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An Experimental Investigation of Product Competition and Marketing in Social Networks

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Abstract

We conduct computational experiment using Facebook data to evaluate competing firms' initial market seeding and subsequent targeted marketing strategies that influence consumers' new product adoption decisions. We find that firms generally overspend their advertising budget in the market seeding phase. In the subsequent market advertising phase, a coupon strategy (equivalent to price discount) generally yields higher market share than the strategy of distributing free product samples. The effect is more significant when both price and product quality are low. We offer managerial insights into firms' effective competition strategies for new product introduction in the presence of consumers' word of mouth effects in social networks.

Keywords: Computational Experiment, Price Competition, Word of Mouth, Targeted Marketing, Social Network

1. Introduction

Advanced information technologies such as smart phones and mobile apps have led to increasing connectivity of consumers through their social media interactions. This paradigm shift has resulted in changing patterns of product evaluation and purchase decisions. When firms introduce new products, they must consider how the word of mouth (WOM) effects among consumers influence the efficacy of product pricing and marketing strategies. In this research, we examine consumers' new product adoption behavior in a social network and study firms' retail competition under the WOM influence and network effects.

Specifically, we consider two competing firms that sell substitutable new products in a social network. Consumers have heterogeneous valuation of the product, which depends on both the product quality and a positive network effect. The product quality is unobservable to a consumer, but the consumer can infer it from the WOM influence through her social interactions with other consumers. The two firms make decisions about product quality, price, initial seeding and subsequent targeted marketing strategies for selling the new product. We investigate two targeted marketing strategies: a *coupon strategy* that offers price discount for a full product purchase without revealing the true product quality, and a *sample strategy* that reveals the true product quality by offering free product samples without giving price discount for the full product purchase.

Because of the inherent dynamics and uncertainty in consumer product evaluation, the structural influence of the social network, and the firm's initial seeding and subsequent marketing

strategies on the propagation of WOM information, it is impossible to perform traditional equilibrium analysis. We therefore conduct computational experiment to evaluate the market equilibrium outcome. We find prisoner's dilemma exists in social media marketing under retail competition—because of competitive concerns, firms generally overspend on initial market seeding and advertising. In fact, both firms would be better off were they advertise less aggressively. Our results show that coupon strategy generally yields higher market share than the sample strategy. The effect is more significant when both price and product quality are low. We offer new insights into firms' marketing strategies for new product introduction in the presence of both WOM influence and social network effects.

2. Related Literature

Research on consumer behavior shows that consumers' product evaluation and purchase decisions are influenced by their reference groups (Bearden and Etzel, 1982). For example, Chen and Xie (2008) study how firms should manage and strategically influence the consumers' online WOM interactions. Aral et al. (2011) and Dou et al. (2013) show that firms can strategically engineer the strength of network effects via social media.

In addition, prior research shows that initial seeding of the network plays a significant role in maximizing the spread of influence. How the firm maximizes its product sales by strategically influencing the WOM diffusion in a given network through a targeted set of individuals is termed as the influence maximization problem (Kempe et al. 2003). Consumers' new product adoption behavior in a social network can be modeled as cascading processes, where actions chosen by nodes (consumers) influence the subsequent behavior of neighbors in the network graph (Chierichetti et al., 2012; Martin et al., 2014). We complement this line of research by considering firms' competition in a social network.

3. Problem Formulation

3.1 Sequence of the Game

In this section, we describe the firms' strategies and consumers' decision making.

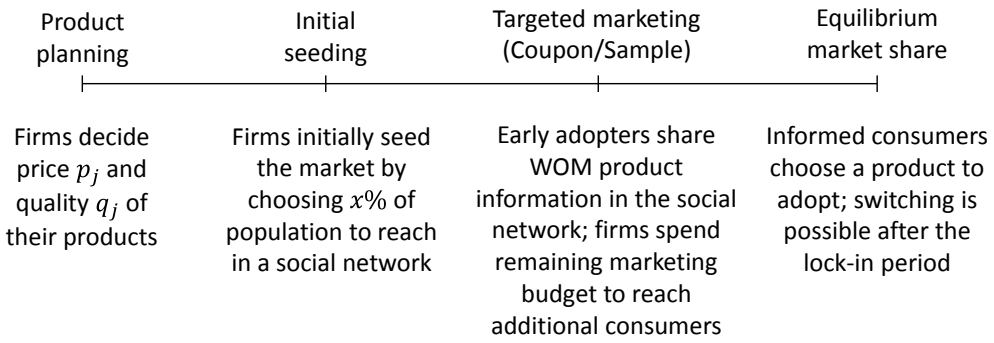

Figure 1. Sequence of the Game

Figure 1 depicts the sequence of the game. Consider two firms developing competing new products. In the product planning period, the two firms choose to produce either a high quality (q_H) or low quality (q_L) product. They engage in price competition. Let p_j, where $j = 1,2$, be the price firm j charges. We assume the product price information is common knowledge.

When introducing the new product to market, each firm makes two strategic decisions to target consumers and influence consumers' subsequent adoption behavior: 1) the *initial seeding* phase that triggers the first time purchase of a new product and brings product awareness to these early

adopters; 2) the subsequent *targeted marketing* phase that aims to reach additional prospective consumers and to convert them to final purchasers, considering the WOM influence from early adopters in the social network. We assume each firm has a fixed budget. We allow each firm to allocate its budget between the two phases. In our computational experiment, the initial seeding is implemented in round 0 and the targeted marketing is implemented from round 1 onwards till convergence to the market equilibrium.

Consumers who are aware of a product make product adoption decisions. Upon adoption, there is a lock-in period τ in which the consumer cannot switch to the other firm's product. Rational consumers may switch to the other firm's product if she is unlocked and if her overall utility derived from alternative product is higher than the adopted product. Because the consumer's product valuation depends on both the perceived product quality and the network value, both can be influenced by the consumer's network neighbors, switching is definitely possible. The final market equilibrium is achieved when no consumers have incentive to change their adoption decisions.

3.2 Firms' Decision Making

The firm's decision making includes two phases. The first is the initial seeding phase. The two firms simultaneously make the initial seeding decisions to bring consumer awareness. Each firm decides the proportion of population to reach in round 0, expressed as $x_j\%$. We assume convex cost of advertising, which implies that advertising cost increases at an increasing rate when firms attempt to reach more consumers.

The second phase is the targeted marketing phase. Starting from round 1, each firm has opportunities to reach more consumers in each subsequent round with the remaining marketing budget until the budget runs out. In this phase, firms preferentially reach potential customers based on their *centrality* measures in the social network (i.e., either *highest* degrees to maximize reach or *lowest* degrees to minimize competition). There are two strategies to choose from: *sample strategy* and *coupon strategy*. The two strategies have different cost implications to the firms. When the firm gives out free samples to the consumers, firm incurs a fixed investment cost b per consumer, regardless of whether the consumer adopts the product or not. When the firm uses the coupon strategy, the investment cost only occurs when a potential consumer is converted to a real adopter of the firm's product, as the price reduction only takes effect when being redeemed.

The two strategies also have different product quality implications to consumers. Because consumers who receive the sample can physically evaluate the product quality, we assume they observe the true product quality under the sample strategy. This is different from the coupon strategy, in which the coupon works just as a price discount upon redemption. The true quality of the product cannot be directly observed.

3.3 Consumer's Decision Making

We define firm j's informed consumer as a consumer who is aware of firm j's product because either at least one of the consumer's neighbors has already adopted firm j's product, or firm j contacts the consumer directly via the firm's marketing effort. Other consumers are uninformed by firm j and are unaware of firm j's product.

In each round, all informed consumers make simultaneous adoption decisions based on their evaluation of utilities. We assume a consumer's utility has both an individual effect and a local network effect. The individual effect refers to a consumer's intrinsic valuation (genuine interest) in obtaining the product. Following a standard vertical product differentiation model, we assume

consumer valuation for high quality product is v, and that for low quality product is δv. Here the parameter $0 < \delta < 1$ is the discount factor.

The local network effect refers to the increased consumption utility a consumer derives when a large number of immediate neighbors have adopted the product. Consider a social network with N nodes. Denote n_{ijt} as the number of consumer i's neighbors who have already adopted firm j's product at time t. This information is observable. Let k measure the strength of the positive network externality. The term $k\frac{n_{ij}}{N}$, $j = 1,2$, captures the benefit to each consumer from having n_{ijt} neighbors adopting firm j's product at time t. Therefore, an informed consumer i who observes firm j's product quality q and has n_{ijt} neighbors who have already adopted firm j's product will derive the following utility at time t:

$$U_{ijt}^{q} = v_i^q - p_j + k\frac{n_{ijt}}{N} \tag{1}$$

where

$$v_i^q = \begin{cases} v_i & if\ q = q_H \\ \delta v_i & if\ q = q_L \end{cases} \tag{2}$$

We denote firm j's uninformed consumer's utility $U_{ijt}^{q} = 0$ and assume the reservation utility is s. In the initial seeding phase, if a consumer is only reached by firm j, then the consumer adopts the firm's product if $U_{ij0}^{q} \geq s$. If a consumer is reached by both firms, then the consumer adopts firm j's product if the utility she derives from adopting firm j's product not only is greater than her reservation utility but also gives her higher utility than that from adopting the other firm's product. In case there is a tie, the consumer randomly picks one firm's product to adopt. For notation convenience, we use $\bar{j}$ to denote the other firm (not firm j). The consumer adopts firm j's product if $U_{ij0}^{q} > \max[U_{i\bar{j}0}^{q}, s]$. Once a consumer has adopted a product, the consumer has a lock-in period of τ rounds. No change of adoption can be allowed within the lock-in periods, thus no decision is necessary for the locked-in consumers. After the elapse of the lock-in periods, the consumer can reevaluate her choice and can change her adoption decision.

We assume initially product quality is unobservable. There are two cases that consumers know the true product quality. The first case is when consumers adopt the product. The second case is when the firm uses sample strategy, where consumers who get the firm's sample know the true product quality. The product quality is unobservable to other consumers. They use Bayes' rule to update their belief about the two firms' product quality based on the signals shared by their network neighbors who have already adopted the products. Assume the prior belief that a product is of high quality is $P(q_H) = p$. A consumer who has adopted a firm's product shares the product quality information with his/her directly connected friends. We assume the WOM signal of the product takes two values: good or bad. Moreover, an earlier adopter is more likely to share good (denote as *G*) or bad (denote as *B*) WOM signals when the true quality of the product is high or low, respectively. So $P(G|q_H) = P(B|q_L) = \lambda > \frac{1}{2}$. For a focal node, assume N_i neighbours have adopted firm i's product, among whom α_i neighbours have shared good signals and $\beta_i = N_i - \alpha_i$ neighbours have shared bad signals. The posterior quality is expressed as $E(q|\alpha_i, \beta_i) = P(q_H|\alpha_i, \beta_i)v_i^{q_H} + P(q_L|\alpha_i, \beta_i)v_i^{q_L}$. In the case of unobservable product quality, v_i^q in Equation (1) is replaced by $E(q|\alpha_i, \beta_i)$ and is interpreted as perceived product quality.

4. Experiment

We take the real Facebook network as our experimental testbed. The anonymized Facebook dataset is obtained from Stanford Network Analysis Project, which contains 4,039 nodes and 88,234

friendship links, constituting a scale-free network that follows power-law distribution. Given this network structure, we initialize each node with a product valuation randomly drawn from a uniform distribution [0,1]. We set up our controlled experiment as follows.

Parameter	Description
Price	$p \in \{low, high\}$, low or high price of the product
Quality	$q \in \{low, high\}$, low or high quality of the product
Marketing Strategies	$m \in \{sample, coupon\}$, product sample and price discount
Initial Seeding	$s \in \{H, L\}$, a high or low percentage of the population to reach in round 0
Targeting Method	$t \in \{H, L\}$, preferentially reach the highest or the lowest degree consumers

Table 1. Experiment Design

We have four price-quality pairs: {*low-low*, *low-high*, *high-low*, *high-high*}. For each pair, we compare two marketing strategies: the sample strategy and the coupon strategy. Under each strategy, there are 2×2 initial seeding and subsequent targeted marketing strategies: {HH, HL, LH, LL}. For example, HH indicates that a high proportion of population is being seeded in the seeding phase and the highest degree nodes being selected first in reaching out to consumers. Other strategies can be understood in a similar way.

In each round of iteration, both firms take efforts to reach potential consumers and consumers make subsequent purchase decisions. The market converges after many iterations when both firms run out of marketing budget and when no consumers have incentive to switch their adoption decisions. Upon convergence, market equilibrium emerges. For each experiment, we generate 10 instances of the heterogeneous valuation in the Facebook network. We compute the average equilibrium market share of both firms as the final performance measure of the market outcome, which we use to construct the payoff matrix under different strategy pairs. Then the equilibrium outcome can be analyzed as the usual normal form game. Multiple equilibria or no equilibrium is possible. Table 2 shows our equilibrium initial seeding and targeted marketing strategies under the non-cooperative game and cooperative game, respectively.

Price	Quality	Equilibrium Outcome	Sample Strategy	Coupon Strategy
low	*low*	Non-cooperative	HH (30.4%)	HH (40.1%)
		Cooperative	**LL (35.6%)***	LH/LL(40.2%)
	high	Non-cooperative	HH (38.4%)	HH (40.1%)
		Cooperative	**LL (41.8%)***	LH/LL(40.2%)
high	*low*	Non-cooperative	LL (13.3%)	No pure strategy equilibrium
		Cooperative	LL (13.3%)	LL/LH/HL/ HH (26.9%)
	high	Non-cooperative	LH (29.7%)	HH (26.9%)
		Cooperative	LL (29.7%)	LL/LH/HL/ HH (26.9%)

Note: * indicates the difference of equilibrium market shares between the non-cooperative strategy and cooperative strategy is statistically significant at 0.05 level.

Table 2. Equilibrium Market Share under the Sample and Coupon Strategies

The non-cooperative game outcome is the pure strategy Nash equilibrium based on the payoff matrix constructed for the normal form game. The cooperative equilibrium outcome refers to the market outcome when both firms can cooperate to generate the highest mutual benefits. Interestingly, we find prisoner's dilemma type of game outcome. For example, when both the product price and quality are low, under the sample strategy, if both firms play non-cooperatively, the pure strategy equilibrium is HH, in which both firms seed a high proportion of population in

the seeding phase and target the highest degree nodes to reach out remaining potential consumers in subsequent marketing phase. Finally both firms achieve 30.4% market share, respectively, which is lower than 35.6% if they can coordinate and both choose LL strategy (which suggests a lower percentage of budget in the seeding phase, and target at the lowest degree consumers). The reason that HH strategy is suboptimal is as follows. In the initial seeding phase, firms have spent higher than necessary budget to seed the market, being fear of the rival firm would gain early mover advantage. Because both firms try to reach the highest degree nodes, they are likely to advertise to the same highly connected consumers. Because each consumer only adopts one product, some of the advertising budget will be waste in the competition. Both firms would be better off if they target the lowest degree nodes to avoid head-to-head competition, and if they save their budget to later targeted marketing rather than initial advertising.

Overall, we find the firm's non-cooperative strategy yields lower market share than the cooperative strategy. In the non-cooperative game, the coupon strategy yields higher market share than the sample strategy, especially when both the product price and quality are low. The market share difference is statistically significant at the 0.05 level when the product price is low under the sample strategy.

5. Conclusion

As social media marketing gains the momentum and the retail competition becomes more intense, firms seek the most effective marketing strategies to influence consumers' product adoption decisions in the social network. We employ an experimental approach to study product awareness building, influence propagation and final product adoption by considering various marketing strategies, such as coupon redemption and product samples to compete for market share. Based on computational experiment, we determine the market equilibrium and analyze the corresponding market outcomes.

In this research, we focus on symmetric game. Future work may look at the asymmetric game. For example, firms may choose different product price and quality levels. In the current analysis, we randomly generate the intrinsic utility among network users. Future research may allow correlation in product valuation. We conjecture some types of niche-seeking strategy of the firms might emerge.

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