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RESEARCH PAPER

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Is More Information Better? An Economic Analysis of Group-Buying Platforms

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Abstract

Group buying as a new form of e-commerce has experienced rapid development over the past few years. Group-buying platforms offer a new channel for local small- to medium-sized companies to promote themselves, and also provide consumers with the opportunity to experience new products and services at deep discounts. In this paper, we examine merchants' pricing strategies and consumers' purchasing decisions when different types of information are available on a group-buying platform. Consumers purchasing deals from group-buying platforms face a high level of quality uncertainty, due to lack of experience with the products and incomplete information about the products and merchants on group-buying platforms. The lack of face-to-face communication between customers and merchants before redeeming the deals also intensifies the uncertainty between the transacting parties. Group-buying platforms seek to alleviate such uncertainty by designing a rich user interface that contains various types of information about the merchants or the deals. We use a game-theoretic model to capture the interactions between merchants and consumers under three cases, contextualized by a simple, moderate, or complex information environment. We show that merchants benefit when the environment moves from a simple to moderate information environment, but further movement from a moderate to a complex information environment leads to a more intriguing effect on merchants' discount strategies. In particular, very high-quality merchants or very low-quality merchants benefit from larger discounts in the context of complex information versus a moderate information environment; therefore, such merchants are disadvantaged when more than a moderate amount of information is provided. Our analysis shows that providing more information can harm merchants under certain conditions; we offer implications for merchants as well as for the group-buying platforms concerning their information strategies.

Keywords: Group Buying, Online Platforms, Information Asymmetry, Game Theory

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1 Introduction

Group buying constitutes an adventurous exploration of the e-commerce world by entrepreneurs who foresee the potential of social commerce. The success of Groupon, LivingSocial, and many other similar group-buying websites have made group buying a popular and sometimes necessary option for an enormous number of local merchants and consumers. Local merchants offer products and services at a discounted price through an online group-buying platform, and consumers purchase vouchers through the platform entitling them to consume the product later from the merchant directly. The popularity of group buying is supported by the multiple benefits it offers to both merchants and consumers. Since merchants on group-buying websites tend to be small-to medium-sized local merchants, group-buying platforms offer an economical and efficient promotion channel for such merchants to reach new customers. Merchants share a percentage of their revenue from vouchers sold as a commission to the platform, and there is no up-front cost to join the platform. Consumers, on the other hand, get the opportunity to experience previously unfamiliar products and services at a discounted price and therefore at lower risk. One prominent and common feature on group-buying platforms is a rich user interface, which provides multiple sources of information to facilitate consumers' purchasing decisions, a promotional setting that is scarcely possible offline. Through deal pages, merchants can share information about their products, such as the original price, the discount level, the discounted price, a description of the merchant, a description of the product characteristics, etc. Along with the above information from the merchants, platforms also display another important type of information—the number of vouchers sold.

This study analyzes the role of information disclosure on the effectiveness of group-buying promotions. We develop a game-theoretic model in order to capture the interactions between merchants and consumers on a group-buying platform, with the objective of developing a theoretical framework for the optimal information structure that suits different types of merchants with different market characteristics. This paper answers two research questions. (1) How does the information available on the group-buying platform, such as price, discount level, quantity sold, etc., affect consumers' purchasing decisions and merchants' pricing decisions? And (2) under what information structure can merchants most effectively promote themselves in the context of a group-buying platform?

For this study, we consider an incomplete information setting, in which merchants disclose partial quality attributes to consumers. There are several things that make the information setting incomplete. First, vendors on group-buying platforms are mostly small- to medium-sized local merchants and customers on these platforms are mostly first-time shoppers with the merchants (Dimoka et al., 2012). This thus naturally engenders a high level of uncertainty between the trading parties, and this uncertainty is difficult to eliminate through the information revealed on a deal's webpage. Furthermore, most products contain both *search attributes*, which are easy to describe through words or pictures, and *experience attributes*, which customers can evaluate only through consuming the product (Nelson, 1970). The quality of a product is determined by the quality of both types of attributes, which we refer to as search quality and experience quality throughout the paper. Both experience quality and search quality can vary among vendors. In this paper, we use high- and low-quality vendor to refer to vendors whose product is of overall high or low quality. Experience quality introduces uncertainty into consumers' purchases because it cannot be evaluated before purchase. Additionally, merchants may strategically withhold certain information from customers in order to influence consumers' purchasing decisions in favor of the merchants. The incomplete nature of the information provided on these sites naturally complicates consumers' purchasing decisions (Dimoka et al., 2012).

Merchants' main objective on these platforms is to advertise their products to consumers who are unaware of their products but who would be willing to purchase them at the regular price once acquainted with the product quality. The group-buying mechanism allows merchants to offer such consumers an opportunity to sample the product at a discount, with the anticipation that, after experiencing it, they will continue to purchase the product at the regular price. Dholakia's (2012) survey indicates that up to 80 percent of customers on group-buying websites are first-time customers. However, merchants must contend with two challenging categories of customers: Some first-time customers may purchase the product through the group-buying platform at a deep discount, but do not value the product enough to purchase it at the regular price. As such, this type of consumer will not become a long-term customer. Second, some consumers on the group-buying platform are existing customers of the merchants and have already experienced the product quality.

We refer to customers with prior experience about the product as *informed customers*, while *uninformed customers* indicate customers with no prior knowledge of the product. Informed customers have already experienced the quality attributes of the product, while uninformed customers are new customers with no prior experience with the product. Informed customers thus have an information advantage over the uninformed customers. As discussed and modeled below, this information advantage is reflected in the purchasing decisions of the informed customers, which can help uninformed customers form an expectation about the attributes of the unknown product.

Inherent to group-buying websites are some unique features that reveal different types of information and are capable of bridging the information gap between the two types of consumers. The most significant feature is information about the number of vouchers sold, which is usually displayed in a prominent position on a deal's web page. A high number of vouchers sold indicates that many customers have viewed this product and decided to purchase it. Early consumer purchasing decisions serve as an important piece of information for later consumers facing the same decision-making process. We argue that the early purchasers tend to be informed customers who are well aware of the product quality; therefore, we maintain that the quantity sold is a reflection of informed consumers' purchasing decisions, which are based on their personal knowledge of the true value of the product quality. Another feature is the discount level displayed on a deal's page. Although discounts lead to economic savings for customers, they can also be coupled with negative effects on consumer decision-making. Due to their online context, group- buying platforms inherently invoke a high degree of uncertainty for consumers, which is further elevated by the fact that most consumers on the websites are new customers (Dholakia, 2012; Tuttle, 2012). As such, a large discount can operate as a negative signal about product quality and hence reduce the number of purchases.

However, it is worth noting that, beyond the unknown quality attributes, consumers with no prior experience with the merchants also lack another critical piece of information—that is, the proportion of existing customers of a product. In other words, consumers who are new to the merchants' products know that informed customers exist, but they do not know the market coverage—i.e., the ratio of informed versus uninformed customers. As a result, consumers are unable to assess the true level of quality in the traditional learning context. Therefore, they can only assume that different types of information influence customers' belief positively or negatively, and we thus investigate the effect of different levels of information exposure on the effectiveness of group-buying promotions.

Merchants determine the price or the corresponding discount level with the objective of attracting uninformed customers who would be willing to purchase the product at the regular price in the future. We refer to these customers as *convertible* customers. A large discount imposes two opposing forces on uninformed consumers' purchasing decisions. On the one hand, it invokes consumers' suspicions about product quality and negatively affects their intention to purchase. On the other hand, a large discount not only leads to high price savings, but also results in a higher number of vouchers sold from informed consumers; both factors can encourage uninformed consumers to purchase from an unfamiliar merchant. Also, a large discount can induce many informed consumers to purchase, leading to a higher quantity of vouchers sold. The quantity sold can then positively affect the uninformed consumers' purchasing decisions. We examine merchants' pricing strategies, accounting for all these potential factors, and analyze the impact of various factors on the optimal price decisions.

We analyze both merchants' and consumers' strategies in scenarios with (1) a simple information environment with no information signal, (2) a moderate information environment with quantity signals, and (3) a complex information environment with both quantity and discount signals. Our analysis generated several main findings: First, the information environment on a group-buying platform has a critical impact on merchants' decisions to join the platform and offer discount promotions. When the platform provides no information signal to facilitate consumers' purchases, the platform appeals to a limited group of merchants offering high experience quality, while the rest of the merchants do not benefit from discount promotions. When the platform reveals more information on the platform to guide consumers, it motivates other merchants with low experience quality to join the platform and offer discount promotions. Second, information signaling is crucial for effective discount promotions. The objective of attracting all convertible customers can only be achieved when the platform provides quality signals to consumers. Further, more information can also be harmful to some merchants because merchants may be forced to offer higher discounts as more information signals become available. For instance, vendors with very low or very high experience quality offer higher discounts in the complex information environment than they do in the moderate information environment. The reason for this is that more information motivates more merchants to join the price promotion, and intensifies the competition among merchants to gain customers. We also provide insights on the effect of market composition and consumers' belief formation on merchants' discounting strategies.

This paper makes several contributions. First, we offer a unique focus on the signal structure of group-buying platforms, and we assess the effects of different signals on merchants' promotion effectiveness. Our analysis generates the counterintuitive result that more information can be bad for both merchants and platform owners. Second, our findings have important implications for entrepreneurs about the intricate role of information for merchants' and consumers' behaviors. When establishing an online business, entrepreneurs face the critical decision of how to create an online environment with various types of information displayed across webpages in order to entice consumers to make purchases. Understanding the consequences of information on consumers is therefore a critical element in designing an online shopping platform and creating an online consumer experience. Finally, our study adds to the growing group-buying literature in two ways. To the best of our knowledge, this is the first study that examines different information structures present on group-buying platforms and that focuses on the potential negative effects of information. Also, most existing studies on group buying are based on the critical assumption that consumers know the market situations of the products and that they can rationally learn the true quality of the products in equilibrium (Subramanian and Rao, 2016). We emphasize the fact that consumers have little knowledge about merchants and their products or services on group-buying platforms. We examine these customers' reactions to deals on sites such as groupon.com and we offer suggestions to merchants as well as the platforms to better capture these uninformed and valuable customers.

The remainder of the paper is organized as follows. In Section 2, we survey the related literature. Section 3 describes the model setup. Section 4 presents the model analysis. Section 5 discusses the implications of providing more information. We conclude the paper in Section 6.

2 Related Literature

Our study is closely related to studies on group-buying platforms. Selling through a platform offers strategic values to online retailers (Kwark et al., 2016). Yang et al. (2016) study vendors' decisions to join a group-buying platform or not and discover a critical range where vendors are better off by joining such a platform. Jing and Xie (2011) compare group selling to conventional single-unit selling and promotion strategies and focused on the information gap between the two sales channels. Our current study further explores the information structure that enables customers to bridge the information gap, and investigates the effectiveness of group selling in different product contexts. Hu et al. (2013) compare simultaneous and sequential group-buying mechanisms for the categories of necessity and luxury goods. Our study examines more generally the impacts of product features on group-buying platform strategies. Shivendu and Zhang (2013) study the strategic interactions between merchants and the group-buying platform, and derive the optimal discount strategies. In comparison, we study merchants' discount strategies from the perspective of quality signals and customer acquisition. Edelman et al. (2014) and Kumar and Rajan (2012) study the profitability of selling through group-buying platforms. Subramanian and Rao (2016) examine the signaling effect of discounts and how consumers learn about product quality through the discount levels. Our study differs from the above literature in that we adopt an incomplete information structure, according to which consumers cannot infer the true quality of the product even in equilibrium. Also, we combine two sources of information signals—quantity and discount level—in consumers' decisions. We take the unique angle of comparing merchants' performance when different types of signals are available.

Another related stream of research examines the signaling role of prices. Prior studies offer evidence that prices can affect how consumers perceive the quality of corresponding products. A high price can be used as a signal that differentiates high-quality sellers from low-quality sellers, and, therefore, customers tend to rationally perceive that high quality correlates with a high price tag in equilibrium (Kirmani and Rao, 2000; Rao, 2005). There is an extensive literature in information economics showing that price can be a credible signal of quality in various market settings (Bagwell and Riordan, 1991; Wolinsky, 1983; Daughety and Reinganum, 2007, 2008; Janssen and Roy, 2010). In particular, Wolinsky (1983) and Bagwell and Riordan (1991) both demonstrate that such signaling effect can result from the presence of customers who are more informed about product quality. In an experimental study, Shiv et al. (2005) shows that customers may lower their expectations of product quality when they pay a discount price, and later overevaluate the actual performance of the product. Rao (2005) provides similar evidence showing that consumers are cognitively miserly and are likely to adopt a price-quality heuristic. Our paper contributes to this literature by examining the signaling role of discounted price in a group-buying setting where the price is set strategically with the unconventional objective of effectively promoting the product, beyond the objective of generating revenue. Our study shows that, in this setting, price continues to moderate consumers' purchasing decisions.

Our study is also related to the vast literature on product uncertainty in online commerce. The time and spatial separation between online sellers and buyers leads to a high level of information asymmetry between the trading parties, which in turn leads to high levels of perceived uncertainty in the online environment (Dewan and Hsu, 2004; Jin and Kato, 2006; Ghose, 2009; Li et al., 2009; Dimoka et al., 2012). Studies have shown that consumers' purchasing decisions are significantly affected by the existence of product uncertainty (Brynjolfsson and Smith, 2000; Ba and Pavlou, 2002; Overby and Jap, 2009; Kim and Krishnan, 2015; Kwark et al., 2016). Kwark et al. (2014) discovered that product reviews, while containing information about product quality, can harm the retailer or the manufacturer. Our study extends this literature to the context of group-buying websites, where the platforms engage in various information structure designs to alleviate the product uncertainty involved in the transactions, and also demonstrates that releasing more information can actually harm vendors under certain conditions.

3 Model Description

We consider a game between a vendor and a mass of 1 consumer. The vendor sells one type of product in two periods. In the first period, the vendor sells through a group-buying platform (GBP) at a discounted price p_1. In the second period, the vendor sells through his or her own store at the regular price of p. Let $1-d$ be the discount rate in the context of group buying, then $p_1 = dp$. The product contains two types of attributes, search and experience. The quality of the product therefore depends on both types of attributes. The vendor reveals information about the search attributes through the group-buying website, and we denote the quality related to the search attributes as a_0. The experience attributes cannot be revealed through the website, and can only be assessed through consumption of the product (Nelson, 1970). We assume that it is public knowledge that the quality of the experience attributes is uniformly distributed on $[\underline{a}_1, \bar{a}_1]$. We use a_1 to refer to the true value of the experience quality. The consumers also differ in their misfit τ with the product, and τ is uniformly distributed on $[0,1]$. The misfit characterizes consumers' horizontal difference in their evaluation of the product, and consumers know their own misfit.

There are two types of consumers. A proportion λ of the consumers are informed (I) consumers, who have prior experience with the product and know the true quality of the experience attributes a_1. The rest $1-\lambda$ are uninformed (UI) consumers, who have no experience of the product and hold a belief $\tilde{a}_1$ about the quality of the experience attributes. Each consumer demands at most one unit of the product in each period[1]. The utility from the product is $u = a_0 + a_1 - \tau$ and $u = a_0 + \tilde{a}_1 - \tau$ for informed and uninformed consumers respectively. We assume the informed and uninformed consumers are independently distributed in τ. In other words, τ captures the characteristics of the consumers and is independent of one's prior experience with the product.

Given price p, there exists a consumer who is indifferent between buying and not buying the product. We define this consumer as $\bar{\tau}_I$ and $\bar{\tau}_{UI}$ respectively, with the subscript indicating whether the consumer is informed, and they satisfy the following conditions:

$$p = a_0 + a_1 - \bar{\tau}_I, \tag{1}$$

$$p = a_0 + \tilde{a}_1 - \bar{\tau}_{UI}. \tag{2}$$

[1] In practice, group-buying websites, such as groupon.com, often include a limit on the number of vouchers that a customer is allowed to purchase, which is intended to prevent repeated purchases by consumers. We believe repeated purchases will not affect our model and findings. With the uncertainty that uninformed consumers face, informed consumers would be more likely to purchase multiple vouchers than uninformed consumers—in which case, as discussed below, the quantity sold would be a less accurate signal and could be easily captured through a lower α, making more of our results robust to different levels of α.

We solve for the cutoffs as $\bar{\tau}_I = a_0 + a_1 - p$ and $\bar{\tau}_{UI} = a_0 + \tilde{a}_1 - p$. We denote $q(p)$ as the proportion of informed consumers who purchase at price p, and $q(p) = \bar{\tau}_I$. We denote and q_{UI} as the proportion of uninformed consumers who purchase in the first period at the promotion price, and $q_{UI} = \bar{\tau}_{UI}$.

The vendor's profit from selling through a group-buying platform in period 1 is

$$\pi_1 = (\lambda q(p_1) + (1-\lambda) q_{UI}) p_1. \tag{3}$$

In period 2, some of the uninformed consumers who purchased in period 1 may continue to purchase at the regular price. The demand from uninformed consumers in period 2 is therefore $(1-\lambda)\min\{q(p), q_{UI}\}$. The vendor's profit in period 2 is

$$\pi_2 = (\lambda q(p) + (1-\lambda)\min\{q(p), q_{UI}\}) p. \tag{4}$$

Note that, $(1-\lambda)q(p)$ are the uninformed consumers who would have bought under the regular price p if they knew a_1, and we call these customers the *convertible* customers. On the other hand, the rest of the uninformed customers, $(1-\lambda)(1-q(p))$ are not convertible because their valuation for the product is so low that they would not purchase at the regular price p even if they had complete information about the product. When $q_{UI} < q(p)$, the vendor attracts some of theconvertible customers through group selling, and when $q_{UI} \geq q(p)$, all convertible customers are attracted through group selling. In the following analysis, we focus on the case where the vendor can attract all convertible customers to purchase in the promotion. This assumption allows us to focus on vendors whose objective for the promotion is not only to generate revenue, but also to promote the product to uninformed customers, particularly the *convertible* customers.

The vendor's decision is to choose the discount price p_1 to maximize the overall profit across period 1 and period 2. We describe the objective formally as the following.

$$\pi = \max_{p_1} \pi_1 + \psi \pi_2. \tag{5}$$

We use ψ to describe the relative importance of the long-term profit from sales at the regular price and the current profit from group selling. For example, spas, movie theaters, and restaurants have more incentive to attract long-term buyers, and buyers also tend to go back to the same vendor if they are satisfied. On the other hand, vendors with low ψ either have a high discount factor or expect fewer repeat purchases due to the nature of the products. Examples include durable goods, such as electronic devices, hospital services, etc.

In the following, we consider an ideal case where all consumers are informed and a_1 is public knowledge. In this special case, the vendor chooses a price to optimize its revenue, without any consideration for attracting uninformed consumers. Since there is no uncertainty among the consumers, the vendor has no incentive to offer discounts through the group-buying platform and will set the same price for both periods. This benchmark shows the vendor's and the consumers' strategies in the absence of uncertainty. The optimal price is determined by the following:

$$\pi = \max_{p} p\,q(p) + \psi p q(p)$$

$$= \max_{p} (1+\psi) p \int_{a_1+a_0-p}^{1} f(x) dx.$$

which leads to $p^* = \frac{a_0+a_1}{2}$. Consumers with $\tau \in [0, \frac{a_0+a_1}{2}]$ purchase the product.

It is worth noting that, if the vendor can successfully attract all *convertible* customers in the first period, their second period pricing follows the above strategy.

4 Information Environment

Our focus of analysis is on the information environment that a group-buying platform designs for the vendors and its impact on vendors' pricing power, as well as the effectiveness in converting all *convertible* customers. We examine three different information environments and compare vendors' and customers' strategies under each of them. The objective is to investigate the role of different information sources, such as different product properties, as well as different market positions, in inducing effective promotion. In the following, we assume that the informed consumers move first to make purchases before the uninformed consumers do. The assumption allows us to focus on the informational advantage of the informed consumers. In practice, however, it is possible that uninformed consumers purchase right after a deal is posted, especially if the price if low enough. We decided to exclude this scenario from our study because the information role of the informed consumers is silent in this case.

4.1 Simple Information Environment

We start with a simple information environment, where the vendor sells the product at a discount in the first period without providing any additional information for the consumers to learn about the product. We observe such promotions in both online and offline settings, where consumers cannot see previous buyers in the promotion. This simple information case allows us to focus on the impact of the discount itself. With no additional information, the consumers use their prior belief, the average $\hat{a}_1 = \frac{a_1 + a1}{2}$ to make their purchase decision, and the corresponding cutoff consumer has $\tilde{\tau} = a_0 + \hat{a}_1 - p_1$; that is, consumers with $\tau \le \tilde{\tau}$ will purchase. In the second period, $\tilde{\tau}$ of the uninformed consumers have discovered the true a_1, and consumers with $\tau \ge a_0 + a_1 - p$ are willing to purchase at p. Hence, the demand from the uninformed consumers is $\min\{a_0 + a_1 - p, \tilde{\tau}\}$. In other words, an uninformed consumer is *convertible*, when his or her willingness to pay exceeds p once becoming informed of a_1. We denote the optimal price in this case with a superscript s to indicate that it is the simple information scenario.

When $a_0 + a_1 - p < \tilde{\tau}$, some of the consumers attracted by the low price in the first period will not make further purchases. The demand in the second period from both the informed and the uninformed consumers is $a_0 + a_1 - p$. The optimal promotion price p_1 can be derived through the first-order condition of π_1 as

$$p_1^s = \frac{a_0 + \lambda a_1 + (1-\lambda)\hat{a}_1}{2}.$$

In the second period, the demand from both informed and uninformed consumers is $a_0 + a_1 - p$. The optimal regular price can be solved by maximizing π_2 (following similar procedures as in the case with full information) as $p = \frac{a_0+a_1}{2}$. If we reorganize p_1^s as $p_1^s = p + (1-\lambda)\frac{\Delta a_1}{2}$ and denote the discount in this case as d_s, then $d_s = 1 - \frac{p_1^s}{p} = \frac{(1-\lambda)(a_1-\hat{a}_1)}{a_0+a_1}$. It is easy to see that, only vendors whose quality is below average will offer discounts when the information environment is simple, i.e., $a_1 > \hat{a}_1$.

To ensure that all convertible consumers purchase in the promotion, we need $a_0 + a_1 - p < \tilde{\tau}$, which is equivalent to $a_1 < \hat{a}_1$. Note that, this condition contradicts the earlier result that only above-average vendors offer discounts. In other words, for a group-buying platform with a simple information environment, only high-quality vendors participate; however, they cannot motivate all *convertible* customers to purchase through the promotion. We present this finding formally in the following.

Lemma 1. For a platform with a simple information environment, vendors whose experience quality is above consumers' prior beliefs have incentives to offer promotions; however, not all convertible consumers purchase during the promotion.

This result states that a platform with no additional information is more favorable to vendors with superior quality, but that even these high-quality vendors cannot necessarily promote effectively, as there will always be some valuable consumers who will not purchase at the discounted price. In the simple information case, the platform plays a weak role in assisting consumers' purchasing decisions, and consumers face high uncertainty in making their purchasing decisions.

Our finding points to two drawbacks of a platform with a simple information environment. On the one hand, such a platform is suitable only to high-quality vendors, who have a large proportion of consumers who are *convertible*. Low-quality vendors will not benefit from price promotion because the benefit from their low proportion of *convertible* consumers is outweighed by the high cost of offering discounts. On the other hand, high-quality vendors who indeed offer discounts may fail to attract all valuable customers through the promotion. Customers with very low misfit cost will purchase through the promotion, but those with relatively high misfit cost will find it not worthwhile to purchase the deal, due to the high uncertainty they face regarding the vendor's experience quality. Overall, the above result highlights the necessity of enhancing the information environment and we discuss two such cases in the following subsections.

4.2 Moderate Information Environment

We now turn to a more sophisticated information environment, where the platform discloses to consumers the number of vouchers sold. When an uninformed consumer comes to the platform, the quantity sold (which is provided and often updated on websites like Groupon, LivingSocial, etc.) is an indicator of how previous buyers perceive the quality of the underlying products/services. The higher the quantity sold, the more popular the deal is, i.e., the more people perceive the deal as worthwhile. We hence assume an updating rule of $\tilde{a}_1 = \mu a_1 + (1-\mu)\hat{a}_1$, where $\mu = \alpha\lambda q(p_1)$.

We interpret this updating rule as follows. The demand from informed consumers, $\lambda q(p_1)$, contains information about the true quality a_1. However, consumers cannot infer the true quality a_1 accurately since they lack information about the proportion of existing consumers, λ. Instead, they find out the true quality a_1 with a probability μ, and with probability $1-\mu$, they continue to use their prior belief $\hat{a}_1$. The probability μ is increasing in the observed demand from the informed consumers, and α is a scalar to ensure $\mu \in [0,1]$, and we let $\alpha \in [0, \frac{1}{\lambda(a_0+\bar{a}_1)}]$. In other words, the observed demand determines the accuracy of consumers' updated beliefs.

We next analyze consumers' purchasing decisions based on the above updating rule. We focus on the case where all *convertible* customers purchase during the promotion. We use the superscript m to indicate the optimal decision from the case of the moderate information environment, as the consumers update their beliefs based on the number of vouchers sold. The vendor chooses the optimal discount price p_1^m to maximize the following objective

$$\pi_1 = (\lambda q(p_1^m) + (1-\lambda)q_{UI})p_1^m.$$

First order condition leads to $p_1^m = \frac{a_0+\lambda a_1+(1-\lambda)\hat{a}_1-\Delta a_1\alpha\lambda(1-\lambda)(a_0+a_1)}{2(1-\Delta a_1\alpha\lambda(1-\lambda))}$, with $\Delta a_1 = \hat{a}_1 - a_1$. The second period price is derived by optimizing π_2 in a similar fashion as in the full information benchmark, and $p = \frac{a_0+a_1}{2}$. We rearrange the discount price as $p_1^m = p + \frac{(1-\lambda)\Delta a_1}{2(1-\Delta a_1\alpha\lambda(1-\lambda))}$.

The vendor has an incentive to offer a price promotion when $p_1^m < p$, i.e., $\frac{(1-\lambda)\Delta a_1}{2(1-\Delta a_1\alpha\lambda(1-\lambda))} < 0$. We derive the condition as $\Delta a_1 > \frac{1}{\alpha\lambda(1-\lambda)}$ or $\Delta a_1 < 0$. In other words, vendors offer discounts when their experience quality is above average or significantly below average. We summarize the result formally in the following.

Lemma 2. When the group-buying platform provides moderate information environment,

vendors offer discounts when $\underline{a}_1 < a_1 < \hat{a}_1 - \frac{1}{\alpha\lambda(1-\lambda)}$ or when $\hat{a}_1 < a_1 < \bar{a}_1$.

This result states that when consumers can update their beliefs through the observed quantity of sales, not only vendors with above average experience quality join the promotion, but also those with very low experience quality. Recall that in the case with simple information, price promotion is only favorable for high-quality vendors. This shows that by facilitating consumers' purchasing decisions, group-buying platforms provide an additional opportunity to low-quality vendors.

We next verify that all *convertible* customers are attracted through the promotion, i.e., $a_0 + a_1 - p < a_0 + \tilde{a}_1 - p_1^m$. We introduce $a_1 = A_1$ as the solution to $a_0 = \frac{1}{\alpha\lambda} - \frac{1}{\alpha[\Delta a_1\alpha\lambda(1-\lambda)-1]} - a_1$. We summarize the result formally in the following proposition.

Proposition 1. When the group-buying platform provides a moderate information environment, vendors can attract all convertible customers if

(1) their experience quality a_1 is above average, i.e., $\max\{\hat{a}_1, A_1\} < a_1 < \bar{a}_1$, or

(2) when a_1 is significantly below average quality, i.e., $\underline{a}_1 < a_1 < \min\{\hat{a}_1 - \frac{1}{\alpha\lambda(1-\lambda)}, A_1\}$.

With moderate information, the platform is more suitable for vendors with either very high or very low experience quality. Vendors with very high experience quality can easily attract a high number of informed consumers to purchase their deals. The resulting high quantity of sales can in turn encourage the uninformed consumers to purchase. Similarly, vendors with very low experience quality also benefit because they have a very small proportion of *convertible* customers. Despite their low quality, these vendors can offer very deep discounts to boost the sales from the informed consumers, and in turn attract all *convertible* customers. It is worth noting that, without quantity information, neither the high-quality nor the low-quality vendors can attract their *convertible* customers, even if they offer deep discounts.

We also compare the discount level in this case with the simple promotion case. Since the simple promotion only applies to vendors with above average experience quality, we restrict our comparison to $\Delta a_1 < 0$ .The following corollary summarizes the result.

Corollary 1. When the group-buying platform provides a moderate information environment, vendors with the same experience quality choose to offer smaller discounts in comparison to the simple information case.

4.3 Complex Information Environment

We now turn to the case where more complex information is provided to consumers. Besides observing the quantity sold, the platform also emphasizes the role of discount (price) information in consumers' decision-making. We assume the following updating rule:

$$\tilde{a}_1 = \mu a_1 + (1-\mu)\hat{a}_1,$$

where $\mu = m\alpha\lambda q(p_1) + (1-m)\beta p_1$.

In the above updating rule, both α and β are scalars to ensure that $\alpha\lambda q(p_1) \in [0,1]$ and $\beta p_1 \in [0,1]$. To be more specific, we let $\alpha \in [0, \frac{1}{\lambda(a_0+\bar{a}_1)}]$ and $\beta \in [1, \frac{1}{a_0+\bar{a}_1}]$. The term m reflects the relative weight of the two sources of information. A higher m means that consumers put more weight on the observed number of vouchers sold, and vice versa.

Note that this updating rule captures the effect of the discount in two opposing directions. As the discount level increases, meaning that p_1 decreases, on the one hand it has the direct effect of lowering consumers' belief about the unobserved quality. It is worth noting that this direct effect of the discount has been established in the prior literature on price as a signal for quality—i.e., it has been discovered that low prices (i.e., a large discount) may operate as a negative signal for quality, leading consumers to think negatively about the product quality (Bagwell and Riordan, 1991; Daughety and Reinganum, 2007; Janssen and Roy, 2010). On the other hand, large discounts may lead to a higher number of vouchers sold, and therefore can indirectly lead to an increase in consumers' beliefs in the unobserved quality of the product. With these two opposing forces in place, we find it interesting to examine the overall effect of discounts on consumers' purchasing decisions, as well as to compare consumers' behavior under this updating rule to that of the previous case. We use superscript c to refer to this case with the complex information environment.

We first derive the optimal price under this case. The first-order condition of vendors' profit function leads to $p_1^c = \frac{a_0+a_1+(1-\lambda)\Delta a_1 - m\alpha\lambda(1-\lambda)\Delta a_1(a_0+a_1)}{2[1+(1-\lambda)\Delta a_1(1-m)\beta - m\alpha\lambda(1-\lambda)\Delta a_1]}$, which can be reorganized as $p_1^c = p + \frac{(1-\lambda)\Delta a_1[1-(1-m)\beta(a_0+a_1)]}{2[1-\Delta a_1(1-\lambda)(m\alpha\lambda-(1-m)\beta)]}$.

We have the following result on vendors' incentives for participating in group buying. Recall that in our previous analysis, we discovered that certain vendors of below average quality may not benefit from offering discounts through a group-buying platform.

Lemma 3. When the group-buying platform provides complex information environment, vendors offer discounts under the following two sets of conditions:

(1) when $\frac{m}{1-m} > \frac{\beta}{\alpha\lambda}$, and $\hat{a}_1 < a_1 < \bar{a}_1$ or $\underline{a}_1 < a_1 < \hat{a}_1 - \frac{1}{(1-\lambda)[m\alpha\lambda-(1-m)\beta]}$, or

(2) when $\frac{m}{1-m} < \frac{\beta}{\alpha\lambda}$, $\hat{a}_1 < a_1 < \min\{\hat{a}_1 - \frac{1}{(1-\lambda)[m\alpha\lambda-(1-m)\beta]} < \Delta a_1 < 0, \bar{a}_1\}$.

The above result states that when multiple sources of information are provided, and when the platform is able to engageconsumers to put a relatively high weight on the observed number of vouchers sold, vendors are willing to participate as long as their quality is not too low, i.e., below $\hat{a}_1 - \frac{1}{\alpha\lambda(1-\lambda)}$. The platform is therefore able to exclude very low-quality vendors from joining the platform. We next analyze whether the participating vendors can attract all *convertible* consumers.

To see this, we check if this condition holds: $a_0 + a_1 - p < a_0 + \tilde{a}_1 - p_1^c$.

We denote A_2 as such that when $a_1 = A_2$ the following equation holds:

$a_0 = \frac{\lambda+1+(1-\lambda)\Delta a_1((1-m)\beta - m\alpha\lambda)}{\lambda m\alpha[\frac{(1-m)\beta}{m\alpha}+1+(1-\lambda)\Delta a_1((1-m)\beta-m\alpha\lambda)]} - a_1$. Also denote $\bar{m}$ as the solution to $\frac{(1-m)\beta}{m\alpha} + 1 + (1-\lambda)\Delta a_1((1-m)\beta - m\alpha\lambda) = 0$. We state the conditions for converting all *convertible* customers in below.

Proposition 2. When the group-buying platform provides a complex information environment, vendors can attract all convertible customers under any of the following three cases:

(1) the vendor's experience quality is above average, i.e., $\max\{\hat{a}_1, A_2\} < a_1 < \bar{a}_1$, or

(2) customers put significant weight on quantity information and the vendor's experience quality is low, i.e., $\frac{1+\lambda+(1-\lambda)\Delta a_1\beta}{(1-\lambda)\Delta a_1(\beta+\alpha\lambda)} < m < 1$ and $\underline{a}_1 < a_1 < \min\{\hat{a}_1, A_2\}$, or

(3) when customers put significant weight on the discount information and the vendor's experience quality is not much lower than the average, i.e., $0 < m < \bar{m}$ and $A_2 < a_1 < \hat{a}_1$.

It is easy to show that $\bar{m} < \frac{1+\lambda+(1-\lambda)\Delta a_1\beta}{(1-\lambda)\Delta a_1(\beta+\alpha\lambda)}$. This result describes three different sets of conditions, under which the vendor can attract all *convertible* customers through a group-buying promotion. One direct observation is that under the complex information condition, vendors with any level of experience quality can effectively promote through a group-buying platform, as long as the platform can guide customers to update their beliefs properly. In other words, under complex information environments, the platform can cater to vendors with different experience qualities, through adjusting the parameter m. Recall that m measures the relative importance of quantity information for consumers' decisions. One potential way of influencing m is by varying the accuracy or timeliness of quantity information. For example, if the platform updates the quantity information every ten minutes, instead of in real time, the customers may rely less on the quantity information and hence adopt a lower m.

We next compare p_1^c to p_1^m and summarize the results below. We define $N(a_1)$ as $N(a_1) = \frac{\beta(a_0+a_1)}{(1-\lambda)(\beta+\alpha\lambda-\alpha\lambda\beta(a_0+a_1))}$, and A_3 as $A_3 = \hat{a}_1 + N(A_3)$.

Corollary 2. When the group-buying platform provides complex information environment,

(1) vendors of below-average experience quality, i.e., $\underline{a}_1 < a_1 < \hat{a}_1$, always offer larger discounts compared to the moderate information environment scenarios;

(2) vendors of above-average quality offer larger discounts compared to the moderate information case if $A_3 < a_1 < \bar{a}_1$ and $\bar{a}_1 > \hat{a}_1 + N(\bar{a}_1)$; otherwise, they offer lower discounts.

When the platform provides a complex information environment, vendors with low experience quality must offer larger discounts compared to the moderate information case in order to effectively promote themselves. Platforms may have incentives to provide more information in order to reduce the uncertainties faced by consumers and facilitate transactions. However, we discovered that in the setting of group-buying promotions, some vendors were worse off when more information was provided to customers. In the complex information environment, low-quality vendors face the challenge of further increasing the number of vouchers sold in order to entice uninformed consumers to purchase, which requires them to further lower their prices. Some high-quality vendors benefit from the complex information environment, particularly those of very high experience quality. The reason for this is that a large discount, while increasing the quantity sold, can also lead to a negative perception by consumers about product quality, and vice versa for a small discount. The trade-off between these two forces determines vendors' optimal discounting strategy.

5 Implications of More Information

Is more information beneficial to vendors? We discovered that there exists a trade-off between the two types of information, which leads to different discounting strategies by vendors with different levels of experience quality. Both quantity and discount carry useful information about the vendors' experience quality, and they reduce the uncertainty and risk faced by uninformed consumers. Vendors with high quality therefore do not need to engage in deep discounting, as informed customers who are aware of their product and quality will "advertise" for them through the quantity sold. In the meantime, reducing their discount level also prevents uninformed consumers from thinking negatively about their high experience quality. On the other hand, vendors with low experience quality offer higher discounts than in the simple promotion case, because they need to encourage more informed customers to purchase by using high discounts, and in turn attract uninformed customers.

Combining findings from Corollary 2 and Corollary 1, we draw comparisons about vendors' discounting strategies under the three levels of information.

Proposition 3. Comparing the vendor's discounting strategy under all three cases,

(1) when a vendor's experience quality is below average, i.e., $\underline{a}_1 < a_1 < \hat{a}_1$, the vendor offers lower discounts under the moderate information environment than under the complex information environment, that is $p_1^m > p_1^c$, and the vendor has no incentive to offer discounts in the simple information environment;

(2) when a vendor's experience quality is much higher than the average, i.e., $A_3 < a_1 < \bar{a}_1$, and $\bar{a}_1 < \hat{a}_1 + N(\bar{a}_1)$, the vendor offers the lowest discount under the moderate information environment, and offers the highest discount under the simple information environment, i.e., $p_1^s < p_1^c < p_1^m$;

(3) in all other cases, the vendors offer the lowest discount under the complex information environment,

and offer the highest discount under the simple information environment, i.e., $p_1^s < p_1^m < p_1^c$;

One main finding from the above analysis is that additional information leads to different effects for different types of vendors. On the one hand, high-quality vendors always prefer either moderate or complex information to simple information; on the other hand, some of them would choose moderate information over complex information. In other words, more information can harm high-quality vendors. In contrast, for low-quality vendors, the finding is more unanimous in that all low-quality vendors prefer moderate information to complex information. Our explanation for this intriguing finding is that in the complex information environment, vendors' discount choices have opposite effects on customers' purchasing decisions. This complexity is particularly harmful for low-quality vendors, because they must offer very deep discounts in order to increase the quantity sold and hence influence convertible customers' decisions. However, complex information can also harm vendors with very high quality, i.e., $A_3 < a_1 < \bar{a}_1$. As the platform switches from a moderate information to a complex information environment, these high-quality vendors must offer even larger discounts because they have a very high proportion of convertible customers. In other words, as more information becomes available to customers, vendors must adjust their discounting strategy in order to influence customers' updated beliefs, and hence their purchasing decisions. Our analysis highlights an aspect that is very important and yet different from previous studies. Information, while alleviating the quality uncertainty concerning consumers' purchasing decisions in the online environment, can also harm vendors through the indirect effects of their discount strategies on their customers.

6 Conclusion

In this paper, we analyzed the information structure on group-buying platforms and its impact on customers' and vendors' strategies. We focus on three types of information contexts: simple, moderate, and complex information environments. We have several main findings. First, only high-quality vendors join the platform under the simple information case scenario. As more information is provided to customers, low-quality vendors also have incentives to promote on the platform. Second, in both the moderate and complex information environments, both high- and low-quality vendors can promote effectively and attract all convertible customers, under certain conditions. Third, not all vendors prefer complex information to moderate information, although all of them prefer either complex or moderate information to simple information. In other words, more information is not necessarily better for the vendors or the platform.

These results highlight the importance of information structure to group-buying platforms. By offering different types of information to customers, the platform may become popular with vendors of different qualities. For instance, to cater to low-quality vendors, the platform should provide a very rich information environment to facilitate customers' purchasing decisions. This can be done by placing the discount and quantity information at prominent places on a deal's web page. The platform can also educate consumers on how to make more informed decisions by using not only quantity information, but also discount information. In contrast, to attract high-quality vendors, the platform should be cautious and not provide too much information to customers. It is worth highlighting that more information is not necessarily better for group-buying platforms, depending on the type of information.

This study can be potentially extended in a few directions. First, future studies may look at the case scenario of vendors promoting through group-buying platforms who do not attract all convertible customers. In the current study, we chose to focus on the scenario in which vendors experience effective promotion, meaning that all customers who are interested in buying at regular prices are attracted by the promotion. While we believe our focus fits the objectives of most vendors promoting on group-buying platforms, examining other case scenarios may provide complementary insights. Second, the current model assumes a uniform distribution of consumers, and this distribution can be extended to other more complex formats to potentially capture other consumer characteristics. It would also be interesting to examine other types of information on group-buying platforms, such as social information. Groupon.com now displays social information such as Facebook "likes" and Yelp review excerpts on deal pages. Although this information is selected by the vendors themselves, social information like this may nevertheless influence consumers' purchasing decisions.

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Appendix

Proof to Proposition 2

The condition is equivalent to $a_1 - p < \hat{a}_1 - \Delta a_1 \alpha\lambda(a_0 + a_1 - p_1^m) - p_1^m$, and can be reorganized as $p_1^m(1 - \Delta a_1 \alpha\lambda) < p + \Delta a_1(1 - \alpha\lambda(a_0 + a_1))$. Substituting in p_1^m, the condition becomes $\frac{(1-\lambda)\Delta a_1(1-\Delta a_1 \alpha\lambda)}{2(1-\Delta a_1 \alpha\lambda(1-\lambda))} < \Delta a_1(1 - \alpha\lambda\frac{a_0+a_1}{2})$. Note that, to ensure $p_1^m < p$, we already know that $\frac{\Delta a_1}{2(1-\Delta a_1 \alpha\lambda(1-\lambda))} < 0$. Therefore, if we multiple both sides of the condition with $\frac{2(1-\Delta a_1 \alpha\lambda(1-\lambda))}{\Delta a_1}$, the condition becomes $(1-\lambda)(1-\Delta a_1 \alpha\lambda) > 2(1 - \Delta a_1 \alpha\lambda(1-\lambda))(1-\alpha\lambda)\frac{a_0+a_1}{2}$, which can be simplified as $[\Delta a_1 \alpha\lambda(1-\lambda) - 1][1 - \alpha\lambda(a_0 + a_1)] > \lambda$. When $\Delta a_1 > \frac{1}{\alpha\lambda(1-\lambda)}$, the condition is solved as $a_0 < \frac{1}{\alpha\lambda} - \frac{1}{\alpha[\Delta a_1 \alpha a(1-\lambda)-1]} - a_1$. When $\Delta a_1 < 0$, the condition is solved as $a_0 > \frac{1}{\alpha\lambda} - \frac{1}{\alpha[\Delta a_1 \alpha\lambda(1-\lambda)-1]} - a_1$. We introduce A_1 as such that when $a_1 = A_1$, the following equation holds: $a_0 = \frac{1}{\alpha\lambda} - \frac{1}{\alpha[\Delta a_1 \alpha\lambda(1-\lambda)-1]} - a_1$. It is easy to see that the right side of the equation in decreasing in a_1. Therefore, when $a_1 > A_1$, $LHS > RHS$, and vice versa. Therefore, the condition for $a_0 + a_1 - p < a_0 + \tilde{a}_1 - p_1^m$ can be summarized as $a_1 > \max\{\hat{a}_1, A_1\}$ or $a_1 < \min\{\hat{a}_1 - \frac{1}{\alpha\lambda(1-\lambda)}, A_1\}$.

Proof to Corollary 1

Compare p_1^s with p_1^m is equivalent to comparing $\frac{(1-\lambda)\Delta a_1}{2}$ with $\frac{(1-\lambda)\Delta a_1}{2(1-\Delta a_1 \alpha\lambda(1-\lambda))}$. Since $\frac{\Delta a_1}{2(1-\Delta a_1 \alpha\lambda(1-\lambda))} < 0$, this can be reorganized as comparing 1 with $1 - \Delta a_1 \alpha\lambda(1-\lambda)$. It is easy to see that $LHS < RHS$ when $\Delta a_1 < 0$, meaning vendors with the same quality offer lower discount when quantity is observable to consumers.

Proof to Lemma 3

Vendors offer a discount if $p_1^c < p$, meaning $\frac{(1-\lambda)\Delta a_1[1-(1-m)\beta(a_0+a_1)]}{2[1+\Delta a_1(1-\lambda)((1-m)\beta - m\alpha\lambda)]} < 0$. It is easy to see that $1-(1-m)\beta(a_0 + a_1) > 0$. When $\Delta a_1 > 0$, the condition becomes $1 + \Delta a_1(1-\lambda)((1-m)\beta - m\alpha\lambda) < 0$. When $\frac{m}{1-m} > \frac{\beta}{\alpha\lambda}$, this condition holds when $\Delta a_1 > \frac{1}{(1-\lambda)[m\alpha\lambda-(1-m)\beta]}$. When $\frac{m}{1-m} < \frac{\beta}{\alpha\lambda}$, the condition cannot hold. When $\Delta a_1 < 0$, the condition becomes $1 + \Delta a_1(1-\lambda)((1-m)\beta - m\alpha\lambda) > 0$. When $\frac{m}{1-m} > \frac{\beta}{\alpha\lambda}$, this condition always holds. When $\frac{m}{1-m} < \frac{\beta}{\alpha\lambda}$, the condition can be simplified as $\frac{1}{(1-\lambda)[m\alpha\lambda-(1-m)\beta]} < \Delta a_1 < 0$.

Proof to Proposition 2

The condition $a_0 + a_1 - p < a_0 + \tilde{a}_1 - p_1^c$ is equivalent to $[1 + \Delta a_1((1-m)\beta - m\alpha\lambda)]p_1^c < a_0 + \hat{a}_1 - \Delta a_1 m\alpha(a_0 + a_1) - \frac{a_0+a_1}{2}$. Substituting in p_1^c, we can further simplify the condition as $(a_0 + a_1)\lambda m\alpha[\frac{(1-m)\beta}{m\alpha} + 1 + (1-\lambda)\Delta a_1((1-m)\beta - m\alpha\lambda)] > \lambda + 1 + (1-\lambda)\Delta a_1((1-m)\beta - m\alpha\lambda)$. We already know that, Δa_1 and $1 + (1-\lambda)\Delta a_1((1-m)\beta - m\alpha\lambda)$ must hold different signs in order for vendors to participate in discount promotion. Therefore, when $\Delta a_1 < 0$, the condition becomes $a_0 + a_1 > \frac{\lambda+1+(1-\lambda)\Delta a_1((1-m)\beta-m\alpha\lambda)}{\lambda m\alpha[\frac{(1-m)\beta}{m\alpha}+1+(1-\lambda)\Delta a_1((1-m)\beta-m\alpha\lambda)]}$. When $\Delta a_1 > 0$, we know that $1 + (1-\lambda)\Delta a_1((1-m)\beta - m\alpha\lambda) < 0$. If $\lambda + 1 + (1-\lambda)\Delta a_1((1-m)\beta - m\alpha\lambda) < 0$, or equivalently, $m > \frac{1+\lambda+(1-\lambda)\Delta a_1\beta}{(1-\lambda)\Delta a_1(\beta+\alpha\lambda)}$, then the condition becomes $a_0 + a_1 < \frac{\lambda+1+(1-\lambda)\Delta a_1((1-m)\beta-m\alpha\lambda)}{\lambda m\alpha[\frac{(1-m)\beta}{m\alpha}+1+(1-\lambda)\Delta a_1((1-m)\beta-m\alpha\lambda)]}$. If $\frac{(1-m)\beta}{m\alpha} + 1 + (1-\lambda)\Delta a_1((1-m)\beta - m\alpha\lambda) > 0$, then the condition becomes $a_0 + a_1 > \frac{\lambda+1+(1-\lambda)\Delta a_1((1-m)\beta-m\alpha\lambda)}{\lambda m\alpha[\frac{(1-m)\beta}{m\alpha}+1+(1-\lambda)\Delta a_1((1-m)\beta-m\alpha\lambda)]}$.

Denote $\bar{m}$ as the solution to $\frac{(1-m)\beta}{m\alpha} + 1 + (1-\lambda)\Delta a_1((1-m)\beta - m\alpha\lambda) = 0$. It is easy to see that the left side in decreasing in m. As a result, $\frac{(1-m)\beta}{m\alpha} + 1 + (1-\lambda)\Delta a_1((1-m)\beta - m\alpha\lambda) > 0$ holds when $m < \bar{m}$. In any other cases, the condition cannot hold.

Denote A_2 as such that when $a_1 = A_2$ the following equation holds: $a_0 = \frac{\lambda+1+(1-\lambda)\Delta a_1((1-m)\beta-m\alpha\lambda)}{\lambda m\alpha[\frac{(1-m)\beta}{m\alpha}+1+(1-\lambda)\Delta a_1((1-m)\beta-m\alpha\lambda)]} - a_1$.

The right side can be reorganized as $\frac{1}{\lambda m\alpha}\frac{\lambda-\frac{(1-m)\beta}{m\alpha}}{[\frac{(1-m)\beta}{m\alpha}+1+(1-\lambda)\Delta a_1((1-m)\beta-m\alpha\lambda)]} - a_1$, and it is easy to verify that it decreases in a_1. We can therefore restate the conditions above as follows. To ensure $a_0 + a_1 - p < a_0 + \tilde{a}_1 - p_1^c$, we need (1) $a_1 > \max\{\hat{a}_1, A_2\}$, or (2) when $\frac{1+\lambda+(1-\lambda)\Delta a_1\beta}{(1-\lambda)\Delta a_1(\beta+\alpha\lambda)} < m < 1$, and $a_1 < \min\{\hat{a}_1, A_2\}$, or (3) when $0 < m < \bar{m}$, $A_2 < a_1 < \hat{a}_1$.

Proof to Corollary 2

Note that $p_1^m - p_1^c$ is equivalent to $\frac{(1-\lambda)\Delta a_1}{2(1-\Delta a_1\alpha\lambda(1-\lambda))} - \frac{(1-\lambda)\Delta a_1[1-(1-m)\beta(a_0+a_1)]}{2[1+\Delta a_1(1-\lambda)((1-m)\beta-m\alpha\lambda)]}$, which can be simplified as $\alpha a_1[1 - \Delta a_1(1-\lambda)(m\alpha\lambda - (1-m)\beta)] - \Delta a_1[1 - (1-m)\beta(a_0 + a_1)][1 - \Delta a_1\alpha\lambda(1-\lambda)]$, or equivalently $\Delta a_1(1 - m)[\beta(a_0 + a_1) + \Delta a_1(1-\lambda)(\beta + \alpha\lambda - \alpha\lambda\beta(a_0 + a_1))]$. We denote this expression as M. When $\Delta a_1 > 0$, it is easy to see that $M > 0$, and consequently $p_1^m > p_1^c$. When $\Delta a_1 < 0$, or $a_1 > \hat{a}_1$, we have $M < 0$ if $a_1 < \hat{a}_1 + \frac{\beta(a_0+a_1)}{(1-\lambda)(\beta+\alpha\lambda-\alpha\lambda\beta(a_0+a_1))}$, and vice versa. Denote $N(a_1) = \frac{\beta(a_0+a_1)}{(1-\lambda)(\beta+\alpha\lambda-\alpha\lambda\beta(a_0+a_1))}$. It is easy to verify that $N(a_1)$ is strictly positive and increases in a_1, and $\hat{a}_1 < \hat{a}_1 + N(a_1)$. Therefore, if $\bar{a}_1 < \hat{a}_1 + N(\bar{a}_1)$, then $M < 0$ and $p_1^m < p_1^c$ as long as $a_1 > \hat{a}_1$. If $\bar{a}_1 > \hat{a}_1 + N(\bar{a}_1)$, then there exist A_3 such that $M < 0$ and $p_1^m < p_1^c$ when $\hat{a}_1 < a_1 < A_3$ and $M > 0$ and $p_1^m > p_1^c$ when $A_3 < a_1 < \bar{a}_1$, where $A_3 = \hat{a}_1 + N(A_3)$.

Proof to Proposition 3

We also need to compare p_1^s with p_1^c under $\Delta a_1 < 0$, which is equivalent to comparing $LHS = m[\beta(a_0 + a_1) + \beta\Delta a_1(1-\lambda) + \Delta a_1\alpha\lambda(1-\lambda)]$ with $RHS = \beta(a_0 + a_1) + \beta\Delta a_1(1-\lambda)$. Note that $\beta(a_0 + a_1) + \beta\Delta a_1(1-\lambda) = \beta(a_0 + a_1 + (1-\lambda)(\hat{a}_1 - a_1))$ is positive, and $[\beta(a_0 + a_1) + \beta\Delta a_1(1-\lambda) + \Delta a_1\alpha\lambda(1-\lambda)] < \beta(a_0 + a_1) + \beta\Delta a_1(1-\lambda)$. When $[\beta(a_0 + a_1) + \beta\Delta a_1(1-\lambda) + \Delta a_1\alpha\lambda(1-\lambda)] > 0$, we have $LHS < RHS$ due to $m < 1$. When $[\beta(a_0 + a_1) + \beta\Delta a_1(1-\lambda) + \Delta a_1\alpha\lambda(1-\lambda)] < 0$, we also have $LHS < RHS$ due to $LHS < 0$ and $RHS > 0$.

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