

The Impact of Digital Marketing on Firms' Strategies and Consumers' Post-purchase Behavior

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**ABSTRACT**

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Companies have for decades built up their business around the traditional brick-and-mortar channel. The rise of the Internet and the surging popularity of online shopping have offered rapid growth in e-commerce and embodied the emerging click-and-mortar (e.g. Target.com) or solely online business model (e.g. Amazon.com). As the focus of market moves away from brick-and-mortar to e-commerce, companies have sought to adapt best digital marketing strategies to obtain competitive advantage over their rivals. Meanwhile, the prevalence of user-generated content has given consumers unprecedented power to influence the market performance of various products and services. Such transformation has created many opportunities and challenges for modern e-businesses. It has opened several new pages for IS literature as well. In my dissertation, I intend

to study the impact of digital marketing on firms' pricing strategy as well as on consumers' intrinsic behaviors in the post-Internet era.

In the first study, I examine a novel hybrid pricing model, featuring both online advertising and digital promotion. Endogenizing product prices as a decision variable, I explicitly consider the implementation costs and the distribution effectiveness associated with the underlying mechanism. From consumers' perspective, cashback shopping provides an attractive saving opportunity as the prices they pay are perceived lower. Surprisingly, under some conditions the "low" post-cashback price is actually "high", relative to the level in the absence of cashback mechanism. As a consequence, the introduction of cashback may reduce consumer surplus and social welfare.

In the second essay, I investigate a fundamental question: Under what conditions are consumers more likely to post product ratings voluntarily? Unlike existing literature, I follow an established theory and propose a novel approach, decomposing consumer satisfaction into product quality and quality disconfirmation. I find that the discrepancy between a consumer's expected and realized product quality has a significant impact on her propensity to share product experience. Such intension to contribute is subject to the crowding-out effect, meaning that the underlying propensity declines as more peer consumers have already shared their opinions. Furthermore, the more credible a consumer perceives the online review system, the less prone she would be to interact with the system. A series of simulations are designed to further understand: (1) the association between product evaluation and lurking behavior, (2) the evolution pattern of product ratings, and (3) the effect of review manipulation on subsequent rating activities.

In sum, these investigations provide a better understanding of how information systems and IT-enabled marketing methods reshape merchants' competitive strategy and consumers' decision-making processes. I briefly introduce the background, motivate the research questions of my interest, and summarize the main findings of this dissertation in the first chapter. In the following two chapters, I review related literature and highlight the contribution of my work from both academic and managerial perspectives for each of two studies. Then, I discuss model development and setting, describe research design and methodologies, and summarize main findings and implications of those two studies.

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# Chapter 1 Introduction

## 1.1. Background

Companies have for decades built up their business around the traditional brick-and-mortar channel. The rise of the Internet and the surging popularity of online shopping have offered rapid growth in e-commerce and embodied the emerging click-and-mortar (e.g. Target.com) or solely online business model (e.g. Amazon.com). As the focus of market moves away from brick-and-mortar to e-commerce, companies have sought to adapt best digital marketing strategies to obtain competitive advantage over their rivals. Meanwhile, the prevalence of user-generated content has given consumers unprecedented power to influence the market performance of various products and services. Such transformation has opened several new pages for IS literature. In my dissertation, I intend to study the impact of digital marketing on firms' pricing strategy as well as on consumers' intrinsic behavior in the post-Internet era.

## 1.2. Online Cashback Affiliate

The rise of the Internet and the surging popularity of online shopping have offered rapid growth in e-commerce and garnished companies' interest around adapting best digital marketing strategies. Specifically, affiliate marketing, an online advertising where a business pays the affiliates for every visitor or sale brought in by the affiliates' own effort, has become a prevalent strategy for online businesses to boost sales volume at low costs (Swan 2011b). In the early days of e-commerce, companies relied on web traffic to establish popularity; now the attention has turned to converting such traffic into actual purchases.

Table 1-1 shows the breakdown of affiliate type among top 20 sales-generating websites in the United Kingdom from 2006 to 2012 (Swan 2011a). The statistics highlight a dynamic shift in

online advertising practice, moving from ordinary methods such as pay-per-click (PPC) to the novel cashback model. Over the years, *cashback* affiliate— which incentivizes consumers to purchase by reimbursing them with a portion of transactional amount – has received substantial acceptance among online merchants<sup>1</sup> due to its capability of converting traffic into sales. Such higher conversion rates stem from an interesting online shopping habit noted in *Forbes*: “*One good way to find deals is to find the cheapest price ... and then check at Ebates.com to see if there’s a cashback offered for the merchant you found*” (Rand 2005).

**Table 1-1.** Breakdown of affiliate type among top 20 sales-generating websites

<b>Affiliate Method</b>	<b>2006</b>	<b>2007</b>	<b>2008</b>	<b>2009</b>	<b>2010</b>	<b>2011</b>	<b>2012</b>
PPC	13	14	9	7	5	2	3
Coupon code	0	0	3	3	3	5	3
Cashback	2	2	2	4	5	6	7
Content/Others	5	4	6	6	7	7	6

Websites built simply upon the cashback concept, such as Ebates.com and MrRebates.com, are extremely successful. Ebates, the leading cashback site in the U.S. with 12 million registered users, has reimbursed over 250 million dollars to its members since 1998. In 2011 it brokered 900 million dollars in merchandise sales for its 1,600 affiliated merchants. Its revenue growth has trended 50 percent higher for the second year in a row since 2010 (Hoge 2011). Interestingly, cashback sites are not the only ones trying to exploit this new marketing concept. Software giant Microsoft in 2008 implemented the cashback feature that allows its search engine Bing to act as a cashback publisher. One year later, Google also introduced its Google Checkout as a platform on rewarding customers.

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<sup>1</sup> By online merchants we mean manufacturers and retailers in both click-and-mortar and online-only business model.

There is every reason to believe the cashback concept will continue to grow its popularity. Major consumer banks in the U.S. gradually roll out cashback feature to their online shopping channels<sup>2</sup>, such as Ultimate Reward Mall (Chase Bank), ThankYou Bonus Center (Citibank), and Add It Up Program (Bank of America). Bank of America in August 2012 further leveraged the cashback concept by launching BankAmeriDeals, an innovative program that allows consumers to earn cashback from shopping at physical stores. It has become clear that cashback concept is a catalyst for collaboration between merchants and their affiliate partners, and the enabler for a level of interaction between customers and merchants that has not been possible until now.

### **1.1.1. Industry Practice**

The cashback affiliate model is a novel digital marketing solution featuring both promotion and price discrimination in a digital context. On one hand, it allows online merchants to boost sales volume through discounts. Once affiliating with a cashback site, a merchant can post an “*affiliate link*” (or, a “referral link”) on the cashback site. This hyperlink re-directs consumers to the merchant’s online storefront where actual purchasing transactions are taken place. Thanks to the advance of web technology, e-businesses are able to trace back whether a transaction is led via an affiliate link or made by a consumer without referral. If consumers make purchases through those links, the cashback site, as a transaction broker, collects a fee from the merchant. It then entices consumers into purchasing by rewarding them with a preannounced portion of the

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<sup>2</sup> Credit card issuers commonly reward “cash back” to card holders when they make payments by cards; however it is different from the “cashback” as discussed in this paper in two aspects. First, the former merely incentivizes card holders to use the cards whereas the latter further allows merchants to price-discriminate among consumers. Second, card issuers run the reward programs and dictate cash back percentages without taking merchants’ interest into account. In our cashback model, however, merchants will decide whether to affiliate with intermediaries, and that given an affiliation is formed, cashback rates are then determined through a process in which both merchants and intermediaries are involved.

transactional amount, also known as cashback.<sup>3</sup> This monetary incentive to consumers makes the cashback affiliate one of the most effective advertising approaches to generate more sales. On the other hand, the cashback pricing model can also serve as a pricing device to achieve market segmentation. Products can be listed for one price for non-cashback users and a lower price for the cashback users at the same time. This unique nature allows the merchant to exercise third-degree price discriminating among consumers through a self-selection process.

Depending on how the affiliate fee is collected, the current cashback practice can be further categorized into two fee models: (1) commission-based fee model (implemented at *MrRebates.com*) and (2) lead-based fee model (implemented at *eBates.com*).<sup>4</sup> With the commission-based fee model, the merchant first decides and shares a certain percentage of the revenue generated via referral links with the affiliate as a commission. The site then sets a cashback rate to incentivize its users. With the lead-based fee model, two firms move in a reverse order. The cashback site first announces a fixed fee for every lead it generates and then the merchant determines the cashback rate on its own.

### **1.1.2. Cashback vs. Coupons**

In practice, cashback holds advantages over other promotional vehicles such as coupons and mail-in rebates in two aspects. First, from a consumer's point of view, this concept is straightforward. Searching for coupons could be time-consuming and the use of coupon could be a hassle as well as. Coupon redemption is typically subject to some terms and conditions (e.g.,

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<sup>3</sup> To earn cashback, a consumer needs to: (1) register for membership at a cashback site, (2) click on a merchant's referral link which will direct the shopper's browser to the merchant's own website, and (3) make a purchase. Accumulated cashback can be claimed via checks or PayPal online transfers. Some sites (e.g., *MrRebates.com*) provide price-comparison feature and merchant-specific coupon codes which allow consumers to obtain a bigger discount.

<sup>4</sup> To understand the cashback industry we conducted an interview with the president at *MrRebates.com* and a sales associate at *eBates.com*. Our analytical model is built according to the current industry practice.

valid for a short period of time and cannot be used with other deals) and the redemption cost associated with mail-in rebates is state-dependent and is thus uncertain to consumers (Lu and Moorthy 2007). Cashback on the contrary has the capability of providing constant and certain discounts. Price-prone consumers can simply get a lower price (after factoring in with cashback) by shopping through affiliate links.

Second, from a merchant's point of view, the cashback practice is simple yet efficient. A big concern for coupon practitioners in early days is that they have been struggling to reach desired consumers. Take coupon for example. According to NCH Marketing Services, in 2013, coupon redemption rate is as low as 2.8% in the United States. This low figure clearly exhibits the notorious inefficiency associated with the traditional distribution method. Unlike coupons, the cashback mechanism attracts bargain hunters by offering publicly and constantly available monetary incentives. Cashback affiliate, with a huge base of loyal users, instead provide an efficient solution for reaching price-prone consumers.

### **1.1.3. Findings**

The introduction of the cashback mechanism poses some intriguing questions for both practitioners and researchers. Motivated by the lack of theoretical examination on this still-nascent marketing approach, we develop a game-theoretical framework to fully understand the economic impact of the cashback affiliate model. The key concern for merchants is whether the fee being paid to the affiliates is justifiable. Our result shows that the adoption of the cashback pricing is profitable as long as consumer valuation is diverse enough and the size of the cashback market is sufficiently small. The intuitive behind is that, the advantage of being able to price-discriminate over the uniform pricing increases in the gap of reservation price between cashback users and non-users. Also, the fraction of the cashback users undermines the profitability of

affiliation as the cashback site would collect a larger portion of the merchant's total revenue as an affiliate fee. Utilizing such principal, we further characterize the circumstances under which the novel cashback model is preferred to traditional coupon models.

Another interesting question to ask is how firms determine the optional prices. One would expect that the cashback users will enjoy a lower price, relative to the price they face when the merchant do not price discriminate. However, our result reveals that saving opportunity from cashback may not be as good as consumers perceive to be. Under some conditions, consumers as a whole may end up paying higher prices, no matter which affiliate fee model is adopted. The market force behind such paradox is driven by the fact that two affiliate members can independently maximize their own profits. The introduction of cashback shopping, in fact, may hurt consumer surplus and social welfare. We propose coordination as a remedy to improve market efficiency and shed light on optimal profit-sharing scheme between affiliated firms.

Our basic model is extended to investigate how affiliate competition would impact the prices and social welfare. It seems to be intuitive that the existence of multiple affiliates should lead to a downward pressure on the affiliate fees. Surprisingly, we find that competition among downstream members, in fact, raises the price for the cashback users and thus hurts social welfare. We also investigate how asymmetric merchants can use the cashback pricing to gain incremental profits. Merchants should take a more aggressive move in affiliate decision when the competition intensifies. Furthermore, the disadvantageous merchants would have higher incentive to strategically enlist to compete with its rival.

### 1.3. Online Customer Ratings

It has been well recognized that online product reviews and ratings have a substantial impact on consumers' pre-purchase decisions. According to surveys, 82% of the respondents agree that online reviews directly influence their decisions on what product to buy (Deloitte 2007) and over 75% of them consider recommendations from those who have experienced the product the most credible information source (Nielson 2007). Through observing the product evaluation shared by peer consumers, a prospective buyer can reduce the product uncertainty and make a more informed purchase, leading to higher satisfaction and lower merchandise return rates (PowerReviews 2010). As a result, the prevalence of online reviews enhances the information transparency and therefore improves the efficiency of online marketplace.

An online product review platform is an information system which facilitates information exchange among its users. Users of an online rating system can be categorized into two groups based on how they interact with the system. The first type of users is review reader (information receiver) who gathers product information stored in various formats, such as numeric ratings, textual contents, multi-media files, etc. After purchasing and experiencing the product, the review reader has an opportunity to become a review poster (information provider) by sharing her own evaluation about the product. Interestingly, a majority of system users are observed to behave as "lurkers", which refers to those who read reviews only but do not post. While how observed ratings can be related to product performance has been studied in a variety of contexts, lesser attention is paid to the underlying factors that induce posting behavior from consumers. Moreover, the distribution of product ratings<sup>5</sup> is commonly found to have a right-skewed U-shape or J-shape across various contexts and platforms (McGlohon et al. 2010). Although

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<sup>5</sup> By *rating* or *score* we mean the numeric value indicating overall product satisfaction experienced by consumers.

researchers have shown that individuals with extreme experiences tend to be more vocal from a statistical approach (Anderson 1998; Dellarocas and Narayan 2006), research to date has not provided an economic-grounded explanation to such observation in the information systems literature. In this study, we empirically examine online consumers' product rating behavior and attempt to explain above-mentioned phenomena commonly observed across online rating systems.

Motivated by the dual roles consumers can play when interacting with the system, we model review-posting behavior from two novel aspects. First, research has shown that, when making rating decision, an individual tends to first observe the opinions expressed by others and then adjust her own opinion accordingly. Such framework assumes that the previously posted ratings influence a focal individual's rating decisions in the post-purchase stage only, ignoring the fact that review posters are often review readers as well. In this paper, we posit that the impact of antecedent ratings may actually take place when the focal individual observes the rating signal in the pre-purchase stage. The general rationale is that before making a purchase, a consumer forms the *expected quality* of the product based on the review signal she observes and the intrinsic perception of the system credibility she has. Upon product consumption, the consumer obtains the *realized quality* of the product and encounters *quality disconfirmation*, referring to as the deviation between her expected and realized quality obtained from the same product. We hypothesize that the realization of quality disconfirmation may have a direct impact on consumers' decision of whether or not to post a product rating and leave it as an empirical question.

The second novelty of this research is that we allow the underlying mechanism governing consumers' rating behavior to be dynamic. In particular, we consider that at a given time, an

individual possesses a *perception of the system credibility*, a subjective attitude underlying how she interprets rating signals she observes. Such perception would evolve over time, depending on quality disconfirmation realized from each product experience. In this paper, we also investigate whether an online rater's posting behavior is dynamically affected by her perceived system credibility.

The richness of our data allows us to directly observe online consumers' decision of "whether to post" (posting vs. lurking) as well as the decision of "what to rate" in the post-consumption stage. To model the interdependence between two decisions, we adopt a Heckman selection model (Heckman 1979) to account for the raters' posting decision in the first stage, and generalize it to reflect the discrete outcomes observed in the second stage. To the best of our knowledge, this is the first research that studies how consumers' rating behavior evolves over time at the individual level. Using a panel data set consisting of each individual consumer's complete purchasing and rating activities taken place on an e-commerce site, we attempt to provide a more comprehensive understanding on the formation of online product opinions based on a richer economic reasoning.

Our estimation results show that a consumer's review-posting behavior is, at least partially, driven by the magnitude of quality disconfirmation she encounters, perhaps due to an intention to "correct" the review signal. This finding provides an economic explanation to the commonly observed U-shaped distribution of online ratings. Moreover, the impact of quality disconfirmation on review contribution is further moderated by the rating environment where a focal consumer is exposed. In particular, the disconfirmation effect is weakened by the level of dissension among posted ratings; however, it is intensified by the total number of submitted

reviews. We also find that consumers tend to be more vocal if they perceive the review system to be noisy, relatively to the scenario where the system is perceived highly reliable.

To highlight the significance of the disconfirmation effect identified in this research, we perform a series of simulations to better understand consumers' posting behavior and evolution of online product ratings. First, we recover the unobserved ratings for purchase occasions that do not lead to a review entry. Our simulation results show that, at the population level, the relationship between review posting percentage and realized product quality is best described as a left-skewed U shape. That is, negative product experiences strongly induce posting behavior. Our second simulation demonstrates that the average of posted product ratings will converge to the true quality in the long run. Although other researchers have explained why average product ratings decline over time (Li and Hitt 2008; Moe and Schweidel 2012), we believe that the disconfirmation effect provides an alternative explanation as it can explain other different evolution patterns observed in practice.

## Chapter 2 Online Cashback Affiliate: A New Promotional Pricing Model

This chapter is organized as follows. Section 2.1 reviews the related literature and positions our research. In Section 2.2, we set up the basic model and analyze the best affiliate and pricing decisions for a monopolistic firm. In Section 2.3, we present a welfare analysis and propose an alternative profit sharing scheme to improve market efficiency. Section 2.4 extends our basic model to investigate the economic impact of competition among upstream and downstream members. Concluding remarks and future research directions are provided in Section 2.5.

### 2.1. Literature Review

While researchers have studied devices that can achieve segmentation for decades, to the best of our knowledge, there is no research that examines the economic impact of the cashback mechanism. Research focusing on making differentiated offers to markets with heterogeneous consumers is most related to this paper. Narasimhan (1984) empirically demonstrates coupons' capability of sorting out consumers by showing that coupons can serve as a price discrimination device to provide a lower price to a particular segment of consumers. Since then, a variety of coupons are invented and their effect on firm profits are widely investigated by researchers both analytically and empirically. For example, coupons take various formats such as direct mail coupons (e.g., Bawa and Shoemaker 1987), newspaper coupons (e.g., Neslin 1990), package coupons (e.g., Raju et al. 1994), cross-ruff coupons (e.g., Dhar and Raju 1998), and mail-in rebates (Chen et al. 2005). Although these pricing devices differ in various aspects such as how they are distributed to and redeemed by consumers, they possess a fundamental similarity. In general, couponing utilizes a "*push method*" by which businesses proactively distribute deals to mass consumers. Such approach naturally leads to an effectiveness issue of matching the right price with right consumers at the right time, as indicated by constantly low coupon redemption

rate in the past decades. However, issues related to coupon distribution is not modeled in most, if not all, prior analytical framework. For example, Shaffer and Zhang (1995) examine the effect of coupon targeting on firms' prices and profits. They build an analytical model based on an assumption that a firm can perfectly and costlessly discern coupon users from non-users as well as distinguish brand loyalists and switchers among all coupon users. On the contrary, the cashback mechanism adopts a "*pull method*" by which consumers take action to claim discounts that are constantly and publicly available (Swan 2010). This first and subtle difference distinguishes the cashback mechanism from other promotional devices and makes it a more efficient solution to pursue segmentation.

However, there is no free lunch. Unlike couponing where the marketing expense is set upfront and thus under a merchant's full control, the cashback mechanism involves a third-party online website serving as a transaction broker. The presence of this intermediary leads to the second and perhaps a more important distinction from an economic perspective. Cashback sites, no matter which fee model is adopted, possess some degree of control in price setting. The shift of some market power could potential undermine the attractiveness of the cashback mechanism as a price-discriminating tool. In an analogous supply chain setting, Neslin (1990) studies the effect of promotion on incremental sales. Using scanner panel data, he empirically shows that coupons have an evident effect upon market share after controlling for competitive couponing activity. Despite several similarities, our research is different from Neslin's work in the following. First of all, both upstream and downstream members can run promotions in Neslin whereas the depth of promotion is determined by either party (while is also affected by the other). Second, in a traditional supply chain setting products are available at the retailer only, while in the context of cashback consumers can purchase products either on the merchant's online

storefront or via the affiliate site. Lastly, the main objective of his work is to empirically test whether couponing can lead to incremental sales and thus increase profits while our research characterizes market conditions under which adoption of the cashback affiliate is profitable. We also identify conditions when the cashback affiliate performs couponing.

The role of promotional vehicles is intensively studied in competitive settings as well. Economists have studied on how price discrimination affects total output and social welfare in the presence of competition (Borenstein 1985; Holmes 1989; Katz 1984). Shaffer and Zhang (1995) consider a market in which two competing firms can distribute coupons either to targeted consumers or via mass media. They demonstrate that coupon targeting leads to a prisoner's dilemma which makes both firms worse off. Corts (1998) find similar result by arguing that competing firms may wish to refrain from price discrimination. A relevant search question is also explored in a more general setting with two asymmetric firms. Lal (1990) and Rao (1991) conclude that national brands at equilibrium should promote to mitigate encroachment by a private label. Dogan et al. (2010), on the other hand, find that if one firm has absolute competitive advantage over its rival, in the equilibrium the disadvantaged firm would offer rebates alone. In this paper, we also investigate the impact of the cashback mechanism in a competitive setting where merchants have asymmetric brand valuation. Specifically, we attempt to answer whether one merchant has a higher incentive to adopt the cashback affiliate than its rival. Moreover, we also examine the economic impact of competition among downstream members.

This paper extends the literature related to promotions by addressing the following questions:

- When should a merchant adopt the cashback affiliate and how should affiliated members set their respective price terms? Under what conditions does the cashback mechanism outperform the traditional couponing?
- How would the adoption of cashback impact the society from a welfare perspective? What can firms proactively do to improve market efficiency?
- What is the effect of affiliate competition and merchant competition on the optimal pricing scheme and social welfare?

We analytically examine the strategic use of the cashback affiliate model, and conclude that the ability to price-discriminate at the expense of giving away some market power to the affiliates can help the merchant increase the total profits when the market is diverse enough in consumer reservation price.

## **2.2. Basic Model**

In this section, we first introduce the consumer response, consumer segments, and the merchant's pricing alternatives in the absence of cashback. The preliminaries developed from non-cashback pricing serve as a benchmark for our analysis of the cashback mechanism. Next, we set up the cashback pricing model and derive optimal pricing and affiliate decisions at equilibrium. Finally, we extend the basic model to analyze the coupon mechanism and compare it with the cashback mechanism.

### **2.2.1. Non-Cashback Pricing – A Benchmark**

*Consumer response.* In the spirit of a general spatial model, we assume that consumers are uniformly distributed on a line segment with a length normalized to 1. The merchant's product is located at one end of the line segment and the location of a consumer identifies the valuation (alternatively, reservation price or willingness to pay) she has for the product. Denote the highest

reservation price consumers could possibly have by  $V$ . A consumer at distance  $x$  away from the product has a reservation price of  $V - x$ .<sup>6</sup> Suppose the merchant offers the product at price  $p$ . A consumer with location  $x$  away from the product would derive a consumer surplus of  $U(x) = V - x - p$ . Each consumer has a unitary demand and will buy the product if her consumer surplus is non-negative. As a result, the demand can be expressed by  $Q(p) = V - p$ .

*Consumer segments.* Normalizing the total market size to one, we consider the market with two types of consumers,  $l$  and  $h$ , with fraction  $\theta$  and  $1 - \theta$ , respectively. For the merchant's product, the highest valuation is  $v$  for type- $h$  consumers and  $\delta v$  for type- $l$  consumers, where  $\delta \in (0, 1)$ .<sup>7</sup> When type- $l$ 's relative valuation is low, (i.e.,  $\delta$  is small) we say the valuation difference between two consumer types is salient. Given the model setting, the demands generated from type- $l$  and type- $h$  segments are  $Q_l(p) = \theta \cdot (\delta v - p)$  and  $Q_h(p) = (1 - \theta) \cdot (v - p)$ , respectively.<sup>8</sup> The market configuration, measured by  $(\theta, \delta)$ , plays an important role in determining firms' pricing strategy, as we shall see shortly.

*Uniform Pricing.* Consider a market served by a monopolist. With the simplest pricing scheme, the merchant charges a uniform price  $p_u$ , to the entire market and face a pricing problem:

$$\max_{p_u} \pi_m^U = p_u \cdot Q_l(p_u) + p_u \cdot Q_h(p_u) . \quad (2.2.1)$$

Maximizing Equation (2.2.1) we have the optimal uniform price,

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<sup>6</sup> The model is a spatial model with the transportation cost normalized to 1. We will release this assumption in the analysis of a competitive market in section 2.5.

<sup>7</sup> The setting of asymmetric reservation price is widely adopted in marketing and economic literature on price discrimination. See Lu and Moorthy (2007) and Desai (2001) for example.

<sup>8</sup> Two quantities are bound between  $[0, \theta]$  and  $[0, 1 - \theta]$ , respectively.

$$P_u^* = \begin{cases} \delta v - 1 & \text{if } (v, \theta, \delta) \in R^{U(a)}; \\ v - 1 & \text{if } (v, \theta, \delta) \in R^{U(b)}; \\ v/2 & \text{if } (v, \theta, \delta) \in R^{U(c)}; \\ (\theta\delta + 1 - \theta)v/2 & \text{if } (v, \theta, \delta) \in R^{U(d)}, \end{cases}$$

$$\text{where } R^{U(a)} = \left\{ (v, \theta, \delta) \left| \begin{array}{l} 2 \leq v, \frac{1}{v} < \delta < 1 - \frac{1}{v}, \frac{v(1-\delta)}{v-1} < \theta < 1 \\ 2 \leq v, 1 - \frac{1}{v} < \delta < 1, 0 < \theta < 1 \end{array} \right. \right\},$$

$$R^{U(b)} = \left\{ (v, \theta, \delta) \left| \begin{array}{l} 2 \leq v, 0 < \delta < \frac{1}{v}, 0 < \theta < 1 \\ 2 \leq v, \frac{1}{v} < \delta < 1 - \frac{1}{v}, 0 < \theta < \frac{v(1-\delta)}{v-1} \end{array} \right. \right\},$$

$$R^{U(c)} = \left\{ (v, \theta, \delta) \left| \begin{array}{l} 0 < v \leq 1, 0 < \delta < \frac{1}{2}, 0 < \theta < \frac{1-2\delta}{(1-\delta)^2} \\ 1 < v \leq \frac{4}{3}, \left\{ \begin{array}{l} 0 < \delta \leq \frac{2-2v}{2-3v}, 0 < \theta < 1 \\ \frac{2-2v}{2-3v} < \delta < \frac{2v-2}{v}, \left\{ \begin{array}{l} 0 < \theta \leq \frac{1-2\delta}{(1-\delta)^2} \\ \frac{2-v}{(1-\delta)v} \leq \theta < 1 \end{array} \right. \\ \frac{2v-2}{v} \leq \delta < \frac{1}{2}, 0 < \theta \leq \frac{1-2\delta}{(1-\delta)^2} \end{array} \right. \\ \frac{4}{3} < v < 2, \left\{ \begin{array}{l} 0 < \delta \leq \frac{2-2v}{2-3v}, 0 < \theta < 1 \\ \frac{2-2v}{2-3v} < \delta \leq \frac{1}{2}, \left\{ \begin{array}{l} 0 < \theta < \frac{1-2\delta}{(1-\delta)^2} \\ \frac{2-v}{(1-\delta)v} \leq \theta < 1 \end{array} \right. \end{array} \right. \end{array} \right. \right\},$$

$$R^{U(d)} = \left\{ (v, \theta, \delta) \mid \mathbb{R} - \{R^{U(a)} \cup R^{U(b)} \cup R^{U(c)}\} \right\}, \text{ and } \mathbb{R} = \left\{ (v, \theta, \delta) \mid 0 < v, 0 < \theta < 1, 0 < \delta < 1 \right\}.$$

**PROOF.** The merchant's profit maximization problem can be expressed by a general form:

$$\max_{p_u} \pi_m^U = p_u \cdot Q_l(p_u) + p_u \cdot Q_h(p_u).$$

Given the model settings, the profit function is discontinuous in price due to the asymmetry of reservation price across two segments. More specifically, the merchant may have an incentive to serve type- $h$  consumers only. Under this scenario the second term would drop from (2.2.1). We analyze the merchant's pricing problem under four scenarios, depending on the coverage of two segments.

- (a) *Both segments are fully covered.* The optimal price is a corner solution,  $p_u^{a*} = \delta v - 1$ , and the merchant makes a profit of  $\pi_m^{U(a)} = p_u^{a*} \cdot \theta + p_u^{a*} (1 - \theta) = \delta v - 1$ .
- (b) *Only type- $h$  segment is served and fully covered.* The optimal price is another corner solution,  $p_u^{b*} = v - 1$ , and the merchant makes a profit of  $\pi_m^{U(b)} = p_u^{b*} \cdot \theta = (v - 1)\theta$ .
- (c) *Only type- $h$  segment is served but not fully covered.* Under this scenario, the merchant's profit function will be  $\pi_m^{U(c)} = p_u \cdot Q_h(p_u)$ . Solving it for  $p_u$ , it's easy to get  $p_u^{c*} = v / 2$  and the merchant makes a profit of  $\pi_m^{U(c)} = (1 - \theta)v^2 / 4$ .
- (d) *Both segments are served but not fully covered.* Under this scenario, the merchant's profit function will be  $\pi_m^{U(d)} = p_u \cdot \theta(\delta v - p_u) + p_u \cdot (1 - \theta)(v - p_u)$ . It is straightforward to verify that the second order condition (SOC)  $\frac{\partial^2 \pi_m^{U(d)}}{\partial p_u^2} = -4 < 0$ . Setting  $\frac{\partial \pi_m^{U(d)}}{\partial p_u} = 0$  and solving for  $p_u$ , we know that the merchant will charge  $p_u^{d*} = (\theta\delta + 1 - \theta)v / 2$  and earn a profit of  $\pi_m^{U(d)} = (\theta\delta + 1 - \theta)^2 v^2 / 2$

To derive the equilibrium condition for each scenario, we need to identify the conditions under which the merchant has no incentive to deviate by changing the price. Take scenario (a) for example. For equilibrium wherein both segments are fully covered, we find the parameter region,  $R^{U(a)}$ , such that the following inequality system holds:

$$R^{U(a)} = \left\{ (v, \theta, \delta) \mid \left\{ \pi_m^{U(a)} > \pi_m^{U(b)} \right\} \cap \left\{ \pi_m^{U(a)} > \pi_m^{U(c)} \right\} \cap \left\{ \pi_m^{U(a)} > \pi_m^{U(d)} \right\} \right\}.$$

Using a similar approach, we can also find the equilibrium condition for other coverage scenarios. For scenario (d), the equilibrium condition must also satisfy the price constraint,  $p_u^{d*} > \delta v$ , such that  $Q_l(p_u^{d*}) > 0$ .  $\square$

The optimal uniform price is dependent of market configuration  $(v, \theta, \delta)$ . When product valuation  $v$  is sufficiently large, full coverage in one or two segments may happen. If the valuation gap between two segments is small ( $\delta$  is large), the merchant would set the price at  $\delta v - 1$  to fully cover both segments; Otherwise, it would set the price at  $v - 1$  such that only type- $h$  segment is served with full coverage. When the value of  $v$  is small to moderate, we should expect an uncovered market. If the total valuation of type- $l$  consumers is low ( $\delta$  is small), the merchant would set the price at  $v / 2$  and serve type- $h$  consumers only; Otherwise, it would have incentive to serve both segments by charging one half of the total market valuation.

*Asymmetric Pricing.* Now consider a case where the merchant can perfectly discern consumer types with an exogenous cost of  $K$ . The monopolist would have incentive to charge two asymmetric prices: a low price  $p_l$ , to the low-type and a high price  $p_h$ , to the high-type. As a result, the merchant's profit maximization problem with the adoption of coupon is given by:

$$\max_{p_l, p_h} \pi_m^D = p_l \cdot Q_l(p_l) + p_h \cdot Q_h(p_h) - K, \quad (2.2.2)$$

The asymmetric prices allow the merchant to separately maximize profits in two different segments. Under the case where the market is not fully covered, the optimal prices are  $p_l^* = \delta v / 2$  and  $p_h^* = v / 2$ .<sup>9</sup>

**PROOF.** Two decision variables allow the merchant to maximize the overall profit by setting asymmetric prices to different segments. A general expression of the merchant's profit maximization problem with discriminating pricing is:

$$\max_{p_l, p_h} \pi_m^D = p_l \cdot Q_l(p_l) + p_h \cdot Q_h(p_h) - K$$

Plugging  $Q_h(p_h)$  and  $Q_l(p_l)$  into (2.2.2), we have  $\pi_m^D = p_l \cdot \theta(\delta v - p_l) + p_h \cdot (1 - \theta)(v - p_h)$ . The

Hessian matrix is  $H(p_l, p_h) = \begin{vmatrix} \frac{\partial^2 \pi_m^D}{\partial p_l^2} & \frac{\partial^2 \pi_m^D}{\partial p_h \partial p_l} \\ \frac{\partial^2 \pi_m^D}{\partial p_l \partial p_h} & \frac{\partial^2 \pi_m^D}{\partial p_h^2} \end{vmatrix} = \begin{vmatrix} -4\theta & 0 \\ 0 & -4(1-\theta) \end{vmatrix}$ . The determinant

$$D(p_l, p_h) = \left( \frac{\partial^2 \pi_m^D}{\partial p_l^2} \right) \left( \frac{\partial^2 \pi_m^D}{\partial p_h^2} \right) - \left( \frac{\partial^2 \pi_m^D}{\partial p_l \partial p_h} \right)^2 = 16\theta(1-\theta) > 0 \text{ and } \frac{\partial^2 \pi_m^D}{\partial p_l^2} = -4\theta < 0 .$$
 The second partial

derivative test (SPDT) suggests the maximum exists. Under this case, the merchant sets  $p_h^* = v / 2$ ,  $p_l^* = \delta v / 2$  and makes a profit of  $\pi_m^{D*} = (\theta\delta^2 + 1 - \theta)v^2 / 4$ .  $\square$

Comparing the optimal prices with two different strategy yields the following observations.

**LEMMA 1.** (1) *The optimal pricing terms follow the pattern:  $p_l^* < p_u^* \leq p_h^*$ ; (2) The merchant would adopt Asymmetric Pricing as long as the cost for price discrimination is justifiable:  $\pi_m^D - \pi_m^U \geq K$ .*

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<sup>9</sup> The solution set is not very interesting for a fully covered market. Throughout the paper, we mainly focus on the economic impact of different pricing schemes in a setting where the market is not covered.

**PROOF.** It is easy to show  $\pi_m^{U^*} < \pi_m^{D^*}$ , as the ability to set two asymmetric prices make the merchant strictly better off, and so is  $p_l^* \leq p_u^* \leq p_h^*$ .  $\square$

Compared to the optimal uniform price, the Asymmetric Pricing lowers the price for one segment while raises the price for the other. But the question is: Does such straightforward argument still hold in the cashback pricing model?

### 2.2.2. Cashback Pricing

A merchant who adopts cashback affiliate is actually operating a digital dual channel. When a consumer desires to buy a certain product, she could purchase it directly from the merchant's online storefront (called direct channel<sup>10</sup>) or via the affiliate link posted on a cashback site (called cashback channel). Of course, cashback shopping is not costless to consumers. Cashback shoppers incur transaction costs that include the disutility derived from extra works throughout cashback shopping process, such as registering on the cashback site, searching for the merchants, clicking through affiliate links, and waiting for rewards to be redeemable<sup>11</sup>. Nevertheless, a consumer would still choose to shop through the cashback channel if the monetary incentive obtained from cashback is greater than the transaction costs. In the case where transaction costs are perceived to be higher, the consumer is assumed to make the purchase via the direct channel.

Denoting the transaction costs incurred from cashback shopping by  $c_i$  ( $i = l, h$ ), and since the values of time are different across segments, we assume that the costs are lower for type- $l$  consumers, i.e.  $c_l < c_h$ . The assumption that transaction cost is positively correlated with the reservation price is widely accepted in the prior literature (Coughlan and Soberman 2005).

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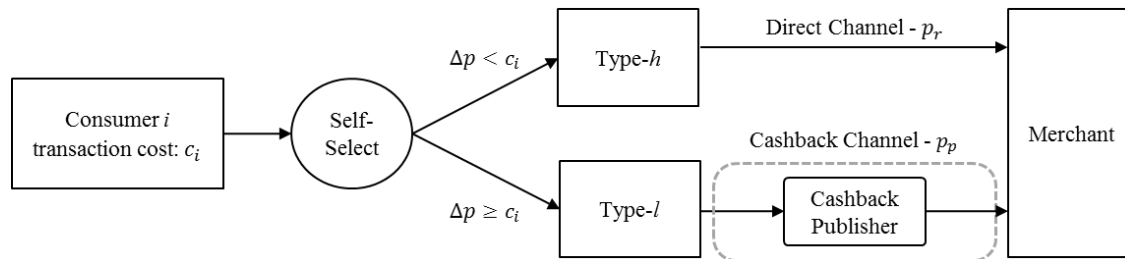
<sup>10</sup> By the direct channel we mean a merchant's e-commerce site, while the term can be generalized to include the merchant's physical stores.

<sup>11</sup> It usually takes 30-60 days for the rewards to be available for redemption.

Without the loss of generality, we normalize  $c_l$  to zero. This normalization is justifiable in the following senses. From a consumers' perspective, cashback shoppers are a group of consumers who value saving beyond the time associated with getting discounts (Swan 2010). From an analytical perspective, the incentive for price discrimination still holds even if  $c_l > 0$ , as long as  $c_l < c_h$  (Gerstner et al. 1994).

Consumers self-select whether to pay a regular price  $p_r$ , or a lower post-cashback price  $p_p$ <sup>12</sup>, depending on whether they use the cashback site. The relative magnitude between one's transaction cost  $c_i$ , and the incentive obtained from cashback shopping,  $\Delta p$  (defined as  $\Delta p = p_r - p_p$ ), determine the self-selection outcome (Figure 2-1).

**Figure 2-1.** Consumer's self-selecting process via an electronic dual-channel



To best model the current cashback practice, we consider a three-stage Stackelberg game with two players: a merchant and a cashback site (or for brevity the site). In this paper, we examine two most popular affiliate fee models in the U.S.: the commission-based fee model and the lead-based fee model. From an economic perspective, which firm moves first affects the sequence of moves of game players and thus the firms' pricing power.

<sup>12</sup> The post-cashback price is an *ex post* price perceived by consumers after factoring in with the cashback rewards.

*Commission-based Model.* In the first stage, the merchant decides whether or not to affiliate with the cashback site. If the merchant decides to enlist, it then chooses a regular price  $p_r$ , and a commission rate  $b$  ( $b \in [0,1]$ ) in the second stage. From the merchant's perspective, the commission paid to the affiliate can be considered the premium of being able to price-discriminate. In the third stage, the intermediary site makes  $b$  times the total revenue it brokers. Meanwhile it chooses a cashback rate  $a$  ( $a \in [0,b]$ ), and rewards site users with  $a$  times the transactional amount in a form of cashback. The site incurs a zero marginal cost since it merely operates as an intermediary and does not directly deal with transactions (see Section 2.1.1 for industry practice).

The merchant's marginal cost is assumed constant and can be normalized to zero by interpreting consumers' reservation price as net of marginal cost. Two firms work independently and maximize their respective profits:

$$\max_{p_r, b} \pi_m^C = p_r(1-b) \cdot Q_l(p_p) + p_r \cdot Q_h(p_r), \quad (2.2.3)$$

$$\max_a \pi_p^C = p_r(b-a) \cdot Q_l(p_p) \quad (2.2.4)$$

where  $p_p = p_r(1-a)$ . The superscript  $C$  on  $\pi$  indicates the commission-based fee model and subscriptions  $m$  and  $p$  denote the merchant and the cashback site, respectively.

For the cashback model to work as a price discrimination device, consumers' incentive compatibility (IC) constraints must be satisfied.<sup>13</sup> Critical readers may argue that the merchant's desire to sort out consumers is not necessarily aligned with the site's best interest, in that the site

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<sup>13</sup> Consumers' IC constraint is  $0 < \Delta p < c_h$ . If  $c_h$  is too small such that the interior solution doesn't exist, then we would end up with the corner solution  $a = c_h / p_r$ . The merchant's profit-maximization problem degenerates to a simple case with only one decision variable  $p$ . This scenario deviates from the main interest of this study, and hence we focus on the interior solutions for the rest of this paper.

may have incentive to entice also type- $h$  consumers by setting a higher cashback rate. In fact, this would never happen in practice. Once both consumer types become cashback shoppers, all consumers would pick the cashback channel and pay the lower price: nominal asymmetric prices actually work like a single price. The merchant's net profit, defined as sales revenue subtracted by commission, is strictly less than the level that can be achieved by the optimal uniform price. If this were the case, the merchant would rather simply set a uniform price and leave the site, which ends up making a zero profit without any commission revenue. Such credible threat tightly aligns the interests of two affiliate partners under the cashback pricing model.

*Lead-based Model.* In this model, the cashback site moves first by announcing a fixed fee  $f$  for every lead it generates via the affiliate link. Observing this preannounced fee, the merchant then makes the affiliate decision. If the merchant decides to enlist, it then sets a regular price  $p_r$ , and chooses a cashback rate  $a$  faced by the cashback site users. Unlike the commission-based fee model where the site has a say on the cashback rate, the merchant with the lead-based fee model can dictate two asymmetric prices targeted at different types of consumers. The profit-maximizing problems for two firms now become:

$$\max_f \pi_p^L = Q_l(p_p) \cdot f \quad (2.2.5)$$

$$\max_{p_r, a} \pi_m^L = (p_p - f) \cdot Q_l(p_p) + p_r \cdot Q_h(p_r) \quad (2.2.6)$$

### 2.2.3. Pricing Decision

Solving (2.2.3) - (2.2.6) using backwards induction gives us two firms' optimal pricing terms.<sup>14</sup>

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<sup>14</sup> Here we list and discuss the optimal solutions under an uncovered market only. If the market is fully covered, the site's problem would become linear. In this case, the merchants' optimal prices would reduce to corner solutions (i.e. profitability of the cashback model would solely rely on how revenue is spitted between two firms).

**LEMMA 2-1.** *With the commission-based model, the merchant sets regular price  $p_r^* = \frac{v}{2}$*

*and commission rate  $b^* = 1 - \delta$ . The site chooses cashback rate  $a^* = 1 - \frac{3}{2}\delta$ .*

**LEMMA 2-2.** *With the lead-based model, the cashback site announces a fixed fee  $f^* = \frac{\delta v}{2}$  for every lead. The merchant sets regular price  $p_r^* = \frac{v}{2}$  and cashback rate  $a^* = 1 - \frac{3}{2}\delta$ .*

**PROOF.** Backwards induction can be used as the solution concept to find the merchant's best affiliate and pricing decisions.

With the commission-based fee model, we first solve the site's problem, followed by the merchant's:

$$\max_{p_r, b} \pi_m^C = p_r(1-b) \cdot Q_l(p_r(1-a)) + p_r \cdot Q_h(p_r), \quad (2.2.3)$$

$$\max_a \pi_p^C = p_r(b-a) \cdot Q_l(p_r(1-a)). \quad (2.2.4)$$

With the fee-based fee model, solving procedure proceeds in a reverse order:

$$\max_f \pi_p^L = \theta \cdot Q_l(p_p) \cdot f, \quad (2.2.5)$$

$$\max_{p_r, a} \pi_m^L = (p_p - f) \cdot Q_l(p_p) + p_r \cdot Q_h(p_r). \quad (2.2.6)$$

Solving (2.2.4) gives us the publisher's best choice on cashback rate  $\tilde{a}(p_r, b) = \frac{b}{2} + \frac{p_r - \delta v}{2p_r}$ ,

given the merchant's pricing decisions. Plugging  $\tilde{a}(p_r, b)$  into (2.2.3) and solving it, we have the

merchant's best response  $(p_r^*, b^*) = (\frac{v}{2}, 1 - \delta)$ , given the site chooses  $\tilde{a}(p_r, b)$ . Plugging  $(p_r^*, b^*)$  back

into  $\tilde{a}(p_r, b)$ , we have the optimal cashback rate  $a^* = 1 - \frac{3}{2}\delta$ . It is simple to verify that the

maximum exists by checking SPDT for (2.2.3) and SOC for (2.2.4). Similarly, we can use the same procedure to derive the optimal pricing terms for lead-based cashback model.  $\square$

When market is not covered, the post-cashback price  $p_p^* = \frac{3}{4}\delta v$ , no matter which affiliate fee model is adopted. The cashback mechanism allows the merchant to extract the highest surplus from type- $h$  segment by raising the targeting price to  $p_h^*$ .<sup>15</sup> Such price hike is consistent with the second inequality presented in Lemma 1(1) (i.e.  $p_u^* \leq p_h^*$ ). Following the first inequality of the same pattern (i.e.  $p_p^* < p_u^*$ ), one may expect the post-cashback price targeted at type- $l$  segment  $p_p^*$  to be lower than the uniform level. However, our common intuition is not always true when the cashback model is adopted.

**PROPOSITION 1.** *The “cashback paradox”, where the post-cashback price is higher than the uniform price, will happen as long as market configuration falls in the region*

$$R_x = \left\{ (v, \theta, \delta) \mid v < 2, \underline{\theta} < \theta < \bar{\theta}, \delta < \frac{1}{2} \right\}, \text{ where } \underline{\theta} = \begin{cases} \frac{1-2\delta}{(1-\delta)^2}, & \text{if } 0 < \delta \leq \frac{1}{3}; \\ \frac{2-3\delta}{2-2\delta}, & \text{if } \frac{1}{3} < \delta < \frac{1}{2}, \end{cases} \text{ and } \bar{\theta} = 1 - \frac{\delta^2}{2(1-\delta)^2}.$$

**PROOF.** In Lemma 1, we have shown  $p_l^* \leq p_u^* \leq p_h^*$ , suggesting that if the merchant is able to price-discriminate, it will increase the price for type- $h$  segment but decrease the price for type- $l$ . The goal here is to verify whether this intuitive still holds with the cashback mechanism, i.e.  $p_p^* \leq p_u^* \leq p_r^*$ . Since the optimal price with the uniform pricing is discontinuous over the parameter

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<sup>15</sup> Under the scenario where the market is fully covered, the merchant with uniform pricing would leave type- $h$  consumers some surplus. If the cashback pricing is adopted, then the merchant would lower the regular price (i.e.  $p_r^* < p_u^* = p_p^*$ ). The consumer welfare would have an unambiguous decrease.

space, our analysis proceed in four scenarios defined in Lemma 1. The inequality can be verified by checking if the merchant has an incentive to deviate.

(a) *Both segments are fully covered.* The uniform price  $p_u^{a*}$  must be sufficiently low to fully cover type- $l$  market. The merchant will increase the regular price,  $p_u^* < p_r^*$ , to extract surplus from type- $h$  market.

(b) *Only type- $h$  segment is served and fully covered.* The type- $l$  market is not served due to a high value of  $p_u^{b*}$ . Firms will lower the post-cashback price,  $p_p^* < p_u^*$ , to serve some type- $l$  consumers.

(c) *Only type- $h$  segment is served but not fully covered.* Under feasible condition  $\theta < \theta_1 \equiv \frac{1-2\delta}{(1-\delta)^2}$ , it immediately follows  $p_p^* < p_u^*$ . To have  $p_p^* > p_u^*$ , the condition  $\theta > \theta_1$  must hold.

(d) *Both segments are served but not fully covered.* To have  $p_u^* = \frac{(1-\theta+\theta\delta)v}{2} > \frac{3\delta v}{4} = p_p^*$ , the condition  $\theta > \theta_2 = \frac{2-3\delta}{2-2\delta}$  must hold.

Clearly, the merchant would adopt cashback pricing only when its revenue is justifiable. To derive the condition for the cashback paradox to happen, we need to identify the region where (1) the cashback mechanism is profitable<sup>16</sup> and (2) both  $\theta > \theta_1$  and  $\theta > \theta_2$  hold. These conditions together specify a region  $R_x \in \{\theta > \theta_1\} \cap \{\theta > \theta_2\} \cap \{\theta < \bar{\theta}\} \cap \{\delta < 1/2\}$  under which the cashback

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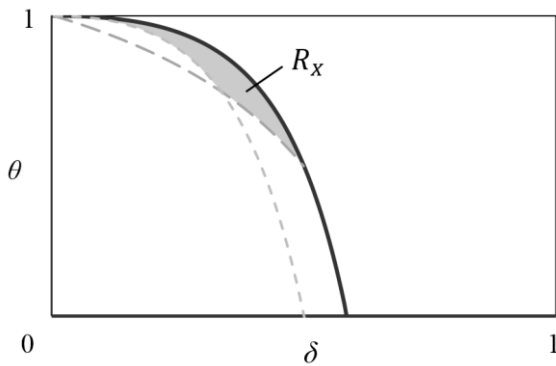
<sup>16</sup> We deem it makes more logical sense to present the optimal pricing terms first and then introduce the necessary condition for the affiliate decision. However, the condition under which the cashback model is profitable (presented in Proposition 3) must be used here to complete our price analysis.

paradox will happen. Formally,  $R_X = \left\{ (\nu, \theta, \delta) \mid \nu < 2, \underline{\theta} < \theta < \bar{\theta}, \delta < \frac{1}{2} \right\}$ , where  $\bar{\theta} = 1 - \frac{\delta^2}{2(1-\delta)^2}$  and

$$\underline{\theta} = \begin{cases} \theta_1 = \frac{1-2\delta}{(1-\delta)^2}, & \text{if } 0 < \delta \leq \frac{1}{3}; \\ \theta_2 = \frac{2-3\delta}{2-2\delta}, & \text{if } \frac{1}{3} < \delta < \frac{1}{2}. \end{cases} \quad \square$$

From consumers' point of review, Proposition 1 indicates a shocking result. Cashback shopping provides an attractive saving opportunity for cashback users as the prices they pay are perceived lower. Surprisingly, under some circumstances this seemingly "low" post-cashback price is actually higher, than the uniform price when the merchant does not price discriminate. As a consequence, consumers end up facing a higher price (i.e.  $p_r^* > p_p^* > p_u^*$ ) if the cashback pricing is implemented.

**Figure 2-2.** Region for cashback paradox



**Figure 2-3.** Comparison of various prices

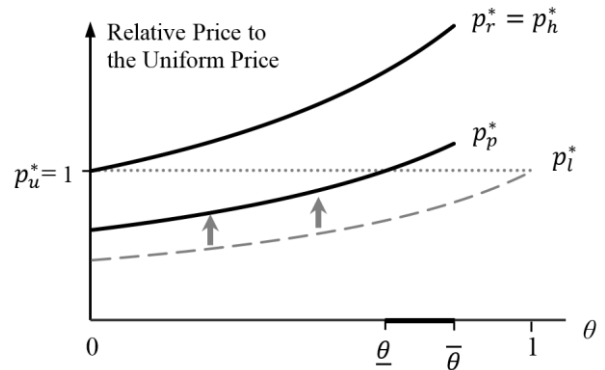


Figure 2-2 plots the region  $R_X$  (on a  $\theta$ - $\delta$  coordinate) in which the *cashback paradox* will occur. What is the driving force behind such counterintuitive result? Recall from Lemma 1(1) that the optimal uniform price  $p_u^*$ , is bound between  $p_l^*$  and  $p_h^*$ . Figure 2-3 illustrates various

prices at optimum as a function of  $\theta$ .<sup>17</sup> Clearly, when  $\theta = 0$ ,  $p_u^* = p_h^*$  as all consumers are high type; when  $\theta = 1$ ,  $p_u^* = p_l^*$  as all consumers are low type. Given the current cashback practice, the cashback site can choose a cashback rate in the commission-based fee model whereas set a fixed fee in the lead-based fee model. Such ability to set a desired fee allows the intermediary to seek its own highest profit margin. In fact, this allocation of pricing power is an analogy to a traditional supply chain setting (Dellarocas 2012) where the manufacturer and the retailer independently choose their respective prices. The upward price distortion stems from double marginalization raises the price targeted at type- $l$  consumers from  $p_l^*$  to  $p_p^*$ . Interestingly enough, when  $\theta$  lies in the interval  $[\underline{\theta}, \bar{\theta}]$ , the merchant can still make a higher net profit by simultaneously increasing two asymmetric prices, compared to the highest profit that can be achieved by a uniform price. The explanation to this counterintuitive result is given as follows. When the merchant has incentive to serve both segments, the optimal uniform price  $p_u^*$ , is decreasing with the fraction of type- $l$  consumers  $\theta$ . If  $\theta$  is sufficiently large (i.e.  $\theta > \underline{\theta}$ ), the uniform price is relatively low, compared to the optimal price when only type- $h$  segment is served. Under this condition cashback affiliation not only allows the merchant to extract the highest surplus from the high-type but also generates a positive net profit from the low-type. It is worth noting that while we assume linear demand for simplicity, none of our analyses are dependent on this assumption.<sup>18</sup>

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<sup>17</sup> The curves for  $p_r^*$  and  $p_p^*$  are truncated at  $\theta = \bar{\theta}$  since beyond this point the merchant will switch back to the uniform pricing. Details on affiliate decision will be discussed in section 2.3.4. The figure is plotted with  $\delta=0.4$ .

<sup>18</sup> The impact of double marginalization, including price distortion and welfare reduction, would be stronger if the marginal revenue curve is convex, since the publisher would try to get a bigger pie by setting a cashback rate further from the channel optimum.

#### 2.2.4. Affiliate Decision

While different affiliate fee models lead to identical prices and demand, the attractiveness of the cashback mechanism is sensitive to how the game proceeds. Which type of fee model should be used? The subgame perfect equilibrium gives the answer.

**PROPOSITION 2.** *For an uncovered market, the site should adopt the commission-based fee model if segment parameters  $(\theta, \delta) \in R_p^C$ , whereas the lead-based fee model should be used*

*if  $(\theta, \delta) \in R_p^L$ , where  $R_p^C = \left\{ (\theta, \delta) \mid 1 - \frac{3\delta^2}{4(1-\delta)^2} < \theta < 1 - \frac{\delta^2}{2(1-\delta)^2}, 4 - 2\sqrt{3} < \delta < 2 - \sqrt{2} \right\}$  and*

*$R_p^L = \left\{ (\theta, \delta) \mid 0 < \theta < 1 - \frac{3\delta^2}{4(1-\delta)^2}, 0 < \delta < 4 - 2\sqrt{3} \right\}$ . The merchant should adopt uniform pricing*

*otherwise.*

**PROOF.** Plugging the optimal pricing terms (Lemma 2) into firms' profit function, we can show the merchant and the site earns  $\pi_m^{C*} = \frac{2(1-\theta)v^2 + \theta(\delta v)^2}{8}$ ,  $\pi_p^{C*} = \frac{\theta(\delta v)^2}{16}$  with the commission-based model, and  $\pi_m^{L*} = \frac{4(1-\theta)v^2 + \theta(\delta v)^2}{16}$  and  $\pi_p^{L*} = \frac{\theta(\delta v)^2}{8}$ , with the lead-based model. Setting  $\pi_m^{C*} > \pi_m^{U*}$  ( $\pi_m^{L*} > \pi_m^{U*}$ ) and reducing terms, we can derive the condition under which the commission-based (lead-based) fee model is profitable from a merchant's point of view. Since the site strictly prefers the lead-based fee model, it would propose it whenever it's profitable for the merchant. Otherwise, it would use the commission-based fee model to get the merchant "on board".  $\square$

The profitability of the underlying mechanism is determined by two components: (1) the incremental revenue obtained from being able to price-discriminate, and (2) the affiliate fee

being paid in order to acquire the price-setting weapon. In what follows, we first examine the effect of segment parameters on profitability of the cashback mechanism. Then we discuss why one fee model is preferred to the other.

Given the fraction of type- $l$  consumer  $\theta$  is fixed, the advantage of asymmetric pricing over uniform pricing is diminishing in type- $l$ 's valuation coefficient  $\delta$ . If the valuation gap between two segments vanishes ( $\delta=1$ ), the optimal uniform price yields the highest profit. Given  $\delta$  is fixed, the fraction of type- $l$  consumers,  $\theta$ , moderates attractiveness of the cashback affiliate. A high value of  $\theta$  implies more sales volume is generated via the cashback channel, and therefore the merchant pays a larger portion of its total revenue to the site. Combined, these two effects suggest that the cashback model is profitable if and only if  $\theta$  and  $\delta$  are sufficiently small. As  $(\theta, \delta)$  becomes smaller (larger), the market will shift towards (away from) the cashback model. We will use this principal to facilitate our subsequent discussion.

Our analysis so far is based on an implicit assumption that the cashback site can choose what type of fee model to implement. A closer look at the revenue allocation between two firms reveals an inclusive decision on the choice of fee model if the merchant also has a say. With the commission-based (lead-based) fee model, the merchant and the site make a profit of

$$\frac{(1-\theta)v^2}{4} + \frac{\theta(\delta v)^2}{8} \left( \frac{(1-\theta)v^2}{4} + \frac{\theta(\delta v)^2}{16} \right) \text{ and } \frac{\theta(\delta v)^2}{16} \left( \frac{\theta(\delta v)^2}{8} \right), \text{ respectively.}$$

Clearly, the merchant strictly prefers commission-based model while the site desires to collect a fee for every lead it generates. Since the merchant is able to keep more revenue if it moves first by setting a commission rate, there must exist a region for  $(\theta, \delta)$  such that the commission-based model is profitable but the lead-based model is not. If  $(\theta, \delta)$  falls in the region where both types of model are profitable, the site should always collect a fixed fee for every lead. In the section 2.4, we

will examine the impact of two firms' relative bargaining power on the current cashback mechanism.

### 2.2.5. Cashback Mechanism vs. Couponing

In this subsection, our goal is to highlight the difference between the cashback mechanism and traditional promotional devices such as coupons. We first develop a model for the coupon mechanism using our basic framework. Then, we compare the result derived from the couponing model with that obtained from the cashback model.

Suppose the merchant can also exercise price discrimination using coupons that are distributed to consumers via mass media. Realistically, some type- $l$  consumers are not able to take advantage of such saving opportunity. This may happen because the coupons have expired, cannot be combined with other offers, or are not available to consumers at all. Let an exogenous parameter  $\omega \in (0, 1)$  denote the fraction of the low-type who successfully redeem the coupon. We call the value of  $\omega$  the consumer redemption of the coupon. When  $\omega = 1$ , our coupon model reduces to our Asymmetric Pricing model in which all type- $l$  consumers are perfectly identified. When  $\omega \neq 1$ , some of them will face the price that is not targeted at them. These consumers are referred as *mismatched buyers* while those who enjoy the saving opportunity are referred as *coupon buyers*. The fractions of the cashback, mismatched and type- $h$  buyers are  $\omega\theta$ ,  $(1-\omega)\theta$ , and  $1-\theta$ , respectively.

With the introduction of  $\omega$ , we endogenize the effectiveness of segmentation (or, coupon redemption rate) in the merchant's pricing problem. In fact, this modeling aspect is commonly ignored in most, if not all promotion literature. When  $\omega$  is high, the majority of targeting consumers go through the self-selection process, resulting in better segmentation. When  $\omega$  is low,

couponing fails to sort out most type- $l$  consumers into their true type. The merchant's pricing problem with couponing can be written as:

$$\max_{p_c, c} \pi_m^{Coupon}(\omega) = (p_c - c) \cdot \omega \cdot Q_l(p_c - c) + p_c \cdot (1 - \omega) \cdot Q_l(p_c) + p_c \cdot Q_h(p_c), \quad (2.2.1)$$

where  $p_c$  and  $c$  denotes the regular price and the coupon face value, respectively. The expression  $(1 - \omega) \cdot Q_l(p_r)$  in the second term captures the fraction of mismatched buyers who face the regular price.

**LEMMA 3.** *With couponing, the merchant's optimal full price and coupon face value is given by  $p_c^*(\omega) = \left( \frac{(1 - \omega)\theta\delta + (1 - \theta)}{1 - \omega\theta} \right) \frac{v}{2}$  and  $c^*(\omega) = \left( \frac{(1 - \theta)(1 - \delta)}{1 - \omega\theta} \right) \frac{v}{2}$ .*

**PROOF.** Following the procedure introduced in the proof of Lemma 2, we can solve for the optimal full price and coupon face value:  $p_c^*(\omega) = \left( \frac{(1 - \omega)\theta\delta + (1 - \theta)}{1 - \omega\theta} \right) \frac{v}{2}$ ,  $c^*(\omega) = \left( \frac{(1 - \theta)(1 - \delta)}{1 - \omega\theta} \right) \frac{v}{2}$ .

With these prices, the merchant makes a profit of  $\pi^{Coupon*} = \frac{1}{4} \omega\theta(\delta v)^2 + \frac{[(1 - \theta) + (1 - \omega)\theta\delta v]^2}{4(1 - \omega\theta)}$ .  $\square$

With couponing, the optimal full price is lower than that under the Asymmetric Pricing. To understand the effect of  $\alpha$ , consider the following two extreme cases. When  $\omega = 1$ , segmentation is perfect and the merchant sets  $p_r^* = p_h^*$  to extract the highest surplus from type- $h$  segment. When  $\omega = 0$ , the optimal full price reduces to the uniform level (i.e.  $p_r^* = p_u^*$ ). Between these two extreme cases, the magnitude of  $p_r^*(\alpha)$  depends upon  $\frac{(1 - \omega)\theta\delta + (1 - \theta)}{1 - \omega\theta}$ , a weighted average of valuation among buyers who face the regular price (with a fraction of  $(1 - \omega) \cdot \theta$  from mismatched buyers and a fraction of  $1 - \theta$  from type- $h$  buyers). With better segmentation (i.e.  $\omega$  is higher), it is

in merchant's best interest to set a higher full price and simultaneously choose a higher coupon face value.

**LEMMA 4.** *With the uniform pricing as a benchmark, the revenue of the coupon model is verifiable as long as segment parameters  $(\omega, \theta, \delta) \in R_p^{Coupon}$ , where*

$$R_p^{Coupon} = \left\{ (\omega, \theta, \delta) \left| \begin{array}{l} 0 < \theta < 1 - \frac{(1-\omega)\delta^2}{(1-\omega)(1-\delta)^2 - \omega\delta^2}, \quad 0 < \delta < \frac{\sqrt{(1-\omega)} - (1-\omega)}{\omega} \\ 0 < \theta < 1, \quad \frac{\sqrt{(1-\omega)} - (1-\omega)}{\omega} < \delta < 1 \end{array} \right. \right\}. \quad \text{Otherwise, the}$$

*merchant should charge a uniform price and serve type-h segment alone.*

**PROOF.** Setting  $\pi^{Coupon*} > \pi^{U*}$  and simplifying terms gives the condition under which couponing dominates the uniform pricing.  $\square$

Obviously, the attractiveness of couponing is increasing in  $\alpha$  because efficient segmentation reduces the mismatch between type- $l$  consumers and the price targeted at them. If issuing coupons is costless, the coupon model would dominate the uniform pricing as the ability to separate segments makes the merchant better off, even if segmentation is not efficient ( $\omega < 1$ ). Therefore, whether couponing is profitable depends upon its relative advantage over serving the high-type alone.

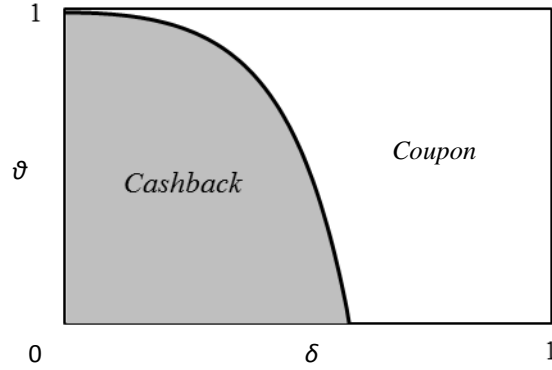
Given a fixed  $\alpha$ , the attractiveness of serving type- $h$  segment alone relative to couponing is decreasing in the fraction and the total valuation of type- $l$  market. As a result, the market is in favor of the coupon mechanism as segment parameters  $(\theta, \delta)$  become larger, which impacts the attractiveness of the cashback mechanism in the opposite direction. Based on such nuisance, we can expect that which mechanism the merchant should adopt would depend upon market

configuration. Specifically, the pull cashback mechanism outperforms the push couponing if the value of  $\delta$  and  $\theta$  are below a certain level. Also, the upper bound values for  $(\delta, \theta)$  is decreasing in  $\omega$ , since the efficiency of segmentation achieved by couponing moderates the relative advantage of the cashback mechanism.

**PROPOSITION 3.** *The cashback mechanism outperforms couponing as long as market configuration  $(\alpha, \theta, \delta) \in R^{CB*}$ , where*

$$R^{CB*} = \left\{ (\alpha, \theta, \delta) \mid \alpha < \bar{\alpha} = \frac{4(1-\theta)(1-\delta)^2 - 3\delta^2}{4(1-\theta)(1-\delta)^2 - 3\theta\delta^2}, 0 < \theta < 1 - \frac{3\delta^2}{4(1-\delta)^2}, 0 < \delta < 4 - 2\sqrt{3} \right\}.$$

The pull-based cashback mechanism outperforms the push-based couponing when the consumer redemption of the coupon,  $\alpha$ , is lower than a critical value  $\bar{\alpha}$ . Figure 2-4 illustrates the merchant's best choice of price-discriminating device when two mechanisms are both available. The value of  $\alpha$  would shift the "border line" between two price-discriminating methods. If segmentation by couponing is poor (i.e.  $\alpha$  is small), the border line would shift toward the northeast corner of the parameter coordinate. Realistically, we should expect the area of the region "Cashback" (highlighted in grey) to expand, as the relative attractiveness of the cashback model would increase after taking into account implementation costs of the coupon model.



**Figure 2-4.** Profitable region of cashback affiliate

### 2.3. Cashback Coordination

In this section, we first turn our attention to the impact of the underlying mechanism on consumers and the entire society. Then, we propose an alternative approach to improve market inefficiency which stems from the issue of double marginalization.

When market configuration falls in the region where only type- $h$  segment is served, the cashback pricing possesses all the merits: it increases overall consumer surplus, sellers' surplus and social welfare. When market configuration falls in the region where market is not covered, however, the adoption of the cashback pricing leads to a reduction in market efficiency, compared to that under the uniform pricing. In both cases, since each firm is able to set its own

profit margin, two firm's joint profit, given by  $\frac{4(1-\theta)v^2 + 3\theta(\delta v)^2}{16}$ , is below the joint optimum

$\frac{(1-\theta)v^2 + \theta(\delta v)^2}{4}$  if they work as an integrated firm (Jeuland and Shugan 1983). In our research

context, coordination in determining affiliate fees is the most straightforward solution to this problem. In what follows, we investigate how coordination can be achieved in the context of the cashback affiliate through a bargaining mechanism. For distinction purpose, we call our proposed mechanism *Coordinated* cashback, as opposite to the current cashback practice.

### 2.3.1. Bargaining Process and Coordinated Cashback

We denote the site's and the merchant's bargaining power by  $\varphi$  and  $1-\varphi$ , respectively. Based on the prior literature, the values of bargaining parameters are exogenous and may depend on each party's relative market power such as market value, brand image, etc. Two firms (hereafter, together we call them *sellers* for brevity) bargain over the affiliate fee (either a commission or a fixed fee). If bargaining fails, two firms resort to their outside options which are determined by market configuration. The sellers' respective outside options, denoted by a superscript "O" are given by:

$$\pi_m^O = \begin{cases} \pi_m^C = \frac{(1-\theta)v^2}{4} + \frac{\theta(\delta v)^2}{8} & \text{if } (\theta, \delta) \in R_p^C; \\ \pi_m^L = \frac{(1-\theta)v^2}{4} + \frac{\theta(\delta v)^2}{16} & \text{if } (\theta, \delta) \in R_p^L; \\ \pi_m^U = \frac{(\theta\delta + 1 - \theta)v^2}{4} & \text{otherwise;} \end{cases} \quad \pi_p^O = \begin{cases} \pi_p^C = \frac{\theta(\delta v)^2}{16} & \text{if } (\theta, \delta) \in R_p^C; \\ \pi_p^L = \frac{\theta(\delta v)^2}{8} & \text{if } (\theta, \delta) \in R_p^L; \\ \pi_p^U = 0 & \text{otherwise;} \end{cases}$$

If bargaining succeeds, the merchant would split the total revenue according to their bargaining power and respective bargaining position (Dukes et al. 2006). The Nash bargaining solution (Nash 1950)<sup>19</sup> is the optimal affiliate fee that maximize the sellers' joint profit, given the price and the cashback rate at optimum. As the result, the sellers' profit maximization problem can be written as:

(With the commission-based fee model)

$$\max_{b^B} \Pi^C = (1-\varphi) \left[ p_l^* (1-b^B) \cdot Q(p_l^*) + p_h^* \cdot Q(p_h^*) - \pi_m^C \right] \cdot \varphi \left[ p_l^* (b^B - a^*) \cdot Q(p_l^*) - \pi_p^C \right], \quad (2.3.1)$$

(With the lead-based fee model)

---

<sup>19</sup> We choose Nash bargaining solution over Rubinstein model because we assume each consumer's demand is unitary and the cashback game is a static one-shot game.

$$\max_{f^B} \Pi^L = (1 - \varphi) \left[ (p_l^* - f^B) \cdot Q(p_l^*) + p_h^* \cdot Q(p_h^*) - \pi_m^L \right] \cdot \varphi \left[ f^B \cdot Q(p_l^*) - \pi_p^L \right], \quad (2.3.2)$$

where the superscript  $B$  indicates the bargaining game,  $p_h^*$  and  $p_l^*$  are solutions to (2.2.2) and  $a^* = (p_h^* - p_l^*) / p_h^*$ .

The success of the bargaining process eliminates double marginalization existing in the current cashback model. Exogenous bargaining parameters serve to allocate the profit generated through the cashback channel. When  $\varphi$  is large, the site receives a big “pie” of the total revenue generated through two channels, making coordination less attractive to the merchant. We formally state the optimal bargaining solution in the following proposition.

**PROPOSITION 4-1.** *With the commission-based fee model, the optimal commission rate*

$b^{B*} = 1 - \frac{5\delta}{8}$ . *The merchant’s and the site’s profits are  $\frac{4(1-\theta)v^2 + \theta(3-\varphi)(\delta v)^2}{16}$  and  $\frac{\theta(1+\varphi)(\delta v)^2}{16}$ , respectively.*

**PROPOSITION 4-2.** *With the lead-based cashback model, the optimal fixed fee  $f^{B*} = \frac{5\delta v}{16}$ .*

*The merchant’s and the site’s profits are  $\frac{4(1-\theta)v^2 + \theta(2-\varphi)(\delta v)^2}{16}$  and  $\frac{\theta(2+\varphi)(\delta v)^2}{16}$ , respectively.*

**PROPOSITION 4-3.** *In the case where the revenue of the current cashback pricing is not verifiable, two firms will coordinate and split the incremental profit based on their relative bargaining power. The merchant’s and the site’s profits are  $\frac{\left( (1-\theta) + \theta\delta^2 - \varphi\theta(1-\theta)(1-\delta)^2 \right) v^2}{4}$  and  $\frac{\varphi\theta(1-\theta)(1-\delta)^2 v^2}{4}$ , respectively.*

**PROOF.** The optimal affiliate fees can be solved following a standard approach. We first set the first order condition of the firms' joint profit (w.r.t. affiliate fee) equal zero and solve for the optimal value. We then check the second order condition to verify the existence of the global maximum. The Nash Bargaining solution to the firms' pricing problem is given by:

(1) when  $(\theta, \delta) \in R_p^C$ ,

$$\max_{b^B} \Pi^C = (1-\varphi) \left[ p_l^* (1-b^B) \cdot Q(p_l^*) + p_h^* \cdot Q(p_h^*) - \pi_m^C \right] \cdot \varphi \left[ p_l^* (b^B - a^*) \cdot Q(p_l^*) - \pi_p^C \right];$$

(2) when  $(\theta, \delta) \in R_p^L$ ,

$$\max_{f^B} \Pi^L = (1-\varphi) \left[ (p_l^* - f^B) \cdot Q(p_l^*) + p_h^* \cdot Q(p_h^*) - \pi_m^L \right] \cdot \varphi \left[ f^B \cdot Q(p_l^*) - \pi_p^L \right].$$

Under the condition where the cashback mechanism is not profitable, the merchant's total profit given successful bargaining is  $\pi_m^B = \varphi \cdot (\Pi_c - \pi_m^{U*}) + (1-\varphi) \cdot \pi_p^{U*}$ . This expression clearly characterizes that the "pie" of profit either merchant will receive is dependent on its bargaining position and relative bargaining power. Under this scenario, the cashback site has a zero bargaining position since  $\pi_p^U = 0$ .  $\square$

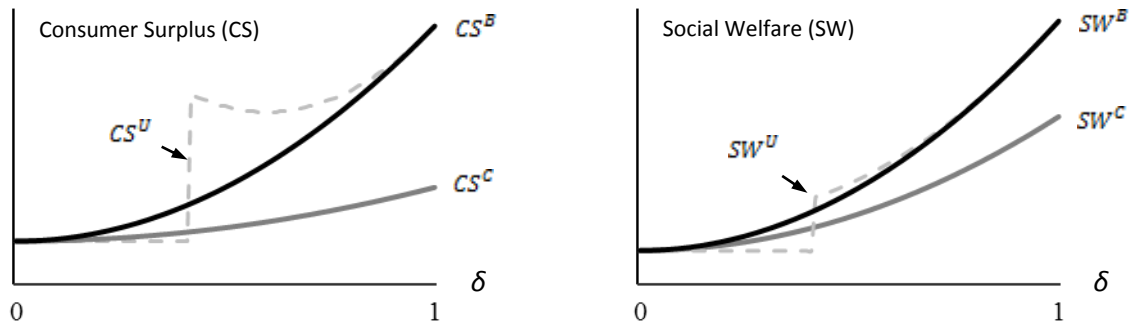
### 2.3.2. Welfare Analysis

We now demonstrate how our proposed mechanism is a more efficient means for firms to practice price discrimination. From sellers' perspective, this alternative approach expands the cashback model's profitable region by taking their bargaining power into decision making process. The success of the bargaining process ensures a win-win situation for both firms.

From buyers' perspective, coordinated cashback increases consumer surplus by restoring the price targeted at type- $l$  segment from  $p_p^*$  to  $p_l^*$ . The left panel of Figure 2-5 shows that

consumer surplus (CS) under coordinated cashback (black solid lines) dominates the current practice (grey solid lines). The cashback paradox will never occur with the coordinated cashback. Channel coordinate leads to an unambiguous increase in social welfare (SW) as well (the right panel of Figure 2-5).

**Figure 2-5.** Change in Consumer Surplus and Social Welfare



## 2.4. Optimal Pricing Strategy in the Presence of Competition

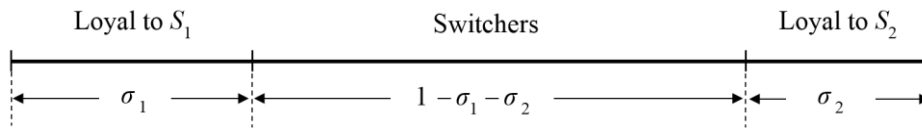
We now turn our attention to e-businesses' affiliate and pricing decisions in a competitive setting. In this section, we first extend our model by investigating the economic impact of competition between two sites. In this case we consider a monopolist facing two cashback platforms that directly compete with each other. Our intention is to see if affiliate competition can alleviate market inefficiency caused by the current cashback mechanism. Then, we examine the case of two competitive merchants each of whom can sabotage the rival through affiliating with the cashback site. In both cases, we base our analysis on a duopoly while our framework can be generalized to an oligopolistic setting.

### 2.4.1. Impact of Affiliate Competition

Consider a market consisting of a monopolist and two asymmetric cashback sites,  $S_1$  and  $S_2$ . Each site has its own "loyalists" who do cashback shopping on one site only. Consumers

formulates site loyalty for many reasons. It could be because some consumers prefer a particular site's interface, prefer to accumulate rewards and redeem for a big check, or are simply not aware of other cashback sites. Denote the relative size of  $S_1$ 's and  $S_2$ 's loyalists by  $\sigma_1$  and  $\sigma_2$ , respectively ( $0 < \sigma_1 < 1$  and  $0 < \sigma_2 < 1$ ). The remaining type- $l$  consumers, with a relative size normalized to  $1 - \sigma_1 - \sigma_2$  ( $0 < 1 - \sigma_1 - \sigma_2$ ), switch between sites (see Figure 2-6). We call this particular type of cashback shoppers "switchers" as they always use the site whichever provides a deeper discount.<sup>20</sup> As a result, the site offering a higher cashback rate wins the switcher market. If announced cashback rates are identical, the switcher market is split evenly by two sites. Such setting reflects shoppers' habit in the context of online cashback and implies that some of them take site preference into consideration when making purchasing decisions.

**Figure 2-6.** Market composition with loyalists and switchers



Since each site can choose either affiliate fee models, we need to consider all three possible scenarios. How the game proceeds is based on what fee models are used. If both sites adopt the lead-based fee model, they move first by independently and simultaneously setting their respect fixed fees and the merchant, in turn, sets the price and cashback rates. If they both use the commission-based fee model, the merchant first decides on the product price and commission rates, followed by the choice of the cashback rates by sites. If two different fee models are adopted, the site who implements the lead-based fee model moves first by announcing a fixed fee. Without loss of generality, we assume  $S_1$  the first mover in this case. The merchant then sets the price and cashback rate for  $S_1$  as well as the commission rate for  $S_2$ , who, in turn, determines the

<sup>20</sup> Please see Narasimhan (1988) and Raju et al. (1990) for applications in a similar setting.

cashback rate listed on its platform. For all cases, we assume that collusion in pricing is infeasible. It is worth noting that the winner-takes-all nature of the switcher market leads to Bertrand-like competition. Thus, it is in affiliates' best to refrain from price war and split the switch market separately.

**LEMMA 5.** *Define  $\Delta\sigma \equiv \sigma_1 - \sigma_2$ . In the case of two cashback affiliates, the optimal cashback rate is: (1)  $1 - \frac{3}{2}\delta$ , when both of them adopt the commission-based fee model; (2)  $1 - \frac{5}{3}\delta$ , when both of them adopt the lead-based fee model; and (3)  $1 - 2\delta + \frac{\delta}{3 - \Delta\sigma}$ , when two affiliates adopt different fee models.*

**PROOF.** Since an affiliate can choose either affiliate fee model, we need to consider all three possible cases: (1) both affiliates adopt the commission-based fee model, (2) both affiliates adopt the lead-based fee model, and (3) two affiliates adopt asymmetric fee models. For each case, we list the firms' pricing problem with an order per timing of the game.

(1) *Both affiliates adopt the commission-based fee model.*

Stage 1:

$$\max_{p_r, b_1, b_2} \pi_m = p_r(1 - b_1) \cdot s_1 Q_L(p_{p1}) + p_r(1 - b_2) \cdot s_2 Q_L(p_{p2}) + p_r \cdot Q_H(p_r);$$

Stage 2:

$$\max_{a_1} \pi_{p1} = p_r(b_1 - a_1) \cdot s_1 Q_L(p_{p1}); \quad \max_{a_2} \pi_{p2} = p_r(b_2 - a_2) \cdot s_2 Q_L(p_{p2}).$$

(2) *Both affiliates adopt the lead-based fee model*

Stage 1:

$$\max_{f_1} \pi_{p1} = s_1 Q_l(p_{p1}) \cdot f_1; \quad \max_{f_2} \pi_{p2} = s_2 Q_l(p_{p2}) \cdot f_2;$$

Stage 2:

$$\max_{p_r, a_1, a_2} \pi_m = (p_{p1} - f_1) \cdot s_1 Q_L(p_{p1}) + (p_{p2} - f_2) \cdot s_2 Q_L(p_{p2}) + p_r \cdot Q_H(p_r).$$

(3) *Two affiliates adopt asymmetric fee model*

Stage 1 ( $P_1$  adopts the lead-based fee model):

$$\max_{f_1} \pi_{p1} = s_1 Q_L(p_{p1}) \cdot f_1;$$

Stage 2:

$$\max_{p_r, a_1, b_2} \pi_m = (p_{p1} - f_1) \cdot s_1 Q_L(p_{p1}) + p_r(1 - b_2) \cdot s_2 Q_L(p_{p2}) + p_r \cdot Q_H(p_r);$$

Stage 3 ( $P_2$  adopts the commission-based fee model):

$$\max_{a_2} \pi_{p2} = p_r(b_2 - a_2) \cdot s_2 Q_L(p_{p2}).$$

We define  $p_{pj} = p_r(1 - a_j)$ , where  $j = \{1, 2\}$ . The value of  $s_j$  represents the share of low-type market belongs to an affiliate  $j$ :  $s_j = 1 - \sigma_{-j}$ , if  $p_{pj} > p_{p, -j}$ ;  $s_j = (1 + \sigma_j - \sigma_{-j}) / 2$ , if  $p_{pj} = p_{p, -j}$ . The winner-takes-all nature of the switcher market leads to Bertrand-like competition. Although it appears that both affiliates have an incentive to price cut in order to compete for switchers at the expense of a lower profit margin, none of them would do so. If one affiliate undercuts the price, the best response for the other is to imitate the move. As a result, two affiliates should never engage in a price war and will split the switch market evenly. Solving firms' problem gives us the optimal cashback rate being: (1)  $1 - \frac{3}{2}\delta$ , when both affiliates adopt the commission-based fee model; (2)  $1 - \frac{5}{3}\delta$ , when both affiliates adopt the lead-based fee model; and (3)  $1 - 2\delta + \frac{\delta}{3 - \Delta\sigma}$ , when they adopt different fee models.  $\square$

When both sites adopt the same fee model, the size of two sites' loyalists has no impact on the optimal cashback rate. In case (1), each affiliate serves its own loyal users and compete for the switchers by setting a lower cashback rate. Although it appears that both affiliates have an incentive to price cut in order to compete for switchers at the expense of a lower profit margin, none of them would do so. If one affiliate undercuts the price, the best response for the other is to imitate the move. As a result, affiliates should never engage in Bertrand-like competition. The merchant with first-mover advantage faces a pricing problem which is exactly identical to that in the single-affiliate commission-based fee model and sets same commission rates for two affiliates. As a result, the prices and market efficiency remain the same in the presence of affiliate competition.

The similar phenomenon of equal cashback rate is observed in case (2) as well. In this case, two affiliates compete by announcing fixed fees, which can be translated into marginal costs in the merchant's profit function. Although affiliates, depending on the fraction of their respective loyal users, may announce asymmetric fees to influence the choice of cashback rates, the merchant's best reaction is, at optimum, to list one single cashback rate on both sites who then evenly split the switcher market. The timing when completion occurs determines whether the entrance of the second affiliate would impact market outcome. Surprisingly, the presence of affiliate competition in the first stage would increase the post-cashback price and thus reduce market efficiency, whereas competition occurring in the second stage would have no impact on market outcome at all.

In the case where different fee models are used, the optimal cashback rate depends upon the difference between fractions of two sites' loyalists. Specifically, the rate increases in the value of  $\Delta\sigma$ , which represents  $S_I$ 's advantage of loyal user base relative to its rival. The optimal

cashback rate would approach  $1 - \frac{3}{2}\delta$ , the level when market is served by one affiliate only, as the value of  $\Delta\sigma$  gets larger. With a large  $\Delta\sigma$ ,  $S_I$  can better exploit the first-mover advantage by enlarging its profit margin. The optimal cashback rate would shrink and approach  $1 - \frac{7}{4}\delta$ , as the value of  $\Delta\sigma$  gets closer to -1. Realistically, we would expect that the price targeted at type- $l$  segment would be equal to or higher than that derived from the single-affiliate case, even if there are multiple affiliates serving the market. This result informs us of the following intriguing finding.

**PROPOSITION 5.** *Compared to the single-affiliate case, the market efficiency is worse in the presence of affiliate competition. Consumer surplus, sellers' surplus and social welfare are no larger than those observed from a market served by one affiliate only.*

**PROOF.** We know from Lemma 5 that, the highest level of the optimal cashback rate is  $1 - \frac{3}{2}\delta$ , which is exactly identical to the level we observed from the single-affiliate case. In other words, the existence of affiliate competition may raise the post-cashback price targeted at type- $l$  consumers, resulting in an even lower market efficiency.  $\square$

One would expect that competition among cashback sites would impose a downward pressure on the affiliate fees which in turn improves market efficiency. However, our analytical result reveals that the existence of multiple affiliates would unfavorably decrease market efficiency, no matter what fee models are adopted.

### 2.4.2. Impact of Merchant Competition

Now, suppose the market is served by two merchants ( $M_1$  and  $M_2$ ). Motivated by Dogan et al. (2010), we consider the differentiation both horizontal and vertical. On one hand, products offered by different merchants have various combinations of attributes. Such horizontal difference is modeled in the following way: two competing merchants are located at two different positions on consumers' preference horizon.<sup>21</sup> Each merchant has its own brand valuation. Factors determining a merchant's brand valuation could be its brand image, level of customer services, reputation, etc. We assume type- $h$  consumers have brand valuation of  $v_j$  for  $M_j$  whereas type- $l$  consumers have brand valuation of  $\delta v_j$  for  $M_j$  ( $j=1,2$ ).<sup>22</sup> Without the loss of generality, we assume  $v_1 > v_2$  and we call  $M_1$  the superior merchant. While we consider horizontal product differentiation in this section, our duopolistic model is generalized enough to model the scenario where two merchants sell the same product, if we interpret the location of each consumer as her brand preference or loyalty to two competing retailers.

Denoting the distance between two merchants' locations by  $d$ , we model the intensity of competition between merchants by the reciprocal of  $d$ . A smaller  $d$  represents a higher degree of competition. Figure 2-7 illustrates type- $h$  consumers' transaction utility derived from two differentiated products. A consumer would prefer to purchase from the merchant who gives her a higher utility. Consumers located at the projection of the intersection of two inwards utility segments on the preference horizon are indifferent between buying from either merchant.

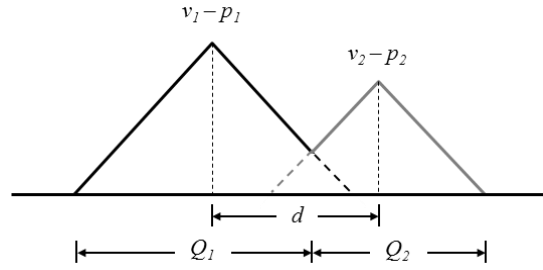
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<sup>21</sup> The reasons why we choose Salop's model over Hotelling's are given as follows. First, Salop's model allows us to ignore firm's location decisions, which is a common concern in marketing and IS spatial model literature (see Dewan et al. 2003 for example). Second, Salop's model is more flexible in a sense that it can be easily extended to a multiple-merchant case. Lastly and perhaps most importantly, Hotelling's spatial model cannot model the publisher's decision when the competition between merchants is present. This is because when market is fully covered, the publisher would have no decision to make. For the tractability purpose, we will consider a covered market (Hotelling model) to investigate merchants' affiliate decision in a competitive setting.

<sup>22</sup> Throughout this section, we use subscript  $j$  to distinguish merchant-specific parameters and variables.

Similarly, consumers located at the intersection of  $M_j$ 's utility segment and preference horizon are indifferent between buying  $M_j$ 's product and not buying at all.

**Figure 2-7.** Consumers' choice over two differentiated products (type- $h$ )



To reduce the number of notations used, we keep the notation set as compact as possible and move some notations to superscripts. In a general format, the merchant  $j$ 's profit maximization problem, conditional on its affiliate decision, are given by:

$$\begin{aligned} \max_{p_j^r, b_j} \pi_j^A &= p_j^r \cdot Q_j^h(p_j^r, p_{-j}) + p_j^r(1 - b_j) \cdot Q_j^l(p_j^r, p_{-j}) \quad \text{if affiliating,} \\ \max_{p_j^u} \pi_j^U &= p_j^u \cdot Q_j^h(p_j^u, p_{-j}) + p_j^u \cdot Q_j^l(p_j^u, p_{-j}) \quad \text{otherwise,} \end{aligned}$$

and the publisher's problem is given by:

$$\max_{a_j} \pi_p = \sum_j^{1,2} p_j^r (b_j - a_j) \cdot Q_j^l(p_j^r, p_{-j}),$$

where  $p_{\square j}$  denotes the price set by  $M_{-j}$  and is dependent on  $M_j$ 's affiliate decision.

#### 2.4.2.1. Optimal Pricing Decisions.

The fact that a merchant's profit also depends on the rival's affiliate decision adds extra difficulty to our duopolistic model. Since each firm has to decide whether or not to affiliate, there are four possible market outcomes: both merchants affiliate,  $M_1$  affiliates alone,  $M_2$  affiliates

alone, and neither merchant affiliates. To derive the subgame perfect solutions, we first solve the publisher's profit maximization problem, given that two merchants' affiliate and pricing decisions are known.

**LEMMA 6-1.** *The optimal cashback rates  $\{a_1^*, a_2^*\}$  under different market outcomes are:*

i. *Competitive Cashback Market:*  $\{a_1^{B*}, a_2^{B*}\} = \left\{ \frac{1+b_1}{2} - \frac{dt+2\delta v_1}{4p_1}, \frac{1+b_2}{2} - \frac{dt+2\delta v_2}{4p_2} \right\}$

ii. *M<sub>1</sub> Monopolistic Cashback Market:*  $\{a_1^{1A*}, a_2^{1A*}\} = \left\{ \frac{1+b_1}{2} - \frac{dt+p_2+\delta(3v_1-v_2)}{6p_1}, 0 \right\}$

iii. *M<sub>2</sub> Monopolistic Cashback Market:*  $\{a_1^{2A*}, a_2^{2A*}\} = \left\{ 0, \frac{1+b_2}{2} - \frac{dt+p_1+\delta(3v_2-v_1)}{6p_2} \right\}$

iv. *No Cashback Market (neither merchant affiliates):*  $\{a_1^{N*}, a_2^{N*}\} = \{0, 0\}$

The second-stage solutions suggest that the site's optimal cashback rate is increasing with the commission rates chosen by the merchants. This finding is consistent with the cashback rates observed on a typical site. For example, merchants belong to magazine/book category usually give a high commission rate (up to 50%) to the publisher, which in turn, assigns high cashback percentages to consumers. Having the solutions to the publisher's problem, we now are able to derive the merchants' best response in the second stage.<sup>23</sup>

**LEMMA 6-2.** *The merchants' optimal price and commission rate under four different market outcomes are:*

i. *Competitive Market (both merchants affiliate):*

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<sup>23</sup> We only present the solutions under the competitive market in the main text of this paper. Complete solutions are available upon request.

$$\{p_1^{B^*}, b_1^{B^*}\} = \left\{ \frac{17v_1 - 3v_2 + 7dt}{35}, \frac{(1-\delta)(17v_1 - 3v_2)}{17v_1 - 3v_2 + 7dt} \right\};$$

$$\{p_2^{B^*}, b_2^{B^*}\} = \left\{ \frac{17v_2 - 3v_1 + 7dt}{35}, \frac{(1-\delta)(17v_2 - 3v_1)}{17v_2 - 3v_1 + 7dt} \right\};$$

ii.  $M_1$  Monopolistic Market ( $M_1$  affiliates only):

$$\{p_1^{1A^*}, b_1^{1A^*}\} = \left\{ \frac{3(68 - \theta - \delta\theta)v_1 - (36 + 31\theta - 33\theta\delta)v_2 + 2(42 - \theta)dt}{6(70 - 3\theta)}, \frac{(1-\delta)(70 - 3\theta)(3v_1 - v_2)}{3(68 - \theta - \delta\theta)v_1 - (36 + 31\theta - 33\theta\delta)v_2 + 2(42 - \theta)dt} \right\};$$

$$\{p_2^{1A^*}, b_2^{1A^*}\} = \left\{ \frac{2(7dt + 17\bar{\delta}v_2 - 3\bar{\delta}v_1) - \theta(dt + \delta(v_2 - 3v_1))}{70 - 3\theta}, 0 \right\};$$

iii.  $M_2$  Monopolistic Market ( $M_2$  affiliates only):

$$\{p_1^{2A^*}, b_1^{2A^*}\} = \left\{ \frac{2(7dt + 17\bar{\delta}v_1 - 3\bar{\delta}v_2) - \theta(dt + \delta(v_1 - 3v_2))}{70 - 3\theta}, 0 \right\};$$

$$\{p_2^{2A^*}, b_2^{2A^*}\} = \left\{ \frac{3(68 - \theta - \delta\theta)v_2 - (36 + 31\theta - 33\theta\delta)v_1 + 2(42 - \theta)dt}{6(70 - 3\theta)}, \frac{(1-\delta)(70 - 3\theta)(3v_2 - v_1)}{3(68 - \theta - \delta\theta)v_2 - (36 + 31\theta - 33\theta\delta)v_1 + 2(42 - \theta)dt} \right\};$$

iv. No Cashback Market (neither merchant affiliates):

$$\{p_1^{N^*}, b_1^{N^*}\} = \left\{ \frac{17\bar{\delta}v_1 - 3\bar{\delta}v_2 + 7dt}{35}, 0 \right\}, \{p_2^{N^*}, b_2^{N^*}\} = \left\{ \frac{17\bar{\delta}v_2 - 3\bar{\delta}v_1 + 7dt}{35}, 0 \right\},$$

where  $\bar{\delta} = \theta\delta + (1-\theta)$ .

**PROOF.** To make sure the solutions are subgame perfect, we first solve the publisher's cashback rate problem, followed by two merchants' pricing problem. In a general format, the affiliate's problem is given by:

$$\max_{a_1, a_2} \pi_p = p_1^r (b_1 - a_1) \cdot \mathcal{Q}_1^l(p_1^p, p_2^p) \cdot I(M_1) + p_2^r (b_2 - a_2) \cdot \mathcal{Q}_2^l(p_2^p, p_1^p) \cdot I(M_2), \quad (2.4.1)$$

where  $I(M_j)$ ,  $j=1, 2$ , is an indicator function taking value of 1 if a merchant  $j$  affiliates; 0 otherwise. In addition,  $p_j^p = p_j^r \cdot (1 - a_j)$  if  $I(M_j)=1$ ;  $p_j^p = p_j^r$  if  $I(M_j)=0$ .

The merchant  $j$ 's problem, conditional on its affiliate decision, is given by:

$$\max_{p_j^r, b_j} \pi_j^C = p_j^r (1 - b_j) \cdot \mathcal{Q}_j^l(p_j^p, p_{-j}^p) + p_j^r \cdot \mathcal{Q}_j^h(p_j^r, p_{-j}^r) \quad \text{if affiliating}, \quad (2.4.2)$$

$$\max_{p_j^u} \pi_j^U = p_j^u \cdot \mathcal{Q}_j^l(p_j^u, p_{-j}^p) + p_j^u \cdot \mathcal{Q}_j^h(p_j^u, p_{-j}^r) \quad \text{otherwise}, \quad (2.4.3)$$

where the subscription  $-j$  denotes a merchant  $j$ 's rival. If  $M_{-j}$  doesn't join the affiliate network, then  $p_{-j}^p = p_{-j}^u$ .

A critical feature of our duopolistic model is that all players' profits are conditional on merchant-publisher affiliation. Since each merchant makes an affiliation decision at the beginning of the game, we need to analyze sellers' pricing terms under four possible cases: both firms affiliate, only  $M_1$  affiliates, only  $M_2$  affiliates, neither firm affiliates. Solving backwards we can find the corresponding optimal pricing terms under different cases. Lemma 5-1 can be obtained by solving (2.4.1). Similarly, Lemma 5-2 summarizes the solutions to equation system (2.4.2) and (2.4.3). It is straightforward to verify that the second order condition and second derivative test for (2.4.1) ~ (2.4.3) are satisfied.  $\square$

The comparative statics of the optimal pricing terms under the competitive cashback market are summarized in Table 2-1. We find that the effect of brand valuation on price  $p$  and that on commission  $b$  move in the same direction. If a merchant is able to enhance its brand valuation, i.e.  $v_j$  is higher, it can charge a higher regular price and assign a higher commission rate to the publisher. The increase in commission rate will in turn lead to a higher cashback percentage. Interpreting the magnitude of  $b_j$  as the attractiveness of cashback affiliate to a merchant  $j$ , we find that a merchant's incentive to adopt cashback mechanism is increasing with its own brand valuation  $v_j$ . This nature is helpful in explaining the market equilibrium derived in the next subsection. A merchant's optimal price and incentive to affiliate decrease with the competitor's brand valuation,  $v_{-j}$ . Unlike brand valuation, the effects of market parameters on merchant's pricing terms  $p$  and  $b$  move in the opposite directions. Recall that  $1/d$  measures the competition intensity between merchants. In a highly competitive market where horizontal product differentiation is insignificant, i.e.  $1/d$  is large, merchants would engage in a price war by cutting the price and taking a more aggressive price discrimination strategy (i.e. a larger  $b_j$ ). If consumers appreciate products attributes more than price, as modeled by a larger  $t$ , merchants would extract larger surplus by pushing the price upwards. If  $\delta$  is larger, indicating the valuation asymmetry between two segments is small, i.e. we will expect that price asymmetry across channels goes down.

**Table 2-1.** Comparative Statics of the Merchants' Pricing Terms

		<i>Parameters</i>				
		$v_j$	$v_{-j}$	$1/d$	$t$	$\delta$
<i>Decision Variables</i>	$p_j$	+	-	-	+	
	$b_j$	+	-	+	-	-

#### 2.4.2.2. *Equilibrium of the Cashback Market.*

Although we have solved for firms' pricing decisions, the solutions themselves do not constitute equilibrium. To derive equilibrium conditions we need to further verify that neither merchant has an incentive to deviate from a particular solution set by changing affiliate decisions. The procedure of deriving the subgame perfect equilibrium requires solving an inequality system with multiple parameters. For tractability purpose, we consider a Hoteling-like setting with full market coverage, which is a special case of our proposed model (with  $d$  normalized to 1). Since the affiliates' problem becomes linear in a fully covered market, we analyze the merchants' strategic use of cashback using the bargaining mechanism introduced in section 2.4.

Suppose  $M_1$ 's and  $M_2$ 's bargaining power relative to the site are  $\varphi_1$  and  $\varphi_2$ , respectively. To investigate which merchant has higher incentive to adopt the cashback model, we examine "equilibrium attraction", which is a concept often used in analysis of games with multiple equilibria (Fudenberg 1998). The process proceeds as follows. We first derive two competing merchants' profit under four possible market outcomes. Then we examine whether each firm has incentive to deviate from a given solution set.

**PROPOSITION 6.** *With full market coverage, the equilibrium outcome depends on merchants' bargaining power and valuation difference between asymmetric merchants (defined as  $\Delta v \equiv v_1 - v_2$ ).*

- (1) *The equilibrium outcome where neither merchant affiliates does not exist;*
- (2) *The equilibrium outcome where  $M_1$  affiliates alone exists as long as  $(\varphi_1, \varphi_2, \Delta v) \in R_{1J}$ ;*
- (3) *The equilibrium outcome where  $M_2$  affiliates alone exists as long as  $(\varphi_1, \varphi_2, \Delta v) \in R_{2J}$ ;*

(4) The equilibrium outcome where both merchants affiliate alone exists for the rest of parameter

$$\text{space, where } R_{1j} = \left\{ (\varphi_1, \varphi_2, \Delta v) \left| \begin{array}{l} 0 < \varphi_1 \leq 3/4, 0 < \varphi_2 < 1, 0 < \Delta v \\ 3/4 < \varphi_1 < 1, 0 < \varphi_2 < 1, 0 < \Delta v < \Delta \bar{v}_{1j} \end{array} \right. \right\},$$

$$R_{2j} = \left\{ (\varphi_1, \varphi_2, \Delta v) \left| \begin{array}{l} 0 < \varphi_1 \leq 1, 0 < \varphi_2 < 3/4, 0 < \Delta v \\ 0 < \varphi_1 < 1, 3/4 < \varphi_2 < 1, 0 < \Delta v < \Delta \bar{v}_{2j} \end{array} \right. \right\},$$

$$\Delta \bar{v}_{1j} = \frac{-64 + (73 - 82\delta + 9\delta^2)\theta - 9(1-\delta)^2\theta^2 + 4[16 + (-19 + 22\delta - 3\delta^2)\theta + 3(1-\delta)^2\theta^2]\varphi_1}{3\theta(1-\theta)(1-\delta)^2(3-4\varphi_1)},$$

$$\text{and } \Delta \bar{v}_{2j} = \frac{64 + (-55 + 46\delta + 9\delta^2)\theta - 9(1-\delta)^2\theta^2 + 4[-16 + (13 - 10\delta - 3\delta^2)\theta + 3(1-\delta)^2\theta^2]\varphi_2}{3\theta(1-\theta)(1-\delta)^2(3-4\varphi_2)}$$

The inequality  $\Delta \bar{v}_{2j} > \Delta \bar{v}_{1j}$  holds for the feasible region for all parameters.

**PROOF.** Given two asymmetric merchants, we have four possible market outcomes: both merchants affiliate,  $M_1$  affiliates alone,  $M_2$  affiliates alone, and neither merchant affiliates. The solutions stated in Lemma 5 themselves do not constitute equilibrium (Dogan 2010) since a merchant may have an incentive to deviate by changing its affiliation decision. To derive the equilibrium condition for each of four market outcomes, we investigate “equilibrium attraction”, which is a concept often used in analysis of games with multiple equilibria.

The process proceeds as follows. We first derive two competing merchants’ profit under four possible market scenarios. Then we examine whether each firm has an incentive to deviate from a given solution set. Take the case where neither merchant enlists. Let  $\pi_j^N$  denote a merchant  $j$ ’s profit under such market outcome and  $\pi_j^{N'}$  denote that if it deviates by adopting the cashback pricing. Setting  $\pi_1 > \pi_1'$  and  $\pi_2 > \pi_2'$  under all of four scenarios, we can obtain the market

configuration under which both players have no incentive to enlist. Finally, the optimal pricing terms (summarized in Lemma 6-2) along with corresponding market configuration conditions constitute the subgame perfect Nash equilibrium. The analytic expressions for thresholds  $\Delta\bar{v}_{1J}$  and  $\Delta\bar{v}_{2J}$  are given below:

$$\Delta\bar{v}_{1J} = \frac{-64 + (73 - 82\delta + 9\delta^2)\theta - 9(1-\delta)^2\theta^2 + 4[16 + (-19 + 22\delta - 3\delta^2)\theta + 3(1-\delta)^2\theta^2]\varphi_1}{3\theta(1-\theta)(1-\delta)^2(3-4\varphi_1)} \text{ and}$$

$$\Delta\bar{v}_{2J} = \frac{64 + (-55 + 46\delta + 9\delta^2)\theta - 9(1-\delta)^2\theta^2 + 4[-16 + (13 - 10\delta - 3\delta^2)\theta + 3(1-\delta)^2\theta^2]\varphi_2}{3\theta(1-\theta)(1-\delta)^2(3-4\varphi_2)}. \quad \square$$

To better understand the competitive nature in the context of the cashback model, consider the second equilibrium outcome. When  $M_1$  affiliates alone, the attraction of the cashback model for  $M_2$  increases with  $M_1$ 's bargaining power  $\varphi_1$ . This is because when  $\varphi_1$  is smaller, the site would be able to keep a larger portion of the total profit, which moderates  $M_2$ 's relative bargaining position. Moreover, the inequality  $\Delta\bar{v}_{2J} > \Delta\bar{v}_{1J}$  implies that attractiveness of the cashback affiliate is relatively higher to the low-valuation merchant than to the superior one. It is worth noting that at least one merchant (either  $M_1$  or  $M_2$ ) should adopt the cashback pricing. Also, with full market coverage, adopting the cashback pricing by one merchant has no impact on the rival's total profit, as such move intensifies the competition in one segment but lessens the competition in the other. In the scenario where the market is not fully covered, we shall expect that one merchant's adoption of cashback would benefit its rival. This is because the merchant exercising price discrimination will inevitably raise the regular price (recall from Lemma 1) and thus lessen the price competition in the more profitable high-type segment.

## 2.5. Impact of Consumer Awareness

So far our consumer response model rests on two implicit assumptions: consumers know (1) the existence of the cashback intermediary and the mechanism through which cashback will be rewarded, and (2) the merchant from which a desired product can be purchased. In this section, we release these assumptions by incorporating two extensions into our basic model. We first examine how the site's user base affects the merchant's pricing strategy. Next, we investigate the publisher's role as an advertising device. Finally, we provide insight into the merchant's affiliate decision, taking two types of consumer awareness into consideration.

### 2.5.1. Consumer Awareness of the Cashback Site

Cashback model allows the merchant to exercise second-degree price discrimination through which consumers self-select whether to pay the regular price or the lower post-cashback price. The underlying mechanism is effective in matching customers and price under the assumption that cashback shopping is common knowledge among consumers. Yet, a more realistic question to ask is: What if some consumers are not aware of the cashback concept?

To model the first awareness effect, we introduce a new parameter  $\alpha$ , which we call the consumer awareness of the site. The value of  $\alpha$  measures the fraction of consumers who know the existence of the cashback site and the underlying mechanism. When  $\alpha = 1$ , the extended model reduces to the basic model in which all type-l consumers pick the cashback channel. When  $\alpha \neq 1$ , some of them are not aware of the publisher and therefore are only faced with the regular price. These consumers are referred as uninformed buyers while those who enjoy the saving opportunity are referred as cashback buyers. Type-h consumers would not use the publisher regardless of whether or not they are informed. The fractions of cashback, uninformed, and type-h buyers are  $\theta \alpha$ ,  $\theta \cdot (1-\alpha)$ , and  $1-\theta$ , respectively (Table 2-2). Since  $\theta \alpha$  represents the

site's consumer base, the value of  $\alpha$  is known to the cashback site. In current cashback practice, information about  $\alpha$  is public to the entire market.

**Table 2-2.** Market composition with uninformed consumers

	Informed $\alpha$	Uninformed $1-\alpha$
type- $l$ $\theta$	Cashback buyers $\theta \cdot \alpha$ (cashback channel)	Uninformed buyers: $\theta \cdot (1-\alpha)$ (direct channel)
type- $h$ $1-\theta$	Type- $h$ buyers $1-\theta$ (direct channel)	

With this extension we are able to endogenize the effectiveness of segmentation, or promotion distribution, which is commonly assumed perfect in the most of prior literature on promotions (e.g., manufacturer coupon). When  $\alpha$  is high, the majority of consumers go through the self-selection process, resulting in effective segmentation. When  $\alpha$  is low, cashback mechanism fails to sort out most consumers, or more precisely the low-type, into their true types. The affiliate partners' pricing problem can be rewritten as:

$$\max_{p_r, b} \pi_m^C(\alpha) = p_r(1-b) \cdot \alpha \cdot Q_l(p_p) + p_r \cdot (1-\alpha) \cdot Q_l(p_r) + p_r \cdot Q_h(p_r), \quad (2.5.1)$$

$$\max_a \pi_p(\alpha) = p_r(b-a) \cdot Q_l(p_p), \quad (2.5.2)$$

where  $p_p = p_r(1-a)$  denotes the post-cashback price perceived by cashback buyers. The expression  $(1-\alpha) \cdot Q_l(p_r)$  in the second term captures the fraction of uninformed buyers who face the regular price.

**LEMMA 7-1.** *After taking into account the consumer awareness of the publisher, the sellers' optimal pricing schedule is given by:  $p_r^*(\alpha) = wp_r^*$ ,  $b^*(\alpha) = 1-\delta'$ , and  $a^*(\alpha) = 1-\frac{3}{2}\delta'$ ,*

where  $w = \frac{\theta(1-\alpha)\delta + (1-\theta)}{1-\theta\alpha}$  and  $\delta' = \frac{\delta}{w}$ .

**PROOF.** Using backwards induction we first solve (2.5.2) for  $a$ , and then solve (2.5.1) for  $p_r$  and  $b$ . Equating the first order condition of (2.5.2) to zero, we have

$$2p \cdot \alpha((1-2a+b)p - \delta v)\theta = 0 \Rightarrow \tilde{a}(\alpha) = \frac{p + bp - \delta v}{2p}. \text{ We check } SOC = -4\alpha\theta p^2 < 0. \text{ Plugging } \tilde{a}(\alpha)$$

into (2.5.1) and solving it, we have the merchant's best response  $p_r^*(\alpha) = w \cdot p_r^*$  and  $b^*(\alpha) = 1 - \frac{\delta}{w}$ ,

where  $w = \frac{\theta(1-\alpha)\delta + (1-\theta)}{1-\alpha\theta}$ . Plugging  $p_r^*(\alpha)$  and  $b^*(\alpha)$  back into  $\tilde{a}(\alpha)$  we have the optimal

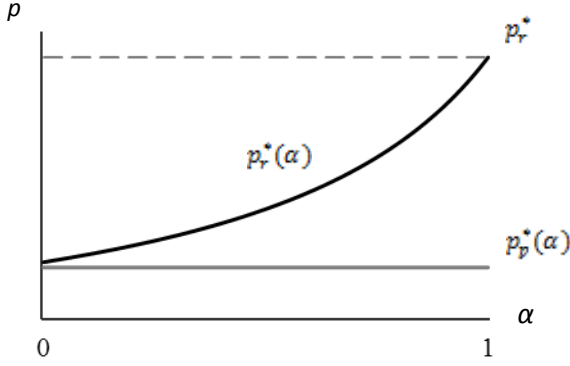
cashback rate  $a^*(\alpha) = 1 - \frac{3\delta}{2w}$ . It is straightforward to verify that the maximum exists by checking

SPDT for (2.5.1).  $\square$

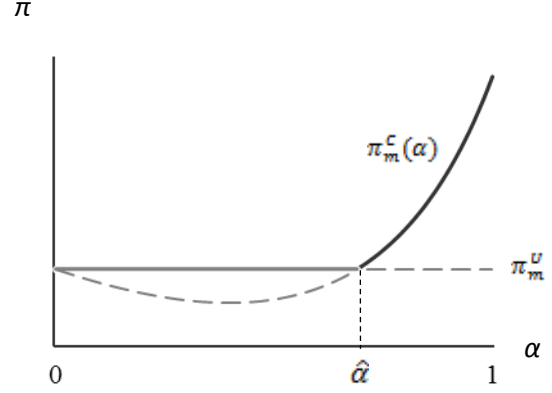
The merchant's optimal regular price  $p_r^*(\alpha)$ , is proportional to the solution to our basic model. To understand the effect of  $\alpha$  on pricing, consider the following two extreme cases. When  $\alpha=1$ , segmentation is perfect and the merchant wants to set  $p_r^* = p_h^*$  to extract the highest surplus from the type- $h$  consumers. When  $\alpha=0$ , the optimal regular price reduces to the uniform level (i.e.  $p_r^* = p_u^*$ ). Between these two extreme cases, the value of  $p_r^*(\alpha)$  depends on  $w$ , a weighted average of valuation among buyers who face the regular price (with  $v$  normalized to 1). As more consumers are aware of cashback shopping (i.e.  $\alpha$  is higher), the merchant would set a higher regular price and simultaneously choose a higher commission rate, which in turn, induces a higher cashback rate chosen by the site. Combined, these upwards tendencies lead to an interesting finding.

**LEMMA 7-2.** Consumer awareness of the cashback site intensifies the asymmetry between regular price and post-cashback price, as shown in Figure 2-8.

**Figure 2-8.** Optimal Asymmetric Prices Over  $\alpha$



**Figure 2-9.** Merchant's Profit Over  $\alpha$



We now examine how the value of  $\alpha$  affects the merchant's affiliate strategy. We formally state the relationship between the site's awareness and the merchant's affiliate decision in the following proposition.

**PROPOSITION 7.** There is a critical value of the consumer awareness of the publisher,  $\hat{\alpha}$ , such that cashback affiliate model is profitable as long as  $\alpha > \hat{\alpha}$ , where

$$\hat{\alpha} = \begin{cases} \frac{\delta^2 - 2(1-\theta)^2(1-\delta)^2}{\theta\delta^2} & \text{if } (\theta, \delta) \in R_{\alpha 1}; \\ 0 & \text{if } (\theta, \delta) \in R_{\alpha 2}, \end{cases} \quad (2.5.3)$$

where  $R_{\alpha 1} = \{ (\theta, \delta) \mid 1 - \sqrt{1 - \bar{\theta}} < \theta \leq \bar{\theta}, \delta < \bar{\delta} \}$ , and  $R_{\alpha 2} = \{ (\theta, \delta) \mid 0 < \theta < 1 - \sqrt{1 - \bar{\theta}}, \delta < \bar{\delta} \}$ . The merchant should adopt uniform pricing if  $(\theta, \delta) \notin \{R_{\alpha 1} \cup R_{\alpha 2}\}$ .

**PROOF.** Plugging the optimal solutions into Equation (2.5.1), we have

$$\pi_m^{C^*}(\alpha) = \frac{\alpha \cdot \theta (\delta v)^2}{4} + \frac{((1-\alpha) \cdot \theta \delta + (1-\theta))^2 v^2}{(1-\alpha\theta)2t}. \text{ Setting } \pi_m^{C^*}(\alpha) - \pi_m^{U^*} > 0, \text{ rearranging and collecting}$$

terms we have the critical value  $\alpha \geq \hat{\alpha} = \frac{\delta^2 - 2(1-\theta)^2(1-\delta)^2}{\theta\delta^2}$ .  $\square$

The profitability of the cashback model is determined by three quantities: (1) the profit gain from being able to price-discriminate, (2) the profit loss resulted from unawareness of the mechanism, and (3) the commission paid to the site. The top line of (2.5.3) confirms the intuition that the merchant should join the site if and only if  $\alpha$  is sufficiently large. When  $\alpha$  is small, the profit gain would be offset by the profit loss, making the affiliate model undesirable. Figure 2-9 depicts the merchant's best profits as a function of  $\alpha$ . When  $\alpha < \hat{\alpha}$ , the uniform pricing is preferred. Once  $\alpha$  exceeds the threshold, the merchant would switch to the affiliate model. From a publisher's perspective, the cashback cite has incentive to exert effort on expanding its user base (i.e.  $\theta\alpha$ ). This finding explains why most of major cashback sites in the U.S. have launched various programs to solicit new users. For example, Mr. Rebates rewards \$5 cashback and Ebates gives \$10 gift card as sign-up bonus to every new registered user. Ebates even introduced a referral program named "Tell-A-Friend" through which a referee receives \$25 for the first friend ever referred and gets \$50 when she refers five friends- all in an attempt to garnish the most user base to gain competitive advantage.

The bottom line of (2.5.3) indicates that the affiliate decision is independent of  $\alpha$  when the market is *strongly* in favor of the cashback model. The intuition is given as follows. Recall that when  $\delta$  is small, the merchant with uniform pricing may abandon type-*l* segment and the revenue stream sorely comes from type-*h* segment. Through operating a second e-channel and charging a

lower second price, the merchant can generate more profit from the segment which is not reachable before.

### **2.5.2. Consumer Awareness of the Merchant**

The advent of the Internet lowers the barrier for new entrants through lower initial capital investment and operation costs. Over past few years there has been an exponential surge in the number of online stores. Per *Statistics of U.S. Businesses* (Department of Commerce 2012), there are currently over 21 thousands firms in the category of electronic shopping and mail-order houses. How to build up brand awareness becomes the most critical issue for newly-operated online merchants.

The cashback site provides a cost-efficient solution for merchants with limited budgets to enhance brand visibility. According to a survey conducted by TopCashback.com (2012), 52% of cashback shoppers strongly agree that they have used cashback sites to purchase from merchants they have never considered or known before (vs. 7% of them strongly disagree). These statistics implies that consumer choice is significantly influenced by whether or not a merchant is available in the affiliated network. This statement is further supported by 25% of respondents stating that cashback sites give new ideas (merchants' brand name) when it comes to purchasing decision. Using by-product search potential buyers can easily find out the merchants who are selling the product they are desire to buy. This way, a new online merchant who affiliate with the publisher is able to achieve its brand awareness and enhance product visibility.

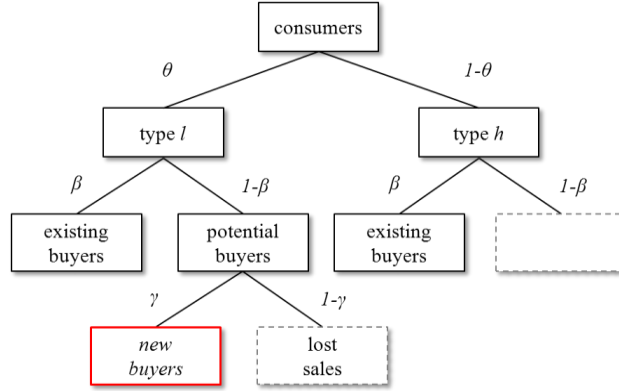
To isolate and emphasize the effect of brand awareness, we for now assume that all consumers are aware of the site, i.e.  $\alpha=1$ .<sup>24</sup> Let  $\beta$  denote the fraction of consumers who are aware of the merchant. We call the value of  $\beta$  the consumer awareness of the brand. Take consumer

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<sup>24</sup> We will revisit and release this assumption at the end of this section.

electronics industry as an example. Famous online retailers (e.g., Newegg.com) have well-established brand awareness while no-name stores (e.g., Adorama.com) are struggling to advertise for their brand name and reach customers. Through cashback affiliation, a new merchant can reach new customers through the affiliate link and other advertising campaigns conducted by publishers such as email newsletters, weekly featured stores, advertising banner, etc. We also introduce  $\gamma$  to capture consumer acceptance of a new brand to model the fact that some consumers are willing to do business with merchants they are not aware of before but some are not. With the entire market normalized to 1, the fraction of new buyers brought by the publisher is  $\theta(1-\beta)\gamma$ . Figure 2-10 illustrates how a low-awareness merchant reaches new customers through affiliation.

**Figure 2-10.** Market Composition for the Low-awareness Merchants



Two affiliated firms' problem can be expressed as:

$$\max_{p_r, b} \pi_m^C(\beta, \gamma) = p_r(1-b) \cdot \beta \cdot Q_l(p_p) + p_r(1-b) \cdot (1-\beta)\gamma \cdot Q_l(p_p) + p_r \cdot Q_h(p_r) , \quad (2.5.4)$$

$$\max_a \pi_p(\beta, \gamma) = p_r(b-a) \cdot \beta \cdot Q_l(p_p) + p_r(b-a) \cdot (1-\beta)\gamma \cdot Q_l(p_p) , \quad (2.5.5)$$

where the second term represents the new demand brought by the affiliate model. Solving (2.5.4) and (2.5.5) we can obtain the optimal profit  $\pi_m^{C^*}(\beta, \gamma)$ . Setting  $\pi_m^{C^*}(\beta, \gamma) > \pi_m^{U^*}$  and rearranging terms gives the following proposition.

**PROPOSITION 8.** There is a critical value of the consumer awareness of the brand,  $\hat{\beta}$ , such that the cashback model is profitable as long as  $\beta \leq \hat{\beta}$ , where

$$\hat{\beta} = \begin{cases} 1, & \text{if } (\theta, \delta) \in R_p; \\ \frac{\gamma\delta^2}{(1+\gamma)\delta^2 - 2(1-\theta)(1-\delta)^2}, & \text{otherwise.} \end{cases} \quad (2.5.6)$$

**PROOF.** The optimal solutions are exactly the same as those derived in the basic model.

Plugging the solutions into (2.5.4), we have  $\pi_m^{C^*}(\beta, \gamma) = \frac{\theta(\beta + (1-\beta)\gamma)\delta^2 v^2}{4} + \frac{(1-\theta)v^2}{2}$ . Setting

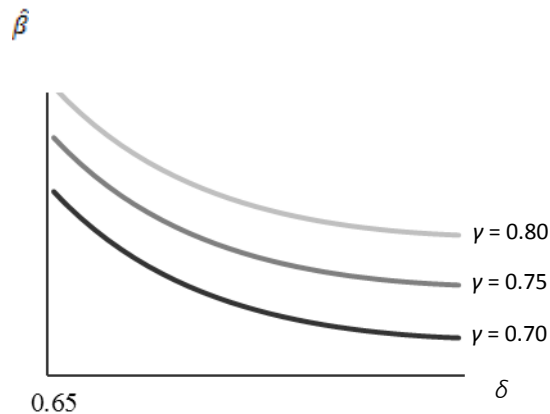
$$\pi_m^{C^*}(\beta, \gamma) > \pi_m^{U^*}, \text{ rearranging and collecting terms gives } \beta \leq \hat{\beta} = \frac{\gamma\delta^2}{(1+\gamma)\delta^2 - 2(1-\theta)(1-\delta)^2}. \quad \square$$

Incorporating this extension we are able to model the effectiveness of the cashback mechanism as an advertising tool. The bottom line of Equation (2.5.6) suggests that when  $(\theta, \delta) \notin R_p$ , the merchant's best decision is dependent on the value of  $\beta$  and market configuration. Affiliation is more attractive for low-awareness merchants since the additional revenue generated from new buyers outweighs the commission paid to the publisher. This is consistent with an industry observation that a large number of affiliated stores at a typical cashback site are those without a sharp brand image, such as Adorama in consumer electronics or Clothesbuy in the apparel category. This finding also explains why some merchants cease the cashback advertising model after they gradually acquire brand awareness among consumers (e.g.,

Amazon and ebay<sup>25</sup>). Amazon’s strategic use of cashback further demonstrates the effect of  $\beta$  on merchants’ affiliate decision. Since late 2012 the retail giant introduced its low-awareness categories, such as watches and jewelries, on Ebates.com and MrRebates.com, in a sign of how affiliation can help bring in new customers. However, it didn’t run such advertising campaign to its popular departments such as books and consumer electronics since the brand awareness of them has already been well-established.

Consumer acceptance of new merchants also determines the attractiveness of the affiliate model. The greater  $\gamma$  is, the more efficient the cashback channel will be as an advertising channel. The magnitude of  $\hat{\beta}$  is increasing with  $\gamma$  given market configuration is fixed (see Figure 2-11). In addition,  $\theta$  and  $\delta$  affect the best affiliate decision in a consistent way as discussed in our basic model.

**Figure 2-11.**  $\hat{\beta}$  as a function of  $\delta$  and  $\gamma$



In sum, the attractiveness of the cashback affiliate model increases with  $\alpha$  but decreases with  $\beta$ . When market is strongly in favor of discriminating pricing, the cashback model is always profitable, regardless of the values of  $\alpha$  and  $\beta$ . When market configuration is weakly in favor of discriminating pricing, the merchant should join the cashback market only if  $\alpha$  is larger than some threshold (as a

<sup>25</sup> ebay decided to leave MrRebates.com in May 2010 based on the results of its internal marketing research.

function of  $\beta$ ). Finally, when market configuration is against discriminating pricing, high-awareness merchants have no incentive to affiliate even if perfect segmentation (i.e.  $\alpha=1$ ) can be achieved through the affiliation.

## 2.6. Conclusion and Future Research

The primary objective of this paper has been to examine the strategic use of the novel cashback affiliate model from a merchant's point of view. Through affiliating with the cashback site, merchants are able to exercise third-degree price discrimination to reap higher profits. While the revenue with the cashback affiliate is verifiable, under some circumstances the underlying mechanism may hurt consumer surplus and social welfare. Surprisingly enough, the introduction of cashback shopping may raise the price faced by the cashback users. Assuming that coordination can be achieved through a bargaining process, we find that "coordinated cashback" can help improve market efficiency. The cashback coordination discussed in this paper is different from traditional profit-sharing contract in that our analyses are intended for a unique setting in which price discrimination is exercised through a digital dual-channel.

This paper makes a few assumptions. First, the seller in our model face a linear marginal revenue curve based on the linearity of demand. However, none of our analyses are dependent of this assumption. One should expect, for example, that the impact of double marginalization would be more salient if the marginal revenue curve is convex. Second, we assume in our duopolistic model that the consumers' sensitivity to horizontal differentiation (as represented by  $t$ ) is the same across segments. It could be more realistic that type- $h$  consumers appreciate product attributes more than the type- $l$ . In fact, our results do not change significantly if we consider this specification. When  $t_h > t_l$ , a monopolist would have higher incentive to price-discriminate, making our extant analysis on affiliate decision conservative. In a duopoly setting, the merchant

with lower brand valuation would benefit more from cashback marketing. Future research could investigate the change of optimal profit-sharing scheme when merchants can multi-home. While we think such research direction goes beyond the main focus of this paper (i.e. merchant's strategic use of the cashback model), it may answer a series of interesting questions: Is multi-homing strategy more beneficial to a merchant? If so, how does multi-homing strategy influence the competition among merchants?

# **Chapter 3 The Effect of Disconfirmation on Online Rating Behavior: A Dynamic Analysis**

## **3.1. Literature Review**

The stream of literature studying why consumers engage in post-purchase WOM is most related to this research. Using survey data, researchers investigate this question from a motivational point of view. In an offline setting, consumers' desire for altruism, product involvement and self-enhancement are main factors leading to positive WOM, whereas consumers spread negative WOM usually for altruism, anxiety reduction and vengeance purpose (Sundaram et al. 1998). With a similar approach, Hennig-Thurau et al. (2004) conclude that social benefits, economic incentives, concern for others, and extraversion are the primary motives for consumer expressing their product experiences on the Internet.

Based on quantitative methods, an extensive literature has also been developed to identify what drives consumers to share their product or service experiences in the absence of explicit reward mechanisms. Dellarocas et al. (2004) examine the rating behavior on an electronic trading platform. They find that such voluntary behavior is driven by the expectation of reciprocal behavior, meaning that a trader evaluates her trading partner in order to solicit feedback from the other party. Shen et al. (2013) look at the review posting behavior by consumers from a strategic perspective. Using the book review data from online book sellers, they conclude that online reviewers are more prone to rate popular but less crowded books in order to gain attention but reduce competition for attention at the same time. They also conclude that reviewers with high reputation costs are more likely to adopt an imitation strategy by posting ratings conforming to the community consensus. Factors affecting the level of WOM have also been studied at the

population level. Rather than taking the common conception of the level of WOM activity as a monotonic function of customer satisfaction, Anderson (1998) discovers that the relationship between them exhibits a U-shaped pattern – customers are more likely to engage in WOM when they are either extremely satisfied or extremely dissatisfied. Using the data from a movie website, Dellarocas and Narayan (2006) also identify a similar association between observed rating density and perceived movie quality. Along this line, Dellarocas et al. (2010) further suggest that movie goers are more prone to post review for the most or least popular movies in terms of box office revenues.

There is an emerging literature stream examining how existing ratings affect subsequent ones. In a lab setting, Schlosser (2005) identifies the “self-presentational” phenomenon in which a review poster strategically adjusts her product ratings downwards after observing negative opinions by others in order to present herself as intelligent. She also finds that a consumer would make her opinions more balanced if the opinions from the crowd demonstrate a high level of dissention. Li and Hitt (2008) conclude that predominant declining trend of book ratings can be attributed to consumers’ “self-selection” bias, meaning that early buyers have higher perceived quality and therefore tend to give higher ratings than do later buyers. Using reviews posted on an online retailer of bath, fragrance and home products, Moe and Schweidel (2012) show that consumers’ rating behavior is influenced by rating environment they are exposed to. In particular, they find that a consumer is more inclined to share her experience when the posted ratings are more positive as measured by high valance and high volume. In addition, active posters are found to be more negative and exhibit differentiation behavior, which is consistent with the self-presentational strategy suggested by Schlosser (2005). Lee et al. (2013) distinguish prior ratings by the friends from those by the strangers and investigate whether these two measurements have

different impact on a focal individual's opinions. They find that friends' opinions always induce herding and the presence of social networking dampens the impact of opinions from the crowd.

In terms of research context and methodology, our work is most relevant to the following two papers that explicitly model online reviewers' rating behavior at the individual level. Ying et al. (2006) argue that knowledge that a product was rated (selected) should affect analyst's prediction of that rating. After accounting for reviewers' selection problem, they show that the performance of movie recommendation can be substantially improved. Moe and Schweidel (2012) further generalize Ying's model by flexibly linking a reviewer's decision of "whether to rate" and that of "what to rate".<sup>26</sup> Research studying consumers' review posting decision naturally leads to another stream of literature which investigates whether consumer-generated reviews can represent true product quality. This particular literature stream can be further categorized into two sub-streams, depending on whether publicly available reviews are completely generated by consumers or partially manipulated by firms. Following the notion that online ratings are truly truthful, Hu et al. (2006) discuss whether the mean of posted ratings can represent true product quality. In particular, they develop an analytical model which assumes that a consumer would post online reviews only when the level of her satisfaction is either above or below a "brag-and-moan" interval; she would otherwise behave as a lurker. Based on this assumption, they show that the average rating can serve as an unbiased signal if and only if two bounds of the interval are equal or symmetrically deviate from the true quality. On the other hand, Dellarocas (2006) assumes that the observed ratings may not be fully trustful and could be strategically boosted by firms. He demonstrates that inflated reviews are still informative since the firm producing high-quality products benefits the most through manipulation.

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<sup>26</sup> We provide a detailed discussion on the difference between our work and Moe and Schweidel (2012) in Section 5.

In this paper, we attempt to contribute to the online review literature by looking at the relationship between posted ratings and subsequent ones from a novel perspective. In contrast to extant work that focus on how others' opinions influence a consumer's rating behavior in the post-purchase stage, we postulate that the interaction between them may take place when a prospective buyer reads reviews for information acquisition in the pre-purchase stage. Such modeling novelty allows us to develop a utility-based framework and examine the underlying mechanism driving consumers to voluntarily share their product experiences. In addition, we account for the dynamics of rating behavior by modeling how a raters' perception of system credibility evolves over time and how such perception affects her propensity to post dynamically.

### **3.2. Research Framework and Context**

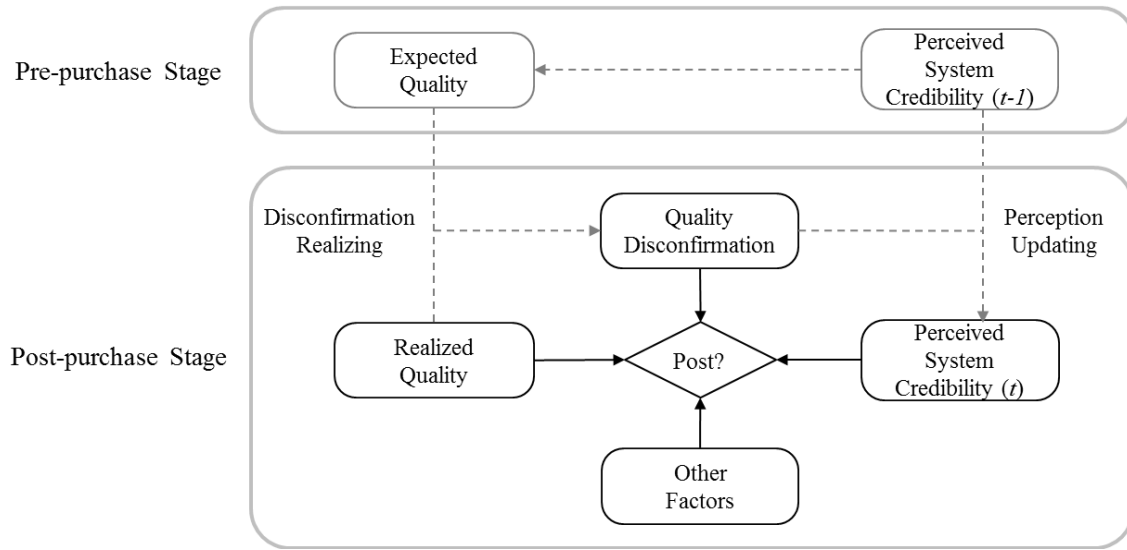
In this section, we introduce our conceptual framework and illustrate the underlying mechanism governing consumers' rating behavior<sup>27</sup>. According to the theory of buying decision, after consumers recognize the need for a certain product, consumer would gather information about the product in the pre-purchase stage. The emergence of online product rating system facilitates communication among consumers such that they can easily exchange their product experiences. In our research context, the e-commerce website displays the arithmetic mean and other aggregate statistics of all posted ratings at the top of a product's landing page.<sup>28</sup> In the pre-purchase stage, a prospective buyer observes the rating signal associated with the product she desires to purchase and formulates an expected quality. Upon product consumption, the consumer obtains realized quality of the product per how much she enjoys the product. In the

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<sup>27</sup> We use the term *rating* as a general expression of consumers' product review behavior, whereas the term *posting* as a decision-making process in which consumers decide whether to post a product review after product consumption.

<sup>28</sup> Like other typical e-commerce sites, the total number and the distribution of all posted ratings are also publicly available on product landing pages.

post-purchase stage, the consumer has another choice to make. She could either become a review poster by expressing her own product opinions; or, she could simply remain silent and become a “lurker”. The realized quality has been shown to have explanatory power in eWOM engagement in many contexts such as movies (Dellarocas and Narayan 2006), bath, fragrance, and home products (Moe and Schweidel 2012), etc. Along this research stream, we further speculate that consumers’ posting decision may also be influenced by “*quality disconfirmation*”, defined as the discrepancy between one’s expected and realized quality acquired from the same product (see Figure 3-1).



**Figure 3-1.** Conceptual Framework of Online Rating Behavior

The effect of quality disconfirmation is considered to have a short-term impulse on the rating decision. While survey-based research (Hennig-Thurau et al. 2004; Sundaram et al. 1998) has identified several motivations for consumers engaging in WOM from a *normative* perspective, our utility-oriented framework provides *positive* explanations on why people share their evaluation after product consumption. For example, concerns for other are found to be one of the most important motives. In our framework, the motive “concern for others” can be

explained as an altruistic behavior driven by consumers' quality disconfirmation. If an individual perceives that the average rating overrates (underrates) the true product quality, she would have incentive to "correct" the rating signal by reporting her own evaluation and bringing the mean score downwards (upwards). Similarly, other motivations such as anxiety reduction and vengeance can also be triggered by negative disconfirmation. If the hypothesized disconfirmation effect does exist, we are also interested in whether such effect is moderated by the rating environments to which online consumers are exposed.

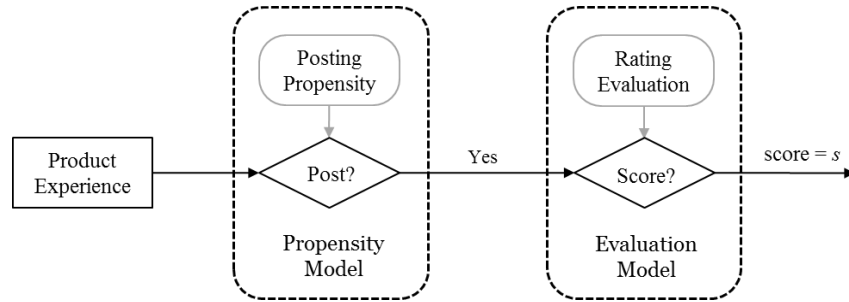
Since a review poster is often a review reader as well, we posit that a consumer's perceived system credibility may also affect her willingness to interact with the system. In particular, we model consumers' perception of the system credibility is composed of two components: biasness and reliability. Consider a consumer who possesses a certain perception of system credibility. Before purchasing a product, she first observes the previously posted ratings, which provides some information about the product quality. Based on this rating signal, the consumer forms the expected quality of the product, taking into account her own perception of the system biasedness and reliability. For example, if the consumer perceives the system to be unbiased, she would formulate an expected quality based on the rating signal she observes. If she perceives the review system to be positively biased (i.e. the rating signal inflates the product quality), she would adjust her prior expectation downwards, and vice versa. Having experienced the products, the consumer encounters quality disconfirmation and then uses this private information to update her beliefs in system biasedness and reliability. If the rating signals consistently portray her own product evaluation, she would perceive the system to be more reliable. On the other hand, if the rating signal consistently deviates from her product evaluation to a large degree, she would perceive the system to be noisy. Since the perceived system credibility is individual-specific and

time-variant, we are able to investigate whether such perception would affect one's review-posting decisions over time. While credibility has been investigated in different applications such as how it determines the persuasiveness of communication (Chaiken 1980), its effect on online opinions expression still remains unstudied. Incorporating the credibility component allows us to model consumers' rating behavior in a dynamic fashion.

We assume that an individual's rating behavior is governed by a two-stage mechanism<sup>29</sup> (Ying et al. 2006), illustrated in Figure 3-2. In the stage 1, she decides whether or not to express her opinion by posting a product rating (posting decision). If she decides to leave a review, at the same time, she also chooses what rating to give (rating decision) in the stage 2. While a large body of literature implicitly assumes review incidences occur haphazardly, we believe this assumption is unrealistic. In particular, we model that a consumer's posting decision is determined by an attitude which we call *posting propensity*. The posting propensity is composed of four components: an individual's realized quality, quality disconfirmation, perception of system reliability and some other factors such as product price and characteristics of posting ratings. If an individual's posting propensity exceeds a certain threshold, she would share her own experience through leaving an online product review. Meanwhile, she would also need to decide what score to submit according to her *rating evaluation*, an attitude mainly determined by her overall evaluation of product experience.

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<sup>29</sup> We call it a two-stage mechanism for the sake of modeling. Consumers can make two decisions simultaneously.



**Figure 3-2.** Consumers' Online Rating Decisions

### 3.3. Data

The data for this study is provided by an online e-commerce site which sells a variety of search goods, such as home and kitchen items, toys, electronics, etc. The data set contains complete purchase history and review entries made by 1,000 heavy users who made at least 10 purchases each. The transactional record set consists of order-specific information such as the product name, price, order handling time, order submission date, the statistics of all posted ratings associated with the product when the order was placed.<sup>30</sup> The rating data set stores user-generated reviews in a typical format, including a review title, a review body, submission date, and an overall product rating on a discrete 5-star scale, with 5 being the best. The data spans from January 2008 to October 2011. During this period of time, the site had not gone through any policy or system design change that could influence consumers' rating behavior. It did not implement any monetary and reviewers' reputation mechanisms that could possibly encourage posting. Participation in product review can be considered voluntary and self-driven.

It is worth noting that our data set is collected at the individual level. This nature distinguishes our work from others that commonly use review data at aggregate (product) level.

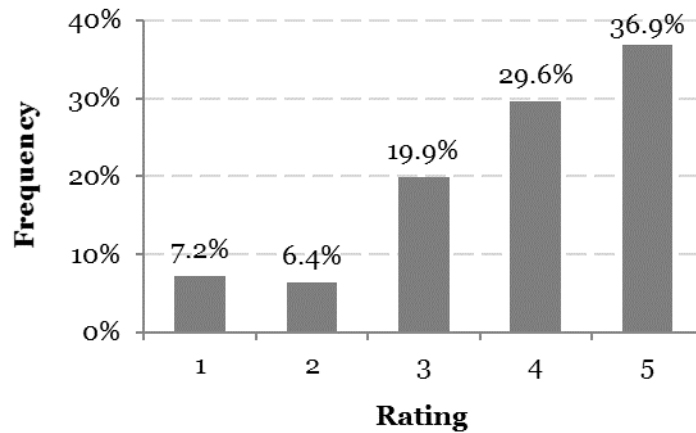
<sup>30</sup> Like other online merchants, the user-generated textual reviews and numeric ratings are publicly available on the e-commerce site. Using the time stamp of purchase orders, we are able to recover the rating environment (characterized by the valence, volume and variance of posted ratings) at any time in the past.

The complete logs of purchasing and rating activities allow us to discern whether a purchase occasion leads to a rating entry. The time stamps associated with each activity also enables us to calibrate online rating behavior from a dynamic perspective. To identify the realized quality and consumers' learning dynamics, we exclude users who did not post any review. The resulting data set contains 361 panelists who made 37,209 purchase transactions and 2,257 review entries. We will use this dataset for model estimation. We supplement our primary data set by collecting the aggregate review information from the same platform in June 2013. This supplementary data provides the rating environments for each product and we will utilize this piece of information to proxy true product quality in our empirical model.

Before beginning the model estimation, we briefly present some observations and address the potential issues identified in the data. Table 3-1 reports the descriptive statistics of rating outcomes observed in our final data set. At the population level, the posting percentage is 6.06% and the mean of all posted ratings is about 3.83. Figure 3-3 plots the frequency of each of 5 discrete ratings. The distribution roughly follows a right-skewed U shape, which is commonly found across various rating platforms (Dellarocas and Narayan 2006; McGlohon et al. 2010). Such unique shape implies that consumers are more prone to express opinions when they are either very satisfied (represented by a high score of 4 or 5) or very dissatisfied (represented by a low score of 1 or 2), identified by Anderson (1998). Some control variables, such as price and order handling time, exhibit a long-tail property (see Figure 3-4a). To deal with the over-dispersion issue, we take logarithmic transformation on them. The log-transformed variables appear to be normally distributed (see Figure 3-4b).

**Table 3-1.** Summary of Outcome Variables

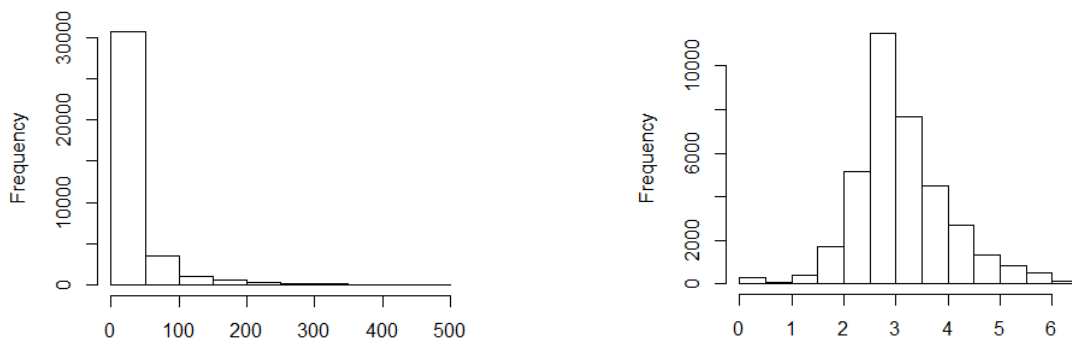
Notations	Description	Mean	St. Dev.	Min	Max
$Y_{ijt}$	A dummy indicating if a purchase occasion leads to a review posting	0.061	0.239	0	1
$Z_{ijt}$	Observed rating scores	3.826	1.200	1	5



**Figure 3-3.** Frequency of Observed Rating Scores

(a) Distribution of *price*

(b) Distribution of  $\log(\text{price}+1)$



**Figure 3-4.** Over-dispersion vs. Logarithm Transformation

### 3.4. The Model

The paper which is closest to this study, both in terms of the research content and model itself, is Moe and Schweidel (2012) (henceforth MS). We develop our model based on MS which, in turn, is a generalization of Ying et al. (2006) who first model online consumers' rating behavior using a two-stage mechanism. Despite several similarities, this paper differs from MS in the following aspects.

*Research question.* The goal of MS is to study how online reviewers adjust their rating decision according to the rating environment they are exposed to. The impact of previously posted ratings on a focal individual's rating decision is assumed to take place in the post-purchase stage only. Instead, we speculate that such impact may occur when the individual consumes review information in the pre-purchase stage. The novelty of our research is that we explicitly model consumers' quality disconfirmation and their perception of system credibility in an effort to better understand what could possibly induce posting behavior from consumers.

*Data.* The data set used in MS includes a total of 3,681 product ratings provided by 2,436 unique reviewers; an individual on average posts 1.5 reviews only. With such limited data points, the estimates of individual-specific parameters in MS may not be able to precisely capture the intrinsic characteristics of each individual. On the other hand, the final data set we use for model estimation contains 361 individuals who made a total of 37,209 purchasing transactions and contributed 2,257 product reviews. The data richness and completeness allow us to more accurately gauge the heterogeneity cross individuals. Moreover, we can exactly discern whether or not a consumer posts an online rating at all after experiencing the product. With such data advantage, we can directly observe the posting decision for each purchase occasion without incorporating a latent purchase model.

*Model specification.* In MS, product quality is estimated using a zero-mean random effect. To utilize publicly available review information, we collect and use the long-term average rating as a proxy for true quality. We also explicitly model the interdependence between raters' decisions of whether to post and what to rate.

*Covariates specification.* MS apply a factor analysis and use the resulting factors as independent variables to explain reviewers' rating behavior. In our framework, we construct quality disconfirmation and perception of system reliability as the main explanatory variables. In addition, we also include several control variables such as product price, order handling time and aggregate statistics of expressed opinions by others to better model consumers' posting decisions.

Following the conceptual framework introduced earlier, we develop a two-stage selection model to explicitly model the interdependence between two rating decisions. The general modeling context is that in the pre-purchase stage, a consumer first formulates an expected quality right before she purchases the product. Such ex-ante expectation is formed based on the product ratings posted by peer consumers and the focal consumer's perceived system credibility. Upon product experience, she obtains the realized (ex-post) quality in the post-purchase stage. With expected and realized quality in mind, the individual encounters quality disconfirmation and use this private information to update her perception of the system credibility. Driven by quality disconfirmation and others factors, the consumer faces a two-stage decision with the first decision being whether to contribute a product rating; if she decides to post a rating, she also needs to choose what rating to leave<sup>31</sup>. The proposed model is described in the following order: 1) formulation of quality disconfirmation; 2) evolution of perceived system credibility; 3)

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<sup>31</sup> Again, these two decision-making processes can happen simultaneously from a consumer's perspective.

consumers' decisions of whether to post and what to rate; and 4) interdependence between two rating decisions.

### 3.4.1. Formulation of Quality Disconfirmation

*Expected Quality.* In the pre-purchase stage, consumers formulate expected quality of the product based on information gathered from different sources. In our context, the e-commerce website displays the aggregate statistics of posted ratings<sup>32</sup> (e.g., arithmetic mean), on the top of product landing pages. Given the significance of online product ratings, it is reasonable to assume that consumers' expected quality of the product is largely influenced by this piece of information.<sup>33</sup> While posted reviews provide objective information about product quality, how such information is perceived could be subjective and heterogeneous across individuals.

Consider an individual  $i$  who is about to purchase a product  $j$  at time  $t$ . We assume the expected quality associated with this purchase occasion,  $\hat{Q}_{ijt}$ , to follow a normal distribution:

$$\hat{Q}_{ijt} \sim N\left(\bar{R}_j + \delta_{it}, (\tau_{it} \cdot T_j)^{-1}\right), \quad (3.1)$$

where  $\bar{R}_j$  and  $T_j$  denote the arithmetic mean<sup>34</sup> and precision<sup>35</sup> of all ratings for  $j$  posted prior to  $t$ , respectively. In this paper, we model that consumers' perception of system credibility is composed of two components: biasedness ( $\delta_{it}$ ) and reliability ( $\tau_{it}$ ). The system biasedness  $\delta_{it}$  measures how biased the review system is perceived by the individual  $i$  at time  $t$  and how she

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<sup>32</sup> These aggregate statistics include the average, the total number and the distribution of previously posted ratings.

<sup>33</sup> Consumers' ex-ante perception of quality is also influenced by textual product reviews (Ghose et al. 2012). However, we cannot observe how many textual reviews each prospective buyer reads before making a purchase decision. Therefore, we use the mean of posted ratings to measure the overall opinions shared by others.

<sup>34</sup> According to a survey conducted by Lightspeed Research (Leggatt 2011), 72% of online shoppers expect to find customer reviews available on the website they are shopping at, while 47% seek them out on company websites and 43% on price comparison sites. Therefore, we assume that one's expected quality is, by large part, determined by  $\bar{R}_j$ , the mean ratings observed on the same site.

<sup>35</sup> We use precision instead of variance because the former gives us a neater expression of belief updating.

adjusts such bias. When  $\delta_{it} = 0$ , the individual  $i$  believes that  $\bar{R}_{jt}$  provides unbiased information about the quality, and therefore, she would formulate an expected product quality centered on  $\bar{R}_{jt}$ . When  $\delta_{it} > 0$  ( $\delta_{it} < 0$ ), she believe that the rating signal  $\bar{R}_{jt}$  underrates (overrates) the true product quality. As a result, she would adjust the mean of her expectation upwards (downwards). The system reliability  $\tau_{it}$  measures how reliable the system is perceived by  $i$  at time  $t$ . When  $\tau_{it}$  is large (small), the individual  $i$  would perceive the review system to be reliable (noisy) such that her expected quality would be tightly (loosely) centered on its mean.

*Realized Quality.* One of the most challenging parts of our modeling task is to model the baseline quality of products. One approach is to model the latent quality of all products using a zero-mean random effect (Moe and Schweidel 2012). To best utilize the publicly available information and enhance the estimation reliability, we use the long-term average rating,  $\tilde{R}_j$ , as a proxy for the baseline product quality.<sup>36,37</sup> In a spirit of Moe and Schweidel 2012, we assume that an individual  $i$  obtains realized quality  $Q_{ijt}$  from product  $j$ :

$$Q_{ij} = \tilde{R}_j + \lambda_{i0}, \quad (3.2)$$

where the parameter  $\lambda_{i0}$  allows for variation in realized quality across individuals.

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<sup>36</sup> We justify our use of long-term average ratings as a proxy for quality in following two aspects. From the perspective of the volume of ratings, the mean and minimal values of the total number of posted ratings at product level are 67 and 11, respectively. From the perspective of time horizon, the time we collected our long-term rating data set (June 2013) is 18 months after the latest purchase occasion observed in our primary data set (November 2011). It is reasonable to justify that our long-term average ratings are representative of opinions from a sufficiently large consumer base and have converged to the true quality.

<sup>37</sup> We perform a robustness check in Section 7.1.3 and the results provide supportive evidence that the long-term average rating well proxy the true product quality.

*Quality disconfirmation.* Having developed the expected and realized quality, we are now able to formally define quality disconfirmation. We model quality disconfirmation as how far away an individual's realized quality deviates from her expected quality:

$$\Delta Q_{ijt} \equiv Q_{ijt} - \hat{Q}_{ijt}. \quad (3.3)$$

Plugging (3.1) and (3.2) into (3.3), we have:

$$\Delta Q_{ijt} \sim N\left(\Delta \bar{Q}_{ijt}, (\tau_{it} \cdot \Gamma_{jt})^{-1}\right), \quad (3.4)$$

$$\text{where } \Delta \bar{Q}_{ijt} = (\tilde{R}_j + \lambda_{i0}) - (\bar{R}_{jt} + \delta_{it}). \quad (3.5)$$

In this paper, we posit that the occasion-specific variable  $\Delta Q_{ijt}$  not only directly affects the individual  $i$ 's posting decision associated with the  $ijt$ -th occasion; it also indirectly influences  $i$ 's long-term posting behavior through the evolution of her perceived system credibility.

### 3.4.2. Evolution of the Perception of System Credibility

Next, we explain how consumers' perception of the system credibility evolves over time. We assume that at time  $t$  an individual  $i$ 's prior beliefs of  $\delta_{it} | \tau_{it}$  and  $\tau_{it}$  jointly follow a normal-gamma distribution<sup>38</sup>:

$$\delta_{it} | \tilde{\tau} \sim N\left(\bar{\delta}_{it}, (\gamma_{it} \cdot \tilde{\tau})^{-1}\right), \quad (3.6)$$

$$\tau_{it} \sim \Gamma(a_{it}, b_{it}), \quad (3.7)$$

where  $\gamma_{it}$  is the precision parameter of a normal distribution,  $a_{it}$  is the shape parameter and  $b_{it}$  is the inverse scale parameter of a gamma distribution. Upon product experience, the individual encounters quality disconfirmation and use this private information to update her beliefs of  $\delta_{it}$

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<sup>38</sup> In Bayesian learning framework, quality disconfirmation defined here follows a normal model with unknown mean and unknown variance. The conjugate prior for this model is a normal-gamma joint distribution.

and  $\tau_{it}$  jointly. As a result, an individual's perceived system credibility will evolve over time, as she is involved in more purchasing and experiencing activities. Based on Bayes' rule, the individual  $i$ 's posterior beliefs after receiving a disconfirmation signal associated with occasion  $t+1$  are given by (DeGroot 1970):

$$\delta_{i,t+1} | \tilde{\tau} \sim \text{N}\left(\bar{\delta}_{i,t+1}, (\gamma_{i,t+1} \cdot \tilde{\tau})^{-1}\right), \quad (3.8)$$

$$\tau_{i,t+1} \sim \Gamma(a_{i,t+1}, b_{i,t+1}), \quad (3.9)$$

where

$$\bar{\delta}_{i,t+1} = \bar{\delta}_{it} + D_{j,t+1} \cdot \frac{\Gamma_{jt}}{\gamma_{it} + \Gamma_{jt}} \cdot \Delta \bar{Q}_{ij,t+1}, \quad (3.10)$$

$$\gamma_{i,t+1} = \gamma_{it} + D_{j,t+1} \quad (3.11)$$

$$a_{i,t+1} = a_{i,t} + D_{j,t+1} \cdot \frac{1}{2}, \quad (3.12)$$

$$b_{i,t+1} = b_{i,t} + D_{j,t+1} \cdot \frac{1}{2} \frac{\gamma_{it} \cdot \Gamma_{jt} \cdot (\Delta \bar{Q}_{ij,t+1})^2}{\gamma_{it} + 1}, \quad (3.13)$$

and  $D_{j,t+1}$  is a dummy variable indicating whether there is at least one rating for  $j$  posted prior to time  $t+1$ .

It is important at this time to point out how perception of the system credibility evolves over time. Consider an individual  $i$  who has beliefs of  $\delta_{it} | \tau_{it}$  and  $\tau_{it}$  at time  $t$ . Suppose that  $i$  observes the rating signal for  $j$  and purchases  $j$  at time  $t+1$ . Upon product experience, she receives one signal of disconfirmation,  $\Delta \bar{Q}_{ij,t+1}$ , and updates her beliefs based on this information. If there is no product rating available at time  $t+1$  (i.e.  $D_{j,t+1} = 0$ ), no belief updating would occur and individual  $i$ 's beliefs remains unchanged. If the rating signal is available (i.e.  $D_{j,t+1} = 1$ ), she

would jointly update her beliefs in system biasedness and reliability. The posterior mean  $\bar{\delta}_{i,t+1}$  is the sum of prior mean and the weighted realization of disconfirmation, with the weight being  $T_{jt} / (\gamma_{it} + T_{jt})$ . The signal precision  $T_{jt}$  and prior precision  $\gamma_{it}$  can be interpreted as the strength of the disconfirmation signal and the individual  $i$ 's confidence in her belief of system biasedness. Similarly, the extent of updating of the scale parameter  $b_{i,t+1}$  is increasing in the magnitude of disconfirmation and the precision of the rating signal. When  $T_{jt}$  is small, a consumer anticipates the review signal to be noisy with a higher probability and therefore updates her belief in a relatively small amount, *ceteris paribus*.

What remain unspecified are the initial beliefs of each individual. The updating rule of the shape parameter implies that  $a_{i0}$  represents the richness of the individual  $i$ 's initial learning experience before receiving any disconfirmation signal. Since we observe complete purchase history for all individuals from our data set, we fix  $a_{i0}$  at a small number<sup>39</sup> across individuals because all consumers have the same and limited amount of learning experience with the e-commerce site at time 0. To allow for heterogeneity across individuals in their initial perceptions of system reliability, we assume  $b_{i0} \sim N(\bar{b}_0, \sigma_b^2)$ , where  $\bar{b}_0$  and  $\sigma_b^2$  measures the mean effect and dispersion of  $b_{i0}$  across individuals, respectively. As for system biasedness, we assume  $\delta_{it} = 0$  since it is reasonable to argue that, before receiving any disconfirmation signal, consumers would initially perceive the review system to be unbiased mainly due to lack of information. We also fix  $\gamma_{i0} = 0.1$  to reflect the fact that consumers have an uninformative initial prior belief in  $\delta_{it}$ .

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<sup>39</sup> The choice of  $a_{i0}$  is subjective. We estimate the proposed model with  $a_{i0}$  fixed at different values (2.5, 5, 10, and 20) and we do not observe noticeable changes for the estimated parameters. Given this result, we report the estimation results with  $a_{i0} = 5$  since it gives the best model fit.

It is worth noting that the belief updating mechanism specified in our model is used to measure consumers' *subjective* perception of system credibility. In terms of interpretation of the learning process, it is somewhat different from the traditional learning framework in which the unobserved knowledge (system biasedness and reliability in our context) is fixed at a certain level.

### 3.4.3. Consumer Decisions on Whether to Post and What to Rate

So far, we have presented a general model of how quality disconfirmation is formulated, how consumers' perceived system credibility is updated, and how these two mechanisms are linked to each other. In this section, we discuss how we model consumers' online rating decisions.

*Propensity Model.* In this paper, we posit that whether a consumer would post a rating after product experience is mainly impacted by the realized quality she has, quality disconfirmation she encounters, and the updated belief in system reliability she has. Given that consumers' perception of system credibility is modelled in a form of a distribution, we use the mean of the distribution to measure her perceived system credibility. Since the belief in system reliability follows a gamma distribution, an individual  $i$ 's expectation of system reliability at time  $t$ ,  $Rel_{it}$ , is given by:

$$Rel_{it} \equiv E[\tau_{it}] = \frac{a_{it} - 1}{b_{it}}. \quad (3.14)$$

Given the belief updating rule, the latent variable  $Rel_{it}$  will become larger if the magnitude of disconfirmation is relatively small, meaning that the individual perceives the review system to be more reliable. To investigate how an individual's idiosyncratic belief in system reliability affects her posting behavior, we incorporate the latent construct  $Rel_{it}$  into the raters' decision-making process.

We model that a consumer's decision of whether to post a product rating is governed by latent *posting propensity*. Specifically, individual  $i$ 's posting propensity for product  $j$  purchased at time  $t$ ,  $Prop_{ijt}$ , is expressed as:

$$\begin{aligned} Prop_{ijt}^* &= Prop_{ijt} + \varepsilon_{p,ijt} \\ &= \beta_{i0} + \beta_1 \Delta \bar{Q}_{ijt} + \beta_2 \Delta \bar{Q}_{ijt}^2 + \beta_3 Rel_{it} + \beta_4 Q_{ijt} + \beta_5 Q_{ijt}^2 + \beta_{6,8} X_{jt} + \varepsilon_{p,ijt}, \end{aligned} \quad (3.15)$$

where  $\beta_{i0}$  allows for heterogeneity in baseline propensity across individuals and can be interpreted as individual-specific net utility the individual  $i$  derives from posting. The covariate  $\Delta \bar{Q}_{ijt}$  is the mean of quality disconfirmation given in (3.5),  $Rel_{it}$  is the time-variant belief variable specified in (3.14),  $Q_{ijt}$  is the realized quality given in (3.2). We also add quadratic terms,  $\Delta \bar{Q}_{ijt}^2$  and  $Q_{ijt}^2$ , to capture possible nonlinear relationship between  $Prop_{ijt}$  and quantities of our interest. To control the price effect and the impact of rating environments on a focal individual's posting decision, we include product price, volume and the statistical variance of posted ratings in  $X_{jt}$ .<sup>40</sup> Finally,  $\varepsilon_{p,ijt}$  is an idiosyncratic error with a mean of 0. Since the outcomes of posting decision is binary (posting or lurking), we assume  $\varepsilon_{p,ijt} \sim N(0, 1)$  and the resulting propensity model has a standard probit specification:

$$\Pr(y_{ijt} = 1) = \Pr(Prop_{ijt}^* > 0) = \Phi(Prop_{ijt}^*), \quad (3.16)$$

where  $y_{ijt}$  is an occasion-specific dummy indicating whether an individual  $i$  posts a product rating for  $j$  purchased at time  $t$ .

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<sup>40</sup> We observe from our data that a typical consumer either posts a product rating within two weeks after the order has been placed or does not express their opinions at all. The rating environments (such as volume, valence and variance of ratings) does not have noticeable changes during such short period of time. Therefore we use review statistics observed at time  $t$  to characterize the rating environment individual  $i$  is exposed to.

The parameters of our main interest are  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$ . The estimates of  $\beta_1$  and  $\beta_2$  together will inform us the impacted of quality disconfirmation on consumers' posting decision. The estimated parameter  $\beta_3$  will indicate whether one's perceived system reliability would encourage (if  $\beta_3 > 0$ ) or deter (if  $\beta_3 < 0$ ) herself to express her own opinions about the product. Moreover, it has been shown that online opinions are subject to a polar effect – consumers with extreme opinions tend to be more vocal (Anderson 1998; Dellarocas and Narayan 2006). We will be able to confirm the existence of polar effect if estimated  $\beta_4$  is negative whereas  $\beta_5$  is positive.

*Evaluation Model.* Now, consider that the individual  $i$  has decided to post a product rating for  $j$ . We assume that  $i$ 's decision of what score to rate is governed by latent *rating evaluation*, which is mainly driven by her realized quality:<sup>41</sup>

$$Eval_{ijt}^* = Eval_{ijt} + \varepsilon_{e,ijt} = Q_{ijt} + \lambda_1 h_{ijt} + \lambda_{2,4} X_{jt} + \varepsilon_{e,ijt}, \quad (3.17)$$

where  $\varepsilon_{e,ijt}$  is a zero-mean random shock. While consumers are advised to provide product-related feedback only, we suspect that some consumers may reflect the level of service they receive from the e-commerce site in product ratings. To account for such possibility, we include log-transformed order handling time (measured by days),  $h_{ijt}$ , in the formulation of rating evaluation. Since rating evaluation is continuous whereas the ordinal ratings only take integer values (1 to 5 in our case), we assume that the relationship between them follows:

$$z_{ijt} = \begin{cases} 5, & \text{if } \kappa_4 < Eval_{ijt}^* < \kappa_5, \\ 4, & \text{if } \kappa_3 < Eval_{ijt}^* \leq \kappa_4, \\ 3, & \text{if } \kappa_2 < Eval_{ijt}^* \leq \kappa_3, \\ 2, & \text{if } \kappa_1 < Eval_{ijt}^* \leq \kappa_2, \\ 1, & \text{if } \kappa_0 < Eval_{ijt}^* \leq \kappa_1, \end{cases} \quad (3.18)$$

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<sup>41</sup> In other words, we assume that the posted ratings are trustful and serve as an unbiased signal of consumers' product evaluation.

where  $z_{ijt}$  denotes the observed rating scores and  $\kappa$  specifies the utility-ratings translating cutpoints. For identification purpose we set  $\kappa_0 = -\infty$ ,  $\kappa_1 = 0$  and  $\kappa_5 = \infty$  (Koop et al. 2007), resulting in three cutpoints  $\kappa_2$ ,  $\kappa_3$  and  $\kappa_4$  to be estimated.

### 3.4.5. Interdependence between Two Rating Decisions

So far we have developed two separate models governing raters' decisions of whether to post and what to rate. However, the covariance matrix of the equation system has not yet been clearly specified. Based on the independence assumption among two decision stages,<sup>42</sup> MS assume that the idiosyncratic error  $\varepsilon_p$  in propensity model and  $\varepsilon_e$  in evaluation model both follow a standard normal distribution and are independent of each other. However, since the realized quality  $Q_{ijt}$  enters two models simultaneously, all parameter estimates could be biased if the interdependence between two decisions is not explicitly specified. As a result, we assume two sets of error terms to follow a bivariate distribution:

$$\begin{pmatrix} \varepsilon_p \\ \varepsilon_e \end{pmatrix} \sim BVN \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right). \quad (3.19)$$

For identification purpose, we fix the standard deviations of  $\varepsilon_p$  and  $\varepsilon_e$  at 1 in order to obtain binary probit and ordered probit specification, respectively. The parameter  $\rho$  is the correlation coefficient to be estimated<sup>43</sup>. Given this covariance structure and the translating cutpoints, the probability of observing a joint event of  $y_{ijt} = 1$  and  $z_{ijt} = s$  is given by:

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<sup>42</sup> They make this simplification mainly because from estimation results they find that correlation between two error terms is small and the parameter estimates are not substantively different.

<sup>43</sup> To estimate  $\rho$ , we first compute inverse Mills ratio,  $IMR_{ijt} = \varphi(Prop_{ijt}) / \Phi(Prop_{ijt})$  and plug  $\rho \cdot IMR_{ijt}$ .

$$\Pr(y_{ijt} = 1, z_{ijt} = s) = \begin{cases} \Phi_2(\infty, Prop_{ijt}, \rho) - \Phi_2(\kappa_4 - Eval_{ijt}, Prop_{ijt}, \rho) & s = 5, \\ \Phi_2(\kappa_4 - Eval_{ijt}, Prop_{ijt}, \rho) - \Phi_2(\kappa_3 - Eval_{ijt}, Prop_{ijt}, \rho) & s = 4, \\ \Phi_2(\kappa_3 - Eval_{ijt}, Prop_{ijt}, \rho) - \Phi_2(\kappa_2 - Eval_{ijt}, Prop_{ijt}, \rho) & s = 3, \\ \Phi_2(\kappa_2 - Eval_{ijt}, Prop_{ijt}, \rho) - \Phi_2(-\infty, Prop_{ijt}, \rho) & s = 2, \\ \Phi_2(-\infty, Prop_{ijt}, \rho) - \Phi_2(-\infty, Prop_{ijt}, \rho) & s = 1, \end{cases} \quad (3.20)$$

where  $\Phi_2$  denotes the standard bivariate normal cumulative distribution function (CDF). Given such specification, our proposed model releases the independence assumption between two observed outcomes ( $y$ 's and  $z$ 's). The probability of observing  $y_{ijt} = 0$  (i.e. lurking) can be expressed as:<sup>44</sup>

$$\Pr(y_{ijt} = 0) = 1 - \Phi(Prop_{ijt}). \quad (3.21)$$

The joint likelihood for observing individual  $i$  who makes  $m$  purchase occasions and posts  $n$  product ratings is given by

$$L_i(y_i, z_i) = \prod_{t \in (y_{ijt}=0)} \Pr(y_{ijt} = 0) \cdot \prod_{t \in (y_{ijt}=1)} \Pr(y_{ijt} = 1, z_{ijt} = s), \quad (3.22)$$

/--- (m - n) terms ---/ /----- (n) terms -----/

and the likelihood of observing the entire decision set made by  $N$  individuals is  $\prod_{i=1}^N L_i(y_i, z_i)$ .

### 3.5. Estimation

We generalize the second stage of the Heckman selection model to reflect ordinal outcomes (rating scores in our context) and directly estimate two interdependent outcomes using a bivariate normal specification for correlated error terms. For parameters that are subject to certain constraints we apply the following transformation strategy. First, since the correlation coefficient  $\rho$  takes value from  $[-1, 1]$  only, we estimate the inverse arctangent transformation of it,

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<sup>44</sup> The marginal distribution of one series of bivariate normally distributed variables is simply a normal density.

which maps the support  $[-1, 1]$  to real line (Ying et al. 2006). Second, we estimate  $\log(\bar{b}_0)$  instead of  $\bar{b}_0$  because the inverse scale parameter of a gamma distribution takes positive values only. Finally, to ensure the magnitude of three cutoffs to obey a desired order (i.e.  $\kappa_2 < \kappa_3 < \kappa_4$ ), we estimate the log of difference between two adjacent cutoffs. For variables having hyperdispersion property such as product price  $p_{ijt}$  and order handling time  $h_{ijt}$ , we take logarithm transformation. We also mean-center all variables using the grand means to reduce the correlation between the estimated intercepts and slopes and avoid potential multicollinearity in the propensity model (especially for variables which enter propensity model in both linear and quadratic forms).<sup>45</sup>

To estimate the proposed model, we use hierarchical Bayes approach which allows us to identify parameters at the individual level. Given the nature of parameter hierarchy, the parameters in our model can be divided into two groups (Netzer et al. 2008): (1) “random-effect” parameters that vary across individuals (denoted by  $\theta_i$ ); and (2) “fixed” parameters that do not vary across individuals (denoted by  $\psi$ ). We allow individual-specific parameters governing propensity intercept, realized quality and initial learning parameter to be correlated by assuming:

$$\theta_i \sim \text{MVN}(\bar{\theta}, \Sigma), \quad (3.23)$$

where  $\bar{\theta}$  denotes the mean effects that persist across individuals and  $\Sigma$  denotes the variance and covariance matrix of  $\theta$ .

We use uninformative priors as we do not have much prior knowledge about model parameters. Specifically, we use diffuse multivariate normal for the fixed parameter  $\psi$ . There are

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<sup>45</sup> We calculate the variance inflation factor (VIF) for the covariates included in the propensity model and the result shows no evidence of multicollinearity ( $\text{VIF} < 2$ ).

18 elements in the vector  $\psi$ , including  $\beta$  capturing the coefficients for 8 covariates in the propensity model,  $\lambda$  measuring the effect of 4 covariates in the evaluation model, cutpoint set ( $\kappa_2, \kappa_3, \kappa_4$ ) mapping continuous rating evaluation and discrete posted scores, and  $\bar{\theta}$  governing the mean effect of baseline propensity and realized quality. A diffuse multivariate normal is used for parameters that vary across individuals. Let  $\xi_i$  denote individual-specific deviation from  $\bar{\theta}$ . We can directly estimate those deviations using  $\xi_i \sim \text{MVN}(0, \Sigma)$ .

We develop a Markov chain Monte Carlo (MCMC) procedure to recursively draw parameters from the corresponding full conditional distributions using the following steps:

$$\begin{aligned}
 &\xi_i | Y_i, Z_i, \psi, \rho, \Sigma; \\
 &\Sigma | \xi_i; \\
 &\psi | Y, Z, \xi_i, \rho; \\
 &\rho | Y, Z, \psi, \xi_i;
 \end{aligned} \tag{3.24}$$

We adopt random walk Metropolis-Hasting algorithm for steps where the conditional posterior distributions do not have a closed form (step 1, 3 and 4). To improve the efficiency of the sampler, we use a two-stage strategy. In the first stage, we run the MCMC for 50,000 iterations and discard the first 25,000 draws as “burn-in” samples.<sup>46</sup> We calculate posterior means and empirical variance based on the remaining 25,000 draws. In the second stage, we run a separate MCMC using the posterior means calculated in the previous stage as the initial values and the empirical variance as the diagonal elements of covariance matrix of the random-walk proposal distribution.<sup>47</sup> We run the MCMC sampler for 100,000 iterations and record every 10th draw only to mitigate the autocorrelation issue which is an evitable consequence of the MCMC simulation (Hoff 2009). The adaptive chain converges immediately and explores the parameter

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<sup>46</sup> The choice of burn-in period is based on the visual observation on the trace plot of MCMC draws. In fact, 25,000 is a conservative number since the chain appears to converge after initial 5,000 iterations.

<sup>47</sup> The scale parameter of proposal distribution is adaptively chosen such that the acceptance rate is around 23%, as suggested for high-dimension vector (Gelman et al. 2003).

space efficiently. To test convergence, we perform Gelman and Rubin diagnostic (Gelman and Rubin 1992) by running 3 parallel chains with different initial values and random seeds. The potential scale reduction factors (PSRF) are below 1.02 for all parameters, suggesting that the chains have converged to the target distributions.<sup>48</sup> We combine draws from three parallel chains, resulting in an effective sample size of at least 500 for all parameters.

### 3.5.1. Model Fit and Comparison

To demonstrate the fit of our proposed model, we compare our full (dynamic) model with its three nested versions:

*Model 1* – Static model (no dynamic learning).

*Model 2* – Static model without quality disconfirmation entering propensity model.

*Model 3* – Static model without quality disconfirmation and realized quality entering propensity model.

**Table 3-2.** Model Comparison

Model	Dynamic Belief Updating	Quality Disconfirmation	Realized Quality	DIC w.r.t. Full Model*
Full	Yes	Yes	Yes	---
Model 1	No	Yes	Yes	349.7
Model 2	No	No	Yes	427.2
Model 3	No	No	No	483.9

\* Lower DIC is preferred.

Table 3-2 reports the deviance information criterion (DIC) proposed by Spiegelhalter et al. (2002) for four alternative models. The full model outperforms its three nested versions, and therefore we report and interpret the estimation results from the full model in the next section.

<sup>48</sup> A series of MCMC draws are considered to achieve convergence as long as  $PSRF < 1.2$ .

Our full model has a better model fit over three static models because the belief updating mechanism provides a general way to explain consumers' posting decision over time. In addition, the model fit becomes worse and worse if we exclude the effect of quality disconfirmation (Model 2) and the effect of realized quality (Model 3) one by one. This pattern provides evidence that it is desirable to incorporate all three components when modeling consumers' online rating behavior.

### 3.6. Results

Table 3-3 reports the posterior means of parameters specified in the propensity model. Since we apply a Bayesian approach to estimate the model, we evaluate the significance of parameter estimates based on the highest posterior density (HPD) intervals. A HPD interval describes the information we have about the location of the true parameter after we have observed the data (Hoff 2009). Parameter estimates are considered significant if the corresponding HPD intervals do not contain zero.

The parameters  $\beta_1$  and  $\beta_2$  indicate that online shoppers' propensity of posting product ratings is, at least partially, driven by quality disconfirmation. That is, the larger the extent to which the *ex-post* perceived quality deviates from the *ex-ante* expectation, the more likely a consumer is to express her own product opinion. If the average rating she observes more or less reflects her own post-purchase evaluation, she is more prone to "lurk". Such behavior could be attributed to many reasons such as altruism. An altruist may praise the product by submitting a rating higher than the current mean rating if her product evaluation is actually higher than the level represented by the rating signal. On the other hand, if her perceived product quality is lower than what review signal indicates, she may warn peer consumers to be vigilant with the product by posting a below-the-average rating. Moreover, the coefficient for the linear term is negative

( $\beta_1$ ), suggesting that consumers are more prone to post a rating when she has negative disconfirmation, compared to the case where disconfirmation she encounters is positive. While existing work has documented several motives why consumers engage in WOM from a normative point of view (Hennig-Thurau et al. 2004; Sundaram et al. 1998), this research provides a positive validation and contribute to literature with an economic-based explanation: the disconfirmation effect identified in this paper serves as one of the underlying forces driving consumers to voluntarily engage in online WOM.

**Table 3-3.** Estimation Results (Propensity Model)

Model	Notation	Description	Coeff.	Signif.
Propensity	$\beta_{i0}$	Mean effect of baseline propensity	-0.831	**
	$\beta_1$	Disconfirmation – Linear	-0.011	**
	$\beta_2$	Disconfirmation – Quadratic	0.025	**
	$\beta_3$	Perceived system reliability	-0.508	**
	$\beta_4$	Realized quality – Linear	-0.268	**
	$\beta_5$	Realized quality – Quadratic	0.065	**
	$\beta_6$	Product Price	0.271	**
	$\beta_7$	Volume of posted ratings	-0.009	
	$\beta_8$	Variance of posted ratings	0.009	*

\*\* (\*) Indicates 95% (90%) HPD interval does not contain 0.

A unique feature of our proposed model is that it models how online raters' posting propensity changes as their perceived system reliability evolves over time. The estimation results show that consumers are less active in generating WOM ( $\beta_3 < 0$ ) as they perceived the review system to be more reliable. Alternatively, we can say that consumers tend to be more vocal when they do not trust rating signals, relatively to the case where they perceived the system to be highly reliable. It should be clear that occasion-specific disconfirmation has a different economic meaning from the perception of system reliability. The former captures the short-term impact of a disconfirmation shock on the corresponding review-posting opportunity, whereas the latter

measures how an individual perceives the system based on all of her past disconfirmation experiences and can be considered to have a long-term and accumulative effect on one's posting behavior.

As for the effect of the realized quality on posting propensity, the estimated coefficient is negative for the linear term ( $\beta_4$ ) but positive for the quadratic term ( $\beta_5$ ). Combined, these two parameter estimates indicate that consumers are more likely to share opinions when they perceive product quality to be either very high or very low. This finding echoes the polar effect observed by Anderson (1998) in an offline setting and by several researchers in an online setting (Dellarocas et al. 2010; Dellarocas and Narayan 2006; Moe and Schweidel 2012). Furthermore, we also find that consumers are more interested in rating products with higher prices ( $\beta_6 > 0$ ). The rating environment, characterized by the volume and variance of posted ratings, has dissimilar impacts on a focal consumer's posting decision. In particular, online raters' posting decision is subject to a crowding-out effect, meaning that a focal individual tends to lurk if there has been a big crowd sharing their opinions ( $\beta_7 < 0$ ). Such finding is analogous to a political phenomenon where voters tend to abstain if public polls have declared clear winners (Sudman 1986). On the other hand, the dissension of posted opinions would encourage the focal individual to share her own opinion ( $\beta_8 > 0$ ).

The estimation results of other parameters specified in the evaluation model, utility-score translating rule and system credibility updating model are reported in Table 4. As expected, the order handling time has a negative impact on rating evaluation ( $\lambda_1 < 0$ ). This shows that online shoppers commonly reflect the service level they receive from the e-commerce site in the product ratings. The coefficient for product price is positive but insignificant, meaning that price in general is a weak proxy for quality. Unlike in the propensity model, the dissension of public

opinions and latent rating evaluation is negatively correlated. For the ease of interpretation, we report the transformed cutoff points of the utility-score translating rule. The posterior mean of our estimate of  $\log(b_i)$  is significant, suggesting that the updating mechanism well captures the dynamic evolution of how consumers perceive the reliability of the review system. Finally, the interdependence between two rating stages is positive yet insignificant.

**Table 3-4.** Estimation Results of Other Mean-Effect Parameters

Model	Notation	Description	Mean	Signif.
Evaluation	$\lambda_{i0}$	Mean effect of realized quality	1.997	**
	$\lambda_1$	Order handling days	-0.104	**
	$\lambda_2$	Product Price	0.033	
	$\lambda_3$	Volume of the rating environment	-0.015	
	$\lambda_4$	Variance of the rating environment	-0.033	*
Cutoffs	$\kappa_1$	Cutpoints for s=1 and 2 (fixed at 0)	0.000	---
	$\kappa_2$	Cutpoints for s=2 and 3	0.486	**
	$\kappa_3$	Cutpoints for s=3 and 4	1.406	**
	$\kappa_4$	Cutpoints for s=4 and 5	2.459	**
Credibility	$\log(b_{i0})$	Mean effect of initial inverse scale parameter	2.189	**
Updating	$a_{i0}$	Initial shape parameter (fixed at 5)	5.000	---
Correlation	$\rho$	Interdependency between two rating stages	0.082	

\*\* (\*) Indicates 95% (90%) HPD interval does not contain 0.

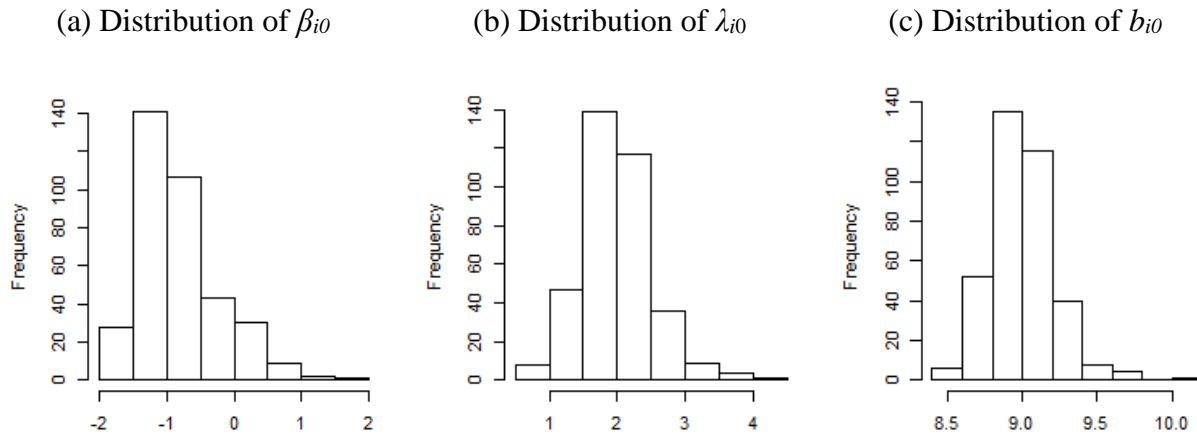
Table 3-5 reports the mean and standard deviation among individual-specific parameters. The large standard deviations for  $\beta_{i0}$  and  $\lambda_{i0}$  suggest that online reviewers are substantially heterogeneous in baseline posting propensity and rating evaluation (also see Figure 3-5). To explore the interdependence between baseline latent parameters at the individual level, we provide the pair-wise correlation matrix<sup>49</sup> among them in Table 3-6. The positive correlation between  $\beta_{i0}$  and  $\lambda_{i0}$  suggests that after controlling for other factors, online consumers who have higher baseline posting propensity appear to be more lenient in terms of giving numeric ratings. This finding is opposite to Moe and Schweidel (2012) who observe that active raters are more

<sup>49</sup> Alternatively, we can evaluate the posterior estimates of covariance.

negative. Finally, our estimate results indicate less heterogeneity across individuals in their initial perception of system reliability, as suggested by a small standard deviation for  $b_{i0}$ .

**Table 3-5.** Individual-specific Parameter Estimates

Model	Notation	Mean among Individuals	Std. dev. among individuals
Baseline propensity	$\beta_{i0}$	-0.831	0.598
Baseline evaluation	$\lambda_{i0}$	1.997	0.520
Initial learning status	$b_{i0}$	8.931	0.208



**Figure 3-5.** Distribution of Individual-specific Parameters

**Table 3-6.** Individual-specific Parameter Estimates

	$\beta_{i0}$	$\lambda_{i0}$	$b_{i0}$
$\beta_{i0}$	1.000	0.142	0.387
$\lambda_{i0}$		1.000	0.876
$b_{i0}$			1.000

### 3.6.1. Extension and Robustness Checks

In this section, we relax some of our model assumptions by incorporating other factors that might affect online raters posting behavior into our proposed model. The estimation results are consistent before and after we consider the following two robustness checks.

### 3.6.1.1. *The Effect of Quality Disconfirmation on Product Evaluation*

In our proposed model, we assume that quality disconfirmation enters the propensity model directly and does not have any impact on consumers' realized quality. That is, consumers do not factor their prior expectation about quality into product evaluation. In fact, marketing literature finds that in offline settings, a consumer overall satisfaction is affected by quality disconfirmation (Anderson and Sullivan 1993) and such relationship is empirically shown to be positive (Rust et al. 1999). Based on this theory, we now assume a consumer's rating evaluation is mainly driven by her overall product satisfaction  $S$ , which is a linear combination of her realized quality and quality disconfirmation:

$$Eval_{ijt} = S_{ijt} + \lambda_1 h_{ijt} + \lambda_{2,4} X_{jt}, \quad (3.25)$$

where  $S_{ijt} = Q_{ijt} + \gamma \cdot \Delta Q_{ijt}$  and  $\gamma$  is a new parameter to be estimated. With this specification, the posting propensity is now written as:

$$Prop_{ijt} = \alpha_i + \beta_1 \Delta \bar{Q}_{ijt} + \beta_2 \Delta \bar{Q}_{ijt}^2 + \beta_3 Cred_{it} + \beta_4 Q_{ijt} + \beta_5 Q_{ijt}^2 + \beta_{6,8} X_{jt}. \quad (3.26)$$

It can be shown that the mean of quality disconfirmation becomes:

$$\Delta \bar{Q} = (\tilde{R}_j + \lambda_{r0}) - (\bar{R}_{jt} - \delta_{it}) / (1 + \gamma). \quad (3.27)$$

Comparing (3.27) with (3.5), we can see that the inclusion of  $\gamma$  will bring the mean value of disconfirmation signal towards zero, provided  $\gamma > 0$ .

The estimation results (including parameter estimates and DIC) of the new model only have marginal deviation from those reported in Table 3, suggesting that the main results of this paper is robust even if we consider the impact of disconfirmation on overall product satisfaction. The

posterior mean of  $\gamma$  is 0.117 and is significant at 95% level. This result indicates that online rates tend to factor in their expected product quality when leaving product ratings.

### 3.6.1.2. *The Interaction between Disconfirmation and Rating Environments*

We have examined how a focal consumer’s posting decision is influenced by disconfirmation she encounters as well as rating environments she is exposed to. An interesting question to ask is: Is the disconfirmation effect itself also moderated by opinions expressed by the crowd? To answer this, we allow the effect of disconfirmation on posting propensity to interact with variables that characterize the rating environment (i.e. volume and variance of posted ratings) and add these two interaction terms into our propensity model. The parameters of interest are reported in table 3-7.<sup>50</sup>

**Table 3-7.** Effects of Rating Environments on Posting Behavior

<b>Effect</b>	<b>Coeff.</b>	<b>Signif.</b>
Volume on propensity	-0.008	
Variance on propensity	<b>0.023</b>	**
Volume on Disconfirmation Effect	0.026	
Variance on Disconfirmation Effect	<b>-0.008</b>	*

\*\* (\*) Indicates 95% (90%) HPD interval does not contain 0.

Consistent with the results shown in Table 3-3, we still find the evidence that the variance of posted ratings induces posting behavior from our extended model. Interestingly, the coefficient for “Disconfirmation  $\times$  Variance” interaction term is negative and significant. This indicates that the effect of disconfirmation is weakened by the level of dissension among posted opinions, perhaps because a consumer anticipates the review information to be noisy and hence become less sensitive to the disconfirmation effect. Moreover, the coefficient of “Volume on

<sup>50</sup> Since the parameter estimates do not have a substantial change, here we report coefficients for variables that are related to rating environments only.

Disconfirmation Effect” interaction has a positive sign. This also makes sense. The higher the volume of posted ratings, the more trustworthy consumers will perceive the review signal, and therefore the more sensitive they will be to the disconfirmation effect.

### 3.6.1.3. *The Use of the Long-term Average Rating as a Proxy for Product Quality*

We use the long-term average rating to proxy true product quality in our realized quality equation. Although we have justified that such proxy is reasonable (in Footnote 10), one may argue that the long-term average rating could still be a biased signal to some extent. Hu et al. (2006) argue that the average product rating would over-report (under-report) the true quality if consumers as a whole are more inclined to brag (moan) about the product when they are highly satisfied (disgruntled). To address this issue, we add a product-level random effect in the realized quality function. As a result, (3.2) can be rewritten as:

$$Q_{ij} = (\tilde{R}_j + \varpi_j) + \lambda_{i0}. \quad (3.28)$$

Parameter  $\varpi_j$  models the randomness that some products are overrated whereas some are underrated such that  $\varpi_j \sim N(0, \sigma_\varpi^2)$ . If the value of the parameter to be estimated  $\sigma_\varpi$  is small, we can conclude that the long-term average ratings more or less reflect true product quality.

The estimation results obtained from this new specification do not have noticeable difference from those obtained from our proposed model. The posterior mean (standard deviation) for  $\varpi_j$  is 0.011 ( $6 \times 10^{-5}$ ), providing supportive evidence that the long-term average rating well captures the true product quality. What makes our finding different from the extant work is that we explicitly consider consumers’ posting behavior is driven by quality disconfirmation (in addition to the realized quality) and such disconfirmation “ensures” that the average rating will

gradually converge to the true quality.<sup>51</sup> On the contrary, the conclusion by Hu et al. (2006) is contingent on an analytical assumption that consumers' decisions of whether to post are solely determined by perceived quality.

### **3.6.2. Simulations and Analyses on Consumers' Rating Behavior**

In this subsection we run two sets of simulations to further highlight the significance of our findings and better understand the online reviewers' rating behavior.

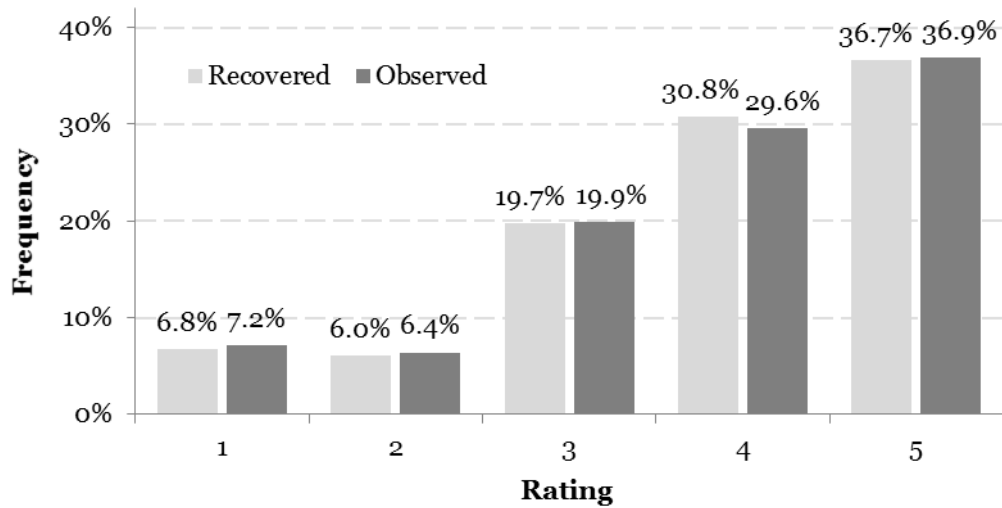
#### *3.6.2.1. Recovering unobserved rating scores*

Since our model explicitly considers online raters' decisions of whether to rate and what score to rate for the product, we are able to compute the latent posting propensity and evaluation for every purchase occasion. Utilizing the estimated cutoff points, we can further recover the unobserved rating scores for purchase occasions that do not lead to review submissions. The simulation procedure for recovering unobserved ratings is summarized as follows:

1. We compute the latent posting propensity per (3.15) and evaluation per (3.17) for all purchase occasions (including those lurking sessions) based on the posterior estimates.
2. Given the computed posting propensity, evaluation and estimated cutpoints, we simulate raters' decisions of whether to post per and what score to rate per (3.16) and (3.18).
3. We repeat Step 2 for 1,000 iterations and compute the average for the quantities of our interests across iterations.
4. To make sure the number of iterations is sufficient, we repeat Steps 2-4 in three parallel processes with different random seeds. We compare simulated results and do not find any inconsistency across processes.

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<sup>51</sup> We have a further discussion on the convergence of average ratings in Section 7.2.2.



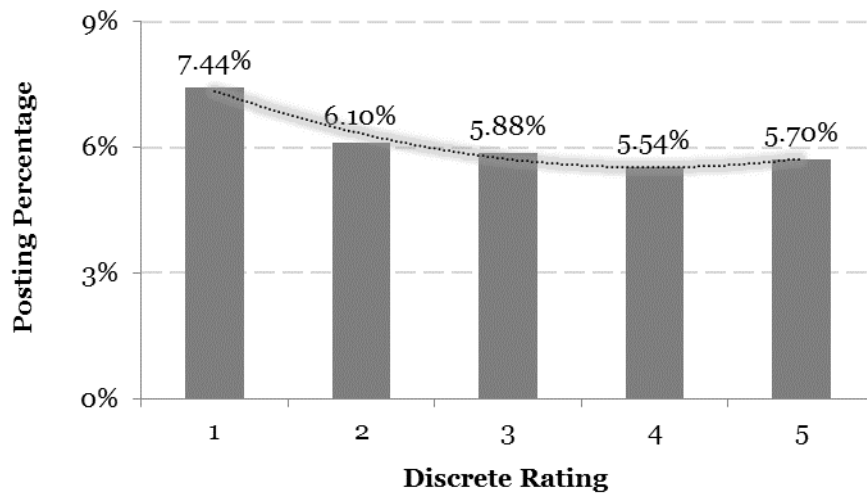
**Figure 3-6.** Simulated vs. Observed Ratings

We begin our analysis by assessing the performance of our model on describing online reviewers’ rating behavior. Figure 3-6 plots the frequency of simulated scores for occasions with review entries (presented by light grey bars) against the frequency of ratings observed in the data set (presented by dark grey bars). Our simulated results are very close to observed outcomes, indicating that the proposed model well captures the mechanism governing consumers’ rating decisions.<sup>52</sup>

To further understand the relationship between posting propensity and perceived product quality, we recover the unobserved scores for missing rating points. For interpretation purpose, we define *posting percentage* of a score  $s$  as  $\frac{\text{frequency of a score } s \text{ being posted}}{\text{frequency of a score } s \text{ being evaluated}}$  and plot the posting percentage for each of 5 scores in Figure 3-7. We find that the relationship between posting percentage and discretized product evaluation is best characterized by a left-skewed U

<sup>52</sup> We also run the same analysis for models without inclusion of quality disconfirmation (defined in Section 6.1). The results show that the proposed model outperforms other alternatives in terms of explaining rating behavior as well.

shape. In particular, negative experiences (rated as 1 or 2) have a higher chance to be reported (7.44% and 6.10%, respectively), relative to neutral (5.88%) and positive evaluations (5.54% and 5.70%). Such systematic difference is primarily caused by the stronger effect of negative disconfirmation. It is worth noting that the prior research observing a conventional U-shaped relationship is grounded on overall consumer satisfaction, whereas in this research we further decompose satisfaction into product evaluation and quality disconfirmation (Anderson and Sullivan 1993) and examine the impacts of both components on eWOM contribution. Such modeling advantage allows us to obtain a sharper insight into online raters' behavior and further confirm the U-shaped or J-shaped distribution of ratings commonly observed in online product review systems.



**Figure 3-7.** Posting Percentage Breakdown by Score

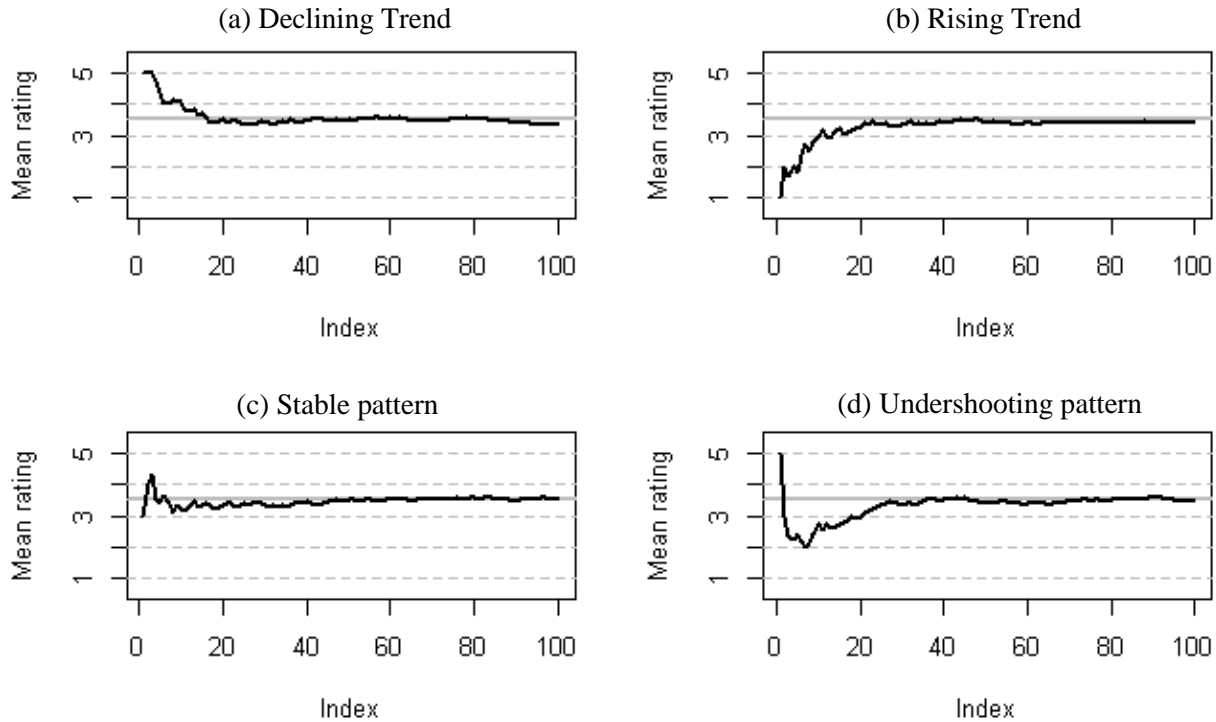
3.6.2.2. *Convergence of product ratings and the effect of review manipulation*

To highlight the effect of disconfirmation and the evolution of online product ratings, we perform our second simulation by following the procedure below.

1. We sample 3,000 individuals from the posterior estimates of population-level parameters ( $\Sigma$ ).
2. For each individual we simulate her decision of whether to post; for individuals who decide to rate, we simulate her decision of what score to rate. If a new rating is posted, we calculate the up-to-date mean ratings as well as other rating environment variables that will be used as control variables in the subsequent rating occasion.
3. We repeat Step 2 until 150 ratings are posted.
4. We repeat Steps 1-3 for multiple iterations.

Figure 3-8 plots different patterns of the evolution of online product ratings identified in our simulation results. It is evident that in the long run the mean rating will converge to its true quality (a 3.5 star in our simulation setting). If earlier buyers over-evaluate the product, perhaps due to the self-selection biases (Li and Hitt 2008), the inflated rating would urge disappointed consumers to express their negative opinions in the later period (see Figure 3-8a). While such declining trend of online ratings have been attributed to different effects such as self-selection biases (Li and Hitt 2008) and environmental factors (Moe and Schweidel 2012), the effect of quality disconfirmation identified in this research can also provide an alternative explanation. Perhaps more importantly, the disconfirmation effect also can be used to explain other commonly observed evolution patterns. For example, if the product is initially underrated, the subsequent buyers who derive positive disconfirmation would praise the product by sharing their pleasant experiences (as shown by Figure 3-8b). Interestingly, we also observe an undershooting property where the average rating first exhibits a steep declining pattern and then bounces back to a steady state (see Figure 3-9d). We believe that the quality disconfirmation is one of the most

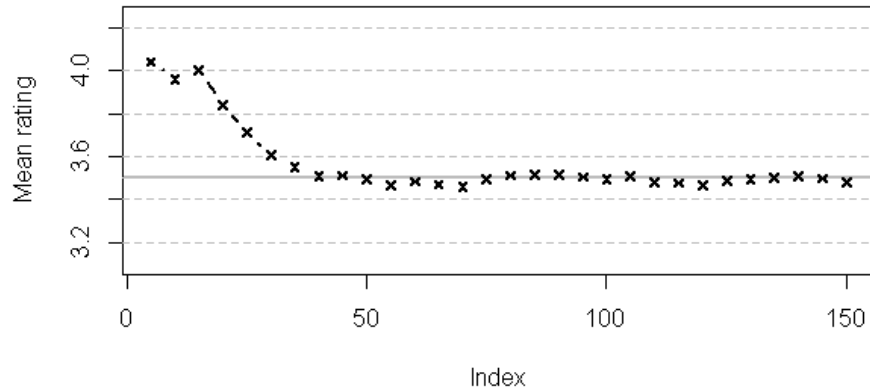
important forces driving consumers' posting behavior and such effect is also validated by different evolution paths of online ratings commonly observed across contexts and platforms.



**Figure 3-8.** Various evolutionary patterns of online product ratings

Our simulation can also be used to understand the effect of strategic manipulation of online product ratings. Similar to previous setting, we consider a scenario where the seller is able to strategically manipulate customer reviews such that the average rating will be as high as 4 at the 15-th entry (an inflation of a half star). We repeat Steps 1-4 listed above for 10 iterations and average the posted ratings cross iterations. As Figure 3-9 illustrates, while the mean rating can be inflated in the early stage through manipulation, it quickly drops and converges to the true quality (3.5). This result suggests that although fake online reviews can elevate prospective buyers' prior expectation, such effect would not last long as more and more disgruntled consumer diffuse negative WOM in order for anxiety reduction or vengeance purpose. On the

other hand, we can also expect that the damage caused by the malicious review manipulation by competing firms should be alleviated by subsequent positive ratings as well.



**Figure 3-9.** Evolution of average rating in the presence of inflated ratings in the early period

### 3.7. Conclusion

This paper examines the online reviewers’ rating behavior and attempts to explain several phenomena commonly observed across online rating systems. The early research on online product reviews has studied how user-generated ratings can be related to market performance whereas the recent work focuses on the impact of existing ratings on subsequent ones from a social dynamics standpoint (Lee et al. 2013; Moe and Schweidel 2012; Shen et al. 2013). Our work contributes to the latter literature stream by proposing a novel framework in which a focal consumer’s posting decisions has been influenced by others’ opinions before the product is purchased and consumed. In addition, we model how consumers’ perception of the system credibility evolves over time. By integrating these two features with other factors such as environmental and price effects, we are able to examine what drives consumers to voluntarily contribute online product ratings from a more comprehensive viewpoint.

Using a rich data set containing complete purchase and review history at the individual level, we empirically show that the rating behavior is driven by the degree to which the realized quality

deviates from the expected quality obtained from the same product. When interacting with the rating environments, the intensity of such effect is decreasing in the variance of posted ratings while increasing in the volume of submitted reviews. We also find that online raters tend to be more vocal when they perceive the review system to be less credible.

The main finding of this paper echoes prior research in some aspects but also provides different insights in others. On one hand, the disconfirmation effect can serve as the underlying driver of why people engaging in WOM such as concerns for others, anxiety reduction, vengeance, etc (Anderson 1998; Hennig-Thurau et al. 2004). The impact of quality disconfirmation on posting behavior can also (at least partially) explain 1) the commonly observed U-shaped distribution of online product ratings; and 2) the declining trend of average ratings at product level. On the other hand, based on our finding we believe that the long-term average rating can represent the true product quality. Through simulations, we demonstrate that consumers' perceived disconfirmation will "ensure" that the average rating converges to the true value in the long run. Our proposition to some extent disagrees with Hu et al. (2006) who argue that the mean score may provide misleading recommendation, which is contingent on an analytical assumption that consumers' posting decisions are solely triggered by their perceived quality.

Our empirical results shed light on the economic value of online product ratings in the following aspects. Manufactures or service providers should be aware that online reviewers are more prone to provide feedback when expectations do not match their own perceived quality. While manipulating product reviews by inflating numeric ratings can temporally boost the sales revenue, fake reviews could turn to be detrimental in the long run as disappointed customers

engage in negative eWOM.<sup>53</sup> Furthermore, online reviewers' perceptions of system reliability have a negative impact on their propensity to contribute reviews. Existing literature also shows that rating environment with smaller volume or lower valence discourages posting incidence (Moe and Schweidel 2012). To keep the online rating environment healthy and prosperous, policy makers and marketers who are in charge of online ratings campaigns should design various incentives for different consumers accordingly.

This study has some limitations and can be improved in several directions. First, our data has limited information which prevents us from examining online rating behavior in a more detailed way. For example, although we have utilized the aggregate review information, such as valence and variance, in formulating quality variables, we do not consider the possibility that some consumers may value positive ratings and negative ones differently. If we were able to observe the distribution of posted ratings at the time of purchase, we might be able to discover more interesting findings on the way consumers interpret review signal in the pre-purchase stage. Second, we think we have not yet fully utilized our valuable data. A promising direct for future research is to apply text mining techniques to extract the sentiments stored in the textual data and incorporate them into our econometric model. The synergy created by the integration of different research methods may allow us to provide a shaper insight into consumers' online rating behavior.

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<sup>53</sup> In our empirical model, we can only show that inflated ratings would drive disappointed buyers to leave negative numeric ratings. However, we cannot gauge the harm those negative textual reviews would do to the firm's reputation.

## Chapter 4 Summary and Conclusion

In my dissertation, I intent to provide a better understanding of how novel information systems reshape merchants' competitive strategies and influence consumers' decision-making processes, using both analytical and empirical methodologies. I hope those proposed studies may contribute to IS literature and open new pages for IS research.

The first essay of this dissertation examines the economic impact of the cashback affiliate model on e-businesses' pricing strategies. Through reimbursing a portion of the transactional amount to consumers in a form of cashback, merchants are able to gain incremental sales, and perhaps more importantly, exercise third-degree price discrimination via a unique digital dual channel. Despite several similarities, the cashback model distinguishes itself from couponing in many aspects. From an economic perspective, the main difference is that the presence of intermediary reallocates the market power between affiliated members and thus blurs the profitability of the underlying mechanism.

We first identify the conditions under which the cashback pricing is profitable. From a consumer's point of view, cashback shopping provides bargain hunters an attractive saving opportunity as the prices they pay are perceived lower. Surprisingly, our result shows that under some circumstances the "low" post-cashback price is actually high, relative to the uniform price in the absence of price dispersion. As a consequence, consumers as a whole could end up facing a higher price when the cashback model is adopted. In addition, the effect of current cashback on welfare is not monotone depends upon practice may increase or decrease the social welfare suffers from market inefficiency which stems from double marginalization. We propose channel coordination as a remedy to mitigate the reduction in social welfare. Our basic model is also

extended to investigate the impact of affiliate and merchant competition. Interestingly, the downstream competition leads to an increase in prices and thus hurts the market efficiency.

In the second essay of my dissertation, I attempt to answer a basic question: Under what conditions are consumers more likely to share their product evaluation online? Unlike prior research which assumes that the influence of existing ratings by others on subsequent ratings occurs in the post-purchase stage only, we postulate that such impact may take place when prospective buyers receive review information in the pre-purchase stage. To investigate the dynamics of consumers' rating behavior, we model how an individual's perception of system credibility evolves over time, and how such perception dynamically affects her decision of whether to post an online rating after product experience.

Our estimation results show that an online consumer's posting decision is driven by *quality disconfirmation*, a term which captures the discrepancy between her expected and realized quality obtained from the same product. That is, consumers are more likely to express their product opinions when the ex-post evaluation further deviates from the ex-ante expectation. Moreover, the effect of quality disconfirmation on posting behavior is moderated by rating environments where the focal consumer is exposed. Our results also show that online consumers tend to become less active in review contribution as they perceive the review system to be more reliable over time. Through simulations, we illustrate 1) the dissimilar reporting propensity across different levels of product evaluation; 2) the evolution of online product ratings over time; and 3) the effect of review manipulation on subsequent rating entries. This research contributes to the literature by providing a comprehensive understanding on the formation of online opinions based on a rich economic reasoning.

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