Selling More without Wasting Food: Can Online Restaurants Use Spending Threshold Discounts?

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Abstract

Spending Threshold Discounts (STDs)—offering discounts or free delivery for orders with total spending above a set amount—are widely used by restaurants on delivery platforms to boost sales. However, they risk increasing food waste if customers add items solely to qualify. We analyze this tension with an economic model wherein a monopolistic online restaurant sells to two groups of rational customers (budget-conscious college students and affluent professionals, both with varying inherent demand) when there is a single threshold. Surprisingly, we find that profit improvement through the STD and waste reduction may not conflict, because the STD affects the restaurant profit through three channels: 1) Order size expansion: Buyers (i.e., customers that make purchases) whose basket values with inherent demand are just below the threshold add items, but their added values are often less than the discount value, causing profit loss and unnecessary consumption or waste; 2) Buyer base expansion: Customers deterred by delivery fees may buy if a low threshold enables the discount with minimal added values; 3) Profit margin enhancement: The threshold creates a sudden drop in effective average price, enabling restaurants to raise marginal food prices. Therefore, under certain conditions, heightened customer aversion to waste can boost profits by curbing inefficient order size expansions without affecting the other two channels. Besides, regulators can achieve a rare triple win—reducing waste, increasing welfare, and maintaining restaurant profits—by capping platform fees. Overall, smarter pricing, consumer awareness, and balanced regulation can harmonize profitability with sustainability in delivery markets.

Keywords: Food Waste; Pricing; Delivery Platform; Sustainability; Regulation

1 Introduction

Spending-Threshold-Discount (STD) pricing is a widely adopted pricing mechanism, in which firms offer a fixed reduction once a customer's spending exceeds a predetermined threshold. Examples include "\$20 off orders over \$100," free delivery for orders above \$100, or tiered pricing such as one scoop of ice cream for \$7, two scoops for \$8, and three scoops for \$12 (equivalently, if X is the number of scoops purchased and Y = 1 when spending $\geq$ \$9, total payment = 3 + 4X − 3Y). Typically, an STD scheme starts with a fixed fee (e.g., a delivery charge), adds a linear per-unit price, and then subtracts a lump-sum discount once spending crosses the threshold. This design amplifies the marginal benefit of the "next" item once customers are close to the threshold, thereby encouraging larger basket sizes.

It therefore seems natural that online restaurants on third-party delivery platforms employ STD schemes. These restaurants and platforms incur significant fixed costs—cooking, packaging, and especially delivery—regardless of order size. Small orders often yield thin or negative margins once delivery costs are accounted for. By charging a delivery fee (which is often charged by the platform) that is "waived" (often by the restaurant through payment reduction) for orders above a threshold, restaurants and platforms shift part of these fixed costs onto buyers with small orders and simultaneously encourage buyers to increase their order sizes. The result could be a more efficient spreading of fixed costs over higher revenues, leading to improved profitability for both restaurants and platforms.

1.1 Potential Pitfalls of STD Pricing

Despite its appeal, STD pricing can sometimes backfire in two ways: 1) buyer arbitrage through low-value items and 2) ethical concerns for encouraging unnecessary purchases.

If a menu includes items whose list prices are below the value of the discount, a rational buyer with an initial basket value just below the threshold can add a cheap item, trigger the discount, and end up paying less than without the extra item. For instance, McDonald's offers free delivery for orders over \$70 on a delivery platform in Hong Kong, with an \$8 delivery fee for small orders. A customer purchasing a McCrispy Combo at \$64 can add large fries and a large drink for \$3 each, bringing the total to \$70 and avoiding the delivery fee—ultimately paying \$2 less than the original total of \$(64+8). Such loopholes—often found in restaurant menus with inexpensive add-ons like rice bowls or soft drinks—can undermine the very profit gains the STD is designed to achieve.

In addition to the profit loss caused by those spending-upgraders, STD pricing can prompt customers to purchase unnecessary food merely to meet the discount threshold. This often leads to leftovers and food waste—especially among college students or young professionals, who may have limited refrigeration options in their living or working spaces. In China, for example, users aged 18–30 accounted for over 58% of Meituan's delivery orders in 2020, a demographic less likely to store excess food (MRI 2020). Similar numbers are observed on DoorDash and Uber Eats in the United States (Mark 2025). Over time, these small increments of waste can accumulate into a sustainability problem: it was estimated that the yearly wasted food in the delivery channel in China can feed the entire population in the city of Shanghai for 34 days (Zhao 2022). Over-consumption is another concern. Research from the UK suggests eating a takeaway meal means consuming 200 more calories per day, on average, than food prepared at home, significantly increasing obesity risks among young people (Roxby 2022). While such issues are not caused by STD pricing alone, these pricing strategies can exacerbate both food waste and public health challenges.

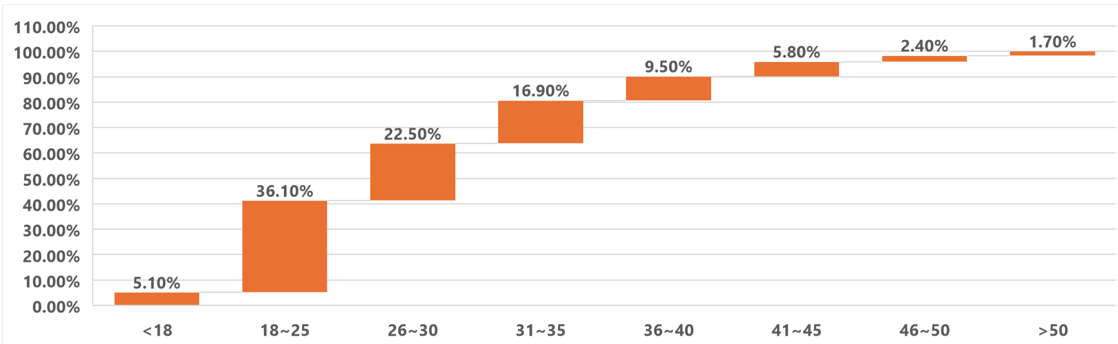

Figure 1: The Age Distribution of Meal Delivery Platform Users in China (Source: Meituan, 2020)

1.2 Research Questions

Motivated by these observations, we ask the following questions.

- **Profitability with rational customers.** If customers are fully rational—maximizing a utility that includes waste aversion without psychological constraints—is STD pricing still profit-enhancing for a monopolistic online restaurant, when small-value items are on the menu? In reality, not all customers are fully rational, but we aim to examine if STD pricing can help improve restaurant profit even in the absence of psychological motivations.
- **Impact on food waste.** Compared to a standard per-unit pricing scheme with a delivery fee charged by the platform, does STD pricing necessarily generate more food waste under the rational-customer assumption? The answer to this question will help us understand how to reduce food waste when restaurants use STD pricing.
- **Trade-off under heightened waste aversion.** If customers become more averse to waste—and hence refrain from buying needless extras—how does this shift affect the restaurant's profitability under STD? Is there an inherent trade-off between reducing waste and maximizing profits? This question will reveal whether restaurants using STD pricing have an incentive to educate customers about food waste prevention.
- **Policy remedies.** Because educating customers to become waste-averse may not be feasible or aligned with the restaurant's profit-maximizing motive, regulatory interventions may be necessary. Due to its dual implications to food waste and social welfare, whether and how regulations related to STD pricing should be formed are still unclear. If regulators seek to curb

food waste without unduly harming overall welfare, what measures can effectively constrain STD practices (e.g., setting minimum thresholds, regulating platform-restaurant contracts)?

1.3 Main Findings

Our analysis yields four surprising insights:

- **STD pricing is robustly profitable.** Even when small-value items are available and buyers derive disutility from needless extras, STD pricing dominates simple per-unit pricing for almost all circumstances from the standpoint of a monopolistic online restaurant.
- **STD pricing affects the restaurant profit in three ways.** When a monopolistic online restaurant introduces a threshold-based discount besides simple linear pricing, there could be three kinds of customers in terms of how they change their purchase decisions: 1) ***new buyers***, who would walk away if the discount does not exist, 2) ***spending upgraders***, who increase their basket sizes to qualify the discount, and 3) ***no-change customers***, who behave as if the discount were not offered. In contrast to simple linear pricing, the restaurant can raise the marginal food price to some extent without losing buyers, because the discontinuity in the average-price-volume curve created by the lump-sum discount allows the restaurant to avoid the trade-off between the marginal price and the number of buyers. As a result, the "new buyers" contribute to the restaurant profit positively as long as neither the threshold nor the profit margin is too low, and buyers among the "no-change customers" will spend more in aggregate as long as there are enough large orders to cover the loss from offering the discount. However, spending upgraders—as long as they are rational—hurt the restaurant profit because they only add items that are cheaper than the discount value offered.
- **Restaurants can benefit from customers' waste aversion when they use STD pricing.** This is because, under certain circumstances (e.g., low margin or large variance in customer willingness to pay), there are no or few "new buyers" and thus educating customers to resist unnecessary purchases can help the restaurant prevent the "spending upgraders" from hurting the profit while still profiting from the "no-change customers."
- **Simultaneous welfare gain and waste reduction is achievable through regulation.** Well-designed interventions—particularly regulating spending thresholds and constraining platform commission rates/service fees—can create alignment between food sustainability and economic goals. Social welfare increases and food waste decreases when platform fees are capped at relatively low levels; conversely, a "double penalty" emerges when platform fees rise.

1.4 Organization of the Paper

The rest of this paper is organized as follows. Section 2 reviews the related literature and explains the position and contribution of this paper. Section 3 introduces the model, which is stylized but captures a sufficient level of complexity. In Section 4, we conduct our analysis in several steps to answer our research questions one by one. In Section 5, we use specific numerical examples to illustrate our main findings and use extensive examples to check the robustness. We finally conclude this paper in Section 6. All the mathematical details and proofs can be found in the appendix and the online supplement.

2 Literature Review

2.1 Food Waste and Sustainability

This research is situated within the expanding field of sustainable operations management, with a particular focus on social responsibility as highlighted by Atasu et al. (2020). A critical and increasingly prominent topic in this area is the reduction of food waste across all stages of the supply chain, including production, shipping, retail, and consumption—an issue with profound societal implications. According to the United Nations Food and Agriculture Organization (FAO (2011)), consumers and retailers in industrialized countries waste approximately 222 million tons of food annually, much of which is perfectly edible. Concurrently, the 2023 State of Food Security and Nutrition in the World report estimates that 691–783 million people faced hunger in 2022, representing an increase of 122 million since 2019 (FAO, IFAD, UNICEF, WFP and WHO 2024). Furthermore, the Food Waste Index Report 2024 by the United Nations Environment Programme (UNEP 2024) notes that food waste generates 8–10% of annual global greenhouse gas emissions—nearly five times the emissions of the aviation sector.

Thus, reducing food waste can simultaneously improve food availability and significantly decrease greenhouse gas emissions, offering substantial benefits for society. Consequently, it has emerged as a growing area of interest within the operations management (OM) community. Akkas and Gaur (2022) recently outline a future research agenda for OM scholars in this domain. The existing literature examines food waste in various contexts, including offline grocery retail, online grocery retail, supply chains, and restaurants.

In offline grocery retail, Belavina (2021), Han et al. (2023), Jain et al. (2023), Wu and Honhon (2023), Keskin et al. (2024), Sanders (2024), Kazaz et al. (2025), and Yang and Yu (2025) are the notable studies. For example, Belavina (2021) investigates the impact of grocery store density on both store- and consumer-level food waste; Han et al. (2023) study the role of ugly produce retailers; Wu and Honhon (2023) examine the effects of Buy-One-Get-One-Free promotions on profit and waste; Sanders (2024) analyzes the welfare effects of dynamic pricing and landfill bans; Keskin et al. (2024) study the impact of blockchain technology on retailer profits and food waste reduction; Yang and Yu (2025) explore the impact of surprise clearance sales; Kazaz et al. (2025) investigate retail strategies to reduce waste from imperfect but edible produce; and Jain et al. (2023) quantify expiration waste related to multiple expiration dates on store shelves. Our study, similar to Wu and Honhon (2023), investigates the relationship between sales promotions and food waste, but our focus is on the online food delivery market.

In the context of online grocery retail, Belavina et al. (2017) compare the environmental and financial performance of per-order and subscription revenue models, while Zhou et al. (2024) examine the effect of disclosing residual shelf life information to consumers. From a supply chain perspective, Akkas and Honhon (2022) analyze the interplay between shipment policies and product expiration, and Astashkina et al. (2019) investigate the environmental impact of online grocery retailing across the entire supply chain. In the restaurant sector, Astashkina et al. (2024) examine how improved food accessibility, such as enhanced buffet convenience, affects plate waste and profitability, while Nu et al. (2024) estimate the reduction in food waste resulting from AI-powered digital tracking systems in commercial kitchens. Similar to Astashkina et al. (2024), we also consider the role of customer education in reducing food waste.

Our contribution to this literature is to highlight a previously overlooked source of food waste: extra purchases made by individuals in the food delivery market, prompted by intentional interactions with pricing mechanisms. Our research integrates the decisions of platforms, restaurants, and individual customers, focusing on their strategic interplay. Although this issue has received limited attention in the past, it is becoming increasingly relevant due to the rapid growth and widespread adoption of food delivery services. For instance, spending threshold discounts offered by restaurants or delivery platforms can incentivize customers to purchase more than they need. Our findings suggest that restaurants can benefit from educating customers to be more waste-averse, thereby improving both sustainability and profitability. To our knowledge, we are the first to examine food waste specifically within the food delivery channel—a rapidly growing sector that processes hundreds of millions of orders daily worldwide and constitutes a significant and rising contributor to overall food waste.

2.2 Food Delivery Industry and Regulations

Our work also relates to the growing literature on food delivery platforms and the related regulations. Modeling studies in this area include Liu et al. (2021), Chen et al. (2022), Feldman et al. (2022), Zhang and Yu (2023), Liu et al. (2023), and Zhang et al. (2022). Empirical and experimental studies include Mao et al. (2022), Li and Wang (2024), Li and Wang (2025), and Lee et al. (2025). Among these, Zhang et al. (2022) study the impact of various regulations on reducing traffic violations and accidents committed by delivery workers; Zhang and Yu (2023) investigate the effects of two government regulations on the delivery workers' welfare; and Li and Wang (2024) empirically examine the impact of commission fee cap regulation on restaurant profits. Collectively, these studies focus on the societal impact and governance issues associated with food delivery platforms. Our research complements this literature by examining the environmental impact of food delivery platforms, with a particular focus on food waste generation and reduction, as well as related policy implications. Furthermore, we highlight that a restaurant's incentive to educate customers to be waste-averse is influenced by its cost structure, which is determined by the contractual arrangement with the delivery platform. Consistent with Feldman et al. (2022), we adopt a linear contract consisting of a commission rate and a fixed fee in our analysis.

2.3 Volume-Discount Pricing

Our study also intersects with the literature on volume-discount pricing, extensively explored in operations management and marketing (e.g., Spence 1977, Oren et al. 1982, Jeuland and Shugan 1983, and Weng 1995). Typically, this stream assumes that a seller offers a price-quantity menu in a take-it-or-leave-it manner, with lower prices for larger purchase quantities. Three principal motivations for volume discounts have been identified in the literature (e.g., Buchanan 1952; Dolan 1987): perfect price discrimination for homogeneous buyers (e.g., Buchanan 1952), partial price discrimination for heterogeneous buyers (Spence 1977; Oren et al. 1982), and channel efficiency (e.g., Jeuland and Shugan 1983, Monahan 1984, Lal and Staelin 1984, Lee and Rosenblatt 1986, Dada and Strikanth 1987, and Weng 1995). For a comprehensive review of this literature, see Dolan (1987). Our work aligns with the second motivation, as STD pricing enables partial price discrimination among heterogeneous customers with varying demand sizes. STD pricing constitutes a discontinuous pricing curve, characterized by a sudden reduction in average price resulting from a payment reduction, in contrast to continuous schemes such as per-unit pricing plus a fixed fee, where the average price changes continuously. Several studies have examined discontinuous volume discounts, including those with a single price break-point (e.g., Federgruen and Lee 1990; Xu and Lu 1998; Altintas et al. 2008) and multiple price break-points (e.g., Chung et al. 1987). We contribute to the literature by highlighting the distinctions between discontinuous and continuous volume-discount schemes for their implications in customer purchasing behavior and waste generation. To the best of our knowledge, this is the first in-depth analysis of the economic value and environmental impact of STD pricing in the food delivery platform context.

3 The Model

We consider a stylized model wherein a single monopolistic restaurant offers "free delivery" for online orders that meet a spending threshold, while the delivery fee is charged by the delivery platform. The restaurant has a unit mass of infinitesimal potential online customers. We focus on the sequential sub-game between the restaurant and the online customers, wherein the restaurant's pricing decision is the first move followed by customers' purchase decisions.

3.1 Customers

Customers are heterogeneous in both their marginal willingness to pay (MWTP) and demand for food. Let θ denote a customer's demand for food (i.e., the ideal consumption level, measured by weight or portion), which is uniformly drawn from $[0, \bar{\theta}]$, and q the actual purchase amount of food from the restaurant. We consider continuous purchase quantities, which reflect the availability of small items on the menu. Each customer knows his/her own θ, decides on q, and aims to maximize the net utility of food consumption, which is the gross utility net of the payment to the restaurant. We assume that the gross utility of a customer is composed of four parts:

1) α, a baseline utility;

2) $-\beta \cdot \theta$, a loss caused by hunger, wherein β is the marginal value of food for the customer;

3) $\beta \cdot \min\{q, \theta\}$, a utility restoration due to food consumption, which is bounded by $\beta \cdot \theta$; and

4) $-\gamma \cdot \max\{0, q - \theta\}$, a loss caused by over-consumption or throwing away the extra food.

Note that such a setting is able to capture the asymmetry between the underage loss (i.e., $-\beta \cdot [\theta - \min\{q, \theta\}]$) and the overage loss (i.e., $-\gamma \cdot \max\{0, q - \theta\}$), wherein $\beta > 0$ and $\gamma \geq 0$ measure, respectively, the marginal losses of utility caused by underage and overage. Regardless of how customers deal with the extra food (i.e., over-consuming or disposing of), we define $\max\{0, q - \theta\}$ as the amount of ***food waste*** generated by a customer. We assume that customers are heterogeneous in β, which is called the MWTP hereafter. Note that, there are two major user groups of food delivery platforms: young white-collars and college students. The former group normally has a higher MWTP than the latter, partly due to more expensive outside options they face (i.e., college students have student canteens as their outside options). Hence, we assume that β follows a two-point distribution on $\{\beta_L, \beta_H\}$, with $\beta_L < \beta_H$ and $h = \Pr(\beta = \beta_H)$ represents the proportion of young white-collars. Since our theoretical results are not sensitive to the heterogeneity of γ, we assume customers are homogeneous in this aspect for the sake of simplicity. Lastly, let $P(q)$ denote the payment value for a purchase order of volume q. Mathematically, a customer with θ, β, and q receives below net utility:

$$U(q|\theta, \beta) = \alpha - \beta \cdot \theta + \beta \cdot \min\{q, \theta\} - \gamma \cdot \max\{0, q - \theta\} - P(q). \tag{1}$$

We define the two-dimensional tuple, (θ, i), as the type of a customer, whose demand is θ and MWTP is β_i ($i = L, H$). A customer of type (θ, i) solves the problem of $\max_{q \geq 0} U(q|\theta, \beta_i)$. Let $q_i^*(\theta|P)$ denote the optimal purchase volume of a type-(θ, i) customer under payment function P.

3.2 The Restaurant

The restaurant serves online customers only (i.e., a "cloud kitchen"; Lucas 2021), knows well the potential demand from the online channel, and is not constrained by a finite inventory of food materials. We also abstract away from potential congestion caused by random customer arrivals and a limited service capacity, because the waiting time is normally well anticipated by online customers. As a result, we assume that the demand is deterministic and sales to customers are independent. The restaurant aims to maximize its total profit from a single interaction with all the potential online customers by designing the payment function P.

The restaurant decides on the marginal food price, p, and the spending threshold, $\bar{v}$, while the delivery fee, L, is always charged by the platform. Accordingly, we have

$$P(q) = L \cdot \mathbb{I}\{q > 0\} + p \cdot q - L \cdot \mathbb{I}\{p \cdot q \geq \bar{v}\}, \tag{2}$$

wherein $\mathbb{I}$ is a binary indicator. Note that, given p, the spending threshold is equivalent to a volume threshold: $Q = \bar{v}/p$. Hence, we focus on Q hereafter instead of $\bar{v}$, and the payment function P is fully characterized by (p, Q).

After receiving the payment from a customer, the platform withholds a sum that consists of the delivery fee (paid by the customer to the platform), the commission based on the value paid by the customer to the restaurant, and a service fee, w. Then, the platform transfers the remaining value to the restaurant. Let s denote the commission rate and c the marginal cost of food. Therefore, given pricing decisions (p, Q), the restaurant's profit from a customer buying q units of food is

$$\begin{aligned}\pi(q, p, Q) =& P(q) - L \cdot \mathbb{I}\{q > 0\} - s[P(q) - L \cdot \mathbb{I}\{q > 0\}] - w - cq \\ =& (1 - s)[p \cdot q - L \cdot \mathbb{I}\{q \geq Q\}] - w - cq \end{aligned} \tag{3}$$

The platform solves the problem of

$$\max_{p,Q\geq 0} \Pi(p, Q) = \sum_{i=L,H} h_i \int_0^{\bar{\theta}} \pi\left(q_i^*(\theta|p, Q), p, Q\right) \frac{d\theta}{\bar{\theta}}, \tag{4}$$

wherein we define $h_H = h$ and $h_L = 1 - h$.

3.3 Technical Assumptions

To avoid unnecessary complexity, we make the following two assumptions throughout the paper.

Assumption 1. Positive Margin: $c < (1 - s)\beta_L$.

This assumption ensures that when the marginal food price $p = \beta_L$, there exists a profitable, finite purchase quantity for the restaurant. In other words, it is a necessary condition for the restaurant to make a positive profit from low-MWTP customers. Otherwise, the restaurant will focus on high-MWTP customers only and thus the results will be trivial.

Assumption 2. Rich Pricing Designs: $L/(\beta_H - \beta_L) + L/(\beta_L + \gamma) < \bar{\theta}$.

This assumption ensures that the set of potentially optimal (p, Q) designs for the restaurant is large enough. It requires that both high- and low-MWTP customers possess significantly high MWTPs and exhibit significant heterogeneity in their MWTPs (i.e., the difference $\beta_H - \beta_L$ is relatively large), compared to the delivery fee L. Without this assumption, the optimal (p, Q) design is trivial because customers are relatively homogeneous and there is not much room for setting the price. Its technical implications will be clearer in the next section.

4 Analysis

In this section, we first solve out $q_i^*(\theta|p, Q)$ for each customer type to see when extra purchases will occur. Then, we optimize the restaurant's (p, Q) design to evaluate whether a discontinuous payment-volume curve (i.e., a finite Q) is preferred to a continuous, linear curve (i.e., $Q = +\infty$). Next, we study when food waste occurs and explore potential regulations to achieve both food waste reductions and social welfare increases. Last, we compare two extreme cases of γ and study the conditions and reasons for the restaurant to share an interest in reducing food waste.

4.1 Customer Purchase Decision

From Equation (1), we can see that the net utility of a customer is piece-wise linear in q and there are only three possible purchase volumes for a customer with inherent demand θ: 0, θ, and Q. The optimal choice depends on the demand value and the (p, Q) design. Some customers strictly prefer one of the three volumes, while others are indifferent between two or more volumes. For the ease of exposition, we define the following critical demand values for type-i customers ($i = L, H$) when $p \leq \beta_i$:

$$\begin{cases} \theta_i^{NJ}(p) & = \begin{cases} \frac{L}{\beta_i - p} & \text{if } p < \beta_i \\ +\infty & \text{if } p = \beta_i \end{cases}; \\ \theta_i^{NT}(p, Q) & = \frac{(\gamma+p)Q}{\gamma+\beta_i}; \\ \theta^{JT}(p, Q) & = Q - \frac{L}{\gamma+p}. \end{cases} \tag{5}$$

In Equation (5), N stands for **N**o purchase (i.e., $q = 0$), J for buying **J**ust enough (i.e., $q = \theta$), and T for buying up to the **T**hreshold (i.e., $q = Q$). Customers with critical demand values are indifferent between the two relevant purchase volumes. Based on the order of these critical values, we define two scenarios to describe the purchase pattern of customers with the same MWTP.

Definition 1. Scenario of Zero "New Buyers" (σ_1): $\theta_i^{NJ}(p) < \theta_i^{NT}(p, Q) < \theta^{JT}(p, Q)$.

Definition 2. Scenario of Some "New Buyers" (σ_2): $\theta^{JT}(p, Q) \leq \theta_i^{NT}(p, Q) \leq \theta_i^{NJ}(p)$.

The meanings and implications of the two scenarios are illustrated by Figure 2. In each subgraph, we plot the three lines in a two-dimensional plane with the horizontal axis representing a customer's inherent demand and the vertical axis representing utility. The three lines correspond to the three purchasing volumes mentioned above. For a customer of a certain demand value θ, the optimal purchase volume corresponds to the highest line. In Scenario σ_1, the MWTP (represented by the slope of the solid line) or the threshold is relatively high, and thus customers with relatively low demand values (i.e., $\theta \in \left[\theta_i^{NJ}(p), \theta^{JT}(p, Q)\right)$) would like to make purchases without qualifying the discount; if we increase the threshold Q, the number of these buyers will increase; even when the discount is removed (i.e., $Q = +\infty$), all the buyers (i.e., $\theta \geq \theta_i^{NJ}(p)$) will still make purchases. Hence, no "new buyers" will be acquired by adding the specific threshold-based discount to the linear pricing scheme in the example. In Scenario σ_2, the MWTP or the threshold is relatively low; if we remove the discount, some buyers (i.e., $\theta \in \left[\theta_i^{NT}(p, Q), \theta_i^{NJ}(p)\right)$) will quit buying. Hence, some "new buyers" will be acquired by adding the specific threshold-based discount to the linear pricing scheme in the example. The distinction between the two scenarios is

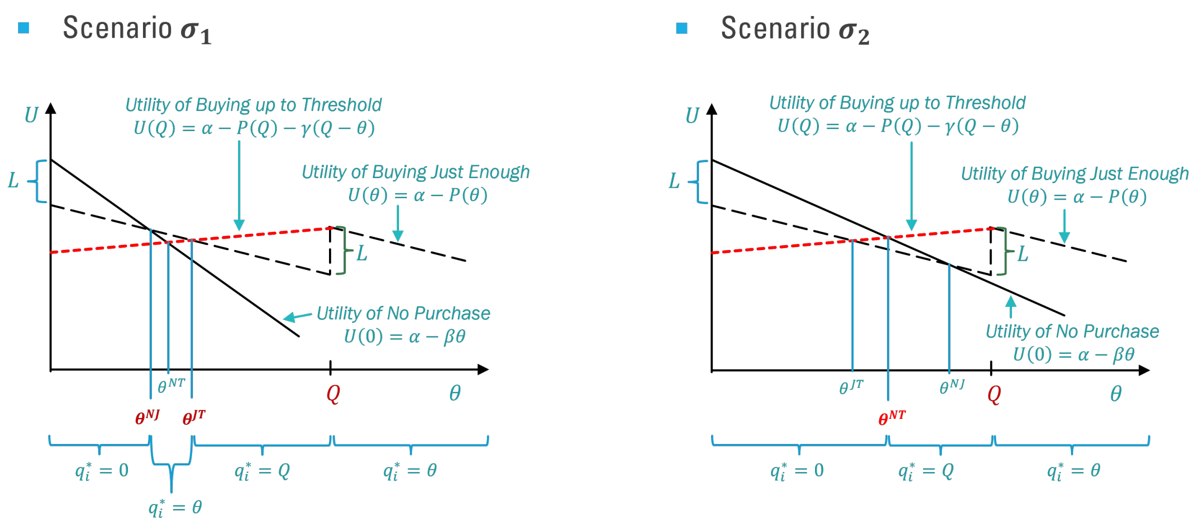

Figure 2: The Two Scenarios of Purchase Pattern for Customers of the Same β

important, because in our model setting the restaurant can benefit from the "new buyers" but will suffer from the "spending upgraders."

Obviously, σ_1 and σ_2 are mutually exclusive for type-i customers ($i = L, H$), and the following lemma shows that they are also collectively exhaustive. The restaurant can determine the scenario for type-i customers by adjusting (p, Q). Given $p < \beta_i$, let $Q_i^e(p)$ denote the maximum volume threshold that puts type-i customers into σ_2; it is easy to derive that

$$Q_i^e(p) = \frac{L}{\beta_i - p} + \frac{L}{\gamma + p}. \tag{6}$$

Hence, $Q > Q_i^e(p)$ corresponds to type-i being in σ_1. In fact, we have $\theta^{JT}(p, Q) = \theta_i^{NT}(p, Q) = \theta_i^{NJ}(p)$ when $Q = Q_i^e(p)$. This reminds us that our Assumption 2 ensures that type-H customers can be put into either σ_1 or σ_2 by adjusting Q when $p = \beta_L$. In this way, we do not constrain the search space for the optimal (p, Q) design to a single scenario.

Lemma 1. *For type-i customers ($i = L, H$), σ_1 and σ_2 are collectively exhaustive given $p \leq \beta_i$.*

Therefore, our analysis can focus on the two scenarios and we derive the following proposition to describe the optimal purchase decisions of customers of different types. The result says that, given any pricing scheme, a customer will purchase extra food only if the inherent demand is close to but not higher than the volume threshold; type-i customers will not make any extra purchases if the price is high enough such that $p \geq \beta_i$. Without loss of generality, we assume that a customer will choose the larger purchase volume when s/he is indifferent between two purchase volumes.

Proposition 1. *Given pricing scheme (p, Q), a type-i customer ($i = L, H$) with demand θ chooses the* *optimal purchase volume $q_i^*(\theta|p,Q)$ in the following way. In Scenario σ_1 wherein $Q > Q_i^e(p)$,*

$$q_i^*(\theta|p,Q) = \begin{cases} 0 & \text{if } p > \beta_i \text{ or } (p = \beta_i \text{ and } \theta < Q) \text{ or } \left(p < \beta_i \text{ and } \theta < \theta_i^{NJ}(p)\right); \\ \theta & \text{if } p < \beta_i \text{ and } \left(\theta \in \left[\theta_i^{NJ}(p), \theta^{JT}(p,Q)\right) \text{ or } \theta \geq Q\right); \\ Q & o.w.. \end{cases} \tag{7}$$

In Scenario σ_2 wherein $Q \leq Q_i^e(p)$,

$$q_i^*(\theta|p,Q) = \begin{cases} 0 & \text{if } p > \beta_i \text{ or } (p = \beta_i \text{ and } \theta < Q) \text{ or } \left(p < \beta_i \text{ and } \theta < \theta_i^{NT}(p,Q)\right); \\ \theta & \text{if } p < \beta_i \text{ and } \theta \geq Q; \\ Q & o.w.. \end{cases} \tag{8}$$

4.2 Optimal Pricing

Given customer optimal purchase decisions, we now solve for the restaurant's optimal (p, Q) design. To begin, we define two types of pricing schemes below.

Definition 3. Boundary Threshold Pricing (BTP): $p \in \{\beta_L, \beta_H\}$ and $0 < Q < +\infty$.

Definition 4. Simple Linear Pricing (SLP): $0 \leq p \leq \beta_H$ and $Q = +\infty$.

Note that both BTP and SLP can be regarded as special forms of STD pricing. In particular, the marginal food price under BTP is restricted to the set of customer MWTPs, while the volume threshold under SLP is restricted to infinity. In addition, while BTP has a discontinuous payment-volume curve, SLP is a continuous volume-discount scheme from a customer's perspective because the average food price is $L/q + p$. As shown later, the optimal STD pricing scheme is either BTP or SLP under a mild condition. Therefore, we can compare optimal BTP against optimal SLP to investigate the impact of average-price discontinuity on the restaurant's profit.

In the next step, we divide our analysis into two parts according the marginal food price level. When the price is high, only customers with high MWTP would purchase from the restaurant, and we call this case *skimming pricing*. When the price is low enough, customers with both high and low MWTPs would make purchases, and we call this case *inclusive pricing*.

4.2.1 Skimming Pricing ($\beta_L < p \leq \beta_H$)

Under skimming pricing, the restaurant only focuses on type-H customers and the problem is equivalent to the optimization of (p, Q) with $h_H = 1$. The following lemma shows that the optimal (p, Q) design is BTP when customers are homogeneous in their MWTP.

Lemma 2. *When $h_i = 1$ ($i = L, H$), the optimal pricing scheme is BTP with $p^* = \beta_i$ and*

$$Q^* = \frac{(1-s)L + w}{(1-s)\beta_i - c}. \tag{9}$$

4.2.2 Inclusive Pricing ($p \leq \beta_L$)

Under inclusive pricing, there are three possible cases. Case I: both type-H and type-L customers are in σ_1. Case II: type-H customers are in σ_1 and type-L in σ_2. Case III: both type-H and type-L customers are in σ_2. Note that, $\theta_i^{NJ}(p)$ is decreasing in β_i and $\theta^{JT}(p, Q)$ is independent of β_i, so it is impossible to have type-H customers in σ_2 (i.e., $\theta^{JT}(p, Q) < \theta_H^{NJ}(p)$) and type-$L$ in σ_1 (i.e., $\theta_L^{NJ}(p) < \theta^{JT}(p, Q)$) at the same time. For $i \in \{L, H\}$, denote $\Pi_i(p, Q|\sigma)$ as the restaurant's total profit conditional on 1) $h_i = 1$ and 2) all the customers are in Scenario σ ($= \sigma_1, \sigma_2$). The following lemma shows how the restaurant can improve its profit from only type-H or type-L customers by adjusting the marginal food price and/or the volume threshold according to σ.

Lemma 3. *Given two pricing designs (p, Q) and (p', Q') such that $p < p' \leq \beta_L$ and $Q' = Q \cdot (p + \gamma) / (p' + \gamma) < Q \leq \bar{\theta}$, the total profit from type-i customers satisfies $\Pi_i(p, Q|\sigma_1) < \Pi_i(p, \infty|\sigma_1)$ and $\Pi_i(p, Q|\sigma_2) < \Pi_i(p', Q'|\sigma_2)$.*

Hence, the restaurant can improve the total profit in Case I by setting Q to ∞ (i.e., removing the "spending upgraders") and in Case III by setting p to p' and Q to Q' (i.e., improving profit margin and acquiring more "new buyers"). In other words, any pricing scheme (p, Q) in Case I is dominated by SLP and any pricing scheme (p, Q) in Case III is dominated by BTP with $p' = \beta_L$ and $Q' = Q \cdot (p + \gamma) / (\beta_L + \gamma)$. However, it is not clear how the total profit can be improved in Case II, because customers are in different scenarios. The next proposition first proves that the restaurant should adopt either SLP or BTP in most cases, and then it gives a sufficient condition for BTP to be the dominant pricing scheme.

Proposition 2. *There exist $\tilde{\theta}_1$ and $\tilde{\theta}_2$, where $\tilde{\theta}_1 \leq \tilde{\theta}_2$. Given $\bar{\theta} \geq \tilde{\theta}_1$, the optimal pricing scheme for the restaurant under inclusive pricing is either BTP or SLP; given $\bar{\theta} \geq \tilde{\theta}_2$, BTP is better than SLP.*

The conditions require $\bar{\theta}$, representing the maximum customer demand, to be sufficiently large. Since a "customer" in our model can represent a group of buyers (e.g., students in a dormitory room, and white-collar workers in a team), $\bar{\theta}$ can be quite large in reality. Under these mild conditions, combining Lemma 2 with Proposition 2, we conclude that the optimal pricing scheme is either the optimal skimming pricing or the optimal inclusive pricing. Our numerical examples in Section 5 show that these results hold even for small $\bar{\theta}$.

4.2.3 Optimal Price Level

Next, we focus on BTP and show how the price level should be determined. In particular, we consider the influence of the market composition parameter h, which represents the proportion of high-MWTP customers. The following proposition characterizes how h affects the restaurant's optimal pricing decision.

Proposition 3. *Given $\bar{\theta} \geq \tilde{\theta}_2$, there exists a threshold $\tilde{h} \in [0, 1)$ such that the optimal pricing scheme for the restaurant is inclusive (i.e., $p = \beta_L$) if $h < \tilde{h}$ and is skimming (i.e., $p = \beta_H$) if $h \geq \tilde{h}$.*

Intuitively, it is optimal for the restaurant to adopt inclusive pricing when the market has a higher proportion of low-MWTP customers, and skimming pricing when high-MWTP customers are more prevalent. Note that when $h = \tilde{h}$, the restaurant is indifferent between skimming pricing and inclusive pricing, but we assume that the restaurant prefers skimming pricing in this case.

4.3 Food Waste

Here, we study whether food waste will be generated if the restaurant optimizes the (p, Q) design. First, under skimming pricing, we know that the optimal price for the restaurant is $p = \beta_H$ and thus the critical demand values for type-H customers are $\theta_H^{NJ}(p) = \infty$, $\theta_H^{NT}(p, Q) = Q$, and $\theta^{JT}(p, Q) < Q$. As a result, type-H customers are in scenario σ_2. According to Proposition 1, we have $q_H^*(\theta|p, Q) = 0$ or θ, so there is no food waste under skimming pricing.

Next, for inclusive pricing, we focus on the case of a sufficiently large $\bar{\theta}$ required by Proposition 2 and thus the optimal pricing scheme is BTP. Therefore, the optimal price for the restaurant is $p = \beta_L$ and thus, according to the above logic, there is no food waste from type-L customers. However, we know from Proposition 1 that all the "new buyers" and "spending upgraders" among the type-H customers (i.e., $\theta \in \left(\max\left\{\theta_H^{NT}(p, Q), \theta^{JT}(p, Q)\right\}, Q\right)$) will purchase extra food and generate food waste. We formally state this result in the next proposition.

Proposition 4. *If the restaurant optimizes the (p, Q) design, food waste is generated only when $h < \tilde{h}$; the food waste, if any, is generated by type-H customers.*

This proposition predicts that white-collar workers are more likely than college students to generate food waste due to their higher MWTP. Given that the restaurant chooses a price level that college students can just afford, the delivery fee is a crucial factor that prevents college students from using the food delivery platform; college students would rather go to their university canteens if the delivery fee cannot be waived or they have to buy extra items to avoid the delivery fee. In contrast, many white-collar professionals can afford to purchase meals online even without the discount, and thus the discount is an extra benefit for them if they can add some small items to get qualified; some other white-collar professionals are reluctant to order food from the restaurant due to their small demand relative to the delivery fee, but they will make a purchase if the delivery fee can be waived by adding some small items.

How does Q affect food waste? In Figure 3, we compare two BTP designs with the same parameters except Q. In the left sub-graph, Q is smaller and food waste is produced by the "new buyers" and "spending upgraders" among the type-H customers. In the right sub-graph, Q is larger; food waste is only produced by the "spending upgraders" among the type-H customers, but there is more food waste. (Note: the two shaded triangles are congruent.)

The next proposition formally states how the food waste is affected by the volume threshold Q. Crucially, we find non-monotonicity in this relationship, which is valuable in guiding the formation of regulations. First, since the restaurant's optimal volume threshold depends on various business parameters—such as the service fee and the commission fee charged by the food deliv-

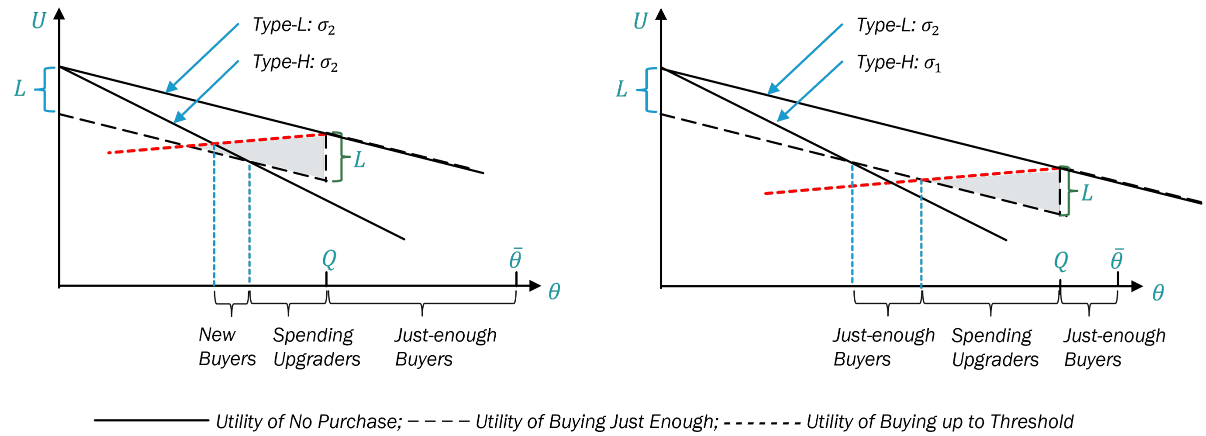

Figure 3: How Food Waste Is Affected by Volume Threshold

ery platform—understanding how Q affects food waste can help guide the regulation of contract terms between a restaurant and a platform. Second, in a hypothetical scenario where a regulator directly imposes a restriction on Q, this analysis can shed light on the potential for such a regulation to reduce food waste. Since food waste is absent when $h \geq \tilde{h}$, our subsequent discussions are restricted to the market scenario of $h < \tilde{h}$.

Proposition 5. *Given that $h < \tilde{h}$ and the restaurant sets $p = \beta_L$, the total food waste is a non-monotonic function of Q: it strictly increases with Q for $Q \in [0, Q_H^e(\beta_L))$, remains constant for $Q \in [Q_H^e(\beta_L), \bar{\theta})$, strictly decreases with Q for $Q \in [\bar{\theta}, \bar{\theta} + L/(\beta_L + \gamma))$, and equals zero for $Q \geq \bar{\theta} + L/(\beta_L + \gamma)$. The food waste ratio (defined as the ratio of total food wasted to total food purchased via the delivery platform) increases with Q for $Q \in [0, \bar{\theta})$, decreases with Q in $Q \in [\bar{\theta}, \bar{\theta} + L/(\beta_L + \gamma))$, and equals zero for $Q \geq \bar{\theta} + L/(\beta_L + \gamma)$.*

Hence, if the restaurant optimizes the (p, Q) design and the optimal Q is relatively low, it is possible for the regulator to reduce food waste by reducing Q through regulating the platform fees or setting an upper bound on Q; if the optimal Q is relatively high for the restaurant, food waste reduction could be achieved by increasing Q through similar measures. Nevertheless, if the (p, Q) design is not optimized, we do not have a theoretical guidance on how to reduce food waste. That being said, we can show with extensive numerical examples (see Section 5.2) that, compared to an arbitrary (p, Q) design, food waste can be significantly reduced in most cases if the restaurant switches to the optimal (p, Q) design. Therefore, optimal pricing is important for food waste reduction. On top of optimal pricing, food waste could be further reduced through regulation. In the next section, we will discuss how to regulate the contract terms.

4.4 Regulating Contract Terms

This section explores regulatory interventions to reduce food waste. Ideally, regulators aim to do so without sacrificing social welfare. For the welfare analysis, we introduce k to denote the platform's fixed service cost for each order, and we assume that the delivery fee is bounded by a multiple of k: $L > k \cdot (\beta_H - \beta_L) / (\beta_L - c)$. The following proposition establishes a key linkage between the total welfare and the volume threshold, and the relationship is non-monotonic.

Proposition 6. *Let $Q_{sb} > 0$ be the socially break-even volume threshold that depends on k. Given $h < \tilde{h}$ and pricing design (β_L, Q), the social welfare decreases in Q for $Q \in [Q_{sb}, \bar{\theta})$, increases in Q for $Q \in [0, Q_{sb}) \cup [\bar{\theta}, \bar{\theta} + L / (\beta_L + \gamma))$, and remains constant for $Q \geq \bar{\theta} + L / (\beta_L + \gamma)$.*

The rationale is straightforward: when Q is below Q_{sb}, increased Q can improve social welfare by discouraging small orders and boosting order sizes; when Q is above Q_{sb}, increased Q reduces the number of buyers and thus reduces the social welfare. Proposition 5 and 6 together indicate the possibility of simultaneously reducing food waste and enhancing social welfare. To be specific, we should reduce Q if the current threshold is relatively low and increase it if the current level is extremely high.

Next, we examine how regulators can influence Q indirectly by targeting the contract terms—s and w—between the restaurant and the platform. Establishing monotonic relationships between Q and these contract terms is crucial for predicting regulatory impact. The following proposition derives a sufficient condition for such relationships to hold. It requires that the profit margin for the restaurant is not too low, the MWTP gap between type-H and type-L customers is not too large, and the fees (i.e., s and w) charged by the platform are not too high. The impacts of s and w on Q are mainly through the restaurant's profit margin. The higher the margin, the easier for the restaurant to set a low threshold that encourages low-demand customers to make purchases.

Proposition 7. *Given $h < \tilde{h}$, the optimal volume threshold increases with both the commission rate and the service fee if*

$$(1-s)\,\beta_L - c > \frac{\frac{w}{L} + \frac{1-s}{1-h}}{\frac{1}{\beta_H - \beta_L} + \frac{1}{\gamma + \beta_L}}. \tag{10}$$

With these monotonic relationships, we can conclude that capping the commission rate and the service fee at low levels can, in most cases, yield a "win-win" outcome—simultaneously improving social welfare and reducing food waste. We formally state this result in the following corollary. It is noteworthy that our theory is built on the assumptions of our base model. Our robustness checks in Section 5.6 confirm that these conclusions generally hold.

Corollary 1. *Given $h < \tilde{h}$ and the condition in Equation (10), the regulator can simultaneously achieve (at least weakly) social welfare improvement and food waste reduction by capping s and w.*

4.5 Increasing Aversion to Waste

Regulation may not always be effective in reducing food waste in the delivery market as it can receive resistance from the firms. An alternative strategy involves educating customers and encouraging them to be mindful of their consumption amounts. However, implementing this approach may impact the restaurant's profitability if customers alter their purchasing behavior in order to reduce food waste. In this section, we examine how the restaurant profit will be affected if we can successfully educate customers and increase their aversion to food waste.

Our theoretical analysis focuses on two contrasting scenarios: one characterized by zero waste aversion ($\gamma = 0$) and the other by infinite waste aversion ($\gamma = +\infty$) among customers. The case of $\gamma = 0$ reflects the current state where individuals exhibit limited sensitivity towards food waste, while $\gamma = +\infty$ represents a society where people are well-informed and actively strive to minimize any wastage. These extreme cases serve as valuable benchmarks for understanding the potential range of behaviors. In addition, our extensive numerical examples consistently demonstrate that the restaurant's preference aligns with either $\gamma = 0$ or $+\infty$; there exist no intermediate scenarios that are preferable from the restaurant's perspective. The next proposition shows how the restaurant's preference over γ depends on the market characteristics.

Proposition 8. *The restaurant's optimal total profit with $\gamma = +\infty$ is higher than that with $\gamma = 0$ if*

$$\frac{w + (1-s)\,L}{(1-s)\,\beta_L - c} \geq \frac{L}{\beta_H - \beta_L} + \frac{L}{\beta_L}; \tag{11}$$

the reverse is true if

$$\frac{(1-h)\,w + (1-s)\,L}{(1-h)\,[(1-s)\,\beta_L - c]} \leq \frac{L}{\beta_H - \beta_L}. \tag{12}$$

Clearly, the parts on the left side of the above inequalities are increasing in the marginal food cost c; if c is large enough, the restaurant's total profit with $\gamma = +\infty$ is larger than with $\gamma = 0$. This is because, when the profit margin is low, the optimal volume threshold for the restaurant tends to be high; otherwise, customers with low demand can get the discount and cause losses to the restaurant. As we mentioned earlier in Section 4.1, STD pricing cannot acquire "new buyers" when the volume threshold is high (i.e., customers are in σ_1), and thus the restaurant prefers to reduce the number of "spending upgraders" by raising γ. Conversely, when c is low and the profit margin is high, the restaurant can afford to offer a low volume threshold that can attract "new buyers" that are waste-insensitive (i.e., customers are in σ_2).

Another important factor is the gap between β_H and β_L; note that the right-hand-side parts of the above inequalities are decreasing in this gap. The underlying rationale is similar. When $\beta_H - \beta_L$ is large enough and the marginal food price is $p = \beta_L$, type-H customers would like to make a purchase even with a low demand; thus, if the optimal volume threshold is not low enough, type-H customers are likely in σ_1, in which STD pricing cannot acquire "new buyers." Hence, the restaurant prefers to have waste-averse customers when $\beta_H - \beta_L$ is large enough, and vice versa.

In addition, the restaurant's total profit with $\gamma = +\infty$ is larger than with $\gamma = 0$ if w is large enough, s is large enough, or L is small enough. The rationales are similar to the impact of c. Therefore, under such conditions, the restaurant should be self-motivated to educate customers about avoiding food waste. In Section 5.4, we will use extensive numerical examples to show that these results about the restaurant's preference over γ generally hold.

4.6 The Value of STD Pricing

The result of the previous section is counter-intuitive to some extent, because people normally think that it is profitable for the restaurant to induce customer extra purchases when STD pricing is adopted. However, the intuition is not always correct, especially when customers are fully rational (i.e., free of psychological effects). According to Proposition 2, we know that BTP is strictly better than SLP regardless of γ as long as $\bar{\theta}$ is large enough. If the restaurant cannot benefit from extra purchases of customers (i.e., $\gamma = +\infty$ is preferred), why should the restaurant use BTP? In this section, we demonstrate that BTP or STD pricing in general can benefit the restaurant by attracting more modest-size orders and enhancing profit margins of large orders.

First, STD pricing can attract more customers with modest demand by offering a lump-sum discount (i.e., acquiring "new buyers"). We formally state this result in the next proposition. To prepare, we define the term "buyer base" as the total number of customers that make a purchase.

Definition 5. Buyer base under pricing scheme (p, Q):

$$B(p, Q) = \sum_{i=L,H} h_i \int_0^{\bar{\theta}} \mathbb{I}\left\{q_i^*(\theta|p, Q) > 0\right\} \frac{d\theta}{\bar{\theta}}. \tag{13}$$

Proposition 9. *$B(p, Q) \geq B(p, +\infty)$.*

Figure 4 illustrates the rationale of how STD pricing expands the buyer base when $\gamma = +\infty$, by showing how the average price changes with the purchase volume. In mathematical terms, SLP has continuous average price curves, and thus the buyer base shrinks if we increase the food price. In contrast, STD pricing has a discontinuous average price curve, which is flat for $q \geq Q$; hence, as long as the marginal food price p is below the MWTP β, the buyer base is determined by the volume threshold Q: the lower Q is, the larger the buyer base. *Essentially, SLP is a form of price discrimination in the sense that the average price decreases with the order size; STD pricing removes the price discrimination for volumes above the threshold by subsidizing the buyers with a lump-sum discount, which allows the restaurant to avoid to some extent the trade-off between the marginal food price and the number of buyers.*

Therefore, in comparison to the case of SLP or continuous volume-discount strategies, the lump-sum discount offered under STD pricing on the one hand induces order-size expansion that causes losses, but on the other hand it increases the restaurant profit in two ways: bringing in more modest-size buyers and enhancing the profit margin for large orders. As long as the profit margin is high enough, bringing in buyers with modest demand can generate positive profits. In addition, with a higher price, the larger the order size, the more the restaurant can extract surplus from the buyer. These ideas are illustrated by Figure 5. In particular, if we compare the top-left sub-graph (representing SLP with a lower food price) against the bottom-right sub-graph (representing STD pricing with a higher price), we can see that the profit increase comes from two parts: a positive profit generated by additional modest-size orders and an additional profit from

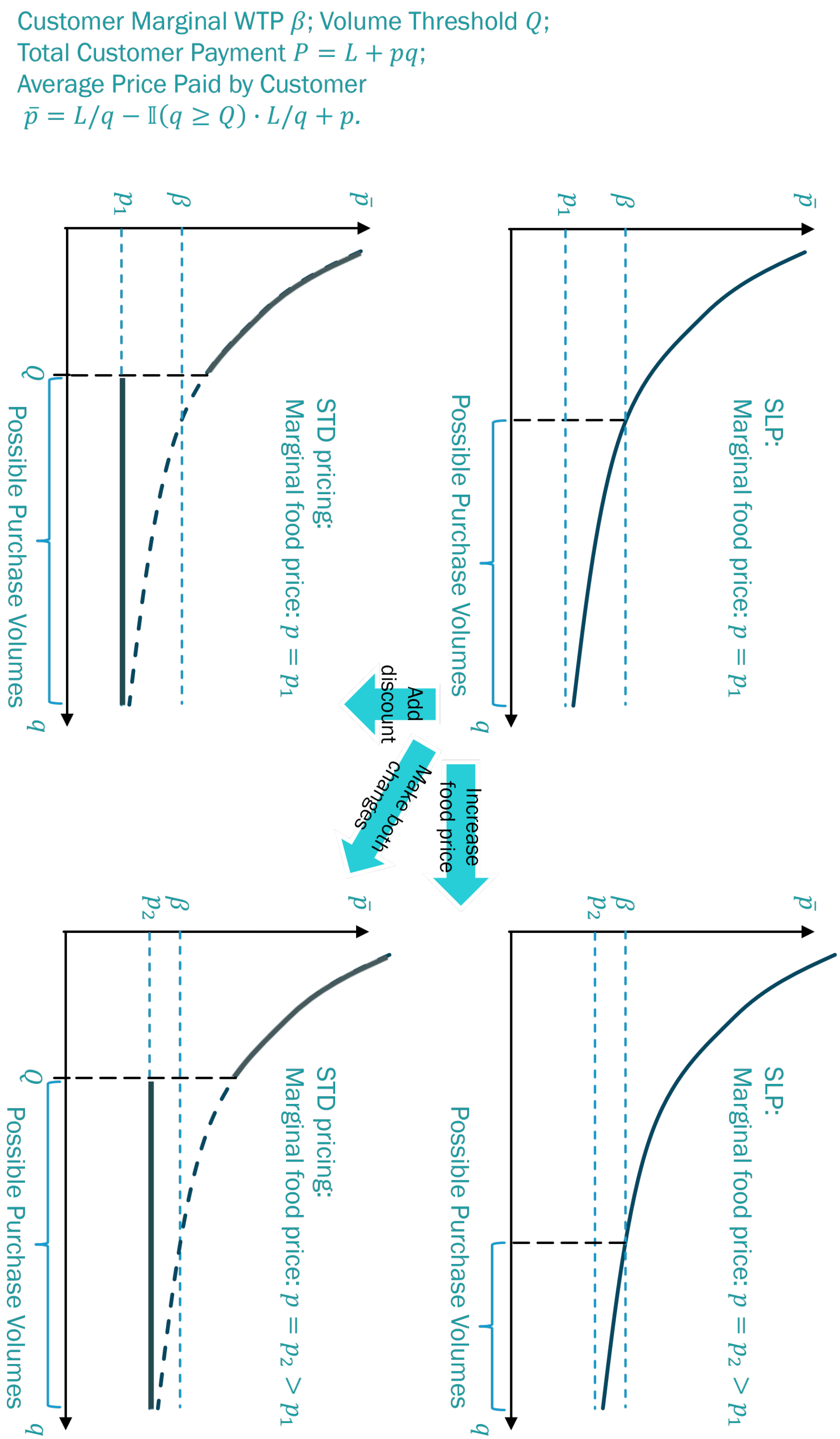

Figure 4: STD Pricing Can Expand the Buyer Base when $\gamma = +\infty$

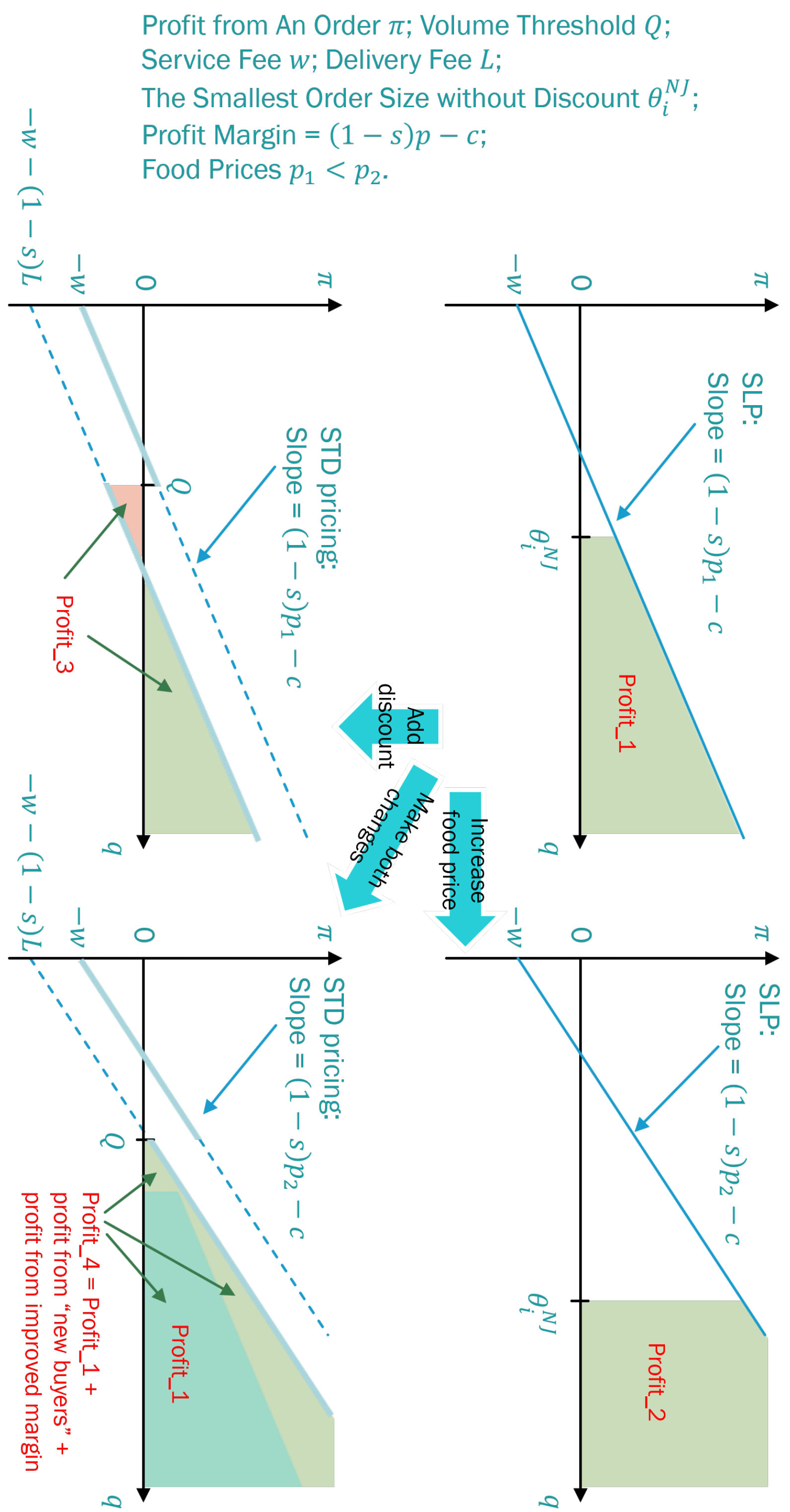

Figure 5: STD Pricing Can Increase Profit when $\gamma = +\infty$

large orders enabled by the increased margin. The following proposition proves this result at the level of individual orders.

Proposition 10. *For any order size $q > 0$ that exists under both (p, Q) and $(p', +\infty)$, wherein $p > p'$, we have $\pi(q, p, Q) > \pi(q, p', +\infty)$ if and only if $q \in (0, Q) \cup (\max\{Q, L/(p - p')\}, +\infty)$.*

As a result, STD pricing can do better than SLP in general. This explains the logic behind Proposition 2 and reveals the true value of STD pricing when customers are fully rational.

5 Numerical Examples

In this section, we use extensive numerical examples to illustrate the main findings of this paper and also to check the robustness of them.

5.1 Optimal Pricing

We first check the possible $\bar{\theta}$ (i.e., the largest possible demand) values to satisfy the conditions specified by Proposition 2 and we depict our computation results in Figure 6. The parameters, $\beta_L = 3, w = 1, s = 0.2, L = 1, \gamma = 0.2$, and $h = 0.3$, are held constant across all examples. In each panel, we explore 2,793 combinations of $(c, \bar{\theta})$, for which c ranges from 0.1 to 2.5 and $\bar{\theta}$ from 2 to 30. In the left panel, where we set $\beta_H = 3.5$, the sufficient condition is relatively difficult to satisfy when the unit food cost is low. We can see that, when the unit food cost is normalized to 1 and the optimal unit price is about 3, the optimal pricing scheme is BTP as long as $\bar{\theta}$ is greater than 8 or the largest possible order value (i.e., $\bar{\theta} \cdot p$) is greater than 24. In the USA, we know that the average order value on the food delivery platforms is about \$30 and the delivery fee is about \$5. If we scale these numbers back to the realistic setting, it means that, the optimal pricing scheme is BTP as long as the largest possible order value is greater than \$120, which is still possible in the real world. When the food cost is higher, the sufficient condition is easier to satisfy. Note that this is a sufficient condition for either BTP or SLP to be the optimal pricing scheme. In fact, the maximum possible order value does not have to be as high as \$120.

Between BTP and SLP, the former is almost always better as long as $\bar{\theta}$ satisfies the above sufficient condition. When the food cost is too high and $\bar{\theta}$ is too low, the restaurant optimal profit is zero under either SLP or BTP. Therefore, STD pricing is always preferable for the restaurant.

5.2 Food Waste

In Figure 7, we investigate the impact of pricing on food waste using three sets of parameters. In each set, we focus on a unique combination of (β_H, c) and explore 100 different combinations of (L, s). The range of L is $[1, 2]$ and for s is $[0.1, 0.5]$ with constant step sizes. The parameters, $\beta_L = 3, w = 1, \gamma = 0.2, h = 0.3$, and $\bar{\theta} = 12$, are held constant across all examples. Within each parameter setting, we explore 10,000 (p, Q) designs through a linear search

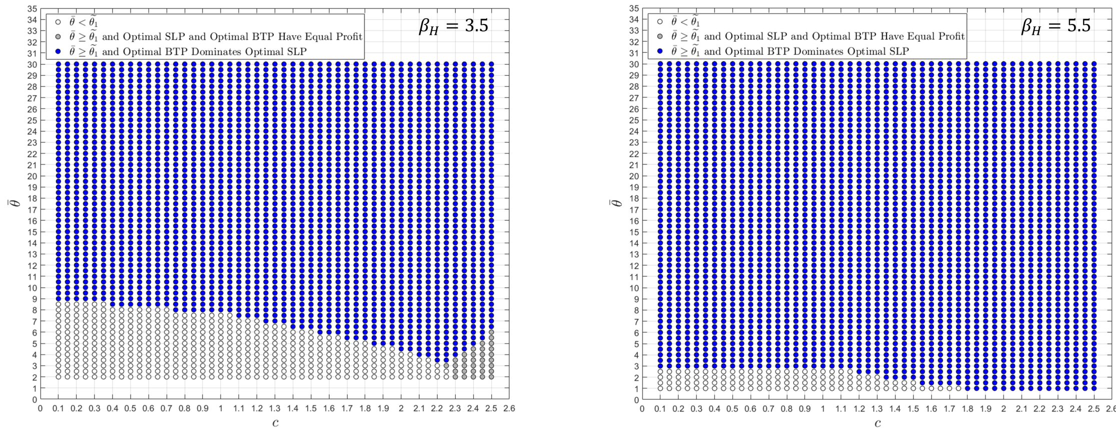

Figure 6: The Sufficient Condition for the Optimal Pricing Scheme to Be SLP or BTP

in $[c, \beta_H] \times [0, \bar{\theta} + L/(\beta_L + \gamma)]$, exclude those infeasible designs that lead to a non-positive profit for the restaurant, and determine the maximum, average, and minimum food waste under the feasible ones. Additionally, we identify the optimal (p, Q) design and the associated food waste, referred to as the "optimal food waste." We then compare the optimal food waste (W_{opt}) with the maximum (W_{max}), average (W_{avg}), and minimum (W_{min}) food waste among the feasible designs, calculating the percentage difference: $100\% \times (W_{opt} - W_j)/W_j$ (where $j = max, avg, min$). For each set, we have 100 samples for these comparisons based on the 100 different combinations of (L, s), and we present them in three histograms.

The percentage difference in food waste between W_{opt} and W_{max} or W_{avg} quantifies the potential reduction in food waste achievable by transitioning from an arbitrary (p, Q) design to the optimal (p, Q) design. As depicted in the left and center panels of Figure 7, optimizing the (p, Q) design can lead to a reduction in food waste ranging from 60% to 100%. Conversely, the percentage difference in food waste between W_{opt} and W_{min} indicates the additional reduction in food waste that could be achieved by regulating the restaurant's volume threshold or revising the contract terms with the platform. The right panels show that even after optimizing the (p, Q) design, there remains substantial potential (over 90%) for further reducing food waste through regulations.

5.3 Regulation

In the next two figures, we delve into the effects of the platform commission rate and service fee on the restaurant's optimal volume threshold, food waste, and social welfare. The objective is to assess whether regulating the commission rate or service fee could lead to a reduction in food waste and an enhancement in social welfare simultaneously, and to elucidate the underlying reasons for such outcomes. Throughout these numerical analyses, we maintain the parameters $\beta_H = 3.5$, $\beta_L = 3$, $\gamma = 0.2$, $L = 1$, $w = 1$, $s = 0.2$, $\bar{\theta} = 12$, and $h = 0.3$ as constants for consistency.

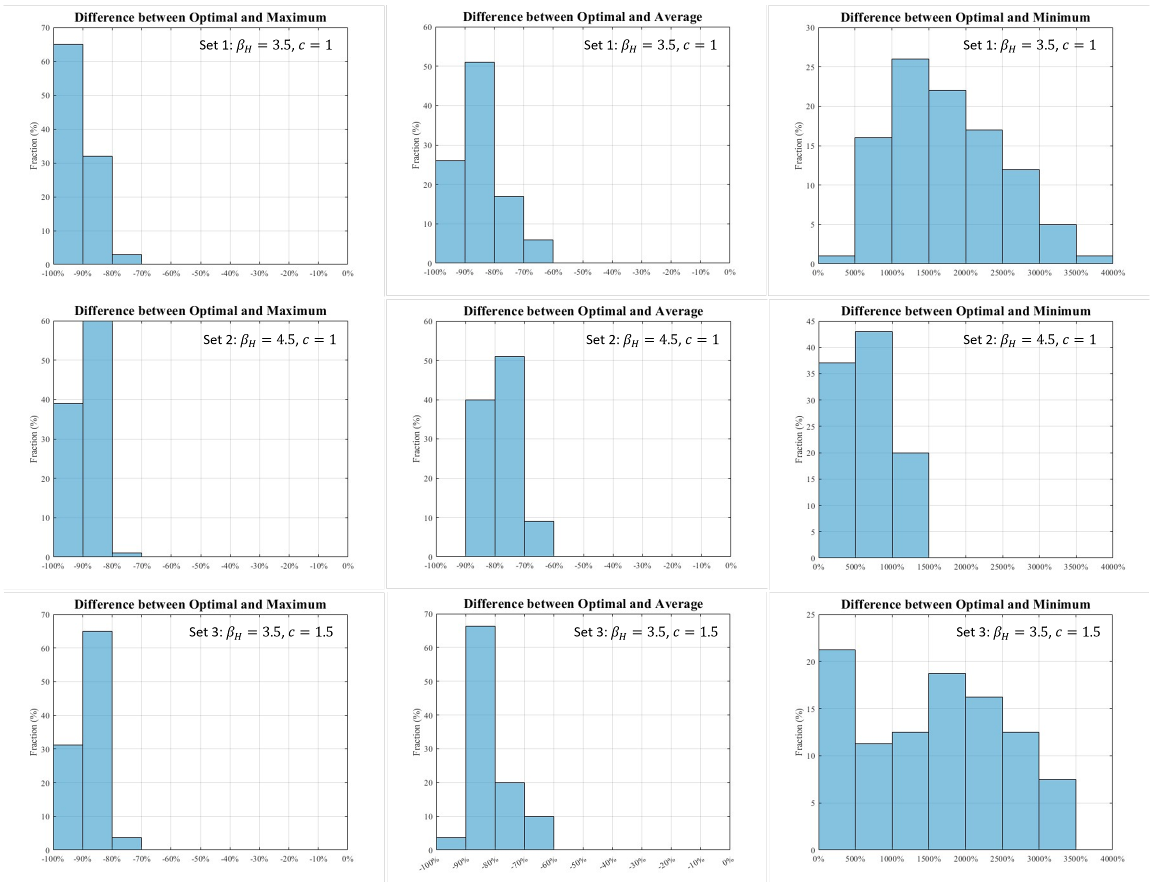

Figure 7: The Impact of Pricing on Food Waste

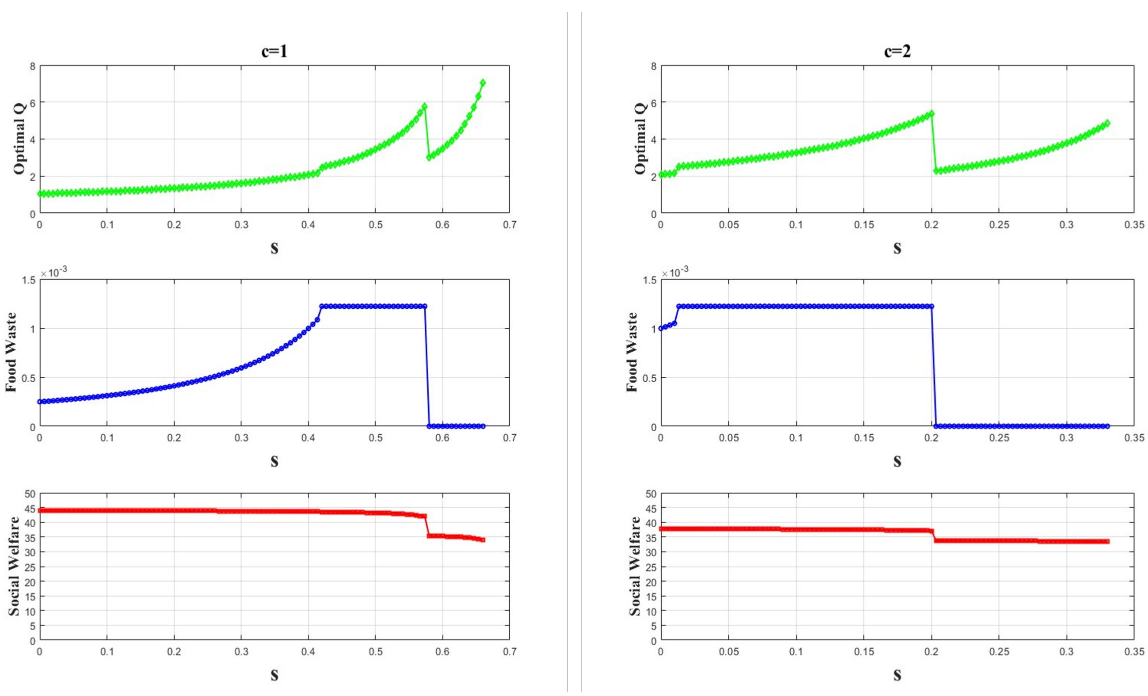

Figure 8: The Impact of Platform Commission Rate

In Figure 8, we examine the influence of the commission rate (s) under two scenarios: low food cost ($c = 1$) and high food cost ($c = 2$). Our findings reveal a non-monotonic relationship between s and the optimal Q: as s increases, the optimal Q initially rises, reaches a peak, then declines when the high s triggers the shift towards skimming pricing, before ascending once more. Consequently, the impact of s on food waste also follows a non-monotonic pattern. However, the effect on social welfare exhibits a monotonic trend: social welfare decreases with increasing s. Thus, a reduction in s could lead to a simultaneous decrease in food waste and an increase in social welfare, provided that s is not already at an excessively high level.

In Figure 9, we explore the effects of the service fee (w) in the contexts of low food cost ($c = 1$) and high food cost ($c = 2$). The findings mirror those observed for the commission rate: the impact of w on the optimal volume threshold, food waste, and social welfare displays similar non-monotonic trends. Consequently, it is plausible to achieve a reduction in food waste and an improvement in social welfare concurrently by lowering the service fee, as long as the initial value of w is not excessively high.

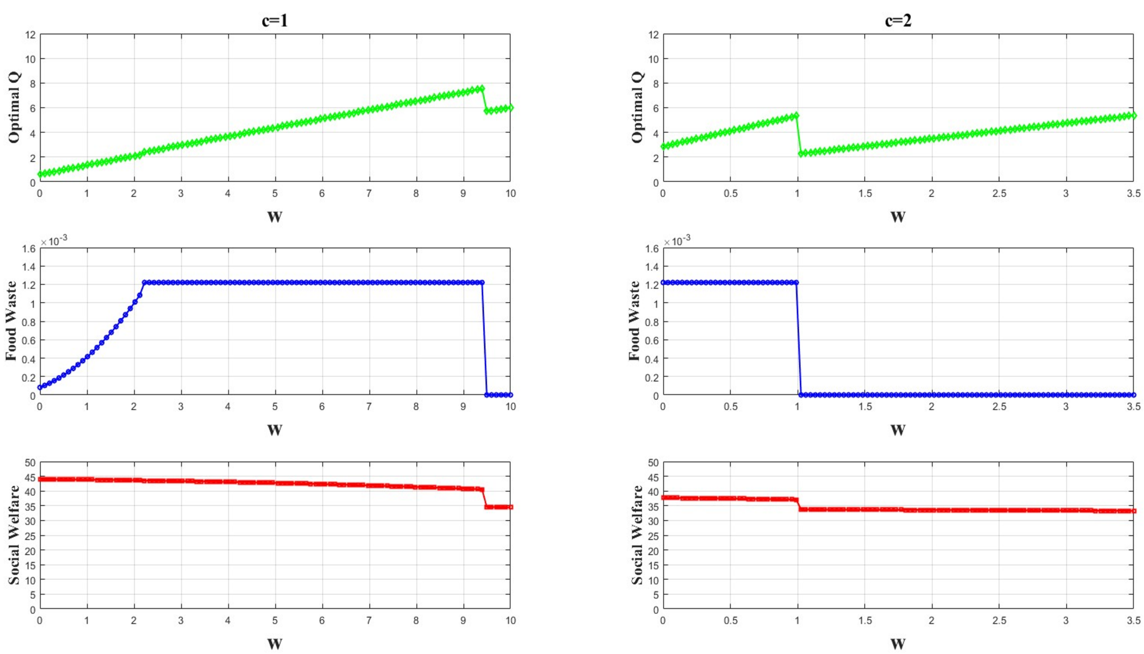

Figure 9: The Impact of Platform Service Fee

5.4 Aversion to Waste

In Figure 10, we investigate the influence of waste aversion (γ) in three scenarios while holding the following parameters constant: $\beta_L = 3, s = 0.4, w = 1, L = 1, h = 0.3$, and $\bar{\theta} = 8$. Across all three cases, food waste exhibits a consistent decrease with increasing γ. However, the impact on the restaurant's optimal profit can vary, showing a decreasing, increasing, or non-monotonic trend in relation to γ.

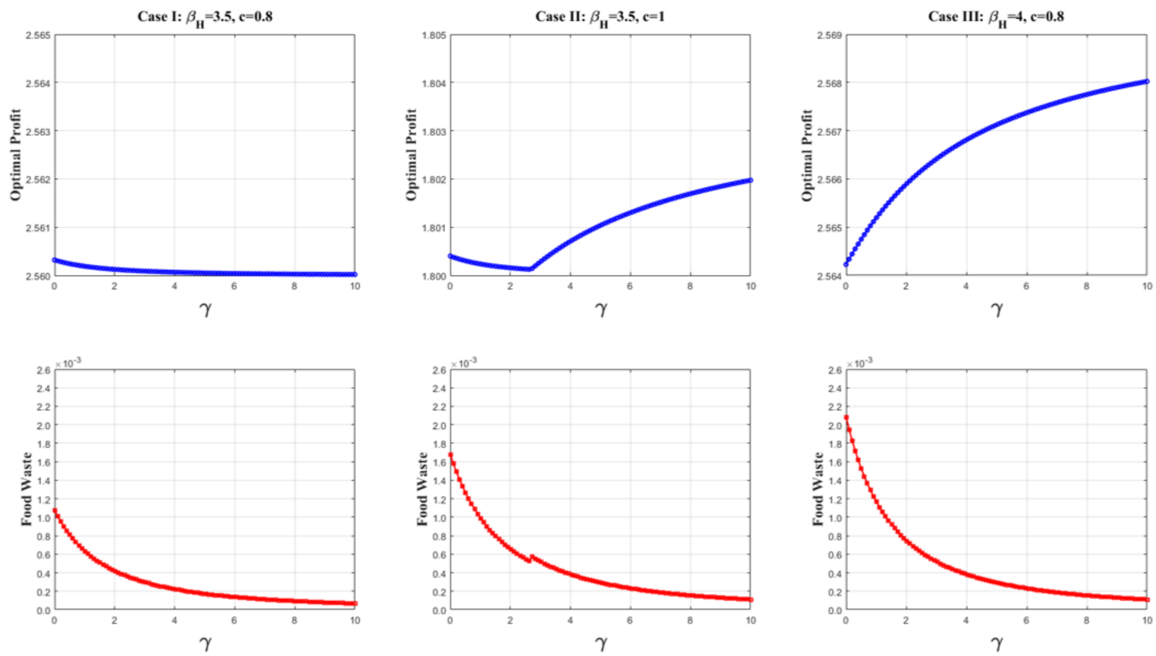

Figure 10: The Impact of Waste Aversion

In Case I, which serves as the baseline, the restaurant benefits from most customer orders, resulting in a low optimal volume threshold. As γ increases, customers with inherent demand below the volume threshold may cease purchasing up to the threshold to avail the discount, consequently impacting the restaurant's profit negatively.

In Case II, where food costs are relatively higher, both the break-even order size and the optimal threshold for the restaurant increase. Initially, an increase in γ may lead to a profit reduction due to a logic similar to that in Case I. However, as γ further increases, more buyers whose demand is near the threshold will choose to give up the discount due to waste aversion and buy just enough, potentially increasing the restaurant's profit. Overall, the impact of γ in this case can be non-monotonic, yet the restaurant tends to favor either $\gamma = 0$ or a sufficiently high γ.

In Case III, customers exhibit a greater disparity in their Marginal Willingness to Pay (MWTP) (i.e., the gap of $\beta_H - \beta_L$ is larger), resulting in low-demand customers with high MWTP choosing to purchase only the necessary amount without the discount. In other words, high-MWTP customers are in Scenario σ_1 and there are no "new buyers." With an increase in γ, more "spending upgraders" with high MWTP opt for this approach, ultimately benefiting the restaurant.

In Figure 11, we analyze the optimal waste aversion (γ^*) for the restaurant across various combinations of (c, β_H). The value of γ is restricted to $[0, 10]$. Note that, in instances where the optimal pricing scheme is skimming pricing and no customers purchase excess food, γ becomes irrelevant. For the remaining cases where γ matters, the restaurant tends to prefer either $\gamma = 0$ or a sufficiently high γ. These observations align with our earlier discussions related to Proposition 8.

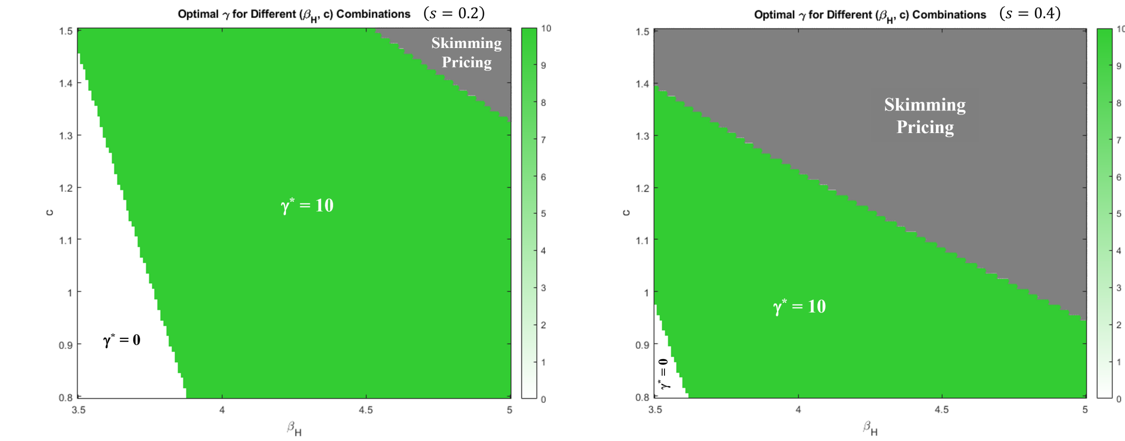

Figure 11: The Optimal Waste Aversion For The Restaurant

5.5 Value of Discount

In Figure 12, we present a graphical representation of the restaurant's profit generated from individual purchase orders based on the order size, comparing the optimal SLP scheme against the optimal STD scheme. We explore two distinct combinations of (c, β_H), with consistent outcomes observed across both scenarios. The parameters, $\beta_L = 3, w = 1, s = 0.2, \gamma = 0.2, h = 0.3$, and $\bar{\theta} = 12$, are held constant across all examples. The solid lines depict the profit associated with feasible order sizes chosen by customers, while the dotted lines represent order sizes that are not actual selections. Within each plot, the break-point in the STD scheme aligns with the volume threshold set by the restaurant. Notably, the per-order profit under the STD scheme consistently surpasses that under the SLP scheme for order sizes exceeding a specific threshold.

Regarding the buyer base, it is important to note that its size is not necessarily greater under the optimized STD scheme compared to the optimized SLP scheme, as the corresponding prices differ between the two. More specifically, the optimal SLP scheme attracts a larger number of type-H customers, whereas the optimal STD scheme results in a greater number of type-L customers making purchases.

5.6 Robustness Analysis

In this section, we conduct two sets of robustness checks. First, we examine the robustness of the main result in Proposition 3, which states that when $\bar{\theta}$ is sufficiently large, the optimal pricing scheme is BTP. We aim to test whether this result continues to hold even when $\bar{\theta}$ is relatively small and the marginal cost of food, c, is low. Second, since our analysis thus far assumes that customer demand follows a uniform distribution, we test whether our main results still hold under other alternative demand distributions, such as the triangular distribution and the beta distribution.

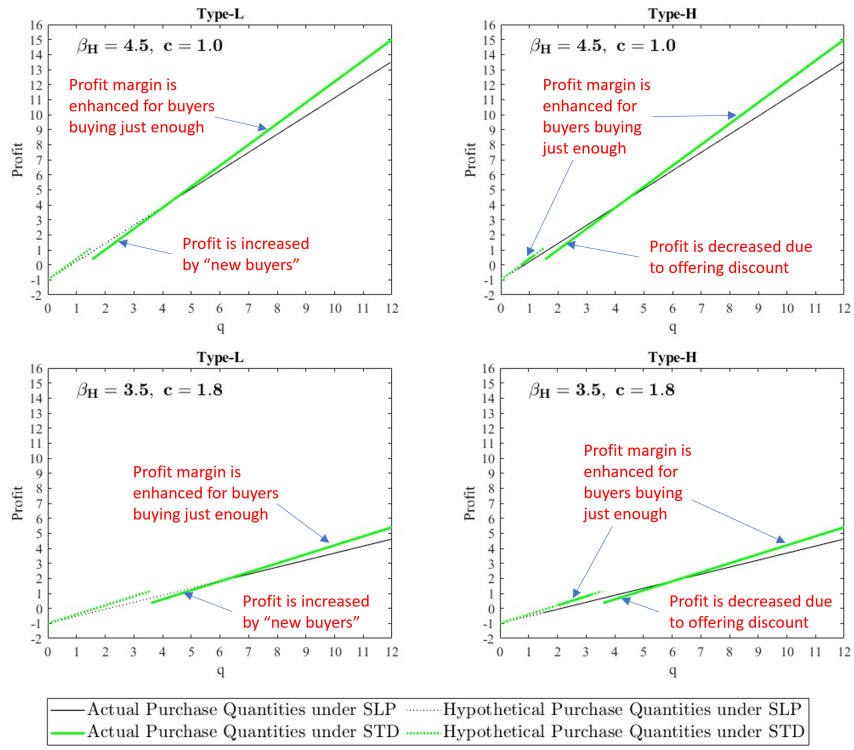

Figure 12: Order Size and Restaurant Profit

5.6.1 Small $\bar{\theta}$

Using the same parameter settings as in Figure 6 and assuming customer demand follows a uniform distribution, we investigate various combinations of $(c, \bar{\theta})$ with $\bar{\theta} < \tilde{\theta}_1$. For each combination, we compute the optimal TSD scheme and determine whether it corresponds to SLP, or BTP or neither. Our results (in the supplement) show that even when $\bar{\theta}$ is sufficiently small and the marginal cost of food c is low, BTP remains the optimal pricing scheme. This finding confirms the robustness of Proposition 2 under more restrictive conditions.

5.6.2 Alternative Distributions of Customer Demand

We next assess the robustness of our results when customer demand θ follows alternative distributions. We consider two sets of alternative distributions. The first set consists of three triangular distributions with three different modes at $\bar{\theta}/4$, $\bar{\theta}/2$ and $3\bar{\theta}/4$ representing negatively skewed, symmetric, and positively skewed demand, respectively. The second set consists of three beta distributions with parameters $(2,4)$, $(2,2)$, and $(4,2)$. They correspond to three different modes at $\bar{\theta}/4$, $\bar{\theta}/2$ and $3\bar{\theta}/4$, respectively, mirroring the skewness profiles of the triangular cases. All the six alternative distributions are illustrated in Figure 13.

For all six alternative distributions, our numerical results (in the supplement) confirm the robustness of the main result in Proposition 2. Additionally, we test the robustness of our key reg-

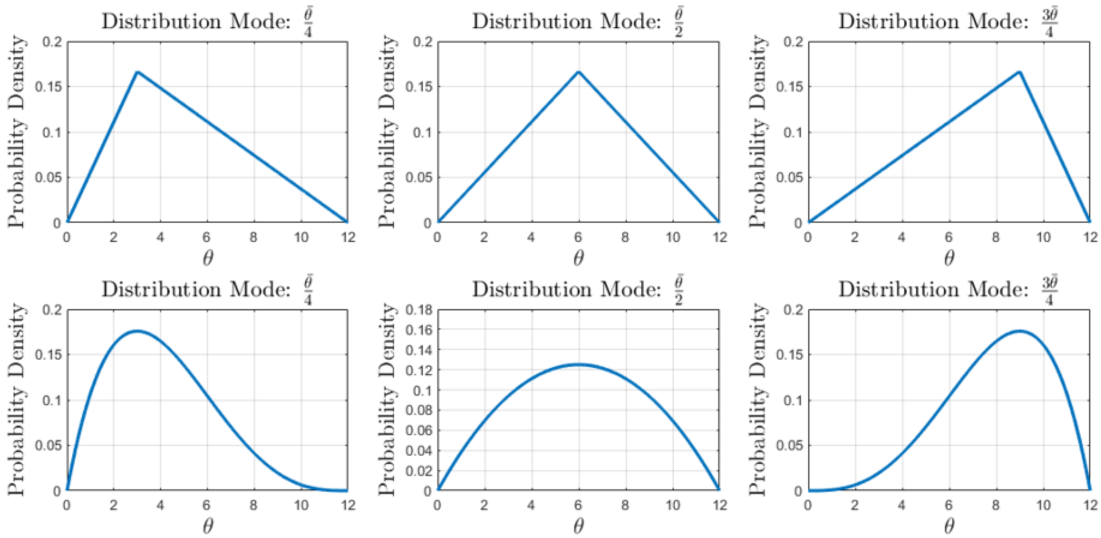

Figure 13: Alternative Distributions for Customer Demand

ulatory insights. Specifically, we find that reducing either the commission rate or the service fee consistently leads to lower food waste and higher social welfare, under these alternative demand distributions. Finally, across all alternative distributional settings, we observe patterns consistent with those illustrated in Figure 10, further reinforcing the robustness of our main findings about the impact of waste-aversion originally derived under the uniform distribution assumption.

6 Concluding Remarks

In this paper, we set out to understand how the common practice of offering "spend-X-get-a-discount" deals on food delivery platforms affects both restaurant profits and the amount of food waste. We look closely at two typical groups of customers—college students with tight budgets and young professionals with a bit more to spend—and we ask: does this kind of deal actually help restaurants make more money, or does it simply encourage people to buy extra food they don't really need? Our findings are surprising.

First, there are three distinct ways these threshold discounts can affect restaurant profits: order size boosting, buyer base expansion, and profit margin enhancement.

- The effect of order size boosting turns out to be negative if customers are purely rational: they will only add little extras if doing so truly saves them money; if not, they will either refrain from buying or purchase only what they need. Hence, restaurants lose from promoting additional items.
- The real profit comes from the other two effects.
  - First, by offering a discount for orders above a certain value, restaurants can encourage customers who might not otherwise order to make a purchase.

- Second, they can set higher effective prices on larger orders by offering the lump-sum discount to most customers: the larger the order size, the less the buyer is subsidized for each unit of food on average.

Second, we show that restaurants can actually reduce the waste caused by “topping up” orders and still keep their earnings strong. By carefully choosing the spend-to-save threshold and the base item price, a restaurant can limit unnecessary add-ons. Even better, when customers become more sensitive to disposing of edible food—such as the restaurant gently reminds them of the waste impact—profits can rise under the right conditions. In other words, a little nudge toward mindful ordering not only reduces waste but can also boost the bottom line. This is because increased waste aversion does not hinder buyer base expansion or profit margin enhancement.

Third, this balance of interests does not rest entirely on restaurants and customers. We demonstrate that simple regulations, such as capping the fees third-party platforms can charge, guide restaurants to set more reasonable discount thresholds. Those lower thresholds mean fewer needless extras, happier customers, and a healthier society—all without shaving off restaurant earnings. In the end, smarter pricing, gentle customer guidance, and light-touch regulation can turn what might seem an uncomfortable trade-off—between selling more food and wasting less—into a genuine win for everyone.

Of course, our analysis has its limits. We have focused solely on “cloud kitchens” that sell only through delivery apps, without looking at restaurants that also serve dine-in customers. We’ve modeled pricing with just one discount threshold, even though many online restaurants employ multi-tiered promotions or loyalty schemes the implications of which remain unexplored in this study. And we treated customers as fully rational decision-makers, despite in reality people may act on impulse, misinterpret savings, or respond to marketing in unpredictable ways. In future work, it would be valuable to see how these findings change when restaurants juggle both dine-in and online orders, when deals come in several tiers, or when customer choices are shaped by limited information or behavioral quirks. Exploring competition between multiple restaurants on the same platform would also bring us closer to the real world and help guide even more effective, waste-aware pricing strategies.

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