Mode choice and credit trading behaviour under the premise of tradeable mobility credits

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SHORT SUMMARY

This research aims to provide empirical insights into the mode choice and trade-off behaviour of travellers under the premise of a tradeable mobility credits (TMC) scheme. By utilising TMC instead of money to pay for travel and allowing travellers to trade TMC among themselves, travellers' behavioural adaptations are likely to be drastically different from other travel demand management schemes. To gain better understanding of traveller's behaviour, we devise a stated preference experiment with two different types of tasks: (1) a conventional mode choice experiment and (2) a TMC trading platform, where respondents may buy or sell. Preliminary results show that the number of credits at the respondents disposal vastly influences their willingness-to-pay (WtP), i.e. higher balance means higher WtP. This finding suggests that, under the right premise, travellers can potentially make substantial alterations to their travel behaviour.

Keywords: travel behaviour research; tradeable mobility credits; discrete choice modelling; traffic, network, and mobility management; pricing and capacity optimization; transport economics and policy

1 INTRODUCTION

Traffic congestion, air and noise pollution, as well as road safety concerns, resulting from high car use, have been the driving force of a vast array of travel demand management (TDM). Broadly, these policies can be divided into pull methods (improving alternatives to car, i.e. better public transport, cycling infrastructure,…) and push methods (various pricing measures or access restrictions). Research shows that pull policies tend to have higher public and political acceptance, but result in a substantially lower reduction in car use (Gärling & Schuitema, 2007; Schlag & Schade, 2000). Studies also show, that bundling push and pull strategies, or committing the revenues from push strategies (pricing) towards pull strategies significantly increases the policies' acceptability.

A TDM measure that is gaining traction and attention are Tradeable Mobility Credits (TMC). People are allocated a certain number of TMC for a specific time period (i.e. a day, week, month) for their mobility needs. They then spend these credits through travelling, with an authority determining the travel price (in TMC) based on the desired effect of the policy. A key merit of TMC over other TDMs is in the possibility of trading. Users may sell surplus credits, giving them a financial incentive to adjust their behaviour, or buy credits if required. For a more detailed overview on TMC allocation, trading, the role of a public authority etc. the reader is referred to the review and classification of TMC schemes by Provoost et al. (2023). A second potential benefit of TMC is their ability to act as both a pull and push approach, integrating the penalising side through pricing and rewarding side through remuneration and lower price of alternative travel modes. Despite these potential advantages, research relating to TMC schemes focused almost exclusively on car route choice behaviour (Balzer et al., 2023; Bao et al., 2020; Dogterom et al., 2017; Fan & Jiang, 2013; Lessan & Fu, 2022) and thus not investigating mode choice and any potential mode-switching behaviour. To the best of our knowledge Dogterom et al. (2018) and Schatzmann et al. (2023) were the only ones to also include other modes in investigating travel behaviour effects of TMC, where the former carried out a stated adaptation experiment and the latter a stated choice experiment.

Due to their unique nature of credit trading and direct price relations between alternatives, TMC present substantial departure from existing TDM measures and may therefore result in a drastically different behavioural adaptation. The goal of this study is to (1) analyse mode choice behaviour under the premise of TMC, (2) credit trading behaviour and (3) the interaction between the two, i.e. how the credit trading market and credit price affects mode choice behaviour, as well as how the pricing of modes affects trading in the credit market.

2 METHODOLOGY

To collect behavioural data, we carry out a stated preference discrete choice experiment. This section starts with describing the of the survey design and setup, followed by the model estimation approach and concludes with information on the data collection process.

Survey design

Respondents start the survey with a predefined number of credits and no expenses (€0), which update throughout the survey, based on usage and credit trading. In each choice situation, respondents are presented with travel options, current credit balance, expenses and exchange rate. Before choosing a travel mode, they have the option to buy or sell credits (see Figure 1).

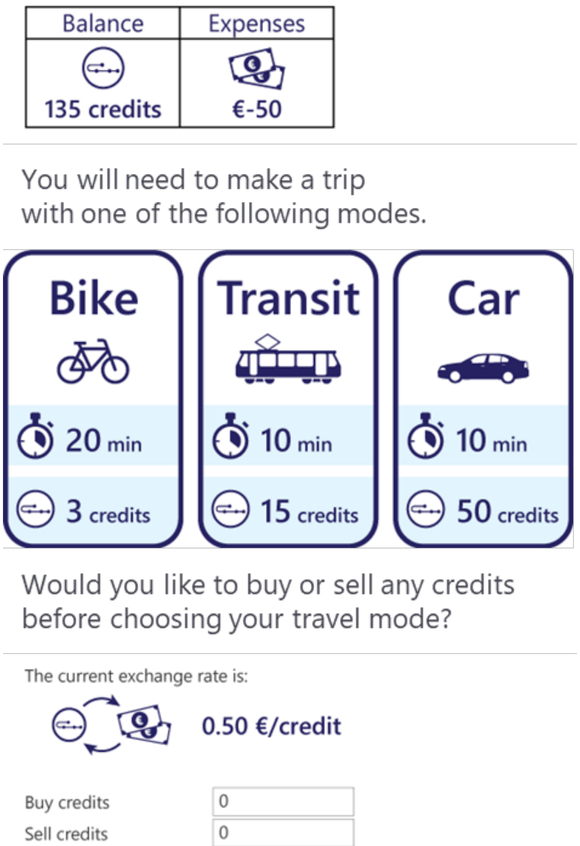

Figure 1. Example screenshot from the survey

For simplicity sake, the mode choice experiment contains only three alternatives (bicycle, public transport and car) with two attributes each (travel time and cost in credits). This is done to limit cognitive burden of the respondents, as the concept of TMC is new for most respondents and dealing with the credits exchange problem is already quite complex. Both attributes vary across three attribute levels. Travel time levels are the same for all three modes, which is deemed realistic for trips in larger Dutch cities. Travel cost is calculated based on the work of Brand et al. (2021), who determined the emissions of different travel modes per passenger-kilometre. In Brand et al. (2021)., the bicycle was also associated with a certain level of emissions; from vehicle production and energy production for electric bicycles (scaled based on modal split). As TMC are proposed as a way for policymakers to (dis)incentivise certain ways of travel (and not only for emissions), a non-zero value for cycling was deemed valid. By varying attribute levels, the varying ratios between credit levels of different modes are also able to account for policies that are not necessarily related to emissions only. Alternatives and attribute levels are shown in Table 1. Due to limited availability of priors and to avoid speculation on the perception of TMC, a labelled orthogonal design is constructed (using Ngene software (ChoiceMetrics, 2021)).

Table 1. Alternatives, attributes and attribute levels

	Bicycle	Public transport	Car
Travel time [min]	[10, 20, 30]	[10, 20, 30]	[10, 20, 30]
Cost [credits]	[1,2,3]	[5, 15, 25]	[40, 60, 80]

The number of credits allocated to respondents at the start is based on the costs (in credits) of each travel mode and the desired modal split. Three different modal splits are chosen; the current (2018), target (2030) and a mid-point between the two (City of Amsterdam, 2018). This results in starting credit values of 150 (2030 target modal split), 250 (mid-point modal split) and 350 (2018 modal split), to which respondents are randomly allocated to.

Finally, the exchange rate for trading credits is determined based on the distribution of individuals' monthly mobility expenditure in the Netherlands (Koopal et al., 2018) (adjusted for inflation) and the average number of short urban trips in the Netherlands (de Graaf, 2015). Since it is assumed that individuals are assigned credits free of charge, converting the monthly budget to TMC would result in no travel expenses. To circumvent this, the credit price is doubled, implying that approximately half the monthly mobility expenses are covered by the allocated credits and the other half through travellers' own out-of-pocket expenses. Individual values are randomly drawn from a log-normal distribution, where the average credit price represents the statistical mode of the distribution and the values are restricted to be positive only. As a different number of starting credits results in different credit prices, we construct three separate log-normal distributions. To test how different exchange rates influence behaviour, we do not link the starting credit value and exchange rates. The distributions used are shown in Figure 2, with mean and mode values, and the exchange rates used in each choice situation presented in Table 2.

Table 2. Exchange rates and distribution characteristics (all values in [€/credit])

		Scenario 1	Scenario 2	Scenario 3
	Mode	0.30	0.42	0.70
	Mean	0.60	0.84	1.40
Choice situation	1	0.40	0.70	1.10
	2	0.30	0.70	1.90
	3	0.30	0.60	4.90
	4	1.00	0.40	0.60
	5	0.20	1.80	1.30
	6	1.20	1.10	2.30
	7	0.40	2.20	0.80
	8	0.40	0.60	0.90
	9	0.30	0.60	0.30
	10	0.20	0.40	1.30
	11	0.60	0.50	1.50
	12	0.60	1.20	0.10

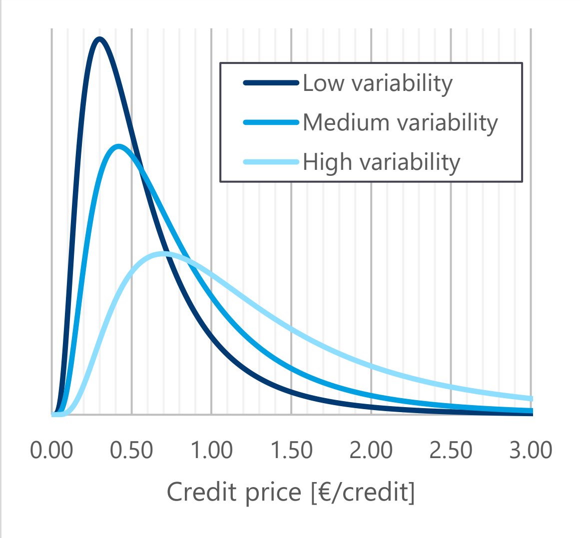

Figure 2. Log-normal distributions of the different exchange rate scenarios

Finally, we gather respondents' attitudes on financial matters, their current travel behaviour and socio-demographic information. For financial matters, we pose 12 statements on behaviour, personality, confidence and attitudes towards risk and return (Zheng, 2013). On travel behaviour, we collect information on respondents' modal preferences for different trip purposes, the frequency of using each mode, household car ownership and driving licence.

Model estimation

The mode choice model is estimated as a discrete choice model (DCM) using Pandas Biogeme for python (Bierlaire, 2023). Past research (Dogterom et al., 2017) suggests that for respondents to process the complex joint task of mode choice and credit exchange, different behavioural and mental approaches may be utilised by decision-makers. Notably in the case of decision rules, Dogterom et al. (2017) highlight a potential loss-aversion / regret minimisation tactic. To test this hypothesis, we model the obtained data by applying the µRRM approach (Van Cranenburgh et al., 2015). This is a generalisation of a regret-based decision-making model with a parameter (µ) that determines the level of trade-off behaviour taking place during the decision-making process, varying from fully compensatory decision-making (random utility maximisation (McFadden, 1974)) to non-compensatory decision-making (random regret minimisation). To test the role and importance of travellers' credit budget and exchange rate, various interaction specifications are modelled to determine which best represents respondents' decision-making approach.

Data collection and filtering

The survey is distributed through an online panel (PanelClix), among individuals living in large urban areas in the Netherlands (Amsterdam, Rotterdam, The Hague, Utrecht and Eindhoven), between 28.11.2023 and 02.01.2024. A total of 1,053 complete responses are recorded. The data is filtered based on several criteria. Firstly, a lower boundary (5min) is set to remove speeders. As the relation between the different questions of the experiment is crucial, a maximal response time of 30min is also set to ensure that respondents are still conscious of this relation. This results in the removal of 30 speeders and 71 respondents above the 30min mark. Next, we check for straightlining behaviour on the 12 finance-related attitudinal statements, removing 26 responses. Finally, eight are removed due to a calculation error in the survey platform.

One further respondent is removed as they played this game by trying to maximise their revenue, buying and selling millions of TMC. While such behaviour is not unexpected or unrealistic in a real-world situation, it is removed as it is a drastic outlier and substantially skews the data.

This results in 917 fully valid responses. Comparing the socio-demographics of our sample to those of the urban areas we aimed to capture, the sample is overall fairly representative. We do observe somewhat of an overrepresentation of higher educated individuals (with a university degree), older individuals (above 50 years old), larger households (with two or more people) and our sample has a higher car ownership (0.9 per household) and driving licence rate (82%) than the population.

3 RESULTS

Estimating a mixed logit model with five parameters (of which three are random), we obtain an adjusted rho-square value of 0.4626, with all but one parameter being highly significant. The full model outcomes are shown in Table 3. The only insignificant parameter estimate is the mean of the random cost parameter. Combined with the highly significant sigma value, this means that the lognormal distribution is not shifted, i.e. starts at a value of 0. For the perception of credits, a normal distribution is also tested, resulting in a significantly lower model fit (p-val. = 0.002 according to the Ben-Akiva & Swait test).

Table 3. Mixed logit model outcomes

Observations	11,004
Null LL	-12,089.13
Fina LL	-6,492.89
Rho-square	0.4629
Adj. Rho-square	0.4626
BIC	13,050.35

	Param. est.	Rob. t-stat [param]	σ	Rob. t-stat [σ]	Type of dist.
Constant [bicycle]	0 [fixed]		2.180	18.50 *	Normal
Constant [PT]	-1.220	-11.40 *	-1.480	-9.74 *	Normal
Constant [car]	-1.940	-10.00 *	-1.390	-6.28 *	Normal
Cost [credits]	-0.030	-0.82	-0.023	-5.83 *	Lognormal
Travel time [min]	-0.086	-20.40 *			

** p<0.01*

In addition, a variety of different MNL models are estimated in order to test various potential interaction effects and especially the perception of TMC. MNL models are first estimated to get an initial insight into possible interaction effects, before applying this in a full mixed logit and latent class choice model.

Results suggest that respondents do not seem to convert their TMC balance or travel cost into monetary terms, as any formulation using the exchange rate (current or past) results in a lower model fit than using a parameter directly accounting for the number of credits.

The starting TMC budget has a substantial impact on the perception of credits, with a higher budget resulting in a less negative perception. For example, respondents starting with 350 credits were willing to trade 4.15 credits to save 1min of travel time. This can be contrasted with a willingness-to-pay (WtP) of only 2.7credits/min for those with 250 at the start and 2.05credits/min if they started with 150. Using a similar formulation, aiming to capture the WtP given the current balance, we see a similar trend, with a higher sensitivity to cost (and thus lower WtP) as the balance decreases. A natural logarithm of the balance also yields a slightly higher (statistically significant) model fit, suggesting that the perception is not linear. With a balance of 10 credits, the WtP is only 1.39credits/min, increasing to 2.39 at a balance of 100 credits, 3.04 at 200 and 3.63 at 300.

We test another model formulation to identify if having just performed a trade (buying or selling credits) changes the perception and WtP. The results show a substantial impact, with a WtP of 2.98credits/min in the case of no trading, 1.61credits/min if the respondent had just sold credits (thereby reducing their balance) and a WtP of 30.14credits/min after purchasing.

4 OUTLOOK

As part of an on-going analysis, we examine the inter-relation between trading choices and the subsequent modal choices made in the experiment. To get a better idea of how/why respondents decided to trade their credits, a multiple linear regression model will be estimated, to identify the main determinants of trading behaviour. A more complex model, potentially incorporating both mode choice and trading behaviour, will also be explored. In addition, we will further investigate respondent heterogeneity with respect to their perception of TMC, by testing both mixed logit models (preliminary results of which are show in Section 3) and latent class choice models, where we can also incorporate respondents' socio-demographic data and financial attitudes to get a better insight into the market segmentation and potentially a better understanding as to how and why they exhibit a particular kind of behaviour.

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