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# Game Theory in Ride-Sharing Apps: How Uber and Lyft Use Algorithms to Set Prices

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ABSTRACT

Ride-sharing companies like Uber and Lyft use game theory-based pricing models to optimize supply and demand. Dynamic pricing models like surge multipliers change prices based on current conditions, optimizing driver availability when demand is high but not charging consumers a lot. The study examines large-scale strategies like "Uniform Pricing (UP)", "Differential Customer Pricing (DCP)", and "Differential Driver Pricing (DDP)" to understand how they influence market equilibrium. The use of machine learning models imposes predictive values on demand variations in order to accommodate precise fare adjustment. Dynamic price schemes also include the waiting time factor, road congestion, and local demand dynamics to optimize effectiveness and user satisfaction. Outcomes are that dynamic pricing, in conjunction with optimized wait times, encourages overall welfare in minimizing idle time for drivers as well as reducing customer waiting time. However, problems like collusion among drivers, price fairness, and regulatory concerns continue to persist. Future research has to focus on developing ethical pricing strategies, improving transparency in algorithmic decision-making, and promoting cross-platform collaboration in order to ensure a sustainable and fair ride-sharing ecosystem.

**Keywords:** Surge Multipliers, Waiting Time, Dynamic Pricing, Machine Learning, Route congestion

## INTRODUCTION

A newly emerging approach has arisen in the last few years within transportation systems: the utilization of collaborative taxi networks [1]. The phrase social taxi network is used to characterize ride-sourcing programs that provide services to riders through a community of personal automobiles. Taxi riders within these groups engage alongside their clients through utilization of smartphones. Lyft and Uber serve as prime examples for such services [2]. Within various taxicab groups, an increasing number of individuals traveling to and from work rely on mobile devices which enable clients to find providers of transport according to their respective geographical areas [3].

Similarly, vendors of services, such as taxi drivers, rely on applications for smartphones to link them with prospective clients according to their geographical vicinity. Since these applications operate upon a spatial schedule, operators select what they want in areas, an alteration with the supply and demand balance being inevitable. Each taxi driver's reasonable decision is to select a location with a heightened likelihood of attracting customers who are interested. For instance, urban centers and retail regions are locales that possess significant appeal to consumers [4].

A significant number of these consumers require door-to-door transportation solutions. Nonetheless, given that this information is well recognized, the majority of service providers focuses on these regions. This resulted in certain regions being excessively saturated by service providers, while others exhibit a scarcity or complete absence of such vendors. Therefore, the bulk about applications for smartphones managing multiple taxi connections have a dynamic pricing model which fluctuates according to service availability [5]. During periods of high demand, transportation costs are elevated, and conversely, these are reduced during off-peak times.

Current alternatives to various taxi service providers such as Uber and Lyft utilize demand-driven strategies like dynamic pricing or pre-established fares [7]. Such strategies integrate dynamic multipliers into the pricing framework. The following structure is susceptible to the phenomenon known as the tragedy of the commons, [8] It relates to scenarios when assets become communal and those making decisions operate in their individual self-interest. The pricing escalation strategy relies on self-scheduling since it is mostly effective and dependable among vehicle operators and service consumers. The objective of the subsequent study is not to provide a replacement, however, to present a method that enhances the current self-scheduling technology. The suggested method depends on addressing the regional allocation issue. The challenge of efficiently assigning the way to workers according to their preferences and personal schedules is referred to as a region sharing game.

A multitude of factors might complicate the territorial allocation game. The primary issue lies in organizing the game to enable the creation of a beneficial model. The game comprises three components: the participants, the smartphone application, as well as the utilized assets. The sophisticated program can function both as a participant or a game overseer. The configuration of the game differ according to its desired objective. Furthermore, if players utilize commodities as techniques throughout their associations, the game can be categorized as either symmetric or asymmetric. In symmetric games, the participants possess identical sets of strategies. A game is deemed symmetric when only two possible actions are accessible to all players. Asymmetric games are generally more inclusive since players may possess varying strategic approaches.

Thus, it is crucial to ascertain if the activity is symmetric or asymmetric. Moreover, after defining a game's attributes, a subsequent issue emerges in identifying a solution mechanism which can produce a stable outcome. A stable outcome is a self-sustaining result that meets specific conditions. This introduces an additional challenge in delineating the territory-sharing game. In game theory, a constant strategy denotes a stable equilibrium. Three principal varieties of equilibria may be identified: The previously prevailing methodology equilibrium, Nash equilibrium, linked to a state of equilibrium [9]. Establishing the preferred equilibrium enables the creation of an effective model. This also guide the assessment of the obtained solution, which presents the final challenge: evaluating the effect of the suggested model on performance as a whole (i.e., system welfare). The question of territorial sharing illustrates the tragedy of the commons; thus, a stable resolution does not guarantee effective resource exploitation. The "Price of Anarchy (PoA)" is employed to determine the (in) efficiency of the proposed solution.

Ride-sharing apps like Uber and Lyft use game theory to optimize pricing and match riders with drivers efficiently. Their algorithms analyze supply, demand, and competition to adjust fares dynamically, ensuring a balance between driver availability and customer affordability. Surge pricing increases fares when demand is high, encouraging more drivers to participate, while lower prices attract riders during off-peak times. This strategic pricing model helps maximize profits, reduce wait times, and improve overall service efficiency.

**Aim of the study**

The current research tries to examine the contribution game theory to ride-sharing companies such as Uber and Lyft through pricing algorithms, surge multipliers, and market equilibrium strategies. The research focuses on the effect of dynamic pricing on drivers' participation, customers' affordability, and efficiency of the system. Moreover, the research contrasts various models of pricing— UP, DCP, and DDP —in order to assess their suitability in the ride-sharing platform's sustainability. Through the determination of issues like driver collusion, price equity, and regulatory issues, the research aims to contribute towards more efficient and equitable ride-sharing price models.

## REVIEW OF LITERATURE

Kim et al. (2025) [15] presented a new method of analysis of strategic interactions on transportation networks through Mobility-on-Demand (MoD) services. Their study focuses on reaching equilibria among firms and customers, where a single firm optimizes pricing and route planning strategies for greater profitability while considering travelers' mode choice through a multinomial logit framework. They point to distinctive challenges in the implementation of profit maximization strategies for transportation networks owing to the effect of network topology and other constraints. Likewise, Cummings et al. (2025) [16] suggested that some of the services can be outsourced by transit agencies to MoD providers, which would result in better quality of service, increased coverage, and lower costs. Their fare-setting strategy simultaneously optimizes fares and discounts within a multimodal system through a two-stage decomposition procedure, ensuring fair treatment and efficacy with regard to transit and profit-maximizing goals.

Koirala et al. (2024) [11] analyzed the competition between ride-sharing platforms like Uber and Lyft, highlighting their dual function of attracting both drivers and passengers. They contended that in theory, competition should translate to improved payouts for drivers, but empirical evidence indicates otherwise. According to their findings, a profitable duopoly can only be achieved if platforms collude to reduce driver wages. Dong et al. (2024) [12] also investigated the effectiveness of ride-sharing systems in analyzing cooperative markets where platforms pool trip requests to achieve maximum efficiency. Their work suggested a dynamic graph-based approach proving that collaboration enhances trip matches, minimizes travel distances, and maximizes overall profitability relative to competitive frameworks, where segmentation limits potential matches.

Katsamakas et al. (2024) [13] proposed the notion of responsible users who decide on the basis of corporate social responsibility (CSR) preferences. Their work investigated market asymmetries and their effects on platform pricing and competition and concluded that user CSR preferences drive platform strategies irrespective of how they are derived. Their work adds to the platform competition literature by incorporating responsible user behavior into strategic decision-making. On another occasion, Tripathy et al. (2023) [14] examined ride-hailing drivers' collusion on ride-hailing platforms and discovered that drivers switch off strategically in order to form artificial shortages and thus induce surge prices. This explanatory framework stresses that cooperative behavior is more likely where customers do not show great reactivity toward waiting times but are instead motivated to benefit the platform by virtue of increased surge prices.

Game theory plays a crucial role in shaping ride-sharing pricing, competition, and strategic behavior. Chenkai et al. (2023) [15] analyzed collusion among drivers, showing that they go offline when fares are low and return when prices rise, leading to cyclic price fluctuations. Their continuous-time, non-atomic model proved that such behavior forms a Nash equilibrium but results in lower payoffs in dense markets. They suggested price floor mechanisms to stabilize the market. Amar et al. (2023) [16] applied game theory to the territory-sharing problem in social taxi networks, using a bargaining-based solution that ensures a no-regret outcome, leading to a fair and efficient allocation of ride-sharing territories.

Matching and driver experience issues have also been investigated using game-theoretic methods. Gao et al. (2022) [17] proposed the VOMA mechanism, a voting-based method that maintains privacy while maximizing ride-matching in community ride-sharing. Their method balances drivers' and riders' preferences without full data revelation. Cram et al. (2022) [18] studied the effects of algorithmic control on Uber drivers, finding both positive and negative techno-stress effects. Transparent algorithmic control was also discovered to improve commitment and lower negative stress. These studies give a balanced understanding of competition, pricing, and driver well-being in ride-sharing markets.

### 2.1 Research Gap

Even with continuous research offering informative feedback on ride-sharing game theory, there are some areas that remain to be addressed. To start with, previous studies emphasize competition and profit maximization but lack detail in explaining how algorithmic pricing tools affect driver retention and long-term sustainability. Second, though the study refers to collusion and surge pricing, limited information is cited about regulatory response and its efficiency in curbing market distortions. Third, cross-platform coordination is shown to be a likely source of efficiency, but its feasibility and probable disadvantages are yet to be studied in depth. Lastly, the moral impacts of algorithmic pricing, especially on poor consumers and market equity, must be studied further. Closing such knowledge gaps has the potential to result in fuller knowledge of how game theory may be utilized to drive pricing efficiency with an even and sustainable ride-sharing market.

## RESEARCH METHODOLOGY

This research examines ride-sharing price models, including dynamic pricing, price-matching algorithms, and market equilibrium. It examines surge pricing for supply-demand matching, explores matching techniques like the first-dispatch protocol and batching, and employs a game-theoretic framework to examine Nash equilibrium in pricing behavior. The study evaluates uniform pricing, differential customer pricing, and differential driver pricing, stressing the way algorithmic pricing raises efficiency, revenue, and service offer.

### 3.1 Analysis of Ride-Sharing Pricing Model

The analysis of ride-sharing price systems targets dynamic prices, surge multipliers, and price-matching algorithms for the purpose of optimizing fares in real-time demand and supply. These maximize efficiency by targeting driver availability and customer affordability. Game-theoretic solutions also guarantee balance, optimizing revenue while ensuring service reliability.

#### 3.1.1 Dynamic Pricing and Surge Pricing Algorithm

The use of dynamic prices in sharing rides, exemplified by Uber's surge pricing, modifies fares according to real-time demand and supply fluctuations. When demand surpasses the number of available automobile drivers, surge multipliers elevate rates to incentivize additional drivers to participate. Dynamic programming utilizes steady-state models to forecast short-term variations in supply, demand, and price elasticity.

The steady-state travel throughput, defined as the mean number of journeys performed per unit of time, is represented by Y. We subsequently possess the flow balance equation.

$$L = \overbrace{O}^{open} + \overbrace{\eta . Y}^{en\,route} + \overbrace{T . Y}^{on-trip} \qquad (1)$$

Let O signify the quantity of open drivers, $\eta$ indicate the en route duration, $\eta \cdot$ Y denote the count of en route drivers, and T · Y represent the number of drivers currently on trip. The travel time $\eta$ is contingent upon the quantity of available drivers: a reduced quantity of available drivers O results in an increased travel duration.

When the driver supply is low, longer en route times reduce efficiency and earnings, causing some drivers to leave, further worsening availability. Drivers also make strategic decisions on when and where to operate based on surge pricing, making DP essential for balancing the platform's efficiency and earnings.

### 3.1.2 Price Matching Algorithm

Ride-sharing services can offer non-shared rides (e.g., UberX) or shared rides (e.g., Uber Pool). In non-shared trips, drivers transition between three phases: open (awaiting dispatch), en route (driving to the pickup location), and on-trip (transporting riders to their destination).

In the uncomplicated scenario of a non-shared ride, drivers utilizing the platform progress through three successive states: "open"—awaiting dispatch, "en route"—traveling toward the pickup location, and "on-trip"—transporting riders to their final destination, as seen here.

··· → open → en route → on-trip → open → ···

Matching requests to drivers can be done through the first-dispatch protocol, where the nearest available driver is assigned immediately. Alternatively, batching consolidates multiple requests before dispatching, improving efficiency, and reducing rider wait times compared to the first-dispatch approach.

The comprehensive mathematical description is as follows. Let N and M represent each set of rider node and driver nodes inside the same batch, accordingly. The value of the binary decision variable $x_{ij}$ assigns a value of 1 if rider i is paired with driver j, and 0 if not.. The compensation for pairing rider i with driver j is represented by $r_{ij}$. The matching problem is expressed as the following integer program.

$$\max_{x} \sum_{i \epsilon N} \sum_{j \epsilon M} r_{ij} x_{ij} \qquad (2)$$

$$s.t \quad \sum_j x_{ij} \leq 1, \qquad \forall i \in N, \qquad (3)$$

$$\sum_j x_{ij} \leq 1, \qquad \forall j \in M, \qquad (4)$$

$$x_{ij} \in \{0,1\}, \qquad \forall i \in N, \qquad \forall j \in M. \qquad (5)$$

The described matching algorithms are myopic, as they do not account for future demand or supply. While forward-looking algorithm offer theoretical benefits, they require complex input calibration, making implementation challenging. Modern algorithms rely on supplementary forecasts, including variable supply and demand arrival rates, to enhance matching performance.

### 3.1.3 Market Equilibrium

Market equilibrium in ride-sharing occurs when ride requests match fulfilled trips in a steady-state system, modeled using a fluid approximation where riders and drivers are matched in fractional quantities.

A game-theoretic approach is used to analyze how pricing algorithms influence market equilibrium. Platforms like Uber and Lyft use surge pricing to balance supply and demand, affecting driver participation and rider willingness to pay. Treating pricing as a strategic player, the analysis examines Nash equilibrium conditions where drivers and riders optimize their payoffs. This provides insights into how algorithm-driven pricing ensures efficiency, maximizes revenue, and maintains service availability while considering driver incentives and rider demand elasticity.

### 3.2 Types of Ride-Sharing Pricing model

The ride-share platform utilizes price and compensation to balance supply and demand. We have constructed a framework to determine the platform's ideal pricing approach. There are various models, including uniform price, differential customer pricing, and differential driver pricing.

#### 3.2.1 Uniform pricing model (UP)

They first outline the standard method within the uniform price concept. The total number of consumers in the marketplace is λ. Let $v_T$ = $v$ and $v_R$= $hv_T$ indicate the consumer's assessment The combination of the transportation provider and the ride-share service, here he represents the extent to which clients prefer the service that provides rides over the taxi service.

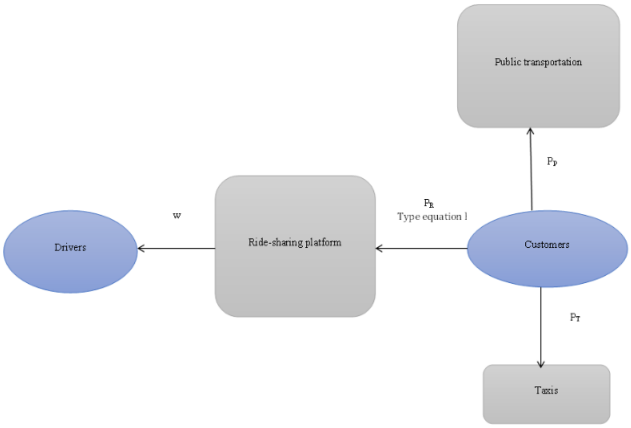


**Fig.1** Uniform Pricing Model

If customers select alternative travel alternatives, they must prepare to pay price pk. To simplify the discussion, they assign a consumer value and expense of zero to public transit due to its poor quality and cost relative to ride-sharing and taxi services. As a result, customer utility is

$U_k$ = $v_k - p_k$ k = R, T, P.

When the utility derived from selecting the ride-sharing service exceeds those of the taxi service and is greater than zero, customers are going to register and submit queries to the platform for rides.

#### 3.2.2 Differential customer pricing model (DCP)

A platform frequently employs a differential customer pricing approach through segmenting clients and imposing varied prices to acquire a larger clientele. For instance, Uber frequently provides discounts to those who are new or those with infrequent usage.

The platform provides value to a customer that not engage with this value, v ∈ [0, ˆ v) a discount coupon c to incentivize the client to select the platform as their choice. The platform has a pair pricing categories: firstly, is the regular price $p_R$ while the other is the discounted price $p_R$− c.

For clients who receive the regular price $p_R$ (the discounted price $p_R$−c), we denote rϕ (−rϕ) as the utility gain (loss) that results from the platform's differential pricing. r denotes the fairness concerns of customers. ϕ represents the price difference, which is $p_R$− ($p_R$ −c) = c. Therefore, customer utility is

$$U_R = \begin{cases} v_R - p_R - r\varphi, & v \in [\hat{v}, 1] \\ v_R - p_R - c + r\varphi, & v \in [o, \hat{v}] \end{cases}$$

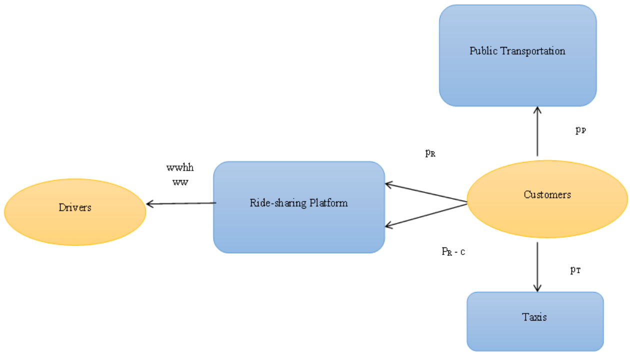


**Fig.2** Differential customer pricing model

#### 3.2.3 Differential driver pricing model (DDP)

As two-sided markets, ride-sharing platforms can implement variable price for both clients and operators. The driver's usefulness is rendered ineffective because δ ∈ [ˆ δ, 1]. Consequently, the scheme offer incentives to motorists who are not currently participating, with the goal to incentivize their enrollment.

In summary, drivers may get two distinct wages: the standard rate w and the supported wage w + s. Drivers who receive a standard wage may nevertheless opt to participate due to their earnings reference-dependent choices, signifying a daily income objective they aspire to achieve.

As drivers are concerned about fairness in a manner akin to our reflection of client problems, we signify e ψ (−e ψ) represents the utility gain (loss) arising from the platform's price differential, where e denotes drivers' worries regarding equity. ψ represents the wage difference, which is (w + s) − w = s. Driver utility is w − δ − e ψ when δ ∈ [0, ˆ δ) and w +s − δ + e ψ when δ ∈ [ˆ δ,1]. The aggregate number of registered drivers is KR = K (w − e ψ) + K (w + s+ e ψ −w) = K(w + s).

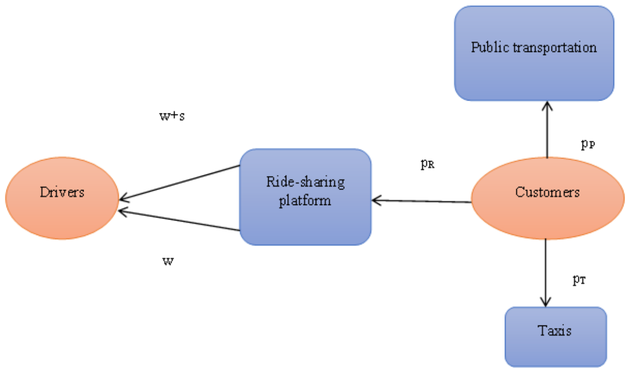


**Fig. 3** Differential driver pricing model (D)

## RESULT AND EVALUATION

The results indicate that dynamic pricing effectively adjusts fares with rising demand, showing exponential price growth during peak periods to balance supply and demand. Dynamic waiting-time surge multipliers maintain market stability better than static pricing models. Additionally, welfare peaks at a surge multiplier of 1.5, confirming that dynamic waiting strategies improve overall system efficiency.

### 4.1 Dynamic Pricing and Demand Relationship

This discussion explores how the fare price changes with ride demand. The diagram illustrates how levels of demand relate to fare prices under a dynamic fare pricing model. At a demand level of 1, which is low, the fare price is approximately $4. The fare is approximately $10 at a demand level of 5, which is the equilibrium fare when demand equals supply. Over this, prices rose sharply to $20-$27 at high demand levels (8-10). This is characteristic of surge pricing, which incentivizes more drivers to join during high-demand periods. The trend is one of non-linear price escalation, i.e., prices rise exponentially with demand, to ensure efficient market balance and driver availability.

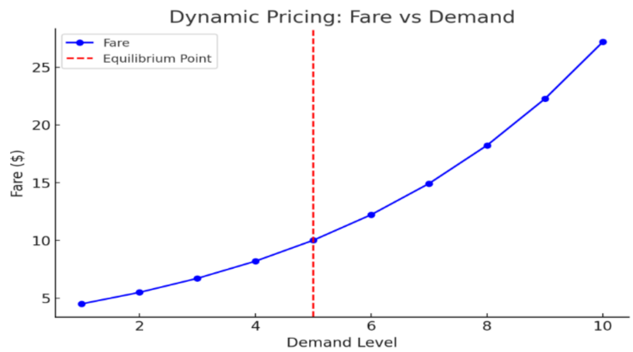


**Fig. 4** Dynamic Pricing: Fare vs. Demand

### 4.2 Optimal Surge Multipliers Across Different Pricing Strategies

The graph is a contrast between theoretical surge multipliers and differing 24-hour pricing schemes. Dynamic waiting-time-based surge pricing (blue line) ranges from 0.2 to 0.6, signifying that it responds to supply and demand changes. Dynamic pricing (red line) without waiting time has peaks because, at hour 9, the price level is 1.2, signaling periods of high demand. Static waiting pricing (green line) is flat at 1.0, or no change. Waiting static pricing (purple line) is low at around 0.2 to 0.3. This type of trend guarantees that dynamic pricing is less sensitive to demand changes, enabling the market to remain well-balanced.

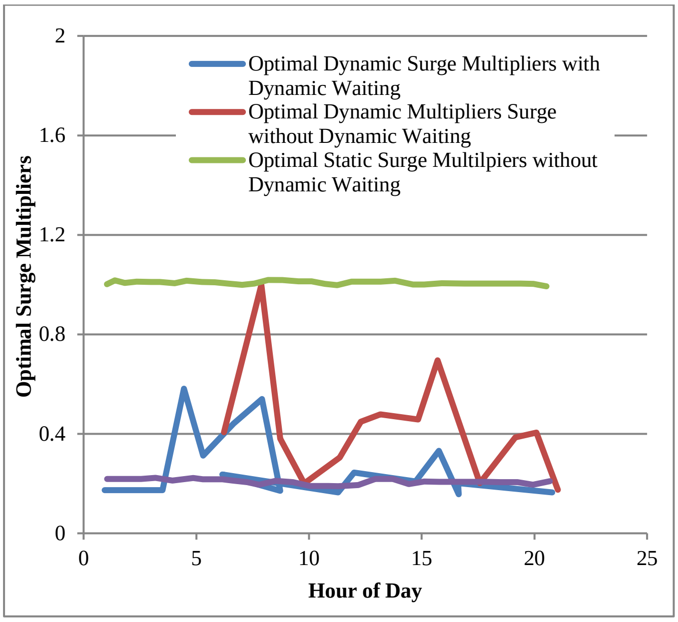


**Fig. 5** Optimal Surge Multipliers across Pricing Strategies

### 4.3 Impact of Surge Multipliers on Welfare

The graph shows the impact of surge multipliers on welfare, both in dynamic waiting (blue line) and non-dynamic waiting (red line). Welfare goes up with surge multipliers, to a peak at 1.5, where dynamic waiting is 250 units and non-dynamic waiting is 240 units. Welfare goes down after this. The findings point out that dynamic waiting enhances overall welfare, such that efficiency in demand-supply balance is enhanced.

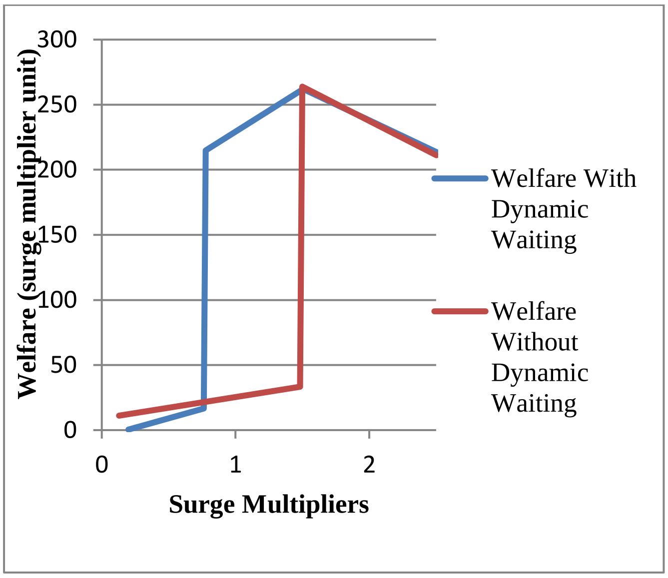


**Fig. 6** Impact of Surge Multipliers on Welfare

## CONCLUSION

The present study examined the role of dynamic pricing, surge pricing, and game-theoretic methods in ride-sharing platforms like Uber and Lyft. The study confirmed that pricing algorithms, particularly surge multipliers, function well to balance supply and demand by encouraging driver participation and regulating customer demand. The findings confirm that waiting time dynamic pricing is more efficient, as seen in welfare maximization trends. In addition, market equilibrium models show that ride-sharing platforms optimize driver assignments and pricing controls to guarantee service reliability and profitability.

The comparison of various pricing models— UP, DCP, and DDP —also favors the platform sustainability effect of strategic pricing. While simplicity is guaranteed with uniform pricing, differential pricing models induce greater usage by customers and driver loyalty. However, problems like collusion and price fairness among drivers are persistent issues. Theory and empirical studies in the future can be directed towards examining regulatory response, cross-platform interaction, and ethical issues in designing a sustainable and fair ride-sharing market.

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