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Author(s): Kent D. Miller, Frances Fabian and Shu-Jou Lin
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STRATEGIES FOR ONLINE COMMUNITIES

KENT D. MILLER,[1]* FRANCES FABIAN,[2] and SHU-JOU LIN[3]
[1] *The Eli Broad Graduate School of Management, Michigan State University, East Lansing, Michigan, U.S.A.*
[2] *Fogelman College of Business and Economics, The University of Memphis, Memphis, Tennessee, U.S.A.*
[3] *Department of Business Administration, Chang Gung University, Tao-Yuan, Taiwan*

This study examines the participation of firms in online communities as a means to enhance demand for their products. We begin with theoretical arguments and then develop a simulation model to illustrate how demand evolves as a function of interpersonal communication and a firm's chosen strategy. In this model, the firm's strategy involves allocating advocates who promote its product in online communities. Our model results point to some key parameters informing firms' strategies when social learning processes shape demand. Copyright © 2008 John Wiley & Sons, Ltd.

INTRODUCTION

Consumers' preferences form within communities as individuals exchange opinions about products and services and observe one another's purchases. Where affluence has spread, essential human needs account for a decreasing proportion of consumers' purchases, and the social context takes on an increasingly important role in shaping consumer behavior (Redmond, 2001). Sociological and psychological explanations for product demand emphasize the social meaning attached to consumption (Belk, 1988; Cherrier and Murray, 2004; Guerin, 2003; Veblen, 1899/1979; Zukin and Maguire, 2004). Consumers may purchase products to either attain or reaffirm their identity in a particular social group (Fitzmaurice and Comegys, 2006). Product utility includes a 'consumption externality' owing to the subjective value associated with shared consumption among members of a social group (Friedman and Grilo, 2005).

The availability of new communication technologies has contributed to changes in how people form social communities, as evidenced by declining participation in face-to-face communication (Nie, Hillygus, and Erbring, 2002; Putnam, 2000). Online communities, consisting of people who engage in computer-supported social interaction (Preece, 2000 : 10), offer an increasingly prominent context for interpersonal exchange. Online communities allow members to continuously express and access others' opinions, with the overall preferences and beliefs often tabulated. As such, online communities provide a highly accessible and efficient source for evaluating and adjusting one's own thoughts and actions in light of input from socially relevant peers within a community. The reach and efficiency of online communities accelerates the dynamics of social learning processes relative to exchanges that are face-to-face or facilitated by other media.

Keywords: online communities; demand; social learning processes; preference formation; threshold effects; computer simulation
*Correspondence to: Kent D. Miller, The Eli Broad Graduate School of Management, Michigan State University, N475 Business College Complex, East Lansing, MI 48824-1122, U.S.A. E-mail: millerk@bus.msu.edu

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Recent research has investigated how anonymity and the use of aliases make online forums susceptible to strategic manipulation by those interested in promoting, or undermining, product sales. Dellarocas (2006) reported that not only do firms post positive messages regarding their own products, they also provide rewards to consumers who post favorable comments. Firms can now employ advertising agencies to engage in 'promotional chat' on their behalf (Mayzlin, 2006). Prior research indicates that online recommendations do influence individuals' purchase decisions (e.g., Chevalier and Mayzlin, 2006; Senecal and Nantel, 2004).

This study presents theoretical arguments and a computer simulation model to explore how social learning processes and firms' product promotion strategies affect the evolution of demand within communities. We consider the implications of firms participating in online communities (i.e., acting as peers in online exchanges of information and opinions) in attempts to shift other participants' preferences toward a favorable view of their products. We identify key variables affecting the diffusion of product preferences and assess the effectiveness, under distinct conditions, of various influence strategies employed by firms. To the extent that online communities present accelerated versions of the dynamics of other social communities, our arguments and model can inform firms' strategies in other social settings.

The opening section of the study provides theoretical background for understanding online communities as contexts for interpersonal learning that shapes preferences. We then develop an agent-based simulation model that highlights some key parameters relevant to choosing among alternative strategies for engaging online communities, where the strategies of interest involve allocating advocates across multiple communities to promote a firm's product. Critical to demand formation are the threshold adoption rate that must be surpassed for individuals to consider adopting a product, the pattern of switching among communities by participants, and whether the firm seeks to influence markets where acceptance of its product is common or rare. We present illustrative results from our model, and then generalize from our findings and discuss their implications. Overall, our study contributes to understanding the social processes behind demand dynamics, and the contingencies relevant to firms choosing strategies to support demand formation.

BACKGROUND

Online communities, firm strategies, and demand dynamics

In contrast with our marketing counterparts, strategy researchers' contributions to understanding demand dynamics have been relatively sparse, though some recent research may indicate a renewed interest in the topic (e.g., Adner and Zemsky, 2006, Robertson and Yu, 2001). Likewise, strategy research addressing Internet markets is rather thin. Most such investigations emphasize efficiency gains, as summarized in an integration and extension of theory by Amit and Zott (2001). Their review covered the implications for firms of transaction cost reductions brought about by the Internet, while giving less attention to the opportunity that the Internet affords to influence product demand. By contrast, our study addresses demand dynamics in online communities. We adopt a strategy perspective by focusing on the role of firms seeking to influence demand. Recent research makes a compelling case for theorizing and modeling based on how firms can exploit the role that social interactions play in consumer choice (Godes *et al.*, 2005).

The term 'online community' encompasses a wide range of Internet forums including markets and auction sites, electronic bulletin boards, list-servers, social networking sites, blog hosts or sites, gaming communities, and shared-interest Web sites. The allure of online communities reflects a number of unique qualities of the online experience, such as the ability to create destinations for interacting around narrow shared interests, an extremely low financial cost for interacting in this realm, and the ease of joining and exiting these forums. Online communities facilitate asynchronous, immediate, interactive, low-cost communication. Most importantly, they enable the formation of interpersonal ties that provide information and social support (Wellman *et al.*, 1996).

Communities can lower search costs, thus economizing on attention, but they also serve as contexts in which identities and preferences form (Ibarra, Kilduff, and Tsai, 2005). Individuals' preferences reflect 'interdependence via reference groups' (Hayakawa, 2000). Communities assign meanings to consumption choices (Richins, 1994). As 'possessions are an important component of sense of self' (Belk, 1988 : 139), the consumption

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of goods and services is a form of personal expression or lifestyle (Chaney, 1996). Thus, through communities, product choices extend one's own perception and others' perceptions of our personal identities (Belk, 1988). Furthermore, communities are contexts for accruing reputations (Bolton, Katok, and Ockenfels, 2004) and recognizing authorities (Martin, 2002). In sum, communities are essential reference groups for assigning and conveying products' intersubjective meanings and values.

Although there is a growing stream of research on the increasing importance of online communities in social life (Wellman and Haythorthwaite, 2002), the potential strategies for conventional firms to engage this phenomenon are generally absent from this research. Hagel and Armstrong (1997) argued for strategies creating virtual communities that bond participants to firms, and some research has investigated how such communities can contribute to product innovation (Jeppesen and Frederiksen, 2006). Other work implies that the most effective strategy for marketing purposes is to interact with a community on a third-party site (Sussan, Gould, and Weisfeld-Spolter, 2006). Despite limited research on the topic, firms can and do play various roles in online communities: (a) observing and collecting information, (b) hosting or sponsoring communities (by creating and managing Web sites and advertising), (c) providing content to communities (such as music, information, or entertainment), and (d) participating as members of online communities (in peer relationships with other participants).

The strategy considered here involves seeding communities with product advocates, rather than trying to control interactions within communities. A firm's advocates participate along with others as peers in online communities. Advocates may be directly employed by the firm or they may be volunteers who seek to promote the product. In either case, their numbers are limited and sustaining them requires ongoing investments by the firm. Anonymity and aliases allow a firm's representatives to disguise their product endorsements as input from peers. Although we have described this strategy as applying to business organizations, our model and its implications should extend to nonbusiness organizations or social movements that seek to influence beliefs and actions by having their representatives participate in online communities.

Our premise that messages initiated or encouraged by firms can influence community members toward a more favorable view of their products requires justification in light of Dellarocas's (2006) conclusion that such attempts prove counterproductive. He argued that in a broad array of settings in which consumer opinions are fairly honest and informed—and thus combine to form an accurate signal about product quality—firm manipulation cannot sustain an exaggerated collective quality signal. As communities become habituated to manipulation, firms must escalate their contributions to online forums to offset participants' tendency to discount favorable product reviews, creating a 'rat race' for firms.

By contrast, we posit a socializing, rather than a solely informational, role for online interpersonal exchanges. Postings do not just signal product quality, they shape the evaluative schema that participants bring to purchase decisions and consumption experiences. Consumption that conforms to collective norms can take on value (i.e., social consumption value) independent of products' empirical characteristics. Communities share information, which may be corrected by gathering further evidence, but they also provide the norms and values that individuals use to interpret product information, which are inherently subjective and not amenable to correction (to some objective standard) through gathering additional data.

Peer support and a sense of social identity are often more prominent motivations for participating in online communities than information seeking (Burnett, 2000; Wellman and Gulia, 1999). Dholakia, Bagozzi, and Pearo (2004) recognized the informational and instrumental (problem-solving) value of participating in virtual communities, but also posited self-discovery, maintaining interpersonal connectivity, social enhancement, and entertainment as motivations. Strength of ties to a group enhances behavioral responsiveness to word-of-mouth communication (Brown and Reingen, 1987; Frenzen and Nakamoto, 1993), although researchers have yet to examine the extent of this moderating effect on product consumption responses to electronic word-of-mouth (see Sen and Lerman, 2007).

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Features of the theory and model

Product and demand

The product of interest is generic: either a physical good or a service, sold through any channel (online or conventional). Product sales correlate with attitudes toward the product (Rothaermel and Sugiyama, 2001). It is most straightforward to think of the product as a consumable purchased repeatedly over time, thereby making the popularity of the product correspond with demand in each period. However, the product could also be a durable good for which purchases only occur at the time of initially adopting a favorable opinion of the product. In this case, community opinion would not translate directly into demand in any given period; nevertheless, as long as its market is not saturated, it still behooves a firm to take an interest in monitoring and influencing the popularity of its product among previous and potential customers.

Demand evolves as a function of comments about the product posted to online forums. Individuals have many different reasons for contributing postings, and among these is the desire to share their consumption experiences (Hennig-Thurau *et al.*, 2004). In addition to sharing product experiences, community members may simply convey impressions of the product apart from having any direct personal experience with it. After gauging the community reaction, individuals may change their opinions of the product, even one that they previously purchased.

Thresholds

The probability of adopting an opinion—either favorable or unfavorable—about a product depends on the proportion of individuals in one's online community expressing that opinion. Individuals remain uninfluenced by opinions rarely expressed within their communities. Opinions are only deemed worthy of consideration and possible adoption if they are expressed by a proportion of the community's members that surpasses an individual's threshold level. Thresholds reflect the tendency of individuals to maintain their existing preferences, even in the presence of alternative viewpoints. Holding an opinion shifts the burden of proof to competing opinions. Seldom-expressed opinions may be disregarded or discounted, and only become compelling if adopted by a sufficient (i.e., threshold-surpassing) proportion of a community's members. In online communities, participants also seek to squelch dissenting perspectives by posting rejoinders that isolate and discredit locally unpopular views.

Positing thresholds is consistent with constraints on individuals' attention and commitments to social identities, which produce shared buying patterns among community members rather than ongoing experimentation with new alternatives. Individuals attend to messages reinforced through repetition by peers within a community, but are less likely to be swayed when messages conflict. A high threshold can also reflect high sunk costs associated with adopting a new product or high switching costs if the product is a substitute for a previously purchased product (Klemperer, 1987). It may also indicate risk aversion, to the extent that the desirability of untried products is difficult to assess—due to unclear product qualities (Darby and Karni, 1973) or uncertainty about one's own tastes (March, 1978).

Not all opinions contribute equally toward changing members' preferences. Perceived authoritativeness and trustworthiness factor into the subjective weights attached to individuals' judgments. Assessing trustworthiness is easiest when relatively few individuals are involved in a social network, there are repeated opportunities to compare product claims and product characteristics, and product characteristics are unambiguous. Also, contextualizing messages by adopting a community's particular culture and vernacular may be necessary to foster trust and perceived authority (Fayard, DeSanctis, and Roach, 2004). Although we do not explicitly model differences in influence across community members, the implications of such an extension can be inferred from our model's results.

Cascades and tipping effects

Communities are subject to social contagion effects. A few early adopters within a community can trigger a cascade of interest in a product. Cascades occur when the probability of adopting depends on the rate of adoption by others in a community (Granovetter, 1978). *Tipping points* are threshold adoption levels resulting in cascades, as observed in a variety of social phenomena (Gladwell, 2002; Schelling, 1978)—including segregation, bandwagon effects, and technology

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diffusion. A cascade of product adoption decisions can be furthered when products have associated positive network externalities (Shapiro and Varian, 1999) and as people tend to imitate others' buying patterns in order to economize on learning costs (Bikhchandani, Hirshleifer, and Welch, 1998). Bandwagon effects occur when purchases are positively correlated across individuals; snob effects (i.e., reverse bandwagons) occur when purchases are negatively related to others' adoption (Leibenstein, 1950). Of particular interest are individuals who may be uniquely positioned within social networks to initiate 'epidemics' within communities (Gladwell, 2002).

Granovetter (1978) modeled different threshold values across individuals, with cascades resulting when one or a few low-threshold individuals initiate action, which triggers similar responses from individuals with slightly higher thresholds, and such responses continue to spread throughout the population. The outcomes from serial decisions by individuals can diverge dramatically from concurrent decisions when observing others' choices affects decision making (Macy, 1991). Granovetter and Soong (1986) extended this logic to model consumer preferences resulting in bandwagon and snob effects. Our model is unique in that we analyze the effect on demand dynamics of thresholds held in common across the entire population, but with differing initial distributions of opinions across communities.

Switching

Individuals self-select into communities on the basis of shared interests, concerns, and beliefs (Churchill and Halverson, 2005; Swann, Rentfrow, and Guinn, 2002). Homophilous affiliation patterns are reinforced over time as community participants learn from one another. Such interactions expand the range of understandings shared among community participants beyond those that initially attracted the participants to a community. Likewise, it is probable that holding views that diverge from those that predominate in a community promotes exit. Although demographic differences are associated with exit (e.g., O'Reilly, Caldwell, and Barnett, 1989), such differences are less observable and less relevant to forming ties in online communities than in face-to-face interactions (McKenna, Green, and Gleason, 2002).

Switching membership among communities is important to the evolution of preferences because it determines the transmission of opinions across communities. We compare the implications for demand dynamics of three different switching patterns: no switching, random switching, and affinity switching. No switching occurs when loyalty is high, or the costs of searching for an alternate community and transitioning to it are prohibitive. In the absence of switching, communities are isolated from others' influence. Random switching reflects indifference to whether a community's preferences align with one's own in selecting a community in which to participate. We could view random switching as based on criteria independent of opinions about the particular focal product. Affinity switching occurs when the perceived desirability of an alternative community increases with the correspondence between one's own preference and those expressed in the community. Our interest is in how the rate and type of switching across communities affects the level of demand, and the sensitivity of demand to manipulation by firms.

Random switching and affinity switching map well to controversies regarding the sociological effects of modern media (Mendelsohn and Nadeau, 1996). Specifically, the expansion of the Internet as a facilitator of multiple communities can either lead to (a) changes of opinion as more participants are exposed broadly to other opinions in the population or (b) entrenched and polarized perspectives, to the extent that individuals restrict their participation to communities with likeminded participants. These alternatives reflect heterophilous and homophilous responses to the social networking opportunities afforded by the Internet. Although these two possibilities have been discussed theoretically, we formally model these distinct processes.

Firm strategies

Libai, Muller, and Peres (2005) described three alternative strategies for allocating marketing resources across multiple markets. A *support-the-strong* strategy invests in proportion to the percentage of adopters in each market. A *support-the-weak* strategy invests based on the remaining market potential, that is, the percentage of nonadopters. A *uniform strategy* allocates marketing resources in proportion to market size, independent of the proportion of adopters or nonadopters.

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Unlike Libai *et al.* (2005), who considered country markets, we examine these alternative strategies in online communities where consumers can move from one community to another with negligible switching costs.

Libai *et al.* (2005) used a cellular automata setup for their agent-based simulation model. In their model, agents had fixed geographic locations and their propensity to adopt a product depended upon the observable preferences of agents in nearby cells (i.e., strong links to one's own region) as well as the preferences of a limited set of agents in distant cells (i.e., weak links to other regions). They assumed two possible states—adoption or nonadoption—with adoption being an irreversible state. Because adoption was irreversible, their model produced adoption cascades even in the absence of marketing investments by the firm.

Our model differs from theirs in some important ways. The distinct features of our model reflect some key characteristics of social learning processes in online communities. In our model, there is no direct one-to-one communication. We assume that learning takes place within a community through a centralized process of posting and reading posted messages. No one has a privileged position within these networks. All postings are equally available to all members of a community, but unaccessed by outsiders. We allow for both positive and negative opinions. Both preferences for and against the product are reversible.

MODEL AND RESULTS

Model specification

Our model begins with a population consisting of n individuals who participate in c online communities of initial size n/c. We chose n and c so that n/c was an integer. Let n_i be the number of participants in community i in a given period, where $\sum_i n_i = n$.

An individual's preference for a product takes one of three possible values: -1 (opposes buying), 1 (favors buying), or 0 (no preference). Individuals need not have firsthand experience with the product to form an impression about its merits; in the absence of direct experience, preferences can be presumptive responses to product descriptions or based on others' opinions.

In a given period, individuals' participation in online communities takes two forms—posting to the online community and learning from the same. In any given period, individuals holding favorable or unfavorable views of the product post their opinions with probability p_1. No-preference individuals do not post messages regarding the product. Let f_i and u_i be the number of posted favorable and unfavorable opinions in community i in a given period. Thus, $f_i \big/ (f_i + u_i)$ and $u_i \big/ (f_i + u_i)$ are the relative frequencies of favorable and unfavorable opinions among all postings in community i.

For an agent to consider adopting an opinion other than the one it currently holds, the proportion of postings exhibiting an alternative view must exceed a threshold level. We designate the threshold levels for indifferent individuals (i.e., those with a preference of 0) and those having defined preferences (either -1 or 1) as τ_0 and τ_1, respectively. For a no-preference individual, the probability of adopting a favorable view is $p_2 \left[f_i \big/ (f_i + u_i) - \tau_0 \right]$ if $f_i \big/ (f_i + u_i) > \tau_0$ and 0 otherwise. The probability of adopting an unfavorable view is $p_2 \left[u_i \big/ (f_i + u_i) - \tau_0 \right]$ if $u_i \big/ (f_i + u_i) > \tau_0$ and 0 otherwise. The expressions for the probabilities of adopting favorable and unfavorable views are similar for individuals with defined preferences, except that the relevant threshold is τ_1. In general, we would expect that $\tau_1 \geq \tau_0$, reflecting that the entrenchment of committed opinions is at least as great as for indifference. The parameter p_2 $(0 \leq p_2 \leq 1)$ reflects the level of attentiveness to, and willingness to learn from, others' postings.

Individuals switch communities with probability r. The choice of a different community can be either random or an increasing function of the correspondence between an individual's preference and the preferences of a community's members. In the former case, the choice of a new community is independent of one's preference regarding the particular product. We model this as randomly choosing any of the $c - 1$ alternative communities, that is, choosing any other community with probability $1 \big/ (c - 1)$.

We refer to switching based on shared preferences as *affinity switching*. Affinity switching produces homophilous affiliation patterns. In this case, the probability (q_i) of choosing a particular community i $(i \neq k)$ as an alternative to the current community k increases with the proportion of postings in the prospective community that match an

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agent's preference. Let x_{jk} denote the preference of individual j in community k. Hence, we have three sets of probabilities, conditional on whether x_{jk} equals 1, -1, or 0:

$$q_i|(x_{jk}=1)=\frac{\left[f_i\big/(f_i+u_i)\right]^b}{\sum_{i\neq k}\left(f_i\big/(f_i+u_i)\right)^b}$$

$$q_i|(x_{jk}=-1)=\frac{\left[u_i\big/(f_i+u_i)\right]^b}{\sum_{i\neq k}\left(u_i\big/(f_i+u_i)\right)^b}$$

$$q_i|(x_{jk}=0)=1\big/(c-1).$$

The third expression indicates random selection of an alternative community when an individual has no preference regarding the product. The parameter b reflects the strength of the preference for a community of individuals who share the same preference. For $b=0$, these switching rules simplify to random switching. As b increases above 0, the propensity to choose a community with a higher proportion of individuals who share the individual's preference rises. As an addendum to the affinity switching rules, if an agent likes ($x_{jk}=1$) or dislikes ($x_{jk}=-1$) the product but there are no other communities with postings that match its own preference, it stays in its current community.

Each period consists of members choosing whether to stay in the same community or switch to another, posting to online communities, and learning from online communities. Agents only participate in one community per period, and can move to a different community in the next period.

A firm has a advocates that it dedicates to participate in online communities ($a \ll n$). The firm's goal is to influence preferences toward a favorable view of its product. Its agents have a fixed preference of 1. An advocate posts this preference to a single community (with probability 1). The information about communities that is available to the firm is limited to the online postings—favorable and unfavorable—and the number of participants per community. The firm observes the favorable and unfavorable postings in each community and these frequencies become the basis for allocating its advocates later in the same period.

We consider three alternative strategies for allocating advocates. These strategies follow the categories proposed by Libai *et al.* (2005).

1. A *support-the-strong strategy* allocates advocates to communities based on the number of favorable postings about the product:

$$a_i=af_i\left(\sum_i f_i\right)^{-1}.$$

2. A *support-the-weak strategy* allocates advocates to communities based on the number of unfavorable postings about the product:

$$a_i=au_i\left(\sum_i u_i\right)^{-1}.$$

3. A *uniform strategy* allocates advocates in proportion to the sizes of the communities:

$$a_i=an_i\big/n.$$

For each of the strategies, we rounded a_i to the nearest integer. If rounding caused a deviation from the total available advocates, that is, $\sum_i a_i \neq a$, we added (subtracted) advocates to (from) communities selected at random among those already receiving advocates to strictly maintain the constraint that $\sum_i a_i = a$.

Analyses and results

Table 1 summarizes all of the model parameters and their values. Default values for the posting rate (p_1) and the learning parameter (p_2) were set at 0.50. Initially, we assumed no switching among communities, $r=0$, then we raised this rate to 0.10. We designated $b=2$ for affinity switching, but also examined $b=1$ for comparison. The results presented here are based on $\tau_0=\tau_1$ considering two alternative threshold values, 0 and 0.50. The zero-value threshold represents the case in which all postings—even those voiced by a single individual—factor into the probabilities of adopting favorable and unfavorable opinions of the product. For $\tau_0=\tau_1=0.50$, only the view expressed in the majority of a community's postings can induce individuals to alter their preferences.

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Table 1. Summary of parameters and values

Parameter	Values	Definition
n	900	Population size
c	9	Number of communities
p_1	0.50	Posting rate for individuals holding favorable or unfavorable views
p_2	0.50	Individual's propensity to learn from others' postings
τ_0	0, 0.50	Adoption threshold for individuals with neutral preference
τ_1	0, 0.50	Adoption threshold for individuals with positive or negative preference
r	0, 0.10	Probability of individual switching among communities
b	1, 2	Strength of affinity switching
a	0, 18	Number of advocates

Table 2. Initial distribution of preferences across communities

Preferences	i = 1	i = 2	i = 3	i = 4	i = 5	i = 6	i = 7	i = 8	i = 9
1	5	10	15	20	25	30	35	40	45
−1	45	40	35	30	25	20	15	10	5
0	50	50	50	50	50	50	50	50	50
$f_i / (f_i + u_i)$	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
$u_i / (f_i + u_i)$	0.90	0.80	0.70	0.60	0.50	0.40	0.30	0.20	0.10

We modeled a population of 900 individuals participating in nine communities of equal initial size. The firm has enough agents to allocate two per community if it follows the uniform strategy (i.e., $a = 18$). To illustrate the model's properties, we chose the initial distribution of preferences listed in Table 2. The communities differ in their mix of positive and negative opinions regarding the product, even though each of these opinions is equally common in the overall population. Half of each community's members initially are undecided about the product. We programmed the model using MATLAB 7.[1] The results presented here are averages based on 100 repetitions of each model.

Figure 1 shows how each of the nine communities evolves over 150 periods when the thresholds (τ_0 and τ_1) are zero and without any influence from the firm (i.e., $a = 0$). These graphs contrast the evolution of preferences as a function of the three alternative assumptions about switching: no switching ($r = 0$), random switching ($r = 0.10$), and affinity switching ($r = 0.10$ and $b = 2$). Without switching (Figure 1a), the adoption rate in each community increases in the early periods as some of the undecided individuals adopt a positive opinion of the product due to learning from others' postings. Once there are no remaining no-preference individuals, only random fluctuations in the adoption rate occur over time as a result of learning from postings. When switching is random (Figure 1b), the communities' adoption rates converge over time. Following affinity switching (Figure 1c), the preferences expressed within communities tend to polarize; eventually, all members within a given community share the same preference. The long-run outcomes in Figure 1c should be interpreted as indicating the proportion out of 100 runs that the members of a given community converged on a favorable opinion of the product.

Under high affinity switching ($b = 2$), the sizes of the communities expressing the largest proportions of favorable and unfavorable preferences increase in the early periods, while communities that are more evenly split lose members until they achieve consensus and then are able to attract additional members. Once preferences become homogeneous within communities, communities tend to converge in size. Figure 2 illustrates the evolution of community sizes for the extreme ($i = 1$ and 9) and the middle ($i = 5$) initial conditions under different thresholds and strengths of affinity switching

[1] Program files are available from the authors upon request.

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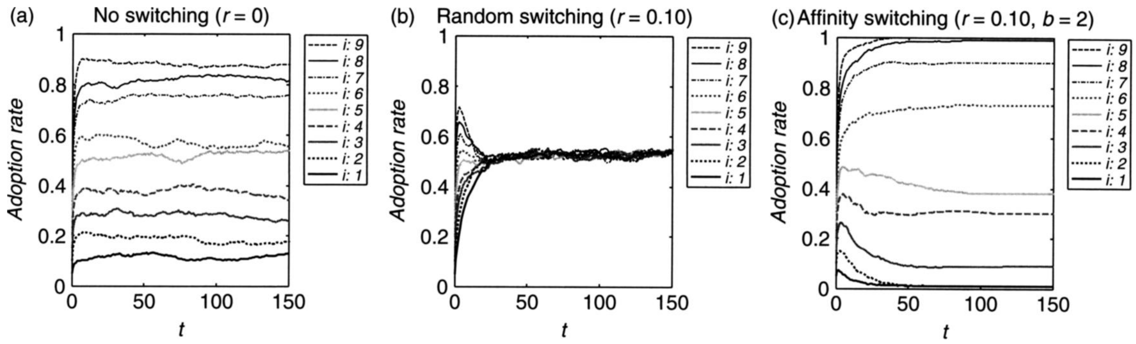

Figure 1. Adoption rates for communities with zero thresholds ($\tau_0 = \tau_1 = 0$) and no advocates ($a = 0$)

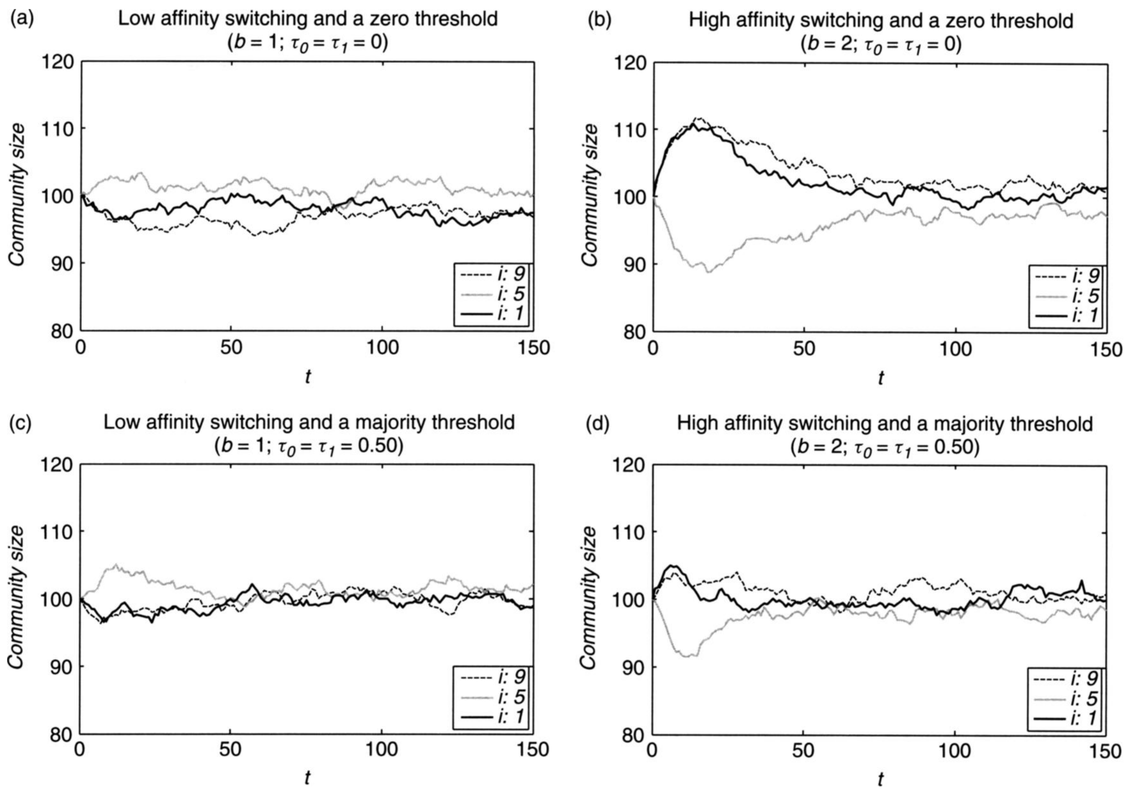

Figure 2. Community sizes with affinity switching

($b = 1$ or 2). The parameter values for Figures 1c and 2b correspond. Low affinity switching ($b = 1$) produces homogeneous preferences within communities, however, community sizes remain more stable than under high affinity switching.

Figure 3 shows the implications of the alternative firm strategies for product adoption across the entire population. For $\tau_0 = \tau_1 = 0$, the support-the-weak strategy dominates the others, irrespective of the switching pattern that agents follow. The differences in the performances of the strategies are most pronounced when agents follow affinity switching (Figure 3c). For affinity switching, a support-the-strong strategy reinforces the preferences of those individuals who often have already adopted the product or would tend naturally to move toward product adoption, even in the absence of the firm's influence. The overall adoption rate under a support-the-strong strategy only improves about 13 percent, relative to the 50

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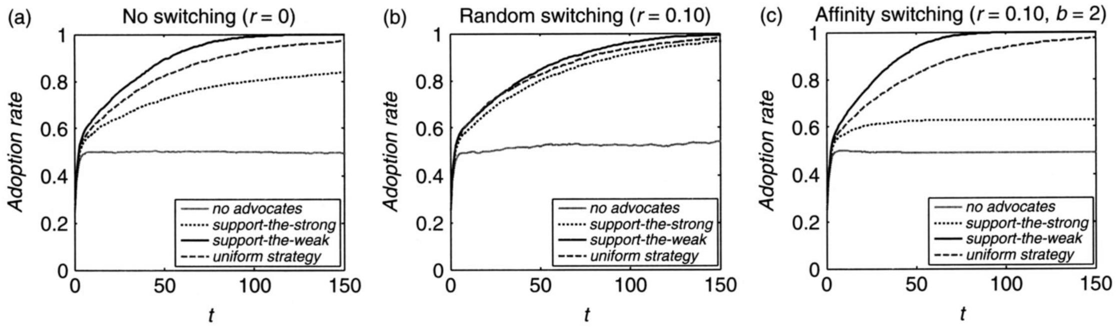
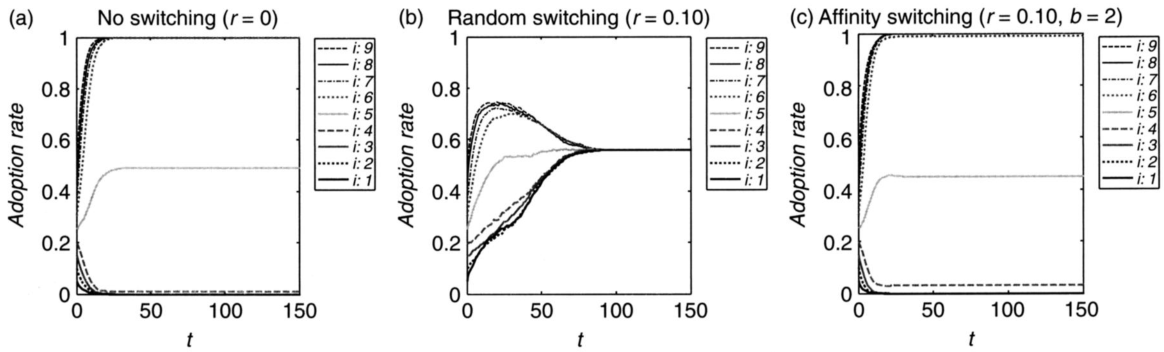


Figure 3. Aggregate adoption with a zero threshold ($\tau_0 = \tau_1 = 0$)



In Figures 4a and 4c, members of community 5 converge on either all favorable or unfavorable opinions with equal probability. In Figure 4b, the entire population reaches a consensus that is favorable or unfavorable with equal probability.

Figure 4. Adoption rates for communities with majority thresholds ($\tau_0 = \tau_1 = 0.50$) and no advocates ($a = 0$)

percent adoption rate that naturally occurs without any advocates. The performances of the alternative strategies converge under random switching (Figure 3b). This is as expected, because random switching makes the firm's choice among alternative allocations of advocates less crucial.

Incorporating a majority threshold changes the natural evolution of the communities in important ways. For $\tau_0 = \tau_1 = 0.50$, agents only learn from the majority view among the posted opinions. Individuals who hold the minority view in a community reduce the probability of adopting the majority view, but cannot influence others to accept their view. Figure 4 shows the average trajectories of each community in the absence of a firm's influence under the three switching rules. The opinions that prevail within communities under no switching (Figure 4a) and affinity switching (Figure 4c) are quite similar. Within 20 periods, these communities tend to move toward intra-community consensus around either favorable or unfavorable views of the product. The key difference is that without switching the communities maintain their initial sizes, whereas affinity switching produces early disproportionate migration to the communities with the most homogeneous preferences (Figure 2d). When switching is random, all communities converge on a common consensus—either a favorable or unfavorable opinion of the product—with both possible outcomes having equal probabilities of occurring (Figure 4b).

The communities in Figures 4a and 4c that are shown as having long-run adoption rates near 50 percent actually converge to either full adoption or zero adoption depending on early random effects. A community that starts with equal representation for positive and negative opinions can tip either way depending on random early learning that establishes one opinion as predominant among the community's postings. Bifurcations occur when small causes determine the resulting evolutionary path (see Prigogine and Stengers, 1984). When there is no switching or

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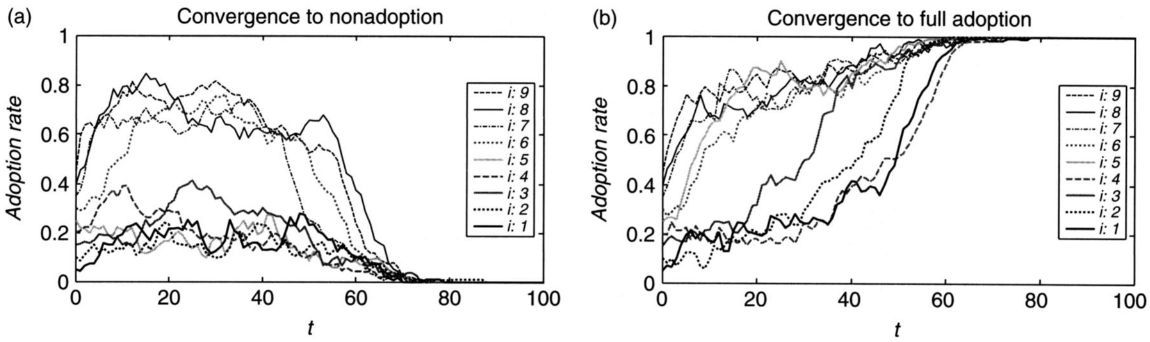
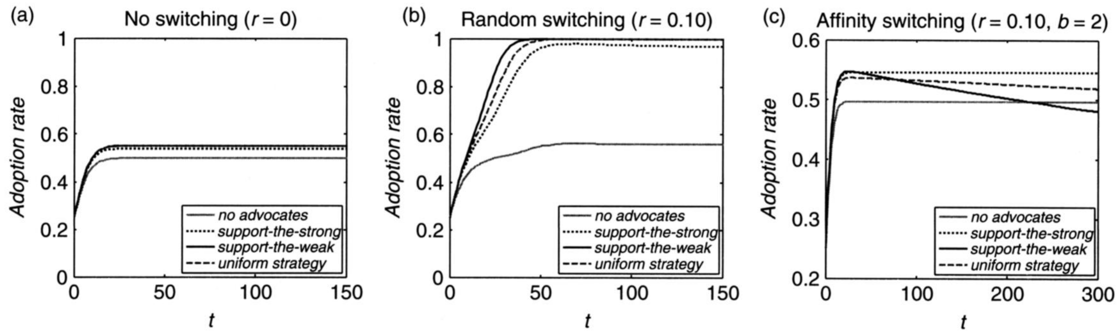


Figure 5. Illustrative runs with a majority threshold ($\tau_0 = \tau_1 = 0.50$), random switching, and no advocates



To more clearly illustrate the outcomes, the axes for Figure 6c differ from those in Figures 6a and 6b.

Figure 6. Aggregate adoption with a majority threshold ($\tau_0 = \tau_1 = 0.50$)

affinity switching, unbalanced preferences in the initial conditions determine whether communities tip toward a favorable or unfavorable consensus.

In the case of random switching, bifurcation takes place at the population level, rather than the community level. To visualize the role of early bifurcation points, Figure 5 graphs two different runs in which the same behavioral rules and initial conditions (specifically, those for Figure 4b) produced population-wide rejection and adoption of the product, respectively. Although early learning can cause the adoption rates of communities to diverge, the eventual effect of random switching is homogenization of preferences across the entire population. The majority threshold prolongs the time until adoption rates homogenize across communities, relative to the zero threshold case (compare Figures 4b and 1b). Homogenization slows because within-community learning tends to reinforce local majority views, which maintains heterogeneity at the population level in early periods.

Figure 6 presents the aggregate adoption rates over time for the alternative firm strategies when a majority ($\tau_0 = \tau_1 = 0.50$) threshold applies. The outcomes for the three strategies are quite similar when there is no switching (Figure 6a). In these cases, preferences within communities become homogeneous but diversity prevails across communities. Because the firm has few advocates relative to the size of the total population, its advocates have little success tipping communities toward a favorable view of the product unless the initial preferences are nearly evenly split between positive and negative opinions within a community, allowing the firm's advocates to determine the majority view.

The random switching case (Figure 6b) produces a very different result. Here, bifurcation takes place at the population level. The support-the-weak strategy causes the adoption rate to improve more rapidly than do the other two strategies. Using a support-the-weak strategy, the firm's advocates, together with adopters who randomly switch into communities where they are underrepresented, move low adoption communities above the threshold adoption level, thereby promoting product adoption. The uniform strategy generally achieves adoption by the full population as well,

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Table 3. Summary of preference outcomes and favored strategies

SWITCHING ASSUMPTION	ZERO THRESHOLD		MAJORITY THRESHOLD	
	Preference outcomes [1]	*Favored strategy*	*Preference outcomes* [1]	*Favored strategy*
None	within-community diversity	support-the-weak	within-community convergence	none[2] [near-threshold]
Random	population convergence	support-the-weak	population convergence	support-the-weak
Affinity	within-community convergence	support-the-weak	within-community convergence	support-the-strong

[1] Reported preference outcomes occur in the absence of firm influence (i.e., no advocates).
[2] All three strategies provide comparable, modest improvements in demand relative to using no advocates. A near-threshold strategy outperforms the other three strategies (see Discussion).

but takes longer to do so. The support-the-strong strategy neglects communities with low product adoption rates, allowing these communities' negative opinions to spread to other communities via random switching, resulting in long-run population-wide rejection of the product in six out of 100 runs.

For affinity switching (Figure 6c), a support-the-weak strategy achieves early success, but underperforms the other strategies in the long run. As bifurcation takes place at the community level, the firm allocates its advocates entirely to communities where negative opinions prevail, and the presence of its advocates fails to induce others to adopt a positive opinion of the product. The presence of these advocates actually erodes product acceptance because their posting of favorable opinions induces agents with favorable opinions to migrate into communities where they subsequently learn to dislike the product. This gradually grows the size of communities with negative views and shrinks those with positive views. The uniform strategy produces a less dramatic version of this same dynamic.

Comparing Figures 3 and 6, we see that majority thresholds are detrimental to the outcomes from all three strategies for the cases of no switching and affinity switching. This reveals that when only the majority view is contagious, and switching is either absent or individuals tend to choose communities that reinforce their preferences, initial conditions strongly affect the eventual outcomes. By contrast, a majority threshold causes more rapid product adoption under random switching. The firm's advocates encourage product adoption in communities where a favorable opinion is in the majority or they help communities achieve a majority favoring the product. Favorably-disposed agents migrate to other communities through random switching, causing other communities to move toward a majority favorable view, which triggers further product adoption. Hence, relatively few advocates can have a potent effect on preferences under random switching with a majority threshold.

DISCUSSION

Interpretation of results

In this final section, we discuss the implications of our model and findings. Our model highlights some key parameters associated with demand dynamics in online communities. These parameters inform the influence strategies firms should pursue.

Threshold and switching effects

Early models of threshold effects on the diffusion of behaviors and consumer preferences (e.g., Granovetter, 1978; Granovetter and Soong, 1986) assumed that the proportion of adopters could be observed by all members of a community. However, impressions regarding adoption patterns depend on the communication channels for word-of-mouth exchanges. Communication limited to dyadic interpersonal exchanges produces impressions regarding adoption patterns based on small idiosyncratic samples drawn from personal networks, and aggregate community-level patterns remain unknown. By contrast, online communication facilitates broad expression and sampling

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of opinions. Hence, in our model of preference diffusion in online communities, the probability of changing one's preference regarding a product is an increasing function of the proportion of an entire community's postings—either favorable or unfavorable—above a critical threshold level.

In addition to highlighting the role of thresholds, our model also demonstrated the implications of three alternative patterns of switching among communities: no switching, random switching, and affinity switching. Determining which of the three switching assumptions applies for a particular community is an empirical question, but all three cases are likely to be relevant in different contexts: no switching in contexts where mobility barriers are high, random switching where mobility barriers are low and individuals seek novel learning opportunities, and affinity switching where mobility barriers are low and individuals gravitate toward likeminded others. In online communities, where mobility barriers are often minimal, switching patterns should reflect primarily individuals' preferences for continuity or novelty, and uniformity or diversity. The Internet facilitates affinity switching by lowering search and switching costs, but these very characteristics also make sustaining long-term participation in communities challenging (see Ren, Kraut, and Kiesler, 2007).

Our model points out assumptions that lead to homogenizing population-level outcomes or community-level cleavages in society (cf. Mendelsohn and Nadeau, 1996; Shaw *et al.*, 1999). Different assumptions about thresholds and switching patterns determine the extent to which convergence in preferences occurs at the population or community level, or only as a result of random learning outcomes (see Table 3). For a zero threshold, population-level convergence in preferences occurs if there is random switching, community-level convergence in preferences occurs if there is affinity switching, and no switching prolongs diversity within communities (in the absence of a firm's influence). In other words, community-level diversity is only retained when people both stay in their communities and are not swayed by the predominant opinion. For a threshold that requires a majority to influence others' learning ($\tau_0 = \tau_1 = 0.50$), convergence in opinions occurs at the population level for random switching, and at the community level for affinity and no switching.

Performance of firm strategies

Our research design evaluated three different strategies under six threshold × switching combinations. Table 3 identifies the favored strategy for each combination in this experimental design.

As long as there is a zero threshold for posted opinions to influence others' preferences, the support-the-weak strategy outperforms the uniform and support-the-strong strategies, irrespective of the initial conditions and pattern of switching among communities. When $\tau_0 = \tau_1 = 0$, the firm increases the likelihood of adopting the product by allocating a_i advocates to community i, resulting in an increase in the proportion of posted favorable opinions: $(f_i + a_i)\big/(f_i + u_i + a_i) > f_i\big/(f_i + u_i)$ for $a_i > 0$. The marginal effect of an advocate is greater the lower the number of posted favorable and unfavorable opinions in the community. The prescriptive implication is that firms' strategies should favor those communities that (1) have many members who are undecided about their product and (2) have low posting rates. The first implication runs counter to arguments for focused allocation of salesforce personnel to high-share markets (Sinha and Zoltners, 2001) and investing to reinforce the loyalty of existing customers. If the zero threshold applies, firms should seek to influence communities in which their products are not currently central to community identity. The second implication commends participation in communities in which few individuals post opinions relative to the community size, allowing advocates to have high visibility and broad influence. These prescriptions follow Watts's observation that, 'cascade size and frequency depend on the *availability* and *connectedness* of *easily influenced* people' (Watts, 2007: 22 italics added).

Conclusions about the performance implications of the alternative strategies become more nuanced when thresholds are positive, such as when participants only learn from the majority opinion. If switching is random, a support-the-weak strategy remains the dominant strategy. As a comparison of Figures 6b and 3b reveals, each of the three strategies produces more rapid demand growth when there are majority thresholds ($\tau_0 = \tau_1 = 0.50$) than when there are zero thresholds. Under random switching favorable population-wide preference cascades occur as long as (1) advocates can tip one community or more toward broad acceptance

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of the product and (2) the population as a whole is near or above the threshold proportion.

In the absence of switching, the three strategies perform similarly and modestly (Figure 6a). The support-the-weak strategy generally is insufficient to raise low-adoption communities above the thresholds (τ_0 and τ_1) and the support-the-strong strategy allocates advocates to communities that would naturally tip toward full adoption without the firm's involvement. In this situation, firms would do well to consider a fourth strategy, namely, allocating advocates to communities near, but not yet attaining, the threshold for positive opinions to diffuse. This we call a *near-threshold* strategy. As a supplemental analysis, we modeled the near-threshold strategy as an allocation of advocates according to the rule: $a_i = aw_i f_i \left(\sum_i w_i f_i\right)^{-1}$ where $w_i = 1$ if $f_i \big/ (f_i + u_i) \leq \tau_1$ and $w_i = 0$ otherwise.[2] This is recognizable as a support-the-strong allocation focused exclusively on the subset of communities that have not yet achieved the threshold. For the case illustrated in Figure 6a, this near-threshold strategy improves the adoption rate by about 12 percent beyond the approximately 55 percent long-run adoption rate achieved by the other three strategies.

For the combination of a majority threshold and affinity switching, the support-the-weak strategy is inferior to the uniform or support-the-strong strategy over the long run (Figure 6c). If online communities facilitate homophilous affiliation patterns, and if individuals are swayed by the predominant views within communities, then a support-the-strong strategy may be advisable. In this situation, not only does a support-the-weak strategy underperform a support-the-strong strategy, but even worse, the migration induced by the firm's advocates and the consequent learning of negative opinions produces poorer performance over time than if the firm were to withdraw its advocates entirely. Communities where affiliation is based on shared interests tend to drive out dissonant messages.

Our analyses incorporated the simplifying assumption that neutral (no-preference) individuals and those holding a favorable or unfavorable view of the product require the same proportion of expressed contrary opinions to consider altering their viewpoints (i.e., $\tau_0 = \tau_1$). However, all our strategy implications regarding positive thresholds remain the same as we lower the learning threshold for individuals with no preference (i.e., $\tau_0 < \tau_1$). A lower τ_0 does not change the favored strategy, because although a smaller τ_0 value can accelerate neutral individuals' move to a defined preference, this does not change the relative proportions of positive and negative opinions at either the community level or population level on average. As such, a lower τ_0 accelerates initial commitments to defined preferences, but thereafter the demand dynamics remain unchanged from the presented results (based on $\tau_0 = \tau_1 > 0$).

Sensitivity to initial conditions

Because our initial conditions involved an equal number of favorable and unfavorable opinions in the overall population and included a median community that was equally split between the two opinions, early random outcomes are critical to the direction of convergence at the community and population levels. As shown in Figure 5, the same initial conditions can lead to either broad adoption or rejection. Random differences in product adoption decisions or switching among communities in early periods can lead to diametrically opposed outcomes at the community or population level. Firms would do well to identify such bifurcation points, when a small number of advocates can cause a cascade of favorable opinion in subsequent periods, or preempt a cascade of negative views.

With positive threshold values, outcomes are quite susceptible to the initial distribution of preferences. Combining positive threshold values with different initial distributions of preferences can either enhance the performance of a strategy or render it irrelevant to the evolution of demand. The support-the-weak strategy fails completely if the firm's allocation of advocates fails to raise the targeted communities above the threshold for product acceptance. For some initial conditions, the support-the-strong strategy can be the only effective strategy because it focuses the firm's advocates on the only communities where they can

[2] A defensive version of the near-threshold strategy would involve allocating advocates to communities where the firm can prevent the proportion of unfavorable opinions from rising above the threshold. For example, a firm could allocate advocates according to: $a_i = aw_i u_i \left(\sum_i w_i u_i\right)^{-1}$ where $w_i = 1$ if $u_i \big/ (f_i + u_i) \leq \tau_1$ and $w_i = 0$ otherwise.

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make a difference. This occurs when allocating advocates according to the support-the-weak or uniform strategy fails to achieve the threshold level needed to expand product acceptance in the targeted communities. The result is a dissipation of resources without any learning effect among the communities' members. However, if some of the communities are close enough to the threshold that the firm's advocates can cause these communities to move beyond the hurdle for adoption, focusing advocates on near-threshold communities will outperform a support-the-weak strategy.

Limitations and possible extensions

Incorporating threshold effects is a distinguishing feature of our model and, as already elaborated, it is a key contingency in our conclusions regarding the implications of alternative strategies for online communities. For simplicity, we assumed just two thresholds (τ_0 and τ_1) across the entire population; however, our model could be extended to accommodate thresholds that differ across persons, preferences, communities, time, or some combination of these. A continuous distribution of person-specific thresholds makes a community susceptible to cascades, independent of a firm's involvement, as shown by Granovetter (1978).

Our model assumes that all agents react similarly to the signals from the online community. However, as elaborated by Kozinets (1999), members in a community differ in their interest and suasion levels. Modelers may want to incorporate heterogeneous responses to information in future efforts. We need further empirical research on preference formation in online communities to better ground our model.

Our background discussion noted the differential statuses of community members, reflecting peer-conferred authority and perceived trustworthiness. Other simulation researchers (e.g., Harrison and Carroll, 2002) have modeled differences in influence within social networks. Our model could easily accommodate agent-specific posting weights, but the implications of such differences in influence are straightforward. For example, if influence increases over time for members who stay in the same community but drops upon moving to a new community, the effects of switching communities on the dissemination of opinions would be less dramatic than in our model, which weights all opinions equally.

In formulating our model, we made the simplifying assumption that firms can costlessly reallocate advocates across communities. This runs contrary to our earlier observation that communities have idiosyncratic cultures and vernaculars that require time and effort to assimilate. Firms' sunk relationship-specific investments inhibit flexibility and can produce hysteresis (Dixit, 1992). Sunk commitments will have a greater effect on implementing the support-the-weak strategy, which relies on flexible redeployment of advocates, than on the support-the-strong strategy, which emphasizes continuity in relationships with established customers. The presence of entry costs should encourage firms to concentrate advocates in a few communities with the greatest potential for attracting new customers, thereby limiting entry costs and spreading them over the most sales. In Libai and his colleagues' (2005) model, fixed entry costs increased the profitability of a support-the-strong strategy relative to support-the-weak and uniform strategies.

The initial conditions for our model assumed heterogeneous distributions of preferences across communities, but suppressed potential effects due to differences in initial community sizes. Our approach allowed differences in community sizes to arise endogenously as a function of random or affinity switching. Allowing the initial sizes of communities to vary would motivate more sophisticated firm strategies that take into consideration not only the relative proportions of different preferences across communities, but also potential market sizes. Furthermore, wide disparities in community sizes can arise over time due to competition among online communities for members. Our model does not reflect such *nonrandom* migration due to factors independent of individuals' opinions regarding the firm's product. In such a context, firms would like to influence rapidly growing communities, but the feasibility of strategies targeting rapidly growing communities turns on whether the firm is able to gain early influence that spills over to subsequent immigrants, or whether the opinions of new immigrants overwhelm the firm's influence.

Online communities offer a common forum for communication among all participating members. As such, this context presents a simple network structure, and diffusion of opinions occurs quite rapidly because messages are nonexclusive. In other kinds of communities, networks build on the basis of dyadic relationships. Communication

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within dyads excludes other community members and slows the diffusion of opinions. Exploring the implications of other kinds of social network structures for firms' influence strategies is another possible direction for extending this line of research. Once we posit other kinds of network structures, then the positioning of advocates (e.g., their centrality) becomes a crucial strategy dimension. However, to the extent that networks are small worlds (Watts, 1999), they should exhibit diffusion patterns similar to our model results and have similar implications for firms' strategies.

We focused on communication within communities and migration between communities. We did not pursue the possibility that some agents or communities mediate communication between communities. It may be interesting to explore the social learning and strategic implications of community-linking roles. For instance, some communities may function as mavens or influentials (Gladwell, 2002; Watts, 2007) affecting preferences in other communities. Research on competitive positioning within social networks (e.g., Burt, 1992) could be extended to examine the strategic implications of communities' roles within intercommunity networks.

We proposed a fourth strategy beyond those offered by Libai *et al.* (2005). A *near-threshold* strategy allocates advocates to communities below, but relatively near, the threshold required for influencing product adoption. Implementing a near-threshold strategy places greater demands on the firm than the other three strategies because it requires estimating threshold levels, which may not be uniform across communities. Future research should consider how firms can improve their assessments of thresholds using product word-of-mouth data (see Godes and Mayzlin, 2004).

Finally, our analyses focused on the strategy of a single firm. We leave the evaluation of multi-firm competition for customers within communities—online and otherwise—as an open direction for future agent-based simulation research. Agent-based modeling is flexible enough to allow researchers to incorporate assumptions informed by empirical findings (Harrison *et al.*, 2007), and is not constrained by the equilibrium assumption and need for analytical tractability required for game theoretic modeling of advertising competition (see Erickson, 2003; Jørgensen and Zaccour, 2004). We anticipate that relaxing the assumption that the focal firm acts exclusively within communities will further clarify the contingencies relevant to choosing among alternative product promotion strategies.

CONCLUSION

This study was an initial effort to develop a theory and model of firms as strategic actors in online communities. Because online communities are contexts for interpersonal communication and learning, the phenomenon lends itself to theory building using agent-based modeling (see Macy and Willer, 2002). Our model allowed us to derive community-level dynamics from simple behavioral rules for individuals and a firm. There is some research underway using agent-based modeling to examine the evolution of online communities (Butler, 2001; Ren and Kraut, 2006; 2007), but our study is the first to introduce firms as participants. Our theoretical arguments link social interactions to preference formation, and point out the potential for firms to influence demand, and even create cascades, by participating in social learning processes. Our model and results identify key contingencies relevant to firms seeking to influence community demand dynamics.

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