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Social Learning in Networks of Friends versus Strangers

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Networks and the embedded relationships are critical determinants of how people communicate and form beliefs. The explosion of social media has significantly increased the scope and impact of social learning among consumers. This paper studies observational learning in networks of friends versus strangers. A consumer decides whether to adopt a product after receiving a private signal about product quality and observing the actions of others. The preference for the product has greater heterogeneity in the stranger-network than in the friend-network. We show that when the network is small, observing friends' actions helps the consumer make more accurate inferences about quality. As the network grows, however, the stranger-network becomes more effective. Underlying these results are two competing effects of network heterogeneity on social learning. These are the *individual preference effect*, which allows one to make a better quality judgment when the preference element of past actions is more certain, and the *social conforming effect*, wherein private signals are underused in quality judgment as people follow others' actions. We find cascading is more likely to occur in the friend-network than in the stranger-network. For a high-quality firm, the stranger-network generates greater sales than the friend-network when the network size is sufficiently large or the private signal is sufficiently accurate. We also examine the existence of experts and firms using advertising to influence consumers. Finally, we show how networks that are highly homogeneous or heterogeneous could impede observational learning.

Keywords: social learning; social interaction; social networks; social media; cascade; observational learning
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1. Introduction

People often make decisions after observing and learning from others' actions (e.g., Banerjee 1992, Bikhchandani et al. 1992). Imagine the following scenario: A consumer is deciding whether to buy a new electronic device. She has some preference for a product but is unsure about its quality. She then notices that a friend has bought it, but someone she does not know has not. How will these observations influence the consumer? What if she observes that 10 of her friends have bought the product but 10 strangers did not?

Conventional wisdom suggests that the consumer is more likely to emulate her friends. As the saying goes, "birds of a feather flock together," i.e., friends often have similar preferences (tastes) while strangers differ to a greater extent.[1] As a result, people tend to follow their friends in decisions such as which movie to watch and which political candidates to vote for (Moretti 2011, Sinha and Swearingen 2001, Dey 1997). However, when people make choices based on both personal preference and the judgment of quality, do they necessarily make better decisions by doing what their friends do? Are they more likely to make a correct inference about quality? From the seller's perspective, what does the underlying consumer learning process imply for performance (e.g., product sales) and firm strategy (e.g., advertising) when the observation is of someone who has a preference similar to the consumer versus others whose preferences she is unsure of?

Networks and the embedded relationships are critical determinants of how people communicate and

[1] In this paper, we use "preference" to refer to the taste of consumers. In terms of product differentiation and positioning, this is about the horizontal attributes of a product (Hotelling 1929, Neven and Thisse 1990).

form beliefs. Traditionally people observe the behavior of others in the physical space. Such observation is often limited due to geographical constraints. Recently, the surge of information technology (particularly social media) has increased the visibility of actions of both strangers and friends in a much broader scope. For instance, Amazon provides information about other consumers' choices on its website (Chen et al. 2011). One can observe *all previous consumers*' choices in the section of "What do customers ultimately buy after viewing this item?" on the product page. Since 2010 Amazon has partnered with Facebook to provide social recommendations to customers. On linking her Facebook account to Amazon, a consumer can view and purchase products after observing the actions or "likes" of her Facebook *friends*, who are also linked to Amazon. As another example, on the Levi Strauss website, a shopper can observe the choices and preferences of her *friends* in the "Friends Store" versus *strangers* in the "Everyone Store." Similarly, search engines such as Bing allow users to engage in social search by connecting with Facebook and Twitter, making it possible for consumers to observe not only the behavior of complete *strangers* but also the actions of their *friends*.

These examples illustrate two profound trends of consumer social learning in both electronic commerce and social life: (1) the consumers' growing capability to observe the actions of others before making their own decisions, and (2) the firm's unprecedented capacity to strategically use different social networks among consumers. Compared with the situation wherein a consumer can only observe others' behavior within a physical range or in a local community, she can now do so on a much larger (often global) scale on the Internet. By providing the mechanisms such as social login with Facebook and other social network services, firms increasingly try to manage whether consumers can observe the behavior of anonymous others or that of friends in the network.

Of course, the traditional meanings of friends and strangers have been diluted in the age of social media. In this paper we use friends and strangers symbolically; the only distinction we model is the degree of preference heterogeneity among different groups. These can be real friends versus strangers in the physical space, friends versus all of the unknown people on the Internet or any groups that differ in terms of preference heterogeneity. With the rise of interest-based social networks such as Pinterest, Quora, and Flipora, consumers are increasingly adopting online social networks based on common interests rather than simply moving offline relationships online (Hendricks 2014).

This paper examines the consequences and implications when consumers can observe the past actions of different types of people to make an inference about product quality. We investigate how social learning differs in the networks of friends versus strangers, and explore the ways in which different networks convey information that shapes people's beliefs and actions. We then draw implications for marketing strategies using these networks.

Past research on observational learning (e.g., Bikhchandani et al. 1992) has primarily focused on quality uncertainty and how a consumer makes quality inferences through observing others' actions. No distinction has been made as to the source of observation and personal preference. Yet, the actions of past decision makers are often based not only on their quality judgment; personal preference matters, too. Depending on whether the consumer observes friends or strangers, the effects of preference (thus quality inference), and the subsequent adoption decision, will be different. In this paper, we introduce preference heterogeneity and the uncertainty about it into traditional cascade models.

The premise of our model is as follows. The theory of homophily (Lazarsfeld and Merton 1954) prescribes that people tend to identify themselves better with those who are similar in terms of education, socioeconomic status, and values. In the words of Plato, "similarity begets friendship" (*Phaedrus*). Therefore, the actions of friends can be more informative and provide better guidance than those of strangers. For example, a book purchased by a friend is more likely to fit a person's preference than that by a random person on the street or the Internet. Because consumer purchase actions are driven by product quality and preference, the higher certainty in preference makes it easier to infer product quality. In our model, we call this the (positive) *individual preference effect* of the friend-network. Yet, preference homogeneity also has a countervailing impact: When preference plays an important role in quality inference, people may imitate the previous actions despite their private information. As a result, the information accumulated over the friend-network becomes less accurate. By contrast, preference heterogeneity makes the past actions less diagnostic for quality, and consumers in the stranger network rely more on their private information for quality judgment. In our model, we call this the (negative) *social conforming effect*. These two competing effects coexist in social learning and pull the inference of product quality in opposite directions.

We characterize these competing effects in a theoretical model and compare the pure-strategy Perfect Bayesian Equilibrium (PBE) of observational learning in a friend-network versus a stranger-network. In the model, each person makes an adopt-or-reject decision about a product after receiving a private signal that reveals something about product quality, and after observing the actions of others in the network. We examine whether a cascading behavior will occur, the probability that an individual makes a correct quality inference, and the sales implications for high-quality versus low-quality firms. The hallmark of a friend-network versus a stranger-network is preference heterogeneity: On average people in a friend-network have more homogeneous preferences than those in a stranger-network.

In addition to shedding light on social learning in an increasingly complex social environment, our analysis produces several findings that have not been documented in the literature. For example, we show that after incorporating preference heterogeneity, the probability of cascading will approach zero as the network size increases. This is in contrast with the literature wherein a cascade would rapidly form as the number of individuals increases (Bikhchandani et al. 1992). Furthermore, we find a robust threshold effect of network size on quality inference. When the network size is small, a friend-network carries more valuable information and the consumer is more likely to make a correct inference. However, as the network grows, the stranger-network gradually accumulates more information and the quality inference becomes more accurate. These results indicate the boundary conditions in which either network type may be superior. They also corroborate the fact that people often flock to large stranger-networks such as Craigslist, Yelp, and Tripadvisor, which are mostly comprised of strangers. Finally, from the firm's perspective, we explore the sales impact of using either friend- and stranger-networks to influence consumers, and how advertising can be adjusted based on the nature of consumer learning. For example, our findings suggest that it is not always beneficial for firms to use friend-networks for promotion, especially for high quality products.

The rest of the paper is organized as follows. Section 2 discusses three related streams of literature. Section 3 introduces the main model, information on the structure and solution concept, and presents a number of lemmas to facilitate interpretation. Sections 4 and 5 present the analysis, insights, and extensions. Section 6 provides concluding remarks including the managerial implications and the limitations of this paper.

2. Related Literature and Theoretical Contributions

A growing number of marketing studies examine social interaction and its implications (Godes et al. 2005). Most of these are empirical studies focusing on the impact of social interaction in different forms, such as word-of-mouth and observational learning (e.g., Chen et al. 2011, Chevalier and Mayzlin 2006, Godes and Mayzlin 2004, Hanson and Putler 1996, Liu 2006, Salganik et al. 2006, Tucker and Zhang 2011, Zhang 2010), "neighborhood effects" (Bell and Song 2007, Choi et al. 2010, Grinblatt et al. 2008), social contagion (Van den Bulte and Lilien 2001), and peer recommendation (Zhao and Xie 2011). Theoretical work remains very limited in this area. A few scholars (e.g., Mayzlin 2006, Chen and Xie 2008) have explored consumer learning based on online product information. However, to our knowledge, no theoretical work has analyzed observational learning when different social environments (e.g., friend versus stranger networks) are taken into consideration.

More broadly, our paper is related to three streams of literature: (1) the economics literature on observational learning, (2) the sociology literature on social networks, and (3) the social psychology literature on conformity. To clearly illustrate our contributions, we present a detailed comparison of our study with these areas of research. Table 1 summarizes the comparisons on research methods, research setting and key assumptions, major findings, and theoretical mechanisms. We now discuss the three research streams in detail.

Our paper contributes to the growing research on observational learning. The current economics literature has primarily focused on the dimension of quality inference (e.g., Banerjee 1992, Bikhchandani et al. 1992, Acemoglu et al. 2011). The implicit assumptions are either that preference is not part of the decision process, or that individual preferences are homogenous. By contrast, we incorporate the issues of networks and preference heterogeneity, and consider a general case wherein individual preferences can be heterogeneous depending on the social network structure. As discussed earlier, a key motivation for this approach is substantive: The growing influence of the Internet and social media technologies has significantly increased the visibility of the actions of both friends and strangers to the consumer. With preference heterogeneity embedded in the networks, we find that the stranger-network makes people use more of their private signals and, as a result, reduces cascading and herd behaviors identified in previous studies.

Conceptually, distinguishing different types of people whom consumers can observe to derive insights for social learning is both theoretically and managerially important. For instance, with preference heterogeneity embedded in the networks, people are more likely to rely on their private information. This reduces the cascading and herding identified in previous studies. Technically our model integrates the marketing and economics research on competitive positioning, which examines both horizontal and vertical preferences among consumers (Hotelling

Table 1 Comparison of Related Literature

Study (method)	Research setting and key assumptions	Major findings	Mechanism
	The economics literature on observational learning		
Bikhchandani et al. (1992), Banerjee (1992) (analytical model)	1. Individuals sequentially make decisions; 2. They observe independent private signals and the actions of all previous individuals; 3. Individuals' preferences are homogeneous.	An information cascade will occur, and everyone makes the identical rational decision. However, those rational decisions may not be the correct one.	Since observed past actions are discrete and imperfect signals of the true state, learning is imperfect. Individuals will rationally ignore their own information and emulate the behavior of others.
Acemoglu et al. (2011) (analytical model)	1. Individuals make decisions sequentially; 2. They observe independent private signals and the actions of their stochastic social network neighbors; 3. Individuals' preferences are homogeneous.	Actions will not converge to the correct action when the network is composed of an excessively influential group.	With an excessively influential group in the social network, they become the sole information source for infinitely many people. The efficient learning and information aggregation ceases to apply.
	The sociology literature on social networks		
Granovetter (1973) (empirical study with survey data)	A person's close friends tend to have the same contacts that this person has.	Weak ties bring in more novel information than strong ties do.	The information close friends receive overlaps considerably with what an individual already knows.
Burt (2004) (empirical study with survey data)	Information is correlated to a greater extent within than between groups.	Employees occupying brokerage positions realize more benefits, including good ideas, compensation, and promotion.	Brokers that span the structural holes between separate groups have access to alternative thinking and behaviors.
	The social psychology literature on conformity		
Janis (1972) (case study)	Policy-making groups are subjected to social pressures and informal norms of solidarity.	Groups affected by group thinking ignore alternatives and tend to make faulty and irrational decisions.	In-group pressures cause the group to have "a deterioration of mental efficiency, reality testing, and moral judgment" (p. 9).
Bond and Smith (1996) (meta-analysis of experiments)	People want to develop and preserve meaningful social relationships.	People conform to the estimates of their confederates in studies using Asch-like line judgment tasks.	People conform to gain social approval of others, to build rewarding relationships, and to enhance self-esteem.
Pool et al. (1998) (experiments)	People want to maintain a favorable self-identity.	People conform to their valued groups.	People identify with and conform to valued groups to maintain positive self-assessment and self-concept.
	This study		
This study (analytical model)	1. Individuals sequentially make decisions; 2. They observe independent private signals on product quality and the actions of all previous individuals; 3. Individuals' taste preferences are homogeneous in the friend-network; 4. Individuals' taste preferences are heterogeneous in the stranger-network.	1. When the network size is large, the stranger-network provides more accurate information on quality inference than the friend-network. 2. Furthermore, beliefs about the quality will converge to the true state as the stranger-network grows.	Heterogeneous preferences among strangers make others' actions less diagnostic. They thus rely more on their private signals, which can provide more useful and accurate information in aggregation. By contrast, friends have more homogeneous preferences, and tend to rely more on others' actions but ignore their own private signals. The accumulated information over the friend-network becomes less accurate than in the stranger-network.

1929, Neven and Thisse 1990, Vandenbosch and Weinberg 1995), with the research on observational learning, which focuses on quality uncertainty and inference (Banerjee 1992; Bikhchandani et al. 1992, 1998). Finally, unlike most studies in this literature, we explore in detail the implications for product sales and marketing strategy.

An important stream of sociology research focuses on social networks, particularly those on tie strength (Granovetter 1973, 1983) and structural holes (Burt 2004). There are several crucial differences between our study and this literature. First, our friend- and stranger-networks are conceptually different from the common notion of strong/weak ties. Tie strength is based on the *connection* between people, whereas our work focuses on preference similarity from the homophily theory (Lazarsfeld and Merton 1954). In fact, the homophily theory suggests that preference heterogeneity could be seen as an antecedent of strong/weak ties and thus captures a more fundamental difference between the friend-network and the stranger-network. Second, the information structures are very different. In the sociology literature, the information people receive is *correlated* and overlaps to a greater extent in strong tie than in weak tie groups (or a brokerage position across structural holes) (Granovetter 1973, Burt 2004). However, in our model, the product quality signals are privately, and *independently*, received by individuals who are totally independent of each other in both friend- and stranger-networks.

Third, unlike most studies in this literature, our paper goes beyond the general finding that weak ties or brokerage are more informative and useful. We identify specific boundary conditions under which the stranger-network can be either more or less useful than the friend-network for quality inference. Note that such analysis of boundary conditions is facilitated by our analytical approach, whereas most of the sociology literature is conceptual or empirical.

Fourth, the mechanism behind our results is quite different from the sociology literature. In our model, when the previous information is sufficiently persuasive, the person will follow others in a cascade, effectively ignoring her own information. This is more likely to occur in the friend-network. Over time the private signals that individuals receive, and their value for quality inference, are lost. In other words, the friend-network can be less informative and even misleading because there is a significant *loss of useful information* in the process. However, in the strong/weak tie context of social networks, *information redundancy* due to overlapping is the primary reason that strong tie does not offer more new insights. There is no information loss. All information is used and always accumulates.

With regard to the social psychology literature on social conformity (see Cialdini and Goldstein 2004), our study uses a different theory when predicting the conforming behavior in a friend- versus stranger-network. The key mechanisms in this literature include group pressure (Janis 1972), social approval (Bond and Smith 1996), and self-identity maintenance (Pool et al. 1998). None of these exist in our model. Rather, the individuals in our study make rational decisions for their own interest. One contribution we provide to this literature is that the rational conforming behaviors can in fact be incorrect and harmful.

3. Modeling Framework

3.1. Assumptions and Decision Rules

In our model, N individuals indexed by $n \in N$ sequentially decide whether to adopt or reject a product. The decision of the nth individual is $x_n \in \{0, 1\}$, with $x_n = 0$ for reject and $x_n = 1$ for adopt.[2] As is standard in the literature (Banerjee 1992, Bikhchandani et al. 1992), the sequence of decisions is exogenous and the individuals know the earlier decisions.

These assumptions are not only typical in consumer learning models, they are also realistic in many scenarios. For instance, when making menu selections in restaurants, consumers often observe what others have ordered, in sequence, before making their own decisions (Cai et al. 2009). Sequential decision making often happens due to individual needs and characteristics, such as venturesome versus cautious, and the willingness to take risk. As Surowiecki (2004, p. 63) points out, "some people are more cautious than others, some are more willing to experiment, some have more money than others." Sequential decision making also occurs due to explicit queuing mechanisms. For example, in the U.S. market for transplant kidneys, the kidney from a deceased donor travels down a sequence for the patients to make the decision to accept or reject the kidney. The sequence is "constructed through a commonly known process" and "observational learning is fully enabled" since each patient (and his or her family) observes earlier decisions (Zhang 2010, p. 316). In online peer-to-peer lending, one of the most innovative financial markets, sequential learning occurs where each lender observes others' funding or no funding decisions on a loan application before making a decision (Zhang and Liu 2012).

Furthermore, note that sequential purchase is consistent with the well known diffusion framework of Rogers (1995). Innovators or early adopters make early decisions; they may observe few, if any, previous purchases when making the decision. This is similar to the situation of the first (or the first few) decision makers in the model. By contrast, majority, late majority, and dawdlers would enter the purchase sequence later; they can observe earlier purchase decisions. As stated earlier, the previous actions of others have also become more visible in many product categories due to various Internet and social network services.

Following the cascading literature, our model focuses on observational learning from past actions. In addition to others' actions, each person also observes a private signal s, the value of which depends on the quality of the product, V.

[2] For ease of exposition, we use $x_n = \{\text{adopt, reject}\}$ and $x_n = \{1, 0\}$ interchangeably in the paper.

Quality. The quality of the product is either 0 (low) or 1 (high), and is indexed by $V \in \{0, 1\}$.[3] Both states are equally likely so that $P(V=1) = P(V=0) = 1/2$ as is standard in the cascades literature. Quality is exogenous and does not depend on the number of consumers who are using the product. In other words, we do not model network externalities.

Preferences. Each person has an exogenous preference or taste for the product. This is represented by the individual's location on a unit line, $t_n \in [0, 1]$ (Hotelling 1929, Thisse and Vives 1988, Desai 2001). Greater t_n indicates greater preference. To illustrate the role of preference in our context, consider the situation wherein a consumer is making a decision about going to a Japanese restaurant. Her overall preference for Japanese restaurants (or Japanese food) is indexed by t_n. The greater t_n, the more likely she will go to the restaurant. However, the quality of the particular restaurant is unknown.

Payoffs. The payoff or utility of individual n depends on her decision x_n, the quality of the product V, and her preference t_n.

$$u_n(x_n, V, t_n) = \begin{cases} V - (1 - t_n) & \text{if } x_n = \textit{adopt} \\ 0 & \text{if } x_n = \textit{reject}, \end{cases} \quad (1)$$

The payoff has two components, i.e., product quality V and individual preference t_n. Total utility is the typical linear function of quality and preference mismatch. Because people know their own preferences, the uncertainty of the payoff comes from product quality, which is driven by the belief in quality based on the information aggregated in the network.

The payoff depends on how much the consumer prefers the product in general. The higher the preference, the higher the payoff. The product quality being either high or low further affects the payoff. If the quality is high ($V = 1$), the product provides a non-negative payoff if the individual adopts it. If the quality is low ($V = 0$), the consumer loses from the adoption. The level of quality determines the overall valence of payoff to be positive or negative. This highlights the central issue of quality judgment in social learning models. In §5.1 we will discuss the situation wherein preference could determine the valence of the payoff.

Going back to the example of Japanese restaurants, the higher the consumer's preference for Japanese food, the greater her payoff from dining at this restaurant. If she does not like Japanese food at all, we assume she will not have a positive experience even if the restaurant is of high quality.

Table 2 **Probabilities That Individuals Receive a Particular Signal**

	$P(s = H \mid V)$	$P(s = L \mid V)$
$V = 1$	p	$1 - p$
$V = 0$	$1 - p$	p

Information structure. The information set I_n of the nth individual consists of the quality signal s_n, her preference t_n, and the previous decisions, $I_n = \{s_n, t_n, x_k \text{ for all } k \in \{1, 2, \ldots, n-1\}\}$. These include private information (s_n and t_n) and social information (x_k for all $k \in \{1, 2, \ldots, n-1\}$). The set of all possible information sets of the nth individual is denoted by $\mathbf{I}_n$.

The random quality signal, s_n, can come in as H indicating high quality or L indicating low quality. The distribution of s_n depends on product quality. If the quality is 1, H is observed more often (with probability $p > 1/2$) and L is observed less (with probability $1 - p$). If the quality is 0, H is observed with probability $1 - p$ and L with p. In real-world situations, the quality signal could come from a variety of sources. For example, the consumer could have read online product reviews or third-party professional opinions such as Zagat.com or *Consumer Reports* (Chen and Xie 2005, Godes and Mayzlin 2004). Table 2 summarizes these probabilities.

Networks. To illustrate the key results and intuition we begin with a model in which the type of network is either a friend or a stranger. We then relax this assumption and examine the general case of networks that contain a mixture of friends, acquaintances, and strangers. Consumer preferences define the nature of networks in our context. Individuals in a friend-network have homogenous preferences whereas those in the stranger-network have heterogeneous preferences (McPherson et al. 2001, Lazarsfeld and Merton 1954). In the friend-network, individuals have preference t, which is common knowledge. In the stranger-network, individuals have preferences $t_n \sim U(0, 1)$. Each person knows her own t_n and the overall distribution, but not the specific value of t for another person. Note that this model accommodates the situation wherein some strangers could have the same preference as the decision maker. It is the heterogeneity and uncertainty of preferences that separate strangers from friends.

As discussed earlier, the notion of friend versus stranger is used symbolically to represent different situations of preference heterogeneity. Not everyone in a person's social network has to be a friend, and a person may have different friends in different situations. In other words, friend can be context-dependent. For instance, in deciding whether to go to a restaurant,

[3] We set the quality of the product at 0 or 1 for analytical tractability. Similar set-ups are common in the literature (e.g., Bikhchandani et al. 1992, Acemoglu et al. 2011). Future research could examine continuous quality values. Because there will be a cut-off value of V above which consumers will adopt for the continuous case of V, decision rules similar to our model could be obtained.

people in the friends-network could be those in the person's social network who share her preferences for food. A colleague can be a member of the friend-network when we choose a textbook for teaching, but this colleague may not be in the friend circle for deciding which movie to watch. The context-specific characteristic of friends is directly illustrated (and enabled) by Google Circles, where people can create separate networks for different relationships.

A pure strategy for individual n is σ_n: $\mathbf{I}_i \to \{0, 1\}$, which maps each possible information set I_n to actions. A sequence of strategies $\sigma = \{\sigma_n\}_{n\in N}$ defines a strategy profile. A sequence of decisions x_n, $n \in N$ is a stochastic process given a strategy profile. A strategy profile σ^* is a pure-strategy PBE if for every $n \in N$, σ_n^* maximizes the expected payoff of the nth individual given the strategies of others, σ_{-n}^*. Given a strategy profile σ, the expected payoff if the nth person adopts is simply $P(V=1 \mid I_n) - (1-t_n)$, and zero if she rejects, where $I_n = \{s_n, t_n, x_k \text{ for all } k \in \{1, 2, \ldots, n-1\}\}$. Therefore, for any equilibrium σ^*, we have

$$\sigma_n^*(I_n) \in \arg\max_{x\in\{0,1\}} \{P_{x=1,\,\sigma_{-n}^*}(V=1 \mid I_n) - 1 + t_n,\, 0_{x=0}\}.$$[4]

Lemma 1. *Let σ^* be an equilibrium of the game. Let $I_n \in \mathbf{I}_n$ be an information set of the nth individual. Then the decision rule for the nth individual, $x_n = \sigma(I_n)$, satisfies*

$$x_n = \begin{cases} \textit{adopt} & \textit{if } P(V=1 \mid I_n) > 1 - t_n \\ \textit{reject} & \textit{if } P(V=1 \mid I_n) < 1 - t_n. \end{cases} \quad (2)$$

Proof. This and all subsequent proofs are provided in the online appendix (available as supplemental material at http://dx.doi.org/10.1287/mksc.2015.0902).

Lemma 1 provides the decision rule for each decision maker. It indicates that, if the conditional (posterior) probability of high quality being is greater than the disutility of mismatched preference $(1 - t_n)$, the decision maker should adopt. Otherwise she rejects. The higher t_n, the lower the disutility from adoption. Thus the person is more likely to adopt. If $t_n = 1/2$, the decision is based on which state is more likely to happen ($V = 1$ or $V = 0$) given her information set I_n.

3.2. Bayesian Updating in the Friend-Network

If the first individual observes a private signal H, the conditional probability for high quality is $P(V=1 \mid H) = p$. If she observes L, the probability is $P(V=1 \mid L) = 1-p$. To exclude uninteresting results we focus on the range of t where $1-p < t < p$.[5] $t = 1/2$ generates the basic model in Bikhchandani et al. (1992). We begin the analysis with $t = 1/2$ in the friend-network. Similar results can be obtained when $1-p < t < 1/2$ and $1/2 < t < p$.

According to Lemma 1, the first person will adopt if she sees H, and reject if she sees L. The second person can then infer the first person's signal from her action. If the first person chooses to adopt (A) and the second sees a signal indicating high quality (H), then the conditional probability that the quality is 1 is $P(V=1 \mid AH) = p^2/(p^2 + (1-p)^2) > 1/2$. Thus, the second person will adopt as well. However, if the second person's signal is L, the conditional probability is $1/2$. Being indifferent, she chooses to adopt with probability $1/2$. Conversely, if the first person chooses to reject, the second chooses to reject if she sees L, and to adopt with probability $1/2$ if she sees H.

The third person faces one of three situations: (1) the first two individuals both adopt, (2) the first two individuals both reject, and (3) one chooses to adopt and the other rejects. In the third situation, based only on her social information (i.e., predecessors' actions), the conditional probability for high quality is $1/2$. Thus the third person acts like the first and decides based on her private signals. The fourth person would be in the same situation as the second, the fifth the same as the third, etc.

If the first two individuals choose the same action, then the third will follow their choices regardless of her private signal. This is where an information cascade begins. A cascade is defined as infinite consumers following previous decisions by others regardless of their private signals. Suppose the first two individuals both adopt. This could imply that the first person sees an H, and the second sees an H and adopts or sees L and flips a coin to adopt with probability $1/2$. Therefore, the probability of seeing the first two individuals adopt given high quality is $P(x_{1,2} = A \mid V = 1) = p^2 + \frac{1}{2}p(1-p)$. The

[4] PBE (Fudenberg and Tirole 1991) is a combination of strategies and beliefs that exist under two conditions: (1) when selecting actions, each person is an expected-utility-maximizer given her belief; and (2) when forming beliefs, each person's belief is consistent with the strategies under consideration derived from the Bayesian rule. In our model, assuming that a person's payoff does not depend on what subsequent people do, there is no incentive to deviate from the equilibrium to try to influence a latter person's decision. Similar to Bikhchandani et al. (1992), if any person is observed to deviate from the correct decision (equilibrium), subsequent decision makers would have the same belief as if the first person has made the correct (equilibrium) decision.

[5] When $t < 1-p$ (i.e., very low preference), the first individual will reject regardless of any private signal she observes. This is because $P(V=1 \mid L) = 1-p < 1-t$, and $P(V=1 \mid H) = p < 1-t$. From Lemma 1, the first person's best strategy is always to choose rejection. In this case, the first person's action does not reveal any useful information about product quality. The second person will decide based solely on her private signal just as the first person did. It is easy to verify that when $t < 1-p$, the equilibrium is everyone chooses rejection regardless of information received. Symmetric results can be obtained for $t > p$ (i.e., a relatively high preference). In this case, the equilibrium is that everyone will adopt regardless of information received.

probability of seeing both adopt given low quality is $P(x_{1,2} = A \mid V = 0) = (1-p)^2 + \frac{1}{2}p(1-p)$. Combined with the third person's private signal, the posterior probability of high quality given two earlier adoptions and a low-quality signal becomes

$$P(V=1 \mid x_{1,2}=A, L) = \frac{(1-p)[p^2+(1/2)p(1-p)]}{(1-p)[p^2+(1/2)p(1-p)]+p[(1-p)^2+(1/2)p(1-p)]} > 1/2.$$

Similarly, the posterior probability for high quality given two adoptions and a high-quality signal is also greater than 1/2. Therefore, the third person will ignore her private signals and choose to adopt. Symmetric results can be derived when the first two individuals both reject.

Thus, as long as two consecutive friends make the same decision, it is optimal for a later friend to follow. Then the probability of no cascade after an even number of friends n is P (no cascade after n) $= (p-p^2)^{n/2}$. Correspondingly, the probability of an information cascade increases exponentially with n: $1-(p-p^2)^{n/2}$. Therefore,

Lemma 2. *In a friend-network, an information cascade almost surely will happen as the network size increases.*

As discussed previously, the model in Bikhchandani et al. (1992) is a special case of our friend-network model ($t = 1/2$). Lemma 2 replicates their finding that the probability of a cascade eventually approaches 1 when there are more people involved, and provides a benchmark for the later comparison against the stranger-network. However, as we show later, a cascade is very unlikely in a stranger-network.

3.3. Bayesian Updating in a Stranger-Network

In the stranger-network, each person knows the distribution of preference $t_n \sim U(0,1)$ but does not know the exact value of other people's preferences. This produces further uncertainty in the implications of others' decisions for product quality. If the first person observes an H, the posterior probability for high quality is p. If $1-t_1$ is smaller than p, she will adopt. Otherwise, she rejects. If the second person observes the first person adopt, the posterior probability for high quality becomes

$$P(V=1 \mid x_1 = A)_s = p^2 + (1-p)^2. \tag{3}$$

We use subscript f to indicate the friend-network and s to indicate the stranger-network. Recall that in the friend-network, the posterior probability of high quality given that the first person adopts is $P(V=1 \mid x_1 = A)_f = p$. It holds that $p^2+(1-p)^2 < p$ when $1/2 < p < 1$. In other words, seeing a friend adopt is a stronger signal for high quality than seeing a stranger adopt. Because of the unknown preference of strangers, the second person is uncertain whether the first person's adoption is due to observing an H signal or based on a strong preference for the product. By contrast, in a friend-network, knowing that friends have similar preferences helps to reduce such uncertainty. How do different networks make people use their private signals differently? Suppose the first individual adopts in the stranger-network. If the second sees H, the posterior probability for high quality is

$$P(V=1 \mid x_1 = A, H)_s = \frac{p^2+(1-p)^2}{p^2+3(1-p)^2}.$$

If the second individual sees L, the posterior probability is

$$P(V=1 \mid x_1 = A, L)_s = \frac{p^2+(1-p)^2}{3p^2+(1-p)^2}.$$

It is interesting to compare $P(V=1 \mid x_1 = A, L)_s$ with $P(V=1 \mid x_1 = A, L)_f$. We know that $P(V=1 \mid x_1 = A, L)_f = 1/2$, and it holds that $P(V=1 \mid x_1 = A, L)_s < 1/2$. Facing the same information $\{A, L\}$ (the first one adopts and a private signal indicating low quality), the second person in the stranger-network is more likely to follow her private signal than in the friend-network.

Another learning pattern in the stranger-network is that, due to the heterogeneous preferences among strangers, there is always a range of preference t, $t \in (\underline{t}, \bar{t})$. As long as a person's preference t_n falls into this range, she will use her own signal to make the decision. Thus, there will be no information cascade. Specifically, following the above discussion for the second person, if $1-P(V=1 \mid x_1 = A, H)_s < t_2 < 1-P(V=1 \mid x_1 = A, L)_s$, she will reject when seeing $\{A, L\}$ and adopt when seeing $\{A, H\}$. In this situation, she uses her own signal. Similarly, for the nth person, when $1-P(V=1 \mid x_{n-1} = A, H)_s < t_n < 1-P(V=1 \mid x_{n-1} = A, L)_s$, she will reject when seeing $\{\ldots, A, L\}$ and adopt when seeing $\{\ldots, A, H\}$. There will be no information cascade. Since $t \sim U(0,1)$ and $0 < P(V=1 \mid x_{n-1} = A, L)_s < P(V=1 \mid x_{n-1} = A, H)_s < 1$, for any person in the stranger-network, it is possible for this person to have a preference t that falls into this range of preference $(\underline{t}, \bar{t})$ that prevents an information cascade. In addition, even if the nth person's preference falls outside of the range $(\underline{t}, \bar{t})_n$ and she does not use her own signal, it is still possible that the $(n+1)$th person's preference will fall between $(\underline{t}, \bar{t})_{n+1}$ and she will still use her own signal. This is very different from a friend-network wherein once a cascade happens, it will automatically continue to all of the following decision makers due to homogeneous preferences. In a stranger-network, the probability that the preferences of the nth person, the $(n+1)$th person, and so forth all fall outside the ranges of $(\underline{t}, \bar{t})_n$, $(\underline{t}, \bar{t})_{n+1}, \ldots,$ decreases rapidly as n increases. In the online appendix, we show that the probability of a cascade converges to zero as n increases. In summary,

Lemma 3. *In a stranger-network, an information cascade almost surely will not happen as the network size increases.*

Having illustrated the basic inference structure, we now turn to the entire network and show that greater reliance on private signals in a stranger-network could generate more useful information about product quality as the network grows.

4. Main Analyses

In this section, we first analyze two important outcomes of observational learning in social networks. These outcomes are: the probability of making a correct quality inference, and the impact on sales. We then discuss two model extensions that accommodate additional information environments. These extensions are when there is an expert, and when the firm considers advertising strategies.

4.1. Probability of Making Correct Inference About Quality

In our model, and for learning models in general, the central issue is when consumers make inferences about product quality. The fundamental question is: Are consumers more likely to make a *correct* inference about quality in a friend-network or a stranger-network? Since the nth individual could face 2^n different information sets, we use I_k to represent the kth possible information set for the nth individual. Mathematically, the probability of making a correct inference about quality for the nth individual is:

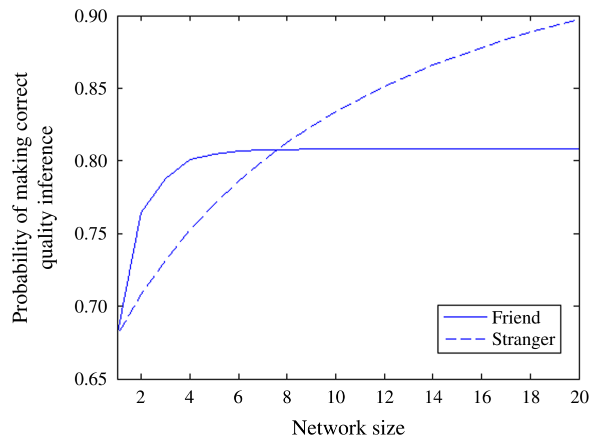
$$P(correct) = P(V=1)\sum_{k=1}^{2^n} P(I_k \mid V=1)P(V=1 \mid I_k) + P(V=0)\sum_{k=1}^{2^n} P(I_k \mid V=0)P(V=0 \mid I_k).$$

By comparing $P(correct)_s$ with $P(correct)_f$, we identify the following result:

Proposition 1. *The probability of making a correct inference about product quality is higher (lower) in the stranger-network than in the friend-network when the network size is greater (smaller) than a threshold $\bar{N}$.*

Figure 1 illustrates Proposition 1 with the example of $p = 0.8$. The x-axis represents the network size N changing from 1 to 20. The y-axis represents the probabilities of the Nth person making a correct inference. When N is relatively small, the probability of making a correct inference is higher in a friend-network than in a stranger-network. As N grows, however, the stranger-network allows the decision maker to make more and more accurate inferences. After a threshold, the person is more likely to make a correct inference about quality in the stranger-network than in the friend-network.

Figure 1 (Color online) Probability of Making Correct Quality Inference in Different Networks ($p = 0.8$)



The intuition behind Proposition 1 is as follows: Compared with the case of strangers, the preference of friends is closer to one's own preference. Having observed the friend's action, which is jointly based on the preference and quality judgment, the consumer can make a more accurate inference about quality as she is more certain about the preference element of the earlier action. Thus, due to the preference element of decisions and inference, a friend's action is more informative than a stranger's action. We term this the *individual preference effect*. At the same time, similar preferences can make a person more likely to follow others' actions and to ignore her own private signal. This is the *social conforming effect* where private signals are used less in quality judgment as decision makers follow others' actions. Because strangers have heterogeneous preferences, private signals are more likely to be used in stranger-networks. Friends' actions are more likely to mask private signals.

When the network size N is small, few private quality signals can be used. In this case, the individual preference effect dominates the social conforming effect, and friends' actions are more informative about product quality than strangers'. As N grows, more private signals are received by the decision makers. These signals will be used to a greater extent in the stranger-network due to the higher uncertainty in preferences. Furthermore, since preferences are homogeneous in the friend-network, the marginal return from observing an additional action decreases as N

grows. Observing just a few friends will cause the person to make an inference about product quality; further observations will do little to change that. The opposite is true for the stranger-network. As a result, the social conforming effect starts to dominate the individual preference effect as N grows, thus increasing the effectiveness of the stranger-network in quality inference. Eventually, the information aggregated in a stranger-network becomes more informative than that in a friend-network.

These effects can be identified in Figure 1. The case of two people ($N = 2$, $p = 0.8$) best illustrates the individual preference effect. The friend-network produces a 76% chance that the inference about product quality is correct. However, in the stranger-network, the uncertainty about the first person's preference lessens the likelihood that the second person will make the correct inference; the probability drops to around 70%. As N increases, the probability of making the correct inference increases more rapidly in the stranger-network than in the friend-network. In the friend-network, observing a small number of past actions helps form a stable inference about product quality. By contrast, the uncertainty in preferences means that those in the stranger-network will continuously benefit from the larger network; private signals further improve the inference accuracy.

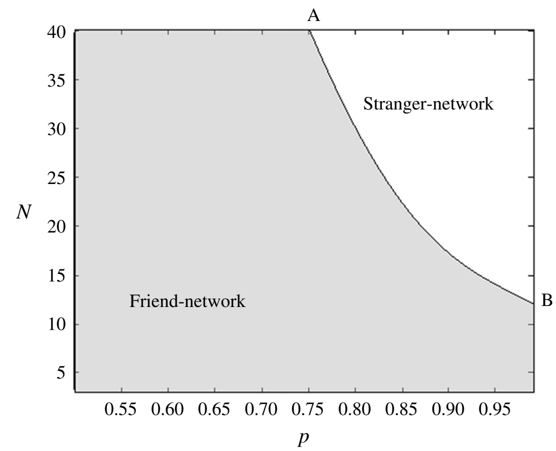
In summary, due to the individual preference effect, greater network heterogeneity has a negative effect on social learning. Because of the social conforming effect, greater network heterogeneity has a positive effect on social learning. The size of the network allows the total effect of these opposite forces to vary. The individual preference effect dominates (is dominated by) the social conforming effect in small (large) networks, making the friend-network more (less) revealing about true product quality.

The individual preference effect suggests that observing friends' actions can be beneficial. This is consistent with the "people who are like me" effect documented in behavioral research (e.g., Gershoff et al. 2001, Naylor et al. 2011, Urbany et al. 1989), and supports the use of friends' choice to influence consumers, such as various referral programs. However, when the size of the network is considered, the follow-my-friends strategy may not always be optimal. Rather, observing the actions of strangers can provide a better judgment about product quality.

4.2. Impact on Sales

As the earlier examples illustrate, firms are increasingly integrating with social network websites and providing information about friends' choices or those of anonymous strangers. The managerially critical issue is whether observing the past actions of friends or strangers is better for product sales. In this subsection, we analyze the total sales units (i.e., number of "adoptions") in different network structures to shed light on the sales impact. As mentioned earlier in the paper, we use the notion of friends and strangers symbolically; the only distinction we model is the degree of preference heterogeneity among different groups of people.

Figure 2 **The Impact of Network Structure on the Sales of High Quality Product**



Note. Curve AB is the threshold of network size when a stranger-network generates higher sales than a friend-network.

Next we examine the case of a high quality product, $V = 1$. The low quality case follows a similar logic. Expected sales is obtained by first multiplying the number of "A"s (adoptions) in a possible choice combination C_i of n people by the conditional probability of such a choice given $V = 1$, then summating across all of the 2^n possibilities: $sales_s = \sum_{i=1}^{2^n} [k_i \times P(C_i \mid V = 1)]$. Here k_i is the number of adoptions of choice C_i. The exponentially growing number of items in the expression makes analytical solutions difficult. We thus numerically calculate the sales for the friend-network and the stranger-network. The comparison provides the following result:

Proposition 2. *For a high-quality product, the stranger-network generates greater sales than the friend-network when the network size is sufficiently large or the quality signal is sufficiently accurate.*

Figure 2 illustrates the sales effect for a high-quality product. In the space above AB, a stranger-network generates higher sales than a friend-network. The reverse holds for the space below AB. As the figure shows, the larger the network or the more accurate the quality signal, the more likely the stranger-network generates higher sales than the friend-network.

The rationale of Proposition 2 closely follows earlier results. Given a certain degree of accuracy in the private signals, when network size N reaches a threshold, a stranger-network with higher preference heterogeneity will aggregate more accurate information for quality inference. Note that for a high-quality product, the seller profits when consumers make a correct inference about quality. So as N increases, a stranger-network is more likely to generate greater sales than a friend-network for a high quality product. Another pattern shown in Figure 2 is that the higher p, the smaller the threshold for the stranger-network to outperform the friend-network in selling high quality products. This is because the stranger-network allows the quality signal to influence the quality inference more than the friend-network. Therefore, *more accurate* signals will enable the stranger-network to outperform the friend-network at *smaller* values of network size. Conversely, as N increases, the probability of making an incorrect inference in a friend-network will be higher than that in a stranger-network. This "mistake" aggregates in the market and eventually benefits the low-quality product. As a result, more people will buy the low-quality product in a friend-network than in a stranger-network.

These results have direct implications for firm strategies. Cautioning against firms jumping on the "going social" bandwagon, the results show that providing consumers with access to friends' purchase history is *not* always beneficial in the digital age, especially for firms with superior quality products and where useful product quality information is available (e.g., third-party reviews). In this situation, the stranger-network with heterogeneous preferences, or the crowds, is more effective in generating higher sales for the high-quality product by helping consumers learn true product quality. In other words, the high-quality firm can leverage the wisdom of crowds on the Internet and let consumers observe, and learn from, the mass behavior.

4.3. Expert in Networks

In this subsection, we consider the scenario wherein some individuals in the network have more accurate signals (i.e., higher p) than others. We call these the experts since it mimics the real-life situation where expert consumers have better knowledge of the product.[6] To better illustrate the impact, we assume the expert makes the decision at the beginning. This is reasonable given that experts tend to enter a market and adopt a new product earlier than novice consumers (Mahajan et al. 1990). To avoid any bias in preference, we assume that the expert has neutral preference for the product ($t_e = 1/2$).[7] We analyze the impact of adding an expert on quality inference in both networks. The signal accuracy for nonexpert consumers remains p. The expert's signal accuracy is p_e, $1/2 < p < p_e < 1$. The probability of the expert making a correct quality inference is $p_e^2 + (1 - p_e)^2$.

In the friend-network, $p_e > p$ makes the second person follow the expert's action no matter what signal she observes. Technically, this means $P(V = 1 \mid A_e, L) > 1/2$ or $P(V = 1 \mid R_e, H) < 1/2$, which is easily proved. A cascade would start as early as the second person, earlier than the case without an expert. Because everyone follows the expert's action, the probability of everyone making a correct quality inference is $p_e^2 + (1 - p_e)^2$. If we compare the probabilities of making a correct quality inference between the expert case and the no-expert case, the second person's probability is higher when the first person is an expert. However, starting from the third person, the situation becomes more complex. Specifically, whether the probability becomes lower or higher when the expert is considered depends on the value of p and p_e. Following the same process to derive the probabilities, it can be shown that $P(correct) > P(correct)_e$ when $1/2 < p < p_e < 1$. For instance, when $p = 0.7$, and $p_e = 0.75$, $P(correct) = 0.655$ while $P(correct)_e = 0.625$. Thus, it is always possible that the third person makes a better quality judgment without the expert. The fourth and subsequent persons' probability of making a correct inference is no smaller than the third. Starting with the third person, everyone is better off without an expert.

Now consider the stranger-network. The second person's probability of making a correct inference is higher when the first person is an expert. This is similar to the friend-network case. However, due to heterogeneous preferences, a cascade does not happen in the stranger-network with an expert. People will continue to use both private signal and previous actions (which starts with the expert). This combination of information benefits subsequent decision makers and allows the expert's knowledge to pass on. In the online appendix, we show that this is the case. The existence of an expert is beneficial in the stranger-network.

Proposition 3. *An expert (one with higher signal accuracy) affects quality inference differently in friend- versus stranger-networks. In a friend-network, an expert can reduce the probability of correct quality inference for later consumers in the network. In a stranger-network, an expert makes quality inference more accurate for them.*

4.4. Effects of Advertising

In this subsection, we consider how consumer learning in different networks may be influenced by firm strategies. We focus on advertising, which is the most

[6] Bikhchandani et al. (1992) call these consumers the "fashion leader," which is a special case of expert in our friend-network model.

[7] We examined the situation wherein the expert's preference is distributed as $t_n \sim U(0, 1)$, and obtained similar results.

commonly used tool in the marketing mix to influence consumer belief and perception. Our purpose is two-fold. We wish to demonstrate that the key results still hold when firm action is considered, and to produce additional insights on marketing strategy. To further capture market reality, we differentiate two types of advertising strategies: targeted versus untargeted advertising.

A key purpose of advertising is to shift consumer opinions in the positive direction. In our model, this means that once exposed to the ad, a consumer's prior belief on product quality will increase. We model this by allowing an increment ε in the prior probability of the product being high quality, $P(V=1)^a = 0.5+\varepsilon$, where ε is the advertising impact ($0 \le \varepsilon \le 0.5$) and the superscript a indicates the case with advertising. Accordingly $P(V=0)^a = 0.5-\varepsilon$. Because in real life people do not often observe whether others have seen an ad, we assume that the exposure to advertising is private information. Thus consumers later in the queue do not know whether a previous consumer has seen the ad, and would assume that prior consumers were neutral, $P(V=1)=P(V=0)=0.5$.

4.4.1. Targeted Advertising. In modeling targeted advertising, we focus on the case wherein the first person is the target. This is not only a parsimonious set-up to accommodate targeting but is also consistent with the firms' common practice of wanting to target opinion leaders and/or early adopters. By contrast, untargeted ads will be seen by everyone in the network.

With the advertising influence, the first person will form a posterior belief that the product is of high quality depending on whether she sees a H or L signal as follows:

$$P(V=1 \mid H) = \frac{(0.5+\varepsilon)p}{(0.5+\varepsilon)p+(0.5-\varepsilon)(1-p)}, \tag{4}$$

$$P(V=1 \mid L) = \frac{(0.5+\varepsilon)(1-p)}{(0.5+\varepsilon)(1-p)+(0.5-\varepsilon)p}. \tag{5}$$

Combining the decision rules and the posterior beliefs, it is obvious that the higher advertising impact ε is, the more likely the person will adopt.

More important, however, the influence of advertising on consumer inference is different in different networks. In the friend-network, ε must be sufficiently large to induce different adoption patterns. Specifically, with preference t, ε must be greater than $0.5(p-t)/(p+t-2pt)$ for the first person to adopt after seeing L. When $\varepsilon < 0.5(p-t)/(p+t-2pt)$, Equation (5) remains less than $1-t$, thus the first person still rejects when seeing L. In this case, advertising is wasted. When $\varepsilon > 0.5(p-t)/(p+t-2pt)$, advertising is effective. In this case, advertising will bias later consumers' beliefs through changing the first person's action. Once the adopt action is observed by later consumers and influences their inference, the probability of an up cascade (i.e., everyone adopts) increases. Note that once ε reaches this critical value, any further increase is wasted as well; the first person will adopt anyway, which is what later consumers observe.

By contrast, in a stranger-network, since $t_n \sim U(0,1)$, no matter how large ε is, as long as ε is smaller than 0.5, it is always possible that the first person will use private signals and will adopt after seeing H and reject after seeing L (when $1-P(V=1 \mid H)^a < t < 1-P(V=1 \mid L)^a$).

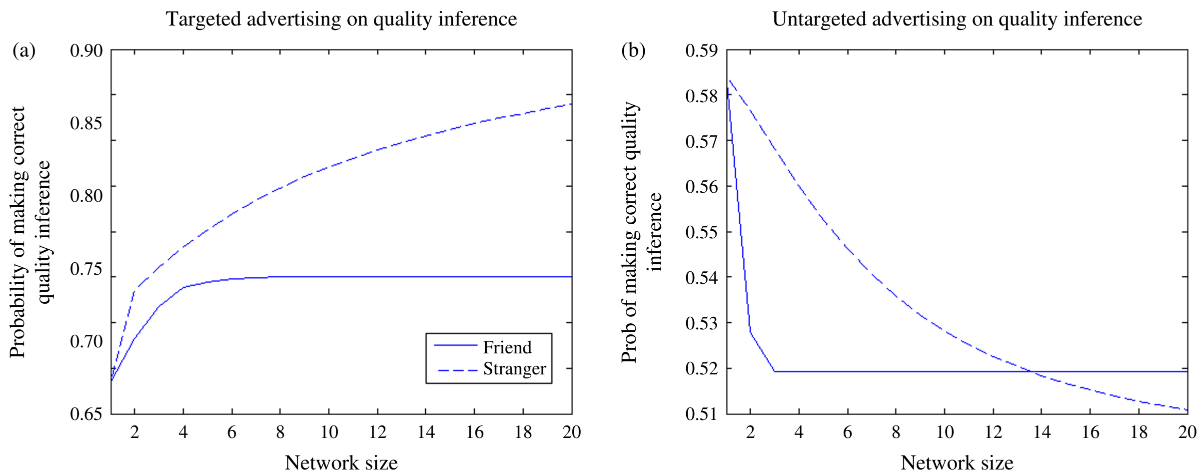
In sum, as long as $\varepsilon > 0.5(p-t)/(p+t-2pt)$, targeted ads can change the first person's behavior (and that of later consumers) in the friend-network. However, it is always possible that the first person and subsequent consumers in the stranger-network are not affected.

Similar to the main model, with targeted advertising added into the model, whereas a cascade easily occurs in the friend-network (an up cascade is even more likely), a cascade is very unlikely in the stranger-network. However, targeted advertising decreases the probability of making a correct inference in both friend- and stranger-networks. We now compare the impact of advertising on quality inference.[8] In the friend-network, we use $t=1/2$ as an illustration. The other values follow a similar pattern. To change the action of the first person, ε must be greater than $p-0.5$. Figure 3(a) plots the probabilities of making a correct quality inference in the friend- and stranger-network as N increases, with $p=0.8$ and $\varepsilon=0.4$. By contrast, with Figure 1, targeted advertising reduces the possibility of correct quality inference to a greater extent in the friend-network than in the stranger-network. At $\varepsilon=0.4$, targeted advertising makes the first person in the friend-network adopt the product, thus increasing the probability of an up cascade. Once the cascade occurs, no further information is accumulated. By contrast, in the stranger-network, even though targeted advertising also increases the first person's probability of adopting the product and thus later consumers' probabilities of adopting as well, heterogeneous preferences make it possible that the first and later consumers use their own information. Thus their actions reveal their private quality signals.

4.4.2. Untargeted Advertising. When everyone in networks sees the ad, their prior belief about product quality is shifted upward by ε. Given the information

[8] Because of mathematical tractability, we numerically analyze the different impacts of advertising on quality inference in the following analysis.

Figure 3 (Color online) The Impact of Advertising on Quality Inference in Friend and Stranger Networks ($p = 0.8$)



set I_n, the posterior belief about product quality becomes

$$P(V=1 \mid I_n) = \frac{P(V=1)^a P(I_n \mid V=1)}{P(V=1)^a P(I_n \mid V=1) + P(V=0)^a P(I_n \mid V=0)} = \frac{(0.5+\varepsilon) P(I_n \mid V=1)}{(0.5+\varepsilon) P(I_n \mid V=1) + (0.5-\varepsilon) P(I_n \mid V=0)}.$$

Figure 3(b) compares the impacts of untargeted advertising on quality inference. Again, the y-axis is the probability of making a correct inference and the x-axis is the network size, with $p = 0.8$ and $\varepsilon = 0.4$.

Contrary to targeted advertising, Figure 3(b) reveals that the negative impact of untargeted advertising is higher in the stranger-network than in the friend-network. In the friend-network, the probability of a correct inference drops noticeably from the first to the third person, and then becomes stable. In the stranger-network, the probability keeps dropping as the network grows. This is because, with untargeted advertising, everyone's private information includes not only the quality signal but also advertisement. In the stranger-network, due to heterogeneous preferences, people keep incorporating their own information into the decision. As a result, the distorted beliefs caused by advertisements are accumulated, making it more and more difficult for the later consumers to make a correct inference. In the friend-network, a cascade starts quickly after the first few consumers. Once it starts, (distorted) belief is no longer accumulated in the network.

5. Quality/Preference Trade-Off and Mixed Networks

In this section, we examine the robustness of insights from the main model to two basic assumptions. First, the main model assumes that product quality affects the direction of consumer utility. As discussed earlier, this allows quality uncertainty and inference, the core issues of consumer learning, to stand out. We now relax this assumption and examine the more general case wherein preference can also drive the direction of consumer utility. Second, we relax the assumption that the network is either a friend- or stranger-network. We look at the more general model in which the network can be a mixture of friends, acquaintances, and strangers.

5.1. When Preference Mismatch Dominates Quality

We now relax the previous assumption that product quality drives the valence of consumption utility. Unlike the main model, we allow product quality to be high, $V = \theta$, or low, $V = 0$, where $\theta \in (0, 1]$. Each consumer still has a preference for the product, t_n, where $t_n \in [0, 1]$. This set-up allows an individual to end up with a negative utility when choosing a high-quality product that does not match her preference.

Lemma 4. *Let σ^* be an equilibrium of the game. Let $I_n \in \mathbf{I}_n$ be an information set of the nth individual. Then the decision rule for the nth individual, $x_n = \sigma(I_n)$, satisfies*

$$x_n = \begin{cases} \text{adopt} & \text{if } \theta \cdot P(V=\theta \mid I_n) > 1 - t_n \\ \text{reject} & \text{if } \theta \cdot P(V=\theta \mid I_n) < 1 - t_n. \end{cases} \tag{6}$$

Lemma 4 shows that when a consumer's preference is small enough ($t_n < 1 - \theta$), she will never adopt the product no matter what information was received. In terms of consumer learning, these are "stubborn" consumers in that their actions do not reveal any information about quality. When $t_n > 1 - \theta$, the lower the product quality (the smaller θ is), the higher the conditional probability (belief) that the product is of high quality and is needed for adoption.

In the friend-network, to exclude uninteresting results, we focus on the range of $1-\theta p < t_n < 1-\theta(1-p)$.[9] The first individual will adopt after observing H and reject after observing L. If the second sees the first adopt and a private signal H, she computes the conditional probability that the product value is θ, $P(V=\theta \mid AH) = p^2/p^2+(1-p)^2 > 1-t_n$. Therefore, the second individual adopts as well. If the second individual sees L, she computes the conditional probability that the product value is θ, $P(V=\theta \mid AL)=1/2$. Here we only look at the range of t_n at $1-\theta p < t_n < 1-(1/2)\theta$. Symmetric results can be obtained when $1-(1/2)\theta < t_n < 1-\theta(1-p)$. That $1-\theta p < t_n < 1-(1/2)\theta$ is equivalent to the case when $1-p < t_n < 1/2$ and $t_n = 1-(1/2)\theta$ is equivalent to the case wherein $t_n = 1/2$ in the main model of friend-networks in §3. The only difference is that θ has been added to the inequalities as a ratio. A similar pattern can be obtained for the case wherein preference mismatch dominates quality.

Proposition 4. *When preference mismatch could dominate quality, and* $2(1-p) < \theta < 1$, *the probability of making a correct inference in a stranger-network is larger than that in a friend-network when the size of the network becomes sufficiently large.*

Thus, the insights from the main model still hold when preference mismatch could dominate product quality in determining the direction of consumption utility.

5.2. Mixed Networks

When a social network is comprised of a mixture of friends, acquaintances, and strangers, the degree of preference heterogeneity will fall between the two cases examined in the main model, i.e., either a friend-network or a stranger-network. To capture this mixed nature, we extend the main model as follows: Network heterogeneity t_n is uniformly distributed from $[1-a, a]$, where $1/2 < a \le 1$. The value of a captures different degrees of heterogeneity. The smaller a is, the more similar the preference. When a is very close to $1/2$, the network is very similar to the friend-network analyzed earlier. When $a=1$, $t \sim U(0,1)$, the network becomes the stranger-network analyzed earlier. Other elements of the model remain similar. We again analyze the pure-strategy PBE.

How does the probability of a person making a correct inference about quality change in correspondence to different network heterogeneity (a)? Here $P(Correct)_n = P(V=1)\sum_{k=1}^{2^n} P(I_k \mid V=1)P(V=1 \mid I_k) + P(V=0)\sum_{k=1}^{2^n} P(I_k \mid V=0)P(V=0 \mid I_k)$.[10] Each $P(I_k \mid V=1)$ and $P(V= \mid I_k)$ is a function of the variable network heterogeneity a. The number of elements in $P(Correct)_n$ exponentially increases with n. Because of mathematical tractability, we numerically analyze the relationship of interests. The results exhibit robustness under different values of p and N.

Figure 4 illustrates the results. The plot is provided for different combinations of p and N. As long as N is finite, the relationship between the probability for the Nth person to make a correct inference about product quality and the degree of preference heterogeneity in the network (a) is approximately inverse-U shaped. When a is relatively low, as in a homogeneous network, the probability of making a correct inference increases as a increases. Once a becomes sufficiently large, the probability begins to decrease as a increases.

This nonlinear relationship is consistent with the previous intuition of network heterogeneity on social learning. At the beginning, when the network is relatively homogeneous (i.e., before a reaches the tipping point), the social conforming effect dominates the individual preference effect. By contrast to the noise it brings into the network, greater heterogeneity is beneficial because it reveals more information about private signals through others' actions. In other words, people would rely more on their own private signals, and the marginal return of an increase in network heterogeneity is positive. However, after network heterogeneity reaches the tipping point, the individual-preference effect begins to dominate the social conforming effect. Further increase in heterogeneity makes the actions too noisy for beneficial learning.

6. Summary and Implications

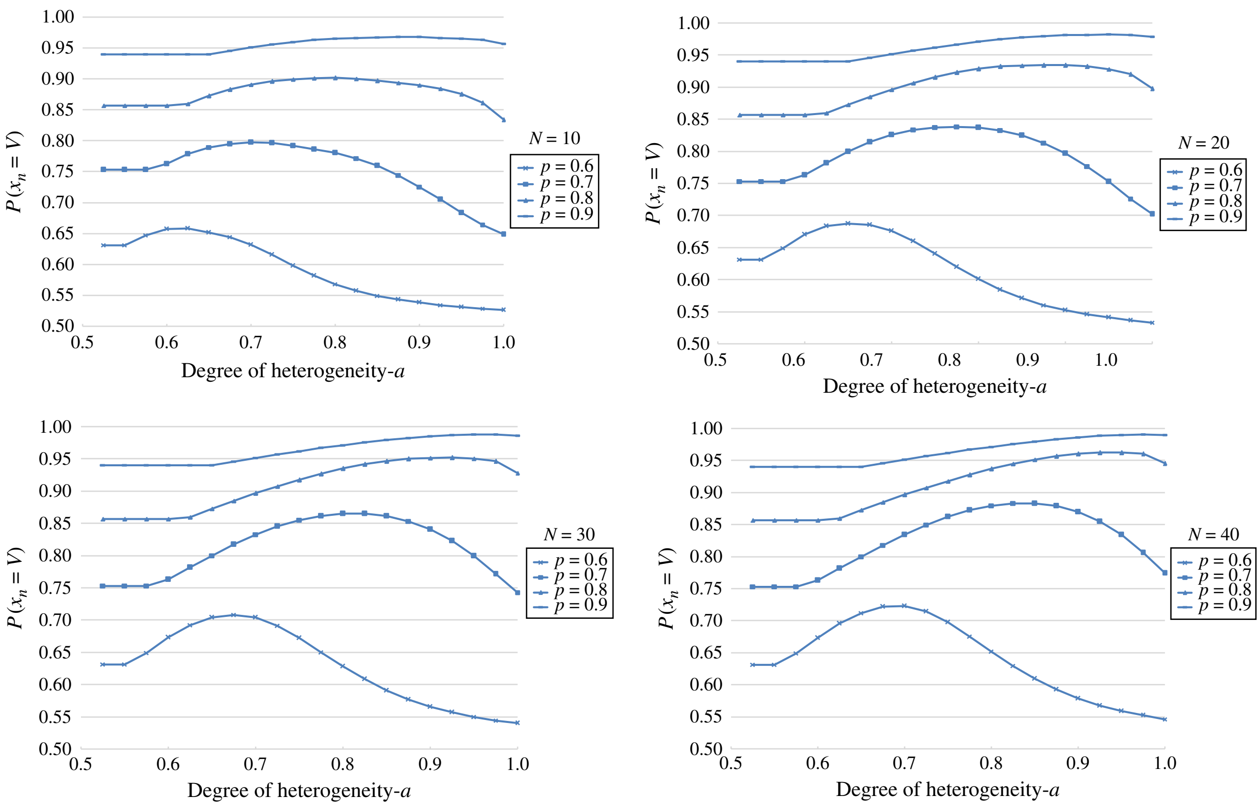
Our goal in this paper is to enhance the understanding of how social learning occurs in different types of networks. We model an important dimension of networks, i.e., the degree of preference heterogeneity. Whereas the heterogeneity is low in a friend-network, it is higher when the network is comprised of strangers. As social media and online networks continue to grow, consumers can more easily observe the behaviors of both friends and strangers. At the same time, firms can strategically manage consumer social network structures by incorporating social media into marketing strategies, and carefully choosing which type of network and what embedded information to provide to consumers. Our results shed light on how consumers should learn from social networks and how firms should use different kinds of networks.

We find a threshold effect of network size as to which network carries more valuable information for consumers: When both networks are small,

[9] See the online appendix for details.

[10] In the online appendix, we provide more detailed descriptions about how agents form their beliefs about product quality in the mixed network.

Figure 4 **(Color online) Impact of Heterogeneity on Social Learning**



Notes. The vertical axis is the probability of making a correct inference about product quality. The horizontal axis is the degree of heterogenity. The larger *a is, the more heterogeneous the network is.*

a friend-network carries more valuable information than a stranger-network. Yet when the network grows and reaches the threshold, a stranger-network carries more valuable information than a friend-network. In a more general model incorporating both friends and strangers, we find an inverse-*U* shaped relationship between network heterogeneity and the amount of information aggregated in networks. These results occur due to two competing effects of network heterogeneities, i.e., the individual preference effect and the social conforming effect. We now summarize the implications of the results for consumer decision making and marketing strategy.

Do consumers always make better decisions by relying on friends' choices? Not necessarily. It depends on the network size and the accuracy of private signals. Theoretical results suggest that when the network gradually grows, stranger-networks (or crowds) are more likely to make the correct choice. Apart from network size, the answer to this question depends on the accuracy of private signals. The more accurate a private signal, the smaller the threshold of the network size for a stranger-network to dominate a friend-network. For instance, in a market where there are many objective reviews about the quality of a product, strangers' actions are more likely to reveal product quality.

When facilitating consumer social learning to promote their products, should firms provide friend-network information with social login options? The advancement of information technology has provided an unprecedented opportunity for firms to strategically manage consumer online social networks to promote products. Our findings suggest that it is not always better for firms to provide friend-networks for consumer social interaction. This is particularly true for a high quality firm. The results show that, because of similar preferences in a friend-network, cascading is more likely to happen in a friend-network than in a stranger-network. By contrast, crowds composed of strangers will be more likely to determine true product quality. For a higher quality product, this generates higher sales than a friend-network, particularly when public information is sufficiently accurate. From a consumer welfare perspective, stranger-networks could help consumers form better judgments about product quality when preference matters. Referring back to the Amazon example in §1, this means it is not always desirable for sellers to jump on the bandwagon of social login.

For what kinds of products should firms provide social login and facilitate friend social network learning for consumers? Our theoretical results show that when the network size is small, observing friends' actions helps the consumer make more accurate inferences about quality. As the network grows, however, the stranger-network becomes more effective. This result has implications for firms that sell niche products (e.g., skin brightening products in the U.S. market). Because niche products only target very specific segments of the market and the potential network size is relatively small for these segments, providing social login with a friend-network will be more effective at selling new niche products. Firms could start by targeting those innovative leaders in friend circles. By contrast, for consumers of mass market products, the stranger-network might be better because of its potentially large size.

When is it optimal for firms to provide friend-network information with a social login option? Our theoretical results show that the threshold for the superiority of the stranger-network decreases with the accuracy of the quality signal. A high-quality firm can benefit from using a friend-network in markets where public information is very noisy (e.g., a new product or a product with new technology for which no third-party review is available). In this case, relying on strangers' behavior will add even more noise to the information aggregated in networks and thus consumers are more likely to draw a wrong inference about product quality. The friend-network, in contrast, contains clearer information and thus is more helpful at inducing a correct inference about quality and generating higher sales.

How should firms strategically manage the consumer information environment if they allow consumers to use social login? Social search engines such as Bing Social Search allow consumers to connect with friends and also access information from "experts." Note that the more accurate the search results are, the more users will come to the site. Even so, our results caution that firms must be aware of the potential drawback of this strategy. Adding experts can make cascade more likely in friend-networks, and thus jeopardize quality judgment. Yet incorporating experts into stranger-networks could enable consumers to make better quality judgments. Therefore search engines such as Bing should not add experts in the search results if consumers used social login. Rather, they should do so when consumers do not use a social search function.

How should online retailers improve recommendation systems for customers? Firms are, of course, well aware that decisions of friends are influential when consumers make decisions. For instance, travel sites such as TripAdvisor allow users to separately see reviews of hotels from people like themselves (families, couples, businesses, etc.). Yelp gives priority to reviews of a user's friends in sorting and displaying reviews. Nevertheless, apart from the preference homogeneity, to make better recommendations, online retailers should also consider network size and the accuracy of public information. The results suggest that the best network for information aggregation is neither too homogenous nor too heterogeneous. A mixed network of friends, acquaintances, and strangers will embrace the most information given the same network size and the accuracy of private information. In addition, when networks become larger and public information becomes more accurate, firms should incorporate more information from strangers, rather than friends, in making recommendations.

In the model, we assume that the value (quality) of the product is exogenous. Yet for some products, such as conspicuous goods (Amaldoss and Jain 2005), the value of a product could be influenced by the number of other people who already own it. Our conjecture is that consumers who are conformists will be even more likely to emulate their friends, whereas those desiring uniqueness will be less likely to do so. Therefore, the total impact of conspicuous goods' social effect on learning is unclear and merits further investigation. Similarly, for products with network externalities, such as software and communication tools (Katz and Shapiro 1985, 1994), people in both friends- and strangers-networks will be more likely to conform to others' decisions. Our conjecture is that network externalities will reduce the threshold of network size. Such a network effect will make consumers more likely to emulate their friends, thus using even fewer of their private signals. Yet in strangers-networks, despite externalities, network heterogeneity still exerts the opposite effect by forcing strangers to use private signals. Therefore, strangers' actions are still useful in revealing private signals. The nature of observational learning makes it an interesting topic for experimental studies. The authors of this paper have initiated lab studies considering information signals and whether the network is composed of friends or strangers. The preliminary evidence on observational learning is consistent with the results of this paper.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2015.0902.

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