Pricing New Goods in the Presence of Multi-channel Social Learning and Online Fake Reviews in Social Networks

Emergent Research Forum papers

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Abstract

Launching a new product usually involves uncertainty. The rapid development of e-commerce stimulates social learning in social networks, profoundly changing consumers’ behaviors. Online product reviews can be classified into first-party and third-party ones regarding publishing channels, but different manipulations of first-party reviews could affect their credibility. Moreover, third-party reviews may provide solutions to above mentioned problems to some extent. However, many prior studies have been conducted on how single-channel social learning affects pricing schemes, ignoring effects of multi-channel social learning and fake reviews. This study aims to fill up the gaps by constructing stylized mathematical and empirical models to investigate consumers’ decision rules and monopolist’s two dynamic pricing policies given dual-channel social learning and different reviews manipulations. The ultimate purpose of this research is to provide useful guidelines for pricing new products and the governance of E-commerce market, which may be relevant to future research of big data in finance.

Keywords

Dynamic pricing, multi-channel social learning, fake product reviews, social networks.

Introduction

The release of new product is always accompanied with quality uncertainty. Traditionally, offline Word of Mouth (WOM) communication is the only means of spread of information about the product, through which consumers gain knowledge of the new product only through friends who have already made a purchase previously. Additionally, traditional business models have continuously tried dynamically revising prices based on the offline WOM communications. However, it always seems too hard for firms to
obtain and refine traditional WOM information timely and efficiently, further suppressing the realization of optimal dynamic pricing schemes.

Fortunately, the rapid development of e-commerce stimulates the appearance of online product reviews and the social learning phenomenon (i.e., consumers learn about product quality from online reviews in social network), which profoundly changes consumers’ evaluation of product and purchase behaviors, and arouses the concern of interdisciplinary research as well (Chevalier et al., 2006; Narayanan et al., 2009; Yu et al., 2013; Kwark et al., 2014; Zhang et al., 2015). Specifically, firms and consumers may not initially know the true quality of the new product, but learn about it through some form of a social learning process, adjusting their estimates on its quality along the way and making possible pricing strategies and purchase decisions accordingly (Papanastasiou et al., 2014b).

Actually, online product reviews can be categorized into first-party and third-party reviews according to the publishing channels. Generally, first-party reviews are published on the platforms set up by sellers to promote its own products or services, and third-party reviews are published freely without promotion purposes on those online channels independent from sellers (e.g., China’s HankowThames, America’s Zagat etc.). However, due to the anonymity of online reviews and the manipulations of first-party reviews for own interests, the credibility of online reviews is greatly affected. Fortunately, third-party reviews (Chen et al., 2005) and consumers’ adaptive learning from own repeated purchases (Zhao et al., 2013) can effectively avoid above problems to some extent. Though explosive studies have been conducted on how single-channel social learning affects inventory decisions and pricing schemes etc. (Jing, 2011; Sun, 2012; Ifrach et al., 2014), few investigate the potential effects of multi-channel social learning and online fake reviews on practical operations.

To cope with above research gaps, we construct stylized mathematical models to investigate consumers’ purchase decision rules as well as the monopolist’s dynamic pricing policies given the coexistence of first-party, and third-party product reviews as well as different reviews manipulations. Finally, to examine our mathematical models, we plan to design appropriate empirical models to test our main theoretical results by utilizing online product reviews. Overall, our ultimate purpose is to provide certain theoretically and practically guiding significance for the pricing of new products and the government of E-commerce market.

Literature Review

The first related literature stream focuses on investigating the interaction between single-channel online product reviews (mostly first-party reviews) and consumer decisions, and demand, and inventory decisions, and dynamic pricing strategies etc. (Chen et al., 2008; Papanastasiou et al., 2014a; Papanastasiou et al., 2014b; Zhang et al., 2015). Yu et al. (2013) study the influence of social learning on a strategic firm’s responsive pricing strategy in the presence of strategic consumers, but they emphasize the additional value for the firm and the consumers. Papanastasiou et al. (2014b) adopt a simple two-period model to analyze two classes of dynamic-pricing polices (i.e., pre-announced pricing and responsive pricing) when consumers may strategically delay their purchase decision in anticipation of product reviews. Social learning among consumers is critically determined by the structure of social networks and significantly influenced by the explosion of various social media. Recently, Zhang et al. (2015) examine consumers’ social learning in friend-network against stranger-network.

The second literature stream is related to the manipulations of reviews. A strand of work in computer science, statistics and engineering have designed various efficient algorithms to detect fake reviews or reviewers (Lau et al., 2011; Jensen et al., 2013; Li et al., 2014). In economics and consumer behavior literature, Dellarocas (2006) theoretically analyzes how strategic manipulation of Internet opinion forums affect firm’s profits and consumer surplus under static pricing policy. Sun (2012) theoretically and empirically examines the impact of the variance of product ratings on market outcomes like demand and profits. Jensen et al. (2013) explore how language expectancy influences the credibility attributions of anonymous online product reviews, by extending the language expectancy theory to the online setting. However, it can be easily noted that majority of the existing literature choose empirical and statistical methods (Hu et al., 2011; Qiu et al., 2012; Jensen et al., 2013; Reichelt et al., 2014), not stylized mathematical models (Dellarocas, C., 2006; Sun, 2012).
Additionally, our study also relates to the literature investigating experience goods (Dellarocas et al., 2007; Floyd et al., 2014) and Bayesian learning rule (Narayanan et al., 2009; Ifrach et al., 2014). To conclude, the study of social leaning has drawn more and more attention from interdisciplinary sciences. However, few scholars investigate the potential effects of multi-channel social learning and different reviews manipulations on practical operations with stylized mathematical models theoretically. Therefore, this paper tries to fill up this research gap, aiming to provide certain theoretically and practically guiding significance for the pricing of new products and the government of E-commerce markets.

**Model Design**

**Dynamic Pricing Models with Credible Dual-channel Social Learning**

We consider a monopolist selling a new product of ex ante quality uncertainty to consumers over two periods. The market involves a continuum of customers with total mass $M$ normalized to one, and at most one unit of the product is demanded by each consumer during the selling seasons. Consumer $i$’s wealth-equivalent net benefit from the purchase comprises two components: a preference component $x_i$, and a quality component $q_i$, in the population are assumed to conform to the uniform distribution $U[0,1]$, and each customer has private knowledge of her idiosyncratic preference component. The ex-ante uncertain quality component $q_i$ represents the product’s quality for customer $i$, whose value can be learnt only after purchase and experience of the new product. Further, the distribution of ex post quality perceptions in the population is hypothesized to be Normal, $q_i \sim N(q, \sigma^2_q)$, where $\sigma_q$ is the product’s unobservable mean quality and $\sigma_q$ captures the degree of heterogeneity in post-purchase quality perceptions.

Specifically, we assume ex post quality perceptions on first-party platform follows Normal distribution $q_i \sim N(q_1, \sigma^2_{q_1})$, and the distribution of ex post quality perceptions on third-party platform conforms to $q_i \sim N(q_3, \sigma^2_{q_3})$. For generality, we also assume that $q_1 = q_3 = q$ if the monopolist doesn’t manipulate the first-party reviews. The two normal distributions are supposed to be independent for simplicity. Thus customer $i$’s gross utility from purchasing the product in period $t, t \in \{1,2\}$, will be defined by $u_{it} = x_i + q_i - p_t$, where $p_t$ is the price of the product in period $t$.

The object of social learning (SL) is the product’s unobservable quality $q$. We assume that both parties (i.e., the firm and consumers) share a common and public prior belief over $q$, avoiding the pricing signals resulting from information asymmetry. Such prior belief over $q$ is expressed in our model through the Normal Random variable $q^*_p$ and $q^*_p \sim N(q_p, \sigma^2_p)$ with $q_p$ normalized to zero for generality (Papanastrasiou et al., 2014b). All customers adopting the product in the first period report their ex post derived product quality, $x_i$, to the rest of the market through product reviews via the first-party or third-party online review platform. In the beginning of the second period, the firm and consumers observe the reviews of first-period buyers and update their common belief over the product’s mean quality from $\widehat{q^*_p}$ to $\widehat{q^*_u}$ according to Bayes’ rule. Specifically, if a mass of $n$ customers purchase and review the product in the first period, we assume $n_1 = \alpha_1 n$ reviews will be generated on the first-party platform, and $n_1 = \alpha_2 n$ ones will be generated on the third-party platform. Moreover, we set $0 \leq \alpha_1 \leq 1, 0 \leq \alpha_2$, which can be interpreted as the penetration rate of reviews on corresponding platform.

The average rating of these reviews on the two platforms is denoted by $R_1, R_3$, respectively. Thus, $R_1, R_3$ are both normally distributed, i.e., $R_1 \sim N(q_1, \sigma^2_{R_1})$, $R_3 \sim N(q_3, \sigma^2_{R_3})$, and the updated belief $\widehat{q^*_u}$ follows Normal distribution $\widehat{q^*_u} \sim N(q_u, \sigma^2_{q_u})$ with mean $q_u = \frac{q_1 n_1 + q_3 n_3}{n_1 + n_3}$ and variance $\sigma^2_{q_u} = \frac{\sigma^2_{q_1} n_1 + \sigma^2_{q_3} n_3}{n_1 + n_3}$, wherein $\gamma_1 = \frac{\sigma^2_{q_1}}{n_1}$ and $\gamma_3 = \frac{\sigma^2_{q_3}}{n_3}$ are defined as the SL intensity parameters on each platforms, respectively.

We propose to examine two pricing policies in the presence of credible dual-channel social learning (a) pre-announced pricing (Yin et al., 2009), and (b) responsive pricing (Cachon et al., 2009). Consumers observe the firm’s announcements and purchase the product only if their expected utility from purchase is non-negative. The firm seeks to maximize its overall expected profit. For simplicity, we neglect the discount factors of consumers’ utility and the firm’s profit as well as the cost the firm incurs serving the
consumers, and the firm operates in the absence of any binding capacity constraints. We will construct stylized mathematical models to reveal the social outcomes produced by credible dual-channel online product reviews under different pricing schemes in the future.

**Dynamic Pricing Models with Fake First-party Reviews and Credible Third-party Reviews**

In this section, we will extend the base models established previously to incorporate different online product reviews manipulations. In particular, based on our assumptions, we go on supposing that the manipulated first-party reviews follows the truncated Normal distribution $TN(q, \sigma^2_1, \alpha_1, \alpha_2)$ on the first-party platform. Thus, we obtain $R_1 \sim TN \left( q - k_1 \frac{\sigma^2_1}{n_1}, \frac{\sigma^2_1}{n_1} \right)$, $R_2 \sim N(q, \sigma^2_2)$.

Here, $k_1 = \frac{\phi(a_2) - \phi(a_1)}{\phi(a_2) - \phi(a_1)}$, $k_2 = 1 - \frac{\phi(a_2) - \phi(a_1)}{\phi(a_2) - \phi(a_1)} - \left[ \frac{\phi(a_2) - \phi(a_1)}{\phi(a_2) - \phi(a_1)} \right]^2$, $\alpha_1 = \frac{a_1 - q}{\sigma^2_1}$, $\phi$ and $\Phi$ denote the standard normal distribution pdf (i.e., probability density function) and standard normal cdf (i.e., cumulative distribution function) respectively. With the new distribution of the updated quality evaluation obtained, similar (to the base models) research will be performed in the future.

**Empirical Models to Test Mathematical Models**

The subsequent empirical models are meant to examine our conclusions derived from above mathematical models by adopting online product reviews data, which will be completed in our future research.

**Conclusion**

In summary, in response to the research gaps and deficiencies of extant research identified, we will try to solve the following four problems (models) in the future, namely (a) pre-announced pricing with credible dual-channel social learning, and (b) pre-announced pricing with credible first-party reviews and credible third-party reviews, and (c) responsive pricing with credible dual-channel social learning, and (d) responsive pricing with incredible first-party reviews and credible third-party reviews. Moreover, results comparisons between the four models will be operated to reveal important implications. Finally, all the theoretical models proposed will be tested with appropriate empirical studies by utilizing online product reviews data.

**REFERENCES**


