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Pricing and referrals in diffusion on networks

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ABSTRACT

When a new product or technology is introduced, potential consumers can learn its quality by trying it, at a risk, or by letting others try it and free-riding on the information that they generate. We propose a dynamic game to study the adoption of technologies of uncertain value, when agents are connected by a network and a monopolist seller chooses a profit-maximizing policy. Consumers with low degree (few friends) have incentives to adopt early, while consumers with high degree have incentives to free ride. The seller can induce high-degree consumers to adopt early by offering referral incentives – rewards to early adopters whose friends buy in the second period. Referral incentives thus lead to a 'double-threshold strategy' by which low and high-degree agents adopt the product early while middle-degree agents wait. We show that referral incentives are optimal on certain networks while inter-temporal price discrimination is optimal on others.

1. Introduction

In this paper, we study the interplay between social learning, efficient product diffusion, and the optimal pricing policy of a monopolist. More precisely, we study the adoption dynamics of a technology of uncertain value, when forward-looking agents interact through a network and must decide not only *whether* to adopt a new product, but also *when* to adopt it. Uncertainty leads to informational free-riding: a potential consumer may wish to delay adoption in order to let other agents bear the risks of experimenting with the technology and learn from their experiences. This complicates the problem of technology adoption and can lead to inefficiencies in diffusion processes, as there are risks from being an early adopter and externalities in early adoption decisions. The possibility of free-riding induces a specific form of social inefficiency: agents with relatively few friends (low degree) have the greatest incentives to try the product since they have the least opportunity to observe others' choices. Given the risks of experimentation, it would be more socially efficient to have high-degree agents experiment since they are observed by many others, thus lowering the number of experimenters needed to achieve a given level of information in the society. This problem occurs in many settings: not only do consumers benefit from the research of friends and relatives into new products, but farmers benefit from the experience of other farmers with a new crop.

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Likewise in industry, research spills over to other firms. People benefit from the experience of their friends and relatives regarding a vaccine of unknown side effects. In developing countries, villagers may learn about a new program from the experience of other members of the community.

We study this problem in a two-period network game in which a monopolist (or social planner) can induce people to experiment with the product in the first period via two types of incentives: price discounts and referral rewards (payments to an agent who tries the product early based on how many of that agent's friends later adopt the product).[3] Price discounts induce more agents to try the product early, but are biased towards low-degree agents since they are the ones with the greatest incentives to try early in any case. In contrast, referral rewards induce high-degree agents to try the product early since they have more friends to refer in the second period and thus expect greater referral rewards. We show that if sufficient referral incentives are in place then early adoption is characterized by a double-threshold pattern in which both low and high-degree agents adopt early while middle-degree agents choose to delay adoption and learn from the behavior of others, before making later adoption decisions. The specifics of the lower and upper thresholds depend on the combination of prices and referral incentives. We then study a monopolist's optimal pricing strategy. The monopolist's incentives are partly aligned with social efficiency since it is costly to induce first-period experimentation – either price discounts or referral incentives must be offered and the monopolist would like to minimize such payments and maximize the number of eventually informed high-paying adopters. The optimal strategy, however, depends on network structure via the relative numbers of agents of different degrees. We characterize the optimal policies for some tractable degree distributions and provide insights into the more general problem. A rough intuition is that if the network is fairly regular, then referral incentives are less effective and price discounts are the main tool to maximize profits. If instead, there is sufficient heterogeneity in the degree distribution and there are some agents of sufficiently high degree, then referral incentives are more profitable. In some limiting cases, in which the network has high enough degree, referral incentive policies (with no price discounts) are both profit maximizing and socially efficient.

Our approach enriches an early literature on social learning (e.g., Chamley and Gale, 1994; Chamley, 2004; Gul and Lundholm, 1995 and Rogers, 2005) that focused on delayed information collection through stopping games. Our analysis brings in the richer network setting and analyzes a monopolist's pricing problem. Our network modeling builds on the growing literature on network diffusion,[4] and uses the mean-field approach to study diffusion developed in Jackson and Yariv (2005, 2007), Manshadi and Johari (2009), Galeotti et al. (2010), Leduc (2014), Leduc and Momot (2017). Our paper is also related to a recent literature modeling monopolistic marketing in social networks[5] (e.g., Hartline et al., 2008; Candogan et al., 2012; Bloch and Querou, 2013; Fainmesser and Galeotti, 2016; Saaskilahti, 2015; Shin, 2017) that builds on an earlier literature of pricing with network effects (Farrell and Saloner, 1985; Katz and Shapiro, 1985). Our approach differs as it considers the dynamic learning in the network about product quality, rather than other forms of complementarities, and works off of inter-temporal price discrimination that derives from network structure and information flows.[6] This enriches an earlier literature on price discrimination that focuses mainly on information gathering costs and heterogeneity in consumers' tastes or costs of information acquisition and/or demand uncertainty for the monopolist (Kalish (1985), Lewis and Sappington (1994), Courty and Li (2000), Dana (2001), Bar-Isaac et al. (2010), Nockea et al. (2011)). Thus, our approach is quite complementary, as it not only applies to different settings but it is also based on a different intuition: the pricing policy in our case is used as a screening device on agents' network characteristics. The monopolist does not observe the network but instead induces agents with certain network characteristics to experiment with the product and potentially later induce other agents to also use it. The latter can then be charged different prices. Referral incentives are useful because they induce highly-connected individuals to adopt early and thus take advantage of their popularity, solving an informational inefficiency at the same time as increasing profits.

The paper is organized as follows. Section 2 presents the dynamic network game in a finite setting. Payoffs are defined and basic assumptions are stated. Section 3 develops the mean-field equilibrium framework that allows us to study the endogenous adoption timing in a tractable way while imposing a realistic cognitive burden on agents. Section 4 illustrates how the dynamic game allows us to study a large class of dynamic pricing policies. Section 5 studies the monopolist's profit maximization problem. Policies involving referral incentives and policies using inter-temporal price discrimination are compared. Section 6 concludes. For clarity of exposure, all proofs are presented in an appendix.

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[3] Referral rewards are seen in many settings with new products or technologies. For instance, in July of 2015, Tesla Motors announced a program by which an owner of a Model S Sedan would receive a 1000 dollar benefit if the owner referred a friend who also buys a Model S Sedan (Bloomberg Business News, "Musk Takes Page From PayPal With Tesla Referral Incentive," August 31, 2015). Dropbox rapidly grew from around one hundred thousand users in the fall of 2008 to over four million by the spring of 2010, with more than a third of the signups coming through its official referral program that offered free storage to both referrer and referree (Forbes, "Learn The Growth Strategy That Helped Airbnb And Dropbox Build Billion-Dollar Businesses," Feb. 15, 2015). Such programs have been used by many new companies from Airbnb to Uber, and also by large existing companies when introducing new products (e.g., Amazon's Prime).

[4] See Jackson and Yariv (2011) for a recent review of the field, and Goel et al. (2012) and Cheng et al. (2014) for recent empirical work.

[5] Papanastasiou and Savva (2016) study dynamic pricing in the presence of social learning and free-riding, but without a network structure.

[6] There are some papers that have looked explicitly at the dynamics of adoption and marketing, such as Hartline et al. (2008), but again based on other complementarities and the complexities of computing an optimal strategy rather than dynamic price discrimination in the face of social learning.