Transregio 391

TRR 391 Working Paper #1

January 2025

Individual Mobility and Public Transport Subsidies

Mark A. Andor, Joschka Flintz, Colin Vance

Suggested citation:
Andor, A., Flintz, J., and Vance, C. (2025). "Individual Mobility and Public Transport Subsidies". *TRR 391 Working Paper #1.* DOI: 10.17877/DE290R-25228.

Version 1.0, January 2025

Corresponding author: mark.andor@rwi-essen.de

Abstract

Politicians around the world are looking for ways to reduce the negative externalities of the transport sector. Subsidization of public transport is a popular remedy, but evidence on the associated causal effects remains scant. Based on a randomized controlled trial that tracks mobility behavior continuously via a mobile app, this study provides causal evidence on how individuals modify their mobility patterns when provided with temporary cost-free access to public transport. We further explore whether such access induces enduring shifts in mobility behavior after the reinstatement of regular fares. We randomly provide roughly half of our around 420 participants – whose selection targeted car users – with a one-month public transport ticket for their local area, and monitor travel behavior across all modes over three months. We find a statistically significant average increase of about two trips per month using public transport during the subsidization period. The rise in public transport utilization, however, is not paralleled by a reduction in car usage, nor does it yield a persistent alteration in mobility behavior in the subsequent month after the ticket expires.

Key words: Public Transport, Mobility, Randomized Controlled Trial, Mode Choice.

1 Introduction

The reduction of negative transport externalities has long vexed policy-makers in Europe. Notwithstanding decades of demand-side and technological policy interventions, including fuel taxes and fuel economy mandates, the number of cars on the road continues to increase (Eurostat, 2024), contributing to transport sector's distinction as the only sector in Europe where emission levels remain at historic highs. To buck this stagnation, policy-makers in several countries have turned to the promotion of more sustainable transportation modes, particularly public transport. Recognizing the political resistance that typically accompanies first-best solutions such as carbon taxes, subsidizing public transport holds promise as an efficient alternative to alleviate externalities such as road congestion, local air pollution, noise, and greenhouse gas emissions (Parry and Small, 2009, Basso and Silva, 2014). Additionally, increased demand for public transportation modes can lead to economies of scale and potentially enhance service quality through higher frequencies via the Mohring effect (Mohring, 1972). Temporary free ticket initiatives, as have been implemented in several cities in Europe and the U.S., offer individuals the opportunity to experience public transit services firsthand, the aim being to draw in riders whose patronage extends after the period of free access has concluded. However, the evidence for their effectiveness is not yet clear, particularly as regards the question of whether such measures reduce car use. Existing studies are typically either based on self-reported mobility behavior or are non-experimental, which makes it difficult to determine the causal effects and often requires hard assumptions.

The present study addresses this gap by analyzing the impact of a free one-month public transport ticket on individuals' transport behavior. We investigate both the immediate effects during the subsidized period and the effects in the subsequent period after the ticket has expired. To this end, we conduct a field experiment involving 421 respondents, the selection of whom targets on car users. Respondents are tracked using a smartphone app that enables us to collect comprehensive information on all trips the individuals take across various transport modes. Following an initial baseline month, we provide a randomly selected treatment group with a public transport ticket valid for one month in their region of residence. The participants are then monitored during the subsidization month and an additional month thereafter to observe potential lasting changes in travel behavior. The study design facilitates the application of a difference-in-differences approach to evaluate the intervention's causal impact on demand for different modes, such as car usage, public transport use, and walking.

We find a statistically significant average increase of approximately two trips in monthly public transport boardings during the subsidization period, implying an increase of public transport use of around 61%. Participants do not appear to substitute regular trips made by car but instead utilize the free public transport to make additional, presumably irregular, trips during off-peak hours. Moreover, the increased transit usage identified during the subsidization period is not accompanied by lasting changes in mobility behavior in the following month after the ticket expires.

Our main contribution is to identify the impact of a free public transport ticket on mobility behavior by using GPS tracking data from a mobile app to infer participants' mode choice and trips characteristics. Early studies have typically relied on self-reported mobility data either through travel diaries or survey questions about the frequency of use of different modes (e.g. Bachman and Katzev, 1982, Fujii and Kitamura, 2003, Thøgersen, 2009, Bull et al., 2021). A major disadvantage of this approach is that self-reported data is susceptible to reporting bias, wherein participants' recordings may deviate from their actual behavior, for example, due to imperfect recollection or a desire to present a more favorable image (e.g. by understating use of unsustainable modes).

More recent studies have consequently used travel card records of actual public transport boardings (e.g. Gravert and Olsson Collentine, 2021, Brough et al., 2022, Guzman and Hessel, 2022). While travel card recordings mitigate reporting bias, they only provide information on public transport usage, with the implications for other travel modes remaining unclear. Therefore, no statement can be made about car use, which is central to understanding the implications for negative externalities. Furthermore, the data obtained through travel cards may be incomplete in cases of fare evasion, alternative payment methods, or participants failing to register their boardings (Brough et al., 2022, Kholodov et al., 2021). Conversely, it may overstate public transport usage when the travel card is shared among friends or family members (Brough et al., 2022).

Relying on GPS tracking data recorded via the participants' mobile phones avoids the problems of both self-reported and travel card data. Similar to Hintermann et al. (2024), who analyze the impact of internalizing the external cost of transport on mobility behavior, we use the GPS tracked data to infer the study participants' mode choice and collect information about trip characteristics such as length and duration. Aside from being free of self-reporting bias, the data enables us to analyze the implications for modes other than public transport, such as car, bike or walking.

The remainder of the paper is structured as follows. Section 2 illustrates the experimental design, while Section 3 explains the data and empirical approach. Subsequently, Section 4 presents our results, closing with robustness checks. We conclude in Section 5 by summarizing the results and discussing policy implications and avenues for further research.

2 Experimental design

Study participants were recruited in collaboration with the professional survey institute *forsa*, which maintains a panel of more than 100,000 households that is representative for the population of German-speaking internet users.[1] We recruited the participants in two steps. First, we carried out a screening by means of a short survey in which we asked about the general willingness to participate in a study using a mobility tracking app. To motivate the study, the screened participants were informed that the tracking app would be used to examine the mobility behavior of the population, i.e. the extent and type of use of different means of transport, and that this would contribute to improving existing mobility offers or developing alternative offers. This screening took place in February 2018,

[1]Further information regarding this panel can be accessed at `http://www.forsa.com/`.

and was limited to people who live in one of ten transport associations, which are among the largest in Germany. The screened participants were required to own an Android or an iPhone smartphone installed with current software that is capable of mobility tracking. As our treatment is a free public transport ticket, we excluded people from the survey who already owned a transit pass, while aiming to include only people who use a car.[2] Of the 18,000 people contacted by *forsa*, 2,100 met the selection criteria and agreed to be contacted again for possible participation in the study.

The second step commenced on the 23^{rd} of April, when the screened participants were contacted again to take part in a longer survey. Participants were asked to download the mobility tracking app and to take part in the experiment by sharing their mobility data. Of the 2,100 screened participants, 82% took part in the longer survey and 52% agreed to take part in the app tracking at the end of the survey. Due to technical issues or a lack of final consent on the app to share the data, a number of participants were prevented from participating in the experiment, leaving 422 participants with usable data in our sample. After the experimental period, we excluded the data of one participant with implausible mobility data,[3] resulting in a final sample of 421 study participants.

The largest fraction of participants in the final sample were recruited from the traffic association of the VRR (131), responsible for public transportation in Dusseldorf and the densely populated Ruhr area, and the VBB (118), covering Berlin and the surrounding state of Brandenburg. 48 participants resided in the catchment area of the Munich transport association (MVV). Around 20 to 27 participants each were located in the vicinity of Aachen, Bremen, Hanover, Leipzig, and Chemnitz, respectively, and were covered by the respective regional transport organizations. Figure A1 in the Appendix shows the participants' place of residence on the postal code level and the corresponding transport associations.

Irrespective of the specific transport authority, the public transport ticket granted participants unrestricted access to all modes of public transportation – buses, trams, and trains – throughout the entire month at no cost. In addition, the ticket encompassed additional privileges such as complimentary transport for a dog, a baby carriage, and, within certain transport associations, a bicycle. The ticket facilitated the free travel of another adult and up to three children on weekdays after 7 pm and throughout weekends. Despite the uniform core service provided by the public transport pass, the tickets were subject to heterogeneity across different transport associations. This variation stems from differences in the extent of the ticket's coverage area and the range of public transport services accessible within that region. In most cases, the ticket's coverage was confined to the participant's city of residence. However, in select instances, it also encompassed neighboring areas. For example, a ticket for Berlin also allowed use of public transport in the adjacent city of Potsdam.

[2] At the beginning of the experimental period, ten study participants stated to hold a ticket that allows them to use public transportation, apparently having purchased the tickets between the screening survey and the start of the field trial. Six of those are part of the control group, four are in the treatment group. Omitting the data of ticket holders has negligible effects on the results.

[3] The user regularly travelled an average of about 240km per day by regional train, suggesting an occupation as a train conductor or driver. She/he furthermore reported not having a public transport ticket and using the car for the commute to work.

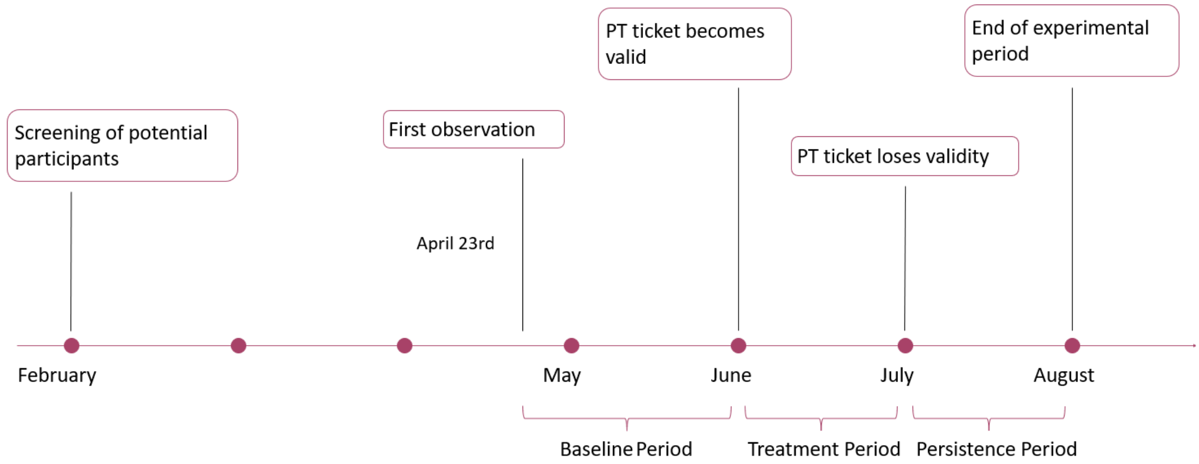

Figure 1: Timeline of the Experiment

Over the final week of April 2018, the screened participants took part in the survey and registered for the app, which tracked their mobility behavior over three months. The app processes each trip using GPS, acceleration and gyroscope data. This allowed us to track participants' trips and obtain information on the mode of transport, distance (in km), start and end times and average speed, giving us a detailed picture of each participant's mode choice. App users received information about their activities, such as the distance travelled by mode, the spatial course of their trip, and the time spent on the road so that they could assess whether they have been tracked correctly and make corrections, if necessary. Figure A2 in the Appendix shows screenshots of the app as used by the participants.

The overall timeline of the experiment is outlined in Figure 1. The period spanning from the end of April through May was used to establish the baseline mobility of all participants. During this period, participants were randomly assigned to the treatment- and control group. The assignment was stratified on location to ensure a balanced distribution of participants across the treatment- and control group for each transport authority. At the end of May, each participant, irrespective of their group assignment, received a letter explaining the functionality of the mobility tracking app in more detail. For participants in the treatment group, the letter also included a one-month public transport ticket specific to their region of residence, valid for June 2018. The letter provided precise details regarding the validity of the ticket and the public transport services in the respective region. Subsequently, we observe the participants for the treatment month and in the following month after the ticket's validity had lapsed, enabling the analysis of lasting changes in mobility behavior. All participants received 60 Euros at the end of the field trial.

For the average participant, the tracking interval spanned about 85 days, 56% of which recorded at least one trip made. There are two possible reasons for days without any recording of a trip, one being that the participants are actually inactive so that the number of trips is zero. A second possibility is that the mobile phone is switched off or left at home, in which case the app cannot monitor mobility behavior. For our analysis, this latter reason would be problematic if the treatment were correlated with mobile phone usage. However, we find no evidence for a treatment effect on app tracking. Descriptively, this is seen by comparing the average number of days that the treatment and control groups were tracked per month after ticket provision, which varies negligibly: In June and July, participants in the control group were tracked for an average of 18.72 and 18.1 days, respectively, while participants who received the public transport ticket were followed for an average of 18.76 and 18.38 days, respectively. Moreover, we estimated models that explore how treatment status bears upon tracking after ticket provision, which corroborate the conclusion that the treatment does not bear on app tracking (Table A1 in the Appendix).

In the main analysis below, we assume that days without a recorded trip represent zeros and include these in the estimation sample. As a robustness check, we eliminate these observations and only include days with tracking data in the sample, with results presented in Section 4.3 and the Appendix. Recognizing the count nature of the dependent variable, we also present robustness checks in Section 4.3 to explore the stability of the results when estimating a Poisson regression model.

3 Data and econometric model

3.1 Data

The final sample of study participants consists of 421 persons ranging in age between 19 and 78, 33% of whom are women. Owing partly to our selection criteria, the tracked participants tend to exhibit higher levels of employment, educational attainment, and household income in comparison with *Mobilität in Deutschland*, a national travel survey that is more representative of the German population (cf. Table A2 in the Appendix). We randomly assigned a free public transport ticket to 209 participants, with the remaining 212 individuals assigned to the control group. As Table 1 demonstrates, the treatment and control groups are well balanced across several variables, including age, gender, the number of children, employment status, household income, and car ownership. The one variable for which we find statistically significant differences is household size. At around 2.62 people per household, households in the control group tend to be slightly larger than the 2.34 people in the treatment group. In the estimations, we control for household size and the other socio-economic attributes via the inclusion of person-level fixed effects. In addition, we undertake a heterogeneity analysis that allows for differential effects of the treatment by several of the socio-economic attributes.

Figure A3 in the Appendix shows the distribution of each participants' average number of car and public transport trips per day in the baseline period, demonstrating that the screening process resulted in a sample that predominantly travels by car and rarely uses public transport. We thereby focus on individuals who have the highest potential to reduce negative externalities of car driving. During the baseline period, the average participant made 1.3 car trips and 0.11 public transit trips per day.

The raw format of the data contains a separate entry for each individual trip undertaken

Table 1: Socio-economic Characteristics of Users in the Treatment and in the Control Group (n = 421 participants)

	Overall Average	Average in Treatment Group	Average in Control Group	Group Difference
Individual Characteristics				
Age	49.97	49.32	50.64	-1.32
Female	0.33	0.30	0.35	-0.05
University Degree	0.41	0.42	0.41	0.01
Currently Employed	0.79	0.81	0.76	0.05
Retired	0.16	0.15	0.17	-0.02
Distance to Closest PT Stop (km)	0.82	0.64	1.00	-0.36
PT Schedule App	0.59	0.60	0.57	0.03
Household Characteristics				
Household Size	2.48	2.34	2.62	-0.28*
No. of Children in HH	0.43	0.36	0.51	-0.15
Income: below €1.700	0.10	0.13	0.07	0.06
Income: €1.700 to €3.200	0.31	0.31	0.32	-0.01
Income: €3.200 to €4.700	0.31	0.27	0.35	-0.08
Income: above €4.700	0.28	0.29	0.26	0.03
No. of Cars in HH	1.53	1.49	1.58	-0.09

*** and * denote statistical significance at the 1% and 5% level, respectively.*

Table 2: Descriptive Statistics of Trips (n = 110,724)

Mode	Average Length (km)	Average Duration (min)	No. Trips in May	No. Trips in June	No. Trips in July	Total No. Trips	Share of All Trips (%)
Public Transport	8.40	14.56	1,157	1,891	1,323	4,371	3.95
Bus	6.42	12.70	463	804	572	1,839	1.66
Local Rail	3.61	11.50	388	738	466	1,592	1.44
Regional Rail	20.38	23.40	306	349	285	940	0.85
Car	16.34	20.10	13,870	15,909	14,461	44,240	39.96
Motorbike	18.06	53.74	248	195	257	700	0.63
Walk	0.56	8.06	14,128	17,181	15,206	46,515	42.01
Bike	3.06	12.69	4,362	5,319	4,627	14,308	12.92
Long Distance Rail & Bus	145.17	92.74	101	164	108	373	0.34
Plane	949.01	107.51	11	10	9	30	0.03
Ship	19.00	82.21	62	55	70	187	0.17

Table 3: Average Mode Use in Baseline Period Across Groups (n= 10,707 participant-days)

	Treatment Group	Control Group	Difference
Public Transport	0.12	0.10	0.01
Bus	0.05	0.04	0.01
Local Rail	0.04	0.04	0.00
Regional Rail	0.03	0.03	0.00
Car	1.32	1.27	0.05

The table presents a participant's average number of trips per day in the baseline period made by the different transport modes. No significant differences are found in this table.

by a participant, comprising 110,724 tracked trips.[4] The data encompasses information on the transportation mode, the distance covered, as well as starting and ending times for each trip, which was used to construct the descriptive statistics presented in Table 2. Public transport trips, which are defined as the sum of bus, local rail, and regional rail trips, comprise roughly 4% of recorded travel instances. Among these, buses emerge as the most favored choice (1,839 trips), followed by local rail transport (1,592 trips) and regional rail (940 trips). On average, bus rides cover a distance of 6.4 km and take approximately 13 minutes. Similarly, local rail trips encompass a comparable duration, yet tend to be notably shorter in distance. Car rides and walking trips are seen to jointly constitute more than 80% of the recorded travel instances, with each contributing roughly 40%. Car rides have an average length of 16.3 km and a duration of 20 minutes.

To finalize the set up of the data for the econometric analysis, we collapse observations on a participant-day basis, yielding 35,909 observations on the number of trips and distance covered per day by each participant, differentiated between alternative transport modes. As we did not find any meaningful effects of the treatment on walking, biking or other means of transportation (motorbike, long distance rail & bus, plane, ship) in the analyses, we will focus on public transport and car usage in the following.[5] In order to obtain an assessment of which specific means of public transport has changed usage in particular, we also look at the effects separately for bus, local rail and regional rail. Table 3, which presents participant-day observations, demonstrates that the randomization worked well and thus the participants in the treatment and control groups are similar in terms of the average number of trips made by public transport, bus, local and regional transport as well as car.

[4]This sample of tracked trips was subject to some preliminary cleaning steps. For example, we excluded walking trips and car trips shorter than 100 and 200 meters respectively, as these often represent brief walks to a vehicle or short car relocations. Similarly, we omitted bus rides and trips using light rail transit, subways, and regional trains shorter than 200 meters, due to the potential for measurement errors. Owing to similarities in their attributes, we also combine bus, mini-bus and O-bus into the category "Bus", subway and light rail into the category "Local Rail", and long distance bus and long distance rail into the category "Long Distance PT."

[5]All analyses can be provided upon request.

3.2 Model

We estimate the effect of a free public transport ticket on mobility behavior using a difference-in-differences model with two-way fixed effects:

$$Y_{it} = \beta_1 Treated_{it} + \beta_2 Persistence_{it} + Weekday + \delta_i + \gamma_t + \epsilon_{it}, \tag{1}$$

where Y_{it} measures the count of trips using a particular transportation mode for individual i on day t. $Treated_{it}$ is a dummy that equals one if participant i received the public transport ticket and it was valid for day t (June 2018). Similarly, $Persistence_{it}$ is a dummy that equals one if the participant was in the treatment group and the day t fell in July 2018, when the ticket had expired. δ_i are fixed effects on the individual level that account for time-invariant differences between participants, and γ_t are month fixed effects to consider common differences in the participants' mobility behavior over time. We also include dummies for the weekday on which Y_{it} was observed. The model is estimated with ordinary least squares (OLS). In addition to this baseline model, several robustness checks are undertaken that use alternative estimators, sub-samples, as well as specifications that include interaction terms to allow for treatment heterogeneity. As we test a series of models, we also apply multiple hypothesis testing to our main results using the procedure proposed by Benjamini and Hochberg (1995) (see Table A3 in the Appendix).

3.3 Pre-specification

While we did not publicly pre-specify this study in a pre-analysis plan, we had presented the general design in a German application for third-party funding to the sponsoring foundation and in a presentation at the Experimental Economics for the Environment Workshop in February 2018, before the experiment started.[6] Given that we analyze a free public transport ticket and observe the mobility behavior of the study participants in the treatment month and the following month, we consider the estimation of the treatment on the different modes of transport as pre-specified. All additional analyses regarding heterogeneity are explorative. Nevertheless, we do acknowledge the advantage of clearly formulated pre-analysis plans, even in straightforward experiments.

An additional consideration regarding pre-specification concerns the question of statistical power. Insufficiently powered studies have high rates of false negatives and may also cause high rates of false positives (Ioannidis, 2005). Experimental designs should therefore endeavor to ensure that a sufficient level of power is achieved. Given our reliance on app tracking data, for which there was little precedent in the literature, we could not obtain the necessary data for a proper power analysis (in particular standard deviation and expected effect on the outcome variable). In interpreting the estimates, we instead avail of the minimum detectable effect (MDE), defined as the smallest true impact that can be detected at a given level of statistical significance and with a given level of statistical power (Bloom, 1995, Ioannidis et al., 2017). The MDE corresponding to a two-sided

[6] The presentation is available upon request.

test assuming 80% statistical power and a 5% significance level is obtained ex-post via multiplication of the standard error by 2.8 (Bloom, 1995). Referencing the MDE allows us to gauge the extent to which the interpretation of the estimates should be tempered by insufficient power.

4 Results

4.1 Main estimates

We begin by discussing models of the number of trips taken by mode, focusing on public transport (PT) and car, and subsequently showing a breakdown of PT by bus, local rail, and regional rail.[7] The estimates, standard errors, and MDEs are reported in Table 4. As seen in the first column, the ticket is associated with a statistically significant increase of 0.069 trips per day by public transport in the month-long treatment period, or about two additional trips per month. This corresponds to an increase of roughly 61% relative to the post-treatment use in the control group. The estimate is also significant when controlling for multiple hypothesis testing (see below) and appears to be adequately powered given a MDE of 0.062. Since this value implies that we are able to detect effects of 0.06 trips per day, we can measure all effects that seem politically relevant with sufficient power. The small and statistically insignificant estimate of -0.003 in the persistence period, however, suggests that the positive treatment effect is not sustained following the expiration of the ticket.

The estimate of the treatment on car trips indicates a small positive effect of 0.083 trips per day, clearly counter to the policy target of reducing car use. The estimate is, however, statistically insignificant. A similar pattern is seen for the persistence period, with a positive, statistically insignificant estimate of 0.034. Both MDE values (0.194 and 0.230) indicate that the significance for this outcome variable is less high than for the other outcomes. Specifically, an increase or reduction of 6 or more car trips per month could be detected with a power of 80% and thus we cannot rule out effects on car driving completely. Yet, given the positive point estimates, strong reductions of car usage seem not likely.

Columns 3 to 5 in Table 4 show the effects of the free one-month PT ticket on more differentiated public means of motorized transport. The results indicate that the main channel through which local public transit increases is through the uptake of local rail services. The provision of a one-month PT pass increases the average number of daily trips in June made by local rail (either light rail or subway) by 0.037. The results further suggest a positive impact on the number of trips made by regional rail services of additional 0.015 trips per day, likely resulting from an increased "S-Bahn" use in larger metropolitan areas. However, the coefficients should be interpreted with caution as the MDEs exceed

[7] As discussed in Section 3.1, we also examined the impact on other modes of transport, in particular walking and cycling, but found no remarkable results. For all observed transport modes (see Table 2), results can be provided upon request.

Table 4: Main Results - Number of Daily Trips

	PT	Car	Bus	Local Rail	Regional Rail
Treatment Period	0.069**	0.083	0.018	0.037*	0.015*
	(0.022)	(0.069)	(0.011)	(0.015)	(0.006)
MDE	0.062	0.194	0.031	0.041	0.018
Persistence Period	-0.003	0.034	-0.012	0.003	0.006
	(0.021)	(0.082)	(0.010)	(0.012)	(0.007)
MDE	0.060	0.230	0.029	0.034	0.021
No. Observations	35,909	35,909	35,909	35,909	35,909
Adj. R2	0.120	0.310	0.112	0.105	0.075

*Fixed effects on individual and month level. Standard errors clustered on individual level. ** and * denote statistical significance at the 1% and 5% level, respectively. PT = Public Transport, MDE = Mean detectable effect size.*

the estimated effects. This likewise applies to the estimates from the persistence period, all of which are statistically insignificant.

As we test a series of models and coefficients, we apply the procedure proposed by Benjamini and Hochberg (1995) to ensure the robustness of our main results in the context of multiple hypothesis testing. This approach controls the false discovery rate (FDR), which is the proportion of incorrect rejections of the null hypothesis. Table A3 reports the lowest FDR at which our estimates remain statistically significant. When setting the FDR at 5%, only the coefficient for the ticket's effect on public transport usage in June remains significant. The estimates for local and regional rail, which are significant in our main results, retain significance if we allow for a 6.4% and 7% chance of incorrectly rejecting the null hypothesis, respectively. Overall, the results confirm the robustness of the ticket's estimated impact on participants' public transport use. This increase, which is limited to the treatment period, appears to be primarily driven by greater use of local rail.

4.2 The extensive margin and heterogeneity analysis

Turning attention to the extensive margin, Table 5 presents the results of linear probability models of daily modal use. The results mirror those in Table 4. We find that the treatment is associated with a statistically significant 2.6 percentage point increase in the probability of public transport usage, one evidently driven primarily by local rail use, with a small and insignificant effect seen on the probability of car use. Moreover, the results do not suggest a higher propensity to use public transport modes in the subsequent month, as evidenced by the statistically insignificant effects in the persistence period. The qualitative findings when using a logit model remain unchanged (Table A4).

Table 6 contains the results obtained from Equation 1 when distinguishing between the

Table 5: Main Results - Probability to Use Transport Mode

	PT	Car	Bus	Local Rail	Regional Rail
Treatment Period	0.026**	0.034	0.010	0.018**	0.007*
	(0.009)	(0.020)	(0.006)	(0.007)	(0.004)
MDE	0.025	0.055	0.018	0.018	0.010
Persistence Period	-0.006	0.018	-0.005	0.000	0.001
	(0.008)	(0.023)	(0.005)	(0.006)	(0.004)
MDE	0.024	0.064	0.014	0.017	0.011
No. Observations	35,909	35,909	35,909	35,909	35,909
Adj. R2	0.122	0.318	0.104	0.102	0.088

*Fixed effects on individual and month level. Standard errors clustered on individual level. ** and * denote statistical significance at the 1% and 5% level, respectively. PT = Public Transport, MDE = Mean detectable effect size.*

Table 6: Results - Number of Trips at Peak and Off-Peak Hours

	PT	Car	Bus	Local Rail	Regional Rail
Peak Hours					
Treatment Period	0.016	0.031	0.007	0.005	0.004
	(0.009)	(0.028)	(0.004)	(0.006)	(0.003)
MDE	0.024	0.079	0.011	0.017	0.007
Persistence Period	-0.005	0.014	-0.002	-0.005	0.002
	(0.009)	(0.031)	(0.004)	(0.006)	(0.003)
MDE	0.026	0.087	0.013	0.016	0.010
Off-Peak Hours					
Treatment Period	0.054**	0.052	0.011	0.032**	0.011*
	(0.016)	(0.051)	(0.009)	(0.010)	(0.005)
MDE	0.046	0.143	0.025	0.029	0.014
Persistence Period	0.003	0.020	-0.010	0.008	0.004
	(0.015)	(0.062)	(0.008)	(0.008)	(0.005)
MDE	0.043	0.173	0.021	0.024	0.014

*Fixed effects on individual and month level. Standard errors clustered on individual level. Peak hours from 07:00 to 09:00 and 16:00 to 18:00. ** and * denote statistical significance at the 1% and 5% level, respectively. PT = Public Transport, MDE = Mean detectable effect size.*

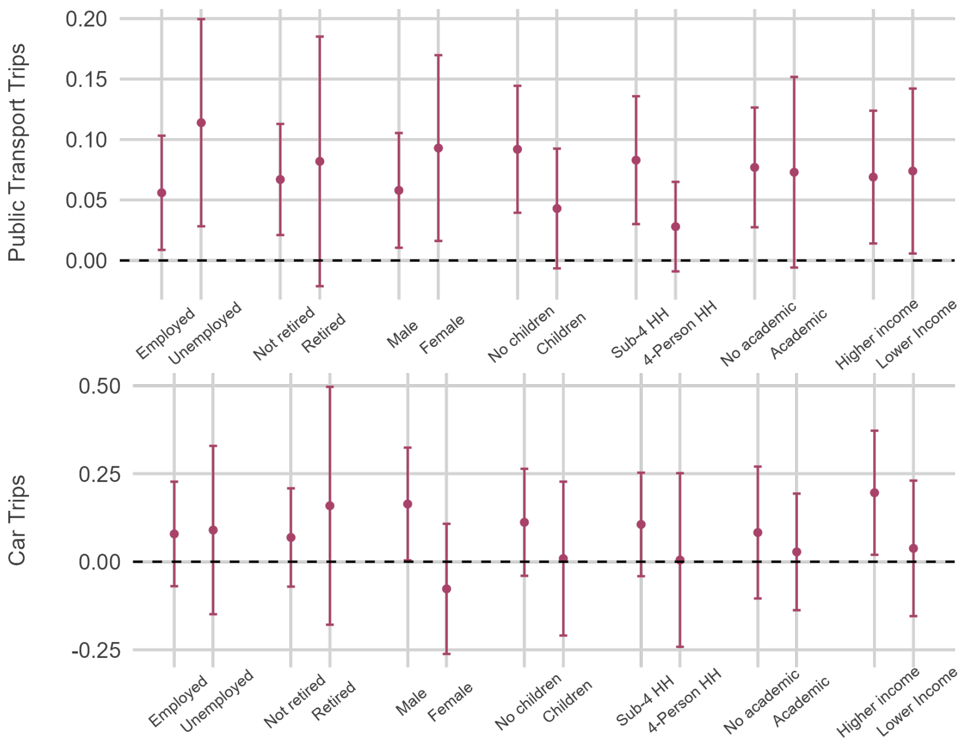

Figure 2: Heterogeneity Analysis - Socio-Economics

number of daily trips started during peak and off-peak hours as dependent variables. Peak hours are defined as the time from 07:00 to 09:00 in the morning and 16:00 to 18:00 in the afternoon, when traffic volume is expected to be high due to a large number of commuters. Off-peak trips are defined as trips that start during all remaining hours. Two patterns emerge from this exploratory analysis. First, as before, we find evidence for a positive and statistically significant effect of the free pass on public transit counts during the treatment period but not during the persistence period, contrasted by the complete absence of significant effects on car travel. Second, the magnitude of the effects of the treatment on transit counts is substantially higher during off-peak hours. While the ticket has no statistically significant impact on the participants' travel behavior during peak hours, the off-peak estimate of 0.054 in the total transit counts model is more than three times as large as the insignificant estimate corresponding to peak hours. Statistically significant and relatively large effects in the treatment period are also seen in the models of local rail and regional rail (though the latter value is exceeded by the MDE). Overall, the results are consistent with the idea that individuals in the treatment group predominantly utilize the opportunity to use public transportation free of charge to make additional non-regular trips, e.g. for shopping or leisure activities, instead of implementing public transport services in their regular commuting patterns.

In order to exploratively investigate whether the effects of the ticket differ according to socio-demographic and spatio-temporal variables, we extend the specification in Equation 1 with interaction terms. To this end, we interact the indicators $Treated$ and $Persistence$ with variables drawn from the participants' survey responses and information on their place of residence. Figure 2 indicates the absence of statistically significant differences across socio-economic characteristics, even if in some instances the point estimates diverge markedly. This especially applies to the indicator for employment. Among unemployed

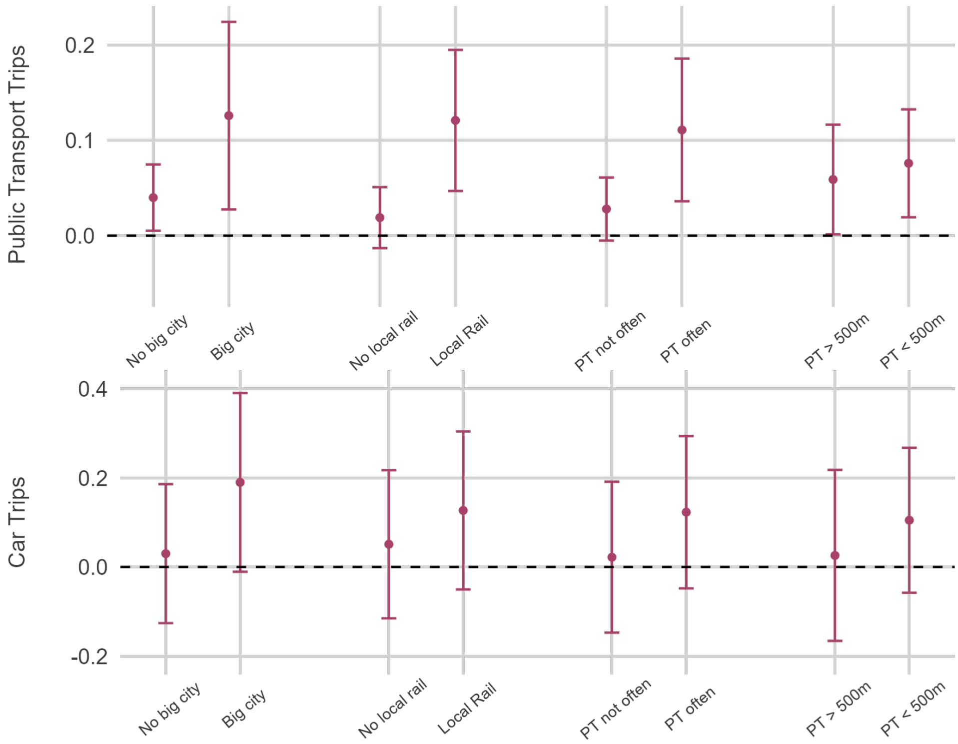

Figure 3: Heterogeneity Analysis - Public Transport Access

people, the effect of the treatment is to increase public transit trips by 0.11, about double the magnitude of the estimate for employed people. With the exception of gender (see Table A5), the allowance for heterogeneity in the model of car trips presented in the bottom panel also indicates no statistically significant differences across socio-economic groups.

Figure 3 presents differential effects by geography and service, highlighting the role of accessibility and frequency as mediating factors for the ticket's effectiveness in fostering public transit uptake. The top panel of the figure indicates some evidence that the positive effect of the free pass on transit use is predicated on spatio-temporal features: Residence in a large city, access to local rail services, or access to frequent public transit, boosts the effect of the free transit pass on public transport usage substantially, by as much as 3.8 additional trips per month. In the absence of any of these attributes, the effect of the free transit pass is smaller, and, in the case of accessibility and frequency, is statistically insignificant. As shown in Table A6 in the Appendix, there is no evidence for sustained increases in public transport usage during the persistence period, nor are statistically significant effects seen for car usage.

4.3 Other robustness checks

The dependent variables modelled in the main results presented in Table 4 are counts. As many modes are not used at all on a given day, these counts contain a non-negligible proportion of zeros and tend to have a positively skewed distribution. To account for the non-negative and discrete nature of the data, we estimate conditional (fixed effects) quasi-maximum likelihood Poisson regression models.

As presented in Table A7 in the Appendix, we see that the pattern of estimates using our baseline sample in a Poisson regression is similar to that of Table 4, albeit subject to a different interpretation owing to the nonlinearity of the Poisson estimator. Specifically, we obtain statistically significant coefficients of 0.464 for local public transport and 0.637 for local rail services. Interpreting these coefficients as multiplicative effects by computing e^{β}, we find that the number of local public transport trips increases by approximately 60%, while the number of local rail rides increases by approximately 90%. No statistically significant effects are seen in the persistence period. The effects for cars are statistically insignificant in both the treatment and the persistence period, consistent with our main findings.

Further, to explore the sensitivity of the results to alternative ways of handling days on which no travel is observed, we change the definition of the sample used above and estimate models including only those days on which at least one trip with any mode is observed. The exclusion of days without any trip recording in Table A7 in the Appendix yields estimates that are comparable with our main findings. The results indicate that, on average, the ticket increases public transport use by approximately 0.1 trips per day, also implying a monthly increase in ridership of around 2 trips.

5 Conclusion

This study analyzes the impact of a free public transport ticket for one month on individual travel behavior. We conducted a field experiment in which 421 participants were randomly assigned to a treatment and control group and tracked via a smartphone app that uses GPS data. Since the participants were observed both during the one-month treatment period and in the following month after the free ticket expired, we can also analyze lasting changes in the participants' mobility behavior. In contrast to other studies that rely on self-reported mobility data or data related to public transportation alone, we can observe mobility data on all modes of transportation, similar to Hintermann et al. (2024)'s study looking at Pigovian transport pricing.

Using a difference-in-differences approach, we find a statistically significant increase of approximately two trips per month in public transport boardings during the subsidization period, one that appears to be primarily driven by an increase in usage of local rail services (subway and light rail). We find no evidence that the increase in transit use replaced regular trips made by car. Rather, the evidence suggests that participants instead utilize the free public transport pass to make additional irregular trips during off-peak hours. Moreover, the increased usage of transit during the subsidization period, which lasted a month, is not accompanied by lasting changes in mobility behavior during the month directly following the expiration of the ticket. Taken together, our results suggest that the provision of a one-month free public transport ticket neither replaces car use nor is effective in altering habitual mobility behavior.

The question arises as to the generalizability of this conclusion beyond the study. Randomized controlled trials are well known to have a high degree of internal validity by identifying the causal effect of the treatment, but the transferability of findings is sometimes questioned because of doubts about how much causal effects measured in a particular study population and set-up depend on the particular context (e.g. Allcott, 2015, Dehejia et al., 2019, Gechter, 2023, Peters et al., 2018, Vivalt, 2020). Two features of our study ameliorate concerns that problems with external validity would undermine our main conclusions. First, the sample participants all resided within the boundaries of a major public transport association in a country where the quality of public transport is relatively good by global standards (Buehler, 2009). Second, our screening of respondents selected people who drive regularly and who do not have a public transport ticket. We expect that both these features would tend to make our sample more responsive to receiving a free transit pass than a sample with similar socio-economic characteristics drawn from another country, such as the U.S., or a sample that is more representative of the general population. Consequently, our effect sizes are expected to be overestimated.

Our reliance on app tracking is another factor that may bear on external validity, even as it affords the clear advantages of comprehensive mobility coverage without the shortcomings of self-reported data. While an aversion to being monitored undoubtedly deters participation in such surveys, it seems reasonable to surmise that those people who are willing to participate are, on the whole, also more open to changing their mobility behavior, which is another feature that would likely increase the magnitude of the estimates. Since app-tracking data allows for completely new types of mobility studies and could therefore usher in a new era, the systematic analysis of self-selection effects appears to be an exciting new research agenda.

Based on these considerations and the small magnitude of our estimates, particularly in the persistence period and particularly for car use, we conclude that the issuance of a one-month free public transit pass in Germany, while politically palatable, would not appear to be an effective tool for significantly reducing negative externalities from transportation. We thereby corroborate recent studies that uses different methods and interventions to conclude that reducing car use by subsidizing sustainable modes of transport is difficult (Liebensteiner et al., 2024, Kristal and Whillans, 2020). Alternatively, measures that directly target driving itself, such as carbon pricing (Metcalf, 2009, Frondel and Vance, 2013) or congestion charging (Cramton et al., 2018), have been shown to be highly effective and efficient, even if they are often politically more difficult to implement (see e.g. Douenne and Fabre, 2022). This raises the question of how to increase the acceptance of effective measures or, alternatively, improve the effectiveness of popular ones. One possibility is to mandate a trial period of unpopular measures, which in some cases has led to greater acceptance after the period expires (see e.g. Schuitema et al., 2010, Börjesson et al., 2016). In promoting popular measures, the expansion of infrastructure that supports sustainable mobility is another option, one that our results suggest may be a prerequisite, as the effects are found to be stronger where the quality of local public transport is good. However, as these measures are cost-intensive, the specific effects on car use should also be evaluated and the marginal value of public funds determined (Hahn et al., 2024, Mihailova and Vance, 2024). The treatment evaluated in this study – a one-month public transport ticket – appears to have a very low marginal value of public funds.

Acknowledgments

Special thanks go to Andreas Gerster and Marco Horvarth for their valuable support and feedback. We are also immensely grateful for comments and suggestions by Jörg Ankel-Peters, Thomas Bauer, Massimo Filippini, Manuel Frondel, Ken Gillingham, Christina Gravert, Beat Hintermann, Katrina Jessoe, Michael Price, Armin Schmutzler, Lukas Tomberg, as well as by participants of the Advances with Field Experiments 2020 Conference (AFE), the CEPE & CER-ETH seminar, the 1st IAEE Online Conference, the 9th Mannheim Conference on Energy and the Environment (MCEE), the 8th Workshop on Experimental Economics for the Environment (EE4E), and the 2024 Annual Transportation Research Board Meeting (TRB). Tobias Larysch provided excellent research assistance. We gratefully acknowledge financial support by the Stiftung Mercator, without which this project would not have been possible. Moreover, this research was partially funded in the course of TRR 391 “Spatio-temporal Statistics for the Transition of Energy and Transport” (520388526) and the research training group (RTG) 2484 – “Regional Disparities and Economic Policy” by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation). Lastly, we express our sincere gratitude to the Verkehrsverbund Rhein-Ruhr for sponsoring some of the public transport tickets utilized in our study.

References

Allcott, Hunt (2015). "Site Selection Bias in Program Evaluation". In: *The Quarterly Journal of Economics* 130.3, pp. 1117–1165.

Bachman, Wallace and Richard Katzev (1982). "The effects of non-contingent free bus tickets and personal commitment on urban bus ridership". In: *Transportation Research Part A: General* 16.2, pp. 103–108.

Basso, Leonardo J and Hugo E Silva (2014). "Efficiency and substitutability of transit subsidies and other urban transport policies". In: *American Economic Journal: Economic Policy* 6.4, pp. 1–33.

Benjamini, Yoav and Yosef Hochberg (1995). "Controlling the false discovery rate: a practical and powerful approach to multiple testing". In: *Journal of the Royal Statistical Society: Series B (Methodological)* 57.1, pp. 289–300.

Bloom, Howard S (1995). "Minimum detectable effects: A simple way to report the statistical power of experimental designs". In: *Evaluation Review* 19.5, pp. 547–556.

Börjesson, Maria, Jonas Eliasson, and Carl Hamilton (2016). "Why experience changes attitudes to congestion pricing: The case of Gothenburg". In: *Transportation Research Part A: Policy and Practice* 85, pp. 1–16.

Brough, Rebecca, Matthew Freedman, and David C Phillips (2022). "Experimental evidence on the effects of means-tested public transportation subsidies on travel behavior". In: *Regional Science and Urban Economics* 96, p. 103803.

Buehler, Ralph (2009). "Promoting public transportation: Comparison of passengers and policies in Germany and the United States". In: *Transportation Research Record* 2110.1, pp. 60–68.

Bull, Owen, Juan Carlos Muñoz, and Hugo E Silva (2021). "The impact of fare-free public transport on travel behavior: Evidence from a randomized controlled trial". In: *Regional Science and Urban Economics* 86, p. 103616.

Cramton, Peter, R Richard Geddes, and Axel Ockenfels (2018). "Set road charges in real time to ease traffic". In: *Nature* 560, pp. 23–25.

Dehejia, Rajeev, Cristian Pop-Eleches, and Cyrus Samii (2019). "From Local to Global: External Validity in a Fertility Natural Experiment". In: *Journal of Business & Economic Statistics* 39.1, pp. 217–243.

Douenne, Thomas and Adrien Fabre (2022). "Yellow vests, pessimistic beliefs, and carbon tax aversion". In: *American Economic Journal: Economic Policy* 14.1, pp. 81–110.

Eurostat (2024). *Passenger cars per 1 000 inhabitants reached 560 in 2022.* Accessed: 2024-10-19. URL: `https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20240117-1`.

Frondel, Manuel and Colin Vance (2013). "Re-identifying the rebound: what about asymmetry?" In: *The Energy Journal* 34.4, pp. 43–54.

Fujii, Satoshi and Ryuichi Kitamura (2003). "What does a one-month free bus ticket do to habitual drivers? An experimental analysis of habit and attitude change". In: *Transportation* 30.1, pp. 81–95.

Gechter, Michael (2023). "Generalizing the Results from Social Experiments: Theory and Evidence from India". In: *Journal of Business & Economic Statistics* 42.2, pp. 801–811.

Gravert, Christina and Linus Olsson Collentine (2021). "When nudges aren't enough: Norms, incentives and habit formation in public transport usage". In: *Journal of Economic Behavior & Organization* 190, pp. 1–14.

Guzman, Luis A and Philipp Hessel (2022). "The effects of public transport subsidies for lower-income users on public transport use: A quasi-experimental study". In: *Transport Policy* 126, pp. 215–224.

Hahn, Robert W, Nathaniel Hendren, Robert D Metcalfe, and Ben Sprung-Keyser (2024). *A welfare analysis of policies impacting climate change*. Working Paper 32728. National Bureau of Economic Research.

Hintermann, Beat, Beaumont Maarten Schoeman, Joseph Molloy, Thomas Götschi, Alberto Castro, Christopher Tchervenkov, Uros Tomic, and Kay W. Axhausen (2024). *Pigovian transport pricing in practice*. WWZ Working Paper.

Ioannidis, John PA (2005). "Why most published research findings are false". In: *PLoS Medicine* 2.8, e124.

Ioannidis, John PA, TD Stanley, and Hristos Doucouliagos (2017). "The power of bias in economics research". In: *The Economic Journal* 127.605, F236–F265.

Kholodov, Yaroslav, Erik Jenelius, Oded Cats, Niels van Oort, Niek Mouter, Matej Cebecauer, and Alex Vermeulen (2021). "Public transport fare elasticities from smartcard data: Evidence from a natural experiment". In: *Transport Policy* 105, pp. 35–43.

Kristal, Ariella S and Ashley V Whillans (2020). "What we can learn from five naturalistic field experiments that failed to shift commuter behaviour". In: *Nature Human Behaviour* 4.2, pp. 169–176.

Liebensteiner, Mario, Jakob Losert, Sarah Necker, Florian Neumeier, Jörg Paetzold, and Sebastian Wichert (2024). "Almost Fare Free: Impact of a Cheap Public Transport Ticket on Mobility Patterns and Infrastructure Quality". In: *CESifo Working Paper* 11229.

Metcalf, Gilbert E. (2009). "Market-Based Policy Options to Control U.S. Greenhouse Gas Emissions". In: *Journal of Economic Perspectives* 23.2, pp. 5–27.

Mihailova, Darja and Colin Vance (2024). "Promoting active transportation: A comparative assessment of paths and prices". In: *Transportation*, pp. 1–25.

Mohring, Herbert (1972). "Optimization and scale economies in urban bus transportation". In: *American Economic Review* 62.4, pp. 591–604.

Parry, Ian W H and Kenneth A Small (2009). "Should urban transit subsidies be reduced?" In: *American Economic Review* 99.3, pp. 700–724.

Peters, Jörg, Jörg Langbein, and Gareth Roberts (2018). "Generalization in the tropics–development policy, randomized controlled trials, and external validity". In: *The World Bank Research Observer* 33.1, pp. 34–64.

Schuitema, Geertje, Linda Steg, and Sonja Forward (2010). "Explaining differences in acceptability before and acceptance after the implementation of a congestion charge in Stockholm". In: *Transportation Research Part A: Policy and Practice* 44.2, pp. 99–109.

Thøgersen, John (2009). "Promoting public transport as a subscription service: Effects of a free month travel card". In: *Transport Policy* 16.6, pp. 335–343.

Vivalt, Eva (2020). "How Much Can We Generalize From Impact Evaluations?" In: *Journal of the European Economic Association* 18 (5).

Appendix

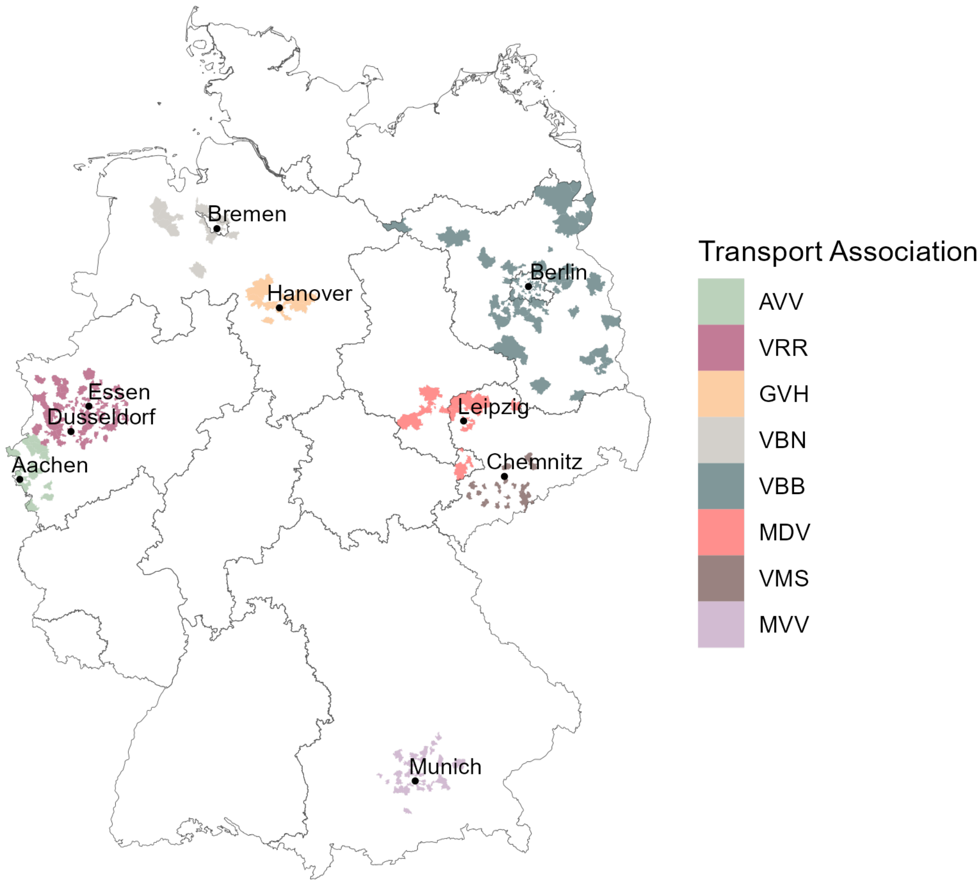

Figure A1: Participants' Place of Residence on Post Code District Level and the Corresponding Transport Association

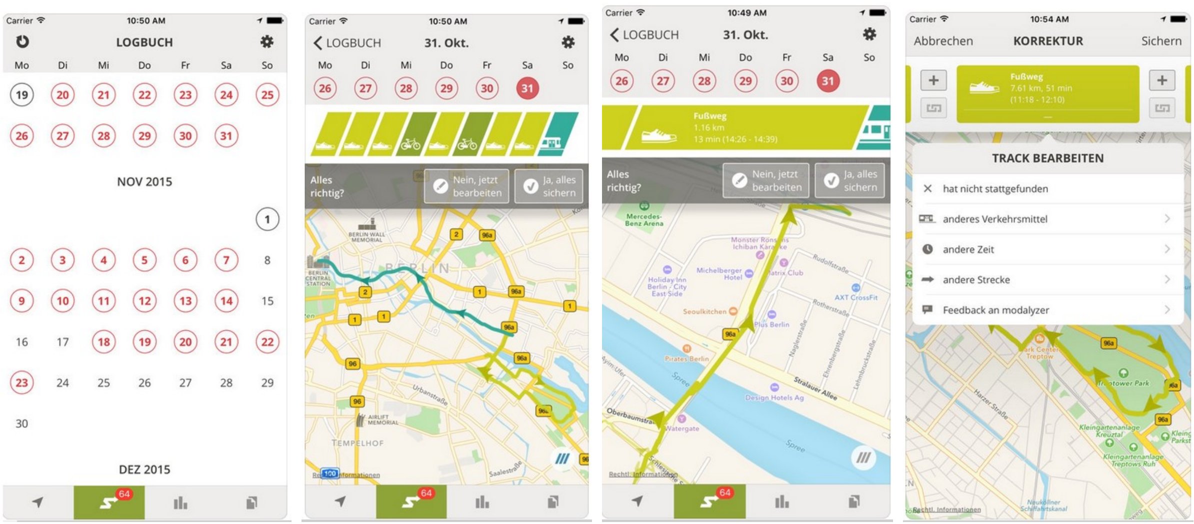

Figure A2: Modalyzer App for Mobility Tracking

Table A1: Frequency of Tracked Days and Treatment Group Status

	Number of Tracked Days in June	Number of Tracked Days in July
Constant	18.534** (3.972)	24.237** (4.081)
Treatment Group	0.690 (0.978)	1.790 (1.009)
Individual Characteristics		
Age	-0.049 (0.055)	-0.145* (0.058)
Female	-1.523 (1.061)	-2.683* (1.092)
Qualification University	3.001* (1.233)	
University Degree	-4.267** (1.199)	-2.483* (1.243)
Currently Employed	2.428 (2.295)	1.430 (2.313)
Retired	4.211 (2.710)	6.374* (2.759)
Distance to Closest PT Stop (km)	-0.229 (0.406)	0.243 (0.416)
App for PT	0.658 (1.028)	-0.020 (1.063)
Household Characteristics		
Household Size	1.409 (0.742)	0.167 (0.749)
No. of Children in HH	-0.987 (1.000)	-0.889 (1.012)
Income: €1,700€ to €3,199	-1.412 (1.874)	-0.662 (1.914)
Income: €3,200 to €4,699	0.183 (1.977)	1.553 (2.014)
Income: above €4,700	-2.305 (2.144)	-0.908 (2.236)
No. of Cars in HH	-1.610* (0.743)	-1.365 (0.758)
No. Observations	322	307
Adj. R2	0.048	0.060

*This table shows the results of regressions of the the number of tracked days in June and July on individual and household characteristics as well as treatment group status, the latter of which is seen to be statistically insignificant. ** and * denote statistical significance at the 1% and 5% level, respectively.*

Table A2: Experiment Participants and "Mobilität in Deutschland"

	Tracked Participants	Mobilität in Deutschland 2017
Individual Characteristics		
Age	49.97	43.6
Female	0.33	0.51
University Degree	0.41	0.18
Currently Employed	0.79	0.48
Retired	0.16	0.21
Daily Kilometers Traveled by Car	35.72	21
Daily Kilometers Traveled by PT	1.81	7
Household Characteristics		
Household Size	2.48	2.1
No. of Children in HH	0.43	0.26
Income above 3,200€ (3,000€)	0.59	0.42
No. of Cars in HH	1.53	1.25
At Least One Car in HH	0.94	0.78

"Mobilität in Deutschland 2017" is a nationwide representative survey administered in 2016 and 2017 that analyzes the travel behavior of the German population.

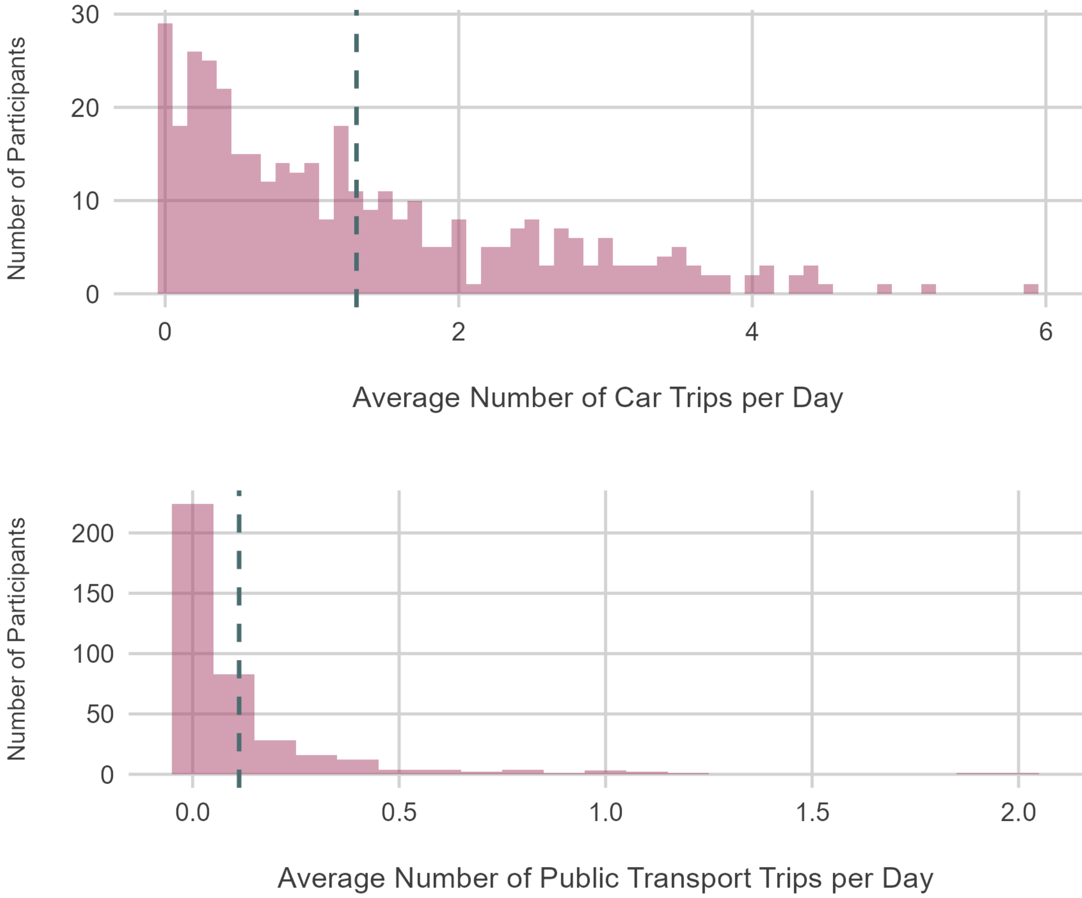

Figure A3: Distribution of Participants' Average Number of Trips per Day in the Baseline Period

The figure shows the distribution of each participant's average number of trips made by car and public transport per day during the baseline period, as well as the number of trips made by the average participant (dashed line). Public transport is defined as bus, local rail and regional rail.

Table A3: Number of Daily Trips - Multiple Hypothesis Testing

	PT	Car	Bus	Local Rail	Regional Rail
Treatment Period	0.069*	0.083	0.018	0.037	0.015
	(0.022)	(0.069)	(0.011)	(0.015)	(0.006)
Lowest FDR	0.019	0.418	0.262	0.064	0.070
Persistence Period	-0.003	0.034	-0.012	0.003	0.006
	(0.021)	(0.082)	(0.010)	(0.012)	(0.007)
Lowest FDR	0.902	0.852	0.418	0.893	0.588
No. Observations	35,909	35,909	35,909	35,909	35,909
Adj. R2	0.120	0.310	0.112	0.105	0.075

*Fixed effects on individual and month level. Standard errors clustered on individual level. The lowest FDR corresponds to the lowest false discovery rate at which the coefficient would pass as significant according to the Benjamini-Hochberg procedure (Benjamini and Hochberg, 1995). ** and * denote statistical significance at a false discovery rate of 1% and 5%, respectively. PT = Public Transport.*

Table A4: Extensive Margin - Logit Model

	PT	Car	Bus	Local Rail	Regional Rail
Treatment Period	0.031*	0.035	0.012	0.038*	0.021
	(0.014)	(0.020)	(0.012)	(0.019)	(0.012)
Persistence Period	-0.006	0.021	-0.007	0.000	0.006
	(0.012)	(0.024)	(0.008)	(0.014)	(0.012)
No. Observations	27,976	35,383	23,199	17,394	13,969
Adj. Pseudo R2	0.125	0.255	0.105	0.099	0.072

*Fixed effects on individual and month level. Standard errors clustered on individual level. The table reports average marginal effects. ** and * denote statistical significance at the 1% and 5% level, respectively. PT = Public Transport.*

Table A5: Heterogeneity Analysis - Socio-Economics

	Treatment Period		Persistence Period	
	PT	Car	PT	Car
Ticket	0.056*	0.079	0.000	-0.039
	(0.024)	(0.076)	(0.024)	(0.092)
Ticket x Unemployed	0.058	0.011	-0.011	0.296*
	(0.047)	(0.130)	(0.037)	(0.145)
Ticket	0.067*	0.069	0.006	-0.018
	(0.023)	(0.071)	(0.023)	(0.087)
Ticket x Retired	0.014	0.090	-0.047	0.305
	(0.055)	(0.176)	(0.042)	(0.187)
Ticket	0.058*	0.164*	-0.011	0.109
	(0.024)	(0.082)	(0.025)	(0.100)
Ticket x Female	0.035	-0.240*	0.026	-0.229
	(0.043)	(0.109)	(0.034)	(0.133)
Ticket	0.092*	0.112	-0.001	0.122
	(0.027)	(0.078)	(0.023)	(0.099)
Ticket x Children in HH	-0.049	-0.103	0.029	-0.289*
	(0.033)	(0.122)	(0.031)	(0.135)
Ticket	0.083*	0.106	-0.010	0.101
	(0.027)	(0.075)	(0.024)	(0.093)
Ticket x 4-Person HH	-0.055	-0.100	0.031	-0.297*
	(0.029)	(0.133)	(0.034)	(0.139)
Ticket	0.077*	0.083	0.008	0.029
	(0.025)	(0.096)	(0.022)	(0.102)
Ticket x Academic	-0.004	-0.055	-0.044	-0.053
	(0.045)	(0.111)	(0.040)	(0.137)
Ticket	0.069*	0.196*	0.000	0.111
	(0.028)	(0.090)	(0.027)	(0.106)
Ticket x Lower Income	0.005	-0.158	0.003	-0.080
	(0.041)	(0.117)	(0.036)	(0.139)

*Fixed effects on individual and month level. Standard errors clustered on individual level. ** and * denote statistical significance at the 1% and 5% level, respectively. PT = Public Transport.*

Table A6: Heterogeneity Analysis - Public Transport Accessibility

	Treatment Period		Persistence Period	
	PT	Car	Local PT	Car
Ticket	0.040*	0.030	0.005	-0.052
	(0.018)	(0.080)	(0.019)	(0.100)
Ticket x Big City	0.087	0.160	-0.019	0.245
	(0.051)	(0.115)	(0.043)	(0.134)
Ticket	0.019	0.051	-0.009	-0.061
	(0.016)	(0.085)	(0.018)	(0.110)
Ticket x Local Rail	0.102*	0.076	0.016	0.191
	(0.038)	(0.108)	(0.033)	(0.136)
Ticket	0.028	0.022	0.009	-0.032
	(0.017)	(0.086)	(0.021)	(0.121)
Ticket x PT Often	0.083*	0.101	-0.020	0.148
	(0.038)	(0.106)	(0.034)	(0.140)
Ticket	0.059*	0.026	0.007	-0.084
	(0.029)	(0.098)	(0.024)	(0.116)
Ticket x PT $<$ 500	0.017	0.079	-0.013	0.183
	(0.038)	(0.113)	(0.031)	(0.139)

*Fixed effects on individual and month level. Standard errors clustered on individual level. ** and * denote statistical significance at the 1% and 5% level, respectively. PT = Public Transport.*

Table A7: Robustness Check - Poisson Regression

	PT	Car	Bus	Local Rail	Regional Rail
Treatment Period	0.464**	0.059	0.250	0.637*	0.546*
	(0.171)	(0.053)	(0.234)	(0.285)	(0.228)
MDE	0.480	0.148	0.655	0.799	0.638
Persistence Period	0.034	0.032	-0.206	0.126	0.311
	(0.207)	(0.069)	(0.244)	(0.325)	(0.298)
MDE	0.578	0.193	0.682	0.909	0.834
No. Observations	27,976	35,383	23,199	17,394	13,969
Adj. R2	0.19	0.259	0.162	0.164	0.116

Fixed effects on individual and month level. Standard errors clustered on individual level. e^{β} *gives the multiplicative increase in the number of trips. For example* $e^{0.464} = 1.59$*, so that the number of local PT boardings increases by roughly 60%, i.e. 0.07. ** and * denote statistical significance at the 1% and 5% level, respectively. PT = Public Transport.*