Modeling the Partnership between On-Demand Meal Delivery Platform and Restaurants in a Three-Sided Market

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Short summary

Despite the rapid expansion of on-demand meal delivery (ODMD), many restaurants have lost their incentives to participate due to high commission costs. Inspired by this issue, this paper studies an ODMD system with a single platform, strategic restaurants, free-lancing couriers, and customers sensitive to price and service quality. We first formulate the three-sided market equilibrium among customers, couriers, and restaurants, and then integrate it into the platform's service design problem in the bi-level programming framework. Our results indicate that a lower commission rate incentivizes restaurants to offer discounts to customers. This helps boost demand and create a win-win situation that benefits all stakeholders. Conversely, a higher commission rate pushes restaurants to impose surcharges on orders, leading to a sharp decline in demand and ultimately jeopardizing system efficiency. Similar negative consequences are observed when the minimum per-order profit for restaurants increases beyond a certain threshold.
Keywords: On-demand meal delivery, multi-sided markets, order bundling, bi-level programming

1 Introduction

The on-demand meal delivery (ODMD) industry has expanded rapidly in recent years, largely due to the widespread adoption of smartphones and mobile payment technologies. According to a recent analysis, the market is projected to grow at an annual growth rate of 13.20% to attain a value of 580 billion USD by 2034 (Expert Market Research, 2024). ODMD market can be deemed as a typical three-sided market, featured by the ODMD platform's single-sided interactions with customers, restaurants, and couriers, respectively. The sustained growth of this market depends on the active participation of all stakeholders and the network effects among them (Belleflamme & Peitz, 2018). For instance, an increase in restaurant participation enhances the variety of dining options available to customers, a larger customer base boosts restaurant revenue, and the rise in order volume generates more job opportunities for couriers.

However, as the market matures following its most rapid user base expansion, many restaurants have lost their incentives to participate due to high commission costs, which typically range from 15% to 30% of the total profit per order (McKinsey, 2021). To alleviate this financial burden, many restaurants have adapted their operational strategies to lower costs and increase revenue. Common approaches include relocating to suburban areas and raising menu prices specifically for ODMD services (Talamini et al., 2022). Previous studies on ODMD have shown that price increases often result in reduced customer willingness to purchase services, which in turn leads to fewer job opportunities and decreased wages for couriers Ye et al. (2024). This vicious cycle, driven by unreasonable commission rates and subsequent restaurant pricing adjustments, poses a potential systemic risk to the industry's long-term sustainability.

Motivated by this dilemma, this paper examines an ODMD system involving a single platform, strategic restaurants, free-lancing couriers, and price- and service-quality-sensitive customers. We aim to assess the associated benefits and challenges to inform the development of sustainable partnerships. The most relevant research pertains to driver commission rates in ride-hailing systems, a typical two-sided market (Chen et al., 2020; Henao & Marshall, 2019). This literature primarily employs market equilibrium models to describe the platform's unilateral interactions with passengers and drivers (Yang & Yang, 2011; Zha et al., 2016; Zhang & Nie, 2021).

To the best of our knowledge, only Bahrami et al. (2023) and Liu et al. (2023) model the complex interactions of the stakeholders within the framework of a three-sided market. Both studies incorporate restaurants' decisions to join the platform, which are reflected in aggregate system equilibrium states through simplified participation rules. Bahrami et al. (2023) modeled the platform's interactions with restaurants, couriers, and customers using variables such as service pricing, commission fees, and wages. They specifically assume that restaurants' willingness to join the platform is determined by the commission fees charged by the platform. Consequently, the platform's optimal pricing problem is formulated as a mathematical programming model that integrates aggregate system equilibrium conditions. In contrast, Liu et al. (2023) address restaurant participation by first determining whether each restaurant offers meal delivery services based on its demand level, availability of an in-house delivery fleet, and profit maximization objectives. The total number of participating restaurants is then computed, enabling the use of a two-sided market equilibrium model to analyze the system. However, these existing studies consider a limited role for restaurants within the system, overlooking key aspects such as their ability to make flexible pricing adjustments.

To address this gap, this study incorporates restaurants' pricing adjustment strategies, allowing flexibility in offering discounts or imposing surcharges on customers. In Section 2, we formulate the three-sided market equilibrium among customers, couriers, and restaurants and integrate it into the platform's service design problem using a bi-level programming framework. Section 3 presents numerical experiments to examine the effects of the platform's commission rate and restaurants' pricing adjustment strategies on the system. Finally, Section 4 concludes the study and outlines directions for future research.

2 Methodology

Market description

In the ODMD system, the platform interacts individually with restaurants, customers, and couriers. When a restaurant partners with the platform, it agrees to pay a commission fee on each order in exchange for promotional services within the system. When a customer places an order, she/he pays the total price to the platform. In the absence of flexible pricing strategies by restaurants, the cash flow for each ODMD transaction is depicted in Fig. 1 (McKinsey, 2021). The total price paid by the customer comprises the meal price and a service fee. The service fee is divided between the platform and the courier as their earnings, while the meal price is split between the platform (as commission) and the restaurant (as revenue).

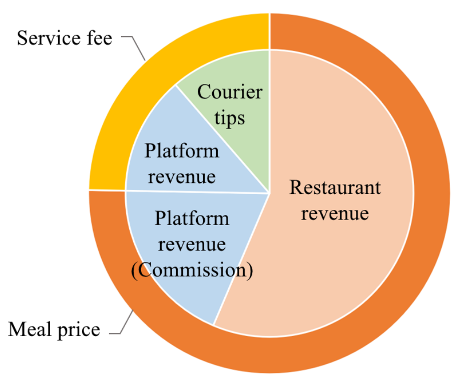


Figure 1: Breakdown of customer payment (outer ring) and corresponding beneficiaries (inner pie chart).

To ensure the traceability of the model, we first quantify the decisions of the participants. The platform's decisions include:

(1) Charging a commission rate of c on the meal price;

(2) Collecting a service fee from customers in addition to the meal price, denoted as f;

(3) Paying couriers wage per unit time duration, denoted as q.

The decisions made by restaurants encompass two key aspects: (1) whether to join the platform and offer products; and, if so, (2) pricing adjustment η of the meals. The restaurant's pricing options are as follows:

(1) $\eta > 0$: A surcharge added to the meal price, allowing the restaurant to pass part or all of the commission onto customers, thereby increasing per-order revenue;

(2) $\eta < 0$: A discount applied to the meal price, enabling the restaurant to partially or fully cover the delivery fee to attract more customers;

(3) $\eta = 0$: No flexible pricing.

To ensure profitability, we assume that the restaurant has an expectation of minimum per-order profit, denoted as $\pi_{r,\min}$. This parameter is exogenous to the model and will be analyzed for its impact on the system through sensitivity experiments in Section 3.

Based on the above, let the average product price be denoted as x_0. The total ODMD price paid by each customer is $f + \eta + x_0$, where $f + \eta$ represents the actual service fee paid by the customer. Accordingly, the restaurant earns revenue of $\eta + (1 - c)x_0$, while the platform earns revenue of $f + cx_0$.

Market equilibrium condition

We introduce the following assumptions for the system:

Assumption 1. *Both restaurants and (idle) couriers are evenly distributed in the service area with densities Λ and Γ (Γ_v), respectively. Each restaurant has the same order arrival rate λ.*

Assumption 2. *Orders are prepared efficiently so that they are ready for pickup before couriers arrive at the restaurants, as per Ke et al. (2024).*

We adopt a demand function based on generalized service cost, a weighted summation of the service price and service time, to calculate the arrival rate. Denote the potential number of potential customers per restaurant in a unit time duration as λ_0. The order arrival rate in each restaurant is then given by Eq. (1).

$$\lambda = \lambda_0 F_D(f + \eta + \alpha(\Delta + t_s)) \tag{1}$$

where Δ and t_s are the order matching time and maximum order delivery time (bundle delivery time), α is the value of time, and $F_D(\cdot) : \boldsymbol{R}_+ \to (0, 1)$ is a continuous and differentiable function that indicates the probability of a customer choosing the ODMD service. Without loss of generality, we assume $F_D' < 0$.

Let Λ_0 be the potential number of restaurants per unit area that may join the system and Γ_0 the potential number of couriers per unit area. Λ and Γ are decided through Eq. (2) and Eq. (1), respectively. $F_R(\cdot), F_V(\cdot) : \boldsymbol{R}_+ \to (0, 1)$ are continuous and differentiable functions, with the former indicating restaurants' willingness to join the system given a commission rate and the latter shows the probability of a courier joining the platform given a wage rate. Specifically, $F_R' < 0$ and $F_V' > 0$.

$$\Lambda = \Lambda_0 F_R(c) \tag{2}$$

$$\Gamma = \Gamma_0 F_V(q) \tag{3}$$

According to Little's law (Little, 1961), the average number of orders in a stationary queue system equals their arrival rate multiplied by the average service time per order. Thus, denoting the average bundle size in the system as k, the courier flow is subject to Eq. (4) at equilibrium.

$$\Gamma_v = \Gamma_0 F_V(q) - \frac{\Lambda \lambda t_s}{k} \tag{4}$$

We further follow the physical model for calculating bundle delivery time developed by Ye et al. (2024), which is given by Eq. (5). Given a bundle consisting of k orders from different restaurants and destinations, the bundle service time is divided into three segments, i.e., pickup time of the first order t_1, pickup time of other orders $(k - 1)t_n$, and delivery time t_d. The physical model estimates the time of each segment using a continuous approximation method based on the density of visiting points. The detailed derivation procedure of the model is referred to in the article.

$$t_s = t_1 + (k-1)t_n + t_d \tag{5a}$$

$$t_1 = \frac{\delta}{2v}\sqrt{\frac{\kappa(\Lambda\lambda\Delta/k)}{\Gamma_v}} \tag{5b}$$

$$t_n = \frac{\delta D_p}{v}\left[1 - \frac{1}{P}\left(1 - \frac{D_o}{D_p}\right)\right] \tag{5c}$$

$$t_d = \frac{\delta}{v}(\beta_1' l + \beta_2' k_{sq}) \tag{5d}$$

where:

$$D_o = \frac{1}{2v\sqrt{\varphi_o\Lambda\lambda\Delta}} \ ;$$
$$P = 1 - \exp(-\varphi_o\Lambda\lambda\Delta \cdot \pi D_p^2) \ ;$$
$$k_{sq} = \sum_{n=1}^{k_{max}} (\sqrt{n} - \sqrt{n-1})P^{n-1} \ .$$

We proceed to analyze restaurants' flexible pricing strategy. When they do not make flexible pricing, $\eta = 0$. Otherwise, we assume that they decide on an optimal η to maximize their profit. Therefore, η can be calculated through:

$$\eta = \arg\max_{\eta} \Pi_R = [\eta + (1-c)x_0]\lambda \tag{6a}$$
$$\text{s.t. } \eta + (1-c)x_0 \geq \pi_{r,\min} \tag{6b}$$
$$\eta \geq -f \tag{6c}$$
$$\eta \leq cx_0 \ , \tag{6d}$$

where Eq. (6a) is the objective function of restaurants' profit maximization. Eq. (6b) ensures that the restaurant meets the minimum profit $\pi_{r,\min}$. Eqs. (6c) and (6d) specify the upper limits for restaurant discounts and price premiums, respectively, which are capped by the service fee and the commission charged from a restaurant. Since Eq. (6b) to (6d) define the bounds for η, Equation (6a) can be rewritten as:

$$\frac{\partial \Pi_R}{\partial \eta} = \frac{\partial \lambda}{\partial \eta}[\eta + (1-c)x_0] + \lambda = 0$$
$$\Rightarrow \eta = \frac{-\lambda}{\partial\lambda/\partial\eta} - (1-c)x_0 \ , \tag{7}$$

where

$$\frac{\partial \lambda}{\partial \eta} = \frac{-F_D' k\lambda_0\left(k + \Lambda\lambda\frac{\partial t_1}{\partial \Gamma_v}\right)}{-k\left(k + \frac{\partial t_1}{\partial \Gamma_v}\Lambda\lambda\right) + \alpha F_D'\lambda_0 k\left[k\frac{\partial t_s}{\partial \lambda} + \frac{\partial t_1}{\partial \Gamma_v}\left(\lambda\frac{\partial k}{\partial \lambda} - k\right)t_s\right]} \ .$$

Thus, Eqs. (1)–(5) and Eq. (7) can be regarded as a mapping from (f, λ) to η. It can be proven that the system forms a fixed-point system defined by (f, q), determining $(\lambda, \Gamma_v, t_s, \eta)$, and that a solution to this system exists (Ye et al., 2024).

System optimization

It is worth noting that although the platform decisions mentioned above fall under long-term decision-making, the decision cycles differ slightly. The delivery fee f and the courier wage rate q usually vary within a day, whereas the commission rate c remains relatively stable and is typically adjusted monthly or on an even longer cycle. Therefore, we set only f and q as decision variables in the optimization, while the commission rate c is treated as a parameter.

We then solve the platform's service design problem in the bi-level programming framework. We regard the platform as the leader and restaurants as followers. Both players wish to maximize their profit in a unit time duration. To this end, the problem can be formulated as:

$$\text{(P1)} \qquad \max_{f,q} \Pi_P(f,q,c) = (f + cx_0)\Lambda\lambda - q\Gamma \tag{8a}$$

$$\text{s.t.} \quad \text{Eqs. (1)–(6).} \tag{8b}$$

where the first term in the objective is the platform's total revenue and the other term indicates couriers' wage.

Under mild assumptions, the decision variables are bounded (Zhang & Nie, 2021), and the lower level problem is equivalent to Eq. (7) and thus can be inserted into the upper level. Therefore, the model can be treated as a single-level optimization problem. We adopt the Particle Swarm Optimization (PSO) algorithm to solve it. For each particle, an equilibrium solution to Eqs. (1)–(5) and Eq. (7) can be obtained through a tailored iterative fixed-point algorithm. Specifically, the lower level is numerically solved through a gradient ascent method within the bounds of η. The pseudocode for this tailored fixed-point iteration algorithm is shown in Algorithm 1

Algorithm 1 Fixed-point iteration algorithm for solving the market equilibrium

Require: Service fee f, courier wage rate q

Initialize $\boldsymbol{x}^{(n=0)} = \left[\lambda^{(n=0)}, \Gamma_v^{(n=0)}, t_s^{(n=0)}, \eta^{(n=0)}\right]$

repeat

Step 1: Update $t_s^{(n+1)}$

$$t_s^{(n+1)} = S_1\left(\lambda^{(n)}, \Gamma_v^{(n)}\right)$$

Step 2: Update $\lambda^{(n+1)}$

$$\lambda^{(n+1)} = S_2\left(t_s^{(n+1)}\right)$$

Step 3: Update $\Gamma_v^{(n+1)}$

$$\Gamma_v^{(n+1)} = S_3\left(t_s^{(n+1)}, \lambda^{(n+1)}\right)$$

Step 4: Update $\eta^{(n+1)}$

$$\text{Repeat } \eta^{(i+1)} = \eta^{(i)} + \rho\frac{\partial \Pi_R^{(i)}}{\partial \eta^{(i)}} \text{ until } \eta \text{ converges } (\rho \text{ is a preset step size})$$

Update $n = n + 1$.

until The residual value is below the convergence threshold, i.e., $\left\|\boldsymbol{x}^{(n)^T} - \boldsymbol{x}^{(n-1)^T}\right\|_2^2 < \varepsilon$, or the maximum number of iterations is reached.

Ensure: $\boldsymbol{x}^{(n)}$

3 Numerical experiments

This section conducts a series of numerical experiments to evaluate the impact of restaurants' minimum per-order profit and the platform's commission rate. We assume that restaurants, customers, and couriers act rationally: restaurants join the system when the commission rate is below their expected value, customers use the ODMD service when the generalized service cost is less than their expected cost, and couriers work for the platform when the wage rate exceeds their expectations. Additionally, the expected values for restaurants, customers, and couriers are assumed to follow normal distributions with mean values μ_R, μ_D, μ_V and standard deviations σ_R, σ_D, σ_V, respectively. Accordingly, the exact forms of F_R, F_D, and F_V are specified as:

$$F_R(c) = 1 - \Phi\left(\frac{c - \mu_R}{\sigma_R}\right), \tag{9}$$

$$F_D(x) = 1 - \Phi\left(\frac{x - \mu_D}{\sigma_D}\right), \tag{10}$$

$$F_V(q) = \Phi\left(\frac{q - \mu_V}{\sigma_V}\right), \tag{11}$$

where Φ is the cumulative distribution function of standard normal distribution. The parameter values are listed in Table 1.

Table 1: Default values and ranges for part of model parameters

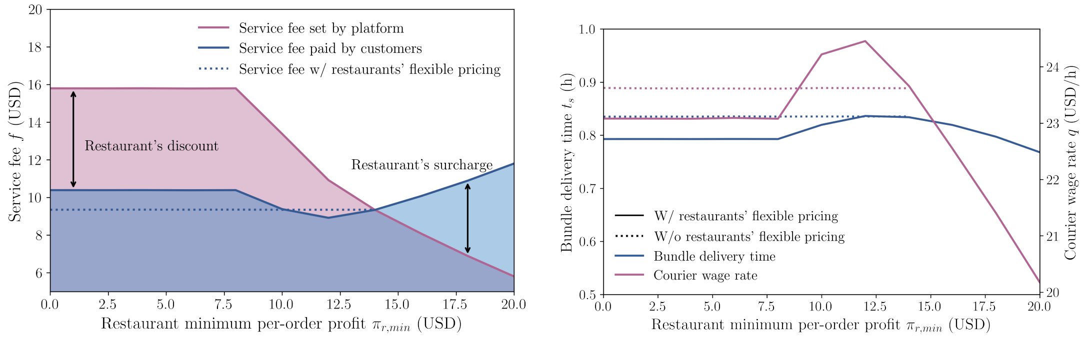
Parameter	**Unit**	**Default value**	**Variation**
Λ_0	/km^2	10	
λ_0		50	
Γ_0	/km^2	200	
μ_R		0.3	
σ_R		0.3	
μ_D	USD	15	
σ_D		5	
μ_V	USD/h	20	
σ_V		10	
c		0.3	$0.1 - 0.6$
$\pi_{r,min}$	USD	10	$0 - 20$
x_0	USD	20	
α	USD/h	4.5	
δ		1.3	
v	km/h	20	
Δ	h	0.1	
D_p	km	1	
φ		0.05	
β'_1		0.6	
β'_2	km	4.3	
k_{max}		5	
l	km	3	

Impacts of restaurant's minimum per-order profit

We first vary the restaurants' minimum per-order profit $\pi_{r,\min}$ and plot the results by stakeholder in Figs. 2–4. In Figs. 3 and 4, we also compare the scenarios with and without the restaurant flexible pricing.

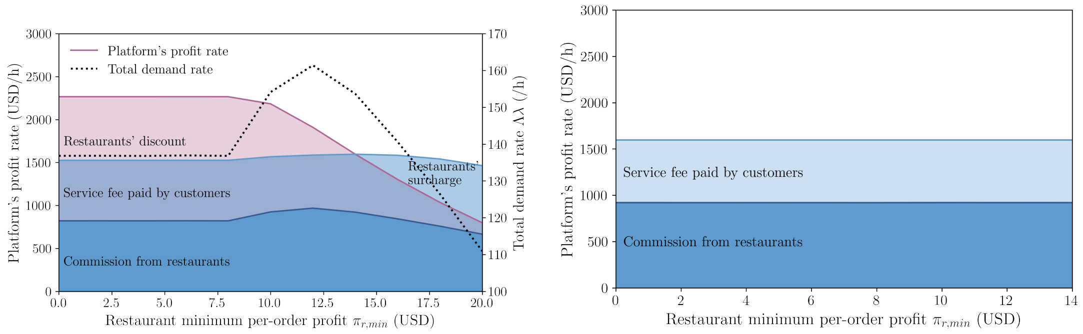
As shown in Fig. 2(a), as the minimum per-order profit increases from zero to 20 USD, restaurants first cover a partial service fee of customers with a discount (i.e., $\eta < 0$) but then start to add a surcharge (i.e., $\eta > 0$). The threshold value is 14 USD, where restaurants neither offer a discount to customers nor require a surcharge from them. Fig. 2(a) also reveals that the platform tends to lower the service fee as the restaurant minimum per-order profit exceeds another threshold of around 7.5 USD, after which it begins to affect restaurants' pricing strategy. As illustrated in Fig. 3(a), the lower service fee first attracts more customers, despite slight increases in bundle delivery time. To accommodate this demand growth, the platform also expands its courier fleet by offering higher wages (see Fig. 2(b)). Meanwhile, restaurants enjoy a mild increase in revenue, thanks to the lower discount and higher demand (see Fig. 4(a)).

However, as the minimum per-order profit continues to grow and restaurants start to put a surcharge on each order, all stakeholders are worse-off. Particularly, as shown in Figs. 2(b) and 3(a),



(a) (b)

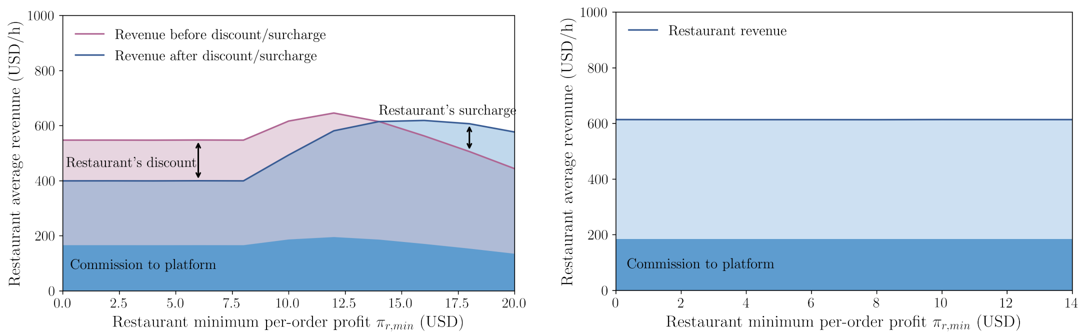
Figure 2: Impact of restaurant minimum per-order profit on (a) customers and (b) couriers



(a) (b)

Figure 3: Impact of restaurant minimum per-order profit on platform with (a) flexible pricing and (b) no flexible pricing by restaurants

the platform profit and courier wage decline sharply, largely due to the loss of demand. The revenue of restaurants also decreases but rather mildly because the loss is offset by the expanding surcharges. These results suggest that the profitability of ODMD platforms in real practice could highly rely on restaurant discounts and may no longer be sustained if restaurants face an increasing cost in their daily operations.



(a) (b)

Figure 4: Impact of restaurant minimum per-order profit on restaurant with (a) flexible pricing and (b) no flexible pricing by restaurants

In summary, the minimum per-order profit plays a major factor in ODMD system efficiency when restaurants implement flexible pricing. A slight compromise in minimum per-order profit incentivizes restaurants to offer customers a modest discount. This not only boosts demand but also benefits the platform, restaurants, and couriers. Conversely, driven by excessively high minimum per-order profits, restaurants transferring the commission costs to customers through surcharges greatly sacrifice the platform and couriers.

Impacts of commission rate

As per Eq. (2), a higher commission rate results in fewer restaurants joining the platform. Yet, its impacts on their flexible pricing strategies and other stakeholders are indeterminate. Hence, we proceed to conduct numerical experiments with the commission rate varying from 10% to 60%.

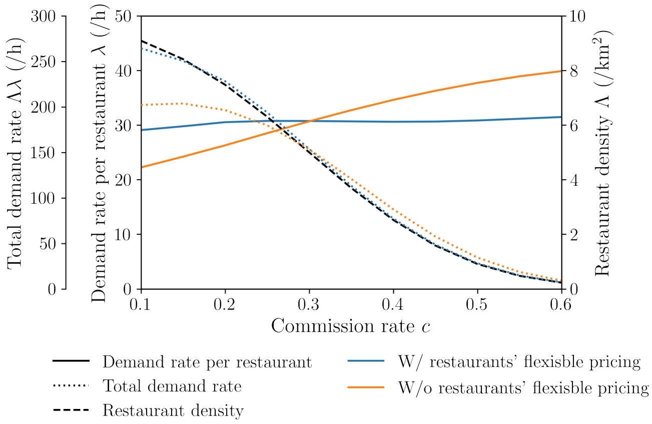


Figure 5: Service demand and restaurant participation against varying commission rate.

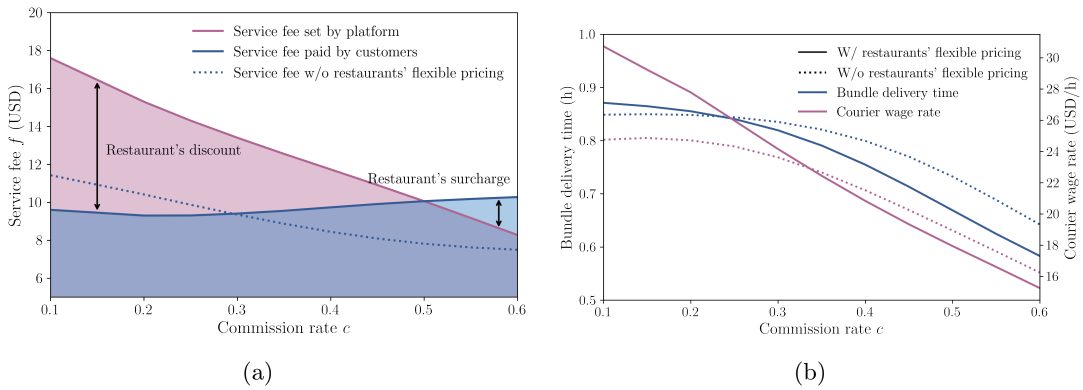
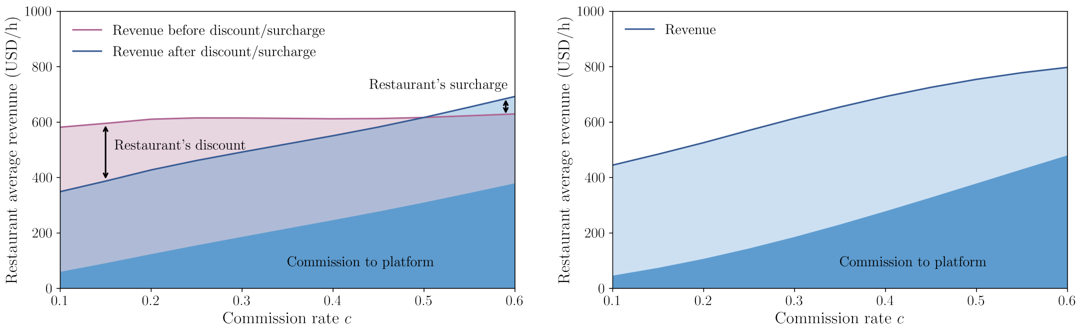


Figure 6: Impact of platform commission rate on (a) customers and (b) couriers

As shown in Fig. 5, although an increasing commission rate sharply reduces total demand, restaurants enjoy a slightly higher average demand rate, particularly in the case without flexible pricing. The result is attributed to the mild increase in service fees paid by customers (after counting the restaurant discount/surcharge) and the better service quality (i.e., a shorter bundle delivery time). As total demand declines, couriers also face fewer job opportunities and receive lower wages (see 6(b)). They are better-off when restaurants implement flexible pricing but the gain is quite marginal.

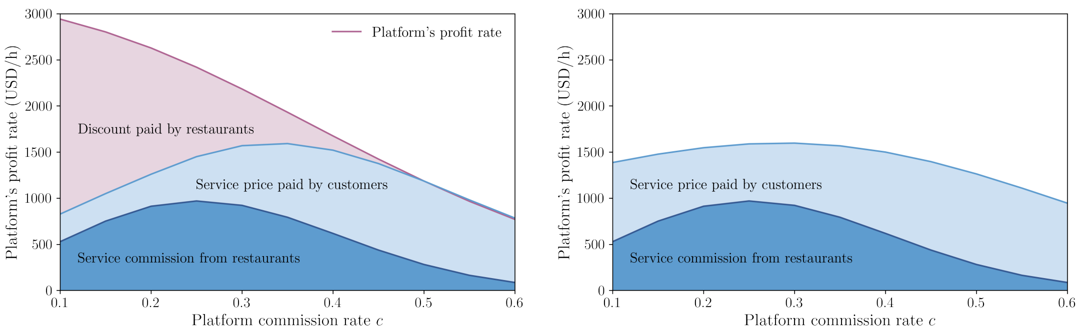
For restaurants, flexible pricing strategies help them maintain a stable profit margin when the platform raises the commission rate, as illustrated by the width of the light blue band in Fig. 7. The comparison between Figs.7(a) and 7(b) shows that the strategies particularly benefit restaurants under high commission rates (e.g., $c > 50\%$), mitigating the declining profit through surcharges. However, these strategies provide no significant revenue improvement under low commission rates.

For the platform, as shown in Fig. 8, the platform reaches the maximum profit at a low commission rate, i.e., 10% under restaurants' flexible pricing. This is primarily due to the high restaurant discounts, which allow the platform to charge a high service fee (see Fig. 6(a)). However, as the commission rate rises further, restaurants start to impose surcharges on customers. Similar to the consequence observed in Section 3, this greatly compromises the platform profit, even lower than



(a) (b)

Figure 7: Impact of platform commission rate on restaurants with (a) flexible pricing strategies and (b) without flexible pricing strategies



(a) (b)

Figure 8: Impact of platform commission rate on platform with (a) flexible pricing strategies and (b) without flexible pricing strategies

the case without flexible pricing shown in Fig. 8(b).

In summary, our numerical results indicate that the platform enjoys the highest profit when charging a low commission while providing restaurants with the option of flexible pricing. In this case, the platform can charge a higher service fee, but customers essentially pay a lower service fee thanks to the substantial discounts offered by restaurants. If the platform increases the commission, restaurants not only start leaving the market but also lose incentives to subsidize customers and instead add surcharges. As a result, both the platform and couriers could suffer from significant loss of earning.

4 Conclusions

This paper investigates a three-sided ODMD market consisting of a single platform, strategic restaurants, freelancing couriers, and customers sensitive to price and service quality. A market equilibrium model is developed to capture the complex interactions among these stakeholders. Specifically, the model incorporates platform decisions, including service fees, courier wage rates, and commission rates, alongside restaurant decisions, such as participation and flexible pricing strategies. Building on this equilibrium, the platform's service design is formulated as a bi-level programming problem, where the platform acts as the leader and restaurants as followers. Numerical experiments are conducted to evaluate the effects of restaurants' flexible pricing strategies and platform commission rates on system stakeholders.

The experimental results indicate that excessively high minimum per-order profits lead to surcharges that adversely affect customers, couriers, and the platform while providing negligible benefits to restaurants. Conversely, substantial customer discounts can drive up service fees, lower courier wages, and reduce restaurant profits. It is noteworthy that modest discounts effectively boost system demand, enhancing the revenues of the platform, couriers, and restaurants.

Besides, flexible pricing strategies are most advantageous when the platform charges a low commission rate. Under such conditions, restaurants are more likely to subsidize customers, resulting in higher platform profits, increased courier wages, and reduced service prices for customers. However, as the commission rate increases further, restaurants' surcharges diminish profitability, resulting in lower profit rates than those observed in scenarios without flexible pricing strategies.

Future research could explore several extensions of the proposed model to enhance its applicability and robustness. On the one hand, expanding the framework to account for restaurants' heterogeneous minimum per-order wage would allow for a better understanding of restaurant competition and its implications for stakeholders. Besides, introducing uncertainties, such as demand fluctuations or variable courier availability, could improve the model's adaptability to real-world scenarios.

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