Does a tradable credit scheme with a trading component influence mode choice? Insights from an SP experiment

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Short summary

Tradable Credit Schemes (TCSs) have recently emerged to manage demand in saturated transportation systems. Previous studies have investigated the impact of the credit fee on mode choice. However, little is known regarding the impact of the trading component. This study examines how the TCS trading component affects mode choice. The data were gathered from a stated preference experiment that compared mode choices with and without a TCS. A mixed logit model analyzed mode choices between bike-sharing systems (BSS), public transportation (PT), and waiting for off-peak public transport use (W). The results indicate that individuals were significantly more likely to choose BSS and W when the TCS was activated and when their revenue from the credit sale increased. The initial credit allocation did not significantly impact mode choice. The main conclusion is that the trading component should be included when investigating mode choices with TCSs.
Keywords: Discrete choice modeling, Stated preferences, Tradable credit scheme, Mode Choice.

1 Introduction

The externalities of passenger vehicle congestion are estimated at $70.4B in the US, $7.5B in the UK, and $3.3B in Germany in 2023 (Pishue, 2024). One way to mitigate the effect of congestion is to implement demand management strategies such as tradable credit schemes (TCSs). With a TCS, all residents receive credits that grant access to the road infrastructure. The government fixes the credit fee for each road section. The credit fee can be distance-based or daily-based. All residents have a credit budget and a price for each trip. Residents with a credit surplus can trade with those with a credit shortage in a free market. Credit prices are determined solely by the market, while the government supervises to prevent speculation. Finally, the government can manage the demand by adjusting the total number of credits in circulation and the price of each road segment (Qin et al., 2022).

Few studies have investigated individual preferences for TCSs based on empirical data. Dogterom, Ettema, & Dijst (2018) and Dogterom, Bao, et al. (2018) collected data from stated adaptation studies. In these studies, respondents had to report their travel diary by car during the previous week and then modify it in response to the TCS. These studies investigated different scenarios for the initial allocation of credit budgets: two budgets of the same amount for every respondent (Dogterom, Ettema, & Dijst, 2018) or 50, 30%, or 15% credits shortage or surplus (Dogterom, Bao, et al., 2018). The impact of socio-economic variables on mode choice was analysed in logit models with three alternatives (increasing the distance traveled, decreasing the distance traveled, and neither). In all experiments, respondents decreased their car use on average, while some respondents increased it in the Beijing experiment. Hamm et al. (2023) and Schatzmann et al. (2023) conducted a stated preferences (SP) experiment in Munich. The TCS framework was as follows: car and PT had a credit fee, walking was credit neutral, and biking had a credit bonus. The credit price was distance-based. The choice situations were designed to give each individual enough credit to use PT daily. The car credit price was twice the credit price of PT, and the bike credit price was a tenth of the PT credit price. The value of a credit was determined in a logit model. Each respondent received 1000 credits at the beginning. The results indicate that the TCS significantly decreases the share of car, increases the bike share, and does not influence the shares of PT and walk. Respondents were more sensitive to the cost when the budget and the remaining days decreased. Recently, Geržinič & Cats (2024) has presented an SP experiment analyzing mode choice under a TCS. The population investigated was city dwellers in the Netherlands. The respondents were randomly allocated an initial credit budget of 150, 250, or 350 credits. A trading component was implemented in the SP design. In logit models, they found that the willingness to pay increased when the initial budget increased and the sensitivity to cost increased when the monetary balance increased. They also found that the willingness to pay decreased after selling and increased after buying credits.

In summary, previous studies have investigated the willingness to change current habits under a TCS without a trading component. A study examined the variability in the cost sensitivity in that scenario (Schatzmann et al., 2023). Only two studies developed a mode choice model under a TCS based on empirical data (Schatzmann et al., 2023; Geržinič & Cats, 2024). A recent study included a trading component and variability in the initial budget but did not analyze its effect on the developed choice model (Geržinič & Cats, 2024). However, the initial credit budget is expected to impact the mode choice because it constrains the total distance traveled. In addition, the trading component can strongly impact the mode choice because it allows users to redistribute the allocated credits. Therefore, these factors should be analyzed in a mode choice model. This study examines the factors influencing mode choice with a TCS, including trading component variables and variability in the initial credit budget. An SP experiment and mixed-logit model were developed to analyze mode choice under such a scheme.

2 Methods

Stated preference survey

We designed an SP experiment to investigate the impact of a TCS on mode choice. The objective of the TCS was to reduce the demand during peak hours. Engineering students (ENTPE, Lyon) were investigated. To adapt the experiment to their actual choice behavior, we designed the credit fee on public transportation (PT). We analysed mode choice without a credit fee in the baseline, and mode choice with a credit fee and a trade choice in the experimental condition. The alternatives were bike-sharing system (BSS), PT with a credit fee, and waiting until the end of the peak hour to use PT without the credit fee (W). Respondents were asked to complete 40 choice situations, representing four weeks of five working days, morning and evening. There was no TCS during the first week (10 choice situations).

The level of service was described by the travel time (TT) and cost for each alternative, and also the waiting time (WT) for W. The cost of PT and W was computed based on the number of times a respondent chose one of those alternatives in a week. The environment was represented by the flexibility of the activity (FA) and the rain for the morning commute, and the night and the rain during the evening commute. To describe the TCS, we used the credit fee (CF), the credit value (CV), the credit budget (CB), and the monetary balance (MB). Each week, the respondents were randomly allocated a credit budget (40, 50, 60, or 70). 60 credits were required to complete the week without using BSS. The CB was reset each week. The MB was 10€ at the beginning of the experiment to represent a voucher from the service provider. The CF was 15 credits, which was chosen arbitrarily. During the trade choice, respondents could either buy or sell credits with a limit of 25 credits per exchange. Negative budgets were forbidden. The CV was assumed to be higher at night and when it rains. Respondents were also aware of the value of the CV during the mode choice.

Experimental design

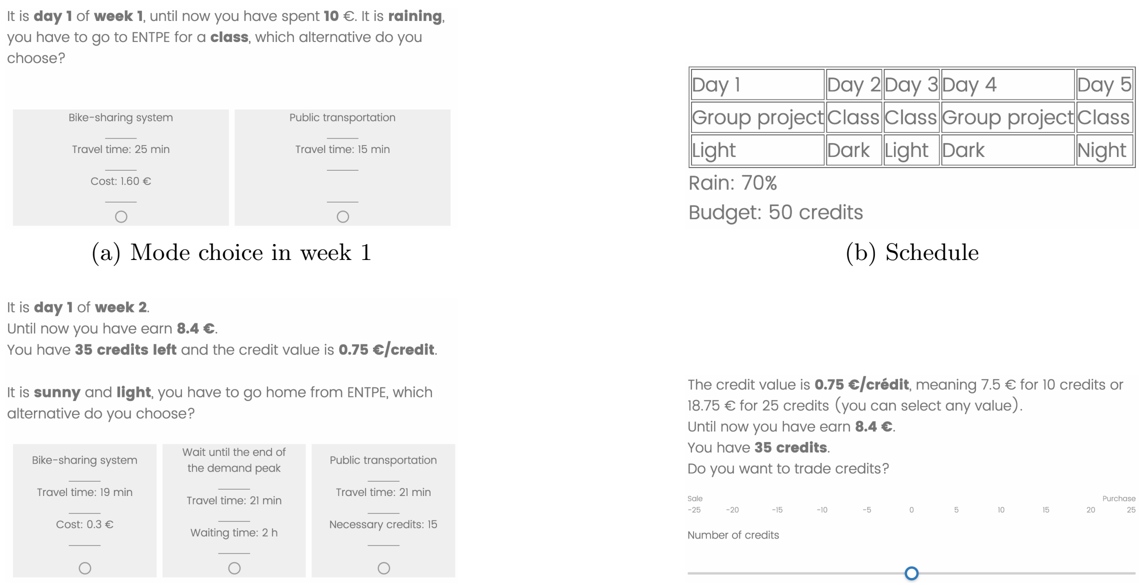
The design was generated using Ngene (ChoiceMetrics, 2018). This software computes efficient design based on a model with alternatives, utility functions, levels of the variables, prior knowledge of the parameter values, and an optimization criterion. We designed two sets: 20 choice situations for the baseline condition and 40 choice situations for the experimental condition with the TCS. We used the S-optimality criterion (Rose & Bliemer, 2013), which gives a lower bound for the number of answers needed to estimate all parameters. The lower bound was 162.80 responses for the baseline condition and 81.13 for the experimental condition. These values are expected to decrease when estimating both conditions in one model. Table (1) presents the variables used to generate the designs for both conditions. The levels of the variables were chosen based on realistic values to ease the decision process of the respondents and reduce potential bias. Due to the lack of priors for the experimental condition, not all variables were included in the generation process.

Table 1: Levels used in Ngene for the design of the experiment

Variable	Unit	Description	Levels					
TT^{PT}	[min]	Travel time PT	15	18	21	24	27	30
TT^{BSS}	[min]	Travel time BSS	13	16	19	22	25	28
WT^{W}	[min]	Waiting time W		30			120	
$Cost^{BSS}$	[€]	Cost of BSS	0	0.3	0.8	1.2	1.6	1.8
CF^{PT}	[1]	Credit fee of PT			15			
CV	[€/credit]	Credit value	0.25	0.5	0.75	1	1.25	1.5
FA	Binary	0 meeting (flexible), 1 class		0			1	
$Rain$	Binary	0 sun, 1 rain		0			1	
$Night$	Binary	0 day, 1 night		0			1	

Data collection

The design was implemented in Qualtrics (2014) (see fig. 1a for an example without the TCS and figs. 1c and 1d with the TCS). At the beginning of each week, the respondents were provided with a schedule of the activity flexibility and lighting conditions, the proportion of rainy situations, and their initial credit budget (see fig. 1b). The experiment was conducted in March 2024. The sample of respondents consisted of 45 first-year students from ENTPE. No personal data were collected.



(a) Mode choice in week 1

(b) Schedule

(c) Mode choice in week 2, 3 and 4

(d) Trade choice

Figure 1: the different components of the SP experiment in Qualtrics.

Data analysis methods

A mixed logit model (ML) was used to analyze the factors influencing mode choice with and without the TCS (Train, 2009). This model was chosen because it can accommodate the panel structure of the data. We used individual-specific error terms to control for unobserved correlations between repeated observations of the same individual over time and across modes. The utility of alternative i for individual n in time period t $U^i_{n,t}$ is given by equation 1:

$$U^i_{n,t} = ASC^i + \beta^i \times X^i_{n,t} + \gamma^i \times \sigma_n + \varepsilon^i_{n,t} \tag{1}$$

Where ASC^i is the alternative specific constant, β^i is the vector of parameters to be estimated, $X^i_{n,t}$ is the vector of explanatory variables, γ^i is the vector of parameters associated with the vector of individual-specific error term $\sigma_n \sim \mathcal{N}(0,1)$, and $\varepsilon^i_{n,t}$ is the i.i.d Extreme Value-distributed error term. The probability that individual n chooses mode i in period t is given by equation 2:

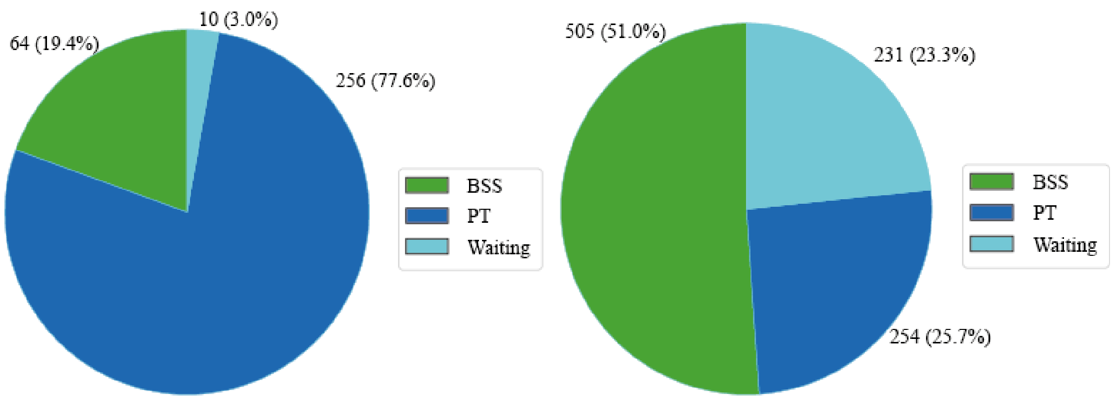
$$P^i_{n,t} = \frac{\exp^{ASC^i + \beta^i \times X^i_{n,t} + \gamma^i \times \sigma_n}}{\sum_{j \in I} \exp^{ASC^j + \beta^j \times X^j_{n,t} + \gamma^j \times \sigma_n}} \tag{2}$$

Where I is the choice set. The Python package Biogeme (Bierlaire, 2023) was used to estimate the models. It allows for complex specifications using interactions between variables and random error terms. All variables were tested in the utility functions one by one and retained based on statistical significance (95%). Likelihood ratio tests or BIC/AIC comparisons were performed to find the best specification. We tested three individual-specific error terms in each utility function to capture unobserved correlations between alternatives. The final error structure was chosen based on statistical significance. A likelihood ratio test was conducted to ensure that the final mixed-logit model fit better than the logit model.

3 Results

Descriptive analysis

The survey was completed by 33 respondents (response rate = 73%). The total number of observations was 1320. BSS was chosen 569 times, PT 510 times, and W 241 times. The proportion of choices without TCS (fig. 2a) and with TCS (fig. 2b) shows a significant decrease in PT choice with the TCS (p-value of the χ^2 test below 0.0005).



(a) Baseline condition without TCS

(b) Experimental condition with TCS

Figure 2: Proportion of chosen mode in the baseline and experimental conditions.

The cumulative probabilities of selling, buying, or doing nothing (fig. 3) show that every respondent used the trading component at least once. Doing nothing has a higher cumulative probability, suggesting respondents did not sell and buy randomly.

Fig. 4 shows that, on the first day, the total amount of credit in circulation (CiC) is below the total number of credits needed to only use PT and to use only PT and W, meaning respondents who don't want to use BSS must trade. The evolution of CiC differs between week 2, and weeks 3 and 4, suggesting a learning process for the respondents. Each week the difference between CiC and the number of credit used increases, suggesting that some respondents bought credits only to sell them. This idea is supported by the large increase in aggregated MB in weeks 2, 3, and 4 (fig. 5). Hence, some respondents might speculate during the experiment to increase their MB against the definition of the TCS. We also notice a pattern in the evolution of the MB, suggesting that the credit value or the time period might have had an impact on the trading. There is a large variability in the value of the final MB across respondents (fig. 6): more than 25% finished with an MB inferior to the initial balance, 2 with a balance below zero, and more than 30% finished with an MB above 100€. This suggests that some respondents did not speculate.

Model specification and estimation results

The utility functions of BSS (U^{BSS}), PT (U^{PT}), and W (U^W) that best describe respondents' choices in eqs. (3) to (5):

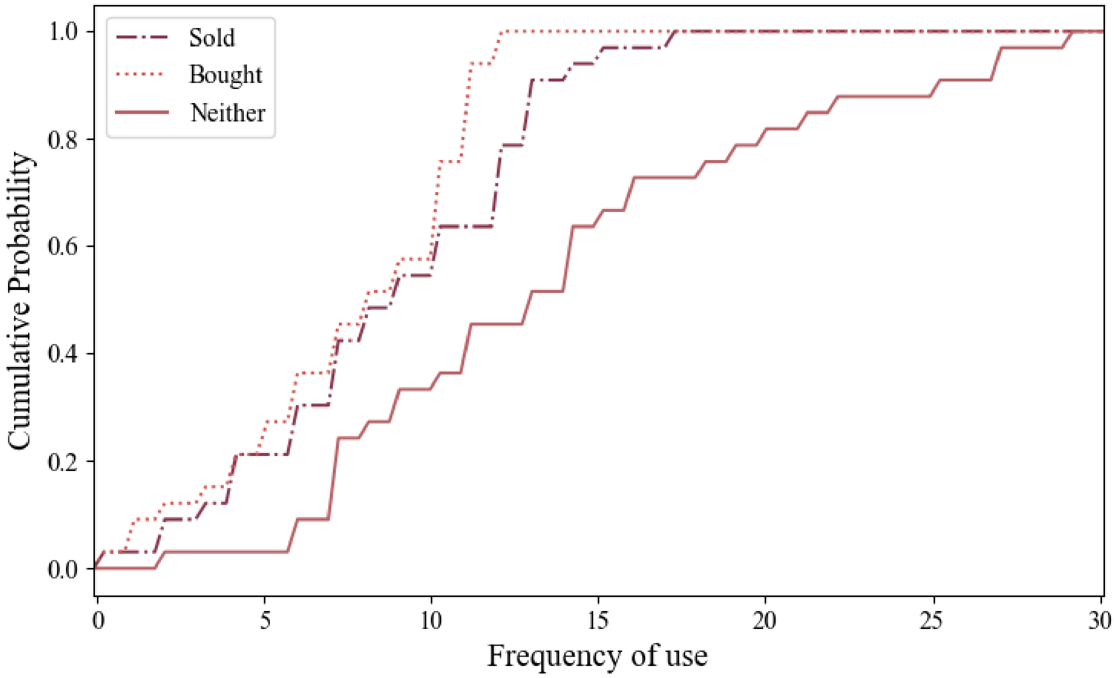


Figure 3: Trading activities frequency during the tradable credit scheme

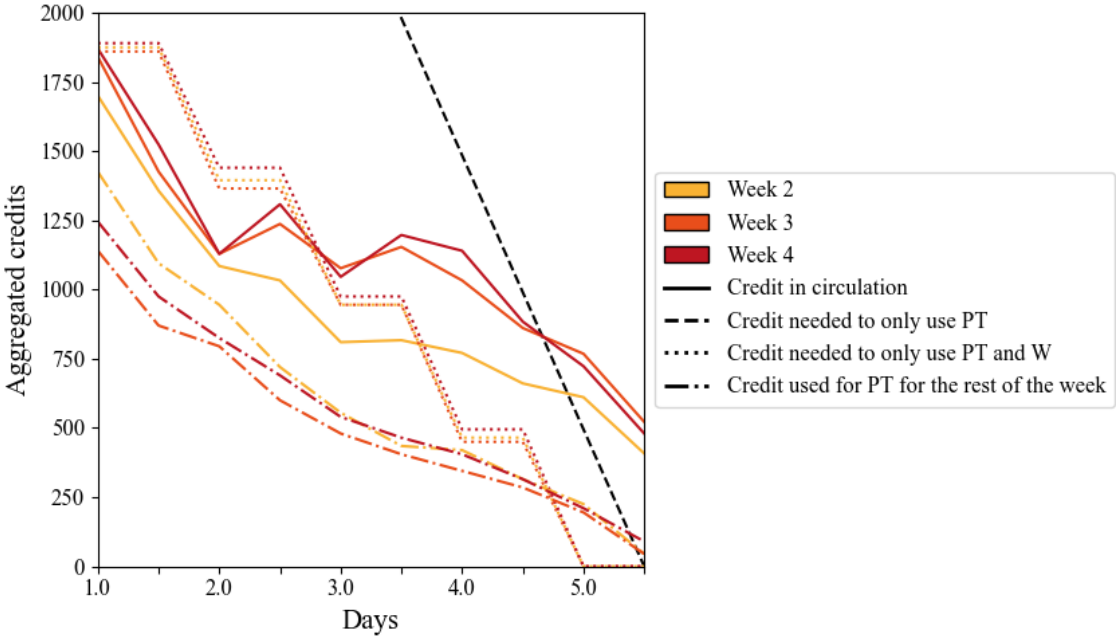


Figure 4: Evolution of the aggregated credit balance and other credit measures during each week. Integers (e.g., 1) indicate morning choices, while decimals (e.g., 1.5) indicate evening choices.

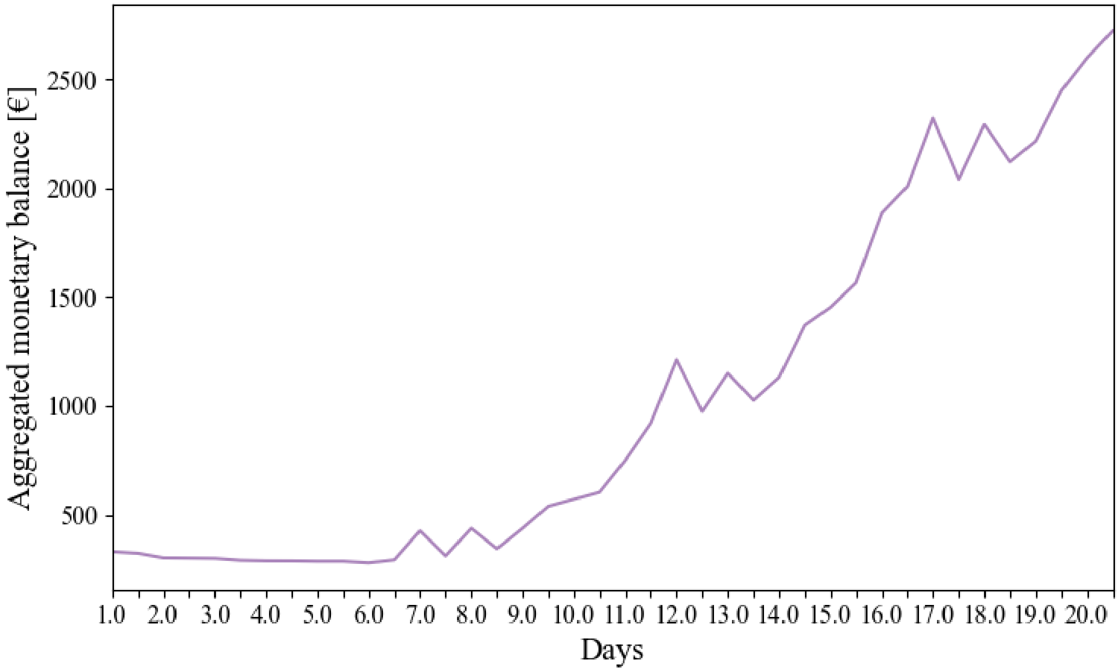


Figure 5: Evolution of the aggregated monetary balance during the whole experiment. Integers (e.g., 1) indicate morning choices, while decimals (e.g., 1.5) indicate evening choices.

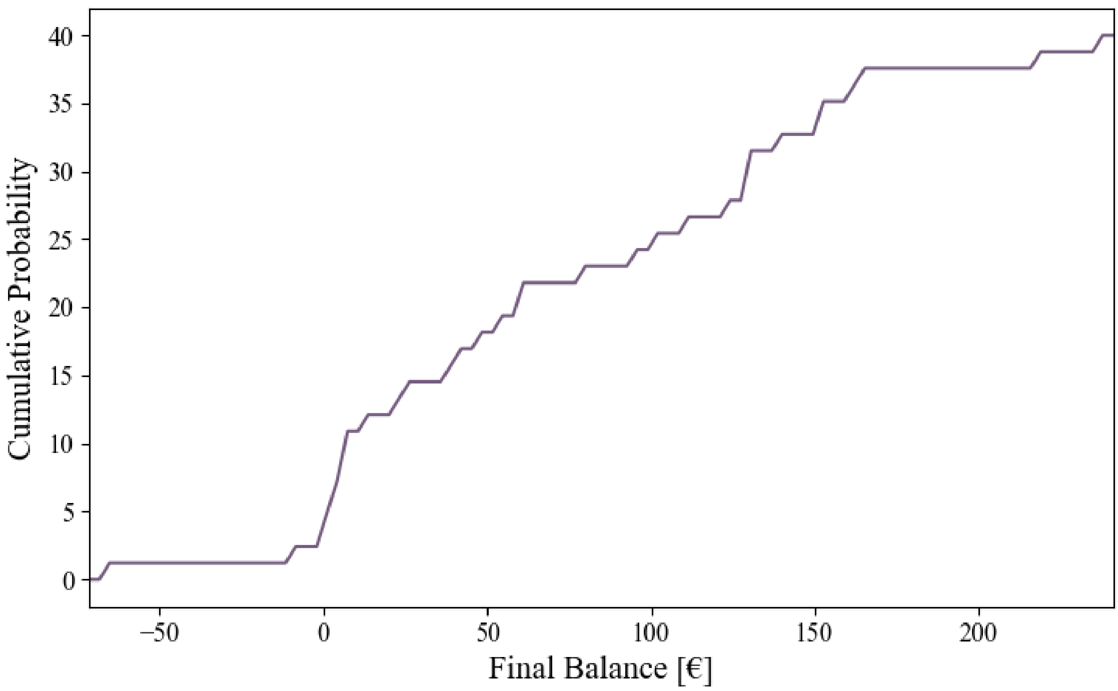


Figure 6: Cumulative density function of the final monetary balance

$$U_{n,t}^{BSS} = ASC^{BSS} + \beta_{Week1}^{BSS} \times Week1_t + \beta_{TT} \times TT_{n,t}^{BSS} + \beta_{Cost} \times Cost_{n,t}^{BSS} + \beta_{SR}^{BSS,W} \times SR_{n,t} + \beta_{MB}^{BSS,W} \times MB_{n,t} + \beta_{NoRain}^{BSS} \times NoRain_{n,t} + \beta_{\sigma}^{BSS} \times \sigma_n + \varepsilon_{n,t}^{BSS} \quad (3)$$

$$U_{n,t}^{PT} = \beta_{TT} \times TT_{n,t}^{PT} + \beta_{Cost} \times Cost_{n,t}^{PT} + \varepsilon_{n,t}^{PT} \quad (4)$$

$$U_{n,t}^{W} = ASC^{W} + \beta_{Week1}^{W} \times Week1_t + \beta_{TT} \times TT_{n,t}^{W} + \beta_{Cost} \times Cost_{n,t}^{W} + \beta_{WT}^{W} \times WT_{n,t}^{w} + \beta_{SR}^{BSS,W} \times SR_{n,t} + \beta_{MB}^{BSS,W} \times MB_{n,t} + \beta_{\sigma}^{W} \times \sigma_n + \varepsilon_{n,t}^{W} \quad (5)$$

With ASC^i the alternative specific constant, $TT_{n,t}^i$ the travel time, $Cost_{n,t}^i$ the cost, $WT_{n,t}^W$ the waiting time, $Week1_{n,t}$ a binary variable equal to 1 in week 1, $SR_{n,t}$ the revenue generated by credit sales, $MB_{n,t}$ the monetary balance, $NoRain_{n,t}$ a binary variable equal to 1 when it is not raining, and σ_n the individual specific error term.
The ASC of PT was fixed to zero for normalization purposes. The continuous variables were centered to zero. The level with most observations in each binary variable was fixed to zero. The estimation results are presented in table 2.

Table 2: Estimated parameters of the mixed logit model

Variable	Variable description	Parameter	Value	Rob. p-value
-	Alternative specific constant of BSS	ASC^{BSS}	-0.477	0.033
-	Alternative specific constant of W	ASC^{W}	0.0516	0.884
$Week1_t$	Binary variable equal to 1 in week 1	β_{Week1}^{BSS}	-0.836	0.0013
$Week1_t$	Binary variable equal to 1 in week 1	β_{Week1}^{W}	-3.19	<0.0005
TT_k^i	Travel time of alternative i (min)	β_{TT}	-0.0597	<0.0005
$Cost_{n,t}^{BSS}$	Cost of alternative BSS (€)	β_{Cost}^{BSS}	-0.836	<0.0005
$Cost_{n,t}^{PT}$	Cost of alternative PT (€)	β_{Cost}^{PT}	-2.59	<0.0005
$Cost_{n,t}^{W}$	Cost of alternative W (€)	β_{Cost}^{W}	-1.84	<0.0005
WT^W	Waiting time (min)	β_{WT}^{W}	-0.0174	<0.0005
$SR_{n,t}$	Revenue generated with credit sales (€)	$\beta_{SR}^{BSS,W}$	0.134	<0.0005
$MB_{n,t}$	Monetary balance (€)	$\beta_{MB}^{BSS,W}$	0.00896	0.0046
$NoRain$	Binary variable equal to 1 when it does not rain	β_{NoRain}^{BSS}	2.26	<0.0005
σ_n	Individual-specific error term	β_{σ}^{BSS}	0.467	0.0014
σ_n	Individual-specific error term	β_{σ}^{W}	1.41	<0.0005

Number of parameters: 14, Log-likelihood: -727.565, Log-likelihood model with constant only: -1148.172, $\bar{\rho}^2$: 0.355, Number of draws: 10000

The ASC of BSS is significant and negative, meaning that PT is preferred to BSS, everything else being equal. The ASC of W is not significant, meaning there is no preference between W and PT. The TCS has a significant impact on individual preferences. Individuals are significantly less likely to choose BSS and W in the baseline when the TCS is not implemented. The parameters significantly differ, meaning that PT is preferred to BSS, and BSS is preferred to W when there is no TCS.
Variables related to the level of service have a significant impact on mode choice. Individuals are less likely to choose an alternative when its travel time, cost, or waiting time increases. There is no significant difference in the impact of travel time across alternatives. However, the impact of cost differs significantly between modes. The cost has the most significant impact on PT, followed by W and BSS.
Some TCS variables also have a significant impact. When the revenue generated by credit sales or MB increases, individuals are more likely to choose BSS or W. For both, the impact doesn't significantly differ between alternatives. Controlled for these factors, the initial CB, the CB, and the final MB do not significantly impact the mode choice.
One variable related to the environment significantly impacts the mode choice. Individuals are more likely to choose BSS when it does not rain. The number of the week was not significant.

Finally, one individual-specific error term is significant. We tested all combinations of error terms, but only one error term had a significant impact on both BSS and W. This means that a group of individuals prefers BSS and W. This impact is larger for W than BSS.

4 Conclusions

This study investigated the factors influencing mode choice under a TCS with a trading component. The data were collected in an SP experiment with the students of ENTPE in Lyon. The experiment proposed a mode choice without a credit fee and with a credit fee and trading. The results of the experiment were analyzed in a mixed-logit model.
The descriptive analysis highlights that the TCS significantly impacted the mode choice, confirming previous results (Schatzmann et al., 2023; Dogterom, Ettema, & Dijst, 2018; Dogterom, Bao, et al., 2018). More specifically, the TCS reduced the share of PT significantly. Each respondent used the TCS trading component. No previous studies analyzed the use of the trading component. The analysis of the trading component variables highlights potential variability in individual attitudes towards the trading component. The difference between the total number of credits used for PT and the CiC, and the increase in the aggregated MB reveal that some respondents might have been speculating. Some respondents had a final monetary balance close to the initial monetary balance, while others had a high final monetary balance. One explanation could be that some respondents used the trading component to access PT and then traded what was left, while others used the trading component to increase their monetary balance and chose the mode with what was left. No previous studies have analyzed the attitude toward the TCS trading component using empirical data.
The results in the ML model confirm that when TT, WT, or cost increases in one of the alternatives, respondents are less likely to choose that alternative, as found in previous studies for TT with a TCS (Geržinič & Cats, 2024) and for TT and cost without a TCS (Krauss et al., 2022; Jaber et al., 2023; Esztergár-Kiss et al., 2022; Curtale & Liao, 2023). Respondents are less likely to choose BSS when it rains, similar to previous studies (Schatzmann et al., 2023; Reck et al., 2022). They were also less likely to choose BSS or W when the TCS is not activated, similar to previous findings with bikes (Schatzmann et al., 2023). The trading component of the TCS had a significant impact on the mode choice. Respondents are more likely to choose BSS and W when their MB or credit sales revenue increases. Previous studies did not analyze these factors. Finally, the individual-specific error term indicates the existence of a group of respondents who prefer BSS and W. Previous studies with TCSs did not have these alternatives. Controlled for these factors, the CB and final MB did not significantly impact the mode choice. However, they are related to MB and sales revenue, which are significant in the model.
There are several directions for future research. First, correlations between decisions over time could be further tested using a dynamic model capturing the impact of previous choices (Danalet et al., 2016) or future choices (Cirillo et al., 2016). Interactions between explanatory variables could be explored as in (Schatzmann et al., 2023). Latent classes could be used to capture different attitudes towards the trading component (Ben-Akiva et al., 2002), and transition latent classes could be used to capture the learning process (Haustein & Kroesen, 2022). The framework of the trading component could be modified such that the price of the bank changes according to the number of credits in circulation (Brands et al., 2020), or the bank could be replaced by peer-to-peer trading to avoid speculation. Finally, the study could be extended to a broader population to generalize the results and investigate socio-economic characteristics.

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- Study conception and design: Nicolas Schoenn-Anchling, Ludovic Leclercq, and Silvia Varotto;
- Analysis and interpretation of results: Nicolas Schoenn-Anchling, Silvia Varotto, and Ludovic Leclercq;
- Data processing: Nicolas Schoenn-Anchling;
- Draft manuscript preparation: Nicolas Schoenn-Anchling, Silvia Varotto, and Ludovic Leclercq.

All authors reviewed the results and approved the final version of the manuscript.

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