




Investigating mode choice preferences in a tradable mobility credit scheme

Working Paper**Author(s):**

Schatzmann, Thomas ; Álvarez-Ossorio Martínez, Santiago; Loder, Allister ; Axhausen, Kay W. ; Bogenberger, Klaus

Publication date:

2023-08

Permanent link:

<https://doi.org/10.3929/ethz-b-000625516>

Rights / license:

[In Copyright - Non-Commercial Use Permitted](#)

Originally published in:

Arbeitsberichte Verkehrs- und Raumplanung 1837

1 **INVESTIGATING MODE CHOICE PREFERENCES IN A TRADABLE MOBILITY**
2 **CREDIT SCHEME**

3

4

5

6 **Thomas Schatzmann**

7 IVT, ETH Zurich

8 ORCID: 0000-0003-1889-5159

9 thomas.schatzmann@ivt.baug.ethz.ch

10

11 **Santiago Álvarez-Ossorio Martínez**

12 VT, TU Munich

13 ORCID: 0000-0002-4958-1614

14 santiago.alvarez@tum.de

15

16 **Allister Loder**

17 VT, TU Munich

18 ORCID: 0000-0003-3102-6564

19 allister.loder@tum.de

20

21 **Kay W. Axhausen**

22 IVT, ETH Zurich

23 ORCID: 0000-0003-3331-1318

24 axhausen@ivt.baug.ethz.ch

25

26 **Klaus Bogenberger**

27 VT, TU Munich

28 ORCID: 0000-0003-3868-9571

29 klaus.bogenberger@tum.de

30

31

32 Primary submission committees: AEP25 & AEP30

33

34

35 Word Count: 7135 words + 1 table(s) × 250 = 7385 words

36

37

38 Submission Date: August 18, 2023

1 ABSTRACT

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

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

19

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

1 INTRODUCTION

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

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

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

43 Numerous publications have discussed the strengths of TCS in comparison to alternative
44 travel demand management measures such as congestion pricing or license plate rationing (15, 16).
45 First, TCS do not only reduce the attractiveness of using motorized vehicles, but they also provide

1 direct incentives to users of sustainable modes (i.e., citizen who travel sustainably will have credit
2 surplus, which can be sold on the market). Besides, TCS outperform congestion pricing in terms
3 of social justice, since they avoid imposing a high tax burden on the poor while only marginally af-
4 fecting the wealthy, and equity, as the revenue generated within the system is redistributed among
5 the users. Interestingly, advocates of TCS argue that these schemes could enjoy greater social ac-
6 ceptance due to their government budget-neutrality and the initial free allocation of credits (17).
7 Finally, a crucial key strength of TCS is that they allow a better quantity control of the system's
8 goal –e.g., the overall emissions– in a context of uncertainty over the agent's price response func-
9 tions (18, 19). On the downside, the complexity of the system is one of the main drawbacks of
10 TCS, making them difficult to implement and hard for the public to understand (20).

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

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

30 **METHODOLOGY**

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

1 Survey

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

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

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

20 Experimental design

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

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

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

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

- 44 • TCS scheme is implemented in the city of Munich. Hence, the following values are as-

1 sumed: average travel distance of 40 kilometers per day and 3.2 trips per day. The modal
 2 share in terms of kilometers is 56% private transport, 36% public transport, 5% cycling,
 3 and 3% walking (32). The kilometer cost for private transport is 0.5 Euro, 1.30 Euro for
 4 public transport trips shorter than 1.5 kilometers, and 2.50 Euro for public transport trips
 5 longer than 1.5 kilometers.

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

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

- 20 (i) the target per-capita travel production (i.e., modal share) is computed based on the
 21 15% reduction factor for car travel, assuming that half of the reduction is shifted to
 22 cycling and half to public transport;
- 23 (ii) the credit charges for all public transport trips obtained from Google's directions
 24 web service are set to the trip distance times 5/6 credits per travel-km, i.e., the initial
 25 1,000 monthly credit budget divided by the monthly travel production per capita to
 26 ensure that all public transport travel does not require any additional credits.
- 27 (iii) the charges for car trips are computed by using the assumed 2:1 ratio. The charges
 28 for bicycle trips, in this case subsidy, are set to 10% of the public transport charge.
 29 The charges for walking trips are set to zero.
- 30 (iv) the market price for credits is obtained using a discrete mode choice model built
 31 using values for Munich and the German value of time (34, 35), where the credit
 32 charges enter the generalized cost of travel through their market price and the value
 33 of time. We then search for each origin-destination pair for the credit market price
 34 where the observed credit spending equals the available budget, i.e., market clearing
 35 balance. This leads to a distribution of market prices with an average market price of
 36 around 0.5 Euro per credit. To account for the possibility of varying market prices,
 37 the price was pivoted as well. As such, three market price levels were implemented:
 38 0.25, 0.5 (reference price), and 1.25 Euros per credit.

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

1 25 days.

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

4 **Sample recruitment**

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

15 **Modeling approach**

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

18 Each mode/alternative i for an individual n in model component m and choice task t is
19 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
20 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
21 parameters β that is estimated based on the attributes given in the choice experiment and sociode-
22 mographic variables of the respondents. For the MMNL, to account for the random heterogeneity
23 across decision-makers, we assume $\beta_n \forall n$ with density $f(\beta|\Omega)$, where Ω is a vector of parameters
24 of this distribution (i.e., its mean and variance). Since we have multiple choices per individual, the
25 likelihood of the sequence of choices for individual n is given by $P_n(\Omega)$ (see Eq. (1)), assuming
26 that sensitivities vary across individuals, but stay constant within. $i_{n,m,t}^*$ represents the individual's
27 chosen alternative i in model component m and choice task t . The MMNL model is estimated by
28 means of Maximum Simulated Likelihood (MSL) where the simulated log-likelihood (SLL, see
29 Eq. (3)) is the probability of reproducing each choice in the sample and $\beta_{r,n,m}$ gives the r^{th} draw
30 from $f(\beta|\Omega)$ for individual n .

$$P_n(\Omega) = \int_{\beta} \prod_{t=1}^T \prod_{m=1}^M P_{n,m,t}(i_{n,m,t}^*|\beta) f(\beta|\Omega) d\beta \quad (1)$$

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

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

31 We estimate a pooled MMNL model parametrized in willingness-to-pay (WTP) space. The term
32 "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

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

$$V_{W,n,SQ,t} = \alpha_W + s_{n,t} \kappa_W + \psi_{n,t} (x_{W,n,SQ,t}^{IC} + x_{W,n,SQ,t}^{II} VTT_{W,n,t}) + v_{SQ,t} \gamma_W \quad (4)$$

$$V_{B,n,SQ,t} = \alpha_B + s_{n,t} \kappa_B + \psi_{n,t} (x_{B,n,SQ,t}^{IC} + x_{B,n,SQ,t}^{II} VTT_{B,n,t}) + v_{SQ,t} \gamma_B \quad (5)$$

$$V_{C,n,SQ,t} = \alpha_C + s_{n,t} \kappa_C + \psi_{n,t} (x_{C,n,SQ,t}^{IC} + x_{C,n,SQ,t}^{II} VTT_{C,n,t}) + v_{SQ,t} \gamma_C \quad (6)$$

$$V_{PT,n,SQ,t} = \psi_{n,t} (x_{PT,n,SQ,t}^{IC} + x_{PT,n,SQ,t}^{II} VTT_{PT,n,t} + x_{PT,n,SQ,t} WTP_{PT}) \quad (7)$$

$$V_{W,n,TCS,t} = \omega_{TCS} \left(\alpha_W + s_{n,t} \kappa_W + \psi_{n,t} (x_{W,n,TCS,t}^{IC} + x_{W,n,TCS,t}^{II} VTT_{W,n,t}) + v_{TCS,t} \gamma_W \right) \quad (8)$$

$$V_{B,n,TCS,t} = \omega_{TCS} \left(\alpha_B + s_{n,t} \kappa_B + \psi_{n,t} (x_{B,n,TCS,t}^{IC} + x_{B,n,TCS,t}^{II} VTT_{B,n,t}) + \right. \\ \left. x_{B,n,TCS,t}^{mb} \iota_{TCS}^{mb} + v_{TCS,t} \gamma_B \right) \quad (9)$$

$$V_{C,n,TCS,t} = \omega_{TCS} \left(\alpha_C + s_{n,t} \kappa_C + \psi_{n,t} (x_{C,n,TCS,t}^{IC} + x_{C,n,TCS,t}^{II} VTT_{C,n,t}) + \right. \\ \left. x_{C,n,TCS,t}^{mc} \tau_{TCS}^{mc} + v_{TCS,t} \gamma_C \right) \quad (10)$$

$$V_{PT,n,TCS,t} = \omega_{TCS} \left(\psi_{n,t} (x_{PT,n,TCS,t}^{IC} + x_{PT,n,TCS,t}^{II} VTT_{n,t} + x_{PT,n,TCS,t} WTP_{PT}) + \right. \\ \left. x_{PT,n,TCS,t}^{mc} \tau_{TCS}^{mc} \right) \quad (11)$$

2 with:

- 3 • ω_m : Parameter to account for scale differences (error variance) between the two model
4 components in pooled estimation (36); $m \in \{SQ, TCS\}$ (SQ = reference; $\omega_{SQ} = 1$)
5 • α_i : Alternative-specific constant (PT = reference; $\alpha_{PT} = 0$)
6 • $s_{n,t}$: Vector of trip-specific and sociodemographic attributes as a shift on the ASC's
7 • κ_i : Vector of parameters for $s_{n,t}$
8 • $\psi_{n,t}$: Scale parameter of VTT & WTP attributes (see Eq. (12))
9 • $x_{i,n,m,t}^{IC}$: Private travel costs
10 • $x_{i,n,m,t}^{II}$: Travel times
11 • $VTT_{i,n,t}$: Vector of VTT parameters (see Eq. (13))
12 • $x_{PT,n,m,t}$: Vector of trip-specific PT attributes (e.g., access & egress time, number of
13 transfers, frequency; excluding PT private travel costs and travel time)
14 • WTP_{PT} : Vector of PT-related WTP parameters
15 • $x_{i,n,TCS,t}^{mc}$: Vector of *MobilityCoin* expenses (external travel cost for car and PT)
16 • τ_{TCS}^{mc} : Vector of parameters for $x_{i,n,TCS,t}^{mc}$
17 • $x_{B,n,TCS,t}^{mb}$: Vector of *MobilityCoin* revenues (external travel incentive for bicycle)
18 • ι_{TCS}^{mb} : Vector of parameters for $x_{B,n,TCS,t}^{mb}$
19 • $v_{m,t}$: Vector of scenario attributes (e.g., weather, bike lane quality)
20 • γ_i : Vector of parameters for $v_{m,t}$.

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

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

11 $VTT_{i,n,t}$ (Eq. (13)) follows a log-normal distribution according to $\beta_{i,n}^{VTT} = exp(\mu_i + \sigma_{i,n} r_N)$ with $r_N \sim$
 12 $N(0, 1)$ and thereby accounting for random individual-related heterogeneity in VTT parameters.
 13 Again, the non-linear interaction term with distance $dist_{n,t}$ additionally allows for heterogeneity
 14 with respect to the trip length. We expect a positive δ^{VTT} , indicating that VTTs marginally in-
 15 crease for longer trip distances. Moreover, we incorporate purpose-specific multipliers z on the
 16 VTT, $\kappa_{i,z}^{VTT}$ times a dummy for each $p_{z,n}$, to account for differences between the three trip pur-
 17 poses mentioned in Section 3.

$$VTT_{i,n,t} = exp\left(\mu_{log(\beta_i^{VTT})} + \sigma_{log(\beta_{i,n}^{VTT})} r_N\right) \left(\frac{dist_{n,t}}{\overline{dist}}\right)^{\delta^{VTT}} \prod_z ((\kappa_{i,z}^{VTT}) p_{z,n} + (1 - p_{z,n})) \quad (13)$$

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

21 RESULTS AND DISCUSSION

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

24 Descriptive analysis

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

31 Non-trading in choice behavior can be an issue in SC experiments as discussed in (42).
 32 It generally refers to the situation where a respondent always chooses the same alternative across
 33 choice tasks for different reasons: extreme preferences, heuristic decision-making, and political
 34 or strategic behavior. In addition, SP data might exhibit further behavioral bias such as the social
 35 desirability or lack of consequentiality bias (43). We observed non-trading behavior for 296 indi-

1 viduals in our sample. After comprehensive testing, we decided to remove these for the following
2 reasons. First, many of those respondents rushed through the survey having an experiment duration
3 time of less than 5 minutes. Second, a substantial share failed the exam question at the end of the
4 survey concerning the purpose of a TCS, which indicates that they did not understand the basic
5 principles of such a scheme. Last but not least, the MNL models tested with only traders gave
6 more reliable results in terms of parameter estimates, model fit, and corresponding VTT values.

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

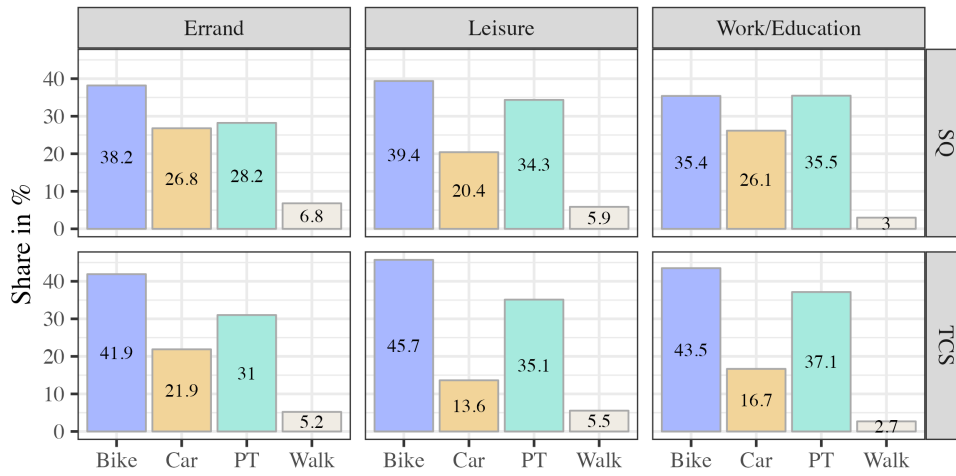
18 Despite the discussed cycling trend and the use of efficient choice designs, we can not rule
19 out the presence of other biases affecting the behavior of the participants. Nevertheless, the ef-
20 fect of introducing a TCS is clearly visible across all trip purposes and price levels. Trips with
21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

33 **Model results**

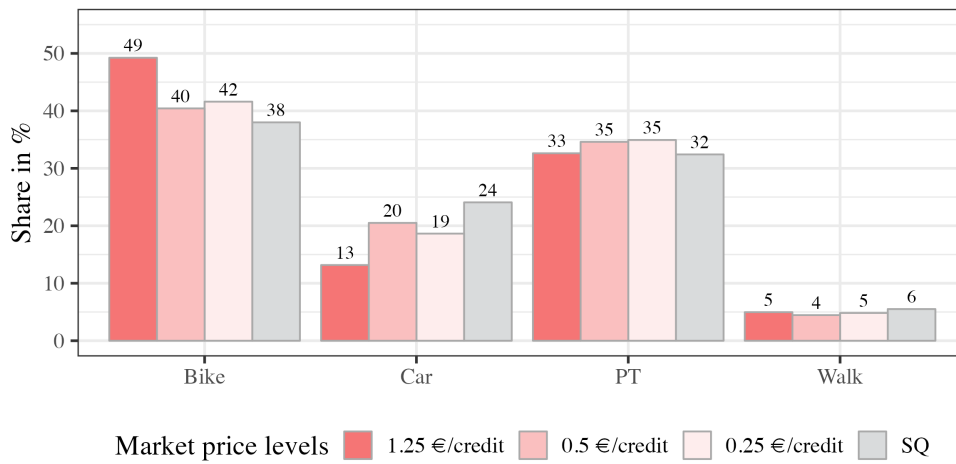
34 The model estimates are presented in Table 1. The discussion focuses on the MMNL 2 model and
35 follows the segmentation used in Table 1. The units of the temporal variables are minutes while
36 those related to costs are Euros. Building upon the recommendations of (45), the table does not
37 present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

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

42 The ASC represent the mean of unobserved factors in the model. For identification reasons,
43 one has to be normalized to zero, which is the one for PT in our case. The same principle holds
44 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

1 we include shifts on the ASC for different trip purposes and sociodemographic variables. To
 2 start, all the purpose-specific shifts included are not significantly different from zero, but show
 3 the expected sign. The coefficients of the non-linear specification for age suggest that –ceteris
 4 paribus– walking, bike, and car are preferred over PT for younger ages, but the latter two become
 5 less attractive than PT after retirement age. With regard to car, male and divers people (0.462;
 6 3.462) are more likely than females to choose car over PT. In contrast, highly educated individuals
 7 holding a University degree (-0.374) are less prone to do so than people with a lower education.
 8 Similar –although slightly lower– effects were found for male and divers people (0.368; 1.913) with
 9 respect to bike. However, higher education does not seem to significantly influence the choice to
 10 ride a bike compared to lower education levels (0.024) and relative to PT. With respect to the ASC
 11 for car, neither the base ASC nor any shift turned out to be significant. However, in general, it is
 12 still important to control for these effects when deriving VTT values.

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

27 The scale was specified as a random continuous parameter in MMNL 2 to possibly reveal
 28 scale heterogeneity in the VTT values. Interestingly, there does not seem to be random scale
 29 heterogeneity as the estimated standard deviation $\sigma_{\log(\beta^{scale})} = 0.166$ is not significant (t-ratio =
 30 1.102). $-exp(\sigma_{\log(\beta^{scale})}) = -0.178$ shows that the parameter is very similar to MNL estimate of
 31 -0.149. The distance elasticity on the scale parameter yields a decreasing marginal effect for longer
 32 trip distances (-0.680), which again is comparable to -0.715 in the MNL model and further confirms
 33 our hypothesis from Section 3.4. This indicates that the VTT values presented in Section 4.2.1 to
 34 a large extent are driven by randomness in the individual sensitivities.

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

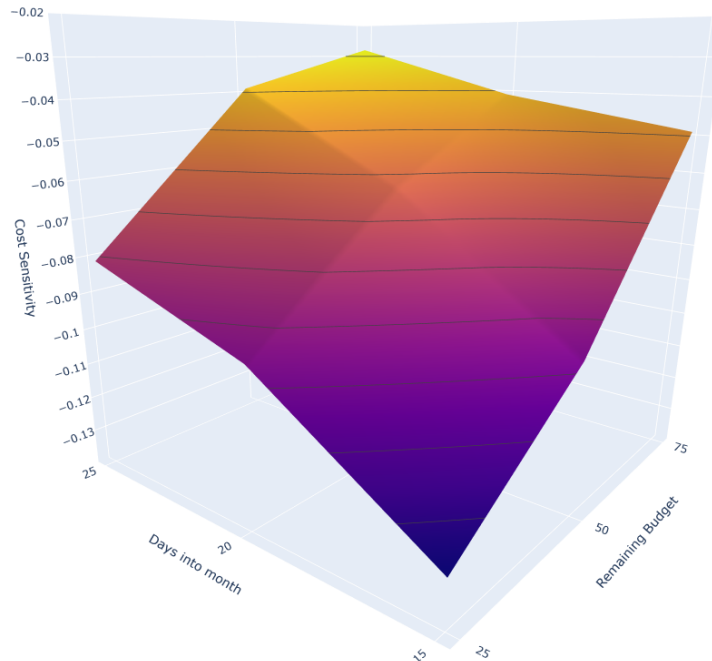


FIGURE 3: External-costs-sensitivity for different remaining budgets and day of the month.

1 VTT, all parameters are statistically significant on the 5% significance level. In contrast to the scale
 2 parameter, the VTT values are only barely affected by trip distance and household income. Nev-
 3 ertheless, both show a slightly positive influence and hence partially confirm our expectation from
 4 Section 3.4. In addition, the alternative-specific multipliers on the VTT yield important differences
 5 between the modes. Whereas the VTT between commute/education and leisure-related PT trips is
 6 not significantly different (0.993 vs. 1), the VTT for errands is almost 30% higher (1.294), which
 7 is often associated with higher discomfort (i.e., mode effect). With regard to the car VTT values,
 8 we observe a higher value for leisure (35%, 1.359) and a lower one for errands (0.727) compared
 9 to commute/education trips. The VTT value for leisure seems somewhat counter-intuitive and
 10 might have picked up unobserved factors (i.e., we did not control for) given that the estimate in
 11 the MNL model is lower. With respect to walking, the VTT for leisure is lower (0.767, approx.
 12 24%) compared to commute/education whereas there is no visible difference to errand related trips
 13 (0.995).

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

21 *Weighted VTT distributions across alternatives and models*

22 In order to present a meaningful comparison between the VTT values across alternatives, trip pur-
 23 poses, and models, we applied weighted sample enumeration, which essentially calculates values

1 for each observation in the data. We used the unconditional posterior distribution that includes
 2 the draws and hence accounts for uncertainty around the mean, instead of using the conditional
 3 posterior means which ignores part of the heterogeneity. Fig. 4 summarizes the resulting VTT
 4 distributions (in €/hour) for each alternative and model, where the dot and solid line represent the
 5 corresponding mean and median respectively.

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

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

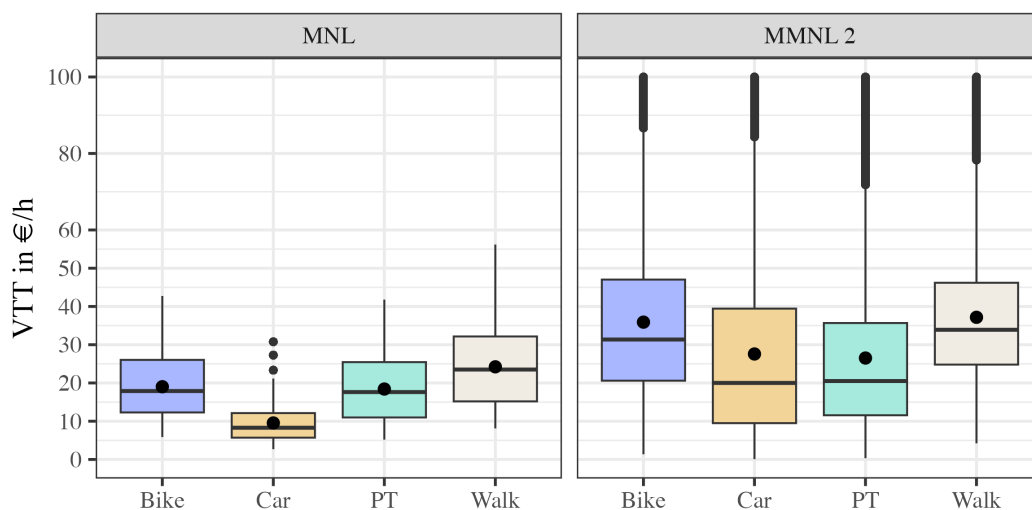


FIGURE 4: VTT comparison between the MNL and MMNL 2 model

TABLE 1: Estimation results

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
<hr/>						
Scale model component						
TCS (ω_{TCS})	0.973	(-0.810)	0.975	(-0.620)	0.975	(-0.640)
<hr/>						
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)
<hr/>						
<i>MobilityCoin</i> expense / revenue						
<hr/>						
Cost sensitivity (τ_{TCS}^{mc}), 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 ($\delta_{TCS}^{mc, dist}$)	-0.785	(-7.881)	-0.902	(-12.328)	-0.898	(-12.024)
Income elasticity ($\delta_{TCS}^{mc, inc}$)	-0.302	(-2.766)	-0.215	(-2.326)	-0.200	(-2.179)
Revenue/incentive sensitivity (ι_{TCS}^{mb})	0.199	(2.003)	0.291	(2.279)	0.286	(2.247)
<hr/>						
Scale parameter						
<hr/>						

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/egress 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 (γ_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	

1

2 CONCLUSION

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

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

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

33 ACKNOWLEDGMENTS

34 The authors acknowledge financial support from the Bavarian State Ministry for Housing, Con-
35 struction, and Transportation for the project '*MoCo – Anreiz statt Gebühr*'. We are grateful to
36 the Kreisverwaltungsreferat München (city administration office) for providing the participant's
37 addresses.

1 REFERENCES

- 2 1. European Commission, *Handbook on the external costs of transport : version 2019 – 1.1*,
3 2020.
- 4 2. European Commission, *Sustainable and Smart Mobility Strategy – putting European trans-*
5 *port on track for the future; COM(2020) 789*. Brussels, 2020.
- 6 3. Nima Shirmohammadi, Mahmood Zangui, Yafeng Yin, and Yu (Marco) Nie, Analysis and
7 Design of Tradable Credit Schemes under Uncertainty. *Transportation Research Record*,
8 Vol. 2333, No. 1, 2013, pp. 27–36.
- 9 4. FHWA, *Integrated Corridor Management, Managed Lanes and Congestion Pricing: A*
10 *Primer*, 2016.
- 11 5. Eliasson, J., L. Hultkrantz, L. Nerhagen, and L. S. Rosqvist, The Stockholm congestion–
12 charging trial 2006: Overview of effects. *Transportation Research Part A: Policy and Prac-*
13 *tice*, Vol. 43, No. 3, 2009, pp. 240–250.
- 14 6. Lehe, L., Downtown congestion pricing in practice. *Transportation Research Part C:*
15 *Emerging Technologies*, Vol. 100, 2019, pp. 200–223.
- 16 7. Dales, J. H., Land, Water, and Ownership. *The Canadian Journal of Economics / Revue*
17 *canadienne d’Economie*, Vol. 1, No. 4, 1968, pp. 791–804.
- 18 8. Verhoef, E., P. Nijkamp, and P. Rietveld, Tradeable permits: Their potential in the regu-
19 lation of road transport externalities. *Environment and Planning B: Planning and Design*,
20 Vol. 24, No. 4, 1997, pp. 527–548.
- 21 9. Goddard, H. C., Using Tradeable Permits to Achieve Sustainability in the World’s Large
22 Cities: Policy Design Issues and Efficiency Conditions for Controlling Vehicle Emissions,
23 Congestion and Urban Decentralization with an Application to Mexico City. *Environmen-*
24 *tal and Resource Economics*, Vol. 10, No. 1, 1997, pp. 63–99.
- 25 10. Bogenberger, K., P. Blum, F. Dandl, L.-S. Hamm, A. Loder, P. Malcolm, M. Margreiter,
26 and N. Sautter, *MobilityCoins – A new currency for the multimodal urban transportation*
27 *system*, 2021.
- 28 11. Hamm, L., K. Bogenberger, A. Loder, S. Weikl, T. Schatzmann, and K. W. Axhausen,
29 MobilityCoins: First empirical findings on the user-oriented system design for tradable
30 credit schemes. In *102nd Annual Meeting of the Transportation Research Board (TRB*
31 *2023)*, 2022.
- 32 12. Hamm, L. and K. Bogenberger, MobilityCoins – First results on social acceptance, sys-
33 tem boundaries and individual budgets in a tradeable credit system in Germany. In *10th*
34 *symposium of the European Association for Research in Transportation (hEART)*, 2022.
- 35 13. Blum, P., L. Hamm, A. Loder, and K. Bogenberger, Conceptualizing an individual full-trip
36 tradable credit scheme for multi-modal demand and supply management: The Mobility-
37 Coin System. *Frontiers in Future Transportation*, Vol. 3, 2022.
- 38 14. Blum, P., A. Loder, and K. Bogenberger, MobilityCoins-Tradable Credit Scheme in Trans-
39 port Project Appraisal. In *Transportation Research Board 2023 – 102nd Annual Meeting*,
40 2022.
- 41 15. Dogterom, N., M. Xu, Y. Bao, and D. Ettema, Willingness to change car use under a
42 tradable driving credits scheme: A comparison between Beijing and The Netherlands.
43 *Journal of Transport and Land Use*, Vol. 11, No. 1, 2018, pp. 499–518.
- 44 16. Fan, W. and X. Jiang, Tradable mobility permits in roadway capacity allocation: Review
45 and appraisal. *Transport Policy*, Vol. 30, 2013, pp. 132–142.

- 1 17. Krabbenborg, L., C. van Langevelde-van Bergen, and E. Molin, Public support for tradable
2 peak credit schemes. *Transportation Research Part A: Policy and Practice*, Vol. 145, 2021,
3 pp. 243–259.
- 4 18. Raux, C., The use of transferable permits in transport policy. *Transportation Research Part*
5 *D: Transport and Environment*, Vol. 9, No. 3, 2004, pp. 185–197.
- 6 19. OECD, *Domestic Transferable Permits for Environmental Management*. Organization for
7 Economic Co-operation and Development, 2001.
- 8 20. Krabbenborg, L., N. Mouter, E. Molin, J. A. Annema, and B. van Wee, Exploring public
9 perceptions of tradable credits for congestion management in urban areas. *Cities*, Vol. 107,
10 2020, p. 102877.
- 11 21. Xu, M. and S. Grant-Muller, Trip mode and travel pattern impacts of a Tradable Credits
12 Scheme: A case study of Beijing. *Transport Policy*, Vol. 47, 2016, pp. 72–83.
- 13 22. Xu, M. and S. Grant-Muller, VMT reduction and potential environmental effects with a
14 tradable credits scheme: a simulation case study of Great Britain. *International Journal of*
15 *Sustainable Development & World Ecology*, Vol. 23, No. 6, 2016, pp. 514–525.
- 16 23. Chen, S., R. Seshadri, C. L. Azevedo, A. P. Akkinapally, R. Liu, A. Araldo, Y. Jiang, and
17 M. E. Ben-Akiva, Market design for tradable mobility credits. *Transportation Research*
18 *Part C: Emerging Technologies*, Vol. 151, 2023, p. 104121.
- 19 24. Wang, X., H. Yang, D. Zhu, and C. Li, Tradable travel credits for congestion management
20 with heterogeneous users. *Transportation Research Part E: Logistics and Transportation*
21 *Review*, Vol. 48, No. 2, 2012, pp. 426–437.
- 22 25. Di Wu, Yafeng Yin, Siriphong Lawphongpanich, and Hai Yang, Design of more equitable
23 congestion pricing and tradable credit schemes for multimodal transportation networks.
24 *Transportation Research Part B: Methodological*, Vol. 46, No. 9, 2012, pp. 1273–1287.
- 25 26. Provoost, J., O. Cats, and S. Hoogendoorn, Design and classification of tradable mobility
26 credit schemes. *Transport Policy*, 2023.
- 27 27. Dogterom, N., D. Ettema, and M. Dijst, Behavioural effects of a tradable driving credit
28 scheme: Results of an online stated adaptation experiment in the Netherlands. *Transporta-*
29 *tion Research Part A: Policy and Practice*, Vol. 107, 2018, pp. 52–64.
- 30 28. Geng, K., D. K. Brands, E. T. Verhoef, and Y. Wang, The impact of tradable rush hour
31 permits on peak demand: evidence from an on-campus field experiment. *Transportation*
32 *Research Part D: Transport and Environment*, Vol. 120, 2023, p. 103775.
- 33 29. Louviere, J. J., D. A. Hensher, and J. D. Swait, *Stated Choice Methods: Analysis and*
34 *Applications*. Cambridge University Press, Cambridge, 2003.
- 35 30. Rose, J. M. and M. C. J. Bliemer, Constructing Efficient Stated Choice Experimental De-
36 signs. *Transport Reviews*, Vol. 29, No. 5, 2009, pp. 587–617.
- 37 31. ChoiceMetrics, *Ngene 1.3 user manual and reference guide: The cutting edge in experi-*
38 *mental design*. ChoiceMetrics. Last access: August 10, 2022, 2021.
- 39 32. Follmer, R. and J. Belz, *Mobilität in Deutschland – MiD Kurzreport Stadt München,*
40 *Münchner Umland und MVV Verbundraum*. Studie von infas, DLR, IVT und infas 360 im
41 Auftrag des Bundesministers für Verkehr und digitale Infrastruktur (FE-Nr. 70.904/15),
42 Bonn, Berlin, 2019.
- 43 33. Schröder, D., L. Kirn, J. Kinigadner, A. Loder, P. Blum, Y. Xu, and M. Lienkamp, Ending
44 the myth of mobility at zero costs: An external cost analysis. *Research in Transportation*
45 *Economics*, Vol. 97, 2023, p. 101246.

- 1 34. Moeckel, R., *Mode choice model*. [https://www.mos.ed.tum.de/tb/forschung/
2 travel-analytics/discrete-choice-models/traveldemand/](https://www.mos.ed.tum.de/tb/forschung/travel-analytics/discrete-choice-models/traveldemand/), 2023, accessed:
3 2023-07-15.
- 4 35. Dubernet, I., T. Dubernet, and K. W. Axhausen, Comparing values of travel time obtained
5 from workplace and short-term decisions. *Travel Behaviour and Society*, Vol. 20, 2020,
6 pp. 83–90.
- 7 36. Hensher, D., J. Louviere, and J. Swait, Combining sources of preference data. *Journal of*
8 *Econometrics*, 1998, pp. 197–221.
- 9 37. Train, K. and M. Weeks, *Discrete choice models in preference space and willingness-to-*
10 *pay space*. in: R. Scarpa and A. Alberini (eds.) *Applications of Simulation Methods in*
11 *Environmental and Resource Economics*, 1–16, Springer, 2005.
- 12 38. Hess, S. and J. Rose, Can scale and coefficient heterogeneity be separated in random coef-
13 ficients models? *Transportation*, Vol. 39, 2012, pp. 1225–1239.
- 14 39. R Core Team, *R: A Language and Environment for Statistical Computing*. R Foundation
15 for Statistical Computing, Vienna, Austria, 2020.
- 16 40. Hess, S. and D. Palma, Apollo: A flexible, powerful and customisable freeware package
17 for choice model estimation and application. *Journal of Choice Modelling*, Vol. 32, 2019,
18 pp. 100–170.
- 19 41. Mobilität in Deutschland, *Mobilität in Deutschland. Regionalbericht: Metropolregion*
20 *Hamburg und Hamburger Verkehrsverbund GmbH*. Technical report, Bundesministeriums
21 für Verkehr und digitale Infrastruktur, 2019.
- 22 42. Hess, S., J. M. Rose, and J. Polak, Non-trading, lexicographic and inconsistent be-
23 haviour in stated choice data. *Transportation Research Part D: Transport and Environ-*
24 *ment*, Vol. 15, No. 7, 2010, pp. 405–417.
- 25 43. Tsoleridis, P., C. Choudhury, and S. Hess, Deriving transport appraisal values from emerg-
26 ing revealed preference data. *Transportation Research Part A: Policy and Practice*, Vol.
27 165, 2022, pp. 225–245.
- 28 44. OpenDataPortal, *Raddauerzählstellen in München*. [https://opendata.muenchen.de/
29 pages/raddauerzaehlstellen](https://opendata.muenchen.de/pages/raddauerzaehlstellen), 2023, accessed: 2023-07-15.
- 30 45. Wasserstein, R. J., A. L. Schirm, and N. A. Lazar, Moving to a world beyond "p<0.05".
31 *The American Statistician*, Vol. 73, No. 1, 2019, pp. 1–19.
- 32 46. Train, K., *Discrete choice methods with simulation*. New York, Cambridge, 2nd ed., 2009.