A Zone-Based Tradable Credit Scheme for Rebalancing Ride-Hailing to Improve Demand-Supply Allocation Efficiency and Mitigate Accessibility Imbalances

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Short summary

Urban multimodal transport systems suffer from inefficiencies arising from spatial and modal misalignment between demand and supply. Public transit (PT) is typically dense in city centers but sparse in peripheral areas, creating a spatial imbalance in access to mobility services. Ride-hailing (RH) can help address this imbalance by providing flexible coverage and first-and-last-mile connectivity to the PT network. Yet profit incentives concentrate RH supply in transit-rich urban centers, where RH diverts demand for short trips from high-capacity PT and consumes scarce road space, while underserving transit-poor peripheries. This misallocation reduces efficient use of road and transit resources and exacerbates accessibility imbalances. To address this, we propose a supply-side, spatially differentiated Tradable Credit Scheme. By assigning higher credit requirements to central zones, the scheme shifts relative profitability, incentivizing RH relocation to peripheries. This supply-side intervention reshapes passenger assignment across modes by altering RH service availability and wait times, reducing inefficient substitution away from PT in transit-rich areas, and improving PT access in peripheral areas through better RH–PT integration. We develop an integrated modeling framework linking the credit market with endogenous multimodal demand and transport operations. We evaluate system performance at a long-term stationary equilibrium in which, given the prevailing credit price, assignments, and travel times, no driver can increase earnings by changing participation or license levels. Numerical results show that the proposed policy weakens RH substitution away from PT, expands RH availability in suburban areas, improves first- and last-mile connectivity, and helps mitigate spatial imbalances in PT-based accessibility across urban and suburban areas.

Keywords: Tradable Credit Scheme, Ride-hailing, Macroscopic Fundamental Diagram, Accessibility Imbalance, Sustainable Transportation, Multimodal Transportation System

1 Introduction

Urban multimodal transport systems often suffer from a spatial and modal mismatch between mobility needs and transport supply. While public transit (PT) is dense in central areas, it is comparatively sparse in peripheral neighborhoods (Singer et al., 2022; Giannotti et al., 2021). Ride-hailing (RH) could theoretically bridge this gap by providing flexible, first- and last-mile access where fixed-route services are limited (Jin et al., 2018; Cats et al., 2022; Z. Li et al., 2022; Bosker et al., 2023). However, driven by profit incentives, RH drivers typically cluster in transit-rich city centers to maximize request density and minimize idle time (Zhang & Nie, 2022b). This creates a dual inefficiency: in central areas, RH diverts trips from high-capacity PT and consumes scarce road space (Rayle et al., 2016; Erhardt et al., 2019; Qiao & Yeh, 2023; Diao et al., 2021), while peripheral areas remain underserved (Schaller, 2018). Consequently, RH overconcentrates where PT is already strong and underprovides where it could be complementary, exacerbating transport inefficiency and spatial accessibility imbalances.

This dual inefficiency presents a difficult policy challenge: curbing excessive RH activity in transit-rich centers while boosting availability in PT-deficient peripheries. Existing literature evaluates numerous regulatory and operational instruments, including taxes, vehicle caps, surge pricing, and matching policies (S. Li et al., 2019; S. Li, Poolla, & Varaiya, 2021; S. Li, Yang, et al., 2021; Zhang

& Nie, 2022a; Banerjee et al., 2015; Cachon et al., 2017; Castillo et al., 2017; Zha et al., 2016; Bimpikis et al., 2019; Zha et al., 2017, 2018; Yang et al., 2020; Xu et al., 2020; Braverman et al., 2019; Vazifeh et al., 2018). However, these approaches primarily rely on uniform price adjustments, rigid quantity constraints, or direct platform intervention. Consequently, they offer limited support for a flexible, decentralized, and spatially differentiated reallocation of RH supply.

To address this gap, we propose a zone-based Tradable Credit Scheme (TCS) for ride-hailing operations. Instead of uniform pricing or rigid caps, this scheme regulates supply through spatially differentiated operating requirements. Drivers, who all begin with an equal initial credit endowment, must hold credits to operate in designated zones. Higher credit requirements in central areas and lower requirements in peripheral ones create incentives to reduce RH concentration in the center and expand service where RH is more complementary to PT. This preserves drivers' flexibility while creating market-based incentives to shift RH supply toward neighborhoods where it complements, rather than substitutes, PT. Unlike traditional TCS applications that target demand-side traveler choices (Yang & Wang, 2011; F. Xiao et al., 2013; Nie & Yin, 2013; Tian et al., 2013; L.-L. Xiao et al., 2015; Balzer & Leclercq, 2022; Balzer et al., 2023), our mechanism applies TCS to the supply side, using decentralized trading to reshape the spatial distribution of RH service and, through its effects on waiting times and service availability, alter passengers' mode choices across urban zones.

To evaluate the proposed policy, we develop an integrated framework that links long-term credit-market equilibrium with short-term operational dynamics. The contributions of this paper are fourfold:

- **Conceptual Innovation:** We conceptualize urban transport inefficiency as a coupled spatial and modal mismatch. This perspective shifts the focus from simple demand management to the spatial-modal alignment of RH supply, explaining why RH simultaneously competes with transit in centers and remains absent in peripheries.
- **Mechanism Design:** We introduce a novel supply-side, spatially differentiated TCS, providing a decentralized market mechanism for rebalancing RH operations across urban zones.
- **Methodological Integration:** We develop a multi-scale framework coupling (i) a TCS market clearing module, (ii) a driver behavior model for participation and licensing, (iii) a MaaS assignment module for multimodal itineraries, and (iv) a trip-based MFD network dynamics module.
- **Policy Insights:** We provide guidance on the adaptive design of the TCS, demonstrating the necessity of dynamic calibration of initial endowments and zonal charges to sustain RH-PT complementarity while preventing unintended market contraction.

2 Spatially Differentiated Tradable Credit Scheme

We model an urban multimodal system partitioned into N_R concentric zones, indexed from the urban core ($r = 1$) to the periphery ($r = N_R$), reflecting diminishing transit density and congestion levels. To regulate the spatial distribution of RH, we introduce a supply-side TCS. Each active driver receives an initial credit endowment k. Operating in zone r requires a license costing τ_r credits, with higher requirements in central areas to address the spatial mismatch of service:

$$\tau_1 > \tau_2 > \cdots > \tau_{N_R} = 0.$$

We adopt a hierarchical license structure: a level-r license authorizes service in zone r and all less-central zones ($r' \geq r$), simplifying the decision space while granting maximum flexibility to core drivers. The net credit charge for license r is $s_r = k - \tau_r$. This mechanism internalizes spatial externalities by making central operations costly ($s_r < 0$) and peripheral operations profitable ($s_r > 0$). Consequently, the scheme creates market-based incentives to shift RH supply toward areas where it complements, rather than competes with, PT.

3 Evaluation Model Framework: Coupling Long-Term and Short-Term Dynamics

We evaluate policy effectiveness by proposing a multi-agent framework involving RH drivers, a MaaS platform, a regulator, and an exogenous demand environment. The system is determined by two coupled feedback loops (Figure 1):

1. **Long-term Strategic Loop**: Drivers maximize profits by making participation and license choices. The credit price p is endogenously determined via market-clearing conditions.
2. **Short-term Operational Loop**: The MaaS platform matches travelers to multimodal itineraries. Realized vehicle movements generate traffic accumulation, which determines network speeds through a MFD.

The system reaches a stationary equilibrium when no driver can unilaterally increase expected earnings by altering their participation or license choice, given the prevailing credit price and operational outcomes.

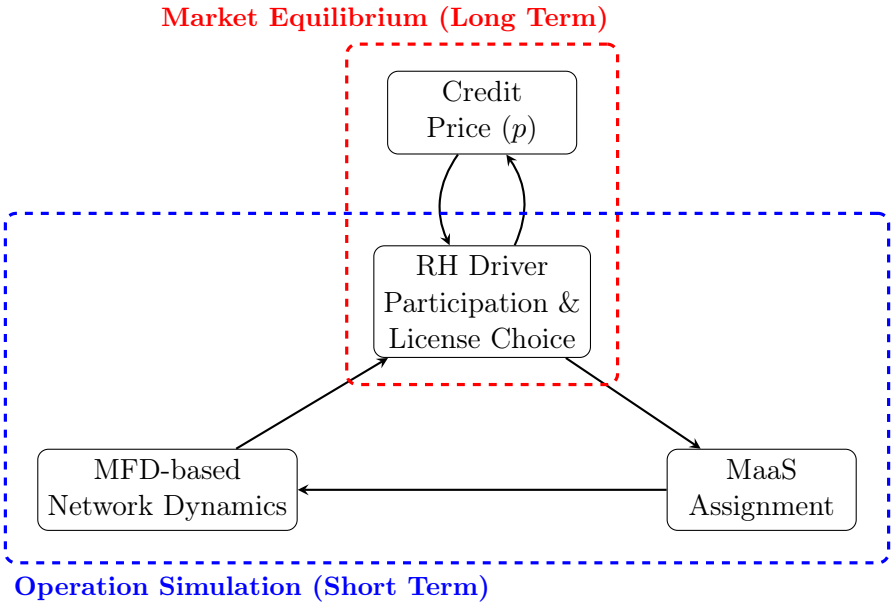


Figure 1: Conceptual framework illustrating the coupled interactions between the long-term credit market equilibrium and the short-term multimodal operational simulation.

4 Short-term Multimodal Operations

The operational simulation captures the microscopic interactions between vehicles and travelers within a discrete-time horizon. This sub-model provides the necessary inputs (waiting times, travel times, and driver revenues) for the higher-level equilibrium model.

Trip-based MFD in a Discrete-Time Horizon

The service area is modeled as a single MFD region. While the credit scheme is spatially differentiated by zones, the traffic congestion dynamics are captured by the aggregate accumulation of motorized vehicles. The total accumulation $n(t)$ at time t is:

$$n(t) = n^{\text{car}}(t) + n^{\text{RH}}(t).$$

Background car traffic $n^{\text{car}}(t)$ is exogenous, while RH accumulation $n^{\text{RH}}(t)$ is endogenously determined by the MaaS assignment. The mean network speed $V(n(t))$ follows an affine MFD relationship (Mariotte et al., 2017):

$$V(n(t)) = V_{\max}\left(1 - \frac{n(t)}{n_{\max}}\right), \tag{1}$$

where $V_{\max}$ is the free-flow speed and $n_{\max}$ is the jam accumulation. To map these speeds to specific trip completion times, we employ the virtual traveler model (Lamotte & Geroliminis, 2018). This approach accounts for time-varying speeds, ensuring that a vehicle entering a segment at t completes it only when the integral of the speed profile over the travel duration equals the trip length.

Travelers' Utility and Integrated Itineraries

The MaaS platform offers travelers a choice among four modes: pure PT, pure RH, and two intermodal combinations (RH-PT or PT-RH). Travelers are assumed to behave rationally by choosing the alternative with the lowest generalized cost. The generalized cost C for each mode combines monetary fares and travel time components weighted by the value of time α_j.
For a request $(o_j, d_j, t_j^{\text{dep}})$, the costs are:

- **Public Transit (PT):** Includes walking to/from stops and expected wait times ($h_\omega/2$).
- **Ride-Hailing (RH):** Includes pickup wait time ($L_{i,o_j}/V$) and in-vehicle time.
- **Intermodal (RH-PT / PT-RH):** These modes use RH for first/last-mile access to a transfer hub h_j. These itineraries are critical for peripheral users who lack direct PT access.

The specific cost functions are formulated as follows:

$$C^t_{j,\text{PT}} = \alpha_j \left(\frac{L^{\text{walk}}_{o_j,s(o_j)}}{v_{walk}} + T^*_{\text{PT},\, s(o_j),\, s(d_j)} + \frac{L^{\text{walk}}_{s(d_j),d_j}}{v_{walk}} \right) + f_{\text{PT}}, \tag{2}$$

$$C^t_{i,j,\text{RH}} = \alpha_j \left(\frac{L_{i,o_j}}{V_{r(o_j)}(t)} + \sum_r \frac{L_r}{V_r(t)} \right) + f_{\text{RH}}\, L_{o_j,d_j}, \tag{3}$$

$$C^t_{i,j,\text{RH–PT}} = \alpha_j \left(\frac{L_{i,o_j}}{V_{r(o_j)}(t)} + \sum_r \frac{L_r}{V_r(t)} + T^*_{\text{PT},\, s(h_j),\, s(d_j)} + \frac{L^{\text{walk}}_{s(d_j),d_j}}{v_{walk}} \right) + f_{\text{RH}}\, L_{o_j,h_j} + f_{\text{PT}}. \tag{4}$$

MaaS Assignment Problem

The MaaS platform solves an Integer Linear Program (ILP) in each batching interval to match available drivers to requests. Let $y^m_{i,j}$ be a binary variable equal to 1 if traveler $i \in I$ is assigned to driver $j \in D$ under alternative $m \in M$, and 0 otherwise. Let $C^m_{i,j}$ denote the traveler's generalized cost for that match, and C^{PT}_i denote the cost of the PT-only alternative.
The platform minimizes the total generalized cost across all travelers, explicitly accounting for the hierarchical license feasibility. The optimization problem is formulated as follows:

$$\min \quad \sum_{i\in I}\sum_{j\in D}\sum_{m\in M} y^m_{i,j} C^m_{i,j} + \sum_{i\in I}\left(1 - \sum_{j\in D}\sum_{m\in M} y^m_{i,j}\right) C^{PT}_i \tag{5a}$$

$$\text{s.t.} \quad \sum_{j\in D}\sum_{m\in M} y^m_{i,j} \le 1, \qquad \forall i \in I, \tag{5b}$$

$$\sum_{i\in I}\sum_{m\in M} y^m_{i,j} \le 1, \qquad \forall j \in D, \tag{5c}$$

$$y^m_{i,j} \le a^m_{i,j}, \qquad \forall i \in I,\ \forall j \in D,\ \forall m \in M, \tag{5d}$$

$$y^m_{i,j} \in \{0,1\}, \qquad \forall i \in I,\ \forall j \in D,\ \forall m \in M. \tag{5e}$$

The objective function (5a) minimizes the sum of costs for matched travelers and assigns unmatched travelers to pure PT (the second term). Constraints (5b) and (5c) ensure one-to-one matching between travelers and drivers in each batch. Crucially, constraint (5d) enforces the hierarchical license feasibility, where $a^m_{i,j} = 1$ if and only if driver j's license level lic_j is sufficient to serve the zones required by itinerary m ($lic_j \le r^m_i$). This mechanism ensures that only drivers holding appropriate central-zone credits can fulfill trips entering the urban core, effectively operationalizing the TCS's supply-side constraints.

5 Long-term Market Equilibrium

The long-term state of the system is defined by the equilibrium in the RH labor market and the credit market. We assume drivers are rational and eventually gravitate toward the most profitable license choices.

Drivers' Participation and License Choices

Participation is modeled at the individual level. Each potential driver i has a reservation earning P_i^{res}. A driver enters the market ($i \in D$) if the expected average market return $\bar{R}$ exceeds their reservation value.
Conditional on entry, drivers must select a license level r. This choice is driven by the average gain G_r^{avg}, which accounts for both operational revenue and credit costs. Under the hierarchical system, a level-r license holder can compete for demand in any region $r' \geq r$. Thus, the gain for license r is:

$$G_r^{\text{avg}} = \sum_{r' \geq r} \frac{R_{r'}}{\sum_{r'' \leq r'} x_{r''}} - p\,(\tau_r - k). \tag{6}$$

The first term represents the expected revenue. Note that the denominator $\sum_{r'' \leq r'} x_{r''}$ represents all drivers eligible to serve zone r', reflecting the higher competition in peripheral zones where both central and peripheral license holders can operate. The second term is the net credit cost/benefit. In equilibrium, drivers will shift between license levels until G_r^{avg} is equalized across all levels with positive driver counts ($x_r > 0$).

Credit Market Clearance

The credit price p acts as the balancing mechanism. It adjusts to ensure that the total demand for credits (from central-zone drivers) does not exceed the total supply (from the endowment and peripheral-zone drivers). This is expressed as a complementarity condition:

$$0 \leq p \perp \left(k|D| - \sum_{r=1}^{N_R} x_r\,\tau_r \right) \geq 0.$$

If there is an excess of credits, the price drops to zero; if the market is tight, p rises until the supply-demand gap is closed.

Fixed-Point Formulation

The stationary equilibrium of the system is a state where driver participation $|D|$, license distribution $\mathbf{x}$, and credit price p are mutually consistent with the operational outputs. Formally, this is defined as a fixed point $(\mathbf{x}^*, |D|^*, p^*)$ satisfying the following conditions:

$$(G_{\max}^{\text{avg}} - G_r^{\text{avg}})\,x_r = 0, \quad \forall r \in \{1, \ldots, N_R\} \tag{7a}$$

$$x_r \geq 0, \quad \forall r \in \{1, \ldots, N_R\} \tag{7b}$$

$$\sum_{r=1}^{N_R} x_r = |D| \tag{7c}$$

$$|D| = \text{count}\{i \in D_0 : \bar{R} \geq P_i^{res}\} \tag{7d}$$

$$\sum_{r=1}^{N_R} x_r(\tau_r - k) \leq 0 \tag{7e}$$

$$p \geq 0, \quad p\Big(\sum_{r=1}^{N_R} x_r(k - \tau_r)\Big) = 0 \tag{7f}$$

Equation (7a) ensures that any license level with active drivers must yield the maximum average gain $G_{\max}^{\text{avg}} = \max_r\{G_r^{\text{avg}}\}$. Equations (7b) and (7c) represent driver conservation, while (7d) endogenously determines market participation. Finally, (7e) and (7f) characterize the credit market-clearing condition: the price p is positive only when the total credit demand exactly matches the total endowment.

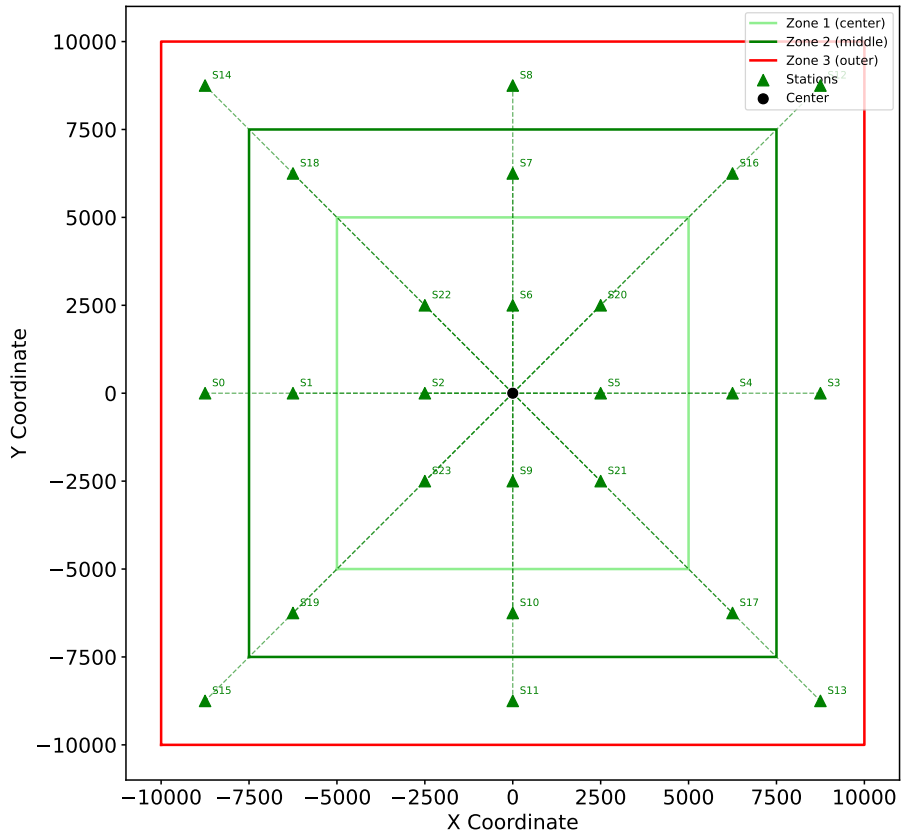


Figure 2: Zonal structure and PT station layout of the simulated network.

Solving this fixed point directly is computationally prohibitive due to the stochastic and non-convex nature of the MFD-based simulation. We therefore treat the equilibrium search as an optimization problem, minimizing the sum of squared residuals of the equilibrium conditions. To find the global optimum, we employ a parallelized Differential Evolution (DE) algorithm. This heuristic search method is particularly suitable for our framework as it is robust against the "noise" and non-linearity produced by the short-run operational simulation.

6 Numerical Experiments and Discussion

We evaluate the proposed TCS in a stylized three-zone city (see Figure 2 as a reference) to examine the structural response of the multimodal system to supply-side regulation. The service area comprises a central core (Zone 1), an intermediate ring (Zone 2), and a peripheral zone (Zone 3). In line with common urban patterns, PT service is dense and frequent in the center but becomes progressively sparser toward the periphery. The simulation models a three-hour morning peak (6:00–9:00 a.m.) involving 500 MaaS users and 3,000 background private-car trips. Potential RH supply consists of 150 drivers with reservation earnings uniformly distributed on $[15, 25]$ Euro. RH fares are distance-based at 2 Euro/km, while PT fares are a flat 1 Euro. Requests are matched in 20-second batches. This setup is designed to isolate the mechanism of spatial reallocation rather than calibrate to a specific empirical city.

We compare a no-TCS benchmark against three policy scenarios. In all TCS cases, each active driver receives a baseline endowment of $k = 10$ credits. Operating requirements are hierarchical: $\tau_3 = 0$ (outer-only), $\tau_2 = 10$ (intermediate and outer), and $\tau_1 \in \{15, 20, 25\}$ for full-city access. By increasing τ_1, the regulator progressively internalizes the congestion and modal-competition externalities of central-area RH operations.

Supply Reallocation and Modal Responses

Our results confirm that the TCS effectively achieves its primary objective of correcting the spatial over-concentration of RH supply by reshaping the geography of service availability. As shown in Figure 3, increasing the central credit requirement from $\tau_1 = 15$ to 25 triggers a sharp exodus of drivers from the urban core. This displaced supply is absorbed by Zones 2 and 3. Notably, at $\tau_1 = 20$, the number of drivers eligible for Zone 1 becomes comparable to those restricted to the periphery, marking a structural departure from the center-heavy allocation of the unregulated market.

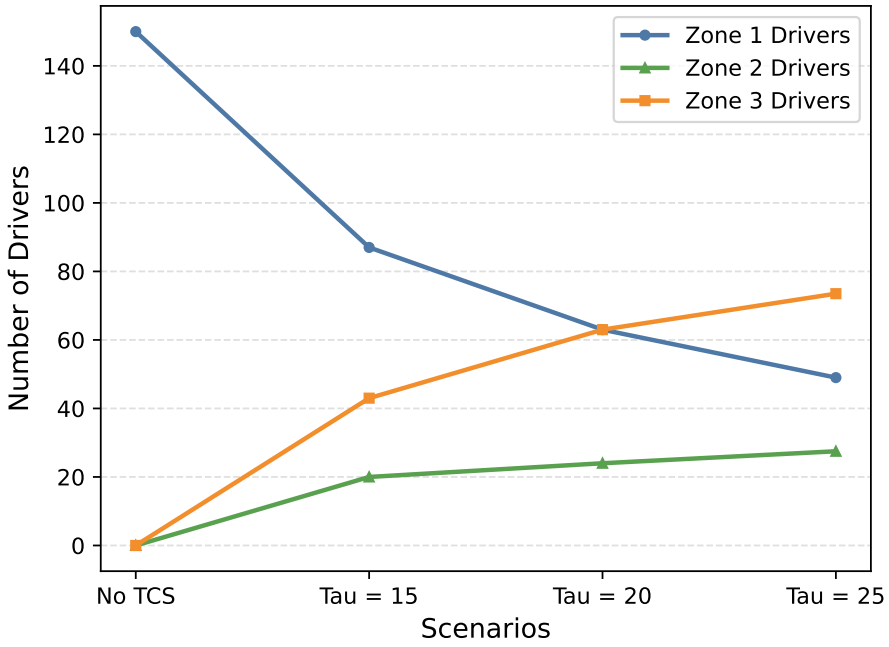


Figure 3: Driver allocation across zones: Higher τ_1 drives spatial sorting.

This supply-side reallocation propagates through the MaaS assignment module to alter traveler mode shares. While citywide PT usage remains stable (67–69%), the zonal shifts reveal a profound modal transformation. In Zone 1, as the cost of holding a central license rises, RH availability drops. This pushes the RH mode share down from 41% to 16%, forcing trips back onto the high-capacity PT network.

Conversely, Zone 3 illustrates the "complementarity" effect (Figure 4). As drivers relocate to the periphery, the RH+PT (intermodal) share grows from 4% to 22%, eventually overtaking direct RH. This suggests that the TCS does not simply suppress demand; rather, it activates RH as a first-mile access mode in areas where it was previously scarce. Zone 2 acts as a transitional area, with relatively small changes in modal shares. Taken together, the evidence shows that the TCS successfully mitigates RH substitution for PT in the center while fostering RH–PT integration in the periphery.

Spatial Trade-offs in Service Quality and Efficiency

A critical insight from the performance metrics is that system-level averages are deceptive. At the aggregate level, total travel time and generalized costs vary by less than 2% compared to the benchmark. However, Figure 5 reveals a stark spatial trade-off.

In Zone 1, the reduction in RH supply increases waiting and pickup times for the remaining users. At $\tau_1 = 25$, central travelers experience a 22% increase in travel time and a 37% increase in walking distance as they shift to PT. This is a deliberate policy outcome: the "loss" of convenience in the core is the price paid for reducing road-space consumption by low-occupancy vehicles.

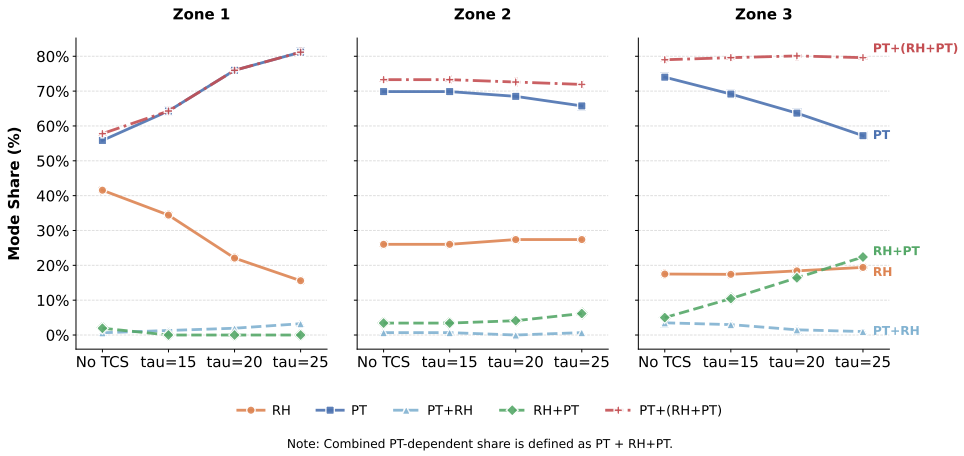


Figure 4: Modal response: From central substitution to peripheral complementarity.

In contrast, Zone 3 sees substantial accessibility gains. Total travel time falls by 8%, and walking distance drops by 19% as RH becomes a viable feeder to PT. This redistribution of service quality suggests that the TCS is a spatial equity tool, reallocating the "convenience" of RH from transit-rich areas to transit-poor ones.

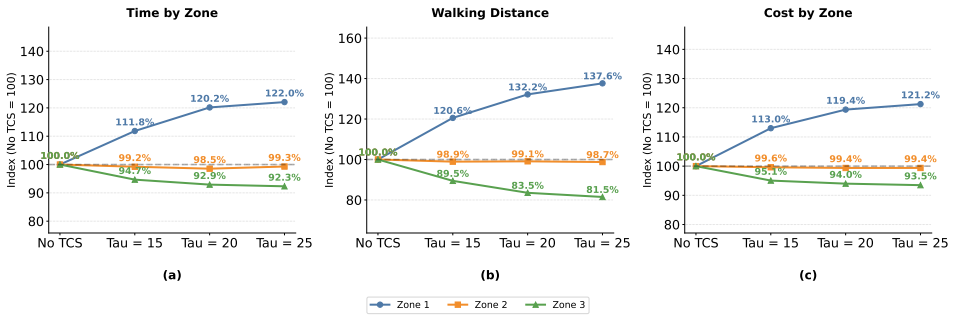


Figure 5: Normalized performance metrics: Peripheral gains vs. central costs.

The operational efficiency of the RH fleet also improves under the TCS. Figure 6 shows that citywide pickup distances and idle times decline, indicating that the fleet is being used more effectively. In the core, although remaining RH users wait longer, the aggregate fleet resource expenditure is lower. In the periphery, the increased density of drivers improves matching efficiency, reducing the "deadheading" distance required to reach passengers. This suggests that the policy screens out low-value central trips while shifting RH operations toward more effective peripheral feeder functions.

In the urban core, the contraction of supply means that remaining RH users face longer pickup distances and wait times. Conversely, in the periphery (Zone 3), the increased density of relocated drivers improves matching conditions, significantly reducing the "deadheading" distance to reach passengers. This reinforces the interpretation that the TCS does not simply suppress RH, but repositions it toward more efficient peripheral feeder functions.

Labor Market Stability: Redistribution vs. Contraction

A key concern for regulators is whether such a policy would substantially shrink the RH market rather than primarily reallocate supply. The main analysis, based on reservation earnings distributed over $[15, 25]$, suggests that the TCS mainly acts as a reallocation instrument: participation remains relatively stable, total revenue declines only modestly, and the spatial distribution of revenue shifts markedly toward the periphery.

Figure 9 considers a higher reservation-earnings range of $[20, 30]$ to examine how this pattern depends on labor supply conditions. Relative to the lower reservation-earnings case, both participation and total revenue are lower overall. However, even within this specification, tightening the TCS from $\tau = 15$ to $\tau = 25$ leads only to gradual declines in participation and revenue, rather

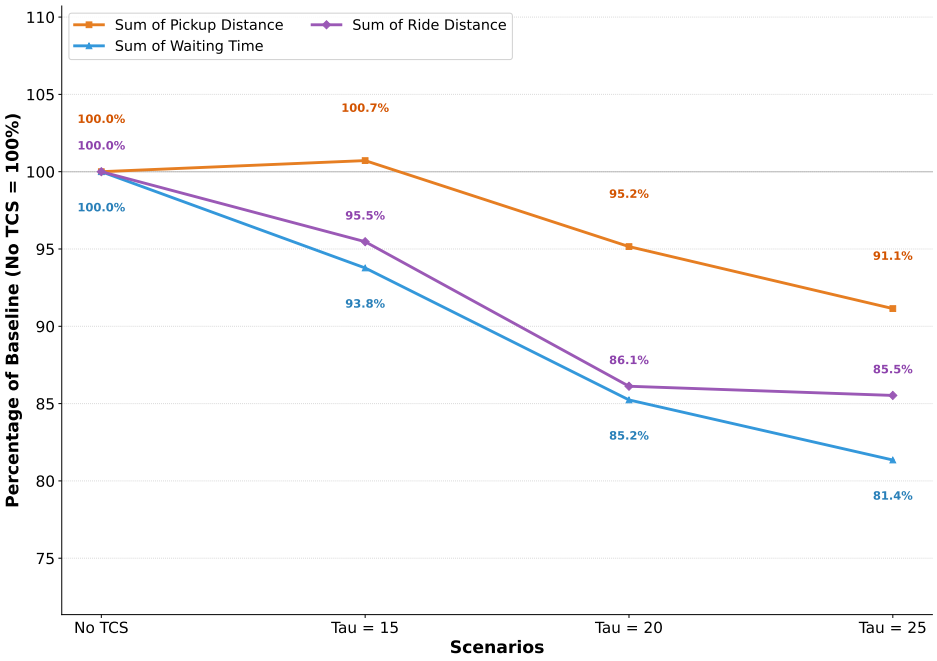


Figure 6: Fleet operational efficiency under increasing policy stringency.

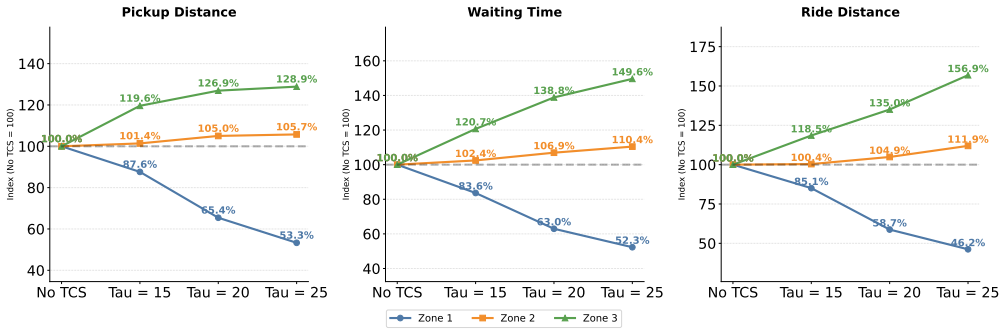


Figure 7: Zone-level RH operational metrics: Improved matching in the periphery at the cost of central efficiency.

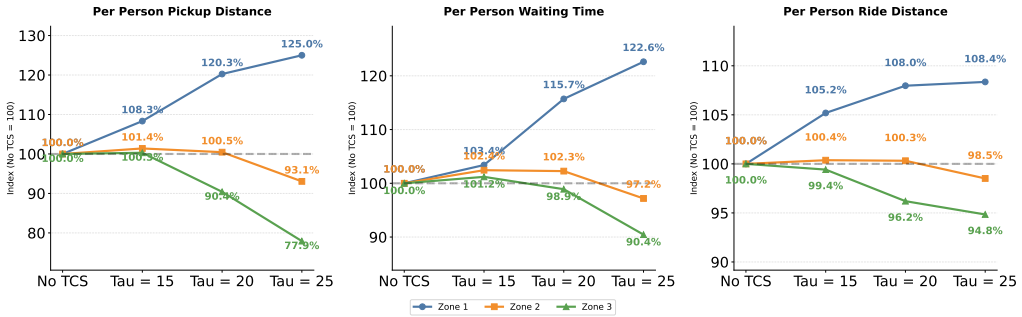


Figure 8: Per-person RH operational metrics: Heterogeneous service quality across space.

than a sharp market contraction. This suggests that higher reservation earnings reduce the overall scale of the RH market, but the marginal effect of stronger TCS remains modest. The policy therefore continues to function primarily as a spatial reallocation instrument, although under a smaller active driver pool.

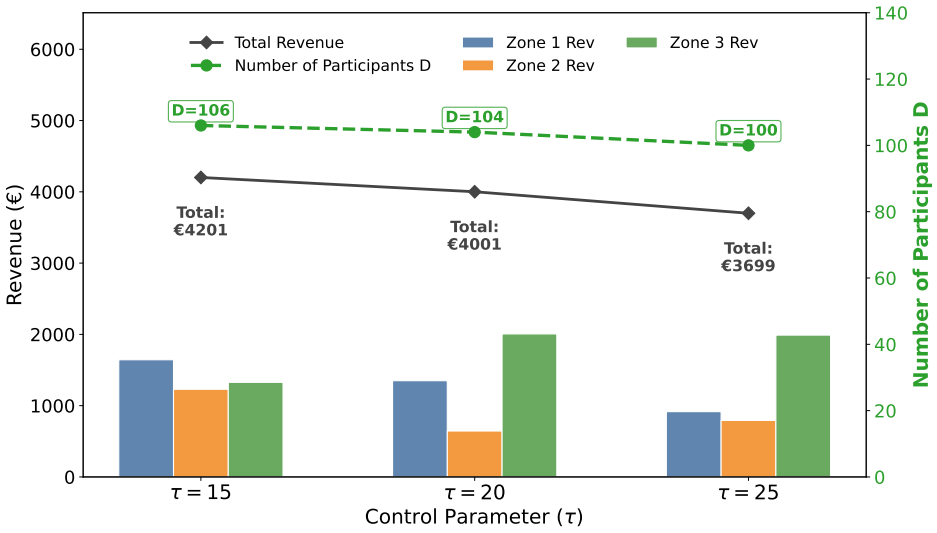


Figure 9: Revenue and participation: The impact of labor supply elasticity.

7 Policy Implications and Conclusion

The numerical analysis supports three main policy conclusions. First, a supply-side TCS is a viable alternative to uniform caps or taxes. By using spatially differentiated requirements, it addresses the spatial misallocation of RH supply while preserving flexibility. It transforms RH from a competitor of PT in the urban core into a vital feeder service in the suburbs.
Second, policymakers must be transparent about the spatial trade-offs. The TCS is not a "win-win" for all travelers; it intentionally reduces convenience in the center to improve suburban equity and system-wide modal efficiency. Evaluating the policy solely on aggregate metrics would fail to capture its true value in improving spatial accessibility.
Finally, the design of the TCS must be adaptive. The initial endowment (k) and the zonal requirements (τ_r) should be calibrated against local labor market conditions to prevent unintended market contraction. If calibrated correctly, the scheme offers a decentralized, market-based mechanism for continuously rebalancing the multimodal transport system.
In conclusion, this paper demonstrates that a supply-side, tradable credit scheme can effectively reshape the spatial distribution of RH service. By linking long-term market clearing with short-run traffic dynamics, we show that the policy successfully promotes PT usage in central areas while enhancing intermodal connectivity in the periphery. As cities continue to struggle with the integration of new mobility services, the proposed TCS provides a flexible and powerful tool for achieving a more balanced and efficient multimodal transportation system.

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