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CIE5050

Additional Graduation Work, Research Project

Research on Ride-hailing Pricing Strategies

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Abstract

Compared to traditional public transport, ride-hailing makes it possible for people to get a more comfortable and faster riding experience with a higher fare. Ride-sharing fall in between the two, offering a discount at the price level of ride-hailing, yet operates with more detours and less comfortable experience. In this study, with different price levels for ride-hailing and discount rates for ride-sharing, we would like to examine the system performance of co-existence of ride-hailing, ride-sharing and public transport services. We would also like to search for an optimal solution for the ride-hailing & ride-sharing company to maximize its profit. We apply ExMAS, an open-source agent-based model for ride-sharing simulation, to simulate passengers' and vehicles' behavior on a microscopic level, and acquire numbers of results. Based on our model, in the case of Amsterdam, when price level is 1.1 euro/km and discount rate is 0.4, the company could enjoy maximum profit and market share. It is also found that, when price level gets higher more people opt for the competitive mode instead, resulting in the overall profit falling significantly.
Keywords: ride-sharing, ride-hailing, Agent-based model, On demand mobility

1 Introduction

1.1 Background

Digital technologies have enabled the emergence of on-demand ride services, such as Uber, Didi and Lyft. In comparison to traditional cruising taxis, ride-hailing services have become more dominant in the market (J.Zhong, 2022), with a 55% revenue growth from 2020 to 2021 (Inc., 2022).

Ride-hailing is meant to not only provide a more comfortable and convenient solution for traffic users, but also to further help reduce emission and congestion. In addition, it plays an essential role in low density areas, reducing their waiting and transfer time (M.D. Dean, 2021). However, it is found that this emerging mode mostly attracts previous public transport users, instead of private vehicle drivers, and therefore has negligible or even negative influences on alleviating road congestion and emission (E. A. Haddad, 2019). Also, in peak hours, supply usually cannot meet the demand in high density areas (X. Zhan, 2021). Ride-pooling, or ride-sharing, could be a possible solution for the problems proposed.

Ride-pooling, in contrast, simultaneously serves several passengers with different departure and arrival locations in a single vehicle, while reducing consumers' riding fare. Based on surveys, it is found that consumers usually stress most on reliability and security while considering usage of pooling service. (A. Kumar, 2022) Delays, discomfort and discount make the most difference between shared rides and private rides (R. Kucharski, 2020). In addition, on the current stage, ride-sharing performs poorly in low density areas(I. Kaddoura, 2021).

Ride-pooling has already come into practice yet was suspended during the COVID period. In February 2022, at the end of the COVID pandemic, Uber has announced its restart in UberXShare services. On company's perspective, it is necessary to come up with a best pricing strategy to find a balance between maximizing its profit and increasing patronage. Thus, the price cannot be too low, yet should be attractive enough to ensure a high market share.

1.2 Literature Review

ABM complies agent decision rules during iteration, thus being able to model heterogeneity in the population. The ride-hailing and ride-pooling system is a complex system with agents with different tastes, and discrepancy among travel distances, waiting time, detouring distance and value of time of passengers could significantly impact their choices of mode. Thus, we adopt the ABM model in this research.

In ride-sharing and ride-hailing problems, ABM has already been widely applied. An agent-based stochastic user equilibrium (SUE) model is successfully adopted to analyze the first/last mile ride-hailing problem in Oakville (S. Djavadian, 2017). Zha et al. (2016) also applied an ABM on service analysis. Andres (A. Fielbaum, 2022) applies game theory and a dynamic model on cost-sharing problems in ride-pooling systems, and succeeded in reaching equilibrium. Although Xingbin (X. Zhan, 2021) proposed a dynamic model, yet it consists of static models of consecutive time steps, and each step being a ABM. Rong (R. Fan, 2022) proposed a commuter service platform, and analyzed the monopoly and duopoly scenarios using ABM. Moreover, the model was further extended to analyze the pros and cons of worksite and home locations.

In this project, we would like to focus on the system performance of a ride-hailing corporation operating within different scenarios, based on different price levels for non-shared options and different discount rates for shared options. We would also like to research on the best pricing strategy for a company to maximize its profits or attractiveness. In the next section, a literature review will be given. Then, based on the identified research gap, a main research question and several sub-questions will be listed. To answer them, the expected research approaches will also be analyzed and selected. Afterwards, in the fourth section, a time plan will be proposed. Finally, organization and risks will be evaluated.

2 Research Questions

The main research question (RQ) would be:

How is the system performance when private and shared ride-hailing services are operated under different price levels and discount rates?

In order to answer the main research question, the following sub-questions will be sequentially answered:

- What would the system performance be like under different pricing strategies and discount schemes if ride-hailing and ride-sharing service given a fixed demand?
- What would the system performance be like under different pricing strategies and discount schemes if ride-hailing and ride-sharing service given a unfixed demand.
- What would be an profit maximizing pricing strategy to maximize the market share of ride-hailing/ sharing services?

3 Model and Simulation

3.1 Assumptions

- The demand generated do not own private vehicles and are already possess membership of ride-hailing services, including both non-shared and shared options.
- Drivers always choose the nearest route from origins to destinations, and the delay due to signal lights and congestion is not considered.
- The pick-up and drop-off point of passengers are all accessible by ride-hailing vehicles, thus the access and egress time of ride-hailing services is omitted.
- Walking time and waiting time for public transport rides is set as averagely 5 minutes.
- Value of Time (VoT) follows exponential distribution.
- Due to model limitations, the highest discount rate cannot exceed 0.4.
- The highest capacity per vehicle is set as 8 passengers, excluding the driver.

3.2 Model

3.2.1 Mode Choice

A utility model is applied to simulate the decision process of passengers while selecting an alternative. In our model, we consider three modes, including public transport (PT), shared ride-hailing vehicles (SH) and non-shared ride-hailing vehicles (NS). are the utility functions for three alternatives.

$$\begin{aligned}\mathrm{U(PT)} = T_{in\_veh} \times VoT \times \beta_{in\_veh} + T_{walk} \\ \times VoT \times \beta_{walk} + S_{trav} \times \beta_{PT\_fare} \times Fare_{PT}\end{aligned} \tag{1}$$

$$\begin{aligned}\mathrm{U(NS)} = T_{in\_veh} \times \beta_{in\_veh} \times \mathrm{VoT} \\ + S_{trav} \times \beta_{NS\_fare} \times Fare_{NS}\end{aligned} \tag{2}$$

$$\begin{aligned}\mathrm{U(SH)} = (T_{in\_veh} \times \times VoT\beta_{in\_veh} + T_{Delay} \times VoT \\ \times \beta_{Delay}) + S_{trav} \times \beta_{NS\_fare} \times Fare_{NS} \times Disc\end{aligned} \tag{3}$$

where T_{in_veh} stands for in-vehicle time, and the coefficient of this attribute for three modes are identical. T_{walk} and T_{delay} represents the walking time to PT stops, and delay of detouring during shared rides, respectively. VoT denotes the value of time, and is set as 0.0035 euro/second in this model. S_{trav} stands for the in-vehicle travel distance, and $Fare_{PT}$ and $Fare_{NS}$ denotes price per kilometer for PT rides and non-shared rides respectively. In addition, there is a discount rate set for shared-rides, which is represented as $Disc$ in equation (3). Thus, the pricing for shared-rides is based on both non-shared pricing strategies and the shared-ride discount rates.

3.2.2 Ride-hailing Service Operation

We apply ExMAS and MaaSSim to simulate the shared and non-shared hailing rides. ExMAS is an open-source agent-based simulator for ride-sharing problems and provides attractive sharing solutions for passengers. By matching attractive shared rides only, this algorithm effectively reduces the computation task.(R. Kucharski, 2020). With the open-source simulator MaaSSim, the interaction between vehicles and passengers could also be modelled(R. Kucharski, 2022). Eventually, the system performance on both sides, namely vehicles' and passengers' side, could both be acquired.

The cost of vehicles should be the product of total travel distance during the simulation period and cost per kilometer(CPK). In Amsterdam, the operational cost is defined as 0.5 euro per km (NIBUD, 2022). From the simulator we are able to acquire the total travel time, hence the distance is defined as the average speed times overall travel time, including Non-shared-rides distance (S_{NS}), shared-rides distance (S_{SH}) and cruising distance (S_{CR}). With the total income and costs per vehicle, we could acquire the profits during the simulation period. This profit includes the income for drivers (P_{Driv}) and commission fee collected by the platform(P_{Platf}).

$$\begin{aligned}\sum P_{Driv} + \sum P_{Platf} &= \sum Fare - \sum Cost \\ = \sum (S_{NS} \times Fare_{NS} + S_{SH} &\times Fare_{NS} \times Disc) \quad (4) \\ - \sum ((S_{NS} + S_{SH} &+ S_{CR}) \times CPK)\end{aligned}$$

3.3 Simulation

The model simulation is applied to city Amsterdam. Demands, including origins and destinations, shown in figure 1 imply that the central part in Amsterdam has a higher travel demand, while demand in the suburban area is sparsely distributed. Travellers in Amsterdam may choose among alternative modes including shared or non-shared ride-hailing vehicles, or public transport. Considering that purpose of trip, personalities and urgency of travelling could vary a lot among travellers, we apply an exponential distribution when defining VoT.

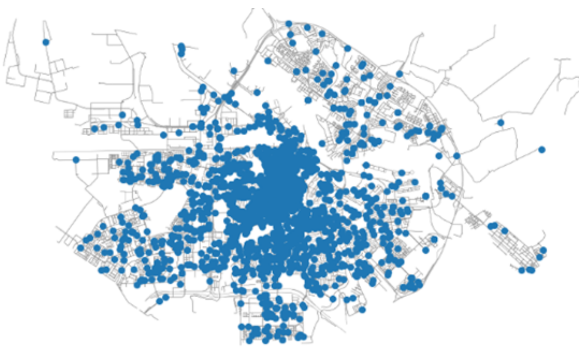


Figure 1: Demand Distribution

Scenarios will be established according to five pricing levels of non-shared rides and five discount rates of shared-rides. Thus, a 5×5 grid (Table 1) is created to examine the system performances under the 25 different scenarios. The horizontal axis presents the five discount rates while the vertical axis presents the price levels (euro/km). It could also be interpreted as, private riding services is responsible for setting a price level per kilometer, while sharing service is in charge of selecting a discount rate. Each of them determines an alternative among an axis, thus the system performance is a consequence of the decision from both services.

	0.20	0.25	0.30	0.35	0.40
1.1	(1.1,0.2)	(1.1,0.25)	(1.1,0.3)	(1.1,0.35)	(1.1,0.4)
1.3	(1.3,0.2)	(1.3,0.25)	(1.3,0.3)	(1.3,0.35)	(1.3,0.4)
1.5	(1.5,0.2)	(1.5,0.25)	(1.5,0.3)	(1.5,0.35)	(1.5,0.4)
1.7	(1.7,0.2)	(1.7,0.25)	(1.7,0.3)	(1.7,0.35)	(1.7,0.4)
1.9	(1.9,0.2)	(1.9,0.25)	(1.9,0.3)	(1.9,0.35)	(1.9,0.4)

Table 1: Scenario Grid

Other fixed parameter values are defined as in table 2. The β_{cost} is defined as utility per euro (N. Gerzinic, 2022), while the in-vehicle, fare, walk and delay beta are defined by the product of multipliers and β_{cost} (N. Gerzinic, 2022).

Parameter	Value
Start Time	17:00
Duration Time	4 hours
Average Vehicle Speed	8 m/s
Average PT Speed	4 m/s
β_{Cost}	-0.1592
$\beta_{In-vehicle}$	$1 \times \beta_{Cost}$
β_{Fare}	$1 \times \beta_{Cost}$
β_{Walk}	$4 \times \beta_{Cost}$
β_{Delay}	$2 \times \beta_{Cost}$
VoT Mean	12.6 €/h
PT Fare	0.2 €/km
Request	1000
Supply	100

Table 2: Parameters in Simulation

4 Simulation Results

4.1 Fixed Demand

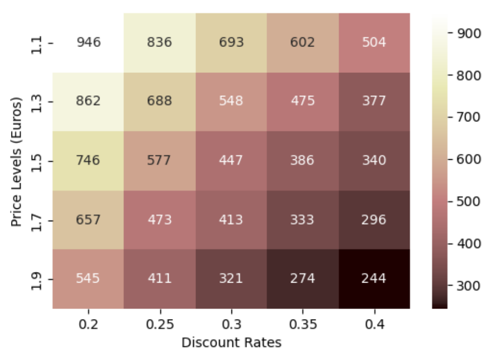


Figure 2: Population Choosing Single Rides when Demand is Fixed

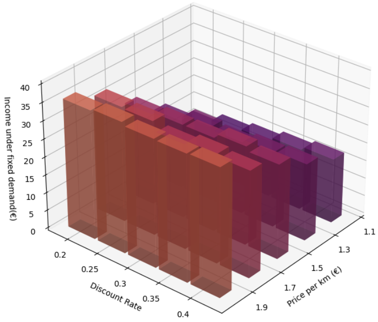


Figure 3: Income when Demand is 1000 (€)

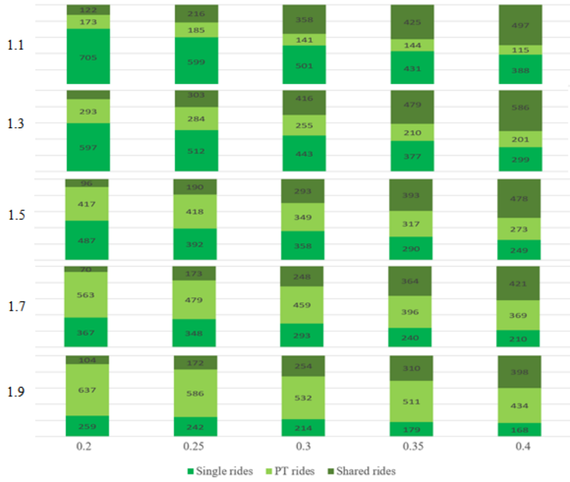


Figure 4: Modal Split under Different Scenarios

Under a fixed demand, we mainly regard the modal split among the two services, and the total income. As the price and discount rate get higher, more people opt their choices to shared vehicles, and the patronage of private rides keep descending. The high riding fare prompts people to choose a less comfortable but cheaper deal. It may not be a satisfying option, but a better one among the two.

The income grid suggests that a higher price with higher discounts could help achieve higher income. The company would gain the most benefit when pricing level is 1.9 while the discount rate for shared vehicles is 0.4. Thus, if we regard this as a monopolistic market without restrictions, which only one company is operating to fulfill the travel demand of a region, social welfare could easily be damaged, since companies would always try to seek the greatest benefits and people need to pay for it.

4.2 Dynamic Demand

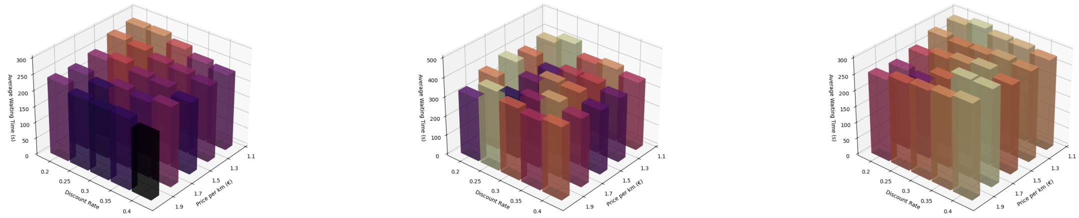
4.2.1 Modal Split

Three alternatives are regarded in this model, consisting of public transport (PT), single rides and shared rides of ride-hailing. As figure 4 suggests, as pricing per kilometer gets lower and discount rate grows higher, the attractiveness of shared rides keeps ascending. Single Rides are only considered appealing when the pricing per kilometer and discount rate for shared rides are both in a low level. Regarding the share of public transport, people may have a stronger bias to opt out ride-hailing services as the pricing per kilometer gets higher, and the discount rate gets lower.

4.2.2 Waiting Time

Although waiting time is not considered in our utility functions, it could negatively effect decisions over day-to-day process when the waiting time is too long. It is an essential factor that increases the disutility of one mode. Figure 5 implies that non-shared rides are likely to result in longer waiting times in comparison to that of shared rides. The pricing strategy does not have significant correlation with the waiting time of private rides, yet when the discount rate and pricing gets higher the waiting time for shared rides would fall even lower. High discount rates prompts more people to choose shared rides, and higher pricing levels make public transport more attractive, both resulting in loss of private ride users. Thus, when more people opt out from private rides, passengers are likely to wait shorter, and the system is likely to result in higher efficiency.
On the other hand, it is obvious that on the same price level, waiting time of of the overall ride-hailing service initially increases as the discount rate increases. Yet, at higher price levels it no longer complies with the trend, and changes to descend. This indicates that, the increase of discount rates has a positive effect on attracting potential customers, thus the system could be too busy to handle with the requests, yet when discounts rate get more higher, the increasing waiting time would be offset by the reduction caused by higher sharing rate.

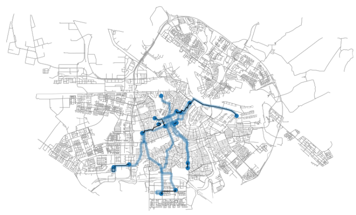
Figure 6(a) and 6(b) also intuitively presents the characteristics of vehicle routes as discount rate grows higher. Green lines stand for the shared rides, and blue lines denote the non-shared rides, while black lines represent trips without passengers, or cruising. In comparison, the discount rate has a significant effect in increasing the weight of shared trips, since there would be more attractive shared rides (R. Kucharski, 2022). Attractive shared rides aim at minimizing detour of vehicles when picking up customers (R. Kucharski, 2022), thus waiting time of passengers would never be too



(a) Average Waiting Time for Shared Rides (s) (b) Average Waiting Time for Non-shared Rides (s) (c) Average Waiting Time (s)

Figure 5: Average Waiting Time for Passengers under Different Scenarios

long. For private rides, however, customers must wait for the nearest idle vehicle after requesting, and sometimes at remote or busy areas an idle vehicle could be far away, leading to longer waiting time.



(a) discount rate = 0.20

(b) discount rate = 0.40

Figure 6: Route of Vehicle 19 when Price is 1.3 euro/km

This could be further verified by the grid of occupancy rate. Occupancy rate is defined as the ratio of total passenger kilometer and total travel distance. As figure 7 suggests, the occupancy rate is higher in high discount rates. This is because more passengers opt for shared rides as the discount rate gets higher, and so the driver is able to carry more passengers simultaneously, resulting in higher efficiency.

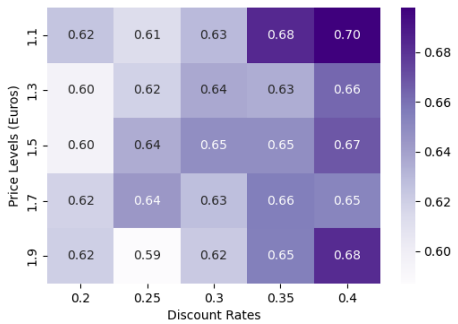


Figure 7: Occupancy Rate

4.2.3 Vehicle Cost

On drivers' perspective, passengers' waiting time is highly related to the cruising distance without passengers. Drivers and platforms incline to reduce the cruising distance, since no passengers would be paying for the operational costs while cruising. If we examine figure 8, it is clear that the trend accords with that of overall waiting time, which there is a peak at each price level, and the peak lags as discount rates gets higher. This is because at higher prices and low discount rates, people opt for public transport mode and vehicles keep idle. The peak always happens when the shared services start to become dominant.

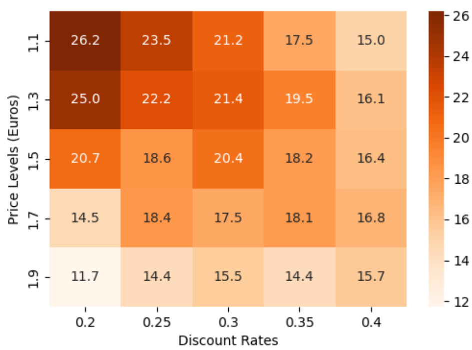


Figure 8: Average Cost per Vehicle (€)

4.2.4 Travel Distance

The average travel distance of private rides reduces significantly in the direction of two axes. Higher price levels could lead to higher fares, increasing its disutility, while higher discount rates decreases the total fare for shared rides and increases its utility, thus also making longer private rides less attractive.

Figure 9: Average Trip Distance of Non-Shared Rides

The average distance of shared rides, in contrast, increases as the discount rate rises higher. When the discount rate is sufficiently high, the savings of fare cost is able to compensate the time cost of detour delay, thus becoming appealing for travellers on long journeys. This also counts for the descending trend among the price level axis at high price levels. However, at low price levels there is not a significant correlation between price and travel distance. This could be explained as insufficiency of samples, since the demand of shared rides are quite low, and the randomness of VoT, as assumed, renders some people with long travel distances to choose the shared mode, which helps increase the average travel distance significantly.

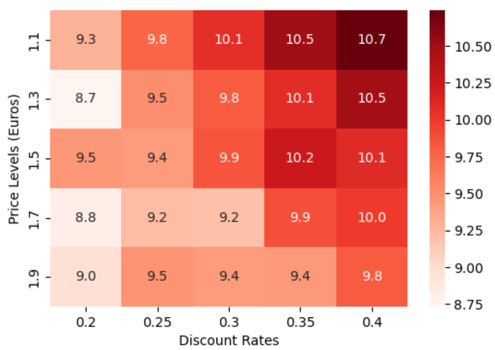


Figure 10: Average Trip Distance of Shared Rides

The theory we mentioned above could be further verified by figure 11. As discount rates grow higher, from 0.2 to 0.3, the maximum travel distance of shared rides grow higher, and so does the 25% quantile and medium value. More people with longer distances are willing to travel with this mode. Besides, Even if randomness of VoT is assumed in the model, the maximum distance of non-shared rides still not comparable that of shared rides. Thus, it is also obvious that the discrepancy of target customers of two services is always huge, which private rides are always more appealing to customers on short tours.

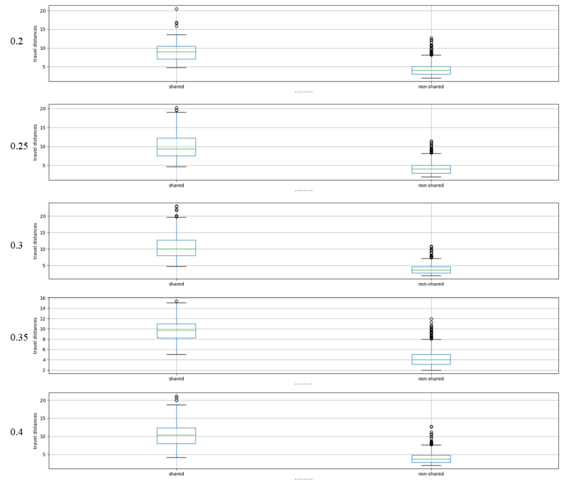


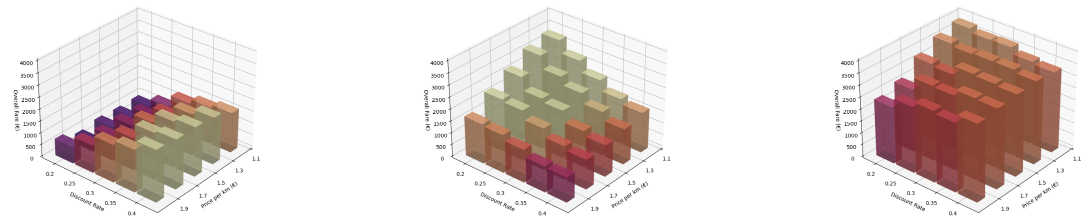
Figure 11: Distribution of Ride Distance when pricing level is 1.1 euro/km

The characteristics of travel distances could account for the variation in fares. For single rides, the riding fare decreases as the price level and discount rate increases, since the number of rides keeps reducing. As price levels become higher, people travelling longer distances may opt out from this mode, resulting in reduction of fare income. However, for shared rides, the overall trend is adverse. Higher discount rates could attract substantial PT and NS users, bringing a huge income. Based on this, we discover a rise-and-fall trend in the total fare income of each price level. In each level, there is a peak among the total fares, at a specific discount rate. As the price level grows higher, the peak lags. Similar trends could also be discovered when examining among the discount rate axes.

4.2.5 Income

For companies, they regard most on the income, since the commission fee is a direct prorated deduction from the drivers' income. The operational cost, including gasoline fee and maintenance cost, should be paid by the platform.

Figure 13 suggests that an optimal solution for drivers is pricing at 1.1 euro/km, while sticking to the maximum discount rate 0.4. To better determine the optimal price level, we also simulated scenarios when the price is lower than 1.1 euro/km, and the results show that there is a peak among price levels on the same discount rate, which the income of 0.9 euros per



(a) Shared Ride Fares (Euro) (b) Non-shared Ride Fares (Euro) (c) Total Fare (Euro)

Figure 12: Total Fares for Passengers under Different Scenarios

km and 0.4 discount rate falls to 17.9 euros averagely. Yet, on a same price level, the income keeps ascending as discount rates increase. As discount rates grow higher, vehicles become busier and drivers have less time idle, enjoying greater income. As price levels get higher, drivers initially enjoy the benefits of higher unit prices, but then have more idle time and passengers with shorter rider distances due to lower patronage.

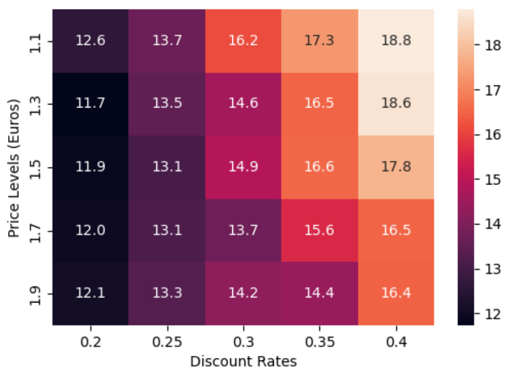


Figure 13: Income per Vehicle

Figure 14 also suggests that corporations have the highest market share at 1.1 euro/km and 0.4 discount rate.

Figure 14: Market Share

5 Conclusion

5.1 Findings and Implication

In this study we examined two basic scenarios, which the demand for ride-hailing services is either fixed or dynamic. In each scenario we examine the operation under a grid of different pricing levels per kilometer, and different discount rates. When the demand is fixed, we regard the market as monopolistic, and the optimal pricing strategy for the ride-hailing company should be tuning the pricing level higher, and offering more discounts.

However, if we add a competing mode into the market, which here we adopted the public transport mode, the company could experience loss of customers if prices are unreasonable. The most optimal strategy would still be ensuring a higher discount rate, yet selecting a price level that balances patronage and income. In our scenario, the value should be 1.1 euro/km.
For passengers, It is found that waiting time could be four times negative than that of in-vehicle times for its utility, thus it is an essential for companies to minimize it. The formation of attractive shared rides greatly helps improve the problem of waiting too long, thus it is wise to choose a pricing strategy that encourage more people using shared options, which discount rates should be relatively high.

Finally, the distribution of travel distances also suggest that people travelling long journeys would be less willing to take private rides, and the target customers of private rides may be people travelling not very long.

5.2 Implications

The results above suggest that shared rides would help increase the overall efficiency of a system, by reducing passengers' waiting time and saving their money, while also increasing the income of drivers and the platform, and also increasing the turnover efficiency and occupancy rate. As we have mentioned, ride-hailing services currently could drive the road congestion level even severe, and by increasing the occupancy rate and decreasing the total operated distance of a vehicle, this problem could be alleviated. It is also obvious that modal split of consumers (figure 4) are sensitive to the changing of pricing strategies, thus not only discount rates could be elevated, but also some other bundles beneficial for promoting shared rides could be launched.

On the other hand, it is essential for public transport companies to enhance their competitiveness and improve passengers' travel experience, thus avoiding too much customers opting out. As the monopolistic scenario suggests, without an efficient public transport network, the ride-hailing company could make more profits by tuning the price level per kilometer higher, which damages the social welfare.

5.3 Limitations and Future Research

For the model itself, in our study the highest discount rate could only be tuned to 0.4, yet in reality it could be tuned even higher, and we stress the necessity to know if the income would continue to rise when higher than 0.4. In addition, the utility functions could be optimized by adding the utility of waiting times, and the comfort of in-vehicle could also be quantified.

For further research, in this study we focus mainly on the competition between public transport and ride-hailing companies, and more other modes could be added to the scenarios, such as bikes and e-scooters. Also, we regarded the ride-hailing services as an integrated company, yet this model could also be developed further to examine a scenario of two companies operating private and shared riding services separately. Since the non-shared riding service controls over the pricing level, while the shared riding service tunes the discount rate, it requires an additional model to help determine the most possible income for two companies on the price grid, such as by applying game theory.

References

A. Fielbaum, O. C. J. A.-M., R. Kucharski. (2022). How to split the costs and charge the travellers sharing a ride? aligning system's optimum with users' equilibrium. *European Journal of Operational Research*, *301*, 956-973.

A. Kumar, M. P. V. C., R. Gupta. (2022). Service quality assessment of ride-sourcing services: A distinction between ride-hailing and ride-sharing services. *Transport Policy*, 61-79.

E. A. Haddad, e. a. (2019). A socioeconomic analysis of ride-hailing emergence and expansion in são paulo, brazil. *Transportation Research Interdisciplinary Perspectives*.

I. Kaddoura, T. S. (2021). The impact of trip density on the fleet size and pooling rate of ride-hailing services: A simulation study. *Procedia Computer Science*, 674-679.

Inc., U. T. (2022). *Uber announces results for fourth quarter and full year 2021.* Retrieved 2022-02-09, from https://www.businesswire.com/news/home/20220209005466/en/

J.Zhong, Y. F., H.Zhou. (2022). The impact of ride-hailing services on the use of traditional taxis:evidence from chinese urban panel data..

L. Zha, H. Y., Y. Yin. (2016). Economic analysis of ride-sourcing markets. *Transportation Research Part C*, 249-266.

M.D. Dean, K. K. (2021). Spatial variation in shared ride-hail trip demand and factors contributing to sharing: Lessons from chicago. *Journal of Transport Geography*, *91*.

N. Gerzinic, S. H.-L. O. C. S. H., N. van Oort. (2022). Potential of on-demand services for urban travel. *Transportation*.

NIBUD. (2022). *Autokosten.* Retrieved 2022, from https://www.nibud.nl/onderwerpen/uitgaven/autokosten/

R. Fan, X. B. (2022). Commuting service platform: Concept and analysis. *Transportation Research Part B*, 18-51.

R. Kucharski, O. C. (2020). Exact matching of attractive shared rides (exmas) for system-wide strategic evaluations. *Transportation Research Part B*, 285-310.

R. Kucharski, O. C. (2022). Simulating two-sided mobility platforms with maassim. *PLoS ONE*, *17*.

S. Djavadian, J. (2017). An agent-based day-to-day adjustment process for modeling 'mobility as a service' with a two-sided flexible transport market. *Transportation Research Part B*, 36-57.

X. Zhan, C. S.-X. C., W. Y. Szeto. (2021). A modified artificial bee colony algorithm for the dynamic ride-hailing sharing problem. *Transportation Research Part E*.