WHAT HAPPENS WHEN SAV FLEETS COMPETE: A FARE-BASED ANALYSIS

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ABSTRACT

In cities across the world, especially those in dense settings, transportation network companies (TNCs) account for a non-trivial mode share. With the introduction of shared autonomous vehicles (SAVs), ride-hailing will become more common. When two TNCs or SAV fleets compete for customers and fares, wait times and other performance metrics are affected. This study simulates the competition between two SAV operators in the Austin, Texas, region. Fare strategies such as a time-of-day (TOD) factor, zone-based surge pricing (ZSP), and a combination of the two are simulated. Customers are assumed to choose operators based on low fare and wait time, after accounting for their preference for an operator. Results from a large-scale agent-based simulator called POLARIS suggest that the implementation of the TOD and ZSP simultaneously appears to be advantageous for fleet operators, as it helps increase their profit. Surprisingly, smaller fleets tend to provide shorter wait times when both operators implement identical pricing strategies. In terms of ride-sharing, similar pricing strategies between operators lead to higher vehicle occupancies, with passengers showing a preference for lower fares, influencing ride-sharing decisions. Finally, the extended operational hours of SAVs, in contrast to TNCs with human drivers, offer a significant operational advantage, enhancing service availability and the potential for increased revenue.

Keywords: SAV, Competition, Time-of-day, Zone-based surge pricing, Fare.

1. BACKGROUND

The usage of on-demand taxi services offered by transportation network companies (TNCs), such as Uber and Lyft, has significantly increased. In 2015, only 15% of Americans had used these services, but by 2018, this number had more than doubled to 36% (Jiang, 2019). In many cities, travelers have the option to choose from two or more TNC operators. Customers make their ride selections based on various factors, such as fare and wait time differences, service quality, loyalty programs, employer-provided benefits, perceived environmental friendliness of the service, and past experiences with TNCs. Many ride-hailing companies also offer enroute pooling or dynamic ridesharing (DRS), where customers can share their rides with strangers for lower fares at the cost of longer travel times.

Autonomous vehicle (AV) use is rising and is expected to bring significant changes in passenger and freight travel over time (Fagnant and Kockelman, 2014). Shared AV (SAV) operators are already providing rides, such as Waymo in Phoenix and San Francisco, Motional in Las Vegas, and Cruise in San Francisco, Phoenix, and Austin. TNCs have three key players: passengers who request rides, drivers who offer rides, and operators matching the passengers to drivers over space and time (Huang et al., 2022; Ni et al., 2021). All three are trying to maximize their own profit (or traveler savings). In the case of SAVs, the situation is simpler, with only passengers and operators interacting in the market.

Studies in the literature have explored TNC competition through various perspectives, contexts, and methodologies. Competition between TNCs and public transit, taxis, and other modes of transport is common. Game-theory-based models have been used widely in simulating competition between TNC operators. For example, Engelhardt et al. (2022) simulated the competition between autonomous ride-pooling services by introducing a broker platform, through which two different kinds of interactions (user decision and broker decision) are compared with a single-operator base case and two independent operators. Ni et al. (2021) used a non-cooperative game-theory-based model to evaluate the behavior of four operators in a ride-sourcing market where the drivers and TNCs aim to maximize their profits, and the passengers' objective is utility maximization. In a San Francisco case study, Li et al. (2021)

used a market equilibrium model to evaluate the impact of minimum wage and congestion charges in a duopolistic setting where two TNCs compete against each other. Bernstein et al. (2018) used a pricing-based game-theoretic approach to evaluate the competition between two platforms (Uber and Lyft). They compared scenarios in which drivers are either restricted to working for one platform or allowed to work for both. In the above studies, TNC competition is studied considering the driver's role. This study on SAVs differs from those above, as the role of the driver is eliminated, and only the fleet managers compete against each other to maximize their profits.

Observed TNC-use data are also used to investigate competition between TNCs, as well as between TNCs and traditional taxi fleets. Huang et al. (2022) evaluated TNC competition using New York City ride-hailing data and found that bigger TNCs benefit from fare competition with pricing and wage strategies that help them gain market shares. The study results also suggest that excessive competition between TNCs makes it economically unsustainable for them to operate and should be limited. Using New York City's taxi data, Jung and Chow (2019) simulated competition between non-electric and electric taxis, and found the daily revenue of non-electric taxis to be 5% higher. With GPS trajectory data from Shenzhen, China, Nie (2017) analyzed the competition between TNCs and the traditional taxi industry and found that taxis compete effectively in high-density areas in peak and off-peak periods. Wang et al. (2022) used a bivariate Tobit model to study the interrelationship between TNCs and traditional taxis using ride data in Xiamen, China. They discovered three different types of relationships–two-way competitive, unilaterally competitive, and complementary–depending on location and time of day.

It is also important to consider how customers select a ride option. Habib (2019) used independent availability and constrained multinomial logit models to evaluate the competition between TNCs (Uber) and taxis using primary household survey data from the greater Toronto area. The results show that younger people prefer Uber, whereas older people are inclined toward taxis, which holds true irrespective of gender. Hu et al. (2022) used SEM to predict traveler selection behavior between TNCs and traditional taxi service modes using survey data from Harbin, China. Similarly, García et al. (2022) carried out a generalized SEM based on a survey in Spain to understand the customers' choices and preferences in choosing ride-sourcing vs traditional taxis, considering individual socio-demographics, psychological attitudes, and mobility-related characteristics.

Public transportation services are often promoted to reduce congestion and emissions. Studies have investigated the competition between TNCs and public transit operators using a variety of methods. For example, Zhu et al. (2021) used a cooperative bi-level game-theoretic model to simulate competition between TNCs and public transit operators. In the upper level, the two operators designed a cooperative plan to solve first-mile last-mile (FMLM) problems, and in the lower level, they individually optimized operational strategies to maximize profits. The proposed model was able to improve FMLM access to transit, albeit by reducing the TNCs' profit. In a Singapore case study conducted by Mo et al. (2021), a game-theoretic approach was used to analyze the competition between SAVs and public transit (PT), both seeking to maximize profit. The competition was evaluated from the perspectives of the SAV operator, PT operator, passengers, and transport authority. Karamanis et al. (2018) used agent-based simulation to investigate the impact of competition between utility-based dynamic pricing with autonomous TNCs and public transport. The study results show that in a competition, shared trips are more popular during peak ride times. Bösch et al. (2018) analyzed the cost structures of traditional public transit, TNC/taxi, and private vehicles and concluded that SAVs would be competitive against private vehicles in all settings, while traditional public transit can still provide value in a dense urban setting. Meredith-Karam et al. (2021) used four different regression models (ordinary least square regression model, fractional regression, spatial log model, and spatial error model) to appreciate the relationship between TNCs and PT use by analyzing individual trip records in Chicago. The dependent variable used in the models is the percent of total TNC trips, and the independent variables include socio-demographics, the TNC network, the PT network, and the built environment. The study evaluated pre- and post-COVID contexts, and found that only 2% of Chicago's TNC trips complement PT. Grahn et al. (2021) also used linear regression to analyze interactions between TNCs and bus services in 10 predefined locations in Pittsburgh, PA. The results show that a university location or bus-way transit influences substitutional behavior between public transit and TNCs.

Several studies have analyzed the competition between TNCs, taxis, and other modes of transport, such as walking and biking, mostly employing discrete choice modeling. Using the 2017 U.S. National Household Travel Survey data, Khattak et al. (2021) calibrated a Bayesian logistic model to assess the choice between TNCs and taxis versus walking. The analysis identified that having a medical condition, requiring longer trip distances, and being tech-savvy are the characteristics that increase the likelihood of preferring TNC and taxi rides over walking. Competition between bicycle-sharing systems and taxis was investigated using a multinomial logit model with New York City data (Faghih-Imani et al., 2017). The results show that during weekdays for trip lengths less than 3 km, the bicycle is either competitive with or faster than taxi mode. These studies used statistical models to evaluate the competition. Similarly, Lee at al. (2022) used a binary logit model was applied to evaluate competition between SAVs and shared electric bicycles through stated preference analysis. Mori et al. (2022) combined revealed and stated preference data to develop a mode choice model and applied it to a network equilibrium model of Nagoya, Japan, to forecast the mode share of SAVs under several scenarios. Guo et al. (2022) studied the competition between SAVs and human-driven private vehicles in Singapore by adding random-utility-based mode choice to a time-space network flow model. The results show that if users are sensitive to the level of service, SAVs can produce higher operating profits. Liu et al. (2022) used a similar approach to model the competition between taxi and ride-hailing services, assessing the effect of fleet size and pricing strategies. The results show that inappropriately low TNC fares are expected to affect the traditional taxi market negatively.

Competition in other shared mobility modes, such as e-scooters, has also been studied. Aarhaug et al. (2023) studied the competition in e-scooter markets in two Norwegian cities, Drammen and Oslo, focusing on price and fleet size. In the first part of the study, they evaluated how a low-cost entry of the e-scooter company in Drammen affected the total market and two incumbent companies. In the second part in Oslo, the fleet size of 8000 e-scooters was evenly divided between 12 companies, and they analyzed the competition between them using GPS location and e-scooter ID data.

The literature reviewed thus far encompasses competition between TNCs considering the driver's role and competition between SAVs and various other modes, including public transit, private vehicles, and micromobility. However, there is a notable knowledge gap: none have specifically explored the competition between two SAV operators considering a wide range of activity-based choices. To this end, this study simulates the competition between two SAV operators in a very large, realistic region using the agent- and activity-based simulator POLARIS (Auld et al., 2016). The use of an agent-based tool allows for the incorporation of diverse choices such as mode, destination, and telecommuting options in the simulation of SAV competition, wherein the two operators offer services independently without a broker platform. The primary objective of this study is to understand how variations in fleet size and fare structures impact the competition between two SAV operators offering dynamic ridesharing (DRS). This approach enables a comprehensive analysis of the pricing strategies each operator may employ in the market to increase their profit.

2. METHODOLOGY

POLARIS, a large-scale agent-based modeling tool, is used to study SAV operator competition. POLARIS has been used to simulate operations of SAVs (Gurumurthy et al., 2020; Gurumurthy and Kockelman, 2022) and Shared Autonomous Electric Vehicles (SAEVs) (Dean et al., 2022; Dean et al., 2023). In POLARIS, person and freight travel can be simulated across large regions using transportation supply and demand models. The demand models, including mode and destination choice models, provide a heterogeneous evaluation of the region's travel demand. Detailed tracking of individual agents and vehicle trajectories at the link level is also available. The impact of different parameter assumptions, such as fleet size, fare, and wait time, on the two competing operators can be captured in great detail. Demand models are aligned with the agent's daily schedule, which is synthesized considering near- and long-term constraints (e.g., workplace choice and vehicle ownership). Final demand is then routed on the network and congestion is captured through a detailed link-level traffic flow model that uses a discretized mesoscopic Newell's model (Souza et al., 2019). High-performance C++ used to build POLARIS ensures efficient simulation of trips made by millions of synthetic agents.

In this paper, the SAV module from Gurumurthy et al. (2020) is extended to include competition between two operators. As in the core module, the vehicles belonging to each operator are distributed throughout the network in a manner inversely proportional to the area of the underlying Traffic Analysis Zones (TAZs). The dispatching algorithm assigns vehicles to requests, while limiting empty vehicle miles traveled (eVMT) and response times (Bischoff and Maciejewski, 2016; Gurumurthy et al., 2020). In the SAV context, the driver is out of the equation, and only the fleet operators and passengers are the primary players. The fleet operator's objective is to maximize their profit by facilitating a high-quality service. Not having to pay driver salaries presents a significant opportunity for cost savings in SAVs (Liu et al., 2020). The passenger's goal is to reach the destination with low fares, minimal wait times for pickups, and a high level of comfort. The competition algorithm implemented here is a heuristic based on the operator-level profit maximization and traveler-level cost minimization. However, each operator is allowed to flexibly define fares, surge factors, discounts, and added fees to attract demand. Customers choose their preferred operator, through a generalized cost function, which includes both fare and wait time. In this study, wait time is assumed to be valued at $1 per minute. Matching algorithms used in the simulation by each operator enforce a minimization of wait time such that the nearest vehicle is matched to a request.

2.1 SAV COMPETITION

Figure 1 illustrates the framework for customers selecting a service provided by an operator. The proposed model involves two SAV operators in competition without a broker platform. The upper level is a multinomial logit mode choice model. The total SAV (taxi) mode share is determined at this level and takes into account average travel times, wait times, and fare estimates, regardless of the operator. These values are calculated using network skims of travel times and distance. In this study, a stable starting point is established by first running POLARIS for the model area. The outputs of this run is used as an input to each of the scenarios. Average fare is calculated using the basic components of base fare, fare per mile, and fare per minute (which are identical the two operators in this study, as later discussed), and fare modifications by pricing strategies are not considered at this level. Therefore, the overall SAV mode share is not affected by the fare strategies. This is to facilitate the comparison between the two operators across scenarios, which is the focus of this study. The lower level is the operator choice model based on the minimization of generalized cost by passengers. When a customer intends to travel from an origin to a destination using an SAV, they compare the expected real-time fares and wait times of the two operators, unless they are a captive traveler who automatically choose their preferred operator without fare considerations. Such loyalty to an operator could be attributed to personal preference due to the type of service received from an operator, the variety of cars in the fleet, and negative experiences with another operator, to name a few. This loyalty concept is implemented to mirror existing offerings by TNCs like Lyft Pink (Lyft, 2023) and Uber One (Uber, 2021), although monthly subscription fees for such services are not considered in this study. The rest of the customers are assumed to have apps for both SAV operators and choose the best option based on fare and wait time when they plan to ride. It should be emphasized that the choice of mode and operator is sequential, not simultaneous as in a nested logit model, which needs to be estimated from data. The proposed approach allows any existing mode choice model to be supplemented by the operator choice model.

In this study, both operators are assumed to offer the same standard service option, associated with a fare. Future studies will consider other service options, such as luxury and large vehicles. The customer selects the service from either operator based on the lowest generalized cost or through loyalty towards an operator. Customers have the choice to select the DRS option in the standard service for a 40% discount, in return for allowing the SAV to serve more customers. However, because the operator has the final say in the matching of vehicles to passengers based on matching feasibility, the discount is only applied if the DRS-requesting customer actually shares the ride with another passenger. This policy is similar to what is currently implemented by Uber for UberX Share (Uber, 2024).

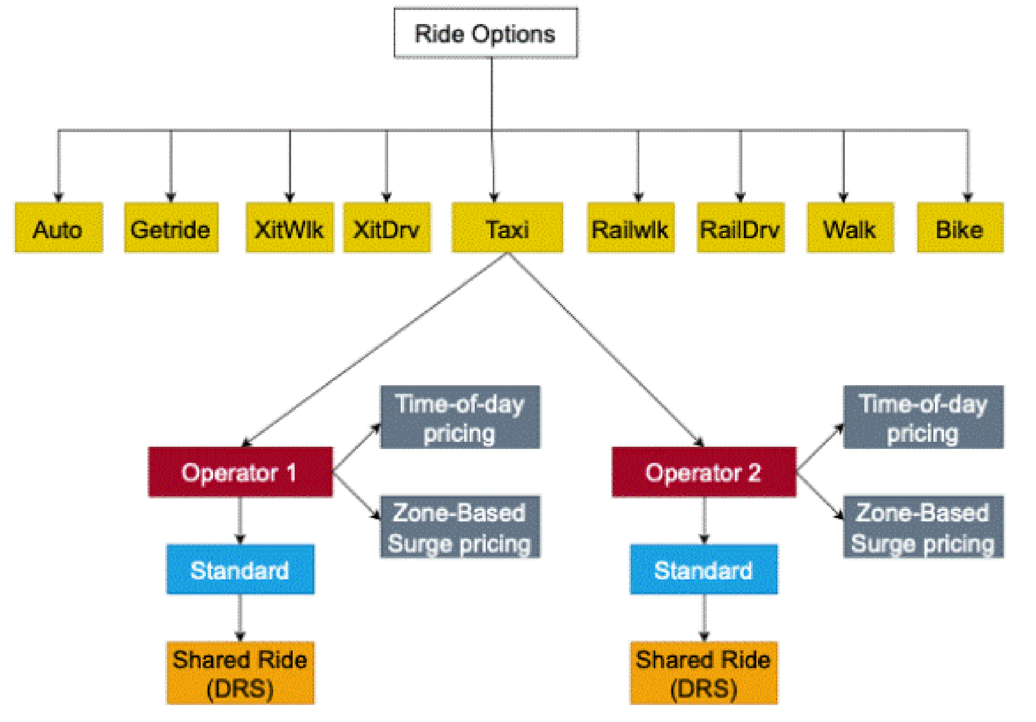

Figure 1 Mode and Operator Choice Framework

The heuristic assigns the vehicles based on customer requests. If the customer requests a ride from a specific operator, the heuristic assigns the nearest vehicle based on the type of service requested. If the DRS option is chosen, the heuristic considers the pickup and drop-off locations of passengers in the SAV and assigns the next possible vehicle within the detour threshold. If customers have both apps for a chosen origin–destination pair, the heuristic assigns the vehicle based on the lowest generalized cost. During peak hours, when demand is high and vehicles are scarce, the wait time for customers is expected to increase. Generally, a larger fleet tends to offer shorter waiting times than a smaller one. If the customer chooses not to take the ride because the wait time is too long, then it is regarded as a decision by the customer to decline the ride.

Total fare relies on three components: a base or "pickup" fare, a fee per mile (while the SAV is occupied by the traveler), and a fee per minute (while occupied). To evaluate the competition between the two operators, three strategies are considered: TOD pricing, ZSP, and the combination of the two. The proposed strategies are discussed in detail in the following sections.

2.1.1 Strategy 1: Time-Of-Day Pricing

In the TOD pricing strategy, higher fares are implemented during two peak time blocks: 6–9 AM and 4–8 PM. The fare multiplier for peak hours, represented as f(T), is implemented. For all other hours outside of the peak periods, normal fares are charged.

Notations

f_T $\quad$ $fare\ for\ the\ ride\ taken\ at\ time\ T$ (\$)

T $\quad$ $Time\ of\ day\ T \in (1,2 \ldots .1440\ minutes)$

ff $\quad$ $Fixed\ fare\ for\ ride\ taken$

Z $\quad$ $Number\ of\ zones\ in\ the\ region$

PU_T $\quad$ $Time\ at\ which\ the\ ride\ is\ taken$

$SM_{T,Z}$ $\quad$ $Surge\ multiplier\ for\ the\ ride\ taken\ at\ time\ T\ in\ zone\ Z$

$S_{T,Z}$ $\quad$ $Supply\ of\ SAV\ to\ passengers\ at\ time\ T\ in\ zone\ Z$

$N_{T,Z}$ $\quad$ $Number\ of\ rides\ at\ time\ T\ in\ zone\ Z$

$$f_T = ff * f(T) \tag{1}$$

$$f(T) = \begin{matrix} 1.5 \\ 1 \end{matrix} \left\{ \begin{matrix} if\ PU_T = T \qquad T\ \in (360\ to\ 540\ min)\ or\ T\ \in (960\ to\ 1200\ min) \\ otherwise \end{matrix} \right. \tag{2}$$

$S_{T,Z}$ encompasses: Idle SAVs, vehicles that are stationary and unoccupied, ready to accept new requests and non-idle SAVs, vehicles that are enroute with passengers but have available seats for additional pickups, provided that taking new passengers is feasible given their current routes and the service constraints.

2.1.2 Strategy 2: Zone-Based Surge Pricing

In this surge pricing strategy, both operators adopt a zone-based approach to determine fare multipliers. The strategy is implemented by comparing the ride requests received in the previous 15 minutes. If the demand in a particular zone exceeds the supply, surge pricing is activated. Otherwise, if the demand is below the supply, normal fares are charged. Rather than predefining the pricing, the model dynamically selects the higher pricing option based on observed ride requests in each zone.

$$f_T = ff * SM_{T,Z} \tag{3}$$

$$SM_{T,Z} = \begin{matrix} 5 \\ 1 \end{matrix} \begin{cases} if \displaystyle\sum_{i=T}^{T-15} N_{i,Z} - S_{i,Z} > 0 & \forall(Z, T > 15) \\ otherwise & \end{cases} \tag{4}$$

$$SM_{T,Z} = 1 \quad \forall(Z, T \leq 15) \tag{5}$$

2.1.3 Strategy 3: Combining TOD and ZSP

This strategy considers both the demand-to-supply ratio in zones and peak hours to determine the surge pricing. If the pickup occurs during peak hours and the demand exceeds supply in that zone, both the TOD and ZSP surcharges are applied to the fare. The combination strategy is applicable only when demand exceeds supply during peak hours. In off-peak hours, if the demand exceeds supply, only the ZSP surcharge is applied, similar to Strategy 2. Additionally, during peak hours, if demand does not exceed supply, only the TOD surcharge is applied, similar to Strategy 1. The TOD pricing is predetermined, while the ZSP is endogenously determined by the model.

$$f_T = ff * f(T) * SM_{T,Z} \tag{6}$$

3. CASE STUDY OF AUSTIN

The study simulates the competition between two SAV operators within the Austin, Texas, region to evaluate the implications of different fleet sizes and fares strategies. In the past, the Austin region has been used as a case study for several SAV (Fagnant and Kockelman, 2018; Fakhrmoosavi et al., 2024; Gurumurthy et al., 2019; Huang et al., 2021) and SAEV (Loeb et al., 2018; Loeb and Kockelman, 2019; Dean et al., 2022; Dean et al., 2023) simulation studies. The fleet was constrained to a six-county Austin metropolitan region, and the road network is shown in Figure 2. The population and area sizes of Austin are 1.8 million and 5,300 square miles, respectively. Furthermore, Austin model has 2,160 TAZs, 16,100 links, and 10,400 nodes. The study evaluates various combinations of strategies employed by the two operators, and the details are presented in Table 1. In all scenarios, passengers are offered a DRS discount of 40%. The TOD and ZSP pricing are set as 1.5 and 5 respectively, but these factors can be adjusted flexibly in the model. It is assumed that the operators are not aware of each other's fare strategies. Operator loyalty among customers is fixed at 20% for both operators (i.e., 40% of passengers choose their preferred operator irrespective of the fare of the other operator), and is determined randomly during operator choice. In each scenario, the SAV demand is derived endogenously from the POLARIS demand model.

Figure 2 6-County Austin Region Network

In all the scenarios, the number of SAVs is assumed to be 10000 for Operator 1 (almost 1 SAV per 180 residents) and 5000 for Operator 2 (almost 1 SAV per 360 residents). Additionally, for both operators, the base fare, or 'pickup' charge, is set at $1. The fee per mile and fee per minute are assumed to be $0.50 and $0.25, respectively. The maximum waiting time for passengers is capped at 15 minutes, after which customers are assumed to cancel the ride. Regarding the operators' expenses, the daily operating costs are assumed as $0.30 per mile, plus an additional $50 per SAV. The operating costs of SAVs include expenses related to fuel, tire wear, maintenance, and other operational factors. These costs were derived from existing literature to ensure accuracy and relevance (Becker et al., 2020; Bösch et al., 2018; Todd Litman, 2023). All the scenarios are evaluated with the DRS option. To save computation time, only 25% of daily trips in the Austin region are simulated.

As shown in Table 1, in the first scenario, serving as the baseline, neither operator employs advanced fare strategies, meaning they both use flat fares. In the following three scenarios, both operators adopt the same pricing strategy. In scenarios 5 through 10, each operator implements a distinct pricing strategy, differing from that of the other operator.

Table 1 Scenarios for Austin Case Study

Scenario #	Operator 1 Pricing Strategy	Operator 2 Pricing Strategy
1	Flat	
2	ZSP	
3	TOD	
4	ZSP + TOD	
5	Flat	ZSP
6	TOD	Flat

7	ZSP+TOD	Flat
8	ZSP	TOD
9	ZSP +TOD	ZSP
10	TOD	ZSP +TOD

4. DISCUSSION OF RESULTS

The results of the 10 scenarios are organized in the following sections. Table 2 presents the fleet performance metrics of the two operators under each of the 10 scenarios. The table provides insights based on several key metrics: average peak hour pick-up wait times, median fare for passenger rides, average daily idle time per SAV, average daily vehicle miles traveled (VMT) by SAVs, average vehicle occupancy (AVO), % eVMT, profit, and demand.

4.1 Wait Times

Table 2 reveals that with flat fares, Operator 2 with the smaller fleet size experiences longer peak hour (6–9 AM and 4–8 PM) wait times than Operator 1. This result initially aligns with the notion that larger fleets generally provide shorter wait times. However, when both operators adopt the same pricing strategy, the operator with the smaller fleet surprisingly offers shorter wait times. This could be due to customer demand patterns, optimized vehicle deployment, and customer loyalty. On the other hand, when the operators implement differing pricing strategies, the average peak hour wait time for pickups is higher for the operator with cheaper fares, which aligns with expectations. The greatest wait time disparity of 37% occurs when one operator uses flat fares and the other employs ZSP strategy, while the smallest difference of 2% is seen when ZSP+TOD and ZSP are implemented by Operators 1 and 2, respectively. This suggests that ride fares significantly influence passenger pick-up wait times under varying strategies. Furthermore, with identical pricing strategies, the operator with the smaller fleet can achieve lower wait times for passengers by leveraging customer demand patterns and optimizing vehicle deployment.

For additional insight into the interplay of pricing, demand pattern and fleet distribution (and consequently wait time), the case of both operators adopting the ZSP strategy is explored further. Figure 3 illustrates the hourly demand for SAV services from the two operators under the ZSP fare strategy. Operator 1, with a larger fleet size, experiences peak demand at 7:00 AM, which gradually decreases to its lowest point at 1:00 PM. The demand then rises again in the afternoon, peaking around 4:00 PM, before tapering off after 8:00 PM. Similarly, for Operator 2, who operates with a smaller fleet, demand is high during the morning hours and rises again during the afternoon and evening periods. Figure 4 provides an hourly analysis of wait times for both operators under the ZSP fare strategy. It is evident that Operator 1 consistently has higher wait times from 2:00 AM to 8:00 PM compared to Operator 2. For example, the wait time for Operator 1 peaks at 8.8 minutes at 7:00 AM, corresponding to the highest demand observed during that hour. Interestingly, even at 4:00 PM, when demand is relatively lower for Operator 1 compared to 7:00 AM, the wait time remains at 8.8 minutes, likely due to fleet redistribution challenges or spatial demand concentration. On the other hand, Operator 2 exhibits relatively stable wait times ranging between 5.5 and 5.9 minutes during peak operating hours (6:00 AM to 8:00 PM), reflecting their ability to better manage demand with fewer vehicles in areas with higher demand density. Although both operators apply the same ZSP strategy and fleet control algorithms, the differences in their fleet sizes and spatial demand distributions result in distinctive outcomes. Operators 1, with its larger fleet, serves more requests overall but faces higher wait times due to dispersed demand and fleet availability constraints. In contrast, Operators 2, with fewer vehicles, operates in areas with higher demand density, maintaining lower wait times. These results reinforce that ZSP can amplify operational disparities between operators of different sizes.

Table 2 Fleet Performance Indicators under Different Pricing Strategy Combinations

Scenario	Operator	Pricing strategy	Avg. peak hour wait time (min)	Median pax fare ($)	Idle time/ SAV/day (hrs)	VMT/ SAV/ day	eVMT (%)	Revenue trip AVO	Profit ($)	Profit/ SAV-mile ($/mi)	Operator demand (p-trips)	Total SAV demand (p-trips)
	1	Flat	4.89 min	$3.5	12.5 hrs	340 mi	24.7%	1.83 pax	$356 K	0.42	404 K	628 K
	2	Flat	4.91	3.8	12.0	354	23.7	2.01	229 K	0.52	224 K	
2	1	ZSP	4.95	12.1	12.5	340	23.2	1.96	2.47 M	2.92	419 K	642 K
	2	ZSP	4.79	14.6	11.8	360	24.1	1.95	1.55 M	3.46	223 K	
3	1	TOD	4.88	4.2	12.3	346	25.0	1.83	531 K	0.62	409 K	636 K
	2	TOD	4.87	4.4	11.9	355	23.5	2.01	334 K	0.76	227 K	
4	1	ZSP+TOD	4.93	14.7	12.6	340	23.2	1.96	3.23 M	3.82	420 K	644 K
	2	ZSP+TOD	4.87	17.4	11.8	359	24.3	1.95	2.00 M	4.46	224 K	
5	1	Flat	5.14	4.1	12.2	351	21.9	2.09	498 K	0.57	447 K	668 K
	2	ZSP	4.76	10.9	11.4	370	28.0	1.71	1.21 M	2.62	221 K	
6	1	TOD	4.86	4.0	12.7	336	25.5	1.77	473 K	0.56	396 K	613 K
	2	Flat	4.89	3.8	12.4	344	23.5	2.02	224 K	0.52	217 K	
7	1	ZSP+TOD	4.85	10.2	13.1	325	25.7	1.69	2.10 M	2.60	367 K	596 K
	2	Flat	4.91	3.9	11.8	362	23.0	2.05	247 K	0.55	229 K	
8	1	ZSP	4.87	9.1	13.0	327	25.2	1.73	1.75 M	2.14	373 K	601 K
	2	TOD	4.90	4.5	11.9	358	23.6	2.04	336 K	0.76	227 K	
9	1	ZSP+TOD	4.83	13.7	12.6	339	23.5	1.92	2.99 M	3.54	418 K	649 K
	2	ZSP	4.85	14.8	11.7	362	24.1	1.98	1.62 M	3.59	231 K	
10	1	TOD	5.12	4.9	12.2	351	22.0	2.08	702 K	0.80	448 K	658 K
	2	ZSP+TOD	4.84	12.7	11.8	357	28.2	1.70	1.45 M	3.26	211 K	

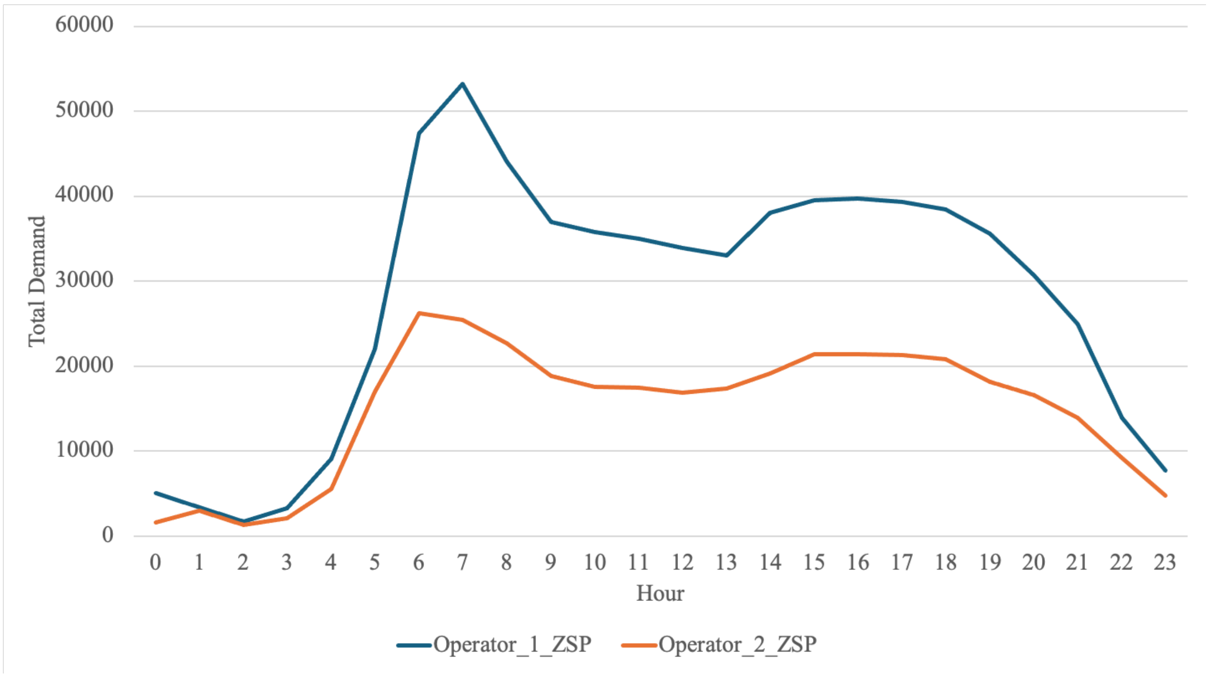

Figure 3 Hourly Demand of Two Operators with ZSP Fare Strategy

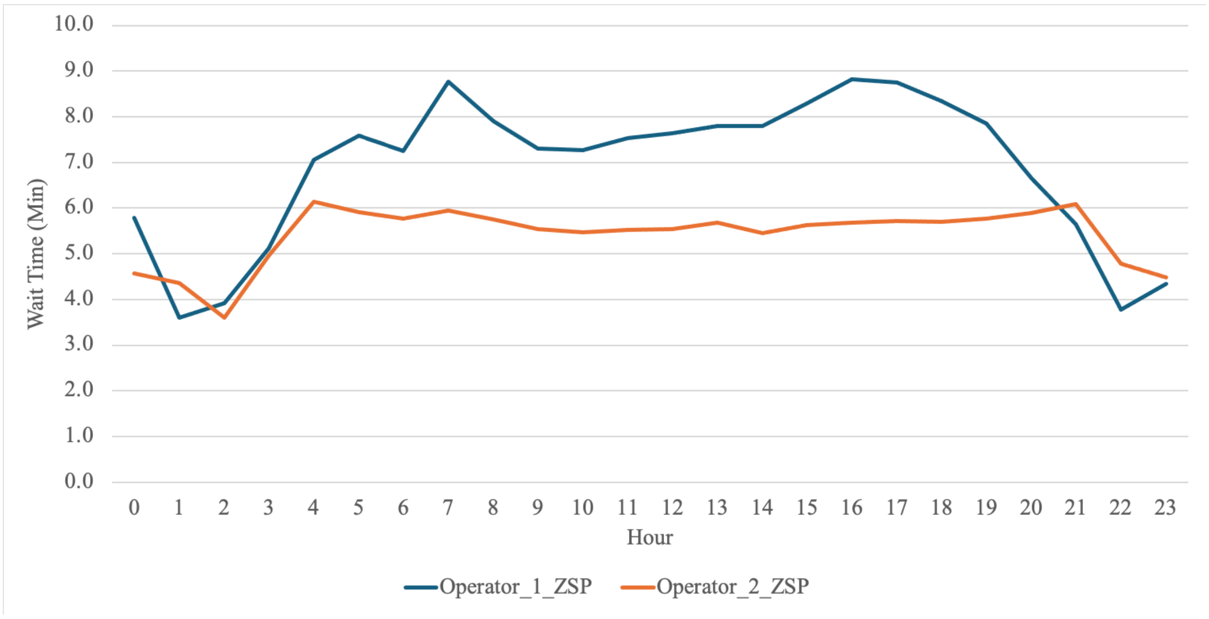

Figure 4 Hourly Wait Times of Two Owners with ZSP Fare Strategy

4.2 Dynamic Ridesharing

Figure 5 illustrates the impact of various pricing strategies by Operators 1 and 2 on their revenue-trip AVO. When both operators adopt flat fares, Operator 2's AVO is higher (2.01) compared to that of Operator 1 (1.83). Operator 2, with a smaller fleet, achieves higher AVO. This is because, the smaller fleet's vehicles are more likely to be occupied at a higher rate due to the limited number of vehicles and the loyal customer base, resulting in higher AVO compared to a larger fleet under the same fare structure. Additionally, both operators experience increased AVOs when they implement the same pricing strategy as opposed to different strategies. This is primarily because similar fare strategies result in higher fares and consequently higher AVOs for both operators. Conversely, when the operators employ differing fare strategies, the AVO tends to be higher for the operator offering lower fares and ranges from 1.98 to 2.09. In contrast, the competing operator's AVO generally falls between 1.69 and 1.77, except for 1.92 when Operator 1 adopts the ZSP+TOD strategy against Operator 2's ZSP strategy. This pattern is logical since passengers often prefer lower fares, and the operator with lower fares also tends to offer more efficient DRS trip matching. Finally, to account for the likelihood of increased ridesharing among passengers, it is important to consider that this tendency escalates when lower fares are offered by the competing operator. Additionally, when both operators employ the same pricing strategy, Operator 2, who operates a smaller fleet, demonstrates superior trip matching efficiency, particularly when a TOD pricing strategy is implemented by both operators. This suggests that factors like fare affordability and fleet size significantly influence the effectiveness of ridesharing and trip matching strategies. In all these scenarios, it is assumed that all users are open to sharing rides, although ultimately, the success of ridesharing programs depend on passengers' willingness to share rides with strangers.

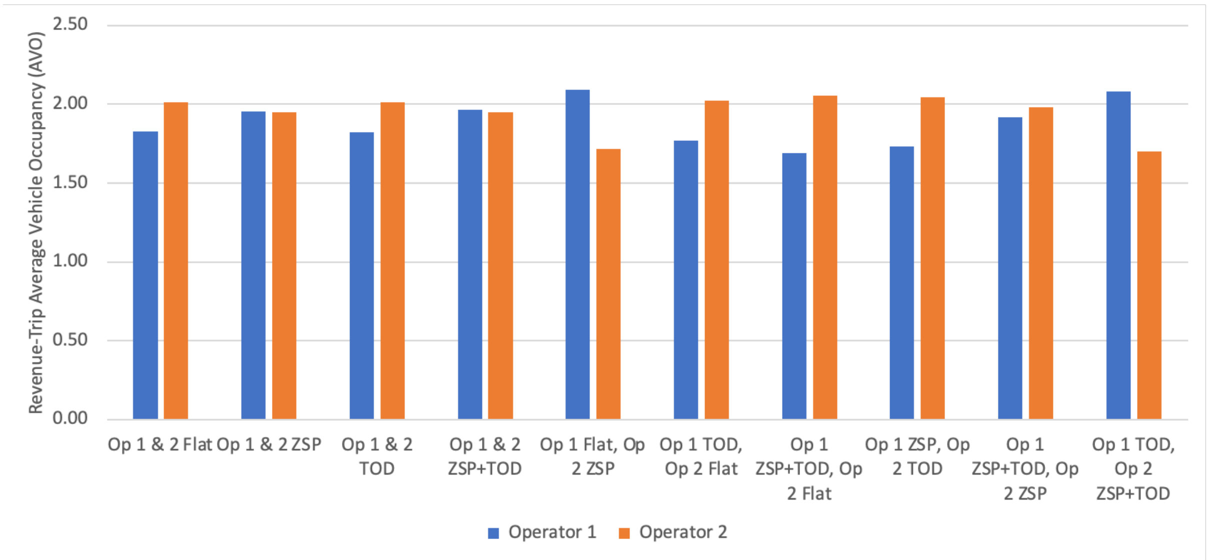

Figure 5 Effect of Pricing Strategies on AVO

4.3 Impact of Pricing Strategies on Operator Revenue

Figures 6 and 7 present the median fares paid and the profits per SAV-mile obtained by the two operators across different pricing strategies. From Figure 6, it can be observed that Operator 2's median passenger fare is \$0.30 (8.5%) higher than that of Operator 1 under the flat-fare scenario. When both operators implement a TOD fare strategy, Operator 2's median fare remains \$0.20 (4.8%) higher than that of Operator 1. In the scenario where both operators adopt ZSP, the profit per SAV-mile is higher for Operator 2 (\$3.46) compared to Operator 1 (\$2.92). This advantage arises because ZSP is triggered when demand exceeds supply in specific zones, allowing operators with smaller fleets, such as Operator 2, to capitalize on higher fares in these high-demand areas. Furthermore, when Operator 1 adopts the TOD strategy while Operator 2 continues with flat fares, Operator 1's median fare is \$0.20 higher than that of Operator 2. The profits per SAV-mile are highest for both operators when they both implement the ZSP+TOD pricing strategy. This is followed by the scenario where one operator adopts ZSP+TOD and the other adopts ZSP. In terms of total profits, Table 2 reveals that when Operator 1 implements flat fares and Operator 2 adopts the ZSP strategy, Operator 1's total profit is higher compared to the case where both operators implement flat fares. Additionally, when Operator 1 implements TOD and Operator 2 adopts ZSP+TOD, Operator 1's total profits in this case are higher than in any other TOD-implemented scenario. These results underscore the significant influence of pricing strategies on competitive dynamics between operators, particularly highlighting the advantages that smaller fleets can gain under dynamic pricing models in urban markets such as Austin.

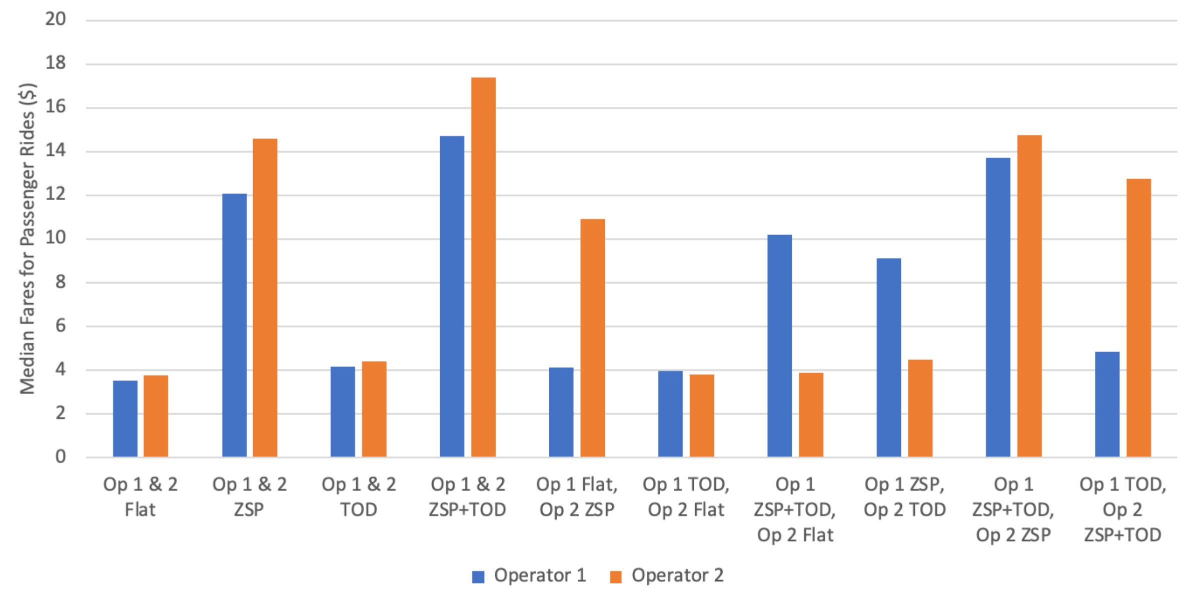

Figure 6 Median Fare for Passenger Rides for the Two Operators under Different Pricing Strategy Combinations

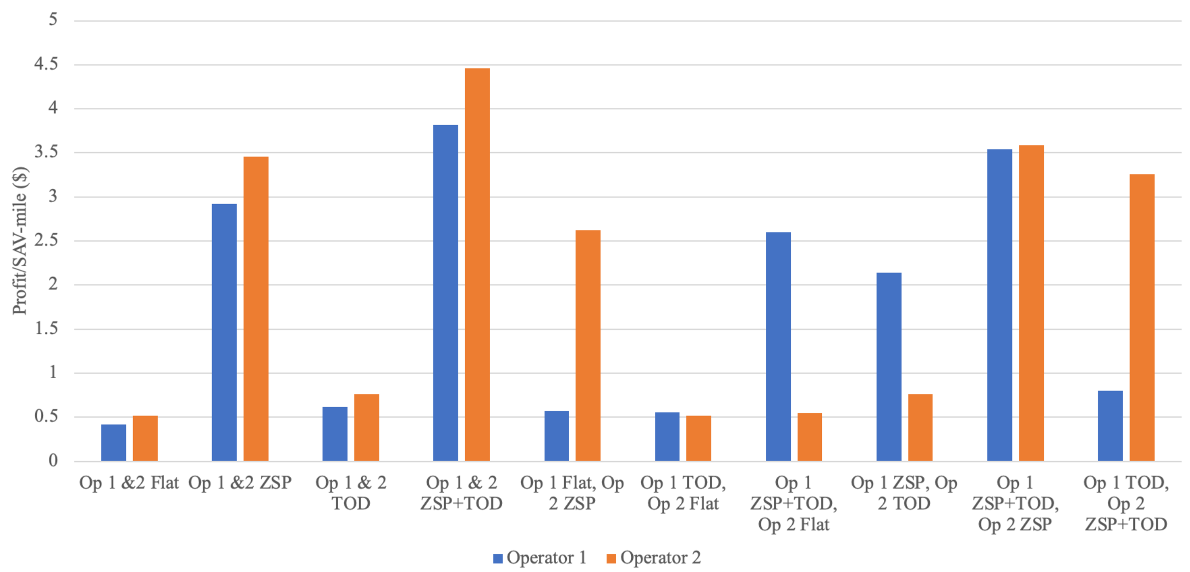

Figure 7 Profit/SAV-mile ($/mi) Obtained by the Two Operators under Different Pricing Strategy Combinations

Figure 8 illustrates the percentage change in demand across different scenarios, with the flat fare scenario serving as the baseline for both Operators 1 and 2. From this figure, it is evident that when Operator 2 implements the ZSP strategy, the demand consistently increases compared to the baseline scenario. The observed increase in demand varies between 0.5% and 6%, indicating that the introduction of ZSP by Operator 2 positively influences demand. However, the dynamics shift when Operator 1 implements a combination of ZSP and TOD pricing while Operator 2 maintains only the ZSP strategy. In this case, compared to the baseline, the demand for Operator 2 decreases. This suggests that Operator 2, who operates a smaller fleet, benefits from the ZSP strategy as long as Operator 1 does not employ the combination strategy of ZSP+TOD.

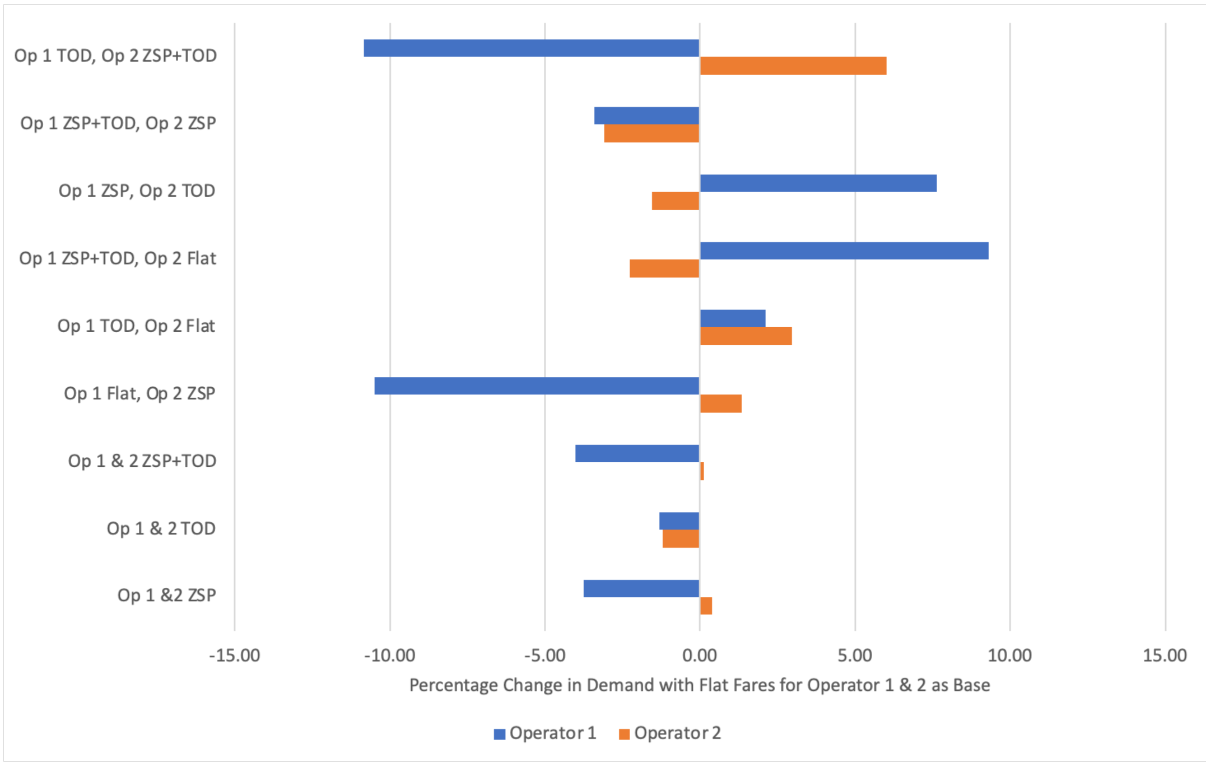

Figure 8 Percentage Change in Operator Demand Compared to Flat Fare Scenario under Different Pricing Strategy Combinations

For example, when Operator 2 employs the ZSP+TOD strategy while Operator 1 only uses a TOD strategy, the demand for Operator 1 decreases by approximately 11%, whereas the demand for Operator 2 increases by about 6%. This indicates that the pricing strategies implemented by one operator can significantly affect the demand for the other, depending on the competitive dynamics and fleet size. Moreover, the results show that the demand for both operators increases relative to the flat fare scenario only when Operator 1 implements the TOD strategy while Operator 2 maintains flat fares. This further underscores the sensitivity of demand to pricing strategies.

In summary, the variations in demand across the different scenarios demonstrate that demand is indeed sensitive to fares and is not static. The differences in demand shifts observed in this study simulations are not solely attributable to customer loyalty but also to the fare strategies employed by the operators.

Furthermore, as shown in Figure 9, when analyzing different fare scenarios with a flat fare as the baseline, there is minimal variation in overall SAV demand for pick-ups and drop-offs within the same zone. However, for pick-up and drop-off across different zones, significant variations emerge across scenarios compared to the flat fare baseline (Figure 10). Notably, in all scenarios except when Operator 1 implements TOD and Operator 2 implements ZSP+TOD, there is an increase in demand.

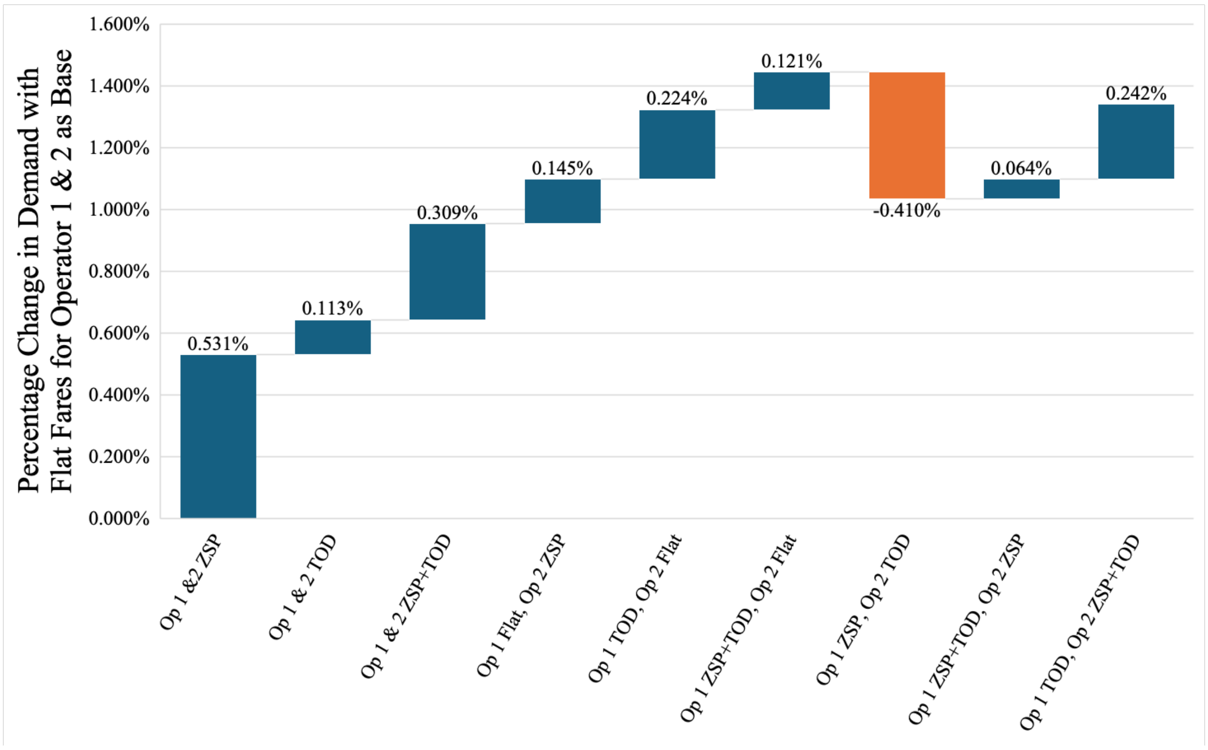

Figure 9 Percentage change in demand under different fare scenarios when pick up and drop in same zone

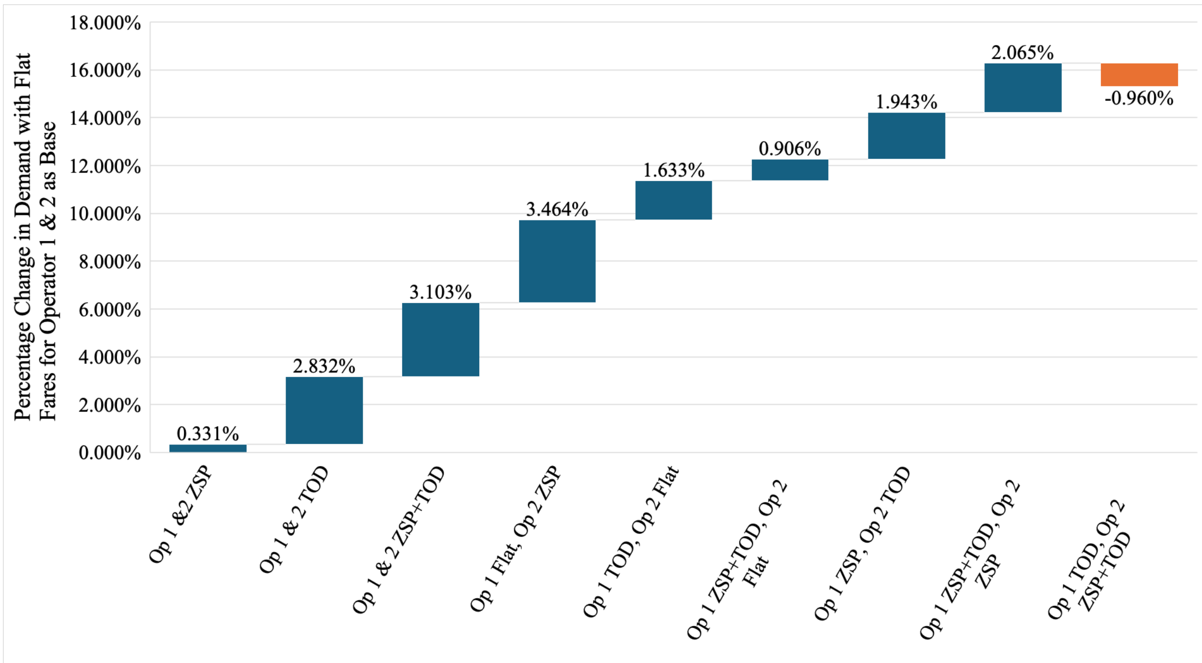

Figure 10 Percentage change in demand under different fare scenarios when pick up and drop in different zone

4.4 Impact of different pricing strategies on eVMT

Figure 11 depicts the percentage change in eVMT for the two operators under various pricing strategies, using the flat fare strategy as a baseline. The emphasis on eVMT is crucial for fleet operators, considering the operating cost of $0.30 per mile. Every mile traveled empty by the fleet represents a direct loss to the operator's revenue, making eVMT a key metric to monitor and minimize for better financial efficiency in fleet operations. In addition, empty travel by SAVs is a key concern from a traffic management perspective. From the figure, it can be observed that when both operators employ the same strategy, such as ZSP or ZSP+TOD, Operator 1's eVMT decreases by about 6%, while Operators 2's eVMT increases by approximately 2%. This change is due to ZSP being activated when demand surpasses supply, allowing Operator 1, who has a larger fleet, to locate the next ride near the drop-off point of the previous passenger more efficiently, unlike Operator 2 with a smaller fleet. Additionally, when Operator 1 uses flat fares and Operator 2 adopts the ZSP strategy, Operator 1's eVMT decreases by 11%, whereas Operator 2's eVMT increases by 18%. This shift can be attributed to Operator 1's competitive fares leading to closer ride matches, while Operator 2, with higher fares, needs to travel further to find the next passenger. A similar pattern is observed when Operator 1 opts for TOD fares and Operator 2 for ZSP+TOD. Operator 1's eVMT decreases by 11% while Operator 2's eVMT increases by 19%. In all scenarios, the operator offering cheaper fares experiences a reduction in eVMT compared to the flat fare strategy, while the eVMT of the competing operator with higher fares increases.

Additionally, from Table 2 it is observed that when the ZSP strategy is employed by both operators (including in combination with TOD, the eVMT of Operator 1 is lower than that of Operator 2. This aligns with expectations, as operators with larger fleets tend to have more vehicles near demand points than those with smaller fleets. From scenario 7 in Table 2, it is noted that when Operator 1 implements ZSP+TOD and Operator 2 implements flat fares, the eVMT of Operator 1 is higher compared to Operator 2. This suggests that competitive pricing allows the operator with the smaller fleet to lower their eVMT compared to the larger fleet operator who implements higher ride fares. A similar pattern is observed in scenario 8, where Operator 1 implements ZSP and Operator 2 implements TOD. Moreover, when only one operator implements ZSP or ZSP+TOD, the eVMT for that operator is consistently higher compared to the other operator. For instance in Table 2, when Operator 2 implements ZSP or ZSP+TOD, while Operator 1 implements TOD or flat fares, the eVMT for Operator 2 is significantly higher compared to Operator 1.

Furthermore, the introduction of ZSP sometimes leads to vehicles being dispatched away from the high-demand zones, which can increase eVMT. This effect can be attributed to the variability in pickup locations, which are not always in close proximity to the previous drop-off points. While this could potentially increase eVMT, operators may still opt to accept this trade-off due to the financial benefits provided by surge pricing, which can significantly enhance profitability. This presents a dilemma for SAV operators: they must balance the objective of minimizing eVMT with the desire to maximize profits. Larger fleets have a natural advantage in this regard, as they can better distribute vehicles across zones to meet demand efficiently. However, smaller operators can also benefit by strategically deploying their vehicles to optimize for both demand and proximity, thereby reducing eVMT while still profiting from surge pricing. Also, consideration should be given to implementing higher fees for trips involving significant eVMT, particularly in rural or less accessible zones. Customer flexibility, such as accepting longer wait times, is another significant factor.

In summary, insights from Figure 11 reveal that larger fleets benefit from ZSP and TOD, experiencing reduced eVMT. Conversely, smaller fleets see an increase in eVMT under these strategies, particularly when competing against lower fares provided by a larger fleet operator.

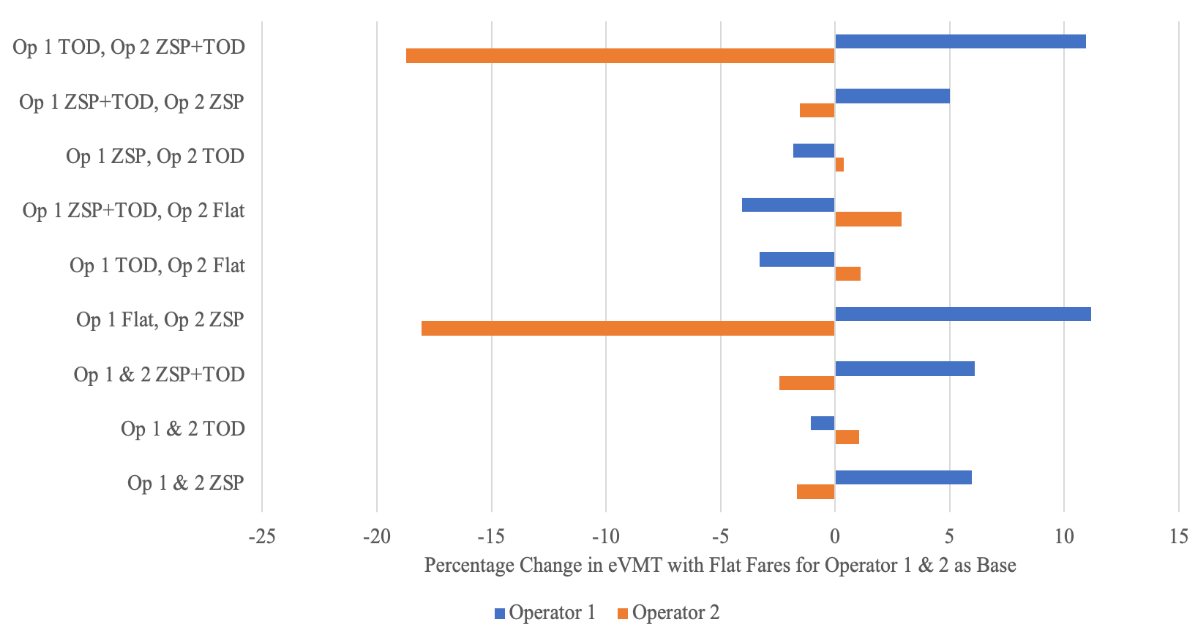

Figure 11 Percentage Change in Operator eVMT Compared to Flat Fare Scenario under Different Pricing Strategy Combinations

4.5 Impact of Various Pricing Strategies on VMT

VMT is a critical metric for evaluating fleet performance. Figure 12 displays the percentage change in VMT across various scenarios, using the flat fare scenario as a baseline for Operators 1 and 2. From the figure, it can be observed that when both operators adopt the same pricing strategy, their VMT consistently shows a decrease compared to the baseline, except when Operator 1 implements ZSP+TOD. Notably, the only scenario where both operators' VMT increases is when one employs TOD pricing and the other sticks to flat fares. This trend may be linked to passenger behavior, as riders often decline rides when fares are significantly high in other scenarios. Furthermore, when Operator 1 combines ZSP and TOD while Operator 2 maintains flat fares, Operator 1's VMT increases by 5%, and Operator 2's decreases by 2% relative to the baseline. This could be due to Operator 1's larger fleet, which is capable of covering more zones and meeting passenger requests more effectively. A similar pattern is observed when Operator 1 uses ZSP and Operator 2 adopts TOD pricing. These insights suggest that fleet size and pricing strategy play pivotal roles in influencing VMT and, by extension, fleet efficiency and profitability.

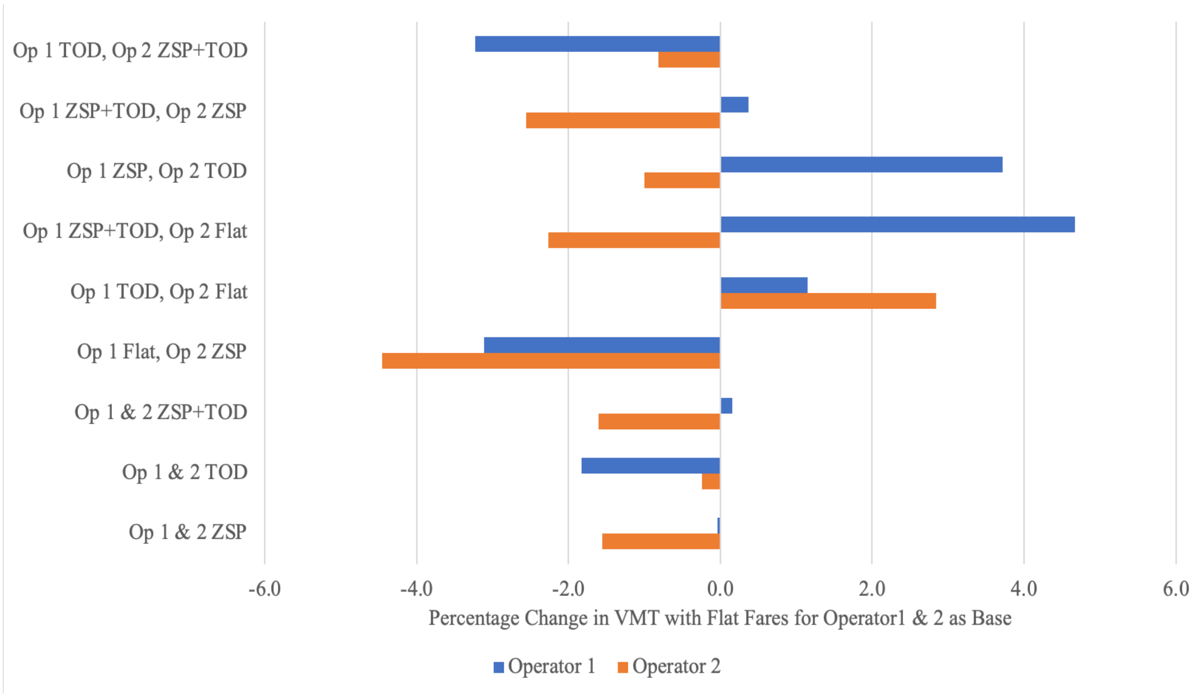

Figure 12 Percent Change in Operator VMT Compared to Flat Fare Scenario under Different Pricing Strategy Combinations

4.6 Idle time under different pricing strategies

From Table 2, it is observed that on average across all scenarios, vehicles operate for 11 to 12 hours per day, which is advantageous from the operators' perspective. This is a notable contrast to TNCs involving human drivers, where driver fatigue often becomes a concern after 8 or 9 hours, limiting service continuity. SAVs do not encounter this issue, offering a significant operational advantage. Additionally, compared to the baseline scenario of flat fares for Operator 2, it is observed that idle time is generally reduced in all other scenarios, with the exception of the scenario where Operator 2 implements flat fares and Operator 1 adopts TOD pricing. For Operator 1, the maximum reduction in idle time compared to the baseline scenario is 2.4% and observed in two specific instances: when Operator 1 implements flat fares while Operator 2 adopts ZSP, and when Operator 1 utilizes TOD pricing while Operator 2 combines ZSP with TOD. This pattern indicates that when Operator 2 employs the ZSP strategy, Operator 1, who operates a larger fleet, can serve more trips. This suggests a competitive dynamic where the larger fleet of Operator 1 is more effectively utilized in scenarios where Operator 2 opts for zone-based surge pricing, potentially due to a better capacity to meet the increased demand or to offer more competitive pricing.

5. CONCLUSION

This study simulated the competition between two SAV fleet operators with different fleet sizes under various pricing strategy combinations. The results indicate that the larger fleet generally offer shorter wait times under flat fare scenarios, but the smaller fleet surprisingly tend to provide shorter wait times when both operators implement identical pricing strategies. This suggests that efficient fleet management and vehicle deployment can outweigh the advantages of fleet size. In terms of DRS, similar pricing strategies between operators lead to higher AVOs, with passengers showing a preference for lower fares, influencing ridesharing decisions. Regarding revenue impact, pricing strategies like ZSP and TOD are found to significantly boost profits and alter fare structures. However, while surge pricing strategies yield higher revenues, they may deter passengers from taking rides due to increased ride costs. Efficient fleet management strategies are crucial, as observed in the reduced eVMT for larger fleets under non-flat pricing scenarios. Moreover, VMT trends indicate that similar pricing strategies result in decreased VMT, underscoring the critical role of strategic pricing in fleet operations. Finally, the extended operational hours of SAVs, in contrast to TNCs with human drivers, offer a significant operational advantage, enhancing service availability and the potential for increased revenue.

Based on the study's findings, several policy recommendations emerge to improve SAV fleet operations. Firstly, SAV fleet operators should be encouraged to adopt efficient fleet management and vehicle deployment strategies, particularly in dynamic pricing environments, to balance fleet size with operational efficiency. Regulatory frameworks need to be established to ensure that pricing strategies like ZSP and TOD maintain a balance between profitability and passenger affordability. Incentives could be provided for fleet operators who demonstrate efficient operational strategies, especially those reducing eVMT and promoting sustainable urban mobility. Smaller fleet operators in particular, may benefit from support mechanisms such as technology grants or operational guidance to help them compete effectively against larger fleets. Regular monitoring and evaluation of the impacts of various pricing strategies on fleet performance and passenger satisfaction are crucial. This will ensure that urban transportation services remain equitable and efficient, improving SAV services for the benefit of both the operators and the public.

6. LIMITATIONS AND FUTURE WORK

The results presented in this work should be interpreted considering some limitations. The assumption that 20% of passengers are loyal to each operator may vary in reality. Additionally, wait time was valued at $1 per minute across all travelers. These factors should be explored with appropriate distributions in future research. Also, it is essential to acknowledge that there may be limits to how much fares (base fare, fare per mile, fare per minute, TOD and ZSP factors) can be increased without negatively impacting passenger demand in real-time. If fares are raised beyond a certain limit, passengers may opt for alternate modes of transportation, which could lead to a reduction in ridership and potential revenue loss for operators. A monthly fee for loyalty program savings or SAV "membership" is not considered here but may be useful to consider in future work. Furthermore, in the current study, the TOD surge pricing is fixed in advance. In future studies, it can be modified to be calculated endogenously by the model.

Also, ZSP is activated as soon as the demand exceeds the supply in a region. However, future modifications could include accommodating varied demand-to-supply ratios. Furthermore, this study only considers the standard option but has the potential to be extended to include multiple options (e.g., large or luxury vehicles) in both operators' fleets. In addition, the combination of service options (standard, large, and luxury) in operators' fleets will be interesting to explore. Nevertheless, with the fast-paced introduction of SAVs in different cities, this study adds significant value to the literature by shedding light on the competition between two SAV operators in a city when they have different fleet sizes and try to implement different fare structures.

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