User Activity in Tradable Credit Schemes: Experimental Evidence

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Short summary

This study analyzes user activity in a five-week field trial of a Tradable Credit Scheme (TCS) designed to reduce commuting-related CO_2 emissions at a university. Participants in the treatment group used a MobilityCoin app to trade credits, while commuting behavior was tracked with a GPS-based mobility app. We first analyze which users actively engage with the system using logistic regression models for app logins and manual trading. We then estimate how activity relates to emission reductions with fixed-effects models and instrumental-variable regressions to address the endogeneity of login behavior. The results show substantial inactivity, but also strong heterogeneity in engagement. Older participants and women were less likely to log in, while a more rational decision-making style was associated with manual trading. Most importantly, early app engagement, especially in the first treatment week, is linked to stronger emission reductions. The findings highlight the importance of simple and user-friendly TCS design.
Keywords: Multi-modal transport, Pricing, Transport Demand Management, Experiment, Travel Behavior

1 Introduction

Transport activities generate a wide range of negative externalities (Santos et al., 2010). These externalities can be internalized using pricing instruments, such as congestion charges or fuel taxes (Sterner, 2007; De Palma & Lindsey, 2011; Lehe, 2019). In practice, however, these policy instruments are highly debated: They often face political opposition because they are seen as unfair or individuals do not trust the government (Axsen & Long, 2025). Tradable Credit Schemes (TCS) are an alternative pricing approach for transport externalities (Verhoef et al., 1997). In a TCS, the government allocates credits to a defined group of individuals. They are charged credits for certain activities, such as departure time choice, route choice, or mode choice. Individuals can sell surplus credits on the market or buy additional credits, depending on their mobility needs (Grant-Muller & Xu, 2014; Provoost et al., 2023). TCS can also be implemented in multi-modal transport systems (Balzer et al., 2023). Compared to a charge or tax TCS offer the following advantages: First, the policymakers can steer the distributional effects with the initial allocation of credits. For example, they can allocate more credits to people with low income or mobility impairment (Hamm et al., 2025). Second, the system is revenue-neutral, meaning that money is redistributed among travelers rather than transferred from travelers to the government (Krabbenborg et al., 2021). Both aspects can lead to higher acceptability.

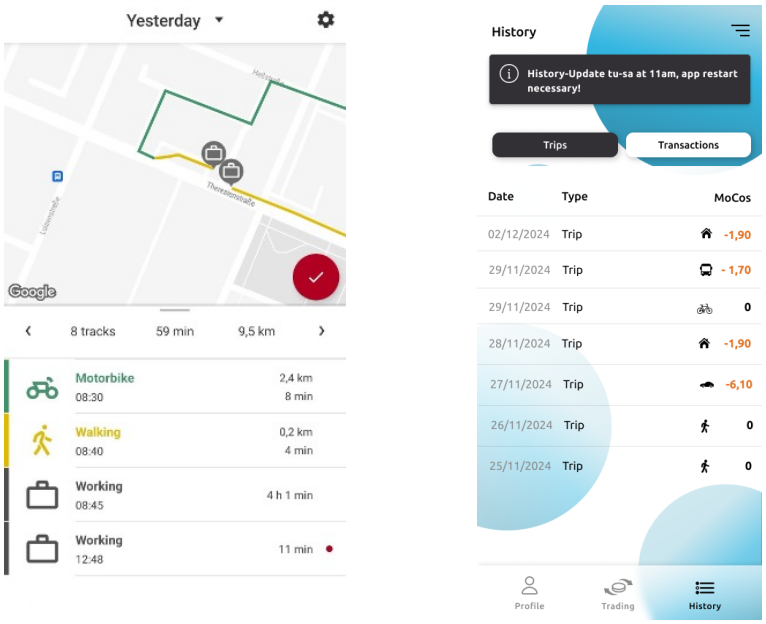
Simulation-based and numerical research highlights the potential of TCS (see Albano et al. (2025) for an overview). There are, however, concerns how real-life users would behave on such markets: TCS are complex systems in which users need to make decisions under uncertainty of future costs over time and use a second currency. These characteristics are likely to lead to deviations from purely rational behavior Dogterom et al. (2016). Previous experimental studies have revealed one issue: Users are inactive on the TCS market. The number of inactive users in experimental studies is very high: 97 out of 180 participants in Brands et al. (2020), 80% in Hara & Hato (2017), a "substantial number" in Brands et al. (2021). To ensure the market still functions, mechanisms such as automatic buys when a user's credit balance falls below zero have been implemented (Brands et al., 2020). However, inactive users can endanger the system's overall efficiency: Their inactivity can raise market prices and lead to inequitable outcomes. Additionally, inactive users seem to react less to policy, reducing its effectiveness Brands et al. (2021).

To improve our understanding of TCS, we must investigate why users remain inactive in TCS markets and how user activity moderates behavioral responses. These results could contribute

to the design of more user-friendly and robust TCS policies. We used data from a randomized controlled trial conducted over several weeks at the Technical University of Munich. In this trial, we implemented the MobilityCoin system, a TCS designed to reduce CO_2 emissions from commuting. By tracking user market activity and login behavior, we gained insights into user activity in TCS.

2 Methodology

Our study was carried out in the fall of 2024 at the Technical University of Munich, Germany. All university member ($\approx 64,000$), both students and employees were invited to participate. The overall sample ($1,046$) was randomly assigned to three groups: Control, TCS and Information. In this paper we focus on the TCS group, compared to the Control group. In order to mitigate the limited sample size we used block randomization (Matts & Lachin, 1988) based on their primary mode of commuting, their function at TUM (employee or student) and their TUM location. To track their daily mobility all groups used a GPS-tracking app (TUM mobility app). The app was a whitelabel app from the company MOTIONTAG and included automated mode recognition. The users could validate and correct these entries. We further processed the data as described in Dahmen et al. (2024).
The TCS group was asked to test the Mobility Coin system for five weeks; a TCS designed to price the negative externalities of daily travel in a multimodal transportation system Bogenberger et al. (2021). In our study, individuals were charged MobilityCoins based on the CO_2 emissions from their morning commute. After an initial three-week data collection period to assess baseline mobility patterns, the TCS group could download the MobilityCoin app. Through the app, they could view their MobilityCoin and Euro budgets, see how their mode choice for the morning commute would affect their MobilityCoin charges, and buy and sell MobilityCoins. They could also view past commutes and transactions. The MobilityCoin market used a dynamic pricing system. This system was adapted from Brands et al. (2020) and Geng (2025) including their rules to prevent undesired speculation. All trading was done via a virtual bank. Using a distance-based allocation scheme, new MobilityCoins were allocated on Sundays for the upcoming workweek and leftover MobilityCoins were automatically sold on Saturdays. Participants were given enough Euros so that no one could lose money in the system. Participants were informed that the higher their remaining Euro budget was at the end of the study, the higher the voucher they would receive.



(a) TUM mobility app (b) MobilityCoin app

Figure 1: Apps for data collection

The aim of the MobilityCoin system was to reduce emissions from commuting by a change of transportation mode. Therefore, our main outcome is the mean emission per commute, measured in kilograms of CO_2 equivalents. We only use data from regular commute, defined by direct commutes from the participant's home to their reported TUM location.

$$\text{MeanEmissions}_{it} = \frac{1}{N_{it}} \sum_{j=1}^{N_{it}} \text{Emissions}_{itj} \tag{1}$$

where N_{it} is the number of recorded commutes for individual i in week t. To evaluate the effect of the MobilityCoin system on emissions we use a fixed effects model. This model accounts for remaining imbalances between the TCS and the control group by including individual fixed effects. Week fixed effects control for common temporal shocks or seasonal effects. We use a linear specification. For activity, we have two indicators: Logins in the first week and weekly logins.
We are interested in the causal effect of user activity on emission reduction. One concern when including user activity in the model is endogeneity. User fixed effects absorb time-invariant individual traits, such as general environmental concern. However, two potential sources of endogeneity remain. First, there could be reverse causality: individuals who change their behavior may log in more often to check the consequences in the MobilityCoin system. Second, there could be time-varying within-person confounding during the treatment period, such as learning effects over the course of the study or temporary increases in attention to and engagement with the experiment. Both sources of confounding are likely more important in the model using weekly logins than in the model using only first-week logins, since feedback effects and learning are likely weaker in the first week.
To address this problem, we use an *instrumental variables* (IV) approach Bowden et al. (1990). We instrument the endogenous login-category variables using pre-treatment app engagement. Specifically, we use the participant's pre-treatment confirmation share in the TUM mobility app, as well as its squared and cubic terms, as instruments. The confirmation share is the fraction of trips that a participant validated before the intervention started. We interpret it as a proxy for baseline engagement with the app: participants who frequently confirmed trips in the tracking app before the experiment are also more likely to use the MobilityCoin app more actively during the intervention. Because the instrument relies on pre-treatment data, it should help address reverse causality. The case is less strong for the second source of confounding, because the instrument should capture baseline app engagement rather than treatment-period willingness to adjust commuting behavior. However, a placebo test in the control group shows that pre-intervention confirmation share does not significantly predict emissions during the treatment period, which supports the interpretation that the main channel operates through app interaction.
We group login behavior into three categories: 0–1 logins, 2–9 logins, and 10+ logins. Let L_{i1}, L_{i2}, and L_{i3} denote indicator variables for these categories. Since the treatment effect is allowed to vary across login groups, the endogenous regressors are the interactions

$$TP_{it} \times L_{i1}, \qquad TP_{it} \times L_{i2}, \qquad TP_{it} \times L_{i3},$$

where $TP_{it} = \text{Treat}_i \times \text{Post}_t$.
TP_{it} is the product of a treatment-group indicator and a post-intervention indicator:

$$TP_{it} = \text{Treat}_i \times \text{Post}_t.$$

It equals 1 only for treated participants in the treatment period, and 0 otherwise.
The excluded instruments are constructed by interacting TP_{it} with the pre-treatment confirmation share and its polynomial terms:

$$TP_{it} \times C_i, \qquad TP_{it} \times C_i^2, \qquad TP_{it} \times C_i^3,$$

where C_i denotes pre-treatment confirmation share.
The first stage consists of one regression for each endogenous regressor:

$$TP_{it}L_{i1} = \pi_{10} + \pi_{11}(TP_{it}C_i) + \pi_{12}(TP_{it}C_i^2) + \pi_{13}(TP_{it}C_i^3) + X_{it}'\gamma_1 + u_{it1}, \tag{2}$$

$$TP_{it}L_{i2} = \pi_{20} + \pi_{21}(TP_{it}C_i) + \pi_{22}(TP_{it}C_i^2) + \pi_{23}(TP_{it}C_i^3) + X_{it}'\gamma_2 + u_{it2}, \tag{3}$$

$$TP_{it}L_{i3} = \pi_{30} + \pi_{31}(TP_{it}C_i) + \pi_{32}(TP_{it}C_i^2) + \pi_{33}(TP_{it}C_i^3) + X_{it}'\gamma_3 + u_{it3}, \tag{4}$$

where X_{it} is a vector of control variables. These regressions yield the fitted values

$$\widehat{TP_{it}L_{i1}}, \qquad \widehat{TP_{it}L_{i2}}, \qquad \widehat{TP_{it}L_{i3}}.$$

In the second stage, we replace the observed endogenous regressors by their fitted values and estimate

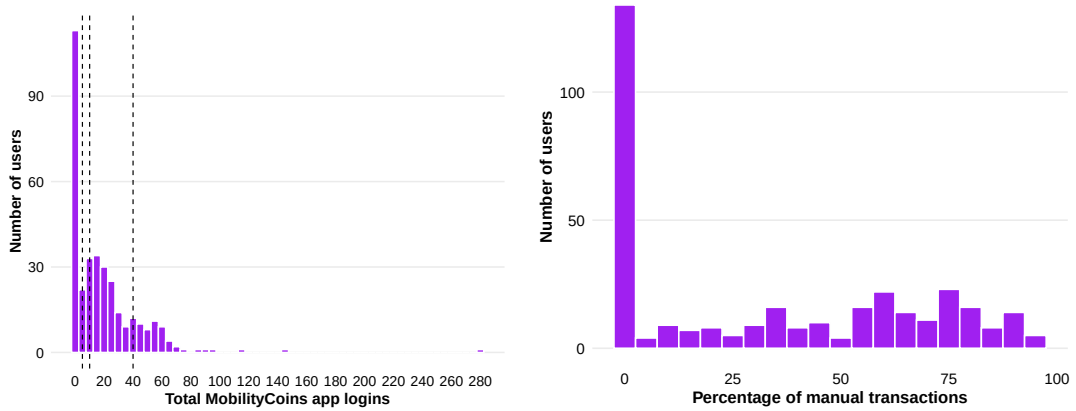
$$Y_{it} = \beta_0 + \beta_1\widehat{TP_{it}L_{i1}} + \beta_2\widehat{TP_{it}L_{i2}} + \beta_3\widehat{TP_{it}L_{i3}} + X_{it}'\delta + \alpha_i + \lambda_t + \varepsilon_{it}, \tag{5}$$

where Y_{it} denotes CO_2 emissions, α_i are individual fixed effects, and λ_t are time fixed effects. This specification allows the treatment effect to differ across activity levels while correcting for the fact that logging intensity may be correlated with unobserved user characteristics. The polynomial terms in the instrument make the first stage more flexible and allow for a nonlinear relationship between pre-treatment engagement and later login behavior.

The validity of this approach relies on two standard IV assumptions. First, the instruments must be *relevant*, that is, they must predict the endogenous treatment-by-login interactions. Second, they must satisfy the *exclusion restriction*, meaning that pre-treatment confirmation behavior affects emissions only through subsequent app usage and not through any other channel.

3 Results and discussion

We recorded both transactions and logins in the MobilityCoin app. The first login could not be recorded for technical reasons, so a value of zero logins corresponds to either zero or one actual login. In our study, approximately 29% of users had zero logins (i.e., zero or one), and 39% did not perform any manual transactions. Figure fig:engagement shows the distribution of logins and the share of manual transactions. A manual transaction is a transaction (buy or sell) performed by the user, as opposed to an automated transaction, in which the system automatically purchases MobilityCoins for a user who would otherwise be in the red. There is significant heterogeneity in both transaction and login behavior. Many participants do not engage with the app at all, while some users access the app an average of four times per commuting day. Since previous studies revealed inactivity issues, we implemented a gamification feature. Users were awarded medals in the app after 5, 10, and 40 logins. These medals did not influence compensation in the study. The absence of a drop in logins after 40 logins suggests that few users only logged in to collect the medals.



(a) Logins (b) Manual transactions

Figure 2: User engagement

To examine which factors influence whether a user (1) logs into the MobilityCoins app and (2) logs in and makes at least one manual transaction, we estimated two logistic regression models with binary outcomes.

$$\text{logit}\big(\Pr(\text{login}_i = 1)\big) = \beta_0 + \boldsymbol{\beta}' \,\text{Covariates}_i, \tag{6}$$

$$\text{logit}\big(\Pr(\text{manualTrade}_i = 1)\big) = \gamma_0 + \boldsymbol{\gamma}' \,\text{Covariates}_i. \tag{7}$$

Alongside socio-demographic, mobility-related, and attitudinal variables, we included a measure of decision-making style based on the scale by Scott & Bruce (1995). This scale was collected in the second survey wave, which took place after treatment had begun. Because the items refer to general decision-making tendencies, we do not expect the scores to be affected by treatment. Only a few variables show a significant relationship with the outcomes. In both models, being in the oldest age category is associated with lower odds of engaging with the app or making a manual trade. In the login model, users in the youngest age category are more likely to log in, while female users are

	≥1 login	manual >0
Constant	−1.27	−3.14
	(3.20)	(2.75)
Age: 18–27 years	1.21*	0.61
	(0.73)	(0.59)
Age: 38–47 years	−0.31	−0.23
	(0.75)	(0.67)
Age: 48–57 years	−0.64	−1.22
	(0.85)	(0.75)
Age: 58–67 years	−2.17***	−2.11***
	(0.82)	(0.81)
Female	−0.87*	−0.56
	(0.48)	(0.39)
Student	−0.71	−0.58
	(0.75)	(0.60)
Low income	0.17	0.22
	(0.70)	(0.57)
High income	0.09	−0.34
	(0.49)	(0.43)
Has children	−0.31	−0.23
	(0.75)	(0.65)
PT stop within 10 min	0.29	1.17
	(1.09)	(0.83)
Baseline mode: Active	−0.91	−0.92
	(0.80)	(0.65)
Baseline mode: PT	−0.87	−0.54
	(0.76)	(0.61)
Trading experience	−0.31	−0.02
	(0.23)	(0.20)
Climate concern	0.18	0.15
	(0.31)	(0.28)
Support for TUM measures	−0.03	−0.15
	(0.27)	(0.24)
Rational style	0.57	0.65*
	(0.43)	(0.38)
Intuitive style	0.50	0.18
	(0.37)	(0.31)
Dependent style	0.18	0.15
	(0.36)	(0.30)
Avoidant style	−0.14	−0.08
	(0.24)	(0.20)
Spontaneous style	−0.10	0.29
	(0.39)	(0.33)
Num.Obs.	219	219
AIC	210.0	260.8
BIC	281.2	332.0
Log.Lik.	−83.994	−109.396
McFadden R2	0.14	0.13
RMSE	0.34	0.40

Standard errors in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 1: Determinants of Logging In and Trading in the MobilityCoin Market

less likely to do so. Finally, in the trading model, a higher score on the rational decision-making scale is associated with higher odds of making at least one manual transaction. Interestingly, prior trading experience (e.g. with stocks or crypto-currency) does not seem to affect market activity. The fact that a lower rational decision making style is related to a lower probability to make a manual transaction suggests that the complexity of the system made it difficult for less rational decision-makers to interact with.

To understand how engagement with the MobilityCoins system relates to emission reductions, we estimate a set of models that interact the treatment effect with measures of user activity.

The login categories are constructed as follows. The first login could not be recorded for technical reasons; therefore, users with zero recorded logins may in fact have logged in once. For this reason, the first bin includes both 0 and 1 logins. Users with more than ten logins typically log in more than twice per commuting day, and we classify them as highly active. We estimate two specifications: (1) using logins in the first treatment week, and (2) using weekly logins. For both models, login counts outside the treated–post period are set to zero, since the MobilityCoins app was irrelevant before treatment or for the control group.

The estimates indicate that the reduction in emissions is substantially larger among highly active users. In particular, the coefficients for the 10+ login group are about three times larger in magni-

tude than those for low-engagement users, suggesting that active participation in the MobilityCoins system is associated with stronger emission reductions.

	Corr. Emissions first week	Corr. Emissions weekly
Model	OLS FE	OLS FE
TP × 0–1 Logins	−0.06	−0.02
	(0.10)	(0.07)
TP × 2–9 Logins	−0.03	−0.07
	(0.05)	(0.05)
TP × 10+ Logins	−0.23**	−0.20*
	(0.08)	(0.09)
Std.Errors	by: user	by: user
FE: user	X	X
FE: week	X	X
Num.Obs.	2915	2915
R2	0.954	0.954
R2 Adj.	0.954	0.954
Within R2	0.003	0.004
RMSE	0.47	0.47

Standard errors in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$.

Table 2: Effect of TP by login intensity: OLS fixed-effects specifications

To assess whether our estimates could be biased by endogenous login behavior, we estimate an additional set of instrumental variable models. The first-stage results show that the pre-treatment confirmation share is a very strong predictor of login intensity during the intervention period, with first-stage F-statistics above 30 for all login categories and substantially higher for the more common categories. The Wu–Hausman test rejects the null hypothesis that the interaction terms between treatment and login categories are exogenous. This suggests some degree of endogeneity in login behavior. The results from the IV specification suggest 1) no significant effect of weekly logins on emissions and 2) a significant effect for the middle login group from the first week logins. The IV results are consistent with the idea that early (first-week) engagement is more important than ongoing engagement. This makes sense as once the users have understood how the MobilityCoins system works and that they can earn money by traveling sustainable, the marginal benefit of additional logins to obtain information decreases. This indicates that logging in mainly matters because it allows participants to learn about and understand the system, not simply because it enables them to carry out transactions.
Also, it is the group with the medium login frequency rather than the group with over 10 logins in the first week that significantly reduces emissions when using an IV. This might indicate that the high login group engaged with the app rather for the gamification of it rather than obtaining information how the system works and how to benefit financially in it.

	F-stat (1st stage)	p-value
Panel A: First-week logins (IV with confirmation-share instrument)		
TP × 0–1 Logins	160.94	< 0.001
TP × 2–9 Logins	268.64	< 0.001
TP × 10+ Logins	68.11	< 0.001
Wu–Hausman (H_0: TP × Logins exogenous)	8.91	< 0.001
Instruments: $D\times$ (pre-treatment confirmation share, pre-treatment confirmation share^2, pre-treatment confirmation share^3)		
Panel B: Weekly logins (IV with confirmation-share instrument)		
TP × 0–1 Logins	109.50	< 0.001
TP × 2–9 Logins	131.45	< 0.001
TP × 10+ Logins	32.09	< 0.001
Wu–Hausman (H_0: TP × Logins exogenous)	8.08	< 0.001
Instruments: $D\times$ (pre-treatment confirmation share, pre-treatment confirmation share^2, pre-treatment confirmation share^3)		

Table 3: First-stage F-statistics and Wu–Hausman tests for IV models using pre-treatment confirmation-share instruments

	Corrected Emissions (IV, first-week)	Corrected Emissions (IV, weekly)
TP × 0–1 Logins	1.12	0.89
	(0.81)	(1.03)
TP × 2–9 Logins	−0.73*	0.12
	(0.43)	(1.73)
TP × 10+ Logins	0.07	−2.26
	(1.33)	(3.75)
Std.Errors	by: user	by: user
FE: user	X	X
FE: week	X	X
Num.Obs.	2911	2911
R2	0.955	0.955
R2 Within	0.010	0.010
RMSE	0.53	0.61

Standard errors in parentheses.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Effect of TP by login intensity, IV using pre-treatment confirmation-share instruments

4 Conclusions

Using data from a multi-week trial of a Tradable Credit Scheme, this paper examines patterns of user activity and their relevance for policy performance. Consistent with earlier studies, we find substantial inactivity: 29% of participants never logged into the app, and 39% did not make a single manual transaction. At the same time, engagement was highly heterogeneous, with some participants logging in more than 200 times over the five-week study period. Our analysis of login and transaction behavior identifies only a limited number of significant predictors. Women and participants in the oldest age group were less likely to log in. The latter may reflect greater technical difficulties, while the gender difference deserves further investigation. We also find that a higher score on rational decision-making style is associated with a greater likelihood of making at least one manual transaction. This suggests that the complexity of the system may have discouraged some participants from engaging with the market. We further examine whether user activity mediates behavioral adjustment, measured as changes in CO_2 emissions. The results indicate that only activity in the first week is associated with a significant reduction in emissions, particularly for

participants in the medium login category. This points to the importance of early engagement: users who access the app early and develop an understanding of the system appear better able to adapt their travel behavior in response to the policy.
Taken together, these findings suggest that user activity is central to both the equity and the effectiveness of Tradable Credit Schemes. Limited engagement may create inequitable outcomes if participants who feel overwhelmed by the system are less able to benefit from market participation. At the same time, low activity may reduce the policy's effectiveness, as inactive users are less likely to understand the incentives and rules well enough to adjust their behavior. The gamification features implemented in our study were not sufficient to overcome this challenge.
Future research should therefore focus on two related questions: first, how to motivate participants to engage more actively with the market; and second, how to reduce system complexity, for example through simpler interfaces, clearer feedback, or user-specific recommendation and decision-support tools.

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