***Individual Mobility, Mode Choice and the Effects of Public Transport Subsidies: Evidence from a Randomized Controlled Trial***

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## Overview

Car traffic still dominates the traffic volume in Germany, and even though CO2 emissions in Germany have decreased quite substantially during the last 30 years, the only sector where CO2 emissions stayed roughly the same is the transport sector (BMU2019). Overall the number of passenger cars in Germany has also been increasing over the last couple of years between 2007 und 2020 from 41.2 mio cars in 2007 to 47.7 million cars in 2020 (KBA2020). This increase in cars on the road is costly as car traffic is associated with a number of externalities, such as air pollution, road congestion and accidents.

One possible solution is a transition away from car traffic to public transport. To this end, in this study we analyze the transport behavior of individuals and the effect of a free one-month public transport ticket. A group of around 420 individuals is tracked via a smartphone app that allows us to collect information on all trips the individuals take with the different modes.

After an initial baseline month, we sent the treatment group a public transport ticket valid for one month in the region they live in. The participants are then observed for the treated month and an additional month. We hypothesized beforehand that there would be an increase in public transport usage during the treatment month but potentially also afterwards, which would indicate a potential habit formation effect. Overall though, while we do find a significant increase in public transport usage during the treatment month, we find no evidence for habit formation.

## Methods

Prior to a starting survey potential participants for the RCT were screened, in collaboration with the survey institute *forsa*. This was conducted in February of 2018 and aimed to identify people who on the one hand have the technical requirements to use the app and on the other hand were not already using public transport and therefore their mode choice would potentially be affected by the treatment.

The experimental period started at the end of April 2018 with the screened participants being asked to take part in the survey and register for the app that tracked their mobility over three months. With the app we received information over every trip the participants took in a given day, complete with information on the mode, the length (in km), the time and the speed. This results in a detailed picture of the mode choice of every participant over the experimental period. We have useable data for 422 individuals.

The first month, until the end of May, served as identifying the baseline mobility of all participants. We then observed the participants for the treatment month (June 2018) and then for another month afterwards, when the ticket we sent to them was not valid anymore, to see if there are possible habit formation effects. After the habit formation month (July 2018) the experimental period ended.

After completion of the experimental period, we received the mobility data by the app provider. Both the mobility data as well as the survey data came with an identifier that made it possible to match the two datasets. The raw format of the mobility data came with one observation for every trip a participant took. In order to make it more manageable, we collapsed the data on a day and mode basis. Doing this we get the variables for each day per mode, for example the number of car trips per day, or the number of kilometers driven by car per day.

In our baseline estimation we estimate the following equation:

$$Y\_{it}= β\_{0}+ β\_{1}treat\_{it}+ β\_{2}habit\_{it}+ ϵ\_{it}$$

where $Y\_{it}$ can be a number of potential dependent variables for individual *i* on a given day *t*: number of trips by car, number of trips by public transport, kilometers by car, or kilometers by public transport (and also for other modes). $treat\_{it} $is a dummy if individual *i* received the public transport ticket and it was valid for day *t*. The variable $habit\_{it} $is also a dummy variable that equals one if the participant was in the treatment group and the day *t* falls into July 2018. $ϵ\_{it}$ is an idiosyncratic error. Equation (1) is estimated for the different dependent variables with fixed effects for the participants.

## Results

Table 1 presents the baseline results on trips taken. The first column depicts the regression with the public transport trips per day as dependent variable. We can already see a small but significant effect of 0.114 additional trips for the treatment group in the treatment month. While the coefficient looks rather small, we have to keep in mind that, given of our screening of habitual car drivers, the baseline number of trips with public transport per day is quite low with 0.22 in May. Therefore an increase of 0.126 represents an increase of roughly one third.

One would expect that this increase in public transport trips is reflected in an equal decrease in car trips. However, looking at column 2 this expectation is not met. While the coefficient of the treatment variable is negative, we do not find a significant effect. Furthermore, both for public transport as well as car, we do not find a habit effect. This could indicate that either, the treatment period is too short for habit formation to kick in or there is simply no habit effect, but just a simple effect of a subsidized mode that is used more during the subsidization.

Robustness checks with different specificiations, e.g., on the distance travelled, confirm our results.

*Table 1: Fixed Effects Regression: Daily use as the dependent variable*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  Public Transport & train trips  |  Car trips  |  Walking trips  |  Bike trips  |
| Treatment received in given week | 0.126\*\*\* | -0.034 | 0.176\*\*\* | 0.021 |
|  | (0.020) | (0.048) | (0.060) | (0.030) |
|  |  |  |  |  |
| Habit formation | 0.003 | -0.067 | -0.057 | -0.046 |
|  | (0.021) | (0.050) | (0.062) | (0.031) |
|  |  |  |  |  |
| Constant | 0.233\*\*\* | 2.202\*\*\* | 2.566\*\*\* | 0.709\*\*\* |
|  | (0.009) | (0.020) | (0.025) | (0.013) |
| Number of observations | 20,414 | 20,414 | 20,414 | 20,414 |
| Number of individuals | 422 | 422 | 422 | 422 |

*Standard errors in parentheses \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01*

## Conclusions

While a few studies have investigated effects of free public transport (for example, Fujii and Kitamura, 2003 and Thøgersen, 2009), we are the first to use an app for tracking the mobility of individuals within a RCT. Overall, we find an increase in public transport in the treated month, which is however not followed by an increased usage afterwards. Furthermore, this increase in the treated month does not seem to reduce car travel, indicating an overall increase in mobility due to the receiving of the free ticket.

## References

BMU (2019). Klimaschutz in Zahlen - Fakten, Trends und Impulse deutscher Klimapolitik, Ausgabe 2019. Bundesministeriumf ür Umwelt, Naturschutz und nukleare Sicherheit (BMU), May 2019, Berlin.

Fujii, S. and Kitamura, R. (2003). What does a one-month free bus ticket do to habitual

drivers? An experimental analysis of habit and attitude change. Transportation, 30(1):81–95.

KBA (2020). Jahresbilanz des Fahrzeugbestandes am 1. Januar 2020“, Kraftfahrt-Bundesamt, January 2020, Flensburg.

Thøgersen, J. (2009). Promoting public transport as a subscription service: Effects of a free month travel card. Transport Policy, 16(6):335–343.