Online Product Reviews-Triggered Dynamic Pricing: Theory and Evidence

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Prior works offer compelling evidence that on the demand side of the market, user-generated online product reviews play a very important role in informing consumers' purchase decisions. On the supply side, however, the interplay between online product reviews and firm strategies is less understood. We build an analytical model that differentiates products based on consumers' preference for tastes (horizontal differentiation) or quality (vertical differentiation) and show that a firm is able to not only manipulate its pricing to influence online product reviews (thus influencing sales), but also adjust pricing dynamically in response to online word-of-mouth. Our model derives rich and testable results on possible price trajectories. To offer empirical support for the analytical predictions, we conduct a panel data study of prices and reviews. We adopt a difference-in-differences framework to address endogeneity challenges.

Key words: Pricing, Online Product Reviews, Analytical Model, Empirical Study

1. Introduction

Online word-of-mouth (WOM) plays an important role in both the demand and supply sides of the market. On the *demand* side, it empowers online consumers by reducing uncertainty, allowing consumers to learn about products and services and make smart purchase decisions (Dellarocas 2003, Wang et al. 2018). The majority of the extensive and growing literature examines online reviews from the *demand* side and finds that WOM has a significant impact on sales (e.g., Chevalier and Mayzlin 2006, Wang and Zhang 2009, Zhu and Zhang 2010).

If consumers rely on WOM information to make purchase decisions, it is imperative for firms to maintain a good online WOM profile. On the *supply* side of the market, how firms make use of WOM information becomes an important and interesting question. Despite the important strategic value of WOM on the supply side, surprisingly few studies address how WOM affects firms' decision-making.

There are several institutional reasons why WOM play an important role in supply-side strategies. First, firms no longer fully control information. In a traditional market, a firm can choose what information to release and how it is released. Today, various social media channels disseminate user-generated content that complements and competes with firm-generated information. Consumers often consider user-generated content to be more credible than information provided by firms (Bickart and Schindler 2011). Second, the availability of tremendous individual-level behavioral data on users and advancements in data analytics enable firms to react more quickly to consumer activities and gain a profit. Organizations such as Amazon and Harrah's have increased their revenue dramatically by making use of the consumer data they collect (Davenport 2006, Brynjolfsson and McAfee 2014). Firms' investments in IT allow them to monitor and analyze a large amount of data in a short period of time, making real-time personalization possible Sun et al. (forthcoming). Finally, an often-neglected effect comes from the tremendous reduction in menu costs. Given the ease of changing product prices online (i.e., reduced menu costs), firms can easily implement pricing strategies that rely on dynamic feeds of consumer and product data (Brynjolfsson and Smith 2000, Zhang and Feng 2011). Taken together, WOM can potentially have a significant impact on firms' strategies.

Firms are known to leverage channels of consumer reviews in several ways. The first, downright illegal, way is to post fake reviews (Dellarocas 2006). There is plenty of anecdotal evidence suggesting that firms fake WOM in their own favor. In September 2013, New York's attorney general fined 19 firms and several "reputation-enhancement" companies a total of $350,000 for posting fake reviews.[1] When there is a whole industry offering the service of providing fake reviews, it is not hard to imagine the size and magnitude of such activities. A recent study by Mayzlin et al. (2014), using a clever empirical design, finds convincing and economically significant evidence that hotels post fake positive reviews for themselves and negative reviews for competitors.

A second, sometimes unethical, way to manipulate WOM is to reward positive reviews and punish negative ones. For example, Ye et al. (2014) find that low-quality sellers may coerce buyers to revoke their negative feedback through retaliation. Many shops encourage people to click the "Like" button on their Facebook pages. Figure 1 shows an ad that encourages positive reviews by offering a raffle to win a $100 gift card. In an attempt to discourage negative reviews, a hotel in Hudson, NY, charged wedding couples $500 for each bad review posted by guests. The policy backfired and resulted in many negative reviews from angry visitors.[2]

[1] Source: http://www.theguardian.com/world/2013/sep/23/new-york-fake-online-reviews-yoghurt. Accessed May 2017.

[2] Source: http://www.cnet.com/news/hotels-500-fine-policy-for-bad-reviews-gets-low-marks/. Accessed May 2017.

Figure 1 **Reward for Positive WOM**

These illegal or unethical ways of managing WOM show firms' desperation with respect to new challenges in marketing. Moving toward more legal means of WOM manipulation, a third way firms can respond to WOM is to engage actively with consumers on social media platforms. Gu and Ye (2013) report that management response to consumers' comments can significantly improve future satisfaction of complaining customers. Adomavicius et al. (2013) find that consumer perceptions can be anchored by online recommendations. Shen et al. (2015) empirically show that platforms, such as Amazon and Barnes & Noble, can design online review systems to improve book reviewers' reputations by allowing them to choose the right product to review and the right rating to post.

This study looks at how WOM analysis enables supply-side strategies that go beyond direct intervention with WOM content. Consistent with existing literature, we argue that sellers can influence WOM generation through pricing, a traditional marketing tool. We model how a profit-maximizing seller needs to strategically monitor and react to online reviews and therefore change price dynamics for potential online reviews. In our model, consumers' utilities are influenced by both consumer characteristics (e.g., misfit costs) and product characteristics (e.g., product quality). These two dimensions are consistent with the horizontal differentiation of tastes and the vertical differentiation of quality levels in the literature.

By incorporating misfit cost and quality level with online reviews, our theoretical model generates some interesting insights into a firm's optimal price trajectory. The impact of online reviews can be quite different on products with different quality levels and misfit costs. More specifically:

1. Not every seller is affected by online reviews, and we identify conditions under which it is optimal for a seller to act as if online reviews do not exist.

2. Contrary to the conventional wisdom that firms need to cut the initial price to induce preferential future reviews, we find that a price-cutting strategy is not always needed, and it may even be beneficial for firms to charge a high initial price. Consequently, both the firm's initial price and profit are non-monotonic on the perceived quality of the product, or consumers' misfit cost.
3. As a result, the arrival of information makes it impossible to judge whether the firm is adopting a penetration or skimming pricing strategy solely from the price trend over time: a downward price trend can be observed even when the firm initially charges a low price, and an upward pricing trend can be observed even when the firm charges a high initial price.

We offer empirical support for these theoretical predictions with a panel dataset of books. We collect data from two sources (Amazon.com, henceforth Amazon, and Barnes & Noble, henceforth BN) to overcome the endogeneity problem of unobservable product and seller characteristics. The causal relationship is established with a difference-in-differences (DID) design, which has been used in the context of WOM by other studies (e.g., Chevalier and Mayzlin 2006, Zhu and Zhang 2010). Using the dataset, our empirical analysis supports the key findings of the analytical model and identifies firms' different pricing behaviors in response to reviews.

Our study is closely related to several prior studies and generates additional results by extending them. Li and Hitt (2010) propose the importance of considering perceived value (the difference between price and quality) in generating WOM. Their two-period model studies how first-period price may influence reviews and how a seller should choose an optimal strategy when facing such "price effects." They also use a linear empirical model to provide supporting evidence that online ratings react differently to price and perceived value. A key difference between their study and ours is that they focus more on how initial price may influence subsequent WOM, while our model goes beyond that and examines how price needs to be adjusted in response to WOM.

Yu et al. (2016) study the impact of consumer-generated quality information on a firm's pricing strategy. Different from their study, our model considers misfit costs and product characteristics and offers a more general theoretical framework. As a result, our model generates more realistic and more complex price patterns. In our model, the price can go up or down depending on these contingent factors. Finally, Kwark et al. (2014) build an analytical model to study the effect of WOM on vertical channel competition. In their model, WOM provides information to consumers about product quality and fit. Our model also captures these two dimensions of differentiation. Our work is different in that we do not study upstream competition; instead we focus our attention on firm's price adjustment decisions.

We contribute to the literature in several ways. First, while most prior WOM literature examines online product reviews' impact on demand, we offer theoretical and empirical implications on how WOM interacts with the sellers' pricing strategy on the supply side. Second, building on studies of customer acquisition, we contribute to the pricing literature by describing a mechanism that dynamically determines products' price trajectories. The dynamic nature of our model makes it highly relevant to e-commerce in the big data era, when real-time and dynamic information is constantly available and the cost of changing price is converging to zero (Brynjolfsson and Smith 2000). We show that the pricing strategies are more sophisticated than "penetration" or "skimming" pricing, depending on the product's misfit cost and perceived quality levels. Third, this research complements prior arguments for price's impact on WOM (e.g., Li and Hitt 2010, Kwark et al. 2014, Yu et al. 2016). Different from these previous studies that model the indirect pricing effect on sales through WOM, this research theoretically and empirically examines sellers' explicit use of WOM in their dynamic pricing strategies. Overall, we first propose a theoretical model to study how firms can improve their pricing by using WOM and then offer empirical evidence that such dynamic pricing strategies may have already been adopted by sellers in some e-commerce markets.

2. Prior Literature

2.1. Dynamic Pricing

Finding an optimal pricing plan is a very challenging task for retailers (Stigler 1964, Shapiro 1983, Villas-Boas 2004). In the current environment of rapid market development, firms need to continually react to changes (Athey and Bagwell 2008). Although useful, static models cannot describe the intricacies of the market in many situations (Zhang and Feng 2011, Mehra et al. 2012). The literature has seen an increased number of studies on dynamic pricing.

There are two commonly observed pricing strategies for new products: penetration pricing and skimming pricing (Hotler and Armstrong 2012). A penetration pricing strategy is helpful for building the reputation of a (perceived) low-quality product (Shapiro 1983), or for a seller of niche products to extract surplus from buyers with low willingness-to-pay (Bergemann and Valimaki 2006). Skimming pricing is effective when the market is highly differentiated, and consumers are not price sensitive (Noble and Gruca 1999).

Wernerfelt (1986) studies the implications of experience curves and brand loyalty for optimal dynamic pricing policy. Prices should decrease over time for high discount rates and steeper exogenous declines in variable costs. Conversely, prices should increase over time if experience curves affect fixed costs and if consumers are brand loyal. Zhao (2000) investigates firms' optimal advertising and pricing strategies when introducing a new product with a duopoly model. Advertising is used both to raise awareness about the product and to signal its quality. A low-quality firm has a strong incentive to increase its advertising spending from its optimal level. To deter the low-quality firm's pooling strategy, the high-quality firm should decrease its advertising spending so that mimicry is not appealing to the low-quality firm. Alba et al. (1999) explore the effects of the frequency and depth of discounts on consumers' price knowledge for competing stores and brands. Their results illustrate the importance of context in determining consumers' price knowledge in a competitive environment. Interestingly, in some situations, firms should increase the price to maximize the profit. Similarly, Krislma et al. (2007) argue that price increases, although rare in practice, may be a valid strategy for firms. They study when firms should raise prices and whether to increase prices across-the-board or target a specific segment of the customer base. Depending on market conditions, such as the market shares of the two firms and price knowledge across consumer segments, a firm may wish to implement targeted price increases in some situations, to introduce across-the-board price increases in others, and to keep the prices unchanged in still others. Su (2007) develops a model of dynamic pricing with endogenous inter-temporal demand. It is found that when high-value customers are proportionately less patient, markdown pricing policies are effective, because high-value customers buy early at high prices while low-value customers are willing to wait. In contrast, when high-value customers are more patient than low-value customers, prices should increase over time to discourage inefficient waiting. Erdem et al. (2008) develop a structural model of household behavior in an environment where there is uncertainty about brand attributes and where both prices and advertising signal brand quality. They show that price is an important signal of brand quality, and frequent price promotions may have the unintended consequence of reducing brand equity.

Although these prior studies generally examine dynamic price patterns, the driving force of dynamic pricing is not the continuous arrival of new information. In contrast to these studies, this paper explores how firms should be constantly aware of changes in the market environment and keep updating their knowledge by monitoring WOM. We argue that WOM-based dynamic pricing opens a new door for firms to achieve competitive advantage.

2.2. Pricing with Consumer Data

With the increasing availability of consumer data, in the age of big data, firms are able to improve their business decisions. Our study is aligned with the literature on dynamic price optimization using consumer data (Kohavi et al. 2002). In this stream of research, Lewis (2005) takes a dynamic programming approach to inspect optimal pricing when consumers' transaction history is available through Customer Relationship Management (CRM) systems. The study uses a latent-class logit model to examine customer buying behavior. The dynamic optimization procedure yields profit-maximizing price paths. In the same vein, Bertsimas and Perakis (2006) discuss a situation when the consumer demand function is not known *ex ante*. They present an optimization approach for jointly learning the demand as a function of price and dynamically setting product prices. In a recent study, Farias and Van Roy (2010) examine a dynamic pricing problem faced by a vendor with limited inventory and uncertainty about demand in a framework with an infinite time horizon. Since the vendor learns from transaction data, the strategy must take into consideration the impact of price on both revenue and future observations. Their proposed heuristic approach to pricing can lead to significant revenue gains over previously proposed methods. Pathak et al. (2010) find that more information regarding quality and fit of products can increase demand. At the same time, providing value-added services, such as WOM and recommendations, allows retailers to charge higher prices. The results of these studies can benefit not only e-commerce companies but also traditional retailers because consumer transaction data are available even without the Internet.

Transaction data are by no means the only source of consumer data that sellers can use. Rusmevichientong et al. (2006) develop a model of price optimization that leverages consumer preferences data that can be collected through a website's recommender system. Similarly, consumer shopping path data in traditional stores (Hui et al. 2009a,b) or browsing records in the form of clickstream data on e-commerce websites (Moe and Fader 2004a,b) can be valuable resources for sellers to optimize operations.

Different from these studies, in this paper, we explore how online product reviews can be useful for sellers, specifically, for pricing optimization.

2.3. Online Word-of-Mouth

One major type of WOM is online product reviews that inform consumers about product/service attributes. Ba and Pavlou (2002) and Chen and Xie (2008) argue that consumer reviews provide product-matching information that helps consumers find products that match their needs. Such supplementary information helps reduce consumers' uncertainty about products and facilitates sales. From this perspective, the elements and writing style of reviews affect their effectiveness. For example, Li and Zhan (2011) find that users prefer product reviews that are comprehensive (providing evidence and referring to product features) and easy to read. They also find that positive emotions in reviews increase perceived helpfulness. Along this line of research, other studies find that product types (experiential or utilitarian) moderate the effect of review features on perceived review helpfulness (Mudambi and Schuff 2010, Pan and Zhang 2011). Some recent studies find earlier reviews affect later reviews (Li and Hitt 2008, Wu and Huberman 2008) and social dynamics affect online reviews (e.g., Trusov et al. 2009, Moe and Trusov 2011, Samiei and Tripathi 2014). There are also studies exploring how to develop WOM systems to induce truthful reporting (Fan et al. 2005) and how user reporting habits may bias ratings (Hu et al. 2009). This stream of studies generally examines the usefulness of online WOM, but such studies look at WOM from only the consumers' point of view.

From the sellers' point of view, one important problem is the causal implications of online WOM on demand. There is a long-standing debate on whether online WOM is a predictor or an influencer of sales (Elberse and Eliashberg 2003). Several studies establish the causal effects of the valence, volume, and variation of online reviews (Godes and Mayzlin 2004, Chevalier and Mayzlin 2006, Duan et al. 2008, Chintagunta et al. 2010, Sun 2012). While generally review valence is associated with more sales (Dellarocas et al. 2007, Zhang et al. 2010), Berger et al. (2010) show that even negative reviews may have positive effects on sales, because they may increase product publicity, especially for lesser-known products. Lee et al. (2008) argue that the effects of negative reviews depend on the type of consumers. A high proportion of negative reviews will increase the conformity of high-involvement consumers only when the quality of those reviews is high. Kwark et al. (2016) show that the mean rating of online reviews of substitutive products has a negative role in purchasing, while the rating of complementary products has a positive role. The causal link between online WOM and sales is found to be affected by product and consumer characteristics or even the textual content of reviews (Forman et al. 2008, Hu et al. 2008, Zhu and Zhang 2010, Ghose and Ipeirotis 2011, Archak et al. 2011, Lee and BradLow 2011). These studies, although appealing to sellers, only examine how WOM changes demand. Fundamentally, they are still studies of *consumer* decision-making. Different from these studies, our paper examines how WOM may affect *seller* decision-making in pricing.

The aggregation of a seller's online WOM becomes its reputation (Utz et al. 2012). On business to consumer (B2C) websites, online reviews are generally on products. On consumer to consumer (C2C) websites (and third-party sellers on B2C websites), seller reputation can either be aggregated from product reviews or given by consumers separately. A high reputation may indicate a high level of seller trustworthiness, accurate product descriptions, and better services (McDonald and Slawson 2002). In general, consumers are willing to pay price premiums to sellers with better service and higher reputation (Venkatesan et al. 2006, Rabinovich et al. 2008, Ba and Pavlou 2002, Li et al. 2009, Liu 2006). There are exceptions, however; some studies find the opposite in the context of e-commerce. For example, Baylis and Perloff (2002) show that “good” Internet retailers of digital cameras and scanners provide superior service and charge relatively low prices, while “bad” Internet retailers charge relatively high prices for poor service. Ba et al. (2008) identify the “adverse price effect” and show that “low-recognition” sellers may decrease their product prices when they improve their services. Recently, Liu et al. (2012) suggest that a high-reputation seller could set higher or lower prices under different conditions. Aggarwal et al. (2012) study the impact of WOM on venture financing and find that negative WOM has greater impact than positive WOM. Although reputation is based on WOM, it is a long-term and relatively static concept.

Different from these prior studies on reputation, this paper focuses more on short-term and dynamic firm strategies in response to WOM changes.

2.4. Firm Pricing Strategies and WOM

Firms’ use of pricing and other operations, such as recommender systems (Oestreicher-Singer and Sundararajan 2012), to influence consumer decision-making is an increasingly important topic in the literature. Dou et al. (forthcoming) study firms’ selling versus leasing models for information goods when the consumer valuation depreciates. Wathieu and Bertini (2007) argue that the posted price has a critical impact on consumers’ willingness to pay. Depending on how consumers perceive the price, a monopolistic firm should either overprice (“transgressive pricing”) or underprice (“regressive pricing”). In the pre-Internet era, Kalish (1985) inspects “epidemic” information diffusion and adoption through advertising and traditional offline WOM, where information from early adopters reduces uncertainty for later adopters. If there is no uncertainty, the optimal price decreases monotonically. If early adopters can generate enough information, then the price can increase, because people are willing to pay a premium for reduced uncertainty. This pioneering paper established the first study of price trajectory patterns.

With the rise of online WOM, firms’ control over available product information is significantly weakened. The literature offers several possible firm strategies related to WOM. Firms can (1) manipulate WOM directly (Dellarocas 2006, Mayzlin et al. 2014), (2) improve WOM-specific services (Gu and Ye 2013, Adomavicius et al. 2013), or (3) use pricing to influence WOM (Jiang and Chen 2007, Li and Hitt 2010, Kuksov and Xie 2010, Jing 2011, Kwark et al. 2014, Yu et al. 2016). The third strategy is most relevant to our study.

Among the studies on using price to influence WOM, Jiang and Chen (2007) examine a seller’s pricing strategy when the product can either match or mismatch a consumer’s taste. They find that it is optimal to set a low price initially to attract expert users to give more positive reviews. Li and

Hitt (2010) investigate the impact of pricing on consumer reviews and find that uni-dimensional ratings can be substantially biased by price. Supporting this view, Chen et al. (2011) find that WOM volume and ratings are correlated with sellers' price setup. The intuition is that some consumers want to wait for initial online reviews before making an adoption decision. This social learning allows sellers to use pricing as a mechanism to manage and manipulate initial online WOM. Jing (2011) studies the market conditions under which *ex ante* homogeneous consumers may delay their purchases. Since consumers are inclined to postpone adoption to make more informed purchases, the firm can lower the first-period price to attract early adopters. Similarly, Kuksov and Xie (2010), using a two-period game, explore how a firm should use frills together with price changes to affect customer ratings. Li et al. (2011) examine the repeated purchase scenario and argue that consumer reviews may intensify price competition by altering consumers' propensity to switch among products. Yu et al. (2016) show that via the initial price, a firm not only influences its revenue but also controls the quality information over time.

Our study differs from these prior studies in several important ways. First, while all previous studies examine how pricing may influence WOM, we consider the mechanism through which WOM influences pricing. In previous studies, such manipulation of pricing is a strategy of second-order impact, because its influence on sales is exerted through WOM. In our paper, pricing is a strategy of first-order impact, as it directly influences profit. Bockstedt and Goh (2011) suggest that when the market becomes more competitive, firm visibility-enhancing and quality-signaling discretionary attributes become more effective tools affecting sales, whereas seller feedback scores become less effective. So the mechanisms behind the direction of influence are fundamentally different. Second, the empirical work in our paper specifically considers and addresses the endogeneity with a difference-in-differences approach to eliminate unobservable confounding factors. While DID designs are often used in examining demand-side causal relations, this study is perhaps the first one adopting this technique on the supply side. Finally, this paper differs from previous studies in that we focus on price trajectory and dynamic pricing. Dynamic pricing is achieved due to fast development of data analytics tools that can process WOM information in real time and the reduced cost of modifying prices according to pricing rules.

3. Analytical Model

Consider a firm that sells a new product to a population of consumers who are uniformly distributed in a straight-line segment [0,1] with density 1.[3] Consumers are differentiated by their horizontal

[3] In this paper, we mainly examine the firms' optimal pricing in Monopoly. When there exist two firms competing on selling the same product, consumers can read reviews at both websites and online reviews become a public good.

taste θ, that is, $\theta \sim U[0,1]$. Without loss of generality, assume that the product is located at 0 in this line segment.[4] Let C denote the misfit cost of a consumer when buying a product that is not at its ideal "location" or "fit." Holding the product quality as a constant, on the horizontal dimension, a high misfit cost C indicates a "niche" product, because only a small portion of consumers enjoy the product and their utility drops quickly as they move away from the product location. A low misfit cost C indicates that consumers' utilities are not heavily affected by their locations, and therefore, the product is likely to be a mass-market product.

Assume all the consumers arrive at the beginning of the game. Since consumer perceptions about the product are affected by the information available in the market, and such information updates frequently in Internet businesses, we model information updating in two stages ($t=0,1$), where $t=0$ represents the stage without any user-generated information, and $t=1$ represents the stage when user-generated information is produced and available. In practice, when a product is first released ($t=0$), there are no online reviews, so consumers make purchase decisions without such information. In the next stage ($t=1$), both consumers and the seller learn from consumer feedback and can form their respective strategies.

The firm sets its price p_t for each stage based on the distribution of consumer valuations, as well as the information available in the market. More specifically, in the initial stage ($t=0$), consumers form their expectations about the product quality (q_0) without any user-generated information. Consumer utility from consuming the product in stage 0 can then be represented by: $U_0(\theta) = q_0 - C\theta - p_0$.

After consuming the product, consumers who purchase the product in stage 0 may comment on the product based on their own experiences. Such information can be viewed by the remaining consumers before they make purchase decisions in stage 1. With such user-generated information, the remaining consumers update their opinions about the product quality to be q_1, which can be either higher or lower than q_0, based on the outcome of the review.

In this study, we focus on the strategies of firms and consider consumers in the simplest case. We assume that consumers are not forward-looking, such that they do not need to form expectations about future product reviews and product prices. Following Liu et al. (2017) and Caminal and Vives (1996), we assume that consumers can observe current prices, but not the previous prices. This

We provide the formulation of the duopoly problem in the Online Appendix 1. Our initial results indicate that while firms will have less incentive to invest in price-cutting strategies to induce good reviews, they may still end up cutting prices more when the competition is fierce.

[4] This is to facilitate the comparison with the duopoly case.

is because, even though technologies such as price comparison and price tracking are commonly observed nowadays (e.g., thetracktor.com), it remains difficult for every consumer to accurately monitor the exact price history due to (1) sellers' "price obfuscation" (Ellison and Ellison 2009) (for example, firms may bundle two or more products together with a single bundling price, or they may offer free shipping/low-price shipping on a product or a bundle of products, etc.), (2) firms' prevention of price comparisons (Wilson 2010), or (3) the existence of "uninformed" consumers who do not search or compare (Chen and Xie 2008, Xu et al. 2011, Geng and Lee 2013).

Then in each stage, the consumers who are indifferent between purchasing and not purchasing can be determined from $E[U_t(\theta)] = 0$; that is,

$$\theta_t = \begin{cases} \frac{q_t - p_t}{C} & \text{if } 0 < q_t - p_t < C; \\ 0 & \text{if } q_t - p_t \leq 0; \\ 1 & \text{if } q_t - p_t \geq C, \end{cases} \tag{1}$$

where $t = 0, 1$. Based on Eq. 1, the stage-0 demand of the firm is then θ_0, and the stage-1 demand is $\theta_1 - \theta_0$ if $\theta_1 > \theta_0$, and 0 otherwise.

3.1. The Interaction Between Price and Online Reviews

The relationship between price and online reviews is complex: on one hand, consumer reviews are affected by the stage-0 price (p_0) (Li and Hitt 2010); on the other, late-stage consumers' perception about the product quality (q_1) is affected by earlier reviews and then determines the product price in that stage. Here, we assume that consumers' perception about the product quality in stage 1 is affected by the stage-0 consumers' reviews (which in turn are affected by the stage-0 product price) in the following way:

$$q_1 = \begin{cases} q_0 + \frac{q_0 - p_0 - \mu}{C} & \text{if } p_0 < q_0; \\ q_0 & \text{if otherwise.} \end{cases} \tag{2}$$

In Eq. 2, the term $\frac{q_0 - p_0 - \mu}{C}$ can be either positive or negative. It is a function of stage-0 consumer welfare and can be understood as the impact of online reviews on consumers' stage-1 perception about the product quality. The parameter μ can be understood as the consumer "harshness," measuring how difficult it is to satisfy a customer, given the product quality and price. The higher the μ, the more difficult it is for a consumer to be satisfied and to give a "favorable" review, and thus the lower the perceived quality q_1 in stage 1. The lower the original price, the more likely consumers are to be satisfied with the product and thus give good reviews, which in turn will lead to a higher stage-1 perception about the product quality. Note that this assumption is consistent with the single-dimension rating framework in both Liu et al. (2017) and Li and Hitt (2010). The rationale is that consumers would compare their utility with the price they pay. For any given level of utility, a lower price is associated with higher satisfaction. As a result, a lower price induces better reviews.

3.2. Pricing Under the Influence of Review Generation

The game proceeds as follows. In each stage t, the firm sets a price p_t based on: (1) the distribution of consumer valuations in the market; and (2) the quality perceived by consumers (q_t), where the perceived quality in stage 1 is determined by Eq. 2. Consumers decide whether to purchase based on p_t (as well as previous consumer reviews about the product if in stage 1). After purchase, they provide product reviews and leave the market.

We use backward induction to solve this game. The firm's stage-1 decision problem is:

$$\max_{p_1} \pi_1 = \begin{cases} \left(\frac{q_1 - p_1}{C} - \theta_0\right) p_1 & \text{if } \frac{q_1 - p_1}{C} > \theta_0; \\ \text{any price} & \text{otherwise,} \end{cases} \tag{3}$$

from which we can obtain that in equilibrium, $p_1^* = \frac{q_1 - C\theta_0}{2}$ if $\frac{q_1 - p_1}{C} > \theta_0$. Plugging in $\theta_0 = \frac{q_0 - p_0}{C}$ and calculating the firm's profit, we have the equilibrium profit as $\pi_1^* = \frac{(q_0 - (1-C)p_0 - \mu)^2}{4C^3}$.

In stage 0, knowing that the price set in stage 0 will affect consumer reviews, which will in turn affect consumers' perception about the product quality in stage 1, the firm solves the following decision problem, which maximizes the total profit in the two stages:

$$\max_{p_0} \pi_0 = \left(\frac{q_0 - p_0}{C}\right) p_0 + \frac{(q_0 - (1-C)p_0 - \mu)^2}{4C^3}. \tag{4}$$

Solving the optimal prices p_0, p_1, we have the following lemmas[5].

Lemma 1. *When $C > \frac{1}{3}$ and $\alpha < q_0 < \beta$:*

$$\begin{cases} p_0^* = \frac{2C-1}{3C-1} q_0 + \frac{1-C}{(1+C)(3C-1)} \mu; \\ p_1^* = \max\{0, \frac{Cq_0 - 2C\mu}{3C-1} \mu\}. \end{cases} \tag{5}$$

$$\textit{where } \alpha = \frac{1-C}{C(1+C)}\mu + 3C - 1, \textit{and } \beta = \begin{cases} \frac{1-C}{(1+C)(1-2C)}\mu & \textit{when } \frac{1}{3} < C < \frac{1}{2}; \\ \infty & \textit{when } C \geq \frac{1}{2}. \end{cases}$$

Lemma 2. *When $C < \frac{1}{3}$ or $q_0 \leq \alpha$ or $q_0 \geq \beta$:*

$$p_0^* = \begin{cases} q_0 - C & if\ \frac{q_0}{2} > C; \\ \frac{q_0}{2} & if\ otherwise; \end{cases} \quad p_1^* = \begin{cases} \frac{C+1}{4C} q_0 + \frac{\mu}{2C} & if\ q_0 > \frac{2}{C+1}\mu; \\ any\ price & if\ otherwise. \end{cases} \tag{6}$$

where in stage 0, the firm's price is the same as the optimal price if there is only one single stage without information arrival.

It is surprising to see that when the product quality is perceived to be very high ($q_0 > \beta$), the firm's pricing strategy is the same as that when the product quality is perceived to be very low ($q_0 < \alpha$)— *in both cases, it is optimal to just maximize the stage-0 profit as if there is only one*

[5] All proofs of the lemmas and propositions are in the Online Appendix 2.

single stage without information arrival. This result is actually intuitive to understand: When the quality of the product is very low, no matter how much the price is cut, it is hard to generate favorable reviews; when the quality of the product is very high, consumers are willing to give favorable reviews even when the product is sold at a high price. In both cases, the firm is better off *to maiximize the single-stage profit without the influence of online reviews.* It is possible, though, that in stage 1 the firm cannot make any sales even with a zero price (if $q_0 \leq \frac{1}{C+1}$).

3.3. Benchmark: When There Are No Online Reviews

We are interested in the impact of online reviews on the firm's pricing strategy. That is, how should the firm adjust its pricing to optimally make use of online reviews? To answer this question, consider a benchmark case where there are no online reviews in both stages. In this case, consumers' stage-1 perception about the product quality is the same as that in stage 0, i.e., $q_1 = q_0$, because there is no additional information arrival. Using backward induction, the firm's stage-2 decision problem is:

$$\max_{p_1} \pi_1 = \begin{cases} \left(\frac{q_0 - p_1}{C} - \theta_0\right) p_1 & \text{if } \frac{q_0 - p_1}{C} > \theta_0; \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

From this we can obtain that in equilibrium $p_1^* = \frac{q_0 - C\theta_0}{2}$ if $\frac{q_0 - p_1}{C} > \theta_0$. Plugging in $\theta_0 = \frac{q_0 - p_0}{C}$ and Eq. 2, and calculating the firm's profit, we have $\pi_1^* = \frac{(q_0 - C\theta_0)^2}{4C}$.

In stage 0, the firm solves the following decision problem:

$$\max_{p_0} = \left(\frac{q_0 - p_0}{C}\right) p_0 + \frac{(q_0 - C\theta_0)^2}{4C}. \tag{8}$$

Solving the optimal prices p_0^b, p_1^b, where the superscript b represent the benchmark case, we have

$$p_0^{b*} = \begin{cases} \frac{2}{3} q_0 & if\ q_0 \leq 3C; \\ q_0 - C & if\ \text{otherwise;} \end{cases} \quad p_1^{b*} = \begin{cases} \frac{1}{3} q_0 & if\ q_0 \leq 3C; \\ \text{any price} & if\ \text{otherwise.} \end{cases} \tag{9}$$

Note that when there are no online reviews, the stage-1 price (if there is any positive sale) is lower than the stage-0 price, the same as in a standard sequential game.

3.4. The Impact of Information Arrival on the Pricing Strategy

3.4.1. Impact of Information Arrival on Stage-0 Price: Comparing Eq. 6 and Eq. 9, we can obtain the difference in firm's stage-0 prices, attributable to information arrival through online reviews. Define $\Delta P_0 \equiv p_0^{b*} - p_0^*$. We are interested in examining the sign of ΔP_0, which indicates whether the firm has an incentive to cut its price in stage 0 to attract favorable online reviews in stage 1. We define a pricing strategy as a "price-cutting" strategy if $\Delta P_0 > 0$.

Intuitively, when there exist online reviews, since the initial price of the product affects consumers' utility and in turn the reviews of the product, which ultimately affect later consumers' perception of the product, the firm has an incentive to cut its price in order to generate favorable online reviews. This price-cutting strategy, however, is contingent on the misfit cost as well as the product quality. For products with high misfit cost, consumers "far away" from the "ideal location" of the product are hard to satisfy and thus are less likely to give good reviews. Then the firm has less incentive to encourage these consumers to purchase the product by cutting its initial price, or may even raise its price to discourage them from buying the product. Similarly, for products with very high quality, since consumers are likely to give favorable reviews even with a relatively high price, the firm does not need to lower its initial price. In summary, whether or not a price-cutting strategy should be adopted depends on the product characteristics (the initially perceived quality level q_0, for example) and how likely consumers are to give favorable reviews (misfit cost C as well as μ.).

Proposition 1. *Compared to the benchmark case where there are no online reviews, the firm's pricing strategy under the influence of online reviews depends on both product characteristics and how likely consumers are to give favorable reviews (C, q_0, μ).*

1. *The firm adopts a price-cutting strategy in stage 0 (compared to the benchmark case) when the perceived quality, q_0, satisfies (1): $q_0 > \frac{3(1-C)}{1+C}\mu$ and $\alpha < q_0 < \beta$ and $C > \frac{1}{3}$; or(2): $q_0 > 3C$, and $C < \frac{1}{3}$ or $q_0 < \alpha$ or $q_0 > \beta$;*
2. *The firm is able to set a higher price in stage 1 than the benchmark case if consumers give good reviews relatively easily (that is, when $q_0 > \frac{10C}{2C+1}\mu$).*

Intuitively, a price-cutting strategy is helpful (Liu et al. 2017, Shapiro 1983, Bergemann and Valimaki 2006) either when the perceived quality is low (so that cutting price helps generate favorable reviews and boosts up the quality perception in stage 1), or when the misfit cost is not too large (so that the impact of favorable reviews is not too small). Proposition 1, however, shows that whether or not a price-cutting strategy is used is non-monotonic in either the perceived product quality or the misfit cost. Rather, it depends on the tradeoff between the cost and the benefit of adopting a price-cutting strategy. According to Eq. 2, the impact of online reviews on consumers' stage-1 product perception is decreasing in the misfit cost. When the misfit cost is very low (e.g., $C < \frac{1}{3}$), even though it is very effective for favorable reviews to enhance consumers' quality perception, the price-cutting strategy may not be necessary, if the perceived quality of the product is not too low ($q_0 > 3C$) and consumers are already satisfied even with a high price. When the misfit cost is higher ($C > \frac{1}{3}$), cutting price cannot effectively enhance consumers' stage-1 perception

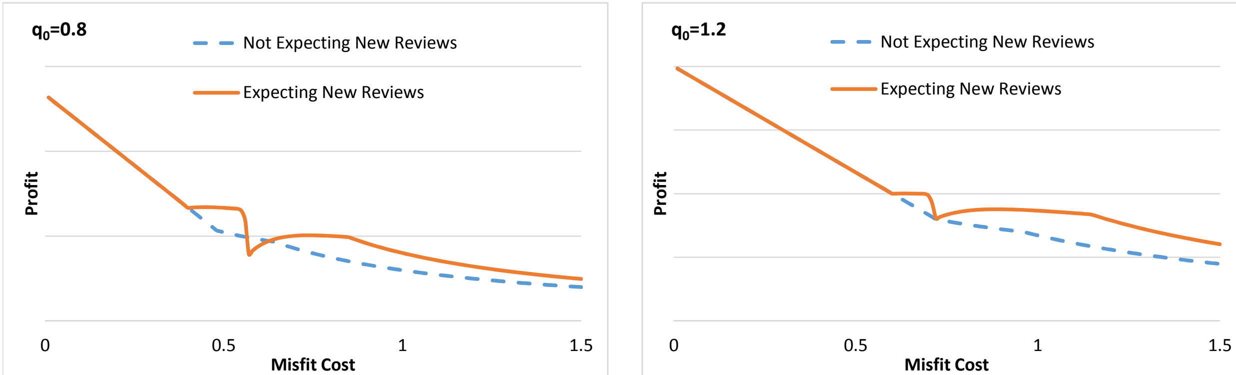

Figure 2 **Effect of Expected New Reviews on Profit**

about the product if consumers are relatively "harsh" ($q_0 < \frac{3(1-C)}{1+C}\mu$). So a price-cutting strategy will be used only when it is relatively easy for consumers to offer favorable reviews ($q_0 > \frac{3(1-C)}{1+C}\mu$).

Interestingly, Proposition 1 also shows that it is sometimes beneficial for the firm to charge a high stage-0 price when it expects information arrival in stage 1, when the perceived quality is either very low or very high. This is because, when the perceived quality is very low ($q_0 < \alpha$) with an expectation of negative reviews in stage 1, it is better for the firm to give up its stage-1 profit and sell as if there is only one single stage by setting a high price in stage 0. When the perceived product quality is high (e.g., $q_0 > \beta\mu$), the firm can also charge a high price in stage-0 without worrying about online reviews, because consumers will be satisfied by the high quality level and will offer favorable reviews even at a high price.

3.4.2. Impact of Information Arrival on Firm's Profit: Given the differences in stage-0 pricing strategies between the cases with and without information arrival, we further study how the existence of online reviews affect a firm's profit level.

Corollary 1. *Compared to the benchmark case where online reviews do not exist,*

1. *The firm's profits are the same with or without online reviews if the misfit cost is very low, or the firm's quality level is extremely high or extremely low: $q_0 > 3C$ and $C < \frac{1}{3}$, or $q_0 < \alpha(\mu, C)$, or $q_0 > \beta(\mu, C)$;*
2. *Online reviews can either enhance or hurt the firm in terms of profit, depending on the level of consumers' misfit cost.*

Figure 2 illustrates the profits in different scenarios. When the misfit cost is very low, the firm's profit is not affected by future information arrival since it adopts a pricing strategy as if there is only one single stage. When the misfit cost is higher, it is possible that the market is not fully covered and online reviews is possible to affect the firm profit. When the misfit cost is in the

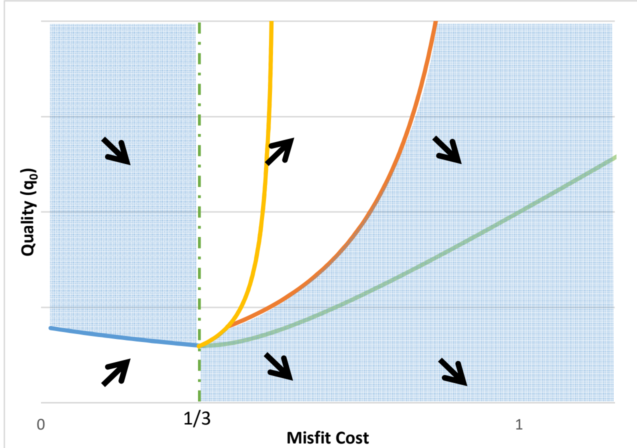

Figure 3 **Price Change from Stage 0 to Stage 1**

medium range, online reviews can be relatively effective in influencing consumer perceptions about the product. The firm is enticed to implement a costly price-cutting strategy. If such a cost is too high and the firm cannot make it up through future sales, online reviews hurt the firm's profit. The lower the quality level of the product, the more likely the price-cutting strategy is to hurt the firm's profit. When the misfit cost is relatively high, the effect of a price cut in inducing favorable reviews is limited, so the firm does not need to implement the costly price-cutting strategy. Interestingly, it can even charge a high inital price to prevent unwanted consumers who are likely to offer unfavorable reviews from purchasing the product. In this case, the presence of online reviews helps the firm, though the higher the misfit cost is, the less significant the impact of online reviews.

3.4.3. Effect of Information Arrival on the Price Trend Over Time: Proposition 1 shows the impact of information arrival on the firm's pricing strategy. Note that setting a lower price in stage 0 than in the benchmark case does not necessary imply that we will observe an upward price trend over time. It is possible that the stage-1 price is lower than the stage-0 price even with an initial price-cutting strategy, if the online reviews are not sufficiently "favorable" to boost up the price, or if it sells too many products in stage 0 and the remaining consumers' valuations are not sufficiently high. Define the price change between the two stages as $\Delta P \equiv p_1^* - p_2^*$. Proposition 2 studies the firm's prices over the two stages through the sign of ΔP:

Proposition 2. *Expecting that consumers will be influenced by online reviews, the firm's stage-0 price is higher than the stage-1 price in the following scenarios:*

1. *when* $C < \frac{1}{3}$*:* $(C-1)q_0 + 2\mu > 0$ *or* $q_0 > \beta$ *or* $q_0 < \alpha$*;*
2. *when* $\frac{1}{3} < C < 1$*:* $q_0 < \frac{2C^2+C+1}{(1-C)(1+C)}\mu$ *;*
3. *when* $C > 1$.

We illustrate Proposition 2 in Figure 3, where the arrow heads show the upward or downward price trend in each region, defined based on the misfit cost and quality. Combining Proposition 1 and Proposition 2, we can see that even with a price-cutting strategy, we can observe a downward price trend. Similarly, even when the firm raises its price in stage 0, we may still observe an upward price trend. The firm is able to set a higher stage-1 price when it induces sufficiently "favorable" online reviews, but this may (when $C < \frac{1}{3}$ and $q_0 < \frac{2C^2+C+1}{(1-C)(1+C)}\mu$) or may not (when $C < \frac{1}{3}$ and $(C-1)q_0 + 2\mu > 0$) be due to an initial low price. An upward price trend can occur if the product quality is so high that consumers give good reviews even when the product is sold at an a high initial price.

Similarly, a downward price trend can be observed either because it is not able to generate favorable online reviews (when $C < \frac{1}{3}$ and $(C-1)q_0 + 2\mu < 0$), or because consumers have a sufficiently high misfit cost ($C > 1$), such that the impact of online reviews is limited and the firm either does not need to cut its price in stage 0, or only needs a very limited price cut.

In summary, a downward price trend can be observed even when the firm initially sets a low price, and an upward price trend can be observed even when the firm has a high initial price. The arrival of information enriches the pricing literature about penetration and skimming pricing in the literature (Hotler and Armstrong 2012, Shapiro 1983, Bergemann and Valimaki 2006, Noble and Gruca 1999).

4. Empirical Support

Our analytical model suggests that the seller has different optimal pricing strategies in response to product reviews given differences in product quality and consumers' misfit cost. In this part, we empirically examine whether such a phenomenon exists in practice.

4.1. Testable Hypotheses

We focus on companies' pricing strategy along with the change of market information. In the analytical model the change of market information is simplified to two stages, where the second stage has more information than the first stage. Empirically, a product's market information can be reflected in the product description and consumer reviews, where consumer reviews is the part that changes in most cases. In this research we use the number of reviews as a proxy of the market information that can help consumers better understand the product and examine how price changes with the change of the number of reviews.

As shown in Figure 3, the relationship between price and number of reviews has different characteristics in the zones defined by different quality and misfit cost. Based on the analytical propostions, we make the following hypotheses:

H1a: A firm would increase its price with the increase of number of reviews when product quality is low and misfit cost is low.

H1b: A firm would reduce its price with the increase of number of reviews when product quality is high and misfit cost is low.

H2a: A firm would reduce its price with the increase of number of reviews when product quality is low and misfit cost is medium.

H2b: A firm would increase its price with the increase of number of reviews when product quality is high and misfit cost is medium.

H3a: A firm would reduce its price with the increase of number of reviews when product quality is low and misfit cost is high.

H3b: A firm would reduce its price with the increase of number of reviews when product quality is high and misfit cost is high.

4.2. Data

In this study we uses data on books to test the hypotheses. Books are chosen since they are an experience good with both a product quality dimension and a consumer taste dimension that matches well with our theoretical model. Moreover, books have unified ISBN IDs that allow us to match entries on different websites to build an econometric model.

We collect a panel dataset of matched books from Amazon[6] and BN. We choose five categories of books on Amazon for data collection (Contemporary Fiction, General Science, International Politics, Investing, and Pregnancy & Childbirth) and collect price and review information every three days during the period from July 13, 2010 to November 7, 2010. Due to the limitations of Amazon's application programming interface (API), we could not collect all items from each category. Instead, we collect the most popular books and latest books in these five categories to a maximum number that is allowed by Amazon and then find the corresponding items at BN. In our dataset, some popular books are old (up to 55 years old). Since the pricing and sales of these

[6] In this study, the data collected from Amazon are for products sold by Amazon, not by third-party sellers.

books may be quite different from relatively newer books, we keep only the books published within five years of the time of data collection. To have a stable observation of price, we keep items with at least 10 price records. It is also necessary to have both review and sales-rank records on both websites to implement the empirical study. After data cleaning, we have a total of 1,095 books in 40 periods. In this paper, we conduct the analysis on books with 1-year, 3-year, and 5-year histories for robustness tests.

Due to the great variations in prices, we do not directly use price as the dependent variable. We normalize prices by defining a variable called *pricerate*, which is an item's sale price divided by its vendor-provided list price (i.e., pricerate=1-*percentage discount*). This operation absorbs many factors that may explain price differences across items. One major factor that affects product pricing is sales volume. We follow previous studies and use *LogRank=ln(Sales Rank)* to proxy for sales volume (Brynjolfsson et al. 2003). In addition, we use the number of consumer reviews and average rating to characterize the online WOM. Since the distribution of the number of reviews is highly skewed, we use *LogNReview=ln(Nreview+1)* to represent review volume.

4.3. General Setup of the DID Model

Although this paper studies the impact of online reviews on the supply side of products, the endogeneity problem that plagues the demand side continues to pose empirical challenges. We develop a DID model by extending Chevalier and Mayzlin (2006) to rule out possible endogenous factors. In the DID model, the first difference of the model is across the two websites, thus we are able to remove observable and unobservable product-level characteristics. The second difference is on different times of a product's lifecycle through panel data analysis, therefore we are able to control for time-varying factors that influence both websites. We adopt a fixed-effect model to estimate the model parameters. We are cautious and always conduct poolability and Hausman tests to make sure that the fixed-effect model is appropriate for our dataset.

To explain the setup of the DID model, let us look at the impact of determinants $\mathbf{X}$ on the dependent variable *pricerate*. We can build two models on seller A (Amazon) or B (BN), respectively, in the tth time period after item i is on the market. If we assume a one-period time lag between the independent and dependent variables, the model is:

$$pricerate_{i,t}^{A;B} = \lambda_\tau + \psi_i + \eta_{i,t-1} + \phi^{A;B} + \zeta_\tau^{A;B} + \nu_{t-1}^{A;B} + \mu_i^{A;B} + \mathbf{X}_{i,t-1}^{A;B}\Gamma^{A;B} + \epsilon_{i,t}^{A;B}, \tag{10}$$

where τ is the calendar date corresponding to t for product i. λ_τ captures market-level effects, such as the macro economic environment and the seasonal price changes. ψ_i is a product time-invariant effect, which may be caused by the nature of the product, such as author or product quality. $\eta_{i,t-1}$ is a product time-variant effect, such as the discount caused by product lifecycle. ϕ^A and ϕ^B are website-specific time-invariant effects, such as price differences caused by their supply chains or targeted markets. ζ_τ^A and ζ_τ^B are website time-variant effects, such as website-specific promotions. ν_{t-1}^A and ν_{t-1}^B are website-level strategies to promote products according to their lifecycle. (This strategy is the same across products, but changes with respect to t.) μ_i^A and μ_i^B are product-website time-invariant effects, such as website-level special offers for certain types of products. $\mathbf{X}_{i,t-1}^{A;B}$ are our focal independent variables that vary across time, products, and websites. The remaining variables are random noise terms for the two websites, $\varepsilon_{i,t-1}^A$ and $\varepsilon_{i,t-1}^B$, which may include product-website time-varying effects.

With this model setup, the time dimension is the age of products on the market. Thus, $\eta_{i,t-1}$ captures the possible price change if there is no extra information over time and if price is decided solely based on product lifecycle. By taking the differences across the two websites, we can eliminate its impact, the seasonality effect, and the unobserved product quality effect shared by the two websites. We get the following model:

$$\Delta pricerate_{i,t} = pricerate_{i,t}^A - pricerate_{i,t}^B = \phi + \zeta_\tau + \nu_{t-1} + \mu_i + \mathbf{X}_{i,t-1}^A \Gamma^A - \mathbf{X}_{i,t-1}^B \Gamma^B + \varepsilon_{i,t}, \quad (11)$$

where $\phi = \phi^A - \phi^B$, $\zeta_\tau = \zeta_\tau^A - \zeta_\tau^B$, $\nu_{t-1} = \nu_{t-1}^A - \nu_{t-1}^B$, $\mu_i = \mu_i^A - \mu_i^B$, and $\varepsilon_{i,t-1} = \varepsilon_{i,t-1}^A - \varepsilon_{i,t-1}^B$. In the second difference of the DID model, ϕ and ζ would be captured by the time fixed effects. In addition, we also incorporate dummy variables on product age to ν and μ is captured by item fixed effects. After this operation, we are able to obtain the coefficients for $\mathbf{X}_{i,t-1}^{A;B}$.

Similar to Chevalier and Mayzlin (2006), we use a two-way panel model with time fixed effects to conduct the second differencing with respect to time. After this differencing, the parameter estimates Γ will give us unbiased estimates of the effects of online review arrival on price.

4.4. The Impact of Market Information on Book Price

In our econometric model, we consider the number of reviews as the independent variable that is a proxy for market information that help consumers better understand the product. Moreover, in a traditional dynamic pricing model, a seller would inspect the sales volume of a product (i.e., demand) when making changes to pricing. Thus, we capture sales volume using control variables $LogRank_{i,t-1}^{A;B}$.[7] We also control the online product reviews valence $Rating_{i,t-1}^{A;B}$, reflecting consumers' perception of the product. We modify Eq. 11 to:

$$\begin{aligned}\Delta pricerate_{i,t} = {} & \beta_1 LogNReview_{i,t-1}^A + \beta_2 LogNReview_{i,t-1}^B + \gamma_1 LogRank_{i,t-1}^A \\ & + \gamma_2 LogRank_{i,t-1}^B + \gamma_3 Rating_{i,t-1}^A + \gamma_4 Rating_{i,t-1}^B + \phi + \zeta_\tau + \nu_{t-1} + \mu_i + \varepsilon_{i,t}.\end{aligned} \quad (12)$$

[7] As discussed in previous research, there is a linear correlation between Log sales rank and sales volume. The coefficient may vary across websites. In our model, this difference is absorbed in the model coefficients.

According to the analytical model's prediction, the impact of market information (number of reviews) on product pricing depends on consumers' misfit costs and product quality. For book quality, we use the Amazon rating at the end of our data collection period as an indicator of product quality (*Quality*).[8] We create an interaction between *Quality* and number of reviews to capture quality's effect and modify Eq. 12 to:

$$\begin{aligned}\Delta pricerate_{i,t} =& \beta_1 LogNReview^A_{i,t-1} + \beta_2 LogNReview^B_{i,t-1} + \beta_3 Quality_i \cdot LogNReview^A_{i,t-1}\\ &+\beta_4 Quality_i \cdot LogNReview^B_{i,t-1} + \gamma_1 LogRank^A_{i,t-1} + \gamma_2 LogRank^B_{i,t-1}\\ &+\gamma_3 Rating^A_{i,t-1} + \gamma_4 Rating^B_{i,t-1} + \phi + \zeta_\tau + \mu_i + \nu_{t-1} + \varepsilon_{i,t}.\end{aligned} \tag{13}$$

For misfit cost, following Sun (2012), we employ the standard deviation of user ratings on BN.com in our data collection period to represent book misfit cost. A higher variance means the book is niche and misfit cost is higher. To ensure the measurement on standard deviation is valid, we restrict the analysis to products with more than five ratings, resulting in 430 books. The rating standard deviation of these books ranges from 0 to 2.67 with a bell shape. Since the analytical model predicts that misfit cost's effect varies in three levels, we incorporate a quadratic variable of misfit cost and create interactions between it and other independent variables in Eq. 14:

$$\begin{aligned}\Delta pricerate_{i,t} =& \beta_1 LogNReview^A_{i,t-1} + \beta_2 LogNReview^B_{i,t-1} + \beta_3 Quality_i \cdot LogNReview^A_{i,t-1}\\ &+\beta_4 Quality_i \cdot LogNReview^B_{i,t-1} + \beta_5 LogNReview^A_{i,t-1} \cdot Misfit_i\\ &+\beta_6 LogNReview^B_{i,t-1} \cdot Misfit_i + \beta_7 Quality_i \cdot LogNReview^A_{i,t-1} \cdot Misfit_i\\ &+\beta_8 Quality_i \cdot LogNReview^B_{i,t-1} \cdot Misfit_i + \beta_9 LogNReview^A_{i,t-1} \cdot Misfit^2_i\\ &+\beta_{10} LogNReview^B_{i,t-1} \cdot Misfit^2_i + \beta_{11} Quality_i \cdot LogNReview^A_{i,t-1} \cdot Misfit^2_i\\ &+\beta_{12} Quality_i \cdot LogNReview^B_{i,t-1} \cdot Misfit^2_i + \gamma_1 LogRank^A_{i,t-1}\\ &+\gamma_2 LogRank^B_{i,t-1} + \gamma_3 Rating^A_{i,t-1} + \gamma_4 Rating^B_{i,t-1} + \phi + \zeta_\tau + \mu_i + \nu_{t-1} + \varepsilon_{i,t}.\end{aligned} \tag{14}$$

4.5. Results

Table 1 shows the summary statistics of our dataset. There are 40 time periods of data in the two datasets. We only provide a summary of the last period for illustration. The table contains variables *Price* (in cents), *pricerate*, *Rank* (sales rank), *LogRank*, *Rating*, *NReview*, and *LogNReview*. In general, Amazon prices are lower than BN prices. Amazon generally has more reviews than BN. The average rating levels on Amazon and BN are similar.

The empirical results of the model are reported in Table 2. In building the model, we calculate robust standard errors with clustering at individual item level to control for potential heteroskedasticity and within-cluster correlation in error terms.[9] The coefficients on control variables are consistent with prior studies. Sales rank has a significant impact on price. For example, the

[8] Note that the smallest Amazon rating increment is 0.5. In our dataset, the ratings range between 1.5 and 5.

[9] Clustering at the Amazon book category level yields similar significant results.

Table 1 **Descriptive Statistics for Time Period Nov 7 2011 on Books**

	n	mean	std dev
$Price^A$	1021	1692.23	1772.37
$Price^B$	1021	1830.53	1731.75
$ListPrice$	1021	2368.52	2351.01
$pricerate^A$	1021	0.73	0.13
$pricerate^B$	1021	0.79	0.10
$Rank^A$	1021	261336.40	531589.50
$Rank^B$	996	181516.60	193772.60
$LogRank^A$	1021	11.02	2.07
$LogRank^B$	996	11.18	1.83
$Rating^A$	1019	4.26	0.61
$Rating^B$	1021	4.14	0.82
$NReview^A$	1021	82.88	295.20
$NReview^B$	1021	64.87	495.46
$LogNReview^B$	1021	3.07	1.43
$LogNReview^B$	1021	2.03	1.53

sales-rank coefficient for Amazon is positive and statistically significant, suggesting that there is a negative relation between demand and price. If the sales of a book is higher (sales rank is lower), the retailer will have room to reduce the price.[10]

As predicted by the analytical model, the response of the seller's price to the market information (number of reviews) varies with misfit cost and product quality. In our main model, Amazon Reviews' effects are significant on all the related variables. Figure 4 illustrates the joint effects of these variables. In the figure we vary the values of quality and misfit cost to create different combinations of zones. Within each zone, we calculate the coefficient on $LogNReview$ to make the color of the zone, where positive coefficients are colored red and negative coefficients are colored blue. We also put up arrows and down arrows to annotate the direction of the correlations. We find that the visualization of the empirical results perfectly matches with the major part of the analytical model's predictions in Figure 3 .

First, when books' misfit cost is low (the standard deviation of BN ratings is less than 1.8 according to the quadratic varible's curve) and book quality is low, product price increases with the availability of more market information. In other words, sellers tend to take a price penetration strategy and set a low initial price to gain positive reviews and later raise the price to gain profit. When book quality is high, product price decreases with market information, which thus demonstrates the price-skimming effect. H1a and H1b are supported.

[10] The dependent variable of the DID model is the price difference between Amazon and BN. Since the left-hand side variable is Amazon minus BN, the opposite signs of variables on the two websites means the same direction of effect. Note that we do not study the price difference in this research. Through the differencing, we are able to extract the unbiased effect of information arrival (through online reviews) on price.

Table 2 Reviews' Impact on Book Price (* p<0.1; ** p<0.05; *** p<0.01)

	Main Result		Sub Sample		AZ Std Dev as Misfit	
	Coefficient	Std err	Coefficient	Std err	Coefficient	Std err
$LogRank^A_{t-1}$	0.003**	(0.001)	0.004**	(0.002)	0.003***	(0.001)
$LogRank^B_{t-1}$	-0.004**	(0.002)	-0.003	(0.002)	-0.009***	(0.003)
$Rating^A_{t-1}$	0.010	(0.008)	0.011	(0.012)	0.020*	(0.012)
$Rating^B_{t-1}$	0.005	(0.005)	-0.004	(0.005)	0.003	(0.006)
$LogNReview^A_{t-1}$	-0.188*	(0.096)	-0.348*	(0.193)	0.124	(0.107)
$LogNReview^B_{t-1}$	-0.006	(0.397)	0.906*	(0.523)	0.023	(0.067)
$Quality \cdot LogNReview^A_{t-1}$	0.062**	(0.026)	0.107**	(0.047)	-0.023	(0.024)
$Quality \cdot LogNReview^B_{t-1}$	-0.003	(0.094)	-0.246**	(0.125)	-0.005	(0.015)
$LogNReview^A_{t-1} \cdot Misfit$	0.671**	(0.264)	0.784*	(0.453)	0.421	(0.874)
$LogNReview^B_{t-1} \cdot Misfit$	-0.040	(0.565)	-1.484**	(0.733)	-1.974**	(0.805)
$Quality \cdot LogNReview^A_{t-1} \cdot Misfit$	-0.187***	(0.066)	-0.228**	(0.108)	-0.175	(0.204)
$Quality \cdot LogNReview^B_{t-1} \cdot Misfit$	0.017	(0.133)	0.400**	(0.175)	0.554***	(0.210)
$LogNReview^A_{t-1} \cdot Misfit^2$	-0.330*	(0.178)	-0.262	(0.273)	-1.576	(1.538)
$LogNReview^B_{t-1} \cdot Misfit^2$	0.012	(0.210)	0.531**	(0.262)	6.089**	(2.446)
$Quality \cdot LogNReview^A_{t-1} \cdot Misfit^2$	0.090**	(0.043)	0.079	(0.063)	0.549	(0.387)
$Quality \cdot LogNReview^B_{t-1} \cdot Misfit^2$	-0.005	(0.049)	-0.141**	(0.062)	-1.708**	(0.677)
Coefficients of dummy variables on seasonal effect omitted						
# Items	430		253		871	
# Data points	12,895		6,684		26,823	
R^2	0.813		0.833		0.777	
$Adj - R^2$	0.796		0.808		0.764	

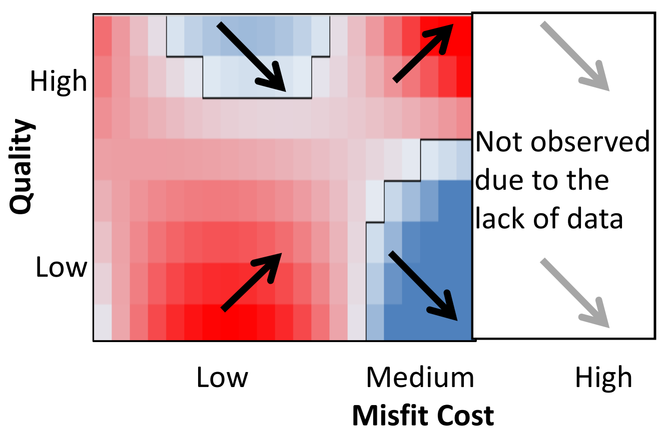

Figure 4 The Relationship Between Price and Number of Reviews Under Different Quality and Misfit Costs

Second, when misfit cost is relatively high (when the standard deviation of BN ratings is greater than or equal to 1.8), sellers tend to increase price for high-quality products, taking advantage of the previously accumulated reviews. For low-quality products, sellers tend to set a high price initially to grab the possibly interested buyers to gain profits. H2a and H2b are supported.

Limited by the dataset we have, we do not fully capture the effect if misfit cost continues to increase in our empirical analysis (there are only 20 products with higher than 2.1 standard deviation of the BN rating in our dataset). Thus, we do not empirically observe the theoretical prediction that both high-quality and low-quality products will take a price-skimming strategy on high misfit cost. However, our empirical analysis generally offers supporting evidence to the theoretical predictions.

To alleviate the concern about unobservable website-product factors that may affect the results, we conduct the same analysis on a subsample with similar demand across websites as a robustness check. We select products that have a similar number of reviews on the two websites; specifically the number of reviews on one website is not more than 3 times the number of reviews on the other website. The subsample accounts for about 35.5% of the entire data. The descriptive statistics of the sample are reported in the Online Appendix 3. The results of the regression are reported in the second column of Table 2. As we can see, the signs of the coefficients of the two samples are consistent, except that BN reviews' effects become significant.

As another robustness check, we use the standard deviation of Amazon ratings as a measure of misfit cost. The major problem of using this measure is that Amazon reports the average rating, which essentially smooths their variations. But its standard deviation still has a correlation with the standard deviation of individual ratings and a relative value in indicating the misfit cost. We restrict the misfit cost calculation to products with more than five ratings, resulting in 871 books with the Amazon rating standard deviation ranging from 0 to 0.7 with a bell shape. The results of the robustness check are reported as the third column in Table 2. As we can see, the Amazon related variables are not significant, since misfit cost essentially is based on Amazon information. But the signs of the significant coefficients of BN variables are consistent with the first robustness check and consistent with the coefficients on Amazon variables in the main results. In Online Appendix 3, we also illustrate the joint effect of quality and misfit cost on the relationship between price and number of reviews.[11] As we can see, it is very much consistent with our main result with the cutoff of low and medium misfit cost becoming 0.35.

In the model, we use quadratic terms of misfit cost to capture the nonlinear relations between variables. One may be concern that the quadratic term may have multicollinearity with the main term. To address this concern, we mean-centered misfit cost and repeated the experiments as a robustness check. Although the numerical values of regression coefficients changed slightly, we find that the general results are consistent and the findings remain valid.

[11] Since the significant coefficients are all on BN reviews, the figure corrects the sign to reflect the relationship between price and review increase.

5. Conclusion

This paper argues that sellers can employ online product reviews to develop better pricing strategies. We first build a theoretical model to examine a seller's optimal pricing strategy when online WOM information is taken into consideration. Without consumer reviews or the WOM effect, the optimal price should go down over time due to reduced demand. With consumer reviews, online WOM's effect on pricing depends on both the consumer characteristics (such as misfit cost) and product characteristics (such as product quality). We find that online reviews have a non-monotonic impact on a firm's pricing strategy, as well as on a firm's profit, in the dimensions of both product quality and misfit cost. Surprisingly, the impact of online reviews is quite limited when the product quality is at an extreme (extremely high or extremely low) or when the misfit cost is very low. Expecting future information arrival (online reviews), the firm can either employ a price-cutting strategy or raise its stage-0 price. The price adjustment strategy is sufficiently sophisticated such that we can no longer conclude whether a price-skimming or penetration strategy is adopted just from observing an upward or downward price trend. That is, when there is information arrival such that the firm can dynamically change the prices, prior pricing insights from static models no longer hold. Predictions of the analytical models are supported by evidences from our empirical study. Extending prior studies on the "price effects" on reviews (Li and Hitt 2010, Yu et al. 2016), we show empirical evidence of reviews' impact on pricing strategies used by market leaders.

Online product reviews are arguably one of the most easily accessible sources of marketing data for online retailers. It is possible to build analytical tools to learn consumers' opinions from online WOM. Few prior studies examine this strategic variable in pricing. We fill this gap by developing a theoretical model to address firms' optimal dynamic pricing problem with a unified framework that features quality uncertainty, risk aversion, and online product reviews. Since menu cost is practically trivial for online retailers and it is not difficult to program automatic price changes based on live feeds of online review data, sellers should be able to adopt similar pricing strategies and respond rapidly to online reviews.

Our work can be improved upon in several ways. First, we only examine the case when the seller has sufficient market power to change its price. Consequently, our results are applicable only to dominant players in various markets. Small retailers may not have such power to influence price and therefore will not be able to adopt the strategies suggested in this paper. In an extension in the Online Appendix, we examine a case where two firms are competing. A possible future direction would be to study a fully competitive market and examine followers' strategies under the influence of dominant players. Second, this research only examines the seller's pricing decision assuming zero marginal production cost. Future work can also look at the case when the costs of producing/acquiring the products are non-zero and examine how such cost influences the seller's price adjustments in the presence of online reviews. Third, the theoretical model has only two stages. While we believe it successfully captures the key features of the market for relatively new products, it is desirable to examine multiple stages of products' life cycles in future studies. Such models may offer a more nuanced view of learning, competition, and strategic reactions and make it possible to extend our empirical study to a longer term. Fourth, by taking a DID framework, our empirical model makes assumptions on the commonalities of two websites' pricing strategies in considering the product's lifecycle and the unobserable product-website time-varying factors to be random and i.i.d. In the future, with more detailed data from the sellers, it is possible to build more sound econometric models to capture the different factors' impacts in a more accurate manner. Fifth, the products we examined are physical books, which can be quite different from other products/services. But our theoretical model does not have assumptions on product categories and is general enough to offer insights for other products/services, too. For virtual products such as ebooks or online videos, with lower marginal cost and reduced complexity of logistics, the results obtained are likely to carry over. Further empirical analysis should be conducted to verify the results for other products such as home appliances, restaurants, etc. Sixth, besides modeling manipulating online reviews through price adjustments, this paper does not consider other forms of review manipulations such as fake reviews. We believe that examining the impact of such "fake reviews" on firm pricing is a promising future direction.

Finally, even with the empirical evidence of such dynamic pricing strategies, we have to caution the reader that the strategies derived from our theoretical model may not have been adopted by practitioners. The reason is that we cannot rule out the possibility that these book sellers could obtain the information from other channels such as traditional offline WOM and firm-initiated market research, etc. But clearly information acquisition from online WOM is cheaper and more timely compared to these more traditional channels. To this end, consistency between our empirical findings and the theoretical predictions should offer support for firms to explore the application of such strategies in more settings.

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