Cooperation between Ride-Hailing and Public Transportation with Tradable Credit Schemes

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Short summary

Ride-Hailing (RH) companies have expanded significantly in urban areas in the past decade. However, they may compete with Public Transportation (PT) instead of completing them. This work proposes to use Tradable Credit Scheme (TCS), a quantity-based policy, to encourage RH drivers to operate in parts of the network not well served by PT. Credits are given to the RH drivers. Operating in some regions requires credits. RH drivers can trade credits between themselves. We use a trip-based Macroscopic Fundamental Diagram (MFD) to compute the dynamic and heterogeneous RH trips. Customers choose between different PT and RH alternatives. The RH drivers' decision to operate in a region is a balance between the potential revenue and the credit charge of this region. We evaluate the equilibrium of different TCS on a test case. TCS fosters multimodal trips, which combine PT and RH to complete the trips.
Keywords: Macroscopic Fundamental Diagram, Ride-hailing, Tradable Credit Scheme, Traffic flow theory, Transport economics and policy

1 Introduction

Ride-Hailing (RH) companies introduced new mobility alternatives in many cities (OECD, 2018). However, RH may negatively affect the transportation network, as they contribute to congestion (Erhardt et al., 2019) and compete with Public Transportation (PT) (Cats et al., 2022). Nevertheless, RH has the potential to complete the PT network.

When studying how RH services operate and compete with other modes, it is important to keep track of the transportation system dynamics, as congestion significantly impacts travel times and service quality. We must also consider the service's full spatial extent and reproduce the vehicles' trip patterns over the day. The Macroscopic Fundamental Diagram (MFD) has been proposed by Daganzo (2007). It defines the average mean speed as a function of the number of vehicles driving in the road network. The MFD concept permits the design of large-scale and low-computation dynamic simulations. In particular, the trip-based formulation (Mariotte et al., 2017; Lamotte & Geroliminis, 2018; Jin, 2020) keeps track of all users' and vehicles' moves, which makes it suitable for reproducing RH driver matching and pick-up.

Several recent contributions regarding RH services are founded on the MFD concept. Nourinejad & Ramezani (2020) study the equilibrium between offer, demand, and service pricing. They use the MFD framework to tune a model predictive controller. Beojone & Geroliminis (2021) encourage passengers to share their rides and park unmatched vehicles to reduce the impact of RH vehicles on congestion.

RH drivers operate in high-demand areas, which may already have a good PT network, as they want to increase their profits. However, the regulator wants them to operate in regions with low PT coverage to achieve system optimum. Traditional taxi license schemes aim to regulate and redistribute the number of operating taxis in a given zone in the long run. More flexible quantity-based tools like Tradable Credit Schemes (TCS) can also be applied. The regulator limits access to a shared resource (access to part of the network) by distributing a given total amount of credits. Their price is not fixed but results from the trading between users, introducing more flexibility. Some early concepts on quantity-based instruments to mitigate congestion have been proposed by Verhoef et al. (1997). Yang & Wang (2011) formulated a TCS to reduce the total travel time in an urban transportation system dealing with route choice. Balzer & Leclercq (2022) implemented TCS in a multimodal context to reduce the share of car drivers and decrease the total travel time and carbon emissions.

For now, TCS has only been proposed for demand management. Here, we want to extend the concept to the offer side. The goal is to encourage RH drivers to shift from the city center to the suburbs, where they can propose efficient first-/last-mile alternatives and complete the PT offer.

2 Methodology

The urban area is divided into N_R different regions. The regions are indexed by increasing order from the center to the outskirts. Each traveler chooses its travel mode $m \in M$ according to the associated costs. The alternatives are riding the PT or using the RH service. The road network is shared with users driving their personal cars. We assume the number of RH drivers N_D is constant. The regulator enforces a TCS to prevent unnecessary competition between RH vehicles and the PT in the city center where the transit offer is satisfying. Its strategy is nudging RH drivers to serve the travel demand in the outskirts to (i) promote PT in the city center (ii) promote multimodal trips where RH drivers permit travelers from the outskirts to ride an RH vehicle to a transit hub at the border of the city center and then use the PT for the remaining trip. Figure 1 presents a schematic representation of the different travel options for a traveler going from the suburbs to the city center.

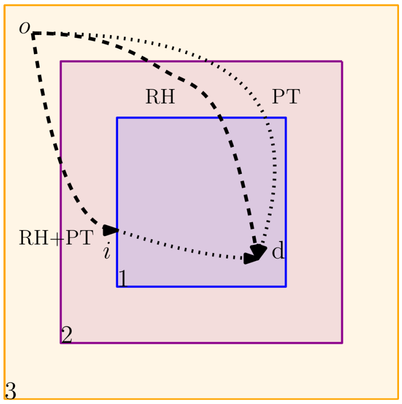

Figure 1: A trip between an origin o in region 3 (suburbs) and a destination d in region 1 (city center) has three alternatives: RH, PT, or RH till the border i and then PT.

We set a framework based on the trip-based MFD to study the effect of the TCS. It considers the congestion dynamics and the heterogeneity of the trips: each customer has its own departure time t_d, origin o, and destination d. RH drivers move only to pick up or drive a customer to its destination. The rest of the time, they park on the street and wait to pick up another customer. Those idle drivers do not contribute to the congestion. The PT mean speed V_{PT,r_o,r_d} depends on the regions of origin and destination. It is faster in the city center (subways) and slower in the suburbs (buses). We use the trip-based MFD to compute RH trips. The mean car speed V depends on the car accumulation n, i.e., the number of cars driving. It includes RH vehicles and also private cars. The actual arrival time t_a for a RH trip of distance l_{RH} is computed using the following relationship:

$$l_{pu} + l_{RH} = \int_{t=t_d}^{t_a} V(n(t))\mathrm{d}t. \tag{1}$$

It accounts for the time the customer waits to be picked up, i.e., for the RH vehicle to travel the distance l_{pu} between the current position of the RH vehicle and the customer's origin.
At their departure times t_d, the travelers choose their travel alternatives according to the different *perceived* travel costs (RH or PT). The user travel costs from origin o to destination d are defined by the travel time and the service price:

$$C_{o,d,PT}(t_d) = \alpha L_{PT,o,d}/V_{PT,r_o,r_d} + f_{PT}; \tag{2}$$
$$C_{o,d,RH}(t_d) = \alpha \left(L_{pu,o,d}(t_d) + L_{RH,o,d}\right)/V(t_d) + f_{RH}L_{RH,o,d}; \tag{3}$$
$$C_{o,d,RH+PT}(t_d) = \alpha \left(L_{pu,o,i}(t_d) + L_{RH,o,i}\right)/V(t_d) + f_{RH}L_{o,i} + \alpha L_{PT,i,d}/V_{PT,r_i,r_d} + f_{PT}; \tag{4}$$
$$C_{o,d,PT+RH}(t_d) = \alpha L_{PT,o,i}/V_{PT,r_o,r_i} + f_{PT} + \alpha \left(L_{pu,i,d}(t_d) + L_{RH,i,d}\right)/V(t_d) + f_{RH}L_{RH,i,d}. \tag{5}$$

α is the value of time. $L_{PT,o,d}$ is the PT trip length from o to d, and $L_{RH,o,d}$ the RH trip length. f_{PT} is the price of a unitary ticket. We assume the ticket price is independent of the trip. The

RH travel cost consists of the pick-up time, the travel time, and the RH charge. The RH charge is the distance-based fee f_{RH} multiplied by the trip length. The pick-up distance $L_{pu,o,d}$ depends on the current position, availability, and licenses of the RH drivers. For the RH+PT alternative, the travel cost is the sum of the RH travel cost until the border i of the destination region and then the PT travel cost from this border to the destination. The same applies to PT+RH in reverse: the traveler rides the PT and then takes an RH vehicle.
Travelers starting at t_d from o to d choose the travel mode m with the probability $\psi_{o,d,m}(t_d)$, depending on the travel costs following the logit rule:

$$\psi_{o,d,m}(t_d) = \frac{e^{-\theta C_{o,d,m}(t_d)}}{\sum_{m' \in M} e^{-\theta C_{o,d,m'}(t_d)}},\ \forall m \in M = \{PT, RH, PT+RH, RH+PT\}. \tag{6}$$

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Each driver gets κ credits for free from the regulator per day with the TCS. The drivers need to spend τ_r credits to buy a license to operate (i.e., pick-up or drop-off passengers) in the regions with an index higher or equal to r for a day. Since the regions are defined for TCS purposes, we assume $\tau_r < \tau_{r-1},\ \forall r \in [2, N_R]$. Drivers can trade their credits on a specific market. The law of the offer and demand determines the credit price p. The regulator does not fix it a priori. It is budget-neutral, as all trades occur only between RH drivers.
We note x_r the number of drivers with a license for region r. They can operate in regions $r' \geq r$. For an RH trip from an origin in region 2 to a destination in region 1, the driver needs a license with the smallest index, i.e., 1. The RH drivers are ordered in the list according to their willingness to acquire licenses. It means the first x_1 drivers will acquire license 1, the next x_2 license 2, and the last x_{N_R} will only operate in region N_R.
We focus on the within-day process. The drivers' assignment x, i.e., the choice of operating regions, balances two markets: the RH market, where travelers buy RH services, and the credit market, where drivers trade credits. Figure 2 summarizes the different interactions. Travelers' mode choice

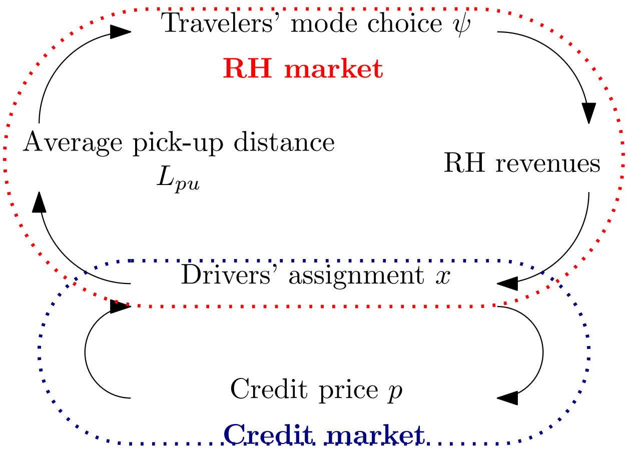

Figure 2: Interactions between drivers, travelers, and credit market.

impacts RH revenue for drivers, which, with the credit price, will change drivers' assignments. The average pick-up distance decreases with the number of drivers available for the trip. The pick-up distance affects the RH perceived costs, thus modifying mode choices.
The equilibrium of drivers' assignment x and credit price p are linked. The RH revenues from the trip requiring access to region r (but not $r-1$) is

$$R_{RH,r} = \sum_{\text{RH trips with } \min(r_o, r_d) = r} f_{RH} L_{RH,o,d}. \tag{7}$$

It accounts for the RH parts combined trips, where o and d refer to the RH part.
To calculate the equilibrium assignment for drivers, we first define the marginal gain of adding access to region r for a driver as the difference between the RH market per driver and the price to access this market. It is the volume of fees paid by travelers using RH for a trip requiring access to region r but not $r-1$, divided by the number of drivers with access to region r minus the increase in credit charge times the credit price:

$$G_r = \frac{R_{RH,r}}{\sum_{s \leq r} x_s} - p(\tau_r - \tau_{r+1}),\ \forall r \in [1, N_R - 1], \tag{8}$$

A positive marginal gain for region r means switching from license $r-1$ to r will increase the driver's profit. On the opposite, negative marginal gain means accessing the new market is smaller than the extra credit cost. The equilibrium for RH drivers is reached when they have no incentive to change their region access, i.e., when the marginal gains of the regions' access are zero:

$$G_r = 0,\ \forall r \in [1, N_R - 1]. \tag{9}$$

We do not look at G_{N_R} because every driver has access to region N_R, the further away from the center. We assume operating solely in region N_R does not require credits and is thus always possible. Equation (9) can be expressed as a fixed-point problem $(x, p) = \Gamma(x, p)$ with

$$\Gamma : (x, p) \mapsto \begin{pmatrix} \frac{R_{RH,1}(x)}{p(\tau_1 - \tau_2)} \\ \vdots \\ \frac{R_{RH,N_R-1}(x)}{p(\tau_{N_R-1} - \tau_{N_R})} \\ x_{N_R} \\ p \end{pmatrix}, \tag{10}$$

under the following constraints:

$$x_r \geq 0,\ \forall r \in [1, N_R]; \tag{11}$$

$$\sum_{r=1}^{N_R} x_r = N_D; \tag{12}$$

$$\sum_{r=1}^{N_R} x_r(\tau_r - \kappa) \leq 0; \tag{13}$$

$$p \sum_{r=1}^{N_R} x_r(\tau_r - \kappa) = 0; \tag{14}$$

$$p \geq 0. \tag{15}$$

The first is that the number of drivers per license is non-negative. The second is the conservation of the number of drivers. The third is the credit cap: the drivers cannot spend more credits than the distributed amount. The fourth is the market clearing condition: all credits are used, or their price is zero. The last one is that the credit price is non-negative. The previous three constraints are specific to the TCS.
Solving the fixed-point problem (Equation (10)) under the different constraints (11, 12, 13, 14, and 15) give the drivers' assignment and the credit price at equilibrium.
The challenge lies in the complex relationship between drivers' licenses and customers' mode choices through the trip-based MFD. We use Bayesian optimization to minimize the cost function J, the sum of the magnitudes of the fixed points errors:

$$J = \sum_{r=1}^{N_R-1} \left| x_r - \frac{R_{RH,r}(x)}{p(\tau_r - \tau_{r+1})} \right|. \tag{16}$$

We use the constraints to reduce the size of the minimization problem. We assume the price is non-zero. Otherwise, the TCS is non-effective, and the state of the system is the same as without TCS, where all drivers can operate in all regions, i.e., $x_1 = N_D$ and $x_r = 0,\ \forall r \in [2, N_R]$. Then the equality holds for the credit cap (Equation (13)). We combine it with the driver conservation (Equation (12)) to remove two variables. We choose to replace x_{N_R-1} and x_{N_R} with

$$\begin{aligned} x_{N_R-1} &= \frac{N_D(\kappa - \tau_{N_R}) - \sum_{k=1}^{N_R-2}(\tau_k - \tau_{N_R})x_k}{\tau_{N_R-1} - \tau_{N_R}}; \\ x_{N_R} &= N_D - \sum_{r=1}^{N_R-1} x_r. \end{aligned} \tag{17}$$

3 Results

To illustrate our preliminary work on the proposed methodology, we set an example with $N_R = 3$ regions, $N_D = 150$ drivers, and 1000 travelers. Region 1 is the city center with high demand and

good PT coverage.
Thanks to the problem size reduction (Equation (17)), there are only two unknowns: x_1 and p, which makes the problem suitable for Bayesian optimization (BO). The agent-based model is run 20 times to remove the stochastic bias for the evaluation of the results. We use the open-source Python package *BayesianOptimization* (Nogueira, 2014) to compute the drivers' assignment and credit price at equilibrium.
Two different TCS are compared against the status quo (i.e., no RH regulation). Every driver gets $\kappa = 1$ credit. Region 3 is always free of charge. In the first TCS (TCS1), region 2 requires 1 credit, and region 1 requires 2 credits. The second scenario, TCS2, is more constraining: operating in region 1 requires 2 credits, and region 1 requires 4 credits. The corresponding equilibriums are compared in Table 1.

Table 1: Impacts of two TCS on all trips; trips within the region 1 (city center); trips from or to the region 1 (exclusive or); and trips outside the region 1.

	Status quo	TCS1	TCS2
Credit charge τ	[0,0,0]	[2,1,0]	[4,2,0]
Credit price p (EUR)	0	23	13
Drivers' assignment x	[150,0,0]	[58,34,58]	[26,23,101]
All trips			
RH revenue (EUR)	1454	1549	1266
Average travel time (min)	18.8	18.4	19.1
Trips within the city center			
PT (%)	74	78	89
RH (%)	26	22	11
Average travel time (min)	6.7	6.9	7.2
Trips from or (but not and) to the city center			
PT (%)	65	65	73
RH (%)	16	12	6
PT+RH (%)	10	12	12
RH+PT (%)	8	10	9
Average travel time (min)	17.6	17.7	18.3
Trips outside the city center			
PT (%)	59	51	55
RH (%)	35	37	30
PT+RH (%)	4	7	9
RH+PT (%)	2	5	7
Average travel time (min)	24.4	23.1	24.1

Without TCS, all drivers choose the license to operate in region 1 and above, as it allows access to the whole RH market without extra costs. With TCS1 and TCS2, the credit cap forces some drivers to not operate in regions 1 and 2. The credit price is lower with TCS2 than TCS1, but the TCS-related cost to operate in region 1 (and above) $p\tau_1$ is higher with TCS2 (52 EUR vs. 46 EUR with TCS1). The TCS decreases RH shares and increases PT ridership in the city center (region 1). For trips from or to the city center, the TCS decreases RH-only trips at the profit of combinations with PT. For trips outside of the city center, where the PT coverage is low, both the number of PT- and RH-only trips decreases, and the combinations of RH and PT increase. The average travel times are better for trips outside the city center by about 5%. The total RH revenue increases by 7% with TCS1. Forcing some drivers not to operate in region 1 reduces the pick-up distance in the suburbs and makes some customers choose RH for relatively long trips. It, however, decreases with TCS2, as it greatly restricts operations in the city center (region 1), which is a lucrative market because of the relatively high demand.

4 Conclusions

This work proposes a tradable credit scheme to foster cooperation between ride-hailing services and public transportation. The TCS nudges RH drivers to serve the suburbs and complete the PT offer to foster multimodal trips: RH in an area with sparse PT infrastructure (suburbs) and PT in a dense area (city center). The main effect for the customer is that increasing the number of RH drivers in the suburbs will decrease the average pick-up distance. We compute the drivers' operating regions and the credit price by solving the equilibrium with BO. We evaluate and compute the equilibrium using the trip-based MFD to calculate the trips. The results in a simplified scenario show the TCS nudge part of the travelers to combine RH and PT for their trips. It makes the PT more competitive for travelers outside the city center.
Further work will apply this methodology for a case study based on a real city.

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