More Than a Match: Balancing Match Quality and Labor Supply via Allocation Algorithm on Gig Platforms[*]

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ABSTRACT

Gig platforms often match demand to supply via allocation algorithms that prioritize workers who provide high-quality service. Using data from a large on-demand delivery platform that matches shippers with independent drivers, we document how the prioritization allocation mechanism directs more orders toward high-quality drivers, improving customer satisfaction and leading to higher hourly earnings for these drivers. To evaluate the welfare implications of such an allocation algorithm and explore its optimal design, we develop a structural model that nests quality-based prioritization in a frictional matching environment with endogenous labor supply. Counterfactual analyses reveal a central trade-off in the design of allocation algorithms: prioritizing high-quality workers can improve match quality and customer satisfaction, but also depress earning opportunities for low-quality workers and discourage their participation, which may shrink total labor supply and ultimately erode platform profitability. Our findings underscore the importance of balancing match quality with labor supply in the design of allocation algorithms.

Keywords: Allocation Algorithm, Two-Sided Platforms, Labor Supply, Structural Modeling

1 Introduction

The rapid rise of two-sided digital platforms has fundamentally transformed the organization of work in the gig economy. A central design problem for these platforms is how to efficiently allocate demand (e.g., ride requests, delivery orders, service tasks) to the supply (e.g., drivers, freelancers) at scale and in real time. Increasingly, platforms use algorithmic - often "quality-based" - allocation mechanisms that prioritize workers with stronger historical performance (e.g., higher ratings, on-time rates, or tenure).

These algorithms can raise average service quality and user satisfaction by matching customers with better-performing providers. At the same time, they reshape labor supply incentives by distributing earning opportunities for workers. Prioritizing high-quality workers typically improves consumer outcomes, such as higher acceptance and lower cancellation, but it may depress earning opportunities for lower-quality or newer workers, discouraging their participation. Such reduced participation lowers labor supply and thus ultimately undermines platform profits. We therefore ask: what are the welfare consequences of a quality-based allocation mechanism? How should the platform balance between consumer satisfaction with sustaining worker participation when designing the allocation algorithms?

We study these questions in the context of a leading on-demand logistics platform in China that matches shippers with independent drivers for delivery services. This institutional setting is well-suited to our questions: drivers apply for the shipping order; the platform allocates the order to exactly one applicant; the shipper then chooses to accept or cancel after viewing the assigned driver's attributes. Importantly, we observe complete application sets for each order, allowing us to recover the platform's allocation rules and the distribution of opportunities across driver types. Using a learning-to-rank machine learning model trained on actual assignment outcomes, we show that the platform systematically favors drivers with stronger performance records (e.g., higher behavioral scores, higher ratings, more completed orders, longer tenure, and better on-time histories), which is consistent with a quality-based prioritization rule. Building on this evidence, we classify drivers into two groups: high-score drivers, who are prioritized by the algorithm, and low-score drivers, who are ranked lower in the allocation process.

We begin with reduced-form evidence that connects the allocation rule to shipper preferences and to differential earnings. We find that shippers are significantly more likely to accept high-score drivers, indicating that prioritization aligns with demand-side preferences. Moreover, conditional on working in the same hour, high-score drivers earn roughly 15% more per hour than low-score drivers because they receive more assignments and cover longer distances within those hours. Together, these facts indicate that prioritizing high-score drivers improves match quality from the consumer's perspective while concentrating revenue opportunities among high-score drivers. They also motivate the central tradeoff in the design of allocation algorithms for platforms: prioritization toward high-score drivers improves consumer satisfaction but risks discouraging participation by lower-score drivers.

To move from partial correlations to equilibrium implications, we develop and estimate a structural model of a two-sided market with endogenous labor supply and an explicit algorithmic allocation rule. On the demand side, the aggregate shipping demand follows a constant-elasticity function at the hourly market level. On the supply side, drivers choose whether to work each hour by comparing expected earnings with their idiosyncratic reservation values. We allow for two observed driver types: high-score (H-type) and low-score (L-type)—that enter the allocation rule, and for unobserved heterogeneity in reservation values via latent groups with distinct intertemporal reservation values. The platform's allocation rule is modeled as a matching function that maps active supply and demand into total matches while accommodating market frictions. It is parameterized by a factor that governs how orders are split between H- and L-type drivers. This structure lets us study how increasing the priority of H-type drivers in the allocation rule propagates through matching probabilities, expected earnings, labor supply, and ultimately platform profits and consumer surplus.

Estimation proceeds in three steps. First, we recover demand elasticity from hourly market aggregates, using nearby-city prices as an instrument to address potential endogeneity. Second, we estimate supply-side parameters by maximum likelihood via an EM algorithm, leveraging observed working histories and drivers' expected matched earnings to infer the distribution of reservation values across latent groups. Third, we calibrate time-varying matching frictions to match observed market throughput. The supply-side estimates reveal substantial heterogeneity of reservation value across hours and driver groups: high-score drivers are disproportionately represented in groups with stronger outside options; and reservation values exhibit a U-shaped daily pattern (lowest mid-day, highest overnight), with magnitudes that differ across groups.

We then conduct counterfactual simulations to quantify the welfare implications of algorithmic allocation and to characterize optimal design. Removing the platform's prioritization toward high-score drivers—i.e., randomly assigning orders among applying drivers—reduces platform commission revenue by about 3.5% and redistributes surplus across driver types: H-types lose surplus by 2.37% as their assignment advantage shrinks, while L-types gain around 2% from more frequent assignment. Consumers also lose because of lower average match quality.

Next, we vary the priority accorded to high-score drivers and trace platform performance. Platform revenue is hump-shaped in the degree of prioritization. At low levels, increasing high-score drivers' priority improves match quality and shipper acceptance with limited participation losses from low-score drivers, raising platform revenue. Beyond an intermediate point, however, further increases in priority disproportionately discourage L-type drivers' participation, reducing effective supply and offsetting gains from improved shipper acceptance. Profits therefore rise and then fall. This interior optimum formalizes the idea that "more prioritization" is not always better: platforms must balance quality gains against participation responses when designing allocation rules.

Literature Review

Our research connects to multiple strands of literature on labor supply in the gig economy, ride-hailing platforms, and the broad implications of algorithms on various markets.

First, our paper is related to previous works on the labor supply in the gig economy, where workers autonomously and flexibly choose working schedules. Several studies have examined the gig workers' labor supply decisions and their welfare gains from the gig platforms (Chen et al., 2019; Stanton and Thomas, 2024). Other research highlights how platforms influence workers' incentives through monetary rewards (Chen et al., 2020; Allon et al., 2023; Chen et al., 2022), and non-monetary nudges, such as rating (Xu et al., 2023) and gamification (Ai et al., 2023). We extend this literature by studying how the platform leverages the allocation algorithm to manipulate workers' earning opportunities and thus labor supply incentives in the gig economy, which is a concern of algorithmic management as platform-based work becomes increasingly prevalent.

Moreover, our study also contributes to the literature on ride-hailing platforms (e.g. Chen et al. 2019; Rosaia 2024; Ghili et al. 2025; Chen et al. 2020; Shin et al. 2023). Previous works have mainly focused on pricing mechanisms and their impact on consumer satisfaction (Xu et al., 2024), driver earnings (Garg and Nazerzadeh, 2022), and social welfare (Castillo, 2023; Buchholz et al., 2020). Other research also explores various platform interventions on ride-hailing platforms. Wang et al. (2019) investigate how the ride-hailing technology affects drivers' behaviors and incomes. Liu et al. (2023) shows how platforms leverage the recommendation algorithm to guide drivers' location choices. Xie and Zhu (2023) study platform leakage, where buyers and sellers bypass platforms to avoid commission fees, and discusses platform strategies to mitigate such disintermediation behavior. Athey et al. (2024) find that platforms can enhance drivers' service quality by providing feedback on their past performance. Castillo et al. (2025) also examine the inefficiencies under a shortage of supply in ride-hailing and propose surge pricing and matching rule adjustments as solutions to improve overall platform efficiency. Our study extends this literature by considering the allocation algorithm as another critical lever for platform management. We show how such allocation algorithms mediate the matching process between two sides and influence drivers' earnings as well as overall platform profitability.

Related to our work, Chen et al. (2024) explore how the centralized assignment algorithm on ride-hailing platforms rewards workers who drive for a longer time and empirically quantify its welfare implications, which aims to deal with the imbalance between demand and supply across time. In contrast, our study focuses on the allocation algorithm that aims to improve match quality by prioritizing drivers who can provide better service, investigates how it intervenes in the decentralized matching process between demand and supply, and explores its optimal design for the platform.

More broadly, this paper is relevant to the growing literature on the market impact of algorithms, such as pricing algorithms (Calvano et al., 2020; Assad et al., 2024; Hansen et al., 2021), search algorithms (Yoganarasimhan, 2020; Zhou et al., 2024; Yang et al., 2024), and product recommendation algorithms (Chen and Tsai, 2024; Donnelly et al., 2024; Wang et al., 2025; Sun et al., 2024; Wan et al., 2024). Our work extends this broad literature by focusing on allocation algorithms, which directly control how demand is distributed among suppliers and thereby influence the matching process in two-sided markets. This further links our works to recent literature on the algorithmic design by platforms (Johnson et al., 2023; Zeng et al., 2024; Calvano et al., 2025). Similarly, our work models the platform's allocation strategy with endogenous labor supply and explores its optimal design.

The remainder of this paper is structured as follows. Section 2 describes the institutional background and the data. Section 3 presents the reduced-form empirical analysis. Section 4 outlines the structural model. Section 5 provides the estimation procedure and results, and Section 6 presents counterfactual simulations. Section 7 concludes.

2 Institutional Background and Data

2.1 Empirical Setting

Our empirical context is one of the leading on-demand cargo platforms in China, which matches shippers (demand) and drivers (supply) to fulfill delivery requests from pre-specified origins to destinations. The platform operates in more than 400 cities nationwide and facilitates over one million transactions per day, connecting more than 14 million active customers with 1 million active drivers by 2025.

This large scale makes the platform an ideal setting to study the impacts of prioritization allocation algorithms. Figure 1 illustrates the transaction workflow on the platform. An order begins when a shipper requests a logistics service on the platform by specifying the origin and destination. The price is set by the platform based on distance and the requested vehicle type. The request is then broadcast to nearby active drivers, who may apply for it. If multiple drivers apply, the platform's allocation algorithm assigns the job to one driver based on their attributes and distance to the pickup location. If only one driver applies, that driver automatically receives the shipping order. After assignment, the shipper observes the matched driver's attributes (e.g., ratings, number of completed orders, vehicle type; see Figure 10 in Appendix for an example). The shipper then decides whether to accept or cancel the match without penalty. If accepted, the platform earns commission fees after the delivery is completed.

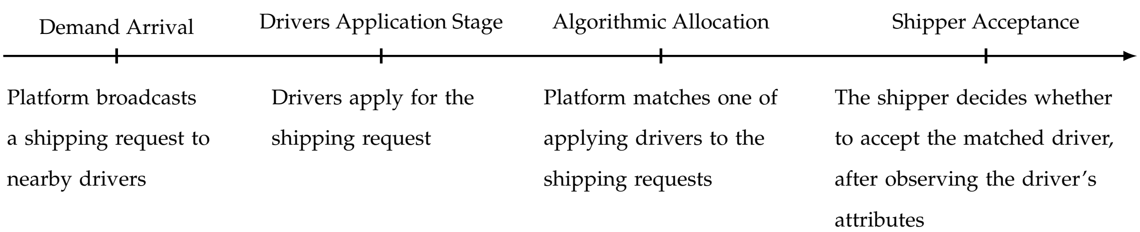
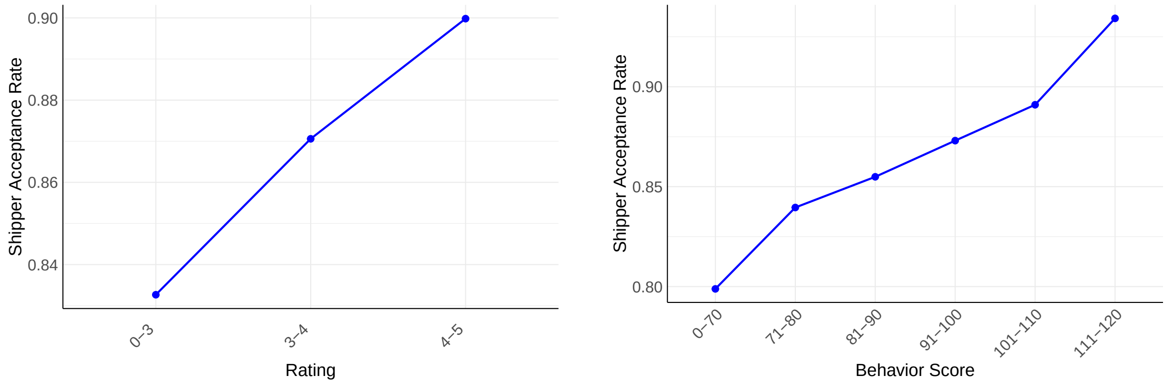


Figure 1: Work Flow on the Platform

The platform specializes in urban and short-haul freight, covering a wide variety of cargo types and service requirements. This heterogeneity creates complexity in matching demand with drivers. A persistent challenge is *post-match shipper cancellation*, which averaged nearly 10% during our study period on the platform. Such cancellations lead to significant economic costs by wasting matching capacity and reducing platform revenues.



(a) Ratings

(b) Platform-generated Behaviroal Score

Figure 2: Relationships between Shipper Acceptance Rate and Driver Attributes

Figure 2 shows the relationships between shipper acceptance rate (i.e., 1 - cancellation rate) and driver's ratings as well as platform-generated behavioral scores, highlighting that shippers are more likely to accept drivers with stronger attributes and underscoring the platform's incentive to allocate more orders to such drivers. These empirical patterns motivate the platform's adoption of an allocation algorithm that prioritizes high-score drivers, as they are more likely to be accepted by shippers. We describe the design of this algorithm in the next subsection.

2.2 Allocation Algorithm on the Platform

When multiple drivers apply for a shipping request, the platform's allocation algorithm determines which driver receives the job. Although the exact allocation rule remains proprietary, we infer its structure by training a machine learning model on historical matching outcomes. Specifically, we employ a LightGBM model with a learning-to-rank framework, which is well-suited for scenarios where the goal is to identify the most preferred candidate among a set of options. The model is trained to predict which driver wins a given order based on standardized attributes such as rating, on-time rate, tenure, rejection rate, and distance to the shipper.[1]

[1]Because only one driver is selected per shipping request, we optimize the model with NDCG@1, which is a ranking metric that emphasizes whether the top-ranked driver matches the actual winner. This criterion closely aligns with the platform's decision structure.

This approach allows us to approximate the platform's allocation mechanism through a ranking rule. The resulting feature-importance scores quantify the contribution of each driver attribute to allocation outcomes. As shown in Figure 3, the inferred mechanism suggests that the platform systematically favors drivers with higher behavioral scores, longer tenure, higher ratings, and a larger number of completed orders — highlighting a preference for drivers who demonstrate both reliability and satisfactory past performance.[2]

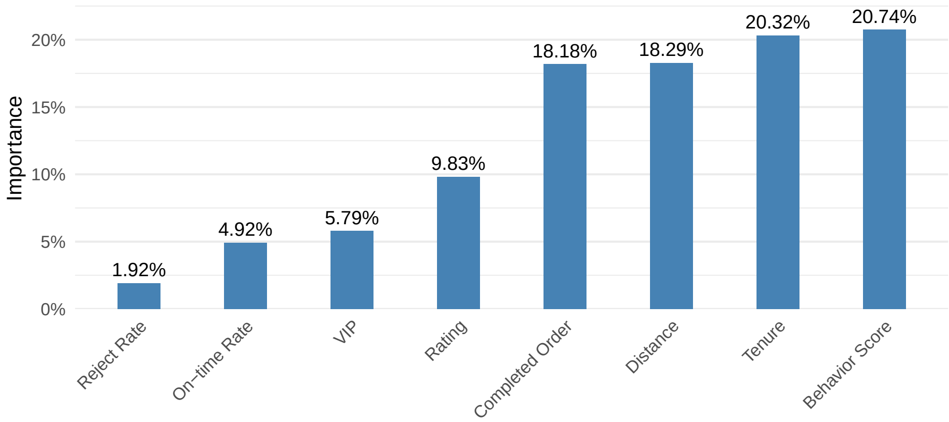


Figure 3: Importance of Driver Attributes in the Platform's Allocation Algorithm

2.3 Data

We acquire a comprehensive transaction dataset from a major city in China with a population of approximately 10 million. Our dataset covers the entire shipping requests placed on the platform from 18 August to 31 August 2022.

The dataset includes both shipping request information and driver-level attributes. For each shipping request, we observe the origin, destination, distance, whether the request was matched with a driver, whether the shipper accepted the match, requested start time, actual completion time, price, and the corresponding payment to the driver. For each driver, we observe experience indicators (e.g., number of completed orders, tenure on the platform), platform-generated behavioral scores, and some additional performance metrics.

A distinctive strength of the dataset is the availability of driver application histories: for each shipping request, we know which drivers applied, their observed attributes, and which driver was ultimately selected. This feature not only enables us to directly document how the allocation algorithm favors drivers with stronger quality attributes (see Figure 3), but also

[2]The platform also considers pickup distance when assigning orders. To isolate the role of drivers' fixed characteristics, we exclude location-based variables in Figure 3.

allows us to construct drivers' detailed working schedules.

Table 1 reports descriptive statistics at the shipping-request level. On average, trips span 21 kilometers, are priced at 88 RMB, and take the driver 1.1 hours to complete. Each request attracted roughly 2.5 driver applications, and overall 88% of requests were matched with one driver. Among matched requests, about 91% are accepted by shippers, implying a cancellation rate of 9% and sizable losses of commission revenues for the platform given its scale of operations.

Table 1: Summary Statistics (Shipping Request Level)

Statistic	Mean	St. Dev.	Min	Median	Max	N
Distance (km)	21.16	21.14	0.11	14.75	520.80	34,802
Price (RMB)	87.84	64.92	14.00	67.80	1,455.00	34,802
Duration (hour)	1.10	0.77	0.01	0.91	17.08	27,795
Number of Applying Drivers	2.53	2.42	0	2	20	34,802
Match	0.88	0.33	0	1	1	34,802
Acceptance	0.91	0.29	0	1	1	30,559

Table 2 summarizes the dataset at the driver level. Part I reports outcomes at the driver-hour level, where the unit of observation is an hour in which a driver is classified as working.[3] On average, during each working hour, drivers spend about 22 minutes actively transporting shipments, cover roughly 7 kilometers, and earn approximately 29 RMB in gross hourly income. Part II aggregates outcomes to the driver level over the entire sample period. On average, a driver works about 26 hours, completes roughly 10 shipping orders, drives more than 200 kilometers, and earns close to 900 RMB during the observation window. Importantly, the variation in driver earnings highlights both the flexibility of participation on the platform and the inequality in realized earnings across drivers.

High-Score and Low-Score Drivers

To capture each driver's overall competitiveness in the algorithmic matching process, we construct an aggregate priority score by taking a weighted sum of standardized driver attributes, where the weights are derived from the feature-importance values of the machine learning model described in Figure 3.

Based on this score, we classify drivers into two distinct groups. High-score (H-type)

[3]Following the literature, we define a driver as actively working in a given hour if he either executes or applies for at least one shipping order that spans at least ten minutes of that hour. Details on data construction are provided in the Appendix.

Table 2: Summary Statistics (Driver-Level)

Part I: Driver-Hour Level						
Statistic	Mean	St. Dev.	Min	Median	Max	N
Driving Time (minutes)	22.64	22.25	0.00	19.27	60.00	80,033
Hourly Earning (RMB)	29.63	31.54	0.00	23.95	295.00	80,033
Driving Distance (km)	7.28	8.98	0.00	4.16	74.89	80,033
Part II: Driver Level over the Entire Sample Period.						
Statistic	Mean	St. Dev.	Min	Median	Max	N
Working Time (hours)	25.62	25.29	0.00	15	111	3,124
Number of Orders	9.78	12.09	0.00	4	93	3,124
Driving Distance (km)	211.97	252.59	0.00	106.88	1,586.04	3,124
Total Earnings (RMB)	892.46	1,010.83	0.00	460.02	5,447.13	3,124

drivers represent high-performing workers who provide consistently reliable service, often reflected in their stronger platform records. In contrast, low-score (L-type) drivers are less experienced and more likely to be rejected by shippers, and thus have a lower priority in the allocation process. For the remainder of the analysis, we use the H-type and L-type to denote these groups.

Table 3 reports the characteristics and performance of high- and low-score drivers. Several patterns emerge. First, H-type drivers exhibit systematically stronger attributes: they hold higher behavior scores, higher ratings, more completed orders, longer tenure, and higher on-time rates. Second, these advantages translate into superior outcomes: over the sample period, H-type drivers work more hours, complete more orders, travel longer distances, and earn higher total income compared to L-type drivers. Finally, even at the driver-hour level, H-type drivers achieve higher hourly earnings and longer driving times per working hour, suggesting that the allocation algorithm consistently allocates more job opportunities toward them.

Together, these patterns indicate that the platform's allocation algorithm does not distribute orders randomly, but instead systematically rewards higher-score drivers with greater earning opportunities. This mechanism creates clear disparities in outcomes across driver types and motivates our reduced-form analysis of how the allocation algorithm affects shipper acceptance and driver earnings.

Table 3: High-Score/Low-Score Driver Performances

	High-Score	Low-Score
Part I: Driver Characteriitics		
Behavior Score	110.57	91.92
Rating	4.90	4.83
Number of Completed Order	923.46	191.82
Tenure (days)	688.45	215.21
On-time rate	94.34%	86.81%
Part I: Performance (over the Entire Sample Period)		
Work Time (hours)	29.98	21.26
Number of Orders	11.53	8.03
Driving Distance (km)	251.02	172. 92
Total Earnings (RMB)	1072.04	712.88
Part II: Performance (in Driver-Hour Level)		
Driving Time (minutes)	23.36	21.63
Hourly Earning (RMB)	31.31	27.26
Driving Distance (km)	7.60	6.83
Numbers of Drivers	1562	1562

3 Reduced-Form Analysis

In this section, we show the underlying mechanism behind the platform's allocation algorithms: by prioritizing high-score drivers, the platform not only improves the match quality but also leads to differential earnings for drivers, thereby affecting drivers' labor supply incentives.

3.1 Shipper Acceptance

A central objective of the allocation algorithm is to increase the likelihood that shippers accept their assigned drivers. To test this mechanism, we regress shipper acceptance on observable driver attributes in Table 4. Columns (1)–(2) show that drivers with higher behavioral scores and more completed orders are significantly more likely to be accepted by shippers. In contrast, pickup distance negatively predicts acceptance, reflecting the shippers' preference for drivers who can arrive quickly. Columns (3)–(4) introduce an indicator for high-score drivers, as defined in Section 2.2. The estimates show that H-type drivers are about four percentage points more likely to be accepted than L-type drivers, an economically meaningful difference relative to the baseline acceptance rate of 91%.

Overall, these results demonstrate that the platform's prioritization of high-score drivers is aligned with shippers' preferences. By systematically steering shipping requests toward drivers with stronger attributes, the platform reduces post-match cancellations and raises overall match efficiency.

Table 4: Shipper Acceptance as a Function of Driver Attributes

Dependent Variable:	Shipper Acceptance			
Model:	(1)	(2)	(3)	(4)
Behavioral Score	0.0015***	0.0012***		
	(0.0001)	(0.0001)		
log(Number of Completed Order)	0.0143***	0.0119***		
	(0.0014)	(0.0014)		
Rating	0.0082	0.0058		
	(0.0060)	(0.0060)		
Pickup Distance(km)		-0.0080***		-0.0086***
		(0.0004)		(0.0004)
H-type			0.0443***	0.0330***
			(0.0033)	(0.0033)
Constant	0.6307***	0.7192***	0.8834***	0.9226***
	(0.0302)	(0.0303)	(0.0026)	(0.0031)
Observations	30,559	30,559	30,559	30,559
R^2	0.01363	0.02709	0.00578	0.02163
Adjusted R^2	0.01354	0.02696	0.00575	0.02157

*Notes: Standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

3.2 Drivers' Differential Hourly Earning

Having established that shippers are more likely to accept high-score drivers, we now examine whether these drivers also earn more than low-score ones, conditional on working in the same hour. We regress drivers' hourly earnings on an indicator of being H-type while controlling for day-hour fixed effects. Columns (1)–(2) in Table 5 show that H-type drivers earn about 4 RMB more per hour than L-type drivers, representing a 15% premium relative to the sample average hourly income of 27 RMB. Columns (3)–(5) suggest that this advantage arises not only from higher shipper acceptance rates but also from greater work intensity: H-type drivers receive more assigned shipping requests, spend 1.7 more minutes per working hour actively transporting shipments, and drive about 0.7 more kilometers.

Taken together, these findings underscore that the platform's allocation algorithm systematically channels more job opportunities to H-type drivers. While this design improves overall match efficiency, it also amplifies earnings disparities between high- and low-score drivers and further shapes their labor supply incentives: it may encourage H-type drivers to remain highly engaged but discourages participation from L-type drivers who face fewer opportunities.

Table 5: Drivers' Differential Hourly Earnings

Dependent Variables:	Hourly Earning		# Assigned Order	Working Time	Distance
Model:	(1)	(2)	(3)	(4)	(5)
H-type	4.053***	3.956***	0.0217***	1.716***	0.7261***
	(0.2258)	(0.2722)	(0.0044)	(0.2020)	(0.0729)
Constant	27.26***				
	(0.1727)				
Day-Hour FE		Yes	Yes	Yes	Yes
Observations	80,033	80,033	80,033	80,033	80,033
R^2	0.00401	0.02270	0.03017	0.02150	0.01523
Within R^2		0.00387	0.00045	0.00147	0.00160

*Notes: Standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4 The Model

The allocation algorithm in the platform prioritizes high-score drivers based on their performance attributes, thereby influencing drivers' earnings and labor supply incentives. To assess the welfare implications of algorithmic allocation and explore its potential optimal design for the platforms, we propose an equilibrium model of the market. Our model consists of three components: the demand system, the drivers' labor supply, and a matching model of algorithmic allocation. First, the demand system describes shippers' aggregate demand for driver working hours as a function of the price of delivery service. Second, on the supply side, drivers endogenously decide whether and when to work by comparing the expected earnings and their reservation values. Third, an aggregate matching function incorporates the algorithm's prioritization of high-score versus low-score drivers and maps supply and demand into matching probabilities, which further affects drivers' expected earnings and their labor supply decision. Importantly, the algorithmic allocation rule distinguishes between two types of drivers: high-score drivers and low-score drivers, with each driver's type exogenously fixed during our data periods.

4.1 Demand Side

We model the decision of market participants for each hour t in the day d. We omit the day index d for simplicity. Shippers only demand and pay for the drivers' working hours. At hour t of the day, the aggregate demand for working hours is denoted $N_t(P_t)$, where P_t is the hourly serving rate set by the platform. We consider a downward-sloping and constant-elastic demand curve[4]

$$N_t(P_t) = \exp(\delta_t) \cdot P_t^{\eta},$$

where η is the constant demand elasticity, and δ_t is a demand shifter that captures time-varying factors that may influence demand at hour t, such as traffic conditions and time of day.

4.2 Supply Side

Each driver j belongs to either H-type or L-type (i.e., high-score and low-score), denoted by $k(j) \in \{H, L\}$, which is exogenously fixed and observable. At the beginning of hour t, the driver j's expected utilities of working on the platform and not working are given by:

$$U_{jt}(1) = W_j(t) + \sigma \cdot \epsilon_{jt(1)} \tag{1}$$

$$U_{jt}(0) = R_j(t) + \sigma \cdot \epsilon_{jt(0)} \tag{2}$$

where $W_j(t)$ is the expected hourly earnings, $R_j(t)$ is driver-specific heterogeneous reservation value from working on something else, and ϵ_{jt} represents the error term and follows the Type-I extreme value distribution. Notice that even with identical expected earnings, heterogeneity in drivers' reservation values can lead to different working schedules. To account for this unobserved heterogeneity, we allow each driver j to belong to one of the latent groups, denoted by $g(j) \in \{1, \ldots, G\}$, such that

$$R_j(t) = R_{g(j)}(t),$$

where $R_{g(j)}(t)$ represents group-specific reservation values that capture variation in preferences for working at different times of the day. Essentially, our model features two dimensions of heterogeneity on the supply side: (1) the observed type $k(j)$, which determines driver j's priority in the platform's allocation algorithm; and (2) the unobserved group $g(j)$, which captures drivers' heterogeneous outside options.

The labor supply decision of the driver j is denoted by $a_{jt} \in \{0, 1\}$, with $a_{jt} = 1$ indicating

[4]Due to data limitation, we do not explicitly model the shipper choice problem among modes of delivery or whether to ship. Following Frechette et al. (2019) and Buchholz (2022), we use a demand function to relate the number of working hours to price.

working at hour t. Drivers form rational expectations about their hourly earnings through their repeated interactions on the platform. The driver j will choose to work at hour t if and only if $U_{jt}(1) \geq U_{jt}(0)$. Therefore, aggregating across individuals, the labor supply for each type of driver is:

$$M_H(t) = \sum_{k(j)=H} \Pr\left(U_{jt}(1) \geq U_{jt}(0)\right) \text{ and } M_L(t) = \sum_{k(j)=L} \Pr\left(U_{jt}(1) \geq U_{jt}(0)\right), \tag{3}$$

where $M_k(t)$ is the expected number of active driver of type $k \in \{H, L\}$ at hour t. These type-specific labor supplies will feed into the platform's matching algorithm, which determines how demand is allocated across driver types and ultimately shapes their realized earnings.

4.3 A Matching Model with Algorithmic Allocation

Having characterized the demand system and drivers' labor supply decisions, we now embed them in a matching model that determines how supply and demand interact under the platform's algorithmic allocation rule. The matching model parsimoniously captures both match friction and the priority given to different driver types in the allocation algorithm. Specifically, we consider active drivers to make individual application decisions, and the allocation algorithm plays a role only when multiple drivers apply for one shipping demand.

First, we drive the total number of matches (before shipper acceptance) in the market, which depends only on the number of active drivers and shipping requests, regardless of how the platform ultimately assigns requests across applicants. Following previous literature (e.g. Burdett et al. 2001; Buchholz 2022; Frechette et al. 2019), we consider an urn-ball matching process in which each driver randomly and independently applies for one shipping request at the beginning of hour t. Given N_t units of demand, and $M_t = M_H(t) + M_L(t)$ drivers, the probability that a unit of demand receives at least one driver's application is $1 - (1 - 1/N_t)^{M_t}$. Thus, the expected number of total matches is $N_t \cdot \left(1 - (1 - 1/N_t)^{M_t}\right) \simeq N_t \cdot (1 - e^{-\frac{M_t}{N_t}})$. To capture heterogeneity in transportation conditions and coordination frictions across markets, we introduce a market-specific parameter γ_t, which scales the efficiency of the matching process. Therefore, the expected total number of matches becomes

$$F(M_t, N_t) = N_t \cdot (1 - e^{-\frac{M_t}{\gamma_t \cdot N_t}}),$$

where a higher value of γ_t decreases the amount of match. This function allows matching friction due to coordination failures, such that some shipping requests may receive no application, and some may have multiple drivers applying.

Next, we incorporate the platform's algorithmic allocation rule and derive the type-k driver's probability of getting a shipping request for $k \in \{H, L\}$. Conditional on multiple applications for the same shipping demand, the platform prioritizes high-score drivers: if these drivers are of the same type, they have an equal probability of getting the demand; if they differ in types, the platform allocates the shipping request to H-type drivers with probability s, and to L-type drivers with probability $1 - s$. This leads to a type-k driver's probability of getting a shipping request, denoted by $\phi_k(s)$ for $k \in \{H, L\}$.[5] As such, we must have:

$$M_H(t) \cdot \phi_H(s) + M_L(t) \cdot \phi_L(s) = F(M_t, N_t)$$

which clearly states that given N_t and M_t, the platform's algorithm only affects the distribution across driver types, but not the total number of matches. Moreover, as s rises from zero to one, $\phi_H(s)$ increases and $\phi_L(s)$ decreases, reflecting the dynamic of algorithmic priority to different types of drivers.

After matching with a shipping request, the driver j's performance metrics are displayed to the shipper, who may accept or reject the driver. We model shipper acceptance as a function of driver attributes, denoted by λ_j, estimated empirically by Column (1) in Table 4. Combining the probability of being allocated a shipping request with the acceptance probability by shippers yields the expected hourly earnings for a type-k driver j at hour t:

$$W_j(t) = (1 - r) \cdot P_t \cdot \phi_{k(j)}(s) \cdot \lambda_j, \tag{4}$$

where r is the commission rate, with a $1 - r$ fraction of the shipping fare obtained by the driver.[6] By choosing s, the platform effectively controls how shipping demand is allocated among drivers and thereby influences drivers' expected earnings and labor supply incentives.

Finally, the platform's expected profit under the design of allocation algorithm s is

$$r \cdot \sum_t P_t \cdot \left(\sum_j \Pr\left(U_{jt}(1) \geq U_{jt}(0)\right) \cdot \phi_{k(j)}(s) \cdot \lambda_j \right),$$

[5] We provide detailed steps to derive these two matching probabilities in Appendix.

[6] In our empirical analysis, we set the commission rate r at 8%.

where $U_{jt}(1)$ and $U_{jt}(0)$ are given by Equations (1) and (2), $\phi_{k(j)}(s)$ is a function of N_t, $M_H(t)$ and $M_L(t)$, where $M_H(t)$ and $M_L(t)$ follow from Equation (3).

5 Estimation

5.1 Demand Estimation

We begin by estimating shipper demand for delivery services at the hourly level. Each hour t is treated as a market, and data is aggregated to the day-hour level. Based on the logarithm of service hour demanded by shippers N_{dt} and the logarithm of hourly service price P_{dt}, we estimate demand elasticity η from the following log-linear demand specification:

$$\log N_{dt} = \log \delta_{dt} - \eta \log P_{dt}.$$

Because the platform may raise prices in response to positive demand shocks, $\log(P_{dt})$ can be endogenous. We therefore use the price in a nearby city within the same province as an instrumental variable. The instrument exploits cross-city supply substitution: a higher price in the city B draws mobile drivers toward city B, reducing effective supply in our focal city A and increasing city A's equilibrium price. Crucially, shippers are locally tied, so prices in city B should not directly affect demand in city A. Day and hour fixed effects absorb common temporal shocks (e.g., weather fronts, regional events), so identification comes from residual cross-city price movements plausibly driven by supply reallocation.

Table 6 reports the results. Column (1) shows the baseline regression without fixed effects, suggesting the possibility of endogeneity. Columns (2) and (3) include day and hour fixed effects to account for temporal demand fluctuations. Once we control for both dimensions of time, the estimated elasticity in Column (3) is -0.90, indicating that a 1% increase in the hourly shipping price reduces total service hours demanded by approximately 0.9%. Column (4) reports the IV estimate using the nearby-city price as the instrument: the elasticity increases in magnitude to -1.32 and remains statistically significant at the 5% level, consistent with upward price endogeneity in OLS. We take this estimate in the counterfactual analysis.

Table 6: Demand Estimation

Dependent Variable:	ln(Service Hours)			
Model:	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	IV
ln(Price)	2.195***	-0.9806**	-0.9005**	-1.3224**
	(0.4366)	(0.4246)	(0.4226)	(0.6050)
rain	0.8418	-0.1633**	-0.2794*	-0.2906*
	(0.6627)	(0.0747)	(0.1471)	(0.1699)
Constant	-5.044***			
	(1.876)			
Hour FE		Yes	Yes	Yes
Day FE			Yes	Yes
Observations	192	192	192	192
R^2	0.12838	0.96127	0.96640	0.96408
Within R^2		0.27629	0.24810	0.19618

*Notes: Standard errors are in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

5.2 Estimation of Supply Side Parameters

This subsection outlines the estimation procedure and results of the supply side model. We first derive the likelihood function and then describe the maximum likelihood approach, implemented via the Expectation-Maximization (EM) algorithm, to estimate model parameters. Finally, we present and interpret the estimation results.

5.2.1 The Likelihood Function

For a driver j, conditional on belonging to latent group g, we observe a sequence of working decisions a_{jt} across hour t. Let $\Theta_g = [R_0^g, \ldots, R_{23}^g]$ denote the 24-dimension vector of reservation value for group g drivers.

To construct the expected matched earnings $W_j(t)$ faced by drivers, we exploit within-hour variation across driver types. Specifically, for each hour h, we compute the average matched demand separately for H-type and L-type drivers. These averages serve as empirical approximations to drivers' type-specific expected matched demand, as denoted ϕ_k for $k \in \{H, L\}$ in Equation (4). Multiplying these expectations by the average hourly price yields the expected earnings $W_j(t)$ for each driver j. Essentially, we assume drivers form rational expectations and base their labor supply decisions on the empirical matching probabilities observed for their type.

Therefore, at each hour t, the conditional choice probabilities of the driver j working and not working are given by

$$\Pr(a_{jt} = 1|g(j) = g) = \frac{\exp(W_j(t)/\sigma)}{\exp(W_j(t)/\sigma) + \exp(R_g(t)/\sigma)},$$
$$\Pr(a_{jt} = 0|g(j) = g) = \frac{\exp(R_g(t)/\sigma)}{\exp(W_j(t)/\sigma) + \exp(R_g(t)/\sigma)}.$$

Therefore, the likelihood of a driver j's working history, conditional on group g is

$$L_{j|g}(\Theta_g) = \prod_t \Pr\left(a_{jt} = 1|g(j) = g\right)^{a_{jt}} \times \Pr\left(a_{jt} = 0|g(j) = g\right)^{1-a_{jt}}.$$

Since each driver may belong to one of the latent groups, the total log likelihood function should marginalize over the distribution of the latent groups as follows

$$\mathcal{L}(\Theta) = \sum_{j=1}^{J} \log\left(\sum_{g=1}^{G} \pi_g \cdot L_{j|g}(\Theta_g)\right),$$

where $\Theta \equiv \{\Theta_g\}$ for $g \in \{1, \ldots, G\}$ groups.

5.2.2 Estimation Methods

We use the Expectation-Maximization (EM) algorithm to estimate Θ and latent group distribution π_g, which is well-suited for maximum likelihood estimation in models with unobserved latent variables. The EM algorithm alternates between the Expectation (E) step and the Maximization (M) step. In the E-step, the latent group probabilities π_g are updated given current parameter values Θ. In the M-step, the group-specific parameters Θ are optimized to maximize the log-likelihood, treating the latent group probabilities π_g as fixed. Those two steps are iteratively repeated until convergence.

To determine the number of latent groups G, we estimate models with different G and compare their Bayesian Information Criterion (BIC). BIC decreases substantially as G rises from one to four, but only marginally beyond four (with relative decreases of 15.8%, 7.1%, 2.0%, 1.1%, 1.1%, and 0.6%), as shown in Figure 9 in Appendix. We therefore select $G = 4$ groups in the following analysis.

5.2.3 Estimation Results

Table 7 reports the model estimation results. The group proportions in the first row indicate that the driver population is dominated by Group 4 (43%), followed by Group 2 (27%) and Group 3 (21%), while Group 1 constitutes only 10%. The results further highlight substantial heterogeneity in drivers' reservation values and quality composition. First, the average reservation values vary across groups, ranging from 31.07 (Group 1) to 40.52 (Group 3). Notably, groups 3 and 4, who make up nearly two-thirds of the population, exhibit relatively high outside options.

Second, the fraction of H-type drivers differs across groups. In Groups 3 and 4, over half of drivers are high-score (52.76% and 53.86%), whereas in Group 1, only about one-quarter (27.04%) fall into the H-type category. This pattern suggests that high-score drivers tend to be concentrated in the groups with higher reservation values.

Table 7: Model Estimation Results for Unobserved Driver Heterogeneity

	Group 1	Group 2	Group 3	Group 4
Group Proportion π_g	0.10	0.27	0.21	0.43
Average Reservation Value	31.07	34.99	40.52	38.56
Fraction of H-type	27.04%	50.12%	52.76%	53.86 %

Third, Figure 4 further depicts the estimated reservation values across latent groups. A common U-shaped pattern emerges: reservation values are lowest during the morning and midday (7 am–12 pm) and peak in the late night to early morning (1 am–4 am). This is consistent with industry practices, as delivery opportunities are relatively scarce overnight and drivers face higher opportunity costs. The magnitude of this variation, however, differs by group. In particular, Group 3 drivers show especially low reservation values during daytime hours but experience a sharp increase at night, reflecting their comparative advantage as daytime workers.

Overall, the estimation results reveal meaningful heterogeneity in both outside options and working schedules. Some groups (e.g., Group 1) are more willing to work consistently at lower reservation values, while others (e.g., Group 3) display strong temporal variation, being highly active during the day but requiring higher compensation at night. These differences are crucial for understanding platform supply dynamics and for evaluating the impact of counterfactual policies on heterogeneous driver populations.

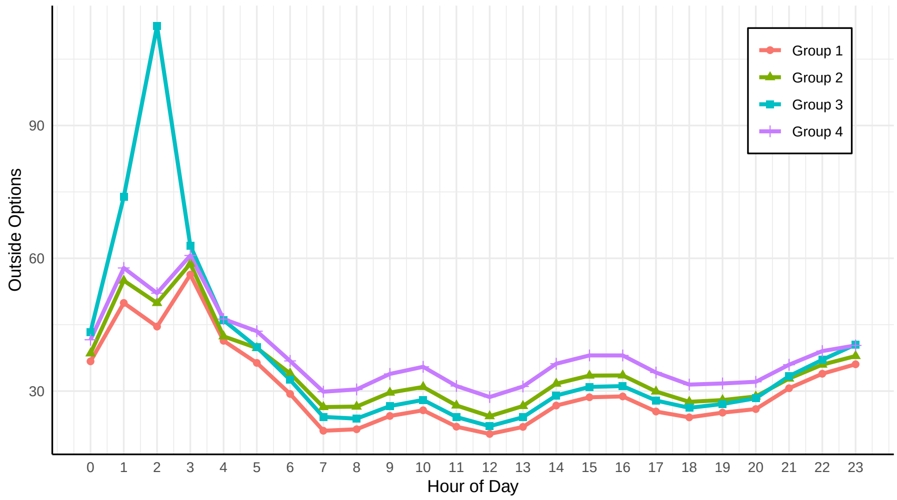


Figure 4: Estimated Reservation Values

5.3 Calibration of Matching Friction

We calibrate the hourly matching friction parameter γ_t, which measures the efficiency of the driver–shipper allocation process. A higher γ_t reflects greater frictions (less efficient matching), while a lower γ_t indicates smoother matching. Figure 5 plots the estimated frictions over the hour of the day, where the dotted line represents the mean friction at hour t, and the shaded area shows the 95% confidence interval. The pattern reveals strong temporal variation, with frictions peaking during early-morning and midday hours when traffic congestion reduces the platform's ability to match drivers with shippers effectively.

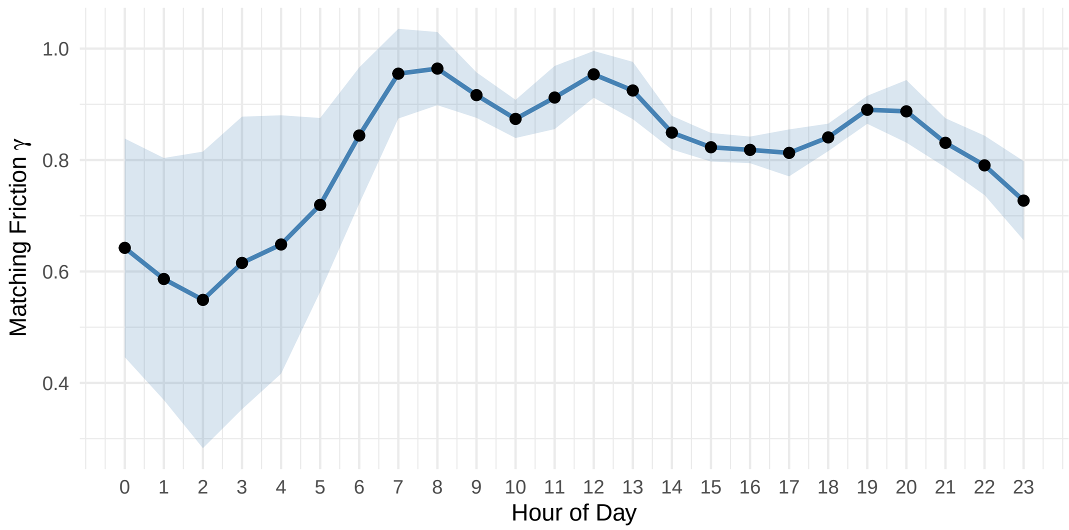


Figure 5: Estimated Market Friction

6 Counterfactual Simulation

6.1 Welfare Implications of Current Algorithm

We begin by evaluating the welfare consequences of the platform's current allocation rule, which prioritizes high-score drivers. As a counterfactual benchmark, we simulate a market in which the algorithm is removed and orders are randomly assigned among applying drivers. In this case, each driver faces the same probability of being matched, given by

$$\phi = \frac{F(M_t, N_t)}{M_t},$$

where $F(M_t, N_t)$ is the total number of matches given active supply M_t and shipping demand N_t. Then, a driver j's expected hourly earnings become

$$W_j(t) = (1-r) \cdot P_t \cdot \phi \cdot \lambda_j,$$

with r is the commission rate and λ_j is the shipper acceptance probability conditional on assignment. Given these new hourly earnings, drivers adjust their hourly labor supply decisions.

Figure 6 depicts how driver supply responds to the removal of the algorithm. H-type drivers reduce their labor supply substantially, especially during peak hours, while L-type drivers expand their participation, highlighting that algorithmic prioritization shifts participation toward H-type drivers. Figure 11 in the Appendix presents absolute supply under the two regimes, showing that the net changes in Figure 6 are driven by reduced participation of H-type drivers and expanded participation of L-type drivers during peak hours.

Quantitatively, we find that removing the allocation algorithm reduces overall platform commission revenues 3.51% and redistributes H-type and L-type drivers' surplus. Specifically, H-type drivers' total surplus falls by about 2.37%. By contrast, L-type drivers gain access to more orders and experience a modest surplus increase of around 2%. [7] These findings underscore the central tradeoff: prioritization toward high-score drivers raises shipper satisfaction and sustains shipper welfare, but redistributes opportunities away from lower-score drivers and reduces their surplus.

[7] On the consumer side, consumer surplus from completed orders is $CS = \sum_t \exp(\delta_t) \int_{P_t}^{\infty} x^{-\eta} dx = \sum_t \frac{1}{\eta-1} \exp(\delta_t) \cdot P_t^{1-\eta} = \frac{1}{(\eta-1)\cdot r} \times$ Platform Commission. This expression shows that shipper surplus is tightly linked to the platform's commission revenues, scaled by the demand elasticity.

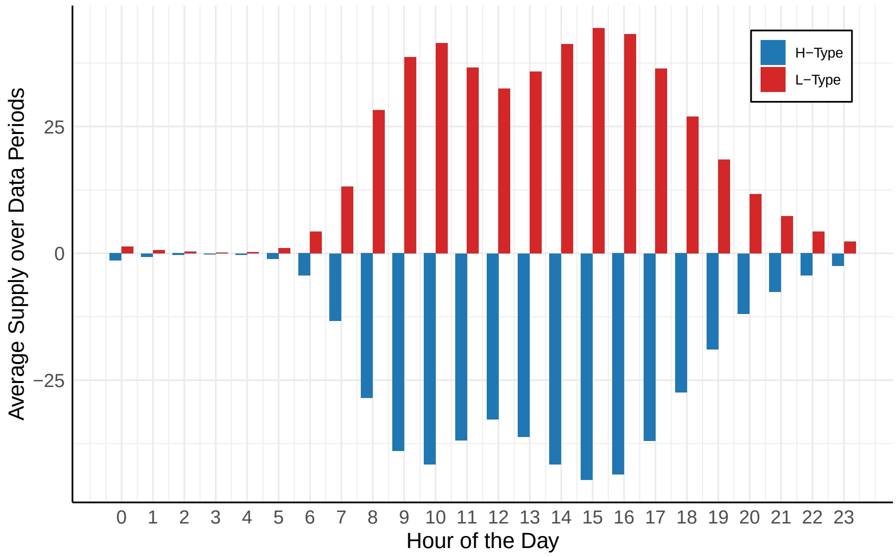


Figure 6: Change in Driver Supply When Removing the Current Allocation Algorithm

Notes: The figure plots the average hourly change in driver supply relative to the baseline with the platform's current allocation algorithm. Positive values indicate higher supply under random allocation, while negative values indicate lower supply. Supply changes are averaged across all days in the sample period.

6.2 Optimal Algorithm Design for the Platform

Having established the welfare implications of the current allocation rule relative to random assignment, we now turn to the question of optimal algorithm design. Recall that the allocation parameter $s \in (0, 1)$ governs the probability that an order contested by both types of drivers is assigned to the H-type. At one extreme, $s = 0$ corresponds to full prioritization of L-types, while $s = 1$ corresponds to full prioritization of H-types.

Figure 7 shows how platform commission revenues vary with s. The relationship is hump-shaped: revenues initially rise as the platform increases s, reflecting greater shipper acceptance and lower cancellations when H-type drivers are more prioritized. However, beyond an intermediate point, further prioritization of H-type drivers reduces revenues. This decline arises because excess concentration of orders among H-type drivers discourages participation by L-types, lowering total effective supply. The platform's commission is maximized at $s = 0.65$, which is highlighted by the blue point.

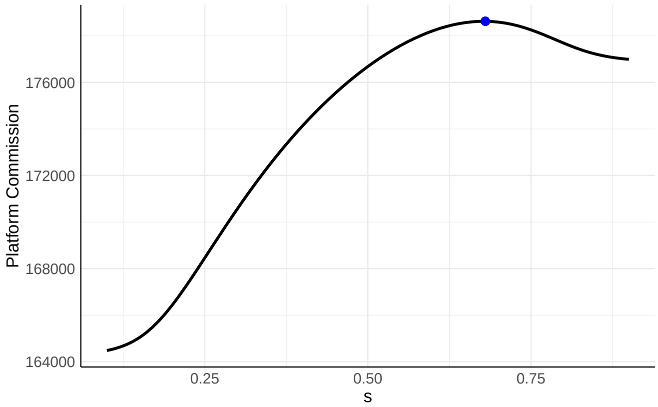
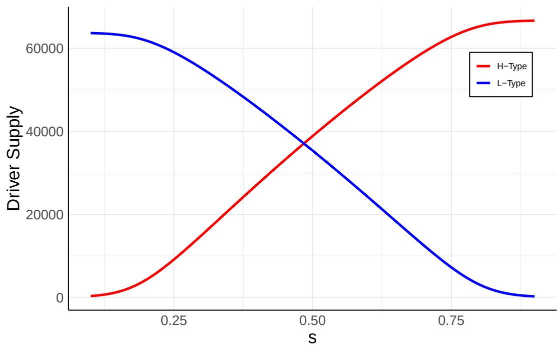
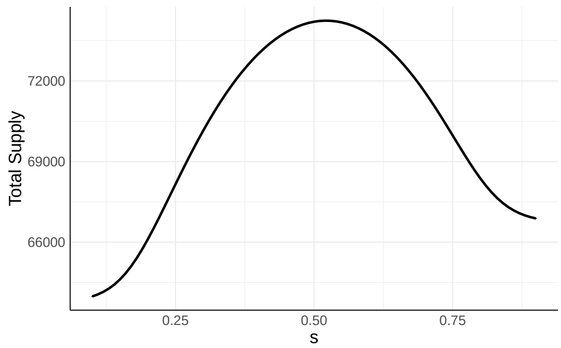


Figure 7: Effect of s on Platform Commission

To unpack the underlying mechanism, Figure 8 examines supply responses by driver type and total supply. Panel (a) shows that as s increases, H-type drivers' labor supply expands monotonically, while L-type supply contracts. Panel (b) aggregates across types and reveals that total supply is also hump-shaped in s: moderate prioritization stimulates participation from H-type drivers without deterring too many L-type drivers, but excessive prioritization discourages L-type participation too much to reduce overall supply.



(a) Supply by Driver Type



(b) Total Supply

Figure 8: Effect of s Driver Supply

Taken together, these results suggest that the platform should balance two competing forces: (i) improved shipper acceptance from prioritizing H-type drivers, who deliver better service and thus reduce shipper cancellation, and (ii) labor supply losses from discouraging L-type drivers when their priority is reduced. The optimal allocation rule instead carefully balances incentives on both sides of the market, ensuring that enough drivers of both types remain engaged to sustain high-quality matches at scale.

7 Conclusion

Gig platforms increasingly match demand to supply via allocation algorithms that favor workers who are providing high-quality services. This paper examines the welfare effects of such prioritization allocation rules in a two-sided platform and provides implications for the design of allocation algorithms for platforms. First, we show that prioritizing high-score drivers raises customer acceptance and improves match quality, but shifts opportunities away from lower-score or newer drivers, creating earnings disparities. Second, we develop a structural model that nests quality-based prioritization in a frictional matching environment with endogenous labor supply. The counterfactual simulation delivers implications for the design of allocation algorithms: while directing more demand to high-score drivers lifts shipper satisfaction and match quality, it can discourage participation by less-experienced and lower-score drivers, thereby shrinking total effective supply and ultimately backfiring by reducing platform profitability.

Naturally, our study has limitations. The data span a short horizon, so long-run dynamics—such as driver learning and quality upgrading by currently low-score drivers—remain open questions. Furthermore, future research may explore how allocation rules interact with other levers such as pricing, bonus incentives. Overall, our results suggest that allocation algorithms are not merely neutral operational tools but active market-shaping instruments. Their design determines not only match quality but also who participates, who benefits, and ultimately whether the platform can sustain efficiency and growth.

Appendix

A Data Sample Construction

This appendix details the procedure for constructing the driver-hour dataset from the raw order-level transaction data and driver application history. First, we acquire the sample of orders with both origin and destination within the city boundary and retain all drivers who applied for these shipping orders. Second, consistent with prior literature (e.g., Chen et al., 2019), we define a driver as actively working in a given hour t if he either executes or applies for at least one shipping order that spans at least ten minutes of that hour. This definition accounts for both realized work and effort spent searching or applying for jobs, thereby capturing drivers' active labor supply decisions more comprehensively. Third, following Chen et al. (2024), we partition shipping orders across hours. Specifically, if an order spans x hours, we divide it into x sub-orders, each corresponding to a single hour. The service price and driving distance associated with the order are proportionally allocated across these hours. Finally, after aligning all orders and applications to the hourly level, we aggregate information to construct the driver-hour panel. For each driver and hour, we compute total earnings, the number of completed orders, and total driving distance. This aggregation yields the core dataset used in our estimation and counterfactual analysis.

B Derivation of Matching Probabilities

Consider a market with $M_H(t)$ high-score drivers (H-type), $M_L(t)$ low-score drivers (L-type), and N_t units of demand. For a particular H-type driver to be matched with a demand, one H-type driver must be chosen and the particular driver in discussion must be the chosen one. The platform allocates a demand to a H-type driver either (i) when no L-type driver has applied to the demand, or (ii) when one or more L-type drivers have applied but the platform favors a H-type driver. Note that $F(N_L(t), N_t)$ is the expected number of demand receiving L-type drivers' application, any demand will receives L-type drivers' application with probability $\frac{F(N_L(t),N_t)}{N_t}$ due to randomness. Therefore, the first case occurs with probability $1 - \frac{F(N_L(t),N_t)}{N_t} = e^{-\frac{M_L(t)}{\gamma_t \cdot N_t}}$, and the second case happens with probability $s \cdot \left(1 - e^{-\frac{M_L(t)}{\gamma_t \cdot N_t}}\right)$.

Conditional on allocating the demand to one H-type driver, the particular one in discussion will obtain the demand with probability $\frac{F(M_H(t),N_t)}{M_H(t)}$. Put together, a H-type driver's probability of being matched with a demand is

$$\phi_H(s) = \left\{ e^{-\frac{M_L(t)}{\gamma_t \cdot N_t}} + s \cdot \left(1 - e^{-\frac{M_L(t)}{\gamma_t \cdot N_t}}\right) \right\} \frac{N_t}{M_H(t)} \cdot \left(1 - e^{-\frac{M_H(t)}{\gamma_t N_t}}\right).$$

Analogously, the matching probability for the L-type drivers is

$$\phi_L(s) = \left\{ e^{-\frac{M_H(t)}{\gamma_t \cdot N_t}} + (1-s) \cdot \left(1 - e^{-\frac{M_H(t)}{\gamma_t \cdot N_t}}\right) \right\} \frac{N_t}{M_L(t)} \cdot \left(1 - e^{-\frac{M_L(t)}{\gamma_t N_t}}\right).$$

C Model Selection

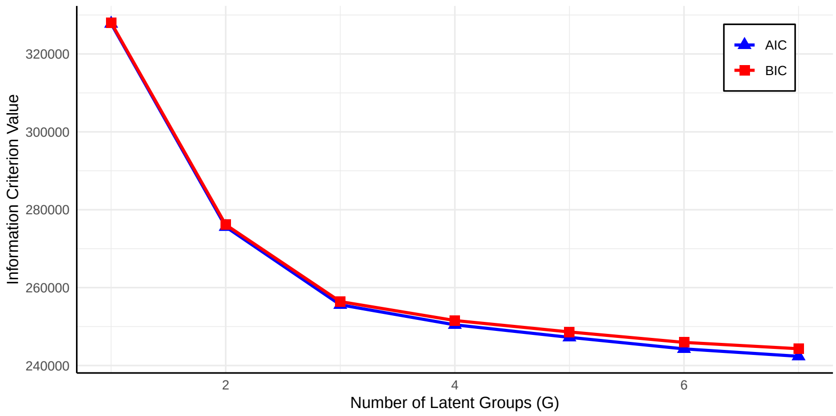


Figure 9: Relationship between Number of Latent Groups and Information Criteria Value

D Driver Information Displayed to Shippers

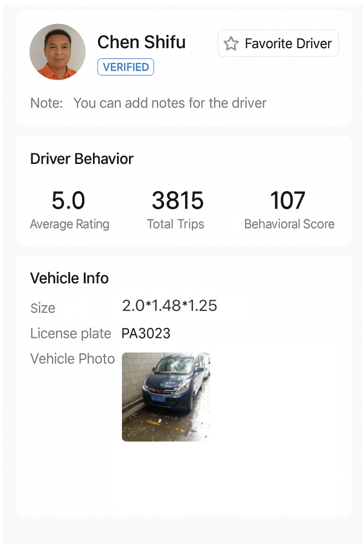
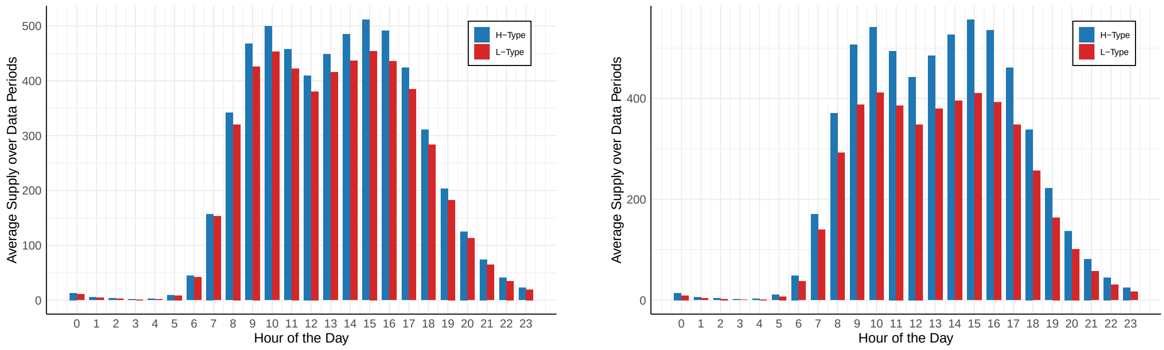


Figure 10: Driver Information Displayed to Shippers

E Driver Supply Under Current Algorithm vs. Random Allocation

Figure 11 plots the average hourly supply of H-type and L-type drivers under two regimes. Panel (a) shows supply when orders are randomly allocated among applicants (no priority rule), while Panel (b) shows supply under the platform's current allocation algorithm. Supply levels are averaged across all days in the sample period. The comparison highlights that algorithmic prioritization increases H-type participation during peak hours while reducing L-type participation.



(a) Current Allocation Rule

(b) Random Algorithm Rule

Figure 11: Driver Supply under Current Algorithm vs. Random Allocation

Notes: Panel (a) shows supply when orders are randomly allocated among applicants (no priority rule), while Panel (b) shows supply under the platform's current allocation algorithm. The comparison highlights that algorithmic prioritization increases H-type participation during peak hours while reducing L-type participation.

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