

Understanding the Commission Structure Model in Ridehailing: An Empirical Analysis

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Abstract

Over the decade, noticeable demands and protests arose from drivers against on-demand transportation firms such as Uber and Lyft. The majority of the protest centers on an opaque, high-commission structure. Despite these developments, empirical research remains notably scarce. To address this gap, our study provides a comprehensive investigation of commission structure within the on-demand transportation ecosystem. We conducted field investigations and collected financial statements from 704 drivers. Our findings highlight that the variability in commission structure is attributed to the platform's algorithmic management systems (AMS) that dynamically adjust the commission deduction mechanism based on drivers' trip history, such as customer payment methods. The actual commission, tax, and total percentage deduction are within 12%, 8%, and 20%, respectively. The study makes novel contributions to the intersection of the digital labor market and on-demand transportation. Furthermore, we provide actionable insights for managers and labor regulators in the on-demand transportation industry.

Keywords

business model, commission structure, gig economy, on-demand transportation, ridehailing.

1. Introduction

Over the past decade, internet-based on-demand transportation platforms have experienced substantial growth in both supply and demand on a global scale (Wang and Yang 2019). These platforms have emerged as pioneers in the realm of shared mobility and have the potential to transform the traditional vehicle ownership model into service-oriented operations (Ashkrof et al. 2022). The ubiquity of the market is conveyed by a compound annual growth rate (CAGR) of 5.06%, resulting in an estimated market valuation of USD 229.98 billion by 2030 (Statista 2026). Leveraging information technology and wireless connectivity, these agile and two-sided asset-light organizations have effectively reduced costs and offered door-to-door service (Furuhata et al., 2013). The platform not only gives passengers the convenience of summoning vehicles but also creates flexible work employment opportunities to millions of drivers.

Drivers constitute the operational backbone of the ridehailing platform, functioning as an intermediary between passengers and the firm. These drivers come from diverse backgrounds and are driven by multifaceted motivations (Hossain and Mozahem 2022). Lower entry barriers and hedonic values often serve as enablers for their participation on the platform economy. They are classified as independent contractors who engaged directly with riders, thereby distinguishing themselves from traditional employees of the platform (Hong et al. 2020; Mäntymäki et al. 2019).

While these riders are characterized by the absence of a fixed workplace (Shaheen et al., 2016), ridehailing platforms like Uber have generated thousands of livelihood opportunities across different nations.

Despite the job opportunities, these ridehailing platforms have faced widespread dissatisfaction and driver protests across multiple nations, predominantly in response to opaque commission rates and high commissions. The commission rate is a form of fee that is used by the platform for providing a match between a rider and a passenger using their proprietary applications. Over the years, these grievances have escalated to extreme measures such as protests across different cities simultaneously and hunger strikes. The issue of opaque and high commission charges remains a subject of active debate with extensive discourse unfolding on social media platforms such as Reddit, as illustrated in Figure 1.

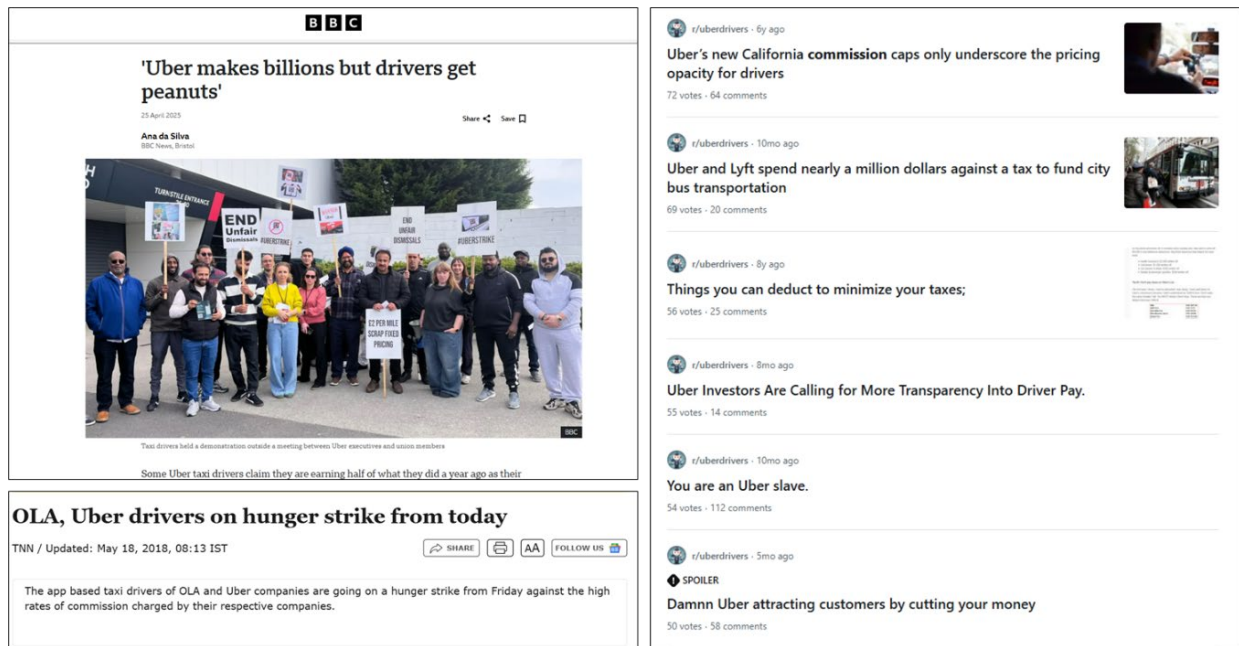


Figure 1. Protest against ridehailing platform due to high commission structure.

1.1 Objectives

Despite the rapid growth and economic importance of ridehailing platforms, the structure and dynamics of commission charges remain poorly understood. The process through which commission rates are determined, sustained and perceived by ridehailing drivers are poorly understood. While theoretical work has examined the commission structure (Chen et al. 2020; Zha et al. 2016, 2018), empirical evidence remains scarce, largely due to the proprietary nature of platform data. Moreover, such opaque commission mechanisms prompted drivers to engage in strategic behavior such as artificially inflating supply during peak hours or negotiating directly with riders to retain full fare to mitigate commission structure (Cameron 2022; Cameron and Rahman 2022). Therefore, our study aims to understand the critical question: *Do ridehailing firms employ fixed or variable commission structures?*

2. Literature Review

Pricing structures are central to the operation and sustainability of ridehailing platforms. Over the years, several theoretical studies have sought to identify optimal pricing mechanisms. Zha et al. (2016) developed an aggregate economic model in which passenger and driver matchmaking is governed by an exogenous matching function. Their analysis shows that passengers' average waiting time is proportional to drivers' search time, and, using Nash Equilibrium, they demonstrate that competition does not necessarily lower prices. The performance of surge pricing and the equilibrium model under different driver behavior was proposed by Zha et al. (2018). Their findings highlight that compared to static pricing, surge pricing increase platform and drivers' revenue, but can make customers worse off during peak hours. Using a proprietary dataset from Didi Chuxing, Chen et al. (2020) propose a dynamic vacant car-passenger meeting model to jointly maximize platform revenue and social welfare, considering surge pricing and

commission rate to balance supply and demand. More recently, Wang et al. (2025) analyzed platform choice between two quality-dependent driver compensation schemes in an oversupplied market. Using a game-theoretic model, they reveal that platform profits are higher under an assignment scheme in high oversupply scenarios, but higher under a commission scheme when oversupply is lower.

In contrast to theoretical analysis, empirical research remains limited. Cook et al. (2021) documented a 7% gender earnings gap among the US ridehailing drivers. This is mainly due to the difference in platform experience, local knowledge, and driving speed preferences. Doğan et al. (2024) tested a variable commission structure that incorporates drivers' transactional histories and service performance with a three-month cluster randomized field experiment. Their study reveals that variable commission, combined with goal-oriented feedback, increased drivers' revenue by 24.5%, referral value by 19.5%, and reduced firm churn by 43.21%.

While the growing body of research has advanced our understanding of pricing mechanisms, relatively less attention has been paid to drivers' discontent arising from the high and opaque commission structure in ridehailing. A smaller body of work examines drivers' perception of commission charges. Hossain and Mozahem (2022) performed 31 in-depth interviews with ridehailing drivers in Qatar and highlighted drivers' distress over variable and high commission structure, which often ranges between 20% and 40%. Ashkrof et al. (2020) conducted a focus group discussion with part-time and full-time drivers, revealing that high commission fees remain a persistent concern, with drivers advocating for lower commission fees and reduced competition. Prior literature has documented how drivers develop strategies over time to 'game' algorithmic management systems (AMS) by strategically positioning themselves by artificial surging supply or negotiating with customers to retain full fare in the precarious environment (Cameron 2022; Cameron and Rahman 2022). Yet, widespread protests among drivers across multiple nations over the commission structure remain unsolved. Our study addresses this gap by providing the first empirical analysis of commission structure, leveraging weekly financial statements from 704 drivers of a global ridehailing firm. Our findings outline multiple tailored policies for firm managers, thereby enhancing both long-term platform sustainability and driver retention.

3. Data Collection

Given the limited insights into commission structure, we decided to start with a qualitative study. Our study provides insights into the drivers' experience of commission deduction. Between March 2023 and August 2024, data were gathered from multiple sources, including interviews with drivers, cab union, and firm managers. We performed pilot interviews by choosing drivers randomly, irrespective of the firm they were working. The pilot survey included questions related to both individual-level aspects, such as drivers' motivation for joining, family background, and income level; and work-level dimensions, such as working hours, commission structure, and the fee deduction process. The pilot survey allowed us to gain familiarity with the field and helped us to approach the cab union members. The union helps drivers by sending messages via informal social media channels such as WhatsApp (predominantly) and Facebook. We outline such groups in Figure 2. While most of these groups permit unrestricted access, some require individuals to request entry, with group admins exercising discretion in granting membership. These groups primarily serve to facilitate networking among drivers, enabling group admins to post job opportunities and provide drivers with practical and real-time information, such as avoiding areas during nighttime, high traffic zones, and locations with frequent police inspections. Additionally, these groups disseminate updates and notifications from multiple ridehailing platforms. Furthermore, these groups help to facilitate updates regarding trips, better surges, new guidelines, and disruptions such as high traffic, waterlogged areas during rainy seasons, and accidents.

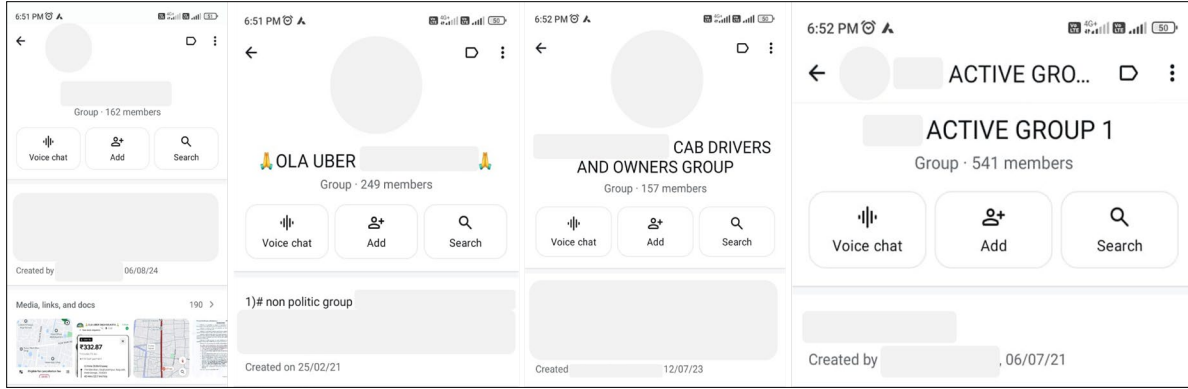


Figure 2. Informal groups among ridehailing drivers.

We interact with union leaders, who helped us to engage in active participation for a year in their groups. Using a network sampling strategy (Heckathorn and Cameron 2017), we collect dataset containing financial statements of 704 drivers of a global ridehailing firm. These financial statements are provided by the firm containing daily trip details of the driver over the week.

In general, all the financial statements have a weekly report on the first page, followed by detailed trip reports, i.e., on a per-trip basis. We have customer prices, customer promotions, third-party fees (referred to as tax), driver earnings, and service fees (referred to as commission). The customer price is the amount finally paid by the customer after promotion (such as coupons) to the ridehailing drivers. The third-party fees include the tax that needs to be paid by the drivers. Finally, the service fee (or commission) is the amount that is charged by the firm for matchmaking between customers and drivers. Table 1 highlights the list of variables used for the present study.

Table 1. Descriptive statistics of the variables

Variables	Description	Mean	SD	Min.	Max
Customer_Price	Aggregated payment made by customers to driver.	5467.075	5230.57	20.38	34529.81
Customer_Promotion	Total promotion amount received by customer due to coupons.	245.014	310.098	0	1839.99
Tax_Original	The amount deducted from drivers in the form of third-party fee.	402.07	393.588	1.46	2431.05
Commission	The amount collected by the ridehailing firm is in the form of commission from individual driver.	615.774	650.251	0	4681.92
Driver_Earning	The final weekly amount (earnings) of the driver.	4204.216	4097.569	15.04	26332.7

A large variation in customer payment is observed because of multiple reasons. It might be possible for a few drivers to work for more than 12 hours a day, while others might work for 2-3 hours as part-time jobs. Some might perform a multi-homing strategy, i.e., they select the trip depending upon the best fare provided by multiple ridehailing platforms. From the given dataset, we observe that it is possible that customers might not always get promotions to avail the service. Additionally, we observe that to encourage drivers, ridehailing firms didn't take service charges (or commission).

4. Methods

Since we know little about the actual commission percentage charged by the ridehailing firm, we used a range of commission percentages, i.e., theoretical commission. Specifically, we charge a range of commission percentages on the customer payment, as the commission is charged. Similarly, we use a range of percentages to calculate the theoretical tax. On the other hand, we have the actual commission and tax. Once we have the theoretical commission

and tax, we calculate the total amount the firm charges from the drivers, which is the sum of theoretical commission and tax based on Equations 4 and 5. Based on that, we perform the *paired t-test* across the range for the drivers' data.

$$\text{Driver_Earning} = \text{Customer_Pay} - \text{Tax} - \text{Commission} \quad (1)$$

$$\text{Commission_Theoretical} = \text{Customer_Pay} \times [\text{Percentage Range}] \quad (2)$$

$$\text{Tax_Theoretical} = \text{Customer_Pay} \times [\text{Percentage Range}] \quad (3)$$

$$\text{Total_Deduction_Theoretical} = \text{Commission_Theoretical} + \text{Tax_Theoretical} \quad (4)$$

$$\text{Total_Deduction_Original} = \text{Commission_Original} + \text{Tax_Original} \quad (5)$$

5. Results

We perform the *t-test* statistics comparing the observed and theoretical percentage deduction applied by the ridehailing platform. As the platform primarily deducts earnings through two channels – commission retained by the firm for matchmaking, and the taxes that are remitted to the government, we extracted commission, tax, and total percentage deductions from the weekly financial statements. We outline the result in Figure 3.

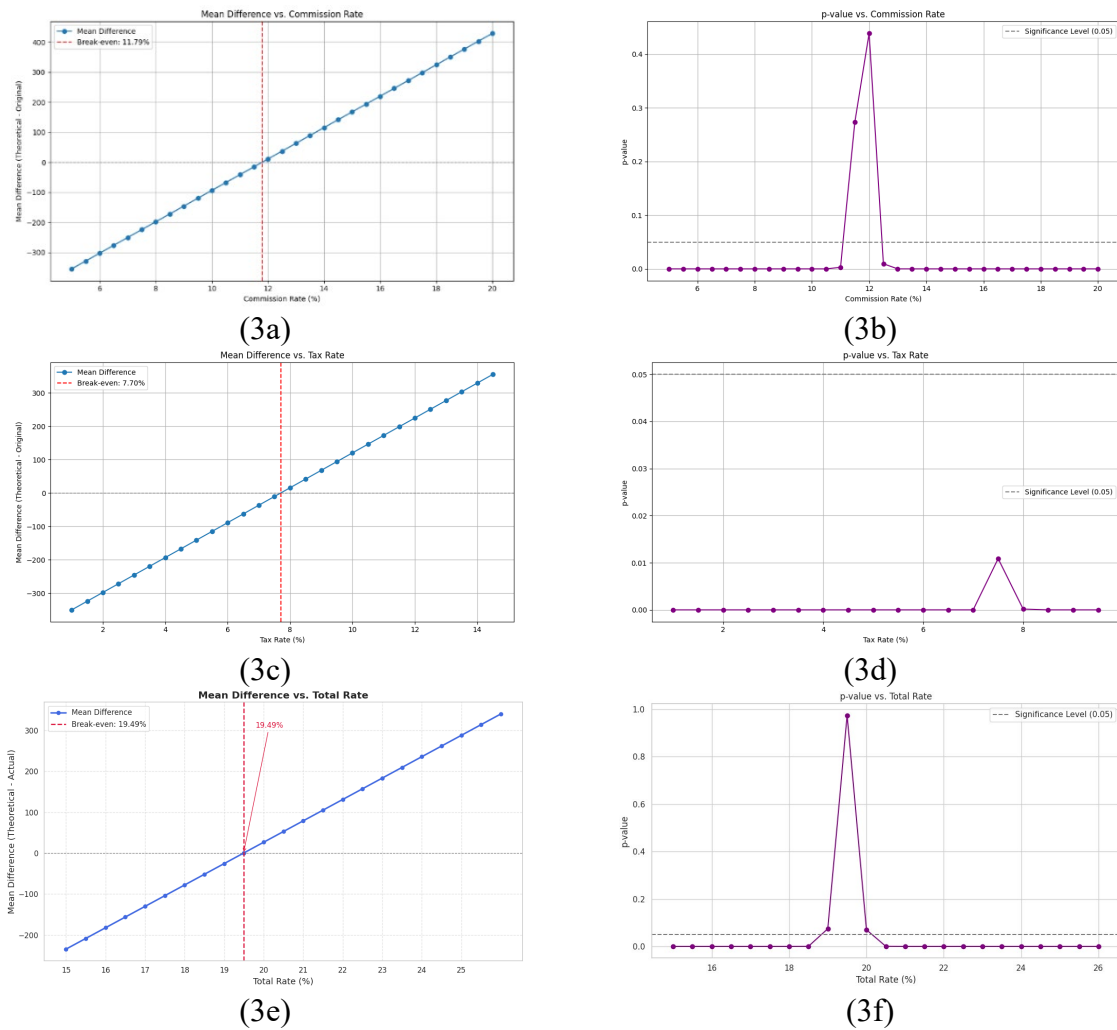


Figure 3. Interpretation of commission, tax and total deduction from ridehailing drivers.

Our findings reveal that there is an average commission deduction percentage of 11.79% (Figure 3a) and an average tax deduction percentage of 7.70% (Figure 3c) from the individual drivers. Therefore, the total deduction as observed by drivers is 19.49% as outlined in Figure 3e. The p-value outlined the point where theoretical deductions align closely with real-world value. These results are broadly consistent with prior studies that use firm's proprietary datasets

(Angrist et al. 2021; Cook et al. 2021; Hall and Krueger 2018). Therefore, we observe that the percentage charged by the ridehailing firm is within the desired range as outlined in their guidelines.

However, we observe a large variation in the commission structure percentage as shown in Figure 4. Therefore, we perform a Kruskal-Wallis test (Kruskal and Wallis 1952; Sueyoshi and Aoki 2001) from the granular daily trip-level dataset. We calculate the commission percentage (i.e., [commission/customer pay]*100) and we develop three different models. The first models consist of six groups by clustering all the trips into the 4-hour time period, i.e., 00:01 – 04:00, 04:01 – 08:00, 08:01 – 12:00, 12:01 – 16:00, 16:01 – 20:00, and 20:01 – 00:00. The second model is clustering all the trips based weekdays, i.e., Monday, Tuesday, and so on. Finally, we clustered all the trips based on different months, i.e., January, February and so on.

We observe ($\chi^2 = 203.31$ and $p < 0.001$) from the first model, ($\chi^2 = 22.18$ and $p < 0.001$) from the second model and ($\chi^2 = 1099.53$ and $p < 0.001$) from the third model, which provides substantial evidence of variability in commission deduction over the short term. For instance, if a particular driver performs a few trips where payment was paid in offline mode such as cash, then once a new trip is completed where the amount is paid online, a higher percentage deduction is observed to account for the commission charges based on the previous trip.

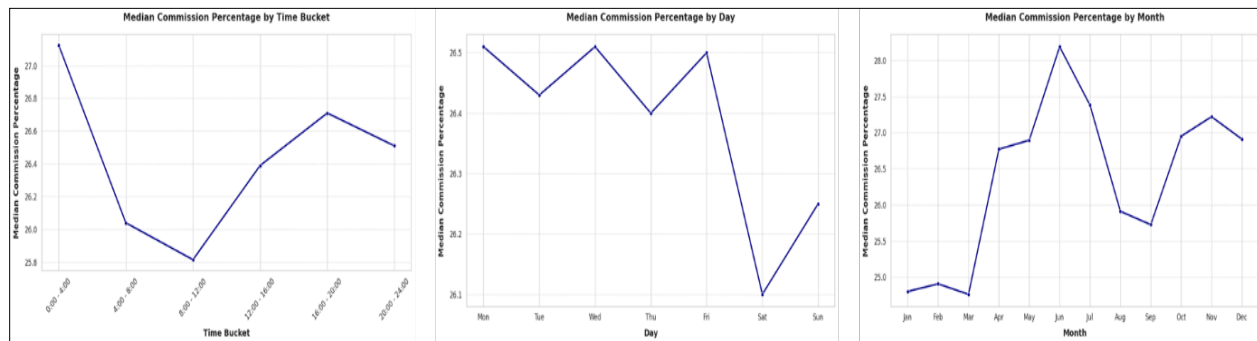


Figure 4. Variation of commission across hours, days, and months.

6. Discussion

One of the important segments in platform-based models is the commission structure. Most of these platforms have a large number of gig workers, classified as independent contractors, and a limited number of legal employees. For instance, Uber has more than 4 million gig workers, i.e., drivers (also known as ‘partners’) across 700 cities (Madrigal, 2019), with only 22000 legal employees (Duggan et al. 2020). Unlike the traditional employment model, these workers have limited in-person interaction with co-workers and no manager supervision (Cameron, 2024), as the algorithmic system controls most aspects of their work (Tarafdar et al. 2023). This digital oversight, akin to a modern form of Taylorism, provides controlled choices that workers navigate in making decisions (Cameron, 2024). Nevertheless, these ridehailing platforms have faced widespread protest due to opaque and high commission percentages imposed by the firm as compensation for facilitating matching between customers and drivers. Our study aims to contribute to the recent discussion of human-algorithmic interactions by understanding the commission structure in ridehailing.

Our study provides the first empirical evidence based on 704 drivers’ weekly financial statements that the commission percentage charged by the firm is fixed over the long term. The total commission, which includes both commission and tax, is nearly 19.49%. However, the commission deduction across hours, days, and months varies, leading to fluctuations in earnings. This is mainly due to the algorithmic management systems that dynamically adjust the pricing based on the prior driver’s trip. For instance, if multiple previous trips performed by the driver consist of offline payment trips, then once a new trip commences with online payment, the algorithm deducts a much higher commission to account for the previous commission. However, the algorithm takes note that full deduction should not be performed to discourage drivers from taking future trips and moving to other competitor platforms. Therefore, it deducts a higher percentage within a given range to recover the previous recurring commission from multiple online payment trips. Once the amount is recovered, the commission deduction is in a range of 20%.

However, drivers fail to acknowledge the commission structure. They misinterpret the commission deduction from the AMS and assume that the firm deducts the amount. Additionally, the myopic nature of drivers allows them to recall only the higher commission deduction. They fail to understand that a few prior offline payment trips cause the algorithmic management system to deduct a higher percentage from subsequent online payment trips until the commission fees are recovered.

We provide two contributions to the ongoing business model of the platform economy. First, our study reveals that the platform operates under a fixed-commission model, charging different yet stable rates to individual drivers. Nonetheless, substantial short-term variability emerges across hours, days, and months. Despite these short-term fluctuations, commission remains stable in the long run. Second, we extend the literature on algorithmic management by revealing how the algorithm policies simultaneously govern commission deduction and fare structure, an operation mechanism central to platform strategy but largely undocumented in prior work. We reveal how some drivers navigate and resist commission as a natural response. While considerable research has explored worker agency (Anicich 2022; Cameron 2022; Möhlmann et al. 2022; Petriglieri et al. 2019), there is a limited understanding on how drivers in understanding commission mechanisms. Our study aims to fill the gap through an empirical approach using financial data.

7. Conclusion

Our study investigates the opaque commission structure business model in the platform economy facilitated by the algorithmic management system within the ridehailing domain. Our investigation provides new insights into the long-standing debates over variable commission structure. The empirical analysis provides a robust understanding of how the commission deduction takes place via management systems.

While the present study offers notable contributions to business operations, it opens two important avenues for future exploration. First, in our study, we consider a dataset from drivers from a particular Asian city and from a single firm. Future studies might consider datasets from multiple cities and multiple firms to provide an in-depth exploration of the commission structure. Second, our findings on variable commission structure raise critical questions about fairness and operational efficiency in ridehailing. Such variability count attract scrutiny from policymakers advocating for standardized commission framework to promote equity and prevent exploitation. This effort could inform changes in organizational practices in on-demand business models.

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