The intraday competition in a duopoly ride-hailing market

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1 Introduction

In many markets, multiple ride-hailing platforms compete fiercely due to low switching costs for both passengers and drivers, who often use several platforms simultaneously (a practice known as multi-homing) (Guo *et al.*, 2023). This intense competition means companies must focus on customer satisfaction factors such as fare and waiting time to retain users, as any attempt to increase prices or commissions risks losing market share. Passengers tend to prefer platforms offering quicker responses and/or lower costs, while drivers value flexibility and the ability to choose among various matching offers based on their preferences for income, pickup times, and locations (Yang *et al.*, 2024).

This paper studies a duopoly ride-hailing market involving passengers, drivers, and two competing platforms: *Platform 1* (our focus) and *Platform 2* (the competitor). Both platforms collect idle drivers and pending passenger requests, assuming all participants use both platforms (multi-homing). They determine fares and wages for each possible passenger-driver pair and present matching options. Passengers and drivers select the most favorable option based on utility maximization or may decline and wait for future opportunities. A match is finalized only if both accept the same offer from the same platform. Impatient participants may enter or exit the market between assignments due to unsuccessful matching attempts. Key characteristics and assumptions include: (i) Passengers and drivers are *multi-homing*, participating in both platforms simultaneously. (ii) Each platform can propose at most one matching offer to each passenger and driver per matching instance, including fare and wage information. (iii) Passengers and drivers select at most one matching from the offers (at most two, from each platform) received. (iv) Each platform knows the aggregated choice behaviors of passengers and drivers from historical data.

The intraday competition is modeled as a repeated game with infinite decision steps, exploring three scenarios: (i) Perfect Information with Fixed Competitive Tactic (PIFCT), where *Platform 1* has full knowledge of *Platform 2*'s strategies and can optimize accordingly; (ii) Limited Information with Fixed Competitive Tactic (LIFCT), where *Platform 1* must predict *Platform 2*'s strategies based on limited market feedback; and (iii) Limited Information with Dynamic Competitive Tactic (LIDCT), where *Platform 2* dynamically adjusts its strategies over time, requiring *Platform 1* to adapt in real time without complete information. These settings address challenges such as real-time strategic decision-making, partial observability of competitor actions, and managing the complexities of high-dimensional decision spaces inherent in the ride-hailing market.

2 Problem Statement

A matching solution for platform i is defined over the set of orders O and idle drivers D collected between two matching instances. The decision variable $x_{o,d,i}$ equals 1 if order $o \in O$ is matched with driver $d \in D$ on platform i, and 0 otherwise. Even if $x_{o,d,i} = 1$, the dispatch occurs only if both the passenger and driver accept the matching on platform i. The platform determines the fare $f_{o,d,i}$ for the passenger and the wage $w_{o,d,i}$ for the driver.

2.1 Passenger and Driver Choice Behaviour

Upon receiving matching proposals, passengers and drivers decide whether to accept them. The utility of passenger o accepting service from driver d on platform i is:

$$u_{o,d,i} = \alpha_{0,o} - \alpha_{1,o} \cdot f_{o,d,i} - \alpha_{2,o} \cdot \tau_{o,d,i}, \quad \forall o \in O, \tag{1}$$

where $\tau_{o,d,i}$ is the estimated pickup time, and $\alpha_{0,o}$, $\alpha_{1,o}$, and $\alpha_{2,o}$ are passenger-specific preference coefficients. Similarly, the utility of driver d accepting order o on platform i is:

$$v_{o,d,i} = \beta_{0,d} + \beta_{1,d} \cdot w_{o,d,i} - \beta_{2,d} \cdot \tau_{o,d,i} - \beta_{3,d} \cdot \xi_o, \quad \forall d \in D, \tag{2}$$

with $\beta_{0,d}$, $\beta_{1,d}$, $\beta_{2,d}$, and $\beta_{3,d}$being driver-specific preference coefficients. ξ_o denotes the estimated travel time from the pick-up location to the drop-off location for o.

Let u_o^{c} and v_d^{c} denote the utility of declining for passenger o and driver d, respectively. The probability that passenger o selects driver d on platform i can be modeled as:

$$p_{o,d,i} = \frac{\exp(u_{o,d,i})}{\exp(u_o^{\mathrm{c}}) + \exp(u_{o,d,i}) + \sum_{d' \in D} \left[\exp(u_{o,d',j}) x_{o,d',j}\right]}, \tag{3}$$

and the probability that driver d selects order o on platform i can be modeled as:

$$q_{o,d,i} = \frac{\exp(v_{o,d,i})}{\exp(v_d^{\mathrm{c}}) + \exp(v_{o,d,i}) + \sum_{o' \in O} \left[\exp(v_{o',d,j}) x_{o',d,j}\right]}. \tag{4}$$

2.2 Opponent Strategy

We model *Platform 2*'s fare, wage, and matching strategy with the following assumptions:

- *Platform 2* uses a linear fare formula based on base fare θ_0, estimated travel distance ETD_o, and estimated travel time ETT_o:

$$f_{o,d,2} = \theta_0 + \theta_1 \cdot \mathrm{ETD}_o + \theta_2 \cdot \mathrm{ETT}_o. \tag{5}$$

- It adopts a fixed commission rate λ for drivers, so the driver's wage is:

$$w_{o,d,2} = \lambda \cdot f_{o,d,2}. \tag{6}$$

- Parameters θ_0, θ_1, θ_2, and λ have bounds to reflect market conditions:

$$\theta_0 \in [\theta_0^{\min}, \theta_0^{\max}], \quad \theta_1 \in [\theta_1^{\min}, \theta_1^{\max}], \quad \theta_2 \in [\theta_2^{\min}, \theta_2^{\max}], \quad \lambda \in [\lambda^{\min}, \lambda^{\max}].$$

Platform 2 assigns drivers to orders using a bipartite maximum-weight matching model:

$$\max_{x_{o,d,2}} \quad \sum_{o \in O} \sum_{d \in D} \mathcal{A}_{o,d,2} \cdot x_{o,d,2} \tag{7}$$

$$\text{s.t.} \quad \sum_{d \in D} x_{o,d,2} \leq 1, \quad \forall o \in O \tag{8}$$

$$\sum_{o \in O} x_{o,d,2} \leq 1, \quad \forall d \in D \tag{9}$$

$$x_{o,d,2} \in \{0, 1\}, \quad \forall o \in O, \forall d \in D. \tag{10}$$

$$\mathcal{A}_{o,d,2} = \frac{f_{o,d,2} - w_{o,d,2}}{\tau_{o,d,2}}. \tag{11}$$

Constraints (8) and (9) ensure that each order is matched with at most one driver and vice versa. The objective maximizes the platform's profit per unit of pickup time.

2.3 Joint Optimization Formulation

The goal is to enable *Platform 1* to dominate the market and achieve an asymmetric equilibrium—a stable state where it holds a significantly larger market share and generates more profit than *Platform 2*. To achieve this, *Platform 1* seeks to maximize its expected profit by optimally choosing matchings, fares, and wages, subject to constraints:

$$\Pi_1 = \max_{f_{o,d,1}, w_{o,d,1}, x_{o,d,1}} \sum_{o \in O} \sum_{d \in D} \mathcal{P}_{o,d,1}\left(f_{o,d,1}, w_{o,d,1} \mid \hat{f}_{o,d,2}, \hat{w}_{o,d,2}, \hat{x}_{o,d,2}\right) \cdot x_{o,d,1} \quad (12)$$

$$\text{subject to} \sum_{d \in D} x_{o,d,1} \leq 1, \quad \forall o \in O \quad (13)$$

$$\sum_{o \in O} x_{o,d,1} \leq 1, \quad \forall d \in D \quad (14)$$

$$x_{o,d,1} \in \{0, 1\}, \quad \forall o \in O, \forall d \in D \quad (15)$$

where $\mathcal{P}_{o,d,1}$ is the expected profit of matching order o with driver d in *Platform 1*:

$$\mathcal{P}_{o,d,1}\left(f_{o,d,1}, w_{o,d,1} \mid \hat{f}_{o,d,2}, \hat{w}_{o,d,2}, \hat{x}_{o,d,2}\right) = p_{o,d,1} \cdot q_{o,d,1} \cdot (f_{o,d,1} - w_{o,d,1}), \quad \forall o \in O, \forall d \in D \quad (16)$$

$\hat{f}_{o,d,2}$, $\hat{w}_{o,d,2}$, and $\hat{x}_{o,d,2}$ are estimated fare, wage, and matching decisions of *Platform 2* from the perspective of *Platform 1.*

3 Methodology

We model the competition between the two ride-hailing platforms as a two-player repeated game $\mathbb{G}$, where each platform $i \in \{1, 2\}$ has private information $s_{i,\text{pri}}$ (invisible to the opponent) and public information $s_{i,\text{pub}}$ (accessible to the opponent). Each platform's strategy depends on its own private information and the opponent's public information, ensuring decisions are independent of the opponent's private data. At each decision step t, we examine three competition settings summarized in Table 1:

Table 1 – *The information positions in the three competition games. (* indicates all information related to the fare, wage, and matching decisions of Platform 1.)*

$\mathbb{G}$	*Platform 1*		*Platform 2*	
	$s_{1,\text{pri}}$	$s_{1,\text{pub}}$	$s_{2,\text{pri}}$	$s_{2,\text{pub}}$
PIFCT	*	$\emptyset$	$\emptyset$	θ_0, θ_1, θ_2, λ, and Eqs. 5-11
LIFCT	*	$\emptyset$	θ_0, θ_1, θ_2, λ	Eqs. 5-11
LIDCT	*	$\emptyset$	$\theta_0(t)$, $\theta_1(t)$, $\theta_2(t)$, $\lambda(t)$	Eqs. 5-11

In the **PIFCT** setting, *Platform 1* has full knowledge of *Platform 2*'s fixed parameters and strategies, allowing it to optimize fares, wages, and matchings directly. The **LIFCT** setting introduces incomplete information; *Platform 1* knows the form of *Platform 2*'s strategies but not the exact parameter values, requiring it to predict these parameters based on observed market outcomes. This prediction is modeled as a continuum-armed bandit (CAB) problem, utilizing market feedback as a proxy for the unknown parameters. The Upper Confidence Bound (UCB) algorithm with Gaussian Processes is employed to iteratively select parameter estimates that maximize expected rewards.

In the more complex **LIDCT** setting, *Platform 2* dynamically adjusts its parameters over time in response to market conditions, using a fuzzy logic controller. *Platform 1* must continuously adapt to these changes without direct knowledge of the adjustments. This scenario is addressed by extending the CAB problem to a non-stationary environment, using a Discounted UCB with Dynamic Tuning (DUCBDT). This approach allows *Platform 1* to update its parameter predictions and strategies in real time, accounting for the evolving tactics of *Platform 2* and the inherent uncertainties in the competitive market.

4 Numerical Experiments

We evaluate the performance of various competitive scenarios within a duopoly ride-hailing market using a simulated environment based on Manhattan's road network from OpenStreetMap. Simulations run during the morning peak hours from 7:00 AM to 9:00 AM, using the first two weekdays of February 2023 as test data. Both platforms collect data on available passengers and drivers, employ optimization methods to determine optimal fares, wages, and matchings, and finalize assignments based on individual choice models.

Passenger demand data are sourced from Yellow Cab trip records. Drivers are synthesized and distributed across different regions, totaling 3,000 drivers in the simulation. We introduce several optimization methods as benchmarks—Static, Perfect Information, Random Guess, UCB, DUCBDT, and

Fuzzy Logic Controller—to compare across six competition scenarios ranging from perfect information to limited information with dynamic competitive tactics.

Table 2 – *Results of different competition scenarios during 07:00 AM - 09:00 AM (averaged over 10 test days). Numbers in parentheses indicate the average matching rate of the platform. The UCB and DUCBDT methods are reset at the start of each test day.*

Scenario	Platform	Methods	Avg. Profit [USD]	Avg. Assignments [trip]	Cancellations [trip]	Attrition [driver]
PIFCT	1	Perfect information	58,205.9	7,007.0 (84.4%)	825.0 (9.9%)	598.0
	2	Static	1,207.3	469.0 (5.6%)		
LIFCT	1	Static	12,942.2	3,788.0 (45.6%)	765.0 (9.2%)	1,655.0
	2	Static	12,551.7	3,748.0 (45.2%)		
LIFCT	1	Random guess	28,272.9	4,883.0 (58.8%)	727.0 (8.8%)	610.0
	2	Static	10,148.1	2,691.0 (32.4%)		
LIFCT	1	UCB	41,966.1	5,788.0 (69.7%)	733.0 (8.8%)	595.0
	2	Static	6,451.8	1,780.0 (21.4%)		
LIDCT	1	Static	4,693.2	1,596.0 (19.2%)	919.0 (11.1%)	682.0
	2	Fuzzy	15,634.6	5,786.0 (69.7%)		
LIDCT	1	DUCBDT	18,685.7	3,972.0 (47.8%)	911.0 (11.0%)	657.0
	2	Fuzzy	4,474.0	3,418.0 (41.2%)		

Based on Table 2, the numerical results over ten test days show that in the "Perfect Information vs. Static" scenario, *Platform 1* achieves the highest profit ($58,205.9) and most assignments (7,007 trips with an 84.4% matching rate), significantly outperforming *Platform 2* due to its complete market information. In the LIFCT scenarios, "Static vs. Static" yields similar performance for both platforms but exhibits the highest driver attrition (1,655 drivers leaving), suggesting that a lack of adaptive strategies may lead to less favorable conditions for drivers. "Random Guess vs. Static" shows *Platform 1* improving its profit to $28,272.9 and assignments to 4,883 trips (58.8% matching rate), while the "UCB vs. Static" scenario further enhances *Platform 1*'s performance to $41,966.1 and 5,788 trips (69.7% matching rate), demonstrating the effectiveness of the UCB algorithm in enabling *Platform 1* to learn and adapt over time even with limited information. In the LIDCT scenarios, "Static vs. Fuzzy" results in *Platform 2* dominating the market with $15,634.6 profit and 5,786 assignments (69.7% matching rate), while *Platform 1* lags behind, indicating the effectiveness of dynamic tactics. However, in "DUCBDT vs. Fuzzy," *Platform 1* employing the DUCBDT algorithm improves its performance significantly to $18,685.7 profit and 3,972 assignments (47.8% matching rate), outperforming *Platform 2*, demonstrating the advantage of adaptive strategies even against a dynamic competitor. Therefore, the findings suggest that intense competition alone does not guarantee better market outcomes.

5 Conclusion

This paper analyzes intraday competition between two ride-hailing platforms in a duopoly market. The findings underscore the importance of information access and adaptive strategies, suggesting future research into cooperative mechanisms between platforms and regulatory frameworks to enhance market efficiency and align platform behavior with societal welfare.

References

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