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Commentary

Identifying Social Influence: A Comment on Opinion Leadership and Social Contagion in New Product Diffusion

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I suggest five broad directions for future research on social influence and opinion leadership that could, if appropriately addressed, dramatically improve how we conceptualize and manage social contagions in a variety of domains.

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Introduction

Iyengar, Van den Bulte, and Valente (2010) (hereafter referred to as IVV) make deep nuanced contributions to our understanding of how opinion leadership and social contagion affect the adoption and diffusion of new products. Their work moves us forward not only by answering several fundamental questions at the heart of diffusion research but also by highlighting important open questions that should form the basis of future inquiry. In this comment, I extend insights gleaned from their empirical analysis to suggest how they may lead to an even more comprehensive understanding of peer influence and social contagion. Their work and the work that lies ahead are not only critical to marketing science and practice but also more broadly to a host of disciplines as diverse as epidemiology, innovation management, organizational performance, development economics, and public health. In what follows, I sketch five broad questions suggested by IVV's findings that could, if appropriately addressed, dramatically improve how we conceptualize and manage social contagions in a variety of domains.

1. What Exactly Is (Causal) Social Influence?

The econometric identification of social influence is fast becoming a critical endeavor in social contagion research—and rightly so—for two basic reasons. First, causal empirical estimation of peer influence is essential to the formulation of effective social contagion management policies. Although numerous studies have documented evidence of the pronounced clustering of human behaviors amongst peers, in both network space and in time (e.g., Christakis and Fowler 2007, Crandall et al. 2008, Aral and Van Alstyne 2009), whether such behavioral clustering is evidence of peer influence is of critical importance for the efficacy of peer-to-peer strategies aimed at promoting or containing social contagions. As IVV point out, the success of network-based marketing and the timing and targeting of such strategies depend on whether (and when) peers actually influence one another, the factors that affect the strength of influence and the dynamics of how peer influence unfolds over product life cycles and time. Second, causal empirical estimation is intimately tied to our most basic understanding of what it means for one peer to influence another. Definitions of peer influence guide the assumptions we make about when social contagion is "at work" and thus our modeling assumptions and econometric specifications. As I later describe, if we accept certain basic assumptions about what it means for peers to influence one another, then estimating peer influence and social contagion by definition requires attention to the causal structure of peer-to-peer induction in diffusion processes as well as to other equally critical modeling choices and estimation strategies.

Several sources of bias in both cross-sectional and longitudinal data on interactions and outcomes among peers can confound assessments of peer influence and social contagion, including simultaneity (Godes and Mayzlin 2004), unobserved heterogeneity (Van den Bulte and Lilien 2001), homophily (Aral et al. 2009), time-varying factors (Bemmaor 1994, Van den Bulte and Lilien 2001), and other contextual and correlated effects (Manski 1993). Although several approaches to the identification of peer effects have been proposed in various literatures, including peer effects models (e.g., Bramoullé et al. 2009, Oestreicher-Singer and Sundararajan 2010), actor-oriented models (e.g. Snijders et al. 2006), instrumental variable methods based on natural experiments (e.g., Sacerdote 2001, Tucker 2008), dynamic matched sample estimation (Aral et al. 2009), structural models (e.g., Ghose and Han 2010), and ad hoc approaches based on specific data characteristics (Christakis and Fowler 2007), many still suspect that peer effects are difficult to identify in observational data (Manski 1993) and that the best we can hope to do, absent controlled variation, is to bound influence estimates from above (e.g., Aral et al. 2009). Although a new line of research is emerging that uses randomized trials to identify peer influence and social contagion in networks (e.g., Aral and Walker 2010), the vast majority of data available to firms and governmental organizations remains observational, making the improved understanding of causal peer influence estimation in such data critical to our knowledge of what drives behavioral contagions in social networks and how we might attempt to promote or contain them.

IVV are diligent on this point and address the issue through a series of modeling and estimation strategies that mitigate bias from confounding factors that could misrepresent the level of social contagion in their data. By explicitly controlling for the number of monthly promotional calls each individual physician receives from the company about the drug in question, IVV go a long way toward holding constant marketing efforts whose omission is known to create upward bias in estimates of social contagion (Van den Bulte and Lilien 2001). By including temporal controls for each monthly period, they hold constant cross-temporal variation, which could confound their results. By examining the symmetry of social ties and the presence of extradyadic cycles, they further assess two other common sources of endogeneity. However, they are also careful to acknowledge that although they account for many observable sources of endogeneity, unobserved heterogeneity and simultaneity could still explain positive contagion estimates in their data.

This begs the question, what exactly does it mean for someone to influence or be influenced by their peers? And what does our conceptualization of peer influence mean for our ability to detect that it is at work in observational data? Whether or not the conceptualization of peer influence is well defined, the models and estimation strategies used in empirical analyses typically impose definitional assumptions on the concept. For purposes of illustration, I provide a broad conceptualization of peer influence and discuss how such interpretations of the concept affect and are affected by the empirical strategies used to estimate its strength. For example, if we begin with a basic conceptualization of peer influence, rooted in utility theory but broadly adaptable to other frameworks, as describing *how the behaviors of one's peers change the utility one expects to receive from engaging in a certain behavior and thus the likelihood that* (*or extent to which*) *one will engage in that behavior*, many possibilities for understanding peer influence and distinguishing it empirically from potential confounds become apparent.

First, this conceptualization includes as potential sources of "peer influence" peer behaviors that change individuals' understanding of the focal behavior as well as those that change their utility function altogether. This leaves room for a variety of influence processes, including those that raise *awareness* of a product or its features as well as those that *persuade* individuals to change their expectations of the utility derived from features of which they are already aware. For example, a friend may influence me to purchase a new mobile phone by making me aware of its global positioning system (GPS) feature or alternatively by convincing me that the GPS feature that I was already aware of is actually more valuable to me than I thought. This formulation also leaves room for influence processes that operate on *imitation* (perhaps driven by status differences) as well as *social learning*. For example, I may change my expected utility from adopting a new GPS-enabled mobile phone because my high-status friends purchased one or because I see that my friend, who used to frequently get lost, always seems to find her way after adopting the device. The conceptualization of peer influence I describe is therefore flexible enough to incorporate several social influence processes noted in previous literature as well as in IVV's setting.

Second, although this conceptualization is flexible in its view of influence mechanisms, it is rigid in its treatment of cause and effect. Peer influence is about how peer behaviors *change* one's expected utility and thus *change* the likelihood that or extent to which one will engage in the behavior. Such a conceptualization defines influence as causal and excludes correlated and confounding effects, making causal estimation essential to peer influence identification. For example, highly central individuals or individuals of high degree are not necessarily influential by this definition. To be influential, individuals must cause behavior change in the network rather than simply being connected to or passing information on to a significant number of people. This conceptualization also regards social influence as part of a dynamic system in which a variety of feedback loops continuously affects behavior in a constantly evolving fashion. Endogenous link formation may drive relationship formation, which may in turn drive changes in behavior, which then feed back into relationship formation decisions and again into influence on behaviors. In this way it is both causally driven and dynamically evolving.

Third, by broadly defining the space of all peer behaviors as potentially influential on the focal behavior in question, this conceptualization allows for a variety of influence processes that do not require peers to adopt the focal behavior itself. A peer need not be activated on the focal behavior in question to influence her peers to adopt the focal behavior. This contrasts with more traditional marketing assumptions about innovation diffusion (Peres et al. 2010) and allows for correlated or complementary behaviors to transmit peer influence and social contagion. For example, if my friend adopts a diet program, it may influence me to join a gym, which in turn may influence my friends to go on a diet. Although I do not adopt the focal behavior, which in this case is going on a diet, influence is transferred through a system of complementary behaviors that link diet and exercise. This conceptualization also allows influence to operate at social distance, through friends of friends. For example, my friend may adopt a specialized piece of software, and although I have no interest in adopting the software myself, I may encourage others who have the same specialized interest to adopt it based on the influence my friend has on my perception of its value to someone with that interest. Finally, this conceptualization allows for indirect influence in cases where some subset of the population is constrained from adopting the focal behavior. For example, men may encourage women to adopt female only contraception such as intrauterine devices because their other female friends use them, or parents may encourage their children to go to particular colleges because of the influence their children's friends' college choices has on them, even though the parents themselves are unlikely to go back to college.

It should be noted that the conceptualization of peer influence implied by IVV's modeling strategy excludes these possibilities. IVV measure contagion effects as a weighted linear additive function of the exposure of physician i at time t to prior adoptions of the focal behavior in their local network ($\sum_j w_{ij} z_{jt-1}$), where w_{ij} captures how relevant each physician j is to i and z_{jt-1} captures the focal behavior of j at time $t-1$. This conceptualization is perfectly legitimate and represents the standard method for estimating contagion effects. However, it also cannot capture the types of influence described in the preceding paragraph. If the behavior in question z_{jt-1} is defined to include complementary behaviors or accumulated exposure to the secondhand behaviors of peers of peers, then some of the scenarios described above can be reincorporated into the modeling strategy and thus the conceptualization of what it means for peer influence and social contagion to be at work.

Fourth, the details of how one specifies *how the behaviors of one's peers change the likelihood that (or extent to which) one will engage in a focal behavior* are critical to both the conceptualization of how peer influence works and how its existence or strength is empirically estimated. For example, IVV's Markovian formulation of the social influence term, which constrains the influence of a physician's peers on his future adoption decision to be independent of their prior activation, conditional on their current activation state, places constraints on the degree to which the modeling strategy can estimate the *cumulative* influence effects of prior adoptions, uses, and prescription volumes in the physician's local network. IVV (p. 8) explicitly discuss this assumption and describe how such a "memoryless" conceptualization of influence privileges the peer influence effects of "recent prescribers" and "recent prescription volume" at the expense of historical or cumulative prescriptions "for reasons of enthusiasm or credibility." In other settings, however, the cumulative influence effects of prior adoptions or sustained use over time may be critical to opinion leadership and social contagion.

As these examples highlight, different conceptualizations of peer influence lead to different modeling and estimation strategies and different perspectives on the level of peer influence and social contagion in a particular setting. Making conceptualizations of peer influence more precise and explicit may lead to more comparable results across contexts. Investigation of the empirical and analytical consequences of different conceptualizations may also help us understand when different types of influence mechanisms are at work. Throughout these endeavors, a focus on causal peer influence identification will help separate social contagion from myriad other explanations that can confound analysis.

2. How Do Product Characteristics Affect Peer Influence and Contagion?

IVV's work also highlights another important question we should ask in seeking a more comprehensive understanding of peer influence: namely, influence over what? Characteristics of the product or behavior in question can enable and constrain the degree to which individuals may be influenced by their peers. Yet relatively little attention is paid to the product or behavior itself in most studies of social contagion, and there are even fewer comparative studies of product and behavioral characteristics that encourage or discourage contagion more broadly. Understanding how the characteristics of behaviors and products enable and constrain opinion leadership and peer influence therefore seems to be a necessary next step in our inquiry into social contagion.

IVV focus on the perceived risk, ambiguity, and uncertainty surrounding physicians' adoption of the prescription drug they study. Because the drug is new and treats a chronic and potentially lethal condition, the risk inherent in the adoption decision is high, and there is uncertainty surrounding its efficacy. In such situations, when there is little accepted or empirically validated wisdom about the likely consequences of adoption and potentially high-stakes outcomes, individuals may be more likely to rely on the opinions and experiences of trusted peers in determining their adoption decisions. These characteristics of the product may affect the degree to which peers influence adoption decisions and may therefore shape how opinion leadership and social contagion operate in this context.

More generally, a variety of product or behavioral characteristics could affect the degree to which peer influence and social contagion are at work in the spread of a product. A small but growing literature has begun to examine the characteristics of content that make certain products viral. For example, Berger and Milkman (2009) find that awe-inspiring news stories that are practically useful, surprising, positive, or affect-laden are more likely to make it into the *New York Times* "most e-mailed" articles list, and Heath et al. (2001) show that disgusting urban legends are more likely to be shared. This work extends a much larger and more general literature on the characteristics of products or innovations that influence collective adoption or diffusion (e.g., Rogers 2003). There is also new work on viral product design—the process of explicitly engineering products so that they are more likely to be shared amongst peers—which examines the incorporation of specific product characteristics and features into a product's design to generate peer-to-peer influence in its adoption process (Aral and Walker 2010).

These studies suggest fruitful directions for future research around how the characteristics, features, and design of products may affect peer influence, social contagion, and product virality. A number of product characteristics may moderate the degree to which peer influence is at work, and two important dimensions to consider are the existence of network externalities and the product's price. The value of a product may be a function of the number of other users of the product resulting from both direct and indirect network externalities. Network effects can speed diffusion as a result of bandwagon effects (Economides and Himmelberg 1995, Shapiro and Varian 1999) or slow initial adoption rates as a result of the "wait-and-see" attitudes of noninnovative adopters (Farrell and Saloner 1986, Goldenberg et al. 2010). Network effects may also be "local" in that the marginal value to a user from other adopters may be higher for peer adopters and for strong-tie peer adopters than for strangers (Sundararajan 2007). For example, Aral and Walker (2010) find that the sustained use of Facebook applications is associated with the number of peers that adopt the application and even more strongly with the peer adopters an individual personally invites to adopt the application. This suggests that network externalities are a function of strong-tie peers or peers that are particularly well suited to or interested in the product in question. Peer influence may also be weaker or stronger for free products than for costly products. Perhaps individuals pay more attention to peer advice regarding costly products or are freer to adopt a costless product that is recommended by peers.

These dimensions provide examples of how a product's characteristics may moderate the degree to which peer influence and social contagion are at work in its diffusion process. Further inquiry into the landscape of product characteristics and how they affect influence processes can help us understand when opinion leadership is at work and, as a result, how managers and policy makers can implement effective peer-to-peer contagion management strategies.

3. What Is the Role of Sustained Use in Creating Sustainable Contagions?

There are many reasons why the sustained use of a product should affect a user's effectiveness at spreading it through peer influence. Sustained use may be correlated with customer satisfaction, increasing the proclivity of a user to persuade others to adopt the product (Biyalogorsky et al. 2001). Alternatively, sustained use may be correlated with an eventual waning of enthusiasm for the product, or as IVV note, heavy users may have already engaged peers, making them less effective spreaders in later time periods. Sustained use may also increase the general awareness of the product amongst users' peers. In particular, the effect of use on peer awareness can be magnified in the context of technology-related products where viral product features are deliberately designed to increase peer awareness in proportion to product use, as in the case of automated referrals (e.g., referral links appended to e-mails sent from a Hotmail account or automated notifications of a user's activity sent by

Facebook applications to a user's Facebook peers). For the same reasons, user churn—the discontinuation of a product's use—is likely to significantly affect adoption and use outcomes among peers. Individuals that stop using a product may have formed negative impressions and may dissuade peers from adopting the product. These effects may be associated with negative influence that curtails contagion more strongly than the loss of positive reinforcement from additional users.

Models akin to the well-studied threshold model of collective behavior conceptualize adoption as a binary and irreversible event (Granovetter 1978). In threshold models, product adoption occurs when a particular threshold number or fraction of adopting peers is exceeded. When one accounts for user churn in these models by allowing the adoption states of users to reverse, the resulting adoption outcomes can be heavily curtailed. Cascade models of social contagion (Goldenberg et al. 2001, Kempe et al. 2003), in which each adopting user has some explicitly defined probability of influencing each of her peers, can be easily adapted to incorporate churn as a dimension of the contagion process. Such adjustments would make these contagion models analogous to well-studied epidemiological models of the spread of infectious diseases. In susceptible–infected–recovered (SIR) models of disease spread on networks (Moore and Newman 2000), churn can be accounted for by introducing a probability that users recover from infection through a recovery rate. Notably, in SIR models, the size and duration of epidemics or contagions depends critically on the ratio of infection probability to recovery rate.

Dodds and Watts (2004) develop a model of social contagion that includes features from threshold and cascade models and could be adapted to incorporate the frequency of sustained product use. In this model, peers exposed to adopters receive a stochastic dosage or exposure to the infectious agent or product. Users retain memory of past exposures and adopt when their cumulative exposure exceeds a certain threshold. Sustained use could be incorporated into such a model by coupling outgoing exposure with sustained use. As a user uses the product, his or her peers are exposed to it more often and thus have a greater probability of infection through cumulative exposure. Such a conceptualization is naturally suited to a variety of products whose use exposes peers to their existence and value. The expected size and duration of a contagion is likely to depend on sustained use and customer churn. Incorporation of these considerations into more-sophisticated analytical models of social contagion and greater attention to empirical estimation of the impact of sustained use on peer influence represent essential steps forward in our understanding of social contagion and opinion leadership.

4. How Do the Distributions of Individual Characteristics Over Network Nodes Affect Contagion?

How different types of people are distributed in a social network can affect cascades of social behavior and behavioral contagions driven by peer influence. In the system examined by IVV, a number of social-mixing processes could drive relationship formation and opinion adjustments, resulting in complex patterns of adoption over network space and time. For instance, the authors recognize the importance of a physician's status in determining her tendency to innovate and affect others. One might therefore expect that different mixing patterns on status characteristics could lead to different innovation diffusion dynamics. Networks in which low-status individuals are clustered around high-status individuals are likely to exhibit significantly different adoption dynamics than networks in which low-status individuals are grouped into isolated peripheral clusters distant from a densely connected core of high-status individuals. All else equal, in the first case, adoption is likely to be confined to small clusters of individuals rather than percolating across communities in the network, with each cluster following its own opinion leader. In the second case, diffusion and opinion leadership are likely to result in clusters of high-status adopters that are isolated from clusters of low-status nonadopters. Competition may be another dimension that affects adoption. If physician referral networks typically connect competitors who service the same types of needs, prescription referrals may not flow to peers as easily as if referral networks connect physicians to specialists who do not directly compete with one another. Such processes would introduce a role-dependent flow of referrals and, as a consequence, potentially confine influence to operate in line with the structure of role relationships (Burt 1987).

These examples highlight how mixing and assortativity on dimensions relevant to the likelihood of adoption can influence the diffusion of behaviors and innovations. Assortativity can affect both relationship formation (Currarini et al. 2009) and the likelihood of behavioral clustering in networks (Aral et al. 2009), creating significant effects on contagion processes. For example, Aral et al. (2009) study the diffusion of a mobile service product over a global instant-messaging network of 27.4 million users and find that previous methods mistake homophily (the common characteristics, values, and needs shared among linked nodes) and other confounds for peer influence. They find that traditional contagion models overestimate peer influence in this network by 300% to 700% and that homophily explains over 50% of the perceived behavioral contagion in the product's diffusion. As Aral et al. (2009) demonstrate, the clustering of individual characteristics and preferences in network space and time can significantly confound estimates of social contagion.

How influential individuals are distributed in a network and how they mix with susceptible individuals, the relationship between dimensions of influence (e.g., persuasiveness) and network properties (e.g., degree), and the role of homophily in tie formation all could contribute to the dynamic process of social contagion in a variety of settings. Future research should consider the distributions of individual characteristics over nodes and the mixing and assortativity in a network when estimating how (and when) behavioral contagions are likely to spread. These inquiries should also consider correlations between covariates. For example, high-status individuals may tend to be of high or low degree, be susceptible or resistant to influence, or be innovators or late adopters. How individual characteristics relevant to adoption are distributed throughout a network and how those characteristics tend to be correlated within and across individuals will likely significantly affect opinion leadership and social contagion.

5. Are There "Systems" of Complementary Contagion Management Strategies?

Finally, IVV's work has direct policy implications. Their analyses help us understand and identify opinion leadership in networks to target leaders to spread influence. Several directions for the strategic use of this knowledge have been proposed in network-based marketing. Two main questions in this line of research are whom to target and how to incentivize them to spread the message. "Influentials" may drive product diffusion (Katz and Lazarsfeld 1955, Katz 1957, Merton 1968, Gladwell 2000), though cascades of influence may instead be driven by "a critical mass of easily influenced individuals" (Watts and Dodds 2007, p. 441). Influentials are typically thought of as persuasive experts with large diverse social networks (Gladwell 2000, Goldenberg et al. 2009). Literature on this latter type of "network" marketing considers how individuals' positions in social network structure enable them to create broad behavioral diffusion through peer influence (e.g., Iribarren and Moro 2009). This work privileges the importance of social hubs (Goldenberg et al. 2009), examines how strong and weak ties and network size interact to affect message propagation (Goldenberg et al. 2001), and studies how similarities within and across cohorts impact product diffusion (Reingen et al. 1984, Hill et al. 2006, Aral et al. 2009). Once a firm identifies whom to target, how to optimally incentivize them to spread the word becomes critical. In this domain, several studies address optimization of profitable referrals (Biyalogorsky et al. 2001, Libai et al. 2003, Ryu and Feick 2007).

These strategies—targeting and referral—are typically considered in isolation, yet it may also be fruitful to consider their complementarities. Different incentives may be more effective for different sets of targets, and message propagation may be optimized differently through different sets of influentials. For example, if influentials are clustered in the core of a network and susceptibles are peripheral, incentives that favor referrals to friends of friends may be optimal. If, on the other hand, influentials and susceptibles are well mixed, incentives that simply promote the recruitment of friends may be more appropriate. If there is significant homophily on age, it may be optimal to target influentials of varying ages and to design referral incentives that increase proportionally to age differences between the referrer and the referee to promote broad-based diffusion of the product across local communities. If, on the other hand, the stickiness of the product is tied to the level of interaction between men and women, the optimal policy may be to encourage one to recruit the other.

These hypothetical examples combine insights gleaned from several of the preceding questions to suggest potential sources of complementarity between targeting and referral marketing strategies. Whether the suggested combinations are more effective than the individual strategies implemented in isolation is an empirical question and one that deserves further study. However, discrete elements of diffusion and contagion dynamics and the interventions we implement to manipulate them are part of a larger interdependent system of social forces that together determine the patterns and strength of behavioral contagions. These interdependencies should not be forgotten as we isolate discrete pieces of the system in order to study them.

Conclusion

IVV's work extends our understanding of opinion leadership and suggests fruitful avenues of future inquiry into social contagion. In particular, understanding (1) causal peer influence, (2) how product characteristics affect contagion, (3) the role of sustained use in contagion processes, (4) how mixing properties of individual characteristics in a network affect diffusion, and (5) how different contagion management strategies complement one another can all provide a more precise and comprehensive picture of peer influence and social contagion at population scale. As social networks become more explicit through information technology-enabled services such as online social networking, collaborative filtering, and social product recommendation, understanding how peer influence creates and sustains behavioral contagions not only becomes more feasible but also more critical (Sundararajan et al. 2010). IVV help us move in these critical directions, and their contribution will therefore undoubtedly be influential.

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