it} = \exp\left(\sum_{j \in \{SC,\, SC+MA\}} \left[\beta_1^j T_i^j \times \tau_t + \beta_2^j T_i^j \times \rho_t\right] + \omega_t + c_i\right) + \eta_{it} \tag{2}$$

using a Poisson pseudo-maximum-likelihood (PPML) estimator (Santos Silva and Tenreyro, 2006). This estimator is well suited to accommodate both large outliers in terms of monthly expenditures that would be influential in linear regression models (see Figure B.1) and the presence of zero expenditures in any given month. The PPML estimator is robust to large shares of zero-observations (Santos Silva and Tenreyro, 2011) and has been suggested when zero-observations prohibit log-transformations of the outcome variable (Chen and Roth, 2022; Norton, 2022). We estimate the PPML estimator with fixed effects using the FIXEST package in R (Bergé, 2018).

4.2.1 Baseline results

Modal choice. We measure extensive-margin responses to the interventions in terms of a change in the propensity to use PT, CT and MT at least once in a given month, which we recover by estimating (1) as a linear probability model. Panel A of Table 3 reports results for PT, Panel B for CT and Panel C for MT.

[27] Z_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.

Table 3: ATE on Monthly Use

	Use Indicator (Monthly)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Public Transportation Use						
SC × Treat. Period	0.02	0.03	−0.01	0.01	0.005	0.02
	(0.05)	(0.04)	(0.06)	(0.04)	(0.05)	(0.05)
(SC + MA) × Treat. Period	0.01	0.02	0.04	−0.001	0.02	0.01
	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)	(0.04)
SC × Post Treat. Period	0.01	0.03	−0.01	0.0005	0.02	0.02
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
(SC + MA) × Post Treat. Period	0.001	0.002	0.03	−0.01	0.03	−0.003
	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)
Observations	3,410	3,410	3,410	4,280	3,140	3,410
R^2	0.0001	0.32	0.001	0.0000	0.0002	0.0002
Panel B: Car Transportation Use						
SC × Treat. Period	−0.03	−0.02	−0.01	−0.01	0.02	−0.01
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
(SC + MA) × Treat. Period	−0.10**	−0.07*	−0.04	−0.08**	−0.08*	−0.09*
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
SC × Post Treat. Period	−0.01	−0.01	0.001	−0.04	−0.01	0.02
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(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)	(0.05)	(0.06)	(0.05)
Observations	3,410	3,410	3,410	4,280	3,140	3,410
R^2	0.002	0.36	0.0003	0.002	0.002	0.002
Panel C: Micromobility Use						
SC × Treat. Period	0.07**	−0.004	−0.04	0.04	0.04	0.08**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
(SC + MA) × Treat. Period	0.10***	0.06**	0.05	0.07**	0.07**	0.09***
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
SC × Post Treat. Period	0.07**	0.004	−0.03	0.06*	0.06	0.08**
	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
(SC + MA) × Post Treat. Period	0.04	0.01	−0.01	0.03	0.04	0.03
	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Observations	3,410	3,410	3,410	4,280	3,140	3,410
R^2	0.005	0.26	0.002	0.003	0.003	0.005
Annual Ticket Users				X		
Survey Particip.					X	
Exp. Outside GER						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. Use is an indicator whether an individual used the corresponding transport mode in a given month. Linear Probability Models, estimated using ordinary least squares. 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. Exp. Outside GER indicates that expenditure items booked outside Germany 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. Standard errors are clustered by participant.

Model (1) displays our preferred specification from equation (1), a difference-in-differences (DiD) approach with employee and month fixed effects controlling for unobserved individual heterogeneity and common time trends. Identification relies on the assumption of parallel trends across the groups in the absence of treatment, which is untestable but highly plausible given randomization.[28] We observe that the Average Treatment Effect (ATE) on the propensity to use PT (Panel A) is not significantly different from zero for both treatments during the intervention, which indicates that the e-mails were not successful at increasing the share of PT users in the treatment groups. By contrast, Panel B shows that treatment SC + MA reduced the propensity to use CT during the treatment period by 10 %-points (significant at the 5 %-level). 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. Interestingly, the decrease in the propensity to use CT induced by treatment 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 MT options in the mobility budget. The results in Panel C provide evidence for a simultaneous increase in the share of MT users in treatment group SC + MA by 10 %-points (significant at the 1 %-level). Together with the results on CT, this suggests that some participants might have substituted micromobility for car-related transportation as a result of treatment SC + MA. We will provide further support for this claim in Section 4.4. In our main specification, we also find significant effects of treatment SC on the share of MT users before and after the treatment period. However, these results are not robust to alternative specifications (in the other columns of the table), which is why we refrain from interpreting them as causal effects.

In columns (2) - (6) of Table 3, we analyze whether our results are sensitive to changes in the estimation equation and the sample. Column (4) shows that including participants holding a public transportation ticket does not increase the size of the coefficients across all three transport modes. As riding PT has no opportunity costs with respect to their mobility budget, we expected stonger reductions in car-related mobility among these participants. Model (5) includes only participants who took part in our midline or our first 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. We do not find evidence pointing in that direction. Adding expenditure items booked outside of Germany in model (6), which most likely reflect travel behavior during holidays and are thus not informative about day-to-day mobility use, does not change the size and significance of the estimated treatment effects much. Across all robustness checks that control for pre-treatment mobility (columns 2 and 4-6), the point estimates are quite similar and statistically significant at the 10 %-level or better. Only when we drop employee controls in model (3) the estimated treatment effect vanishes. This squares with the evidence present in Figure 3 and Table 2 above, emphasizing that controlling for pre-treatment mobility is important in our setting. While our randomization strategy achieved covariate balance across all covariates considered, small but persistent differences remain in pre-treatment mobility.

For the insignificant coefficients for treatment SC in model (1), our estimates do not add

[28] A plot showing that pre-trends are parallel is available in Figure C.1.

precision to the very narrow confidence intervals already estimated for the effect of social comparison interventions on transport mode choice in previous research, in particular by Gravert and Collentine (2021). However, we do find that adding a moral appeal on top of the social comparison intervention can induce changes in transport mode choice that go beyond the effects previously ruled out for pure social comparison interventions.

Expenditures. Table 4 reports results for changes in expenditures across the three transport modes. We observe that the ATE on expenditures is not significantly different from zero in our preferred specification in model (1) for any transport mode and for both treatments. Based on these results, we cannot reject the hypothesis that our treatment did not change mobility expenditures for any of the three transport modes considered. In the specifications in models (2) and (3), the negative coefficient for treatment SC + MA is significant at the 10 %-level. Given the large standard errors (for the effect of treatment SC + MA on CT expenditures in model (1), the 95 % confidence interval includes changes between an increase by 15 % or a decrease by 114 % of the control group average), we do not interpret this result as a null-effect, but rather as an indication that we should focus on outcomes that are less volatile than expenditures, such as the use indicator analyzed before.

Overall use of the mobility budget. If our results in Table 3 were in fact driven by changes in the share of active users of the budget, we would expect to find evidence for changes in the probability to use the budget. Therefore, Table 5 reports estimates of the ATE for the monthly use of the mobility budget across all three transport mode categories PT, CT and MT. The estimated coefficients lack statistical significance, and hence do not support the notion that participants abstained from using the mobility budget in response to our treatments.[29]

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 the regressions in Tables 3 and 4 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 C.2 - C.3, 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 fit Poisson maximum-likelihood models with fixed effects using the same specifications as for expenditures. The results are reported in Table C.4. 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

[29]We analyze the sensitivity of our results in Table 5, using the same specifications as in Tables 3 and 4. The insignificance of the effect of both treatments on total monthly use is robust across all specifications.

Table 4: ATE on Monthly Expenditures

	Change in Expenditures as % of Control Group Average					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Public Transportation Expenditures						
SC x Treatment Period	−0.22	−0.09	−0.06	−0.21	−0.28	−0.13
	(0.20)	(0.18)	(0.19)	(0.18)	(0.20)	(0.19)
(SC + MA) x Treatment Period	−0.14	−0.06	0.01	−0.21	−0.23	−0.14
	(0.19)	(0.18)	(0.19)	(0.17)	(0.19)	(0.19)
SC x Post Treatment Period	−0.01	0.12	0.15	−0.13	−0.16	−0.02
	(0.19)	(0.18)	(0.19)	(0.18)	(0.18)	(0.19)
(SC + MA) x Post Treatment Period	0.12	0.21	0.28	0.09	0.19	0.12
	(0.21)	(0.20)	(0.20)	(0.20)	(0.22)	(0.21)
Observations	3,410	3,410	3,410	4,280	3,140	3,410
R2 Within Adj.	0.002	0.276	0.001	0.002	0.004	0.001
Panel B: Car Transportation Expenditures						
SC x Treatment Period	−0.29	−0.30	−0.26	−0.30	−0.45	−0.06
	(0.34)	(0.29)	(0.28)	(0.30)	(0.36)	(0.32)
(SC + MA) x Treatment Period	−0.49	−0.47*	−0.49*	−0.30	−0.41	−0.36
	(0.33)	(0.28)	(0.28)	(0.31)	(0.37)	(0.33)
SC x Post Treatment Period	−0.04	−0.06	−0.02	−0.44	−0.17	−0.01
	(0.38)	(0.34)	(0.31)	(0.36)	(0.40)	(0.34)
(SC + MA) x Post Treatment Period	−0.07	−0.03	−0.07	−0.30	−0.05	−0.29
	(0.37)	(0.32)	(0.30)	(0.34)	(0.38)	(0.33)
Observations	3,410	3,410	3,410	4,280	3,140	3,410
R2 Within Adj.	0.003	0.318	0.002	0.003	0.003	0.002
Panel C: Micromobility Expenditures						
SC x Treatment Period	0.41	0.32	0.32	0.40	0.34	0.45
	(0.65)	(0.57)	(0.65)	(0.61)	(0.70)	(0.65)
(SC + MA) x Treatment Period	0.23	0.30	0.27	0.24	0.02	0.21
	(0.49)	(0.44)	(0.45)	(0.45)	(0.51)	(0.49)
SC x Post Treatment Period	−0.04	−0.25	−0.13	0.08	−0.16	−0.01
	(0.42)	(0.41)	(0.49)	(0.39)	(0.48)	(0.42)
(SC + MA) x Post Treatment Period	−0.23	−0.16	−0.19	−0.18	−0.24	−0.25
	(0.47)	(0.45)	(0.43)	(0.44)	(0.46)	(0.47)
Observations	3,410	3,410	3,410	4,280	3,140	3,410
R2 Within Adj.	0.002	0.287	0.001	0.002	0.002	0.002
Annual Ticket Users				X		
Survey Particip.					X	
Exp. Outside GER						X
Covariates		X				
Individual FE	X			X	X	X
Month FE	X	X	X	X	X	X

Notes: Significance markers * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Expenditures are measured in Euro per transport mode and month. Poisson fixed-effects regression. 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. Exp. Outside GER indicates that expenditure items booked outside Germany 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. Standard errors are clustered by participant.

Table 5: ATE on Monthly Mobility Budget Use

	Use Indicator (Monthly)					
	(1)	(2)	(3)	(4)	(5)	(6)
Use of the Mobility Budget						
SC × Treat. Period	−0.003	0.03	−0.01	0.01	0.02	0.01
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
(SC + MA) × Treat. Period	0.0001	0.02	0.05	−0.01	0.01	0.02
	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
SC × Post Treat. Period	−0.005	0.03	−0.01	−0.01	0.004	0.01
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
(SC + MA) × Post Treat. Period	−0.01	0.02	0.04	−0.002	0.03	−0.01
	(0.05)	(0.05)	(0.06)	(0.04)	(0.05)	(0.05)
Observations	3,410	3,410	3,410	4,280	3,140	3,410
R^2	0.0000	0.24	0.001	0.0002	0.0003	0.0002
Annual Ticket Users				*X*		
Survey Particip.					*X*	
Exp. Outside GER						*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. Use is an indicator whether an individual used the corresponding transport mode in a given month. Linear Probability Models, estimated using ordinary least squares. 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. Exp. Outside GER indicates that expenditure items booked outside Germany 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. Standard errors are clustered by participant.

%-level) and large negative 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 % of the control group average, which corresponds to a reduction by 0.6 CT expenditure items per month, based on the pre-treatment average monthly CT use of the control group (Table 2). For MT, we estimate significant (1 %-level) positive effects for treatment SC + MA. Coefficients for treatment SC and for the post-treatment period are again insignificant. The estimated increase by 93 % amounts to 0.6 additional expenditure items for MT (Table 2).

4.3 Summary and interpretation of results

The analysis so far has yielded two main results, namely (i) none of the treatments affects the use of public transportation, and (ii) the combined treatment of social norm and moral appeal shifts users from car-related travel towards micromobility.

Several factors could explain the lack of an effect on PT use. On one hand, those participants who frequently used PT already before the intervention would not have much scope to further increase PT use. On the other hand, infrequent users of PT might have been deterred using PT more frequently due to the onset of a new wave of COVID-19 infections which occurred in late October 2021, shortly after the beginning of the experiment. Alternatively, some of those participants might simply have doubted that using PT would lower their carbon footprint. Finally, it is conceivable that those participants who were responding to the moral appeal to reduce transport-related CO_2 emissions did not perceive PT as a good substitute for a more emission-intensive transport mode such as traveling by taxi. Evidence from our final survey refutes the last explanation, as more than 80 % of participants indicated that they consider public transportation a substitute for car-related transportation.[30]

Regarding taxi rides and other car-related travel, we do find robust evidence that combining a moral appeal with a social comparison reduced the the share of individuals using CT in a treatment month by 10 %-points compared to the control group average. Moreover, the share of individuals using MT increased by 10 %-points, suggesting that micromobility is a reasonably good substitute for some CT trips. Competing explanations for the reduction in CT use would be a reduction in overall trips (which is not supported by our data), or substitution to outside options such as a private car or a private bike, which we do not observe.

After normalizing by the standard deviation, the estimated effects correspond to $d = 0.21$ and $d = 0.30$ for CT and MT, respectively, which can be compared to estimates from the few previous studies on social comparisons in the transportation domain (Kristal and Whillans, 2020; Gravert and Collentine, 2021; Götz et al., 2022). Those estimates were not significantly different from zero and would reject effect sizes such as ours with 95% confidence. Notwithstanding this, we argue that the larger effect sizes are credible in our setting for three reasons. First and foremost, in contrast to those previous studies, our intervention combined a social comparison with a moral appeal.[31] In consonance with the previous work, we find that the social comparison alone is not sufficient to change transportation behavior. That adding a moral appeal can generate much larger effects than a social comparison in isolation has previously been shown in the context of water conservation (Ferraro and Price, 2013). Second, large effects are plausible given that transportation decisions in the mobility budget can be very flexibly adjusted in response to treatment. The lock-in effects that arise from buying a car or an annual public transportation ticket and pre-determine transport choices are not relevant here because the mobility budget allows participants to 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 shared by large parts of the sample. In the baseline survey, 44 % of respondents expressed

[30]The exact wording of the three questions was *"Which transport modes do you consider as substitutes for trips by (taxi, UBER or similar)/(rental car)/(car sharing)? [Several answers are possible: i) Long and short distance public transportation. ii) Shared e-scooters. iii) Bikesharing. iii) Transport modes outside the mobility budget. iv) None of these transport modes.]"*

[31]In the mobile application used in the study by Götz et al. (2022), a moral appeal featured prominently on the page shown when opening the app. Participants could additionally select into gamification features, including a social comparison. In contrast, in our experiment a social comparison combined with a moral appeal was administered to all participants in one treatment arm. The difference between the null-result in Götz et al. (2022) and our results is in line with expectations, as previous research (Ferraro et al., 2011) shows that combining a norm-based appeal with a social comparison yields larger treatment effects.

the belief that their social environment (e.g., colleagues) expects them to act environmentally friendly.[32]

The observed effects disappear in the post-treatment period. This result confirms findings obtained in similar experimental settings with messages delivered though emails or apps, in which little or no habit formation was observed following an intervention (see, e.g., Calzolari and Nardotto, 2017), or in which the effects fade over time due to a lack of engagement on the side of the participants (see, e.g., Fosgaard et al., 2021; Enlund et al., 2022).

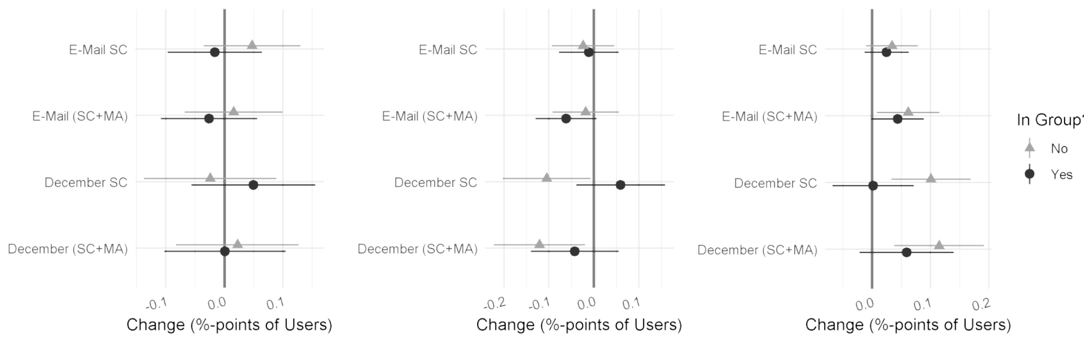
Overall, our results suggest that an insistent message with an injunctive norm can indeed have a short-term effect and reduce car-related transportation, at least in groups with a pre-existing social norm for environmentally-friendly behavior, as is the case in our sample. This result is in line with 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 most effective.

4.4 Heterogeneous treatment effects

In this subsection, we examine whether there are heterogeneous treatment effects over the course of the intervention, for different groups of users, and for the individual transport modes included in PT, CT and MT. Given our main results, we focus on the extensive margin.

Figure 4: Heterogeneous Treatment Effects Over Time

(a) Public Transportation Use (b) Car Transportation Use (c) Micromobility Use



Notes: Treatment effects are estimated according to our main specification for the Linear Probability Model as outlined in Section 4.2. All regressions are estimated separately for the time periods of interest. E-Mail is an identifier for the use of a particular transport mode during a week in which an intervention e-mail was sent, aggregated on the monthly level. December is an identifier for the use of a particular transport mode during the month December. Coefficient estimates and 95 % confidence intervals are displayed. Standard errors are clustered by participant.

Temporal heterogeneity. We begin by examining the time dimension of the estimated treatment effects. We distinguish between (i) weeks in which the e-mails were sent and weeks in which no e-mails were sent, as well as (ii) the treatment months November and December.

[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).

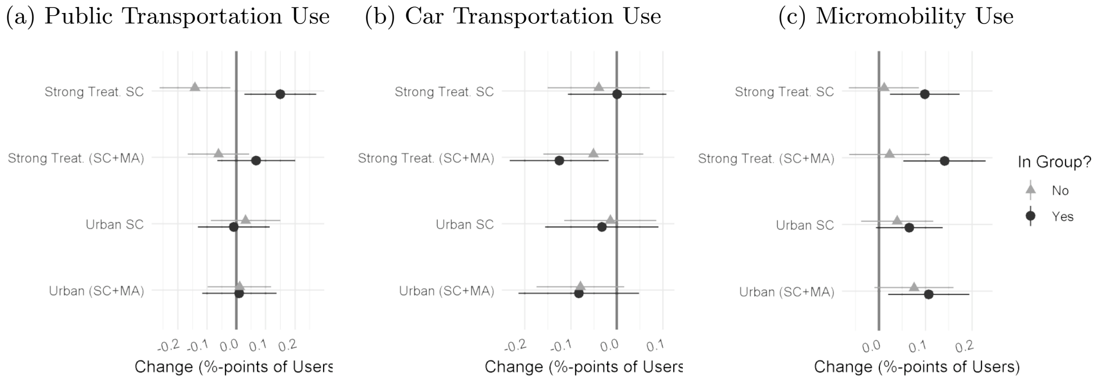
Table C.5 reports the results for these two regressions, summarized in Figure 4. As can be seen in Panel (a) of Figure 4, the two treatments did not significantly change PT use, neither for e-mail/non-e-mail weeks nor for November or December. For CT, Panel (b) reveals that the significant effect observed for treatment SC + MA for the whole treatment period is driven by the reaction during the first month of the treatment. During November, the probability to use CT for participants in group SC + MA dropped by 12 %-points (significant at the 5 %-level), but this treatment effect vanished completely in December. The difference is even more striking for group SC, where a significant decrease in November (a reduction by 10 %-points, significant at the 5 %-level) is counteracted by an insignificant increase in December. Panel (c) displays a similar pattern for MT: there are significant, positive treatment effects for both treatment SC (10 %-points, significant at the 1 %-level) and treatment SC + MA (11 %-points, significant at the 1 %-level) in November, but these vanish completely in December. We interpret this as participants habituating to our e-mail messages. Across the three transport modes, there is no unambiguous evidence for "action and backsliding" (Allcott and Rogers, 2014): While treatment SC + MA had a weakly significant (at the 10 %-level) effect on CT during weeks in which an e-mail was sent but not during subsequent weeks without e-mails, the treatment had a significant effect (5 %-level) on MT both for weeks with and without a treatment e-mail.

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 and (ii) whether a participant received a "strong" or a "weak" social comparison. Note that unlike other studies working with social comparison treatments, we do not look at treatment effects for individuals with below- vs. above-average outcomes. The social comparison message we used did not directly inform individuals about the outcome variables we analyzed. Splitting the sample according to pre-treatment outcomes would imply that for CT and MT, the outcomes would be zero for most observations in one subset. For these reasons, we define a different measure of treatment intensity below.

Table C.6 summarizes the results for the treatment effect heterogeneity, and Figure 5 displays the 95 % confidence intervals for the different groups. Starting with the type of the place of work (at the bottom of all diagrams in 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 much. The coefficients are almost identical. For MT in Panel (c), the effect of treatment SC + MA is significant at the 5 %-level among participants working at urban business locations. Note, however, that the coefficient in the rural sub-sample is of almost the same size and significant at the 10 %-level. The irrelevance of the participant's location of work is somewhat surprising, since one would expect that participants working in more rural areas have very different access to the transport modes considered. 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 our data.

Recall that our treatment messages were getting at PT expenditure *shares* relative to

Figure 5: Treatment Effect Heterogeneity Across Sub-Groups



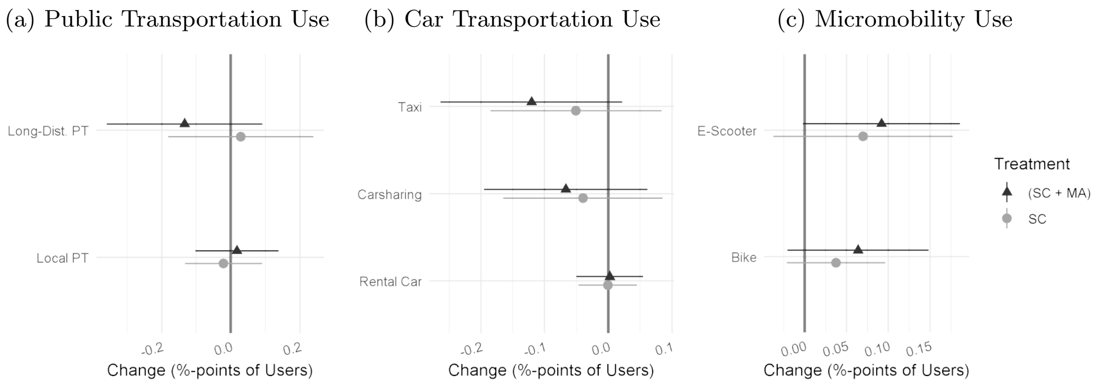
Notes: Treatment effects are estimated according to our main specification for the Linear Probability Model as outlined in Section 4.2. All regressions are estimated separately for the sub-groups of interest. Strong Treat. is an identifier for participants who received 3 or more e-mails with a social comparison stating that they had spent a smaller share of their expenditures on public transportation than their peer group. Urban is an identifier for participants working at a business location in an urban area. Coefficient estimates and 95 % confidence intervals are displayed. Standard errors are clustered by participant.

the peer group. Accordingly, we define a "weak" social comparison as receiving the information that a participant's expenditure share is higher than the average in her peer group. Participants in the treatment groups received four comparison messages in total, together comprising the administered treatment. Furthermore, we define a "weak treatment" as one where an individual received a weak social comparison at least three out of four times. Conversely, the group receiving a "strong treatment" comprises subjects that received a weak comparison at most once. For this distinction to work, we drop 13 subjects that received two weak comparisons.[33]

In Figure 5, we analyze sub-group effects for participants receiving strong vs. weak social comparisons. In Panel (a), we observe counteracting effects for individuals receiving a strong (+15 %-points, significant at the 5 %-level) vs. a weak social comparison treatment (-14 %-points, significant at the 5 %-level). This points to the presence of a so-called "boomerang effect" (Schultz et al., 2007): participants spending a higher than average share of their overall expenditures on PT before treatment are discouraged, while participants using PT less are encouraged to use public transport. In fact, counteracting effects can partly explain the observed null-effect for treatment SC in Table 4, at least for PT use. These effects are no longer significant once an injunctive message (as in treatment SC + MA) is added. 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 the probability to use CT for the strong treatment group (-13 %-points), but not for the

[33]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 third 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



Notes: Treatment effects are estimated according to our main specification for the Linear Probability Model as outlined in Section 4.2. All regressions are estimated separately for the transport modes of interest. Local PT is an identifier for monthly use of local public transport. Long-Distance PT is an identifier for monthly use of long-distance public transport. Taxi is an identifier for monthly use of taxis, shuttle pooling, ride-sharing or ride-hailing services. Car sharing is an identifier for monthly use of car-sharing services. Rental Car is an identifier for monthly use of rental cars. Bike is an identifier for monthly use of bike sharing and subscription services, as well as bike repairs. E-scooter is an identifier for monthly use of e-scooter sharing services. Coefficient estimates and 95 % confidence intervals are displayed.

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 and CT. For MT, the significant positive effect of both treatments SC and SC + MA in our main specification also seems to be driven by reactions among participants receiving a strong social comparison treatment (Panel (c) of Figure 5).

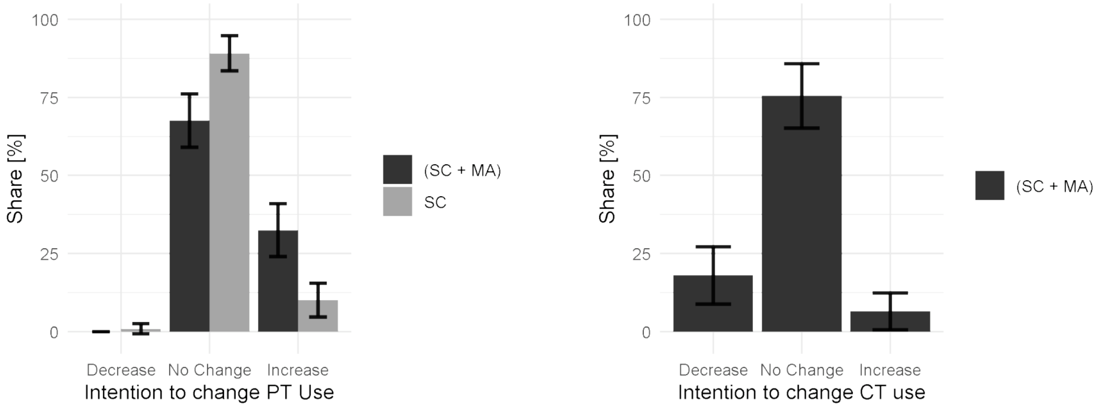
Heterogeneity between transport modes. Third, we analyze treatment effects for the individual transport modes included in the categories CT, PT and MT. Table C.7 presents the results for the different transport modes, and Figure 6 displays the corresponding 95 % confidence intervals for the estimated percentage change in use. For PT, the treatment effects in Panel (a) of Figure 6 remain insignificant, no matter whether we consider long-distance or local PT. For car-related transport, treatment SC + MA has weakly significant monthly treatment effects (at the 10 %-level) 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 use (treatment SC + MA reduced the probability to use taxis by 10 %-points). This indicates that the treatment effect observed for total CT use is driven by reductions in the category Taxi. Parallel to the reduction in the probability to use taxi rides, we find a weakly significant (at the 10 %-level) increase in the probability to use e-scooters in group SC + MA. One explanation for this finding is that the typical taxi ride might have closer (and more) substitutes than, e.g., a rental car. Especially for within-city mobility, e-scooters may be a viable substitute for some taxi rides. In support of that, 52 % of participants in our last survey indicated that they consider micromobility as a substitute for taxi rides, as compared to 30 % for car sharing and 15 % for rental cars.[34] Our findings are also in line with results from other studies. For instance, Gebhardt et al. (2021) find that, in Germany, 10–15 % of the motorized individual transport trips could be made by e-scooter, and Laa and Leth (2020) find, for the City of Vienna, that e-scooter owners show a considerable mode-shift away from private car trips.

5 Survey evidence on channels behind the treatment effects

To shed light on the channels we assumed would be driving our treatment effects, we asked participants of the mobility budget to state how they would react to treatment messages SC and SC + MA in the two endline surveys.

Figure 7: Stated Reaction to the Treatment Messages

(a) Weak Treatment Message (b) Strong Treatment Message



Notes: Stated reactions to our treatment messages in terms of PT use in a survey in April 2022 and in terms of CT use in a survey in January 2023. In the 2022 survey, we assessed reactions to a weak SC treatment, informing participants that they already outperform their peers, in one half of the sample (randomly assigned) and to a weak SC + MA treatment in the other half. The exact wording of the question for treatment SC was: *"Suppose you would receive the following (truthful) information from your employer (you might even have received a similar information): "You have spent 75 % of your expenditures in the [name] program on public transportation. The average participant at our business sites similar to the one you are working at spent 52 % of all expenditures on public transportation." Please indicate how you would change your use of public transportation in response to this information. Please try to honestly assess your actual reaction: [I would use public transportation more often. I would not change my use of public transportation. I would use public transportation less often.]"* For treatment SC + MA, we added the same paragraph as in the actual treatment message (see Appendix A, second e-mail, last paragraph). In the 2023 survey, we assigned treatment SC + MA to all participants. We included a strong social comparison by informing participants that they spent less on PT than their peers *("You have spent 25 % of your expenditures in the [name] program on public transportation.")*, and asked them for their intention to change their use of CT *(" Please indicate how you would change your use of car sharing services, rental cars, or taxi and UBER rides in response to this information.")* 95 % confidence intervals of the means are displayed.

In our first endline survey in April 2022 (n = 236), we asked 50 % of survey participants how they would change their *public transportation* use in response to a *weak social comparison*

[34]The exact wording of the three questions was *"Which transport modes do you consider as substitutes for trips by (taxi, UBER or similar)/(rental car)/(car sharing)? [Several answers are possible: i) Long- and short-distance public transportation. ii) Shared e-scooters. iii) Bikesharing. iv) Transport modes outside the mobility budget. v) None of these transport modes.]"*

message, i.e., the communicated share of individual PT expenditures was already above the communicated peer group average, and we randomly assigned the additional moral appeal to the other 50 % of the survey sample. As can be seen in Panel (a) of Figure 7, almost none of the participants stated that they would reduce their PT use, while 10 % indicated that they would increase their PT use in response to treatment SC and 33 % said so for treatment SC + MA. This result is in line with the revealed preferences analyzed before, in the sense that the combined treatment is more powerful in changing people's behavior. It also demonstrates that a majority is not willing to change PT use even for the combined treatment.

In another survey in January 2023 (n = 200), we asked all participants how they would change their *car-related travel* in response to a *strong social comparison* message combined with a *moral appeal*.[40] As can be seen in Panel (b) of Figure 7, this strong treatment message did not change the intended use of CT for 75 % of survey participants, while 18 % indicated that they would decrease and 7 % indicated that they would increase their use of CT. Interestingly, an even higher share of respondents stated that they would not change their use of CT as compared to PT in the previous survey. This implies that the main effect found earlier for CT use may be driven by the reactions of relatively few participants.

In the endline survey in April 2022 (January 2023) we asked participants who stated that they would *increase* their use of PT (*decrease* their use of CT) to indicate their agreement with the following reasons for this response: competition with their peers, a perceived moral obligation and reactance.[35] For participants who had indicated that they would *not* change their use of PT (or CT), we included reactance, an inability to change the use of PT in either direction, and irrelevance (whether participants agreed that the treatment message was not relevant for their transport mode choice). An increase in PT use (decrease in CT use) can be interpreted as compliance with the social norm. For the *strong* treatment SC + MA, we additionally asked for social learning as a reason to decrease CT use.

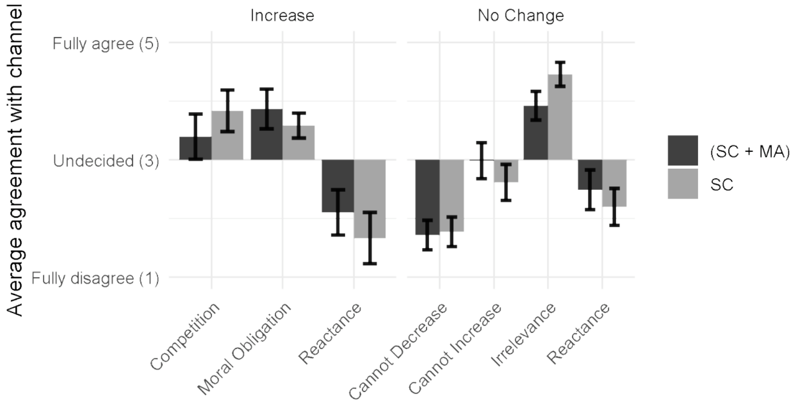
Figure 8 summarizes agreement with the above-mentioned reasons for the survey respondents' stated reactions to our treatment messages. In response to treatment SC + MA, participants who indicated compliance with the social norm on average agreed that they felt a moral obligation to do so, as can be seen in Panels (a) and (b). Besides the directly addressed injunctive norm, this reasoning is also in line with individual preferences for climate-friendly transport mode choices. For treatment SC, participants also agreed that competition with their peers was a motivating factor to increase the use of PT (see Panel (a)). For both treatments, however, the stated increase in the use of PT is not in line with the results of the revealed preference analysis in Tables 3 and 4. This points to an intention-behavior gap for the weak treatment messages. Furthermore, neither reactance nor social learning seem to have played a major role.

In the same figure, we observe that participants not intending to change their use of CT or PT agreed, on average, that they considered the message irrelevant for their transport mode choice and that reactance did not influence their choice. Further, on average, respondents

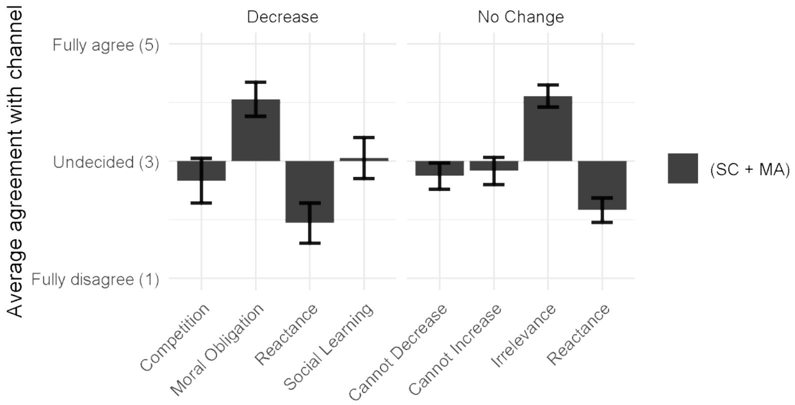
[35]A person perceiving a threat to their behavioral freedom might demonstrate an increased preference for the behavior that is restrained, motivated by a desire to restore the freedom that is perceived as being threatened. This motivational state is called psychological reactance (Van den Bos, 2007).

Figure 8: Reasons for the Stated Reactions to the Strong Treatment Message SC + MA

(a) Reasons for Intention to Change PT Use, April 2022



(b) Reasons for Intention to Change CT Use, January 2023



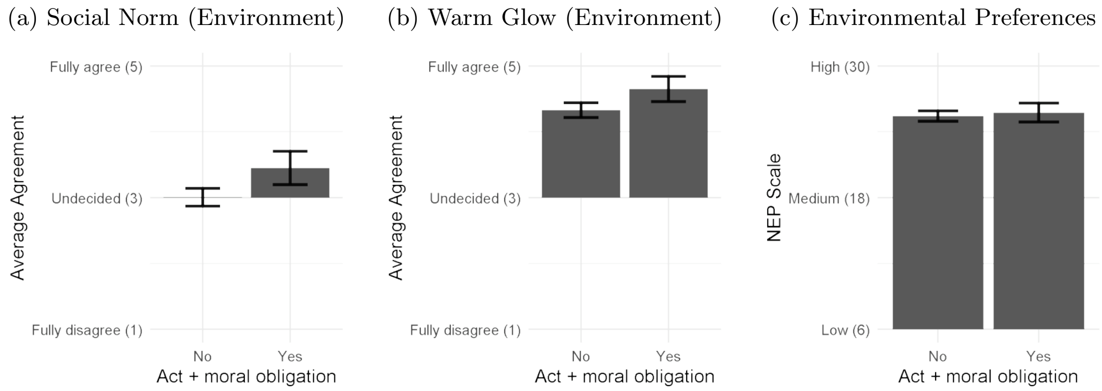
Notes: Agreement with different reasons for the indicated reaction to the treatment messages SC and SC + MA in surveys in April 2022 and January 2023. We split the sample according to the indicated change in the use of PT in 2022 and the indicated change in the use of CT in 2023. The exact wording of the question was: *"Based on your answer to the previous question, please indicate how much you agree with the following reasons for your reaction in the previous question: [1 - Do not agree at all, 2 - Rather disagree, 3 - Undecided, 4 - Rather agree, 5 - Totally agree]"* 95 % confidence intervals of the means are displayed..

To those increasing their use of PT in 2022 (respectively decreasing their use of CT in 2023), the following reasons were provided: *"i) I feel offended by the message. I will use public transportation (the transport modes mentioned above) as much as I please. ii) I feel morally obliged to use public transportation more (the transport modes mentioned above less) often. iii) The fact that I am using public transportation more than my colleagues motivates me to use this transport mode even more (My colleagues are ahead of me, so I should use the transport modes mentioned above less often)."* We label the first reason **Reactance**, the second **Moral Obligation**, and the third **Competition**. For the strong treatment message used in the 2023 survey, **Social Learning** was added as another hypothesized channel: *"iv) Usually, my colleagues make good decisions. If they use public transportation more often than I do, I should reconsider my transportation behavior."*

To those not changing their use of PT in 2022 (respectively not changing their use of CT in 2023), the following reasons were provided: *"i) I feel offended by the message. I will use public transportation (the transport modes mentioned above) as much as I please. ii) The message is irrelevant for my transport mode choice. iii) Although I would like to increase my use of public transportation (the transport modes mentioned above), it is impossible for me. iv) Although I would like to decrease my use of public transportation (the transport modes mentioned above), it is impossible for me.* We label the first reason **Reactance** (as before), the second **Irrelevance**, the third **Cannot Increase**, and the fourth **Cannot Decrease**.

were undecided whether they could increase their use of PT (Panel (a)) or decrease their use of CT (Panel (c)) in response to treatment SC + MA. This confirms that, at least for some participants, there is limited scope to change their current travel behavior.

Figure 9: Reactions to the Strong Treatment Message SC + MA and Underlying Preferences



Notes: On the x-axis, the sample is split into participants who indicated in our endline survey that in response to treatment SC + MA, they would either increase their PT use or decrease their CT use AND agreed that they perceived a moral obligation to do so. The exact wording of the underlying questions can be found in the figure notes of Figures 7 and 8. On the y-axis, Panel (a) displays the average agreement with the following question: *"Please indicate how strongly you agree with the following statement: My social environment (e.g. family, friends and colleagues) expects me to act environmentally friendly."* Panel (b) displays the average agreement with the following question: *"Please indicate how strongly you agree with the following statement: It makes me feel good to act environmentally friendly."* Panel (c) displays average pro-environmental preferences, as measured by 6 questions from the New Ecological Paradigm (NEP) scale. Participants indicated their agreement on a 5-point Likert scale. The scores from these questions are summed up to create the NEP scale. Our reduced scale ranges between 6 (fully disagree with all statements) to 30 (fully agree with all statements). The exact wording of the questions was *"Please indicate how strongly you agree with the following statements: Humans have no right to modify the natural environment to suit their needs. Humans are severely abusing the planet. Plants and animals have the same right to exist as humans. Nature is not strong enough to cope with the impacts of modern industrial nations. Humans were not meant to rule over the rest of nature. The balance of nature is very delicate and easily upset."* 95 % confidence intervals for the subgroup means are indicated.

Finally, we correlate the participants' answers to react to treatment SC + MA due to a perceived moral obligation, as described above, with their answers to questions related to their attitude towards the environment, perceptions about social norms for environmentally-friendly behavior and a "warm glow" from acting environmentally-friendly (by combining answers from the midline survey and the two endline surveys, n = 274).[36] Figure 9 (a) shows that participants who felt morally obliged to change their transportation behavior agreed, on average, to perceiving a social norm for environmentally-friendly behavior. Furthermore, all participants, on average, agreed to feeling a "warm glow" from acting environmentally-friendly (Panel (b)) and endorse a pro-environmental world view (Panel (c)) as measured by a subset of six questions from the New Ecological Paradigm Scale (Dunlap et al., 2000).

Overall, the survey evidence points to an intention-behavior gap, as is common for many issues related to the environment and climate change. It further suggests that, while the average participant considers the transportation behavior of their peers and moral appeals

[36]Note that the questions about underlying preferences were asked in our midline survey, before eliciting reactions to our treatment messages in the endline surveys, but after the end of the experiment.

to combat climate change as irrelevant for their transport mode choice, some participants indeed felt morally obliged to comply with the injunctive norm as spelled out by the moral appeal. Thus, social norm based interventions in the transportation domain may only be able to induce behavioral change for a "climate-ethical minority". The evidence in Panel (a) of Figure 9 suggests that social norms for environmentally-friendly behavior do play a role for transport mode choices. Furthermore, we can rule out reactance as a potential explanation for our result.

6 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). 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 for 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 opposed to, e.g., energy conservation where one-off investments can have permanent effects).

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 the propensity to use car-related mobility, mostly related to taxis and other ride-hailing and ride-sharing services, by 10 %-points. It also increased the propensity to use micromobility by the same share but left the propensity to use public transport unchanged. To put this into perspective, consider that for a reduction of car-related trips by 10 %, a fuel price increase of around 25 % would be necessary (using a relatively high short-run price elasticity of 0.43; for a survey of transport elasticities, see, e.g., Litman, 2022).[37]

That we do not find evidence for 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 period likely deterred some subjects from using public transit in order to minimize infection risks. Second, many participants already used public transport frequently before the intervention and thus might have had little scope to use this mode of transport more often. Third, for some participants public transport options may have been either unavailable or poor substitutes for car-related mobility. Future research may show how influential these factors are.

Our finding that a moral appeal combined with a social comparison can drive mobility choices away from car-based transportation is highly policy relevant as those mobility options

[37] We are aware that our setting is very different from driving decisions with privately owned cars. We thus caution against over-interpreting the above comparison.

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 some decided to 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. As shown by Brandon et al. (2022), the long-term effectiveness of nudges in another domain, residential energy consumption, is mainly driven by the adoption of new, long-lived, energy-efficient technology. Such "commitment technologies" are available in the transportation domain, but were intentionally excluded in the design of our experiment. Previous research found several nudges to be ineffective in inducing the uptake of less emission-intensive transport technologies.[38] Searching for successful behavioral interventions in this domain remains an interesting avenue for future research.

Our partner company decided not to continue the norm-based appeals after the experimental period. Given the lack of persistent treatment effects, we would not advise companies aiming at inducing long-term behavioral change among users of corporate mobility benefits to work with norm-based appeals. However, in settings where a short-lived treatment effect is sufficient, norm-based appeals could be a promising intervention (as already suggested by Ferraro and Price, 2013), e.g., to induce uptake of new corporate mobility benefits.

[38]Consumers can, e.g., decide to purchase a more fuel-efficient car (Allcott and Kessler, 2019) or register for car-pooling services (Kristal and Whillans, 2020).

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Appendices

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 evi-*

dence 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[39] *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

[39]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.

modes, including public transportation.

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.*

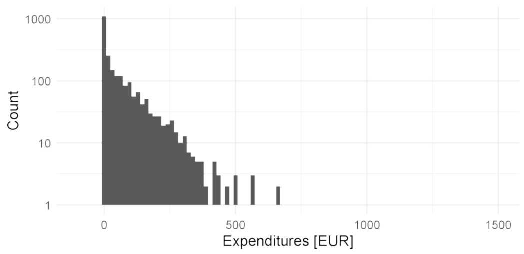
We hope you are enjoying the benefits of the program.
Your [name of the company's team managing the mobility budget]

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.

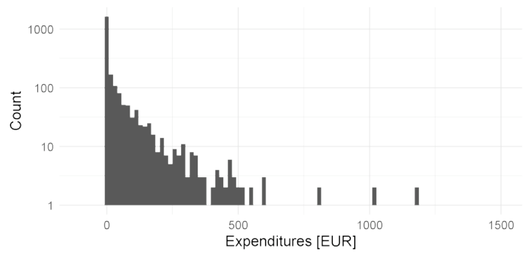
B Details on Expenditures per Participant and Month

Figure B.1: Individual × Month Expenditures During the Pre-Treatment Period

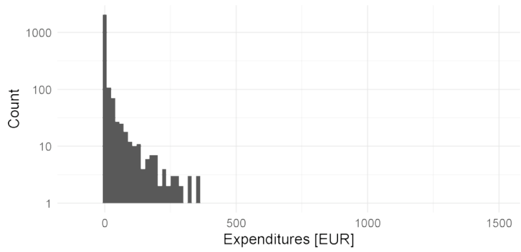
(a) Expenditures Public Transportation



(b) Expenditures Car-Related Transportation



(c) Expenditures Micromobility



Notes: Panel (a) - (c) show a histograms of the monthly expenditures for the corresponding transport modes made by the 341 participants in the sample during the pre-treatment period from April 2021 - October 2023.

The individual × month observations for the outcomes public and car-related transportation expenditures, as well as micromobility 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 12785 expenditure items for PT (excluding annual tickets), 6177 expenditure items for car-related transportation and 1932 expenditure items for micromobility for our main sample. After removing expenditure items booked outside Germany, we are left with 11951 expenditure items for PT, 5087 expenditure items for car-related transportation and 1877 expenditure items for micromobility. As can be seen in Panels (a) to (c) in Figure B.1, 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, which is almost half as large as the average monthly pre-treatment car-related expenditures for the entire control group ($43 * 139 =$ €5977). To reduce the potential impact of very large expenditure items, and to estimate proportional effects, we estimate regressions on expenditures in levels using a Poisson Quasi-Maximum Likelihood approach.

C Additional Graphs and Tables

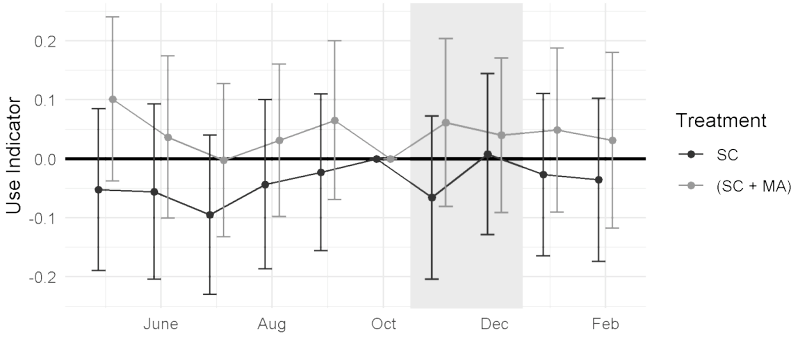
Table C.1: Employees Eligible for a Company Car vs. Users of the Mobility Budget

	Company Car	Eligible, no Company Car	Mobility Budget
Panel A: Gender and Age			
% Gender Male	78.6 %	65.3 %	55.5 %
Age Groups			
$\% \leq 30$ years	4.8 %	13.7 %	9.7 %
$\%$ $31 - 40$ years	20.9 %	35.0 %	39.3 %
$\%$ $41 - 50$ years	32.4 %	25.0 %	27.6 %
$\% \geq 51$ years	43.0 %	26.3 %	23.5 %
Observations	8,854	1,388	341
Panel B: Household Characteristics			
(Experiment Sample Reduced to Survey 3 Participants)			
Household composition			
# Adults	2.04	1.95	1.89
# Children ≤ 17 years	0.89	0.70	0.75
Cars in household			
$\% \geq 1$ private car	48.1 %	64.3 %	44.8 %
$\% \geq 1$ company car	100 %	15.7 - 24.1 %	21.9 %
$\% \geq 1$ car (private or company)	100 %	80.0 %	56.3 %
Observations	8,854	1,388	183
Panel C: Urban vs. Rural Location of Residence			
(Experiment Sample Reduced to Survey 1 Participants)			
Location of residence			
% rather rural	31.8 %	21.8 %	17.5 %
% mixed	34.9 %	30.6 %	Not included
% rather urban	33.6 %	47.7 %	82.5 %
Observations	8,854	1,388	246

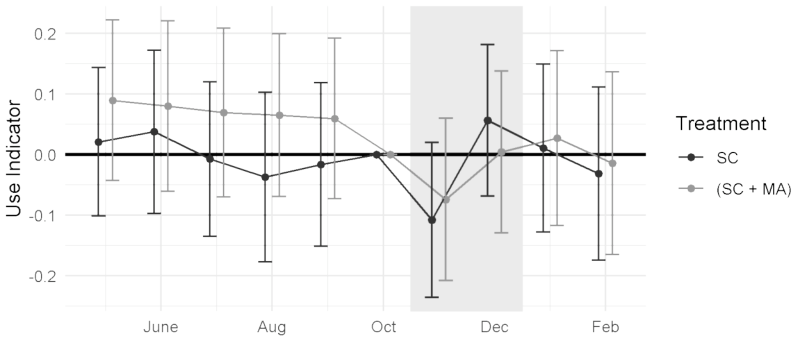
Notes: Columns 1 and 2 display data from an additional survey in February/March 2023 among all employees at our partner company who live in Germany. The survey was about the use and acceptance of electric mobility, and participation was voluntary. We expect that there might be a response bias for this survey, since men are overrepresented as compared to the total population of employees.
Column 3 displays the corresponding information from surveys among participants of the mobility budget. In Panel A, column 3 displays information for the sample of experiment participants used in our main specification. In Panel B, we only have the corresponding information for participants that additionally took part in our endline survey. In Panel C, the corresponding information is available only for participants in our first survey, which could not be linked to the experimental data. Thus, the sample considered here may include some participants excluded from our main analysis, e.g., users holding an annual ticket for public transport. % Gender Male is the share of male participants in each sample. Age Groups is the share of participants in each age group. Cars in Household is the share of households with at least one i) private car, ii) one company car from any company, iii) at least one car (either a private or a company car or both). For the sample of eligible employees, we asked for company cars from our partner company or any other company separately, and can thus only bound the share of households holding any company car. Location of residence is the share of participants that perceive their location of residence as i) rather rural, ii) a mixture of urban and rural, iii) rather urban. For the experimental sample, there was no mixed category.

Figure C.1: Event Study Graph for Differences in Expenditures

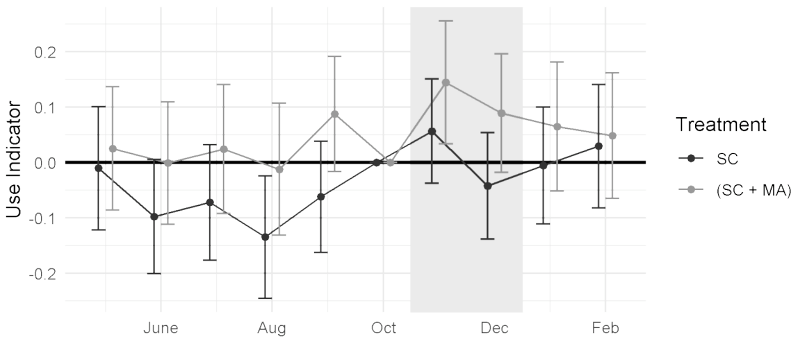
(a) Use of Public Transportation



(b) Use of Car-Related Transportation



(c) Use of Micromobility



Notes: Event study plots showing coefficients + confidence intervals of a linear probability regression of an indicator whether a participant has used the corresponding transport mode in a given month on an 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.

Table C.2: ATE on Monthly Use, Including the First and the Last Month of the Budget Year

	Use Indicator (Monthly)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Public Transportation Use						
SC × Treat. Period	0.03	0.03	−0.01	0.01	0.01	0.04
	(0.05)	(0.04)	(0.06)	(0.04)	(0.05)	(0.05)
(SC + MA) × Treat. Period	0.01	0.02	0.04	−0.01	0.01	0.01
	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)	(0.04)
SC × Post Treat. Period	0.04	0.05	0.004	0.02	0.03	0.05
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
(SC + MA) × Post Treat. Period	−0.004	−0.01	0.03	−0.02	0.01	0.001
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	4,092	4,092	4,092	5,136	3,768	4,092
R^2	0.001	0.29	0.0005	0.0004	0.0003	0.001
Panel B: Car Transportation Use						
SC × Treat. Period	−0.03	−0.02	−0.01	−0.01	0.01	−0.02
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
(SC + MA) × Treat. Period	−0.10**	−0.07*	−0.04	−0.09**	−0.09*	−0.09**
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
SC × Post Treat. Period	−0.02	−0.01	−0.01	−0.04	−0.01	0.005
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
(SC + MA) × Post Treat. Period	−0.07	−0.05	−0.01	−0.06	−0.08	−0.06
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
Observations	4,092	4,092	4,092	5,136	3,768	4,092
R^2	0.003	0.33	0.0003	0.002	0.003	0.002
Panel C: Micromobility Use						
SC × Treat. Period	0.06**	−0.004	−0.04	0.04	0.04	0.06**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
(SC + MA) × Treat. Period	0.09***	0.06**	0.05	0.07**	0.07**	0.09***
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
SC × Post Treat. Period	0.06*	0.002	−0.03	0.04	0.03	0.06*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
(SC + MA) × Post Treat. Period	0.02	−0.003	−0.02	0.01	0.01	0.02
	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Observations	4,092	4,092	4,092	5,136	3,768	4,092
R^2	0.003	0.22	0.002	0.002	0.001	0.003
Annual Ticket Users				X		
Survey Particip.					X	
Exp. Outside GER						X
Covariates		X				
Individual FE	X			X	X	X
Month FE	X	X	X	X	X	X

Notes: Significance markers * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Use is an indicator whether an individual used the corresponding transport mode in a given month. Linear Probability Models, estimated using ordinary least squares. 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. Exp. Outside GER indicates that expenditure items booked outside Germany 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. Standard errors are clustered by participant.

Table C.3: ATE on Monthly Expenditures, Including the First and Last Month of the Budget Year

	Change in Expenditures as % of Control Group Average					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Public Transportation Expenditures						
SC x Treatment Period	−0.18	−0.07	−0.06	−0.19	−0.27	−0.10
	(0.20)	(0.18)	(0.19)	(0.18)	(0.20)	(0.19)
(SC + MA) x Treatment Period	−0.15	−0.05	0.01	−0.24	−0.28	−0.15
	(0.20)	(0.17)	(0.19)	(0.18)	(0.19)	(0.19)
SC x Post Treatment Period	−0.07	0.04	0.05	−0.17	−0.18	−0.05
	(0.19)	(0.18)	(0.18)	(0.17)	(0.18)	(0.20)
(SC + MA) x Post Treatment Period	−0.07	0.02	0.08	−0.07	0.00	−0.05
	(0.20)	(0.18)	(0.18)	(0.18)	(0.20)	(0.19)
Observations	4,092	4,092	4,092	5,136	3,768	4,092
R2 Within Adj.	0.001	0.244	0.000	0.001	0.002	0.000
Panel B: Car Transportation Expenditures						
SC x Treatment Period	−0.23	−0.30	−0.26	−0.26	−0.41	−0.03
	(0.34)	(0.28)	(0.28)	(0.30)	(0.35)	(0.32)
(SC + MA) x Treatment Period	−0.48	−0.46	−0.49*	−0.30	−0.41	−0.35
	(0.32)	(0.28)	(0.28)	(0.31)	(0.37)	(0.33)
SC x Post Treatment Period	0.15	0.09	0.13	−0.16	0.04	0.17
	(0.34)	(0.31)	(0.27)	(0.32)	(0.35)	(0.31)
(SC + MA) x Post Treatment Period	0.00	0.05	0.00	−0.20	−0.07	−0.14
	(0.34)	(0.30)	(0.26)	(0.32)	(0.35)	(0.31)
Observations	4,092	4,092	4,092	5,136	3,768	4,092
R2 Within Adj.	0.003	0.290	0.002	0.001	0.002	0.002
Panel C: Micromobility Expenditures						
SC x Treatment Period	0.44	0.39	0.32	0.44	0.38	0.49
	(0.66)	(0.58)	(0.65)	(0.61)	(0.71)	(0.65)
(SC + MA) x Treatment Period	0.25	0.34	0.27	0.28	0.09	0.25
	(0.48)	(0.43)	(0.45)	(0.45)	(0.50)	(0.48)
SC x Post Treatment Period	−0.19	−0.36	−0.31	−0.36	−0.49	−0.21
	(0.55)	(0.55)	(0.51)	(0.48)	(0.54)	(0.58)
(SC + MA) x Post Treatment Period	−0.42	−0.32	−0.40	−0.55	−0.69	−0.48
	(0.53)	(0.52)	(0.52)	(0.47)	(0.48)	(0.56)
Observations	4,092	4,092	4,092	5,136	3,768	4,092
R2 Within Adj.	0.004	0.218	0.002	0.006	0.008	0.004
Annual Ticket Users				*X*		
Survey Particip.					*X*	
Exp. Outside GER						*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. Expenditures are measured in Euro per transport mode and month. Poisson fixed-effects regression. 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. Exp. Outside GER indicates that expenditure items booked outside Germany 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. Standard errors are clustered by participant.

Table C.4: ATE on the Monthly Count of Expenditure Items

	Expenditure Item Count					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Public Transportation Expenditures						
SC x Treatment Period	−0.05	0.00	−0.06	−0.04	−0.08	−0.11
	(0.15)	(0.14)	(0.18)	(0.14)	(0.16)	(0.14)
(SC + MA) x Treatment Period	−0.13	−0.07	0.08	−0.20	−0.24	−0.24
	(0.14)	(0.13)	(0.17)	(0.16)	(0.18)	(0.15)
SC x Post Treatment Period	−0.17	−0.11	−0.19	−0.28*	−0.32*	−0.12
	(0.16)	(0.16)	(0.21)	(0.16)	(0.18)	(0.18)
(SC + MA) x Post Treatment Period	−0.25	−0.22	−0.04	−0.30*	−0.33	−0.26
	(0.17)	(0.16)	(0.20)	(0.18)	(0.21)	(0.16)
Observations	3,410	3,410	3,410	4,280	3,140	3,410
R2 Within Adj.	0.001	0.486	0.235	0.002	0.002	0.001
Panel B: Car Transportation Expenditures						
SC x Treatment Period	−0.54**	−0.35*	0.03	−0.40**	−0.20	−0.29
	(0.22)	(0.19)	(0.29)	(0.20)	(0.22)	(0.21)
(SC + MA) x Treatment Period	−0.63**	−0.42**	−0.31	−0.54*	−0.36	−0.54**
	(0.28)	(0.20)	(0.28)	(0.28)	(0.27)	(0.25)
SC x Post Treatment Period	−0.18	−0.08	0.39	−0.17	−0.19	0.11
	(0.33)	(0.31)	(0.30)	(0.30)	(0.35)	(0.31)
(SC + MA) x Post Treatment Period	0.00	0.20	0.32	0.10	0.06	−0.04
	(0.38)	(0.33)	(0.32)	(0.32)	(0.38)	(0.35)
Observations	3,410	3,410	3,410	4,280	3,140	3,410
R2 Within Adj.	0.005	0.453	0.001	0.004	0.001	0.003
Panel C: Micromobility Expenditures						
SC x Treatment Period	0.07	−0.01	−0.02	0.02	−0.45	0.17
	(0.76)	(0.59)	(0.50)	(0.68)	(0.80)	(0.73)
(SC + MA) x Treatment Period	0.93***	0.73**	0.71*	0.82***	0.53	0.93***
	(0.32)	(0.30)	(0.39)	(0.28)	(0.40)	(0.32)
SC x Post Treatment Period	0.23	0.11	0.14	0.15	−0.37	0.26
	(0.80)	(0.69)	(0.45)	(0.70)	(0.74)	(0.78)
(SC + MA) x Post Treatment Period	0.39	0.28	0.18	0.18	0.41	0.39
	(0.57)	(0.53)	(0.49)	(0.54)	(0.52)	(0.57)
Observations	3,410	3,410	3,410	4,280	3,140	3,410
R2 Within Adj.	0.008	0.439	0.002	0.005	0.006	0.007
Annual Ticket Users				X		
Survey Particip.					X	
Exp. Outside GER						X
Covariates		X				
Individual FE	X			X	X	X
Month FE	X	X	X	X	X	X

Notes: Significance markers * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Expenditure items are the number of purchase acts per individual and month. Poisson fixed-effects regression. 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. Exp. Outside GER indicates that expenditure items booked outside Germany 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 participant.

Table C.5: Temporal Treatment Effect Heterogeneity

	Use Indicator (Monthly)		Use Indicator (Bi-Weekly)	
	(1)	(2)	(3)	(4)
Panel A: Public Transportation Use				
SC × Treat. Period	−0.02	0.05	0.05	−0.02
	$p = 0.68$	$p = 0.37$	$p = 0.27$	$p = 0.70$
(SC + MA)× Treat. Period	0.02	0.001	0.02	−0.03
	$p = 0.68$	$p = 0.99$	$p = 0.72$	$p = 0.54$
Observations	3,069	3,069	6,138	6,138
Panel B: Car Transportation Use				
SC × Treat. Period	−0.10**	0.06	−0.02	−0.01
	$p = 0.04$	$p = 0.24$	$p = 0.51$	$p = 0.75$
(SC + MA)× Treat. Period	−0.12**	−0.04	−0.02	−0.06*
	$p = 0.02$	$p = 0.40$	$p = 0.63$	$p = 0.08$
Observations	3,069	3,069	6,138	6,138
Panel C: Micromobility Use				
SC × Treat. Period	0.10***	0.002	0.03	0.02
	$p = 0.004$	$p = 0.96$	$p = 0.14$	$p = 0.21$
(SC + MA)× Treat. Period	0.11***	0.06	0.06**	0.04*
	$p = 0.004$	$p = 0.15$	$p = 0.03$	$p = 0.06$
Observations	3,069	3,069	6,138	6,138
November	*X*			
December		*X*		
No E-Mail			*X*	
E-Mail				*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. Linear Probability Models, estimated using ordinary least squares. SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Separate regressions are estimated for specific parts of the treatment period. E-mail indicates that only weeks in which a treatment e-mail was sent were included. November (December) indicates that only the treatment month November (December) was included. Before and after the treatment period, the full sample is used. Standard errors are clustered by participant.

Table C.6: Treatment Effect Heterogeneity Across Sub-Groups

	Use Indicator (Monthly)			
	(1)	(2)	(3)	(4)
Panel A: Public Transportation Use				
SC × Treat. Period	0.03	−0.01	-0.14^{**}	0.15^{**}
	$p = 0.61$	$p = 0.89$	$p = 0.03$	$p = 0.02$
(SC + MA) × Treat. Period	0.01	0.01	−0.06	0.07
	$p = 0.85$	$p = 0.88$	$p = 0.26$	$p = 0.32$
Observations	1,910	1,500	1,590	1,690
Panel B: Car Transportation Use				
SC × Treat. Period	−0.01	−0.03	−0.04	0.0004
	$p = 0.78$	$p = 0.61$	$p = 0.49$	$p = 1.00$
(SC + MA) × Treat. Period	−0.08	−0.08	−0.05	-0.13^{**}
	$p = 0.11$	$p = 0.22$	$p = 0.36$	$p = 0.03$
Observations	1,910	1,500	1,590	1,690
Panel C: Micromobility Use				
SC × Treat. Period	0.04	0.07^{*}	0.01	0.10^{***}
	$p = 0.33$	$p = 0.08$	$p = 0.78$	$p = 0.01$
(SC + MA) × Treat. Period	0.08^{*}	0.11^{**}	0.02	0.14^{***}
	$p = 0.09$	$p = 0.02$	$p = 0.61$	$p = 0.002$
Observations	1,910	1,500	1,590	1,690
Rural	X			
Urban		X		
Weak Treatment			X	
Strong Treatment				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. Linear Probability Models, estimated using ordinary least squares. SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Separate regressions are estimated for subgroups of the sample defined by pre-treatment covariates. Urban (Rural) indicates that only participants working at business locations in predominantly Urban (Rural) areas were included. Strong Treatment (Weak Treatment) indicates that only individuals receiving a strong treatment message were included. A strong treatment 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 weak treatment, where participants were below average in less than one message. Standard errors are clustered by participant.

Table C.7: Treatment Effect Heterogeneity Across Transport Modes

	Use Indicator (Monthly)		
	(1)	(2)	(3)
Panel A: Public Transportation Use			
	Long Distance PT	Local PT	
SC × Treat. Period	−0.02	0.03	
	$p = 0.72$	$p = 0.79$	
(SC + MA) × Treat. Period	0.02	−0.13	
	$p = 0.78$	$p = 0.25$	
Observations	3,410	3,410	
R^2	0.0005	0.001	
Panel B: Car Transportation Use			
	Rental Car	Carsharing	Taxi
SC × Treat. Period	−0.001	−0.04	−0.05
	$p = 0.98$	$p = 0.54$	$p = 0.46$
(SC + MA) × Treat. Period	0.002	−0.07	−0.12*
	$p = 0.94$	$p = 0.31$	$p = 0.10$
Observations	3,410	3,410	3,410
R^2	0.0002	0.002	0.002
Panel B: Micromobility Use			
	Bike	E-Scooter	
SC × Treat. Period	0.04	0.07	
	$p = 0.22$	$p = 0.21$	
(SC + MA) × Treat. Period	0.06	0.09*	
	$p = 0.15$	$p = 0.06$	
Observations	3,410	3,410	
R^2	0.002	0.004	

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. Linear Probability Models, estimated using ordinary least squares. SC is an indicator for the social comparison treatment. SC + MA is an indicator for the social comparison and moral appeal treatment. Separate regressions are estimated for the different outcome variables. All outcome variables are monthly use indicators. Local PT is local public transportation. Long distance PT is long-distance public transportation. Rental cars and carsharing are self-explanatory. Taxi comprises taxi rides and other ride-hailing services like UBER. Bike comprises bike rentals, long-term leases and repairs. E-scooters is e-scooter sharing. Standard errors are clustered by participant.