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Modeling social interactions: Identification, empirical methods and policy implications

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Abstract Social interactions occur when agents in a network affect other agents' choices directly, as opposed to via the intermediation of markets. The study of such interactions and the resultant outcomes has long been an area of interest across a wide variety of social sciences. With the advent of electronic media that facilitate and record such interactions, this interest has grown sharply in the business world as

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well. In this paper, we provide a brief summary of what is known so far, discuss the main challenges for researchers interested in this area, and provide a common vocabulary that will hopefully engender future (cross disciplinary) research. The paper considers the challenges of distinguishing actual causal social interactions from other phenomena that may lead to a false inference of causality. Further, we distinguish between two broadly defined types of social interactions that relate to how strongly interactions spread through a network. We also provide a very selective review of how insights from other disciplines can improve and inform modeling choices. Finally, we discuss how models of social interaction can be used to provide guidelines for marketing policy and conclude with thoughts on future research directions.

Keywords Social interactions · Networking · Social multiplier · Peer effects

1 Introduction

The increasing recognition of the role of social interactions in various domains (e.g., social networking on sites such as MySpace.com or Facebook.com and social search on Yahoo!) has spurred renewed interest in modeling and understanding the implications of interactions among agents. These interactions are of primary importance to firms and policy-makers because they allow a stimulus to one individual to be magnified by its dispersion through the network. Thus, social interactions imply that aggregate level effects of marketing activity to individual agents are much larger than just the sum of the individual-level effects.

Academic progress in modeling and understanding social interactions is likely to have implications for both policy makers and industry. Policy makers will benefit from the facilitation of improved design and measurement of social interventions. Industry will benefit from the development of rigorous metrics for making informed decisions. While spending on social network, advertising is already at $280 million (about 2% of all online advertising spending) and expected to reach about $2 billion (6% of all online advertising) in 2010; currently, there is little understanding and consensus on the definition of social networking and the measurement of the effectiveness of advertising on these sites (AMA 2007). Our hope is that this paper will stimulate further progress on this front.

The existing literature in this area comes from a variety of academic disciplines including development economics, industrial organization, sociology, computation, and marketing. Each discipline emphasizes varying research questions using differing methodologies. There exist immense economies-of-scope in bridging these disciplines and bringing these differing approaches to bear on solving common problems of interest. We offer a selective discussion of the state-of-the-art across these disciplines. Our goal is to summarize the progress made, to highlight the current challenges, and to attempt to provide a common vocabulary for engendering cross-disciplinary research. Since the field is vast, we do not, by any means, attempt or claim to provide a comprehensive summary. Rather, we consider examples from the literature to help us articulate a unifying framework that helps identify actual causal social interactions in data. We distinguish whether these interactions involve spillovers through the network or an even greater compounding of return-on-investments of marketing actions through a "social multiplier." We focus heavily on issues of measurement, considering (1) very specific requirements of primary and secondary data, (2) modeling approaches that can help disentangle the contributors to the multiplier and, hence, the full effect of a marketing activity, and (3) experiments which can uncover multipliers.

Empirical analyses of social interactions seek to understand the manifestation of some underlying model of individual behavior in observed data. We structure our summary of empirical analyses of social interactions around whether relationships have the necessary characteristics to generate social multipliers, as opposed to spillovers. A social multiplier arises in a dyadic relationship when both agents' actions (or outcomes) are affected by the *actions* of the other agent *and* the agents recognize this, and internalize these effects, when selecting their actions. We characterize such interactions as *active*, while a *passive* interaction involves at least one agent being unaffected by the actions of the other. We consider this distinction more formally in "Section 2," but the critical point is that a passive interaction lacks the feedback which generates the social multiplier.

The relevance of the active vs. passive terminology can be illustrated by considering two historical approaches within the literature. In disease spreading models, an agent's probability of infection is a stochastic function of other agents' infections. This forms the underpinnings of many approaches to social interactions, such as those in marketing derived from the Bass model (1969). These models evolve sequentially: adoption choices in one period are specified as a function of adoption choices in the previous period. However, the lack of a forward component prevents adopters at one point in time from internalizing the impact of their action on future adoption decisions. As we discuss later, this feature makes these models passive because of the absence of a feedback loop.

Active social interactions involve feedback loops that create interdependencies between the choices of individuals. In such situations, modeling approaches typically have to deal with issues of simultaneity and considerations of equilibria. Early considerations of equilibria between socially interacting individuals arose in the sociology literature with the work of Schelling (1971) and Granovetter (1978). More recently, models and approaches that explicitly model agents' payoffs as a function of other agents' choices or states have appeared in economic-based models. These models often require unique solutions to evaluate the effect of a stimulus that is subject to a social multiplier and involve a rigorous consideration of identification in data.

Both passive and active interactions are causal in nature and have implications for policy in terms of magnifying the effect of agent-level policy interventions. A challenge for empirical work that tries to uncover social interactions from data on behavior is that both passive and active interactions are confounded with other spurious sources that generate correlation in observed behavior in the data. Throughout, we argue that marketing researchers should seek to use models that distinguish causal effects between agents from other sources of correlated behavior. This will allow marketing researchers to measure policy-relevant effects that inform us about the full effects of marketing mix expenditure and allocation.

2 Modeling social interactions

Social interactions are of key interest to marketers and policy makers due to the presence of *social spillovers* and *social multipliers*. A *social spillover* arises when an intervention or marketing action to an agent affects the behavior of others in the agent's group via a social interaction. In some cases, social interactions also incorporate a feedback loop such that the changed behavior of the group induced by a marketing action to the focal agent feeds back to reinforce the focal agent's action. This, in turn, changes the behavior of the group until a steady-state is attained. In such situations, social interactions also engender a *social multiplier* that multiplies the effect of the intervention to the initial agent. From a normative point of view, spillovers and multipliers may vastly increase the return-on-investment to policy interventions and, hence, are of significant interest to firms. From a positive point of view, spillovers and multipliers can help explain large observed variation in economic outcomes of interest, even in spite of small changes in underlying primitives.

2.1 Spillovers and multipliers

Models of social interactions begin with a framework of how an individual is affected by others in his reference group. The reference group is simply the set of other agents whose behavior the focal agent can be affected by. This definition is broad and can include all other agents in the economy ("macro"-level models) or small social groups ("micro"-level models). We consider a group composed of two agents i and j taking an action, a, which we model via a simultaneous equations framework. The actions form the outcome variable of interest. Denote a_i and a_j as the actions of agents i and j, respectively. We write,

$$a_i = \beta_i x_i + \gamma_i a_j + \mu_i z_j + u_i \tag{1.1}$$

$$a_j = \beta_j x_j + \gamma_j a_i + \mu_j z_i + u_j \tag{1.2}$$

where x_i are characteristics of agent i and z_j are characteristics pertaining to agent j that affects i's outcome (analogously for j). We think of z_j as exogenous in that it is not chosen by either i or j. β and μ respectively measure the effect of these variables on outcomes, which are allowed to be agent-specific. The u's are unobservables or errors affecting outcomes. Here, the γ's are parameters measuring the causal effect of one agent's *actions* on another, while the μ's are parameters measuring the causal effect of one agent's *characteristics* on one another. For now, we assume that both x and z are exogenous.

The system of equations specified above engenders a *social multiplier* if $\gamma_i \neq 0$ and $\gamma_j \neq 0$ and are of the same sign. In this case, i's action affects j's action and vice versa, such that i's action feeds back upon itself through γ_j then γ_i. The multiplier occurs because a small increase in a_j increases a_i through γ_i which, in turn, increases a_j even more through γ_j, and so on, until an equilibrium is attained. The term social multiplier is used because a change in x_i, for example, will have a greater total effect than β_i on a_i because of the feedback through γ_j and γ_i. The key for a multiplier to arise, therefore, is that *actions* of members have a direct, similar effect on each other.

There are two cases in which social interactions exist but create spillovers instead of multipliers. The first is the case of an asymmetry in which one agent's action does not affect the other, e.g., if $\gamma_j=0$, and $\gamma_i \neq 0$. In this case, there is no multiplier because a small change in x_j will shift a_j via β_j, and shift a_i via γ_i. However, since $\gamma_j=0$, there is no feedback loop, and the effect on a_j is limited to β_j. The second case of a spillover without a multiplier arises when $\gamma_i=\gamma_j=0$ but $\mu_i \neq 0$ or $\mu_j \neq 0$. This social interaction results in a *spillover* since an increase in z_j caused, for instance, by changing marketing effort to j, also affects i via μ_i. However, since the γ's are 0, there is no feedback from j back to i and, hence, there is no multiplier.[1]

Finally, note that in the presence of either kind of social interactions, whether involving actions or characteristics, the outcome variables a_i and a_j will be correlated. The goal of econometric work is to use the observed correlation in actions between members, to identify the causal effects, γ's and μ's. Note that correlation can also arise if the unobservables u_i and u_j are correlated. This spurious correlation does not result in any spillovers or multipliers and is, therefore, not policy-relevant.

2.1.1 An extension: Word-of-mouth

The model above captures social interactions arising through interrelated outcomes a_i and a_j. However, many social interactions, such as word-of-mouth (WOM), do not involve a direct relationship between the outcomes of group members. Suppose z_j represents word-of-mouth from individual j that affects the outcome of individual i. Furthermore, to focus on WOM effects, assume for the moment that $\gamma_i=\gamma_j=0$. Without an extension of the model, and under the assumption that $E[z_j u_i]=0$, the μ's are identified, and effect of WOM is measured. However, it is possible that WOM is endogenously chosen by agents and, hence, viewed as an action rather than a characteristic. We, therefore, introduce a more general specification of z:

$$z_i = \theta w_i + \lambda a_j + \delta a_i + e_i \tag{2.1}$$

$$z_j = \theta w_j + \lambda a_i + \delta a_j + e_j \tag{2.2}$$

where w may include variables in x, as well as other variables not contained in x.[2] Conceptually, i's word of mouth to j, z_i, depends on his characteristics w_i,

[1] Manski (2000) refers to the presence of γ in both interacting agents equations as an endogenous social effect and μ as an exogenous social effect.

[2] We do not index the parameters θ, λ, and δ by the indices i and j for expositional simplicity; but conceptually, these parameters can be individual-specific.

unobservables e_i, as well as his actions a_i, and the actions of member j, a_j. As an example, suppose the actions are the decisions to adopt a new technology. The above model says that i's decision to send WOM to j depends on whether i himself adopts, as well as how much i expects j to adopt.[3] Based on the two sets of interrelated simultaneous equations models, a WOM-based social multiplier only occurs if both of the δ's are nonzero. In such a case, a_i affects z_i (through δ) which, in turn, affects a_j (through μ_j), which cycles back to a_i through z_j. An example of this might be prerelease anticipation for a movie or new technology product such as the Apple iPhone. If a measures individual's latent utilities for eventually buying the iPhone, a WOM-based multiplier may exaggerate these latent utilities because an individual is more likely to talk about the iPhone to others the more he likes it (δ's effect on z). This WOM can lead to a reinforcement of his latent utility if his talking about the iPhone increases the other agents' latent utility and how much she, in turn, talks about it.

2.1.2 Sequential decisions

Finally, note that multipliers inherently arose in the above contexts due to the simultaneous nature of decision making. We now consider the question of whether multipliers of this sort disappear in interaction contexts where decisions are made sequentially. Let t denote time and suppose only one agent can take an action in each period.[4] Suppose i takes an action in period t conditioning on j's action in period t-1, following which j takes an action in period $t+1$, conditioning on i's action in period t. Suppose the model generating the actions a_{it} and $a_{j,t+1}$ is,

$$\begin{aligned} a_{it} &= \arg\max_a \left[V\left(a, a_{j,t-1}, x_{it}, z_{jt}, u_{it}\right)\right] \\ a_{j,t+1} &= \arg\max_a \left[V\left(a, a_{it}, x_{j,t+1}, z_{i,t+1}, u_{j,t+1}\right)\right] \end{aligned}$$

where V is the agent's present-discounted payoffs given action a. Consider one iteration of this process for each agent. A social multiplier arises in this context, if a small change in x_{it} increases a_{it} through a feedback effect via the action $a_{j,t+1}$. This arises if i is forward-looking and anticipates that his action a_{it} would change $a_{j,t+1}$.

[3] We could generalize further without any change in the substantive implications of our argument, that only the *expected* action of j drives i's decision to send WOM: e.g.

$$\begin{aligned} z_i &= \theta w_i + \lambda E_i a_j + \delta a_i + e_i \\ z_j &= \theta w_j + \lambda a_i + \delta E_j a_j + e_j \end{aligned}$$

[4] This may be the case because decision making in the group is known *a priori* to be sequential or because the analyst formulates the problem in continuous time with infinitely small time increments. As Doraszelski and Judd (2007) point out, a continuous-time model does not have simultaneity because only one agent can act at an instantaneous point in time.

To clarify, let $v_i(.)$ and $v_j(.)$ denote i and j's immediate payoff from the action. Then, a social multiplier is generated if one can write,

$$V\left(a_{it}, a_{j,t-1}, x_{it}, z_{jt}, u_{it}\right) = v_i\left(a_{it}, a_{j,t-1}, x_{it}, z_{jt}, u_{it}\right) + E\left[V\left(a_{i,t+2}, a_{j,t+1}, x_{i,t+2}, z_{j,t+2}, u_{i,t+2}\right)\right] \quad (3.1)$$

$$V\left(a_{j,t+1}, a_{it}, x_{j,t+1}, z_{i,t+1}, u_{j,t+1}\right) = v_j\left(a_{j,t+1}, a_{it}, x_{j,t+1}, z_{i,t+1}, u_{j,t+1}\right) + E\left[V\left(a_{j,t+3}, a_{i,t+2}, x_{j,t+3}, z_{i,t+3}, u_{j,t+3}\right)\right] \quad (3.2)$$

In the above equation, a small change in x_{it} changes $v_i(.)$ and, thus, affects a_{it}. This, in turn, shifts $a_{j,t+1}$ via $v_j(.)$. However, since the term in expectations in Eq. 3.1 above is a function of $a_{j,t+1}$, there is an additional feedback effect on a_{it}. Hence, a social multiplier can still arise in this system. Intuitively, in sequential decision making, a social multiplier may arise if each agent making a move incorporates that his action today will change the behavior of the agents in his group tomorrow. This is naturally satisfied in most models of dynamic forward-looking interactions.

2.1.3 Discussion and a taxonomy

To formalize the source of multipliers in social interactions, we characterize an interaction as *passive* if the feedback loop does not exist. A *passive* social interaction, therefore, arises when one agent in a dyadic relationship either is not affected by the other or does not recognize the effect of their outcome on the other when choosing it. In contrast, an *active* social interaction arises when both agents in a dyadic relationship affect one another similarly (i.e., the interaction effects have the same sign) and recognize the effect of their outcome on the other when choosing it. An active social interaction may, therefore, manifest itself in a simultaneous decision context as in Eqs. 1.1 and 1.2 above or in a dynamic decision context in which a future outcome of another agent affects the payoffs of the agent's current action/ outcome as in Eqs. 3.1 and 3.2 above.

2.2 The Identification problem

In confronting data, all nonexperimental analyses of social interactions, whether passive or active, using either structural or reduced form models, are subject to an *identification* problem. The identification problem arises due to the challenge of separating correlations in observed behavior from true causal effects of one agent on another. Only causal effects can result in a social interaction effect. Hence, uncovering causal effects accurately is key to formulating marketing and social policy. The primary confounding factors are endogenous group formation, correlated unobservables, and simultaneity. These issues were first formally laid out by Manski (1993) and Moffitt (2001) in the context of a linear model of social interactions. We discuss these and potential solutions outlined in the literature since then.

2.2.1 Endogenous group formation

The endogenous group formation problem arises because agents with similar tastes may tend to form social groups; hence, subsequent correlation in their behavior may reflect these common tastes, and not a causal effect of one's behavior on another. Consider Nair et al.'s (2006) analysis of specialist physicians acting as opinion leaders to general practitioners. A correlation in prescription behavior between these doctors could have arisen because many general practitioner physicians tend to meet and form their relationships with specialist physicians at conferences, some hosted by drug companies, which are organized around specific disease conditions and therapeutic treatment options. Alternatively, in the application of Hartmann (2008) to modeling social interactions in golf demand, correlations in observed golfing activity between two partners may simply be driven by common tastes for golf that induced them to form a group in the first place. A researcher cannot, therefore, conclude directly from observed correlation in behavior that there exists a causal effect of an agent's prescription or golfing behavior on the prescription or golfing decisions, respectively, of others in his reference group.

One solution to the endogeneity of group formation is facilitated by the availability of panel data. With panel data, one can control for endogenous group formation via agent fixed effects (e.g., Nair et al. 2006) or by including a rich specification for heterogeneity (e.g. Hartmann 2008). Both fixed and random effects here serve the role of picking up common aspects of group tastes. In other contexts, researchers can directly model the process of group formation (Bala and Goyal 2000; Glaeser and Scheinkman 2001; Conley and Udry 2003). Nonparametric identification in the latter contexts is similar to selection models (e.g., Lee 1982) and requires an exclusion restriction, i.e., a variable that affects the propensity to join a group but not subsequent behavior. Given the data requirements, studies that attempt this approach are rare.

2.2.2 Correlated unobservables

A second source of correlation is *correlated unobservables* (to the econometrician) that drive the actions of all agents in a reference group similarly. The inclusion of fixed or random effects mitigates the correlated unobservables problem to some extent, since these controls for time-invariant aspects of unobservables driving agents' behavior. In some contexts, one can use a difference-in-difference strategy of using the behavior of other agents *not* in the focal agent's reference group to control for common unobservables (e.g., Nair et al. 2006.) With large enough groups, one can also feasibly think of differencing out common unobservables by modeling *differences* in behavior within a group, as opposed to levels themselves.

2.2.3 Simultaneity

Finally, a *simultaneity* problem arises due to the potentially simultaneous nature of decisions by the focal agent and others in his reference group. Due to simultaneity, correlation in subsequent actions could simply reflect the fact that the agents' decision affects the group's behavior, and at the same time, the group's behavior affects the agent's behavior. This has been referred to as the "reflection problem" in the literature (c.f. Manski 1993). Exclusion restrictions are the most accessible identification approach to solving the simultaneity problem. The researcher needs an instrumental variable that affects a focal agent's decision but can be a priori excluded from the decision of others in his reference group. Nair et al. (2006) discuss how this approach may be used to achieve identification. Nam et al. (2006) and Tucker (2006) use this identification strategy in the related context of measuring local network effects among agents in the adoption of new technology.[5] Alternatively, researchers can directly model the equilibrium being played (e.g., Hartmann 2008).

We now discuss extant models of passive and active social interactions, noting how the identification problems discussed above have been addressed.

2.3 Models of passive social interactions

2.3.1 Epidemiology/disease spreading models

Many models of social interactions and contagion have their roots in the epidemiology literature, which has as its goal the forecasting of the rate of growth of diseases in the population. These models typically start with a specification for the disease-specific probabilities by which agents randomly catch and spread the disease. These models treat agents as passive because agents' states stochastically change based on the state of their reference group (i.e., actions, preferences, and tradeoffs are not explicitly modeled) rather than having the potential to feedback on themselves. The basic disease-spreading model does not control for agent heterogeneity and is susceptible to the endogenous group selection problem (the agent may choose to not be in a group or area that has high prevalence of the disease). Correlated unobservables may also be an issue: e.g., two agents in a community may have caught the disease because they were both exposed to the germ sequentially and developed symptoms sequentially. However, their visits to the location of the germ is unobserved to the econometrician and, hence, he may conclude from the observed data that the first agent infected the second.

One can generate differing models of contagion from the basic epidemiological framework by specifying various specifications of the probability of state transitions. The framework has been successfully applied in marketing via the Bass (1969) model to studying aggregate patterns of diffusion of new products. The Bass model is a particular instance of an epidemiological model with a specification of the probability of social contagion implying a positive concave relationship between sales and the installed bass—that is also commonly observed in aggregate diffusion data. The reader should also note that this pattern is potentially consistent with other explanations, including serial correlation in sales-related unobservables over time. In the absence of microdata, the fact that current sales is statistically significantly

[5] An alternative exclusion restriction imposes a temporal ordering, i.e., the focal individual's behavior in time ($t + 1$) is affected by the group behavior up to time (t; see Manchanda et al. 2004 for an example). However, a caveat to this identification strategy is that unobservables should not be correlated over time, and agents must be assumed not to be forward looking (i.e., agents are passive).

related to the installed base is consistent with, but not evidence of, social interactions at the agent level.[6] In terms of prediction, the Bass model is a relatively simple tool and has difficulty forecasting temporal heterogeneity and high variability in adoption rates. Watts et al. (2005) develop a model that captures these features of adoption data.

A useful distinction for network models generally is between a pure mixing model (e.g., Bass 1969) and a network spatial model. Network spatial models explicitly model network topology and illustrate how the specific network structure can sometimes generate novel and different insights on the diffusion process (e.g., Durett 1999). We refer the interested reader to Van den and Wuyts (2007) for more detail on network models.

2.3.2 Spatial models

An alternative class of models seeks to flexibly describe the correlations that exist in the observed choices of agents within a reference group. Drawing from the spatial econometrics literature (Anselin 2001), models for social interactions in this class specify correlation structures such that responses by individuals near one another in location or attribute space generate similar outcomes. These models are reduced-form representations of a social interaction model that may be either active or passive. Yang and Allenby (2003) consider consumers' decisions to potentially coordinate in buying foreign or domestic automobiles. They model the interrelatedness of these decisions via correlations in underlying preferences. Such correlations may be the result of individuals' desires to buy similar autos but could also be the result of common unobserved beliefs, such as patriotism. The model, thus, fits the data of a social interaction but does not actually distinguish whether an interaction is present.

3 Models of active social interactions

Active models of social interaction originated in sociology and are grounded in sociological and economic theory. We begin by briefly discussing the linear-in-means model, which is a canonical example from the literature. We, then, discuss nonlinear discrete choice models of social interactions. The latter model raises an additional issue related to multiplicity of possible equilibria. We discuss potential approaches to solving this problem. We, then, discuss the sociology literature that leads the research uncovering the rich nature in which payoffs and actions of agents build observed social structures.

[6] Further, as noted by Glaeser et al. (2003), in the presence of social interactions at the individual-level, models estimated on aggregate data are liable to be subject to large aggregation biases that inflate the extent of individual-level social interactions. Hence, "q coefficient-s" in a Bass model are less suited for an interpretation as causal measures of social contagion and are more appropriately interpreted as descriptive parameters capturing the dependence of current aggregate sales on the past-installed base of the product.

3.1 Linear models of social interactions

The linear-in-means model is a specification in which the actions of an agent are linearly related to the characteristics, as well as the mean behavior of others in his reference group. The linear-in-means model can be interpreted as a structural model in which agent's preferences are such that actions are a linear function of other's actions, or as a linear approximation to the reduced form implied by a nonlinear model. The linear-in-means framework captures active interactions because it considers the effect of an agent's action on the actions of others in his reference group.

For a further discussion of simultaneity, endogenous group formation, and correlated unobservables in this model, we refer the reader to Moffitt (2001) or Nair et. al. (2006), which discuss these issues in the context of an application to physician prescription behavior.

3.1.1 The importance of social network information

A desirable data feature when studying social interactions is exogenously defined social network information. Models that use the correlation in observed behavior to bin agents into groups, and then subsequently use the correlation in the actions of the agent and those in these groups to study the effect of social interactions, do not exist yet. A solution is to obtain social network information via direct elicitation from agents or from surveys (see for example, Nair et al. 2006.) A related issue is that if information clearly defining the network is not available, correlated unobservables can be even more problematic. For instance, without clear network information, a researcher may define the network based on geographic location (e.g., all persons in a zip code). In this case, it is difficult to separate the causal effect of members within the zip code on each other from common zip code level unobservables that affect all members similarly and tend their behavior to be correlated.

3.2 Discrete choice models of social interactions

While the linear model is appropriate for a wide range of situations, some choice contexts are nonlinear by definition, e.g., those involving discrete choices. Such models of social interactions extend the typical latent random utility discrete choice model to include the action (or state) of one or more other agents. Since one agent's action also depends on another's action, a typical approach has been to use a game theoretic framework to determine which combinations of actions are possible equilibria.

Discrete choice models of social interactions trace their origins to the sociology literature, in particular, to the pioneering work of Schelling (1971) and Grannovetter (1978). Shelling and Grannovetter described *threshold* models of social interactions, in which the marginal utility that some agents obtain from an action is an increasing function of the proportion of the population taking the similar action. Both Shelling's and Grannovetter's models result in a *critical mass* effect, such that once the proportion of the population choosing the action crosses a threshold point, only extreme outcomes are stable equilibria. The critical effects here are analogous to effects found in models of network effects (for example, Economides and Himmelberg 1995) and has been referred to as “tipping” by the popular press (Gladwell 2000). The basic threshold models formed the kernel for *cascade* models in the mathematics, physics, and computer science literatures that modeled networks as collections of connected agents differentiated by their *vulnerability* (Dodds and Watts 2004, 2005). The vulnerability of an agent is defined as the threshold number of connected agents that should take an action before the agent himself would. Using both analytical tools and numerical techniques, Watts (2002) demonstrated that random networks with sufficiently connected clusters of vulnerables are susceptible to large-scale cascades.

In parallel work, the critical mass model was extended by Brock and Durlauf (2001) who cast the model in terms of discrete choice. Brock and Durlaff show that rational expectations equilibria exist for their model but are not unique. The presence of multiple equilibria creates challenges for empirical work when taking the theory to data. See Bajari et al. (2006b) for a discussion of identification in models analogous to the Brock and Durlaff framework. The requirements for nonparametric identification in these models are twofold: analogous to standard discrete choice models, the payoff from one of the actions needs to be normalized. Further, the researcher needs an exclusion restriction such that one of the variables shifting the payoff of a focal agent can be excluded from the payoff functions of other agents in his reference group.

While the aforementioned models are designed to study large scale social interactions, smaller scale interactions are better suited to complete information models of discrete games as developed by Bresnahan and Reiss (1991). These have traditionally been defined for and applied to firms competing with one another (see the paper by Draganska et al. (2008) in this issue for a more detailed description and analysis of this literature), but the basic model can also be adapted to individuals interacting with one another (e.g., Hartmann 2008, for more details).

A difficult problem facing empirical researchers using either class of models is the problem of multiple equilibria. Note that multiplicity is a feature of the nonlinearity of the model (i.e., the linear model has a unique equilibrium). Multiple equilibria in social interactions require solutions similar to those used in the entry literature. For example, Bajari et al. (2006a) propose estimation of an equilibrium selection equation and generalize their model to include both entry games and social interactions. This would be the reasonable approach in most applications, but it requires an exclusion restriction: the researcher must have available a variable which affects the equilibrium chosen but does not affect the payoffs of the agents involved. In many cases, it may be impossible to find such a variable. In cases where such a variable is not available, researchers have typically defined an equilibrium selection rule which sorts between the equilibria. One nice feature of discrete games with positive externalities between agents (as opposed to the negative externalities commonly associated with entry models) is that when multiple equilibria exist, one is typically Pareto dominant. Ackerberg and Gowrisankaran (2006) note this in the case of network effects, and Hartmann (2008) use Pareto dominance for equilibrium selection in the case of social interactions.

3.2.1 Models with forward-looking consumers

While the preceding describes models of static games, or repeated static games, many social interactions involve agents interacting repeatedly in environments where past and future actions and states are also relevant. Dynamic empirical models of social interactions involve all of the estimation issues discussed above plus the complexities of estimating dynamic interactions. To appreciate the complexity, typical social interaction models with incomplete information involve a nested fixed point algorithm that finds the Bayesian Nash equilibrium of the expected actions of agents. The computational challenge in a typical dynamic choice model involves solving a nested fixed point problem to obtain the value functions measuring the discounted present value associated with states and actions. A dynamic empirical model of social interactions needs to solve both computational challenges. These models broadly fall into the empirical dynamic games literature.

A recent application is Ryan and Tucker (2006), who consider the adoption of a video-conferencing technology by employees of a given firm. The dynamics arise from the fact that adopting the technology involves incurring an adoption cost, but the adoption allows an employee to use the technology to communicate with others in all future periods. They consider active agents in terms of the adoption decisions (though not the calling decisions) and heterogeneous types of agents that can pick up behaviors similar to those defined in the threshold models from the mathematics literature. A related paper considering the dynamic network effects of platform and software markets is Dubé et al. (2007). An important contribution of this paper is that it also demonstrates how demand estimates can be used to solve a “realistic” dynamic equilibrium model on the supply side to evaluate counterfactuals related to network effects. Both papers apply recently developed two-step estimators (Bajari et al. 2007). However, a critical challenge for applying these methods to social interactions data is that they cannot accommodate the estimation of unobserved heterogeneity that may result from the endogenous group formation problem.

3.3 Field experiments

As has been noted until now, the identification of peer effects in social networks is a nontrivial task and is usually obtained by either having very high-quality data or imposing structure and using specific functional forms. One solution may be to exploit a natural experiment where there is random assignment of agents into groups (e.g., Sacerdote 2001). The confinement to natural experiments is, nevertheless, limiting. One possible way to avoid the necessity of either of the above is to carry out experiments directly in the field. The main idea is to exogenously vary the treatment (e.g., a marketing message) across subjects who have been randomly assigned to some treatment groups, as well as to a control group. Fairly straightforward analyses can, then, be used to verify the existence of the peer effect as well as to estimate the effect size. For examples, see Katz et al. (2001), and Duflo and Saez (2003). In general, however, there is a lack of studies that employ this approach—a situation that we hope changes in the future.

It is worth noting, however, that while field experiments are conceptually appealing, they can be problematic to implement in practice. Some common problems in these studies is obtaining buy-in from firms to carry out such studies, the actual cost of the study, low response rates, data recording problems, and lack of foresight to include enough treatments in order to provide an explanation for the detected effect or effect size. Some researchers have turned successfully to the web as experiments are scalable, it is easy to track behavior, and outcomes can also be measured cleanly (e.g., Salganik et al. 2006). However, some online experiments suffer from high attrition rates and operational issues. Generally, online experiments are difficult productions that are best designed to be game-like or fun and provide feedback to be appealing to participants.

Other researchers have focused more on field *studies*, rather than field *experiments*. Here, researchers do not explicitly create treatment and control groups but try and measure (exogenously varying) stimuli and correlate them with outcomes of interest. For example, Godes and Mayzlin (2004) enroll loyal and nonloyal customers of a retail chain and encourage them to generate (positive) word-of-mouth for the chain to “close” (family and friends) and “far” peers (acquaintances). They, then, correlate the sales of the retail chain at the location of the enrollees as a function of the generated word-of-mouth. They find a main effect of word-of-mouth as well as that word-of-mouth seems more persuasive on far peers rather than close peers. In addition, word-of-mouth generated by nonloyal customers is more effective than that generated by loyal customers. Note that while field studies may involve some intervention by the researchers, without an experimental design in place, the identification challenges are usually similar to those using revealed data.

3.4 Sociological inquiry into social interactions

There is, of course, a very strong tradition of work on social interaction in the sociology literature. The classic work that initiated a vast body of research over the last 40 years is the Medical Innovation Study (Coleman et al. 1966). This was followed by other important studies such as Schelling (1971), Granovetter (1973, 1978), and Burt (1987) to name a few. The focus of this literature has changed over time from *whether* people’s behavior was affected by social interaction to *who* was affected, followed by *why* and *how*. There is now a rich and varied set of insights that have emerged from this literature based on the questions of who is affected, why (s)he is affected, and how this effect propagates. Generally speaking, these insights have yet to be incorporated into econometric models of the type discussed above and are likely to prove a rich source of ideas that can be taken to data and models.

Perhaps the richness of this literature can be best exemplified by an example—the role of “status” and its effect on the extent and nature of social interactions. Status can be defined as an intangible asset that is “possessed” by an individual or organization that is highly regarded by others that are highly regarded.[7] The career-

[7] We use the term possessed carefully because, unlike financial or physical capital, status is a form of social capital and, therefore, owned only in part by the individual or organization, whose audience—capable of withdrawing at any time the esteem and recognition on which status rests—also acts as a part owner (cf. Burt 1987)

related consequences of status, especially for scientists, were brought into relief by Merton who used narrative data (interviews, writings etc.) to describe how individuals of high status obtained disproportionate rewards relative to individuals of low status for equivalent levels of output or effort (Merton 1968). Merton named this the "Matthew Effect"—an effect that has been documented widely since (see also Podolny 2005). In addition to rewards, the Matthew effect also influences outcomes such as the propagation and establishment of ideas in social networks. An indirect illustration of this effect may be seen in Nair et al. (2006) where opinion leader physicians influence the behavior of physicians but not the other way around.

More recent research in sociology focuses on providing a richer description of status along with metrics that allow us to measure status. For example, Bothner et al. (2006) allow for status to be multidimensional. The hypothesized dimensions of status in this work are "primary status" (as above) and "complementary status" (where status is based on being in demand by highly regarded others for an auxiliary role, e.g., as a team member rather than a leader). They develop metrics for measuring both kinds of status and use them to investigate the performance of venture capital firms. They find that, net of primary status, complementary status has a positive effect on firm performance. Interestingly, they find that the two types of status interact negatively, suggesting that each kind of status corresponds to a distinct role in the market.

4 Applicability to marketing and policy effects

There are many potential applications of social interactions to marketing. We have already discussed many examples. Other recent applications include television preference relationships between spouses (Yang et al. 2006), spatial diffusion of the use of an Internet grocer (Bell and Song 2007), physician adoption of a new drug (Manchanda et al. 2004), and the effects of service quality and word of mouth on acquisition, usage, and retention for a video-on-demand service (Nam et al. 2006). The last application shows how popular metrics such as Customer Lifetime Value can be understated if the social interaction effects (spillovers) are not accounted for. In terms of the future research, the rise of online media—online social networks, retail sites that explicitly allow and encourage interaction such as reviews and recommendations, etc.—is an exciting development as the network, the links, and the flow of (electronic) information can be captured objectively (e.g., Trusov 2006).

The use of such data also helps answer questions that have not received enough attention in the past. For example, in recent research, Narayan and Yang (2006) models network formation by fitting a model of the time until a link between individuals within a network will occur. Note that even in this case, the reference group is defined ex-ante despite the fact that the timing of connections within the reference group is modeled endogenously. In another interesting example, Fleder and Hosanagar (2007) examine the effect of recommender systems. Recommendation systems create social interactions indirectly by pooling the purchase behavior of similar agents to make recommendations to agents currently making purchase decisions online. The main question that is addressed in this research is whether such systems lead to a long-tail effect in sales by increasing diversity (via exposing consumers to idiosyncratic products that they may not have been aware of otherwise) or a reduction in diversity via a tipping effect. They find that recommendation systems lead to a reduction in average sales diversity online.

5 Conclusion

We hope that the discussion, so far, has made it clear that there are many interesting questions related to social interactions in marketing. These range from tests of theories describing whether, why, and how consumers and firms interact to network formation to applied questions about marketing resource allocation in the presence of social interactions. In conclusion, we would like to reinforce two key points. First, the distinction between passive and active social interactions has significant implications for the identification and magnitude of the effects of marketing policies. While the spillover effect of a passive interaction may help marketing policies spread through a network of individuals, an active type of social interaction magnifies effects even more due to a feedback loop.

Second, whether interactions are expected to be passive or active, empirical applications should explicitly consider how identification problems such as correlated unobservables and endogenous group formation are addressed in the context of their data. While we have been rigorous in drawing upon the literature in listing all the identification challenges, our intention is not to discourage researchers. Rather, our intention is to encourage research to continue to work in this area, while recognizing the boundaries of their analysis, e.g., by pointing out potential confounds. A wish list of social interactions data that we encourage practitioners to collect to avoid these confounds includes data that (1) relay the set of relationships between individuals so network structures can be analyzed, (2) measure actionable marketing variables such as purchases or page views for network members so profitability can be analyzed, and (3) use experimentation to allow researchers to at least measure a “treatment” effect of a stimulus such as advertising to the social network.

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