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INVESTIGATING MODE CHOICE PREFERENCES IN A TRADABLE MOBILITY CREDIT SCHEME

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ABSTRACT

Tradable Credit Schemes (TCS) are gathering increasing attention in the transportation sector as an alternative to traditional pricing measures. TCS could foster the shift to more sustainable modes and limit the production of negative externalities while promoting social justice and equity. Current research has a strong focus on modeling market equilibrium prices, charging designs, social acceptance, and equity aspects. However, most modeling approaches have to make assumptions about user preferences due to a lack of empirical evidence on user's behavior in such a system.

This paper presents the results of a stated mode choice experiment with over 1,000 participants conducted in Munich, Germany, to examine the trade-offs between travel time, private and external travel costs, and other level-of-service attributes within a TCS. A Mixed Multinomial Logit (MMNL) model applied to the data collected revealed three main findings. First, the results confirm that the participants seem to understand the TCS in spite of its complexity and they behave rationally. Secondly, respondents reacted more sensitively to credit charges the smaller their monthly remaining credit budget was and the more days of the month were left. Finally, the variance of the associated values of travel times was found to be largest for cars, indicating higher mean values and hence greater discomfort when considering their external costs. To conclude, this paper sheds light on mode choice preferences in the context of a hypothetical TCS and suggests directions for future research.

Keywords: Tradable credit scheme, Tradable mobility credits, discrete mode choice experiment, choice modeling

INTRODUCTION

Over the past century, the transport sector has become a key economic activity providing countless benefits to society and sustaining millions of jobs worldwide. However, mobility-related activities also have significant negative impacts on human life and the ecosystem, such as their contribution to global warming, air and water pollution, accidents, and sprawl (*1*). The prominence of the effects of climate change and the growing social demands to address them are pushing governments to develop ambitious plans to radically reduce the externalities of the transport sector, promote the shift to more sustainable transport modes, and internalize external costs, thus ensuring that the full cost of their transport is borne by the users rather than by the society as a whole (*2*).

In urban areas, a wide variety of strategies have been proposed and implemented to mitigate the environmental impacts of transport, reduce traffic congestion, and enhance liveability. These strategies include informative, regulative, and economic measures. The latter categories are particularly promising and can be subdivided into two groups: price control measures and quantity control measures. Congestion charging, for example, is a price control mechanism that consists of charging travelers an amount equal to the marginal externalities they impose on society (*3–6*). Conversely, quantity control measures, such as Tradable Credits Schemes (TCS), aim at influencing individual demand for motorized trips and regulating traffic flows by limiting the allowed production of externalities.

TCS are cap-and-trade policy instruments that originated in the field of environmental economics for pollution control (*7*). They consist of the introduction of property rights for the aforementioned production of externalities, which are valued and circulated in a market to achieve optimal allocation. In the urban transportation field, (*8*) and (*9*) were among the first to investigate the possibilities of TCS to reduce emissions and mitigate congestion. As an example, we illustrate the fundamentals of TCS based on the so-called *MobilityCoins* system, a TCS proposed in (*10*) –and further developed in (*11–13*)– in which this research is framed. In a nutshell, in the *MobilityCoins* system eligible users receive periodically a credit budget, which accounts for a given amount of transport externalities (e.g., CO2 equivalent emissions). When a user undertakes a trip, the corresponding credit amount is subtracted from her budget. This amount is decided by the agency issuing the coins depending on the transport mode, engine type, route, and period of the day of the trip. Importantly, the usual ownership and operational costs (e.g., lease, fuel, vehicle maintenance, and public transport tickets) are paid as normal with coins on top. If users require additional credits to meet their mobility needs, or if they have a credit surplus, they can trade with other citizens on the *MobilityCoins* market. As a distinctive aspect with respect to other proposed credit schemes, the *MobilityCoins* system incentivizes the shift to active-mobility modes by rewarding bicycle trips with a small amount of credits (i.e., substantially lower than the credit charge for an equivalent motorized trip, but high enough to influence mode choice). Trips by foot are excluded of this incentive as this would require digital tracking and processing of all pedestrian movements, as well. Additionally, the *MobilityCoins* system introduces the novel idea of giving the users the possibility to invest their remaining credits on infrastructure improvements through crowdfunding, e.g., to build additional cycle lanes or to increase the frequency of a given bus line. Thus, the public's role in the transport planning process shifts from *passive* to *active*, and a balancing mechanism is introduced between the transportation demand and supply sides (*14*).

Numerous publications have discussed the strengths of TCS in comparison to alternative travel demand management measures such as congestion pricing or license plate rationing (*15, 16*). First, TCS do not only reduce the attractiveness of using motorized vehicles, but they also provide direct incentives to users of sustainable modes (i.e., citizen who travel sustainably will have credit surplus, which can be sold on the market). Besides, TCS outperform congestion pricing in terms of social justice, since they avoid imposing a high tax burden on the poor while only marginally affecting the wealthy, and equity, as the revenue generated within the system is redistributed among the users. Interestingly, advocates of TCS argue that these schemes could enjoy greater social acceptance due to their government budget-neutrality and the initial free allocation of credits (*17*). Finally, a crucial key strength of TCS is that they allow a better quantity control of the system's goal –e.g., the overall emissions– in a context of uncertainty over the agent's price response functions (*18, 19*). On the downside, the complexity of the system is one of the main drawbacks of TCS, making them difficult to implement and hard for the public to understand (*20*).

Existing literature on TCS has mostly focused on aspects such as the pricing of credits and the influence on emissions (*21, 22*), market design (*23*), modeling of user and market equilibrium (*24*), and public acceptance and equity aspects of such schemes (*17, 20, 25*). The interested reader is referred to (*16*) for a comprehensive review of different schemes and to (*26*) for a framework guiding their practical implementation. However, the empirical behavior of the users within a TCS has remained largely unstudied. Among the exceptions, (*15, 27*) conducted surveys in Beijing and the Netherlands to analyze the likelihood of changing car use in response to a TCS. Recently, (*28*) provided the first real-life evidence of TCS's ability to manage actual scheduling decisions. As illustrated, existing research lacks a disaggregated analysis of the potential impacts of TCS on mode choice. In this paper, we seek to address this gap by presenting the results of a stated mode choice (SC) experiment conducted to examine the trade-offs between travel time, private and external travel costs, and other level-of-service attributes in a multimodal TCS.

The remainder of this paper is organized as follows: Section 3 provides an exposition of the methodology and modeling framework employed to investigate the disparities in mode choice preferences in a situation where a TCS is absent or present. Section 4 presents a summary of the findings from a Mixed Multinomial Logit (MMNL) model and examines the sensitivity of external travel costs as well as the corresponding values of travel time (VTT). Lastly, Section 5 provides a conclusion that highlights the novel insights gained, limitations of the proposed method, and future research directions.

METHODOLOGY

This section outlines the methodological approach to investigate peoples' mode choices and attributes that drive their decisions when trading-off between different means of transport for various trip purposes. With regards to the challenges the transport sector has been confronted with, many hypotheses evolve around the choice of a mode not only in an existing, but rather hypothetical transport system, such as TCS for example. SP surveys therefore often contain a stated choice (SC) experiment, which allows to introduce and test the effect of such a scenario on mode choice. As such, SP data are rich in attribute trade-off information and hence useful for forecasting changes in behavior, but may be limited by the imposed (lack of) realism of the choice context (*29*). The main features of the survey discussed in this paper are two experiments - the first one resembles the choice of modes in a status quo scenario (SQ), the second accounts for the introduction of the mobility budget and TCS to understand the differences between these regimes.

Survey

The survey software (Qualtrics) was used to implement and conduct the survey online (this includes mobile phones). The questionnaire was divided into six parts:

1. Socio-demographic profile on personal and household level (e.g., age, gender, education, occupation, household composition/-income, residential location, etc.)
2. Mobility tool ownership and behavior:
    - Tools: Public transport subscriptions, driver's license, car ownership and availability
    - Behavior: Simplified travel diary, distance classes for work/education, leisure, errands
3. Attitudes and personality
4. Mode choice experiment 1 (status quo; SQ)
5. Introduction of TCS:
    - Mobility budget and allocation
    - Willingness-to-pay (WTP) and willingness-to-sell (WTS)
6. Mode choice experiment 2 (TCS)

In part 5, the TCS framework was introduced formally and user preferences as well as behavioral responses to a TCS were measured. It included questions on designs of the initial credit allocation (mobility budget) and the WTP/WTS for extra/excess credits (see (*11*) for detailed results). Last but not least, the respondents were then presented with another mode choice experiment, similar to part 4, but under the constraint of a mobility budget for external costs.

Experimental design

As previously mentioned, the survey contained two experiments in order to account for the existence of different scales of choices (i.e., variance in choices) between the two regimes. Therefore, two sets of designs were created. For each regime there are 8 designs according to 4 trip distance classes (0-3, 3-6, 6-12 and longer than 12 kilometers) and the respondent's car availability (i.e., ownership of a driver's license and actual household car availability). Furthermore, and based on the distance class, 4 alternatives were available or not: walking, cycling, car, and public transport (PT). The variation of attribute levels increased with the underlying length of a reference trip to create reasonable trade-offs between the alternatives, and to have trip lengths that slightly overlap. Moreover, three trip purposes were distinguished: work/education, errands, and other leisure activities. These are so-called "scenario" variables and were not explicitly included as an attribute since they were constant between different choice tasks of an individual, but varied between them.

In the end, 16 D-efficient pivot designs were implemented using NGene (*30, 31*). Weak priors were used for travel time and cost attributes. Each design was divided into 4 to 5 blocks. In total, a respondent was faced with 12 choice tasks - 6 mode choice tasks in each regime.

The participants were assigned to one block of an experimental design for each regime. However, in order to have an approximately even distribution of trip lengths over the whole sample, the trip distance class was chosen randomly for each respondent. The trip purpose assignment was partially random, but dependent on the employment status. Only designs with a car alternative available could be assigned to respondents actually owning a driver's license and having access to a car in their household.

Design of reference values in a TCS system. For both studied regimes, reasonable values for the private costs as well as a reasonable TCS design must be presented to the respondents in order to obtain meaningful choices. Thus, the following assumptions are made:

- TCS scheme is implemented in the city of Munich. Hence, the following values are assumed: average travel distance of 40 kilometers per day and 3.2 trips per day. The modal share in terms of kilometers is 56% private transport, 36% public transport, 5% cycling, and 3% walking (*32*). The kilometer cost for private transport is 0.5 Euro, 1.30 Euro for public transport trips shorter than 1.5 kilometers, and 2.50 Euro for public transport trips longer than 1.5 kilometers.

- The target of the scheme is to reduce car travel in terms of kilometers by 15%.
- A monthly budget is set at 1,000 credits for every citizen, divided by the monthly total travel production, this results in approximately $5/6$ credits per travel-km.
- The assigned budget suffices to make all trips using public transport during a month without buying any additional credits on the market.
- A ratio of 2:1 is set between the credit charges for cars and public transport trips based on their external costs in Munich (*33*).

Then, the following steps are taken to generate the reference values for the attribute levels in the designs. First, representative trips between the 25 city districts of Munich are queried using Google's directions web service. For every trip, the mode alternatives walking, cycling, driving, and public transport are requested and their values stored. Second, the reference travel time attribute levels are defined as the values obtained from the web service, while the reference levels for the private cost attributes are calculated using the trip distance and the assumed values (see above). Third, the trip credit charges as well as market prices are calculated as follows:

(i) the target per-capita travel production (i.e., modal share) is computed based on the 15% reduction factor for car travel, assuming that half of the reduction is shifted to cycling and half to public transport;

(ii) the credit charges for all public transport trips obtained from Google's directions web service are set to the trip distance times $5/6$ credits per travel-km, i.e., the initial 1,000 monthly credit budget divided by the monthly travel production per capita to ensure that all public transport travel does not require any additional credits.

(iii) the charges for car trips are computed by using the assumed 2:1 ratio. The charges for bicycle trips, in this case subsidy, are set to 10% of the public transport charge. The charges for walking trips are set to zero.

(iv) the market price for credits is obtained using a discrete mode choice model built using values for Munich and the German value of time (*34, 35*), where the credit charges enter the generalized cost of travel through their market price and the value of time. We then search for each origin-destination pair for the credit market price where the observed credit spending equals the available budget, i.e., market clearing balance. This leads to a distribution of market prices with an average market price of around 0.5 Euro per credit. To account for the possibility of varying market prices, the price was pivoted as well. As such, three market price levels were implemented: 0.25, 0.5 (reference price), and 1.25 Euros per credit.

Furthermore, two attributes with respect to the mobility budget in a TCS are of interest: the remaining budget of *MobilityCoins* (in percentage) in a given month and the number of days into a month. Both are likely to have an impact on cost sensitivity in the decision-making process and should therefore be controlled for. In this sense, we expect that –ceteris paribus– the disincentive to use credit-demanding modes (i.e., car and PT) is stronger as the remaining budget decreases and more days of the month are left. The levels of the remaining share of budget left at a given day into a month were 25, 50, and 75%, while those for the days into month attribute were 15, 20, and

25 days.

Fig. 1 presents an example choice task for both the status quo and the TCS regime to illustrate the outcome of an experimental design.

Sample recruitment

In the survey, we contacted a representative sample of 10,000 inhabitants of Munich, Germany. Their postal addresses were provided by Munich's registry office, and each of them received an invitation letter with a unique code they could use to access an online form. Upon completion of the survey, respondents received a 15 EUR voucher as an incentive. The sample was restricted to residents aged between 18 and 80 years old and having their official residence within the city boundaries. To evaluate the survey design, 500 individuals were invited to participate in a pre-test survey in June 2022, achieving a $14,6\%$ response rate (*11*). Subsequently, we implemented some minor improvements in the design and invited the remaining 9,500 individuals. The data collection spanned between July and October 2022 and, including the pre-test, a total of 1,349 individuals completed the survey ($13,5\%$ response rate).

Modeling approach

The following model formulation represents the MMNL model applied to the data at hand. In Section 4 we present the results of both our MNL and MMNL models.

Each mode/alternative i for an individual n in model component m and choice task t is associated with a utility $U_{i,n,m,t} = V_{i,n,m,t} + \varepsilon_{i,n,m,t}$ with $V_{i,n,m,t} = f(\beta)$ referring to the observed and $\varepsilon_{i,n,m,t}$ to the random (unobserved) part of it. The observed part $V_{i,n,m,t}$ relates to a vector of parameters β that is estimated based on the attributes given in the choice experiment and sociodemographic variables of the respondents. For the MMNL, to account for the random heterogeneity across decision-makers, we assume $\beta_n \forall n$ with density $f(\beta|\Omega)$, where Ω is a vector of parameters of this distribution (i.e., its mean and variance). Since we have multiple choices per individual, the likelihood of the sequence of choices for individual n is given by $P_n(\Omega)$ (see Eq. (1)), assuming that sensitivities vary across individuals, but stay constant within. $i^*_{n,m,t}$ represents the individual's chosen alternative i in model component m and choice task t. The MMNL model is estimated by means of Maximum Simulated Likelihood (MSL) where the simulated log-likelihood (SLL, see Eq. (3)) is the probability of reproducing each choice in the sample and $\beta_{r,n,m}$ gives the r^{th} draw from $f(\beta|\Omega)$ for individual n.

$$P_n(\Omega) = \int_\beta \prod_{t=1}^{T} \prod_{m=1}^{M} P_{n,m,t} \left(i^*_{n,m,t} | \beta \right) f \left(\beta | \Omega \right) d\beta \tag{1}$$

$$LL(\Omega) = \sum_{n=1}^{N} ln \left(\int_\beta \left[\prod_{t=1}^{T} \prod_{m=1}^{M} P_{n,m,t} \left(i^*_{n,m,t} | \beta \right) \right] \left(\beta | \Omega \right) d\beta \right) \tag{2}$$

$$SLL(\Omega) = \sum_{n=1}^{N} ln \left(\frac{1}{R} \sum_{r=1}^{R} \left[\prod_{t=1}^{T} \prod_{m=1}^{M} P_{n,m,t} \left(i^*_{n,m,t} | \beta_{r,n,m} \right) \right] \right) \tag{3}$$

We estimate a pooled MMNL model parametrized in willingness-to-pay (WTP) space. The term "pooled" refers to parameters that are calibrated jointly across both model components. The utility

You travel for the following purpose: **Errand**.
Your average trip distance is **3 to 5.99 km**.
The weather is **rainy**.

Scenario 1	**Option 1: Walk**	**Option 2: Car**	**Option 3: Bicycle**	**Option 4: PT**
Travel time	48 min	12 min	18 min	8 min
Access & egress time				16 min
Frequency				every 15 min
Transfers				2 x
Travel cost		2,9 €		2,5 €
Quality of cycle lane			medium	

(a) Status quo regime

You travel for the following purpose: **Errand**.
Your average trip distance is **3 to 5.99 km**.

It's day **15** of the month and you have a remaining budget of **25 %** .
The weather is **sunny**.

Scenario 1	**Option 1: Walk**	**Option 2: Car**	**Option 3: PT**	**Option 4: Bicycle**
Travel time	1h 6 min	14 min	7 min	18 min
Access & egress time			14 min	
Frequency			every 15 min	
Transfers			0 x	
Travel cost		2,9 €	2,5 €	
MobilityCoin expense		14,25 €	5,25 €	
MobilityCoin revenue				0,5 €
Quality of cycle lane				bad

(b) TCS regime

FIGURE 1: Example mode choice tasks of the two experiments

equations $V_{i,n,m,t}$ are given by:

$$V_{W,n,SQ,t} = \alpha_W + s_{n,t}\kappa_W + \psi_{n,t}\left(x^{tc}_{W,n,SQ,t} + x^{tt}_{W,n,SQ,t}VTT_{W,n,t}\right) + v_{SQ,t}\gamma_W \tag{4}$$

$$V_{B,n,SQ,t} = \alpha_B + s_{n,t}\kappa_B + \psi_{n,t}\left(x^{tc}_{B,n,SQ,t} + x^{tt}_{B,n,SQ,t}VTT_{B,n,t}\right) + v_{SQ,t}\gamma_B \tag{5}$$

$$V_{C,n,SQ,t} = \alpha_C + s_{n,t}\kappa_C + \psi_{n,t}\left(x^{tc}_{C,n,SQ,t} + x^{tt}_{C,n,SQ,t}VTT_{C,n,t}\right) + v_{SQ,t}\gamma_C \tag{6}$$

$$V_{PT,n,SQ,t} = \psi_{n,t}\left(x^{tc}_{PT,n,SQ,t} + x^{tt}_{PT,n,SQ,t}VTT_{PT,n,t} + x_{PT,n,SQ,t}WTP_{PT}\right) \tag{7}$$

$$V_{W,n,TCS,t} = \omega_{TCS}\Big(\alpha_W + s_{n,t}\kappa_W + \psi_{n,t}\left(x^{tc}_{W,n,TCS,t} + x^{tt}_{W,n,TCS,t}VTT_{W,n,t}\right) + v_{TCS,t}\gamma_W\Big) \tag{8}$$

$$\begin{aligned} V_{B,n,TCS,t} = \omega_{TCS}\Big(&\alpha_B + s_{n,t}\kappa_B + \psi_{n,t}\left(x^{tc}_{B,n,TCS,t} + x^{tt}_{B,n,TCS,t}VTT_{B,n,t}\right) + \\ &x^{mb}_{B,n,TCS,t}\iota^{mb}_{TCS} + v_{TCS,t}\gamma_B\Big) \end{aligned} \tag{9}$$

$$\begin{aligned} V_{C,n,TCS,t} = \omega_{TCS}\Big(&\alpha_C + s_{n,t}\kappa_C + \psi_{n,t}\left(x^{tc}_{C,n,TCS,t} + x^{tt}_{C,n,TCS,t}VTT_{C,n,t}\right) + \\ &x^{mc}_{C,n,TCS,t}\tau^{mc}_{TCS} + v_{TCS,t}\gamma_C\Big) \end{aligned} \tag{10}$$

$$\begin{aligned} V_{PT,n,TCS,t} = \omega_{TCS}\Big(&\psi_{n,t}\left(x^{tc}_{PT,n,TCS,t} + x^{tt}_{PT,n,TCS,t}VTT_{n,t} + x_{PT,n,TCS,t}WTP_{PT}\right) + \\ &x^{mc}_{PT,n,TCS,t}\tau^{mc}_{TCS}\Big) \end{aligned} \tag{11}$$

with:

- ω_m: Parameter to account for scale differences (error variance) between the two model components in pooled estimation (*36*); $m \in \{\text{SQ}, \text{TCS}\}$ (SQ = reference; $\omega_{\text{SQ}} = 1$)
- α_i: Alternative-specific constant (PT = reference; $\alpha_{PT} = 0$)
- $s_{n,t}$: Vector of trip-specific and sociodemographic attributes as a shift on the ASC's
- κ_i: Vector of parameters for $s_{n,t}$
- $\psi_{n,t}$: Scale parameter of VTT & WTP attributes (see Eq. (12))
- $x^{tc}_{i,n,m,t}$: Private travel costs
- $x^{tt}_{i,n,m,t}$: Travel times
- $VTT_{i,n,t}$: Vector of VTT parameters (see Eq. (13))
- $x_{PT,n,m,t}$: Vector of trip-specific PT attributes (e.g., access & egress time, number of transfers, frequency; excluding PT private travel costs and travel time)
- WTP_{PT}: Vector of PT-related WTP parameters
- $x^{mc}_{i,n,TCS,t}$: Vector of *MobilityCoin* expenses (external travel cost for car and PT)
- τ^{mc}_{TCS}: Vector of parameters for $x^{mc}_{i,n,TCS,t}$
- $x^{mb}_{B,n,TCS,t}$: Vector of *MobilityCoin* revenues (external travel incentive for bicycle)
- ι^{mb}_{TCS}: Vector of parameters for $x^{mb}_{B,n,TCS,t}$
- $v_{m,t}$: Vector of scenario attributes (e.g., weather, bike lane quality)
- γ_i: Vector of parameters for $v_{m,t}$.

For models parametrized in WTP, the overall model scale is a product of the scale parameter of the extreme value distribution and, as in our case, the private cost parameter. Therefore, the effect of scale heterogeneity, which is shared across coefficients, can not be separated from heterogeneity in individual coefficients when using univariate distributions (*37, 38*). The scale coefficient is then defined as a function (Eq. (12)) that accounts for heterogeneity in all VTT-related attributes. It follows a negative log-normal distribution according to $\beta^{scale} = -exp(\mu + \sigma r_N)$ with $r_N \sim N(0,1)$. The non-linear interaction term with distance $dist_{n,t}$ ($\overline{dist}$ is the sample average) additionally allows for heterogeneity with respect to the trip length. We expect a negative δ_{scale}, indicating that for longer distances, potentially relevant but unobservable features may gain in relative importance, which are omitted in the utility function.

$$\psi_{n,t} = -exp\left(\mu_{log(\beta^{scale})} + \sigma_{log(\beta^{scale})} r_N\right)\left(\frac{dist_{n,t}}{\overline{dist}}\right)^{\delta^{scale}} \tag{12}$$

$VTT_{i,n,t}$ (Eq. (13)) follows a log-normal distribution according to $\beta^{VTT}_{i,n} = exp(\mu_i + \sigma_{i,n} r_N)$ with $r_N \sim N(0,1)$ and thereby accounting for random individual-related heterogeneity in VTT parameters. Again, the non-linear interaction term with distance $dist_{n,t}$ additionally allows for heterogeneity with respect to the trip length. We expect a positive δ^{VTT}, indicating that VTTs marginally increase for longer trip distances. Moreover, we incorporate purpose-specific multipliers z on the VTT, $\kappa^{VTT}_{i,z}$ times a dummy for each $p_{z,n}$, to account for differences between the three trip purposes mentioned in Section 3.

$$VTT_{i,n,t} = exp\left(\mu_{log(\beta^{VTT}_i)} + \sigma_{log(\beta^{VTT}_{i,n})} r_N\right)\left(\frac{dist_{n,t}}{\overline{dist}}\right)^{\delta^{VTT}} \prod_z \left((\kappa^{VTT}_{i,z}) p_{z,n} + (1 - p_{z,n})\right) \tag{13}$$

Note that only β parameters in $\psi_{n,t}$ and $VTT_{i,n,t}$ are random in our specification. The models were estimated using R (version 4.2.0) and the Apollo package (version 0.2.9) on ETH's Euler compute cluster (*39, 40*).

RESULTS AND DISCUSSION

This section presents the results of the choice model mentioned above and discusses the implied effects on mode choice preferences.

Descriptive analysis

A total of 1,349 complete responses were collected in 2022. A comparison of the sample composition with the most recent mobility census from 2017 in Germany filtered for Bavaria (*41*) as well as local data for Munich revealed two noteworthy differences: our sample over-represents younger age cohorts (18-30 & 30-40 years of age) and higher educated people (holding a university degree). Therefore, we re-weighted the model outcome using iterative proportional fitting (IPF) based on gender, age, education level, mobility tool ownership, and household size.

Non-trading in choice behavior can be an issue in SC experiments as discussed in (*42*). It generally refers to the situation where a respondent always chooses the same alternative across choice tasks for different reasons: extreme preferences, heuristic decision-making, and political or strategic behavior. In addition, SP data might exhibit further behavioral bias such as the social desirability or lack of consequentiality bias (*43*). We observed non-trading behavior for 296 individuals in our sample. After comprehensive testing, we decided to remove these for the following reasons. First, many of those respondents rushed through the survey having an experiment duration time of less than 5 minutes. Second, a substantial share failed the exam question at the end of the survey concerning the purpose of a TCS, which indicates that they did not understand the basic principles of such a scheme. Last but not least, the MNL models tested with only traders gave more reliable results in terms of parameter estimates, model fit, and corresponding VTT values.

Fig. 2 presents an overview of the choice frequencies for different trip purposes and regimes, and *MobilityCoin* price levels. The modal split in Fig. 2a shows a high cycling share across trip purposes and regimes, which might either be related to the mobility behavior of the sample or to the experimental design. Regarding the former possibility, the simplified travel diary of the survey revealed that more than 40% of the participants ride their bicycle almost daily and another 20% on 2-3 days per week. Albeit these are high values, Munich and other comparable European cities have seen a substantial increase in cycling usage in the last years (*44*). Furthermore, due to the recruitment strategy of our study, the sample of participants consists exclusively of residents of the city of Munich, presumably with higher accessibility to services and jobs and lower needs to commute by car, and excludes those of the metropolitan area. This would explain the low car shares observed in the SC experiment.

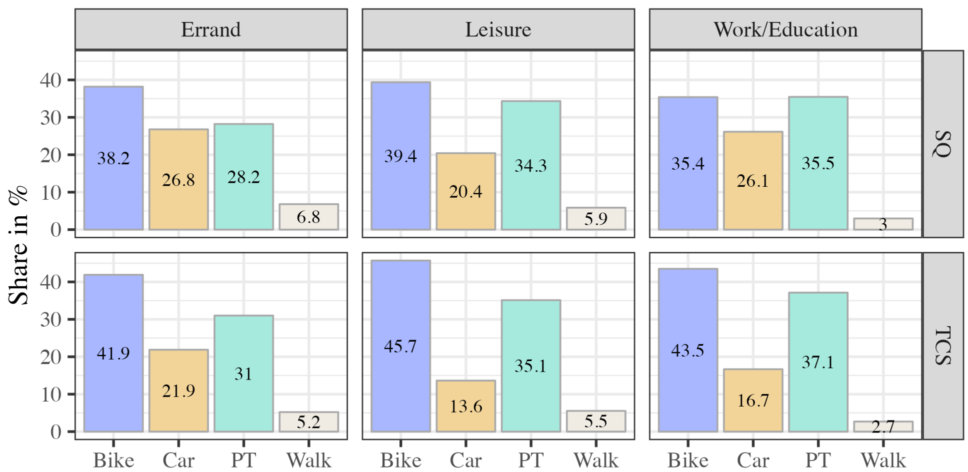
Despite the discussed cycling trend and the use of efficient choice designs, we can not rule out the presence of other biases affecting the behavior of the participants. Nevertheless, the effect of introducing a TCS is clearly visible across all trip purposes and price levels. Trips with work/education purposes experience the strongest reduction in car share (almost 10%) and consequent growth of the bike mode, with a lower observed increase of public transport. Conversely, for errand activities, we observe the smallest reduction in car share, which is distributed evenly between car and public transport. This difference is intuitive as public transport, and bikes in particular, are poor substitutes of cars for the transport of loads (e.g., groceries). Overall, there seem to be only small increases between the regimes for PT, whereas walking is barely affected. Regarding the market price, introducing the TCS leads to a significant reduction of car share for all price levels, but this reduction is strongest for the high market price level. Interestingly, public transport share experiences a slight increase for low and medium market price levels, but falls back to the status quo level for the high market price. A possible explanation is that, for this market level, PT becomes too expensive and its utility degrades excessively in relation to that of the bike mode. Thus, with a high market price level, all the reduction in car share is shifted to bike.

Model results

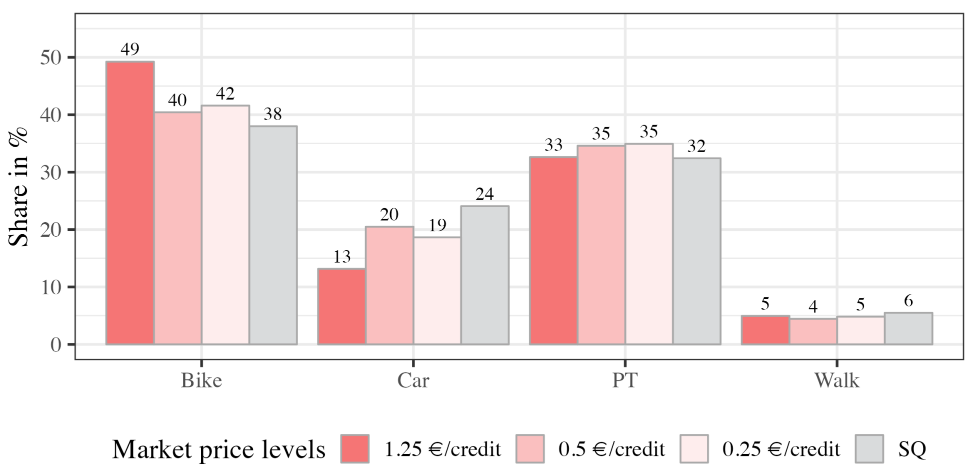
The model estimates are presented in Table 1. The discussion focuses on the MMNL 2 model and follows the segmentation used in Table 1. The units of the temporal variables are minutes while those related to costs are Euros. Building upon the recommendations of (*45*), the table does not present associated p-values. Thus, researchers should recognize the presence of uncertainty and should not assume that effects simply exist due to the statistical significance or lack thereof.

The scale parameter of the TCS model component ω_{TCS} is not significantly different from one, which shows that we cannot reject equal error variances between the two experiments. However, it is still important to control for it.

The ASC represent the mean of unobserved factors in the model. For identification reasons, one has to be normalized to zero, which is the one for PT in our case. The same principle holds for categorical variables, where one level is set as reference to the others. For each alternative,



(a) By trip purpose and regime



(b) By market price levels

FIGURE 2: Choice frequencies

we include shifts on the ASC for different trip purposes and sociodemographic variables. To start, all the purpose-specific shifts included are not significantly different from zero, but show the expected sign. The coefficients of the non-linear specification for age suggest that –ceteris paribus– walking, bike, and car are preferred over PT for younger ages, but the latter two become less attractive than PT after retirement age. With regard to car, male and divers people (0.462; 3.462) are more likely than females to choose car over PT. In contrast, highly educated individuals holding a University degree (-0.374) are less prone to do so than people with a lower education. Similar –although slightly lower– effects were found for male and divers people (0.368; 1.913) with respect to bike. However, higher education does not seem to significantly influence the choice to ride a bike compared to lower education levels (0.024) and relative to PT. With respect to the ASC for car, neither the base ASC nor any shift turned out to be significant. However, in general, it is still important to control for these effects when deriving VTT values.

The external-cost coefficients for different remaining budgets and days into the month (τ^{mc}_{TCS}) are all negative and significant. As shown in Fig. 3, for a given budget at the mean trip distance and monthly household income, the sensitivity to the *MobilityCoins* charge is higher the more days are left until the end of the month, as individuals need to distribute their remaining budget within more days. Conversely, for a given day in the month, individuals are less sensitive to the external costs the larger their remaining budget is. Albeit intuitive, both observations confirm that the participants understood the complexity of TCS and seem to behave rationally by incorporating it into their decision-making process. They also reveal that the same *MobilityCoins* charge could have different impacts on mode choice at different moments in time within a month. Moreover, we found that the cost sensitivity marginally decreases with longer trip distances and higher monthly household income. While the effect of the latter is lower in absolute magnitude (-0.2 vs. -0.898), it is interesting that we found no income effect on all the VTT values (see Section 4.2.1), which in our framework only depend on private travel costs. As expected, a *MobilityCoins* incentive ι^{mb}_{TCS} positively affects the probability to choose a bike.

The scale was specified as a random continuous parameter in MMNL 2 to possibly reveal scale heterogeneity in the VTT values. Interestingly, there does not seem to be random scale heterogeneity as the estimated standard deviation $\sigma_{log(\beta^{scale})} = 0.166$ is not significant (t-ratio = 1.102). $-exp(\sigma_{log(\beta^{scale})}) = -0.178$ shows that the parameter is very similar to MNL estimate of -0.149. The distance elasticity on the scale parameter yields a decreasing marginal effect for longer trip distances (-0.680), which again is comparable to -0.715 in the MNL model and further confirms our hypothesis from Section 3.4. This indicates that the VTT values presented in Section 4.2.1 to a large extent are driven by randomness in the individual sensitivities.

By definition, the value of travel time is the extra cost that a person would be willing to incur to save one unit of time (*46*). A higher VTT generally indicates a larger discomfort when traveling with that mode if user effects (i.e., sociodemographic effects) are controlled for. The VTT estimates presented in the next part of Table 1 were also specified as random continuous parameters as explained in Section 3.4. As with the scale parameters, it is important to mention that the estimates can not be directly compared between the MNL and MMNL 2 model, as the latter are given by the logarithm of it and need back-transformation and sample enumeration to do so. We discuss the resulting VTT values in Section 4.2.1. For now, we observe that there is significant random individual heterogeneity in the VTT estimates for all alternatives, with the largest std. deviation for cars (see $\sigma_{log(\beta_i^{VTT})}$). Except for the distance and income elasticity estimates on the

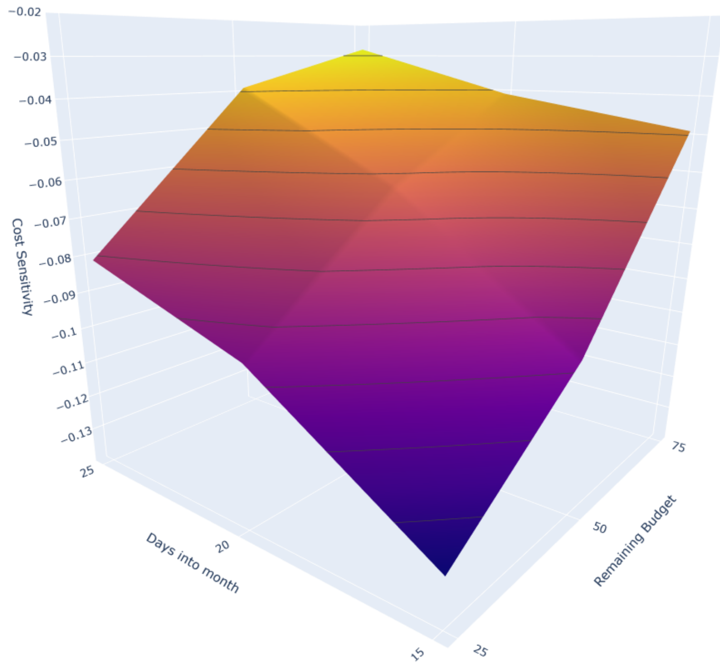


FIGURE 3: External-costs-sensitivity for different remaining budgets and day of the month.

VTT, all parameters are statistically significant on the 5% significance level. In contrast to the scale parameter, the VTT values are only barely affected by trip distance and household income. Nevertheless, both show a slightly positive influence and hence partially confirm our expectation from Section 3.4. In addition, the alternative-specific multipliers on the VTT yield important differences between the modes. Whereas the VTT between commute/education and leisure-related PT trips is not significantly different (0.993 vs. 1), the VTT for errands is almost 30% higher (1.294), which is often associated with higher discomfort (i.e., mode effect). With regard to the car VTT values, we observe a higher value for leisure (35%, 1.359) and a lower one for errands (0.727) compared to commute/education trips. The VTT value for leisure seems somewhat counter-intuitive and might have picked up unobserved factors (i.e., we did not control for) given that the estimate in the MNL model is lower. With respect to walking, the VTT for leisure is lower (0.767, approx. 24%) compared to commute/education whereas there is no visible difference to errand related trips (0.995).

When looking at the scenario variables, we observe very intuitive and significant estimates. Medium and very good cycling lane qualities (a very simplified proxy in the SC experiment for cycling infrastructure) show positive effects on the probability to choose a bike (1.127 & 1.475). Furthermore, sunny weather has a negative influence on choosing a car in comparison to rainy weather and relative to PT (-0.767), while it is associated with substantial positive effects on cycling (3.882) and walking (2.866). As the estimates show, it is important to at least approximate the influence of weather when including active modes in an SC experiment.

Weighted VTT distributions across alternatives and models

In order to present a meaningful comparison between the VTT values across alternatives, trip purposes, and models, we applied weighted sample enumeration, which essentially calculates values for each observation in the data. We used the unconditional posterior distribution that includes the draws and hence accounts for uncertainty around the mean, instead of using the conditional posterior means which ignores part of the heterogeneity. Fig. 4 summarizes the resulting VTT distributions (in €/hour) for each alternative and model, where the dot and solid line represent the corresponding mean and median respectively.

In the case of the MNL model, the median car VTT is lowest (8.3), followed by PT (17.6), bike (17.9), and walk (23.5). In many VTT studies, the values for active modes such as walking or cycling tend to be higher compared to car and PT since they actually resemble physical activity. Note that the median VTT value for PT is relatively high, which might be due to the fact that we do not account for crowding, for example. In the context of a city like Munich this could be important. Furthermore, we assumed zero private travel costs for persons owning a PT subscription to account for mobility tool ownership effects. The median car VTT value observed might (still) be attributed to a general preference for cars in Munich even though we removed non-traders from the sample. However, as explained in Section 3.2, we decided to have evenly distributed trip distances in the SC experiment, leading to a higher mean of trip distances compared to current data and hence higher means of VTT values.

Looking at the VTT values derived from MMNL 2, and taking random heterogeneity into account, we generally observe higher median and mean values as well as a larger spread across alternatives. This primarily is an artifact of our assumption of log-normally distributed VTT parameters, which often exhibit longer tails on the right side of the distribution, what might translate into unrealistically high VTT values. Therefore, Fig. 4 is truncated at VTT values of 100 €/hour. However, the larger variance in VTT values for bike, car and PT indicate that external travel costs or incentives play an important role. This is most pronounced for cars, which then fuels the assumption that part of the random heterogeneity picked up by the model is related to the assumed TCS scenario. This is also supported by the overall higher levels of cost sensitivity for external costs in MMNL 2 compared to the more simple MNL model. Based on these results, a TCS regime will likely increase the perceived VTT value for car and might shift users away from using it.

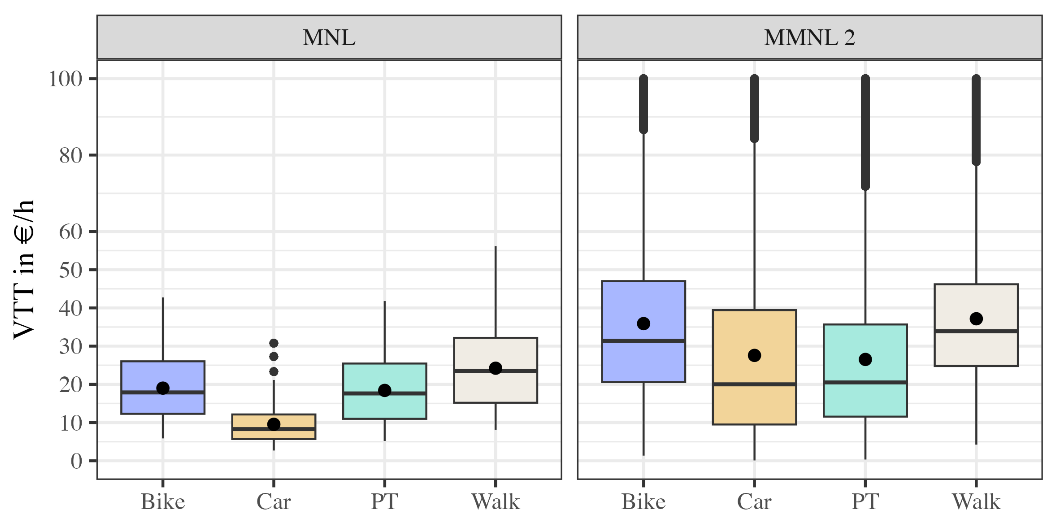


FIGURE 4: VTT comparison between the MNL and MMNL 2 model

TABLE 1: Estimation results

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
Scale model component						
TCS (ω_{TCS})	0.973	(−0.810)	0.975	(−0.620)	0.975	(−0.640)
ASC						
Car (α_C)	−1.370	(−1.988)	−1.865	(−1.754)	−1.886	(−1.462)
Car shift errand (κ_C)	0.558	(1.702)	0.211	(0.514)	0.366	(0.759)
Car shift leisure (κ_C)	−0.397	(−1.144)	0.040	(0.099)	0.269	(0.621)
Car shift male (κ_C)	0.330	(3.049)	0.478	(3.011)	0.462	(2.847)
Car shift divers (κ_C)	1.777	(2.186)	2.913	(1.866)	3.462	(2.052)
Car shift age (κ_C)	0.057	(2.342)	0.096	(2.817)	0.090	(2.480)
Car shift age sq. (κ_C)	−0.001	(−2.514)	−0.001	(−3.044)	−0.001	(−2.691)
Car shift high educ. level (κ_C)	−0.343	(−2.922)	−0.387	(−2.216)	−0.374	(−2.145)
Bike (α_B)	−3.873	(−7.165)	−5.134	(−6.290)	−5.174	(−5.375)
Bike shift errand (κ_B)	0.200	(0.762)	0.252	(0.673)	0.323	(0.615)
Bike shift leisure (κ_B)	0.101	(0.398)	−0.606	(−1.848)	−0.411	(−1.097)
Bike shift male (κ_B)	0.177	(1.956)	0.370	(2.840)	0.368	(2.766)
Bike shift divers (κ_B)	0.140	(0.124)	1.223	(0.685)	1.913	(0.992)
Bike shift age (κ_B)	0.060	(3.217)	0.098	(3.462)	0.094	(3.269)
Bike shift age sq. (κ_B)	−0.001	(−2.994)	−0.001	(−3.443)	−0.001	(−3.270)
Bike shift high educ. level (κ_B)	−0.009	(−0.087)	−0.003	(−0.021)	0.024	(0.164)
Walk (κ_W)	−2.612	(−2.193)	−2.855	(−1.858)	−2.639	(−1.480)
Walk shift errand (κ_W)	0.275	(0.323)	0.456	(0.430)	1.199	(0.936)
Walk shift leisure (κ_W)	0.032	(0.037)	−0.358	(−0.343)	0.122	(0.099)
Walk shift male (κ_W)	−0.193	(−1.045)	−0.148	(−0.609)	−0.169	(−0.649)
Walk shift divers (κ_W)	2.187	(3.131)	2.220	(1.737)	2.771	(2.319)
Walk shift age (κ_W)	0.049	(1.483)	0.094	(1.828)	0.058	(1.145)
Walk shift age sq. (κ_W)	−0.000	(−0.817)	−0.001	(−1.278)	−0.000	(−0.560)
Walk shift high educ. level (κ_W)	0.131	(0.663)	0.256	(0.969)	0.261	(0.949)
MobilityCoin expense / revenue						
Cost sensitivity (τ^{mc}_{TCS}), with:						
75% budget left, 15 days into month	−0.037	(−3.510)	−0.049	(−3.827)	−0.049	(−3.817)
75% budget left, 20 days into month	−0.013	(−1.434)	−0.041	(−3.333)	−0.042	(−3.399)
75% budget left, 25 days into month	−0.010	(−0.950)	−0.028	(−2.138)	−0.026	(−1.891)
50% budget left, 15 days into month	−0.080	(−4.541)	−0.098	(−5.089)	−0.100	(−5.120)
50% budget left, 20 days into month	−0.013	(−1.068)	−0.063	(−3.489)	−0.063	(−3.493)
50% budget left, 25 days into month	−0.014	(−1.028)	−0.039	(−2.219)	−0.038	(−2.165)
25% budget left, 15 days into month	−0.081	(−5.975)	−0.127	(−7.613)	−0.128	(−7.555)
25% budget left, 20 days into month	−0.053	(−4.276)	−0.096	(−5.678)	−0.097	(−5.643)
25% budget left, 25 days into month	−0.058	(−4.166)	−0.081	(−5.291)	−0.080	(−5.075)
Distance elasticity ($\delta^{mc,dist}_{TCS}$)	−0.785	(−7.881)	−0.902	(−12.328)	−0.898	(−12.024)
Income elasticity ($\delta^{mc,inc}_{TCS}$)	−0.302	(−2.766)	−0.215	(−2.326)	−0.200	(−2.179)
Revenue/incentive sensitivity (ι^{mb}_{TCS})	0.199	(2.003)	0.291	(2.279)	0.286	(2.247)
Scale parameter						

Continued on next page

Table 1 – *Continued from previous page*

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
Mean scale ($\mu_{log(\beta^{scale})}$)	−0.149	(−8.009)	−1.731	(−14.345)	−1.725	(−13.248)
Sd scale ($\sigma_{log(\beta^{scale})}$)			0.133	(1.814)	0.166	(1.102)
Distance elasticity scale ($\delta_{TCS}^{tc,dist}$)	−0.715	(−6.514)	−0.654	(−9.394)	−0.680	(−9.765)
VTT (mean & sd) & WTP indicators						
Mean VTT PT ($\mu_{log(\beta_{PT}^{VTT})}$)	0.402	(5.084)	−1.281	(−5.089)	−1.099	(−3.135)
Mean VTT Car ($\mu_{log(\beta_{C}^{VTT})}$)	0.296	(2.822)	−0.855	(−2.605)	−0.903	(−2.532)
Mean VTT Bike ($\mu_{log(\beta_{B}^{VTT})}$)	0.411	(5.283)	−0.483	(−3.236)	−0.487	(−2.902)
Mean VTT Walk ($\mu_{log(\beta_{W}^{VTT})}$)	0.540	(3.451)	−0.288	(−1.180)	−0.417	(−1.295)
Sd VTT PT ($\sigma_{log(\beta_{PT}^{VTT})}$)			−1.000	(−10.286)	−0.862	(−5.903)
Sd VTT Car ($\sigma_{log(\beta_{C}^{VTT})}$)			−1.218	(−8.821)	−1.161	(−7.662)
Sd VTT Bike ($\sigma_{log(\beta_{B}^{VTT})}$)			0.625	(14.423)	0.612	(13.566)
Sd VTT Walk ($\sigma_{log(\beta_{W}^{VTT})}$)			0.459	(7.343)	0.447	(7.286)
Multiplier PT leisure ($\kappa_{PT,leisure}^{VTT}$)	0.893	(4.944)	1.152	(5.148)	0.993	(4.838)
Multiplier PT errand ($\kappa_{PT,errand}^{VTT}$)	0.628	(3.949)	1.459	(4.796)	1.294	(3.295)
Multiplier Car leisure ($\kappa_{C,leisure}^{VTT}$)	0.443	(1.461)	1.263	(3.747)	1.359	(3.787)
Multiplier Car errand ($\kappa_{C,errand}^{VTT}$)	0.444	(1.548)	0.647	(3.722)	0.727	(3.786)
Multiplier Walk leisure ($\kappa_{W,leisure}^{VTT}$)	0.731	(3.514)	0.716	(4.559)	0.767	(3.578)
Multiplier Walk errand ($\kappa_{W,errand}^{VTT}$)	0.755	(3.234)	0.793	(4.640)	0.955	(3.557)
Multiplier Bike leisure ($\kappa_{B,leisure}^{VTT}$)	0.853	(6.598)	0.687	(9.509)	0.730	(7.239)
Multiplier Bike errand ($\kappa_{B,errand}^{VTT}$)	0.693	(5.568)	1.062	(9.114)	1.052	(6.321)
Distance elasticity VTT	0.541	(4.011)	0.047	(0.810)	0.067	(1.054)
Income elasticity VTT			0.018	(0.501)	0.017	(0.425)
WTP PT access/eggress time	0.118	(1.799)	0.231	(3.272)	0.227	(2.552)
WTP PT frequency	0.064	(1.344)	0.160	(3.274)	0.156	(2.900)
WTP PT transfers	0.713	(3.418)	1.101	(4.352)	1.057	(3.885)
Scenario variables (normalized for rain and bad bike lane quality)						
Bike lane medium quality ($\gamma_{medium\ q.,t}$)	0.763	(10.974)	1.125	(12.087)	1.127	(12.040)
Bike lane good quality ($\gamma_{good\ q.,t}$)	0.942	(13.870)	1.477	(15.040)	1.475	(14.945)
Car sunny weather ($\gamma_{C\ sun,t}$)	−0.381	(−4.511)	−0.770	(−7.326)	−0.767	(−7.263)
Bike sunny weather ($\gamma_{B\ sun,t}$)	2.829	(29.240)	3.884	(26.571)	3.882	(26.538)
Walk sunny weather ($\gamma_{W,t}$)	2.107	(12.732)	2.873	(12.020)	2.866	(11.981)
LL(0,SQ)	-6283.166		-6283.166		-6283.166	
LL(final,SQ)	-4594.511		-4184.881		-4181.870	
LL(0,TCS)	-6539.372		-6539.372		-6539.372	
LL(final,TCS)	-4738.993		-4329.226		-4328.746	
LL(0,model)	-12822.537		-12822.537		-12822.537	
LL(final,model)	-9333.504		-8106.550		-8110.860	
Adj. rho squared (model)	0.272		0.367		0.367	
# respondents	1053		1053		1053	
# observations	11172		11172		11172	
# parameters	72		78		78	
# draws	0		500		1000	

CONCLUSION

This paper presents first findings concerning mode choice preferences within the framework of a Tradable Credit Scheme in the city of Munich, Germany. The main objective of the TCS is twofold: Firstly, to curtail the usage of less sustainable transportation modes, and secondly, to promote more sustainable alternatives by implementing a monthly mobility budget in the form of *MobilityCoins*. These coins account for both the external costs and benefits associated with the modes under consideration. To investigate heterogeneity of choice behavior in such a context, we conducted a survey that contained two SC experiments. One resembling the choice between walking, cycling, car, and PT in a status quo regime, and one where we hypothetically introduced the TCS paradigm.

A descriptive analysis of the data gathered revealed that the implementation of a TCS leads to significantly lower car shares for all considered trip purposes and credit market price levels. The bicycle share experiences the largest increase, whereas PT only slightly gains and walking remains unaffected. We estimated a Mixed Multinomial (MMNL) choice model to investigate sensitivities to external travel costs and to derive values of travel time for each mode considered. First, and with respect to the external travel costs, the respondents showed greater cost sensitivity the lower the remaining budget was and the fewer days they were into a given month. Given the complexity of the experiment, we can conclude that the respondents showed rational choice behavior when confronted with mobility budget constraints. Second, the derived median VTT values are higher across all modes when accounting for random heterogeneity in a TCS. However, we observed the largest variance in VTT values for cars, presumably induced by higher external costs that influence the perceived overall cost.

This paper aims to fill a current gap in the literature by presenting the first SC experiment and mode choice model considering a TCS regime. The study leverages an elaborated choice design and relies on a thorough sample recruitment plan. As with everything, there are limitations to our work. First and foremost, our approach did not allow an investigation into real-world trading of *MobilityCoins* in the market. Secondly, the scope of the study is confined to the city of Munich. Lastly, the choice model applied is based on the assumption of log-normally distributed parameters, which can lead to VTT estimates that are not necessarily supported by the data. For future work, it would be of interest to conduct a paired SC and market-trading experiment, and explore feasible TCS design parameters in combination with macroscopic and agent-based models.

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