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Opinion Leadership and Social Contagion in New Product Diffusion

Raghuram Iyengar, Christophe Van den Bulte, and Thomas W. Valente

For marketers experimenting with viral networks, this study confirms the importance of central opinion leaders. As well as reaching more people, these early adopters and heavy users start influencing others sooner and more effectively than less-connected people.

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Report Summary

How do opinion leadership and social contagion affect the adoption of a new product? Marketers have been experimenting with viral network marketing based on assumptions that social contagion is at work, that certain customers' adoptions and opinions have a disproportionate influence, and that firms are in fact able to identify and target opinion leaders. Recent research, however, has raised conflicting opinions about how important opinion leaders are in accelerating the acceptance of new products, whether marketers should identify opinion leaders based on self-reports or on their centrality in social networks, and whether heavy users of a product are more influential than light users.

This study's research setting was the diffusion of a new drug for the treatment of a chronic and potentially lethal medical condition among physicians in three cities. There are several findings. Contagion operated over network ties and was affected by peers' usage volume rather than by whether peers had adopted the new drug. Self-reported opinion leaders were less responsive to their peers' behavior, while sociometric leaders (i.e, those identified by their centrality in social networks) were not differentially responsive. Heavy use at the category level before the new product's launch was associated with early adoption. Both self-reported leaders and sociometric leaders tended to adopt early, with the tendency being more pronounced for sociometric leaders. Self-reported leadership and sociometric leadership were only moderately positively correlated.

The evidence from this study supports the use of network-leveraging campaigns that focus on central opinion leaders. The study also suggests that the industry practice of overweighting marketing efforts at launch on heavy users is sound. The authors' findings about sociometric versus self-reported opinion leadership and about contagion being moderated by usage volume suggest both ways to increase theoretical understanding of social contagion dynamics, and ways through which marketers might increase the effectiveness of network marketing. ■

Introduction

Marketers are increasingly experimenting with various forms of viral network marketing. In the area of new product marketing, where the trend is especially pronounced, the rationale of many viral network marketing strategies rests on three key assumptions: (1) social influence or social contagion among customers is at work, (2) some customers' adoptions and opinions have a disproportionate influence on others' adoptions, and (3) firms are able to identify and target those influentials, or opinion leaders. These assumptions are quite reasonable, as the first two are consistent with several sociological and marketing theories and all three have been supported in at least some studies (e.g., Godes and Mayzlin 2009; Goldenberg et al. 2006; Rogers 2003; Valente et al. 2003; Weimann 1994).

However, managers would be remiss to simply take those three assumptions for granted. For instance, Van den Bulte and Lilien (1997, 2001) have shown that contagion need not be as important as reported in prior studies; Becker (1970) and Watts and Dodds (2007) have raised doubts about the importance of opinion leaders in speeding up the acceptance of new products; and Rogers and Cartano (1962) noted long ago a disagreement about whether to identify opinion leaders based on self-reports or on their centrality in social networks. More recent research by Coulter, Feick, and Price (2002) and Godes and Mayzlin (2009) provides conflicting answers to the question whether heavy users are more influential than light users, an issue of obvious relevance to the identification and targeting of likely influentials.

The present study addresses each of the three assumptions fundamental to viral network marketing. Specifically, we empirically assess three questions about how social contagion and opinion leadership affect new product diffusion. First, is there social contagion operating over social ties such that better-connected adopters exert more influence than less-connected ones, over and above the effect of marketing efforts and marketwide influences that vary over time? Second, to what extent do sociometric and self-reported opinion leadership overlap and have the same influence on the time of adoption? Third, is contagion emanating from prior adopters a function of their product usage, i.e., is their social influence affected by their usage status or volume rather than simply by their having tried the product?

We investigate these three questions by studying the adoption of a new prescription drug by physicians. Our study combines individual-level adoption data, demographic data, a measure of self-reported opinion leadership, network data on discussion and patient referral ties among physicians, and individual-level sales-call data for the new drug. Hence, we are able to investigate the presence of contagion dynamics within social networks in a real market in which traditional marketing efforts are being deployed, the kind of setting that is of greatest relevance to both practitioners and researchers (Van den Bulte and Lilien 2001; Watts and Peretti 2007).

The results are of both theoretical and managerial interest. We find evidence of social contagion, even after controlling for marketing effort and controlling nonparametrically for any marketwide changes over time. This evidence justifies the deployment of network-based marketing strategies in the hope of accelerating new product diffusion. In addition, the influence of prior adopters is moderated by their prescription volume of the new drug, suggesting that heavy users are attractive viral seeding points over and above their greater "stand alone" customer value. Finally, the results indicate that sociometric and self-reported leadership are different constructs. They are only moderately correlated and behave differently in the theoretical or nomological network of constructs we study. Sociometric leadership has a direct, main effect on time of adoption but does not moderate sensitivity to social contagion. Self-reported leadership, in contrast, not only has a main effect but also is associated with a lower sensitivity to social contagion. These findings are of interest to researchers seeking to better understand the relations between opinion leadership, sensitivity to contagion, and time of adoption, a set of issues that recent research has shown to be more complex than previously thought (Van den Bulte and Joshi 2007; Watts and Dodds 2007). Several findings are also of interest to practitioners seeking to identify opinion leaders.

We proceed as follows. We first develop the three research questions into specific hypotheses. We then describe our research setting and research design. Next, we specify the variables created for analysis. Subsequently, we present preliminary data analyses followed by the main statistical analysis. We conclude with a discussion of implications for theory, market research, and marketing practice.

Research Hypotheses

Social contagion

The first assumption, that social contagion among customers is at work, need not always hold. As Van den Bulte and Wuyts (2007) note, contagion is likely to operate only when at least one of the following conditions is satisfied: (1) marketing efforts and media exposure are ineffective in driving awareness and interest, (2) potential adopters seek information from peers, which is more likely when they believe adopting the product is subject to functional or financial risk, (3) potential adopters experience normative pressures, which is more likely when they are not secure in their social identity (e.g., in the case of teenagers) or when the product does not conform to existing norms, (4) potential adopters fear that competitors may gain an advantage by adopting the new product, or (5) the product has several competing standards, leading to direct or indirect complementary network effects. When none of those conditions is met, contagion is unlikely to be an important driver of new product adoption. Furthermore, several studies (e.g., Bemmaor 1994; Bemmaor and Lee 2002) have documented that evidence of contagion is likely to have been inflated in prior research because of estimation problems that stem from using short and noisy data series or theoretically overdetermined models. Another source of error is the failure to control for marketing effort and other changes in the environment (Van den Bulte and Lilien 2001).

The second assumption underlying many viral network marketing strategies—that some customers' adoptions and opinions have a disproportionate influence—should not be taken for granted either. It is likely to hold when some customers have a much more central position in the social network than others or when potential adopters look for advice from experts (see, e.g., Goldenberg et al. 2006). In contrast, when the social network structure is not very centralized and when what spreads is simply information about the product's existence rather than information that mitigates perceived risk, then there need not be much variation in customers' influence (see, e.g., Van den Bulte and Wuyts 2007; Watts and Peretti 2007). Therefore, we assess the following hypothesis:

H1: New product adoption is subject to social contagion operating over and above the effect of marketing efforts and marketwide influences that vary over time, such that better-connected adopters exert more influence than less-connected ones.

Sociometric vs. self-reported opinion leadership

The third assumption underlying many viral network marketing strategies is that firms are able to identify and target influentials, or opinion leaders. Rogers and Cartano (1962) discussed three ways to identify such people: (1) self-designation, i.e., asking survey respondents to report to what extent they perceive themselves to be influential, (2) sociometric techniques, i.e., computing network centrality scores after asking survey respondents whom they turn to for advice or information or after observing interactions through other means (e.g., citations among scientists), and (3) the key informant technique, in which selected people are asked to report their opinion about who key influentials are. Whereas self-designation is the most popular technique among marketing academics (e.g., Childers 1986; Myers and Robertson 1972), the sociometric technique has been more popular among social network analysts (e.g., Coleman, Katz, and Menzel 1966; Valente et al. 2003). The sociometric technique is gaining popularity among marketers trying to identify influential scientists, physicians, and engineers (see, e.g., Dorfman and Maynor 2006) and among some consumer-network marketing firms, like P&G's Vocalpoint, that target people with demographic characteristics associated with having a central network position.

Doubts exist about the value of self-reports and sociometric measures. It is likely that self-reported opinion leadership is biased upward and that it also reflects self-confidence rather than actual influence alone. Conversely, doubts on marketers' ability to effectively identify influentials using sociometric methods have arisen recently, following a simulation study by Watts and Dodds (2007) showing that the customers critical in generating a sudden burst in the speed of diffusion need not necessarily be the best connected. While this possibility is already long known to network and diffusion researchers (e.g., Becker 1970; Locock et al. 2001; Watts 2002), the recent simulation results have created a heated debate (Thompson 2008) among marketing practitioners. Much of that debate seems to ignore that the study by Watts and Dodds was only a simulation demonstrating a possibility, not an empirical study providing actual evidence in support of that possibility. Still, the simulation results do bring to the fore potential difficulties marketers may face in identifying key influentials by using sociometric methods.

To gain a deeper understanding of the issues at hand, we test several hypotheses. Because little is known about whether different methods actually identify the same influentials (convergent validity), we first assess to what extent their leadership scores are correlated:

H2: Measures of sociometric and self-reported opinion leadership are positively correlated.

Even less is known about whether the two leadership constructs have the same association with adoption behavior (nomological validity). A person who is often nominated by his or her peers as someone they turn to for expertise and discussion is likely to be a true source of influence. People who perceive themselves to be influential, in contrast, may indeed be so but may also simply have an inflated sense of self-importance. To the extent that true expertise drives early adoption, self-reported leadership may be less associated with early adoption than sociometric leadership is. On the other hand, early adoption may be affected more by how one perceives oneself than by one's true status. These arguments suggest that sociometric leaders and self-reported leaders need not adopt equally early, but leave open the question about which type of leader adopts before the other.

H3: Measures of (a) sociometric and (b) self-reported opinion leadership are both associated with early adoption.

The distinction between sociometric and self-reported leadership may also affect how sensitive one is to input from one's peers. Following the original two-step flow hypothesis, several studies have documented that the information flow between opinion leaders and followers is not unidirectional. True experts rarely ignore whatever user experience or other information less-prestigious actors have to share (see, e.g., Strang and Tuma 1993; Weimann 1994). This suggests that sociometric leaders may be as responsive to contagion as nonleaders are (assuming leaders do not adopt too early to ever experience peer influence, of course). Self-reported leaders, in contrast, may be more or less sensitive to contagion than their peers. On the one hand, several theories of social identity and status imply that people with a high sense of self-importance may deem it below their dignity to take into consideration, let alone imitate, the behavior of lower-status actors (see, e.g., Berger and Heath 2007; Philips and Zuckerman 2001; Van den Bulte and Joshi 2007). On the other hand, theories of status competition suggest that people who think of themselves as having above-average status might be driven to adopt quickly once they see others of lower status adopting, out of fear that being outpaced by underlings will cause their own status advantage to erode (e.g., Burt 1987). Taken together, these arguments raise the following hypothesis:

H4: Self-reported leaders are differentially (either less or more) sensitive to social contagion compared to nonleaders, whereas sociometric leaders are not differentially sensitive.

Usage volume, time of adoption, and social contagion

Prior research suggests that early adopters and opinion leaders tend to be heavy users (Coulter et al. 2002; Taylor 1977; Weimann 1994). Such a relationship between usage volume, an easily measured construct for which commercial data may be available, and opinion leadership and the tendency to adopt early, two more elusive constructs, would be useful to marketers seeking a good proxy to identify likely early adopters and likely opinion leaders.

No one uses the product before it is launched. Therefore, to be useful in identifying early adopters and to avoid reverse causality problems, usage volume should be measured at the category level prior to the new product's launch. We therefore test the following hypothesis:

H5: Category usage volume before the product's launch is associated with early adoption.

Once the product is launched and adopted by someone, the amount of social influence exerted by that person may vary with his or her usage volume of the new product. Someone who adopted in the past but is not using the product anymore is likely to be less enthusiastic and less credible than someone who is still using the product. Conversely, Godes and Mayzlin (2009) note, heavy users may tend to be connected mostly to people already predisposed to be early adopters. This would imply that heavy users are less likely to generate new adoptions. Theory suggests that whether usage volume enhances or depresses the amount of social contagion exerted depends on whether contagion operates by boosting either new product awareness or evaluation. Using a weak-tie argument (e.g., Granovetter 1983), Godes and Mayzlin (2009) advance the idea that light users will be more effective in creating awareness. For products that do not benefit from marketing communication and that present little perceived risk such that little additional information is required in the evaluation stage, light users will be very effective sources of influence. For products that are supported by a fair amount of standard marketing communication but pose significant perceived risk to potential adopters, contagion fosters adoption by operating at the evaluation stage rather than at the awareness stage. This line of reasoning suggests that highly credible sources—like heavy users—are more likely to be effective for the latter type of products. Hence, we posit

H6: For products with significant perceived risk, social interaction with heavy users is more effective in driving adoption than social interaction with light users.

Testing this hypothesis complements the study by Godes and Mayzlin (2009), who investigated a low-risk product enjoying very little marketing support, for which contagion operated most likely by boosting awareness rather than evaluation.

Research Setting and Data Sources

To provide a valid test of our hypotheses and an informative assessment of the assumptions underlying most viral network marketing efforts, the research setting should ideally satisfy several conditions. First, the newly launched product should have characteristics making it theoretically justified to expect contagion to be at work. Second, one must be able to collect data on self-reported leadership and sociometric leadership for each person whose behavior is analyzed. Third, one must have data on who can influence whom. Fourth, one must have data not only on the adoption by each person whose behavior is analyzed but also on the adoption by and postadoption usage of each person likely to influence them. Fifth, key marketing efforts must be observed or otherwise controlled for.

We were able to secure the cooperation of a pharmaceutical company, to meet those stringent conditions.[1] Like many other firms in its industry, the company was keen on identifying those physicians with the most central and influential positions and on using that information in their medical education and detailing programs. Management realized, however, that its premises were in doubt and was therefore keen on facilitating a study about the importance of social networks, opinion leadership, and marketing effort in new product diffusion.

The product

The product is a newly launched prescription drug used to treat a specific type of viral infection. There are both short-term (acute) and long-term (chronic) forms of the disease. The chronic form can cause severe damage to internal organs and—if left untreated—sometimes even lead to a patient's death. The product we study is the third entry in the category of drugs for treating the chronic condition. No later entries occurred during the observation window.

As the condition is chronic, physicians cannot observe drug efficacy quickly and adjust a patient's therapy if necessary. There is uncertainty in the medical community regarding the best treatment, as little comparative information exists about the three drugs' long-term efficacy. In an issue of a prestigious medical journal featuring two separate studies documenting the focal drug's effectiveness, an editorial by a director of one of the National Institutes of Health warned that even though the new drug seemed an excellent treatment option given its low rate of resistance and outstanding potency, the drug's use should—for the time being—be tempered because the medical condition requires long-term therapy.

In short, the drug treats a potentially lethal condition, but there is considerable ambiguity and risk in making the decision to adopt. In such situations characterized by high risk, high complexity and low observability of results, both theory and research suggest that contagion is likely to be a significant driver of adoption behavior (e.g., Hahn et al. 1994; Rogers 2003).

The Physicians and Their Network

Given the specific medical condition the new drug is treating, the company defined the relevant population as those physicians who had prescribed at least one of the earlier two drugs in the two years prior to the new drug's launch. Based on its own internal records and market research reports, the company supplied us with a list of such physicians practicing in three large U.S. cities: San Francisco (SF), Los Angeles (LA), and New York City (NYC). Hence, the relevant networks were bounded based on both a positional criterion, with each physician practicing in one of a specific set of five-digit ZIP codes, and an event criterion, with each physician having prescribed at least one of two drugs in the past (Laumann, Marsden, and Prensky 1989).

Having described our research setting, we now describe our data sources. These consist of a survey of physicians, a data vendor providing

Table 1
Response Rates across the Three Cities

	San Francisco (SF)	Los Angeles (LA)	New York City (NYC)
Mailing	187	273	372
Returned to Sender	37	76	88
Returned to Sender (%)	19.8	27.8	23.7
Valid Addresses	150	197	284
Surveys Completed	67	57	69
Response Rate (%)	44.5	28.9	24.3

physician prescription data, and company records on sales calls to each physician.

Physician survey

We used a mail survey to collect data on the physicians' social network ties and on some of their characteristics such as patient volume and self-reported opinion leadership. The survey was mailed twice over a 2-month period, with a reminder postcard being used after the first mailing. There was also an online link provided for physicians who wanted to complete the survey online. About 10% of participants did so. A $75 honorarium was promised for completing the survey within 2 weeks of receiving it. In SF, the first mailing took place 2 months before the U.S. product launch, and in LA and NYC it took place 10 months after the U.S. launch.

Table 1 lists the response rate in the three cities. The response rate in SF was markedly higher than in LA or NYC. That may be due to a higher interest in the treatment options in the SF area, where several national thought leaders are based and a sizable population group lives with an above-average risk of contracting the medical condition. The higher response rate may also be due to the higher quality of the SF mailing list. For instance, there were a number of instances in LA and NYC where two entries in the list had the same name but different addresses. In any case, the response rates in all three cities (24%–45%) are quite high by both industry and social science standards and do not generate problems for our network-based covariates, as we explain in the section on covariates.

Physician characteristics. Following Coleman, Katz, and Menzel (1966), we collected data on the type of primary practice and physician specialty. We also asked about the number of patients seen and referred to other physicians, as physicians treating many patients are more likely to prescribe new drugs. To measure self-reported opinion leadership, we adapted the scale of Childers (1986) to our particular research setting. We used six items pertaining to the likelihood and frequency of interacting with other physicians about issues related to the chronic disease. All items were measured on a scale of 1 to 7.[2]

Network ties. Following Coleman, Katz, and Menzel (1966), we collected network data by using a sociometric survey. We asked each physician to name up to eight physicians with whom he or she felt comfortable discussing the clinical management and treatment of the disease (discussion ties), and up to eight physicians to whom he or she typically referred patients with the disease (referral ties). Both lists may but need not overlap. Within the network boundary, 67 respondents in SF generated 37 unique nominees for discussion and 24 unique nominees for referral. In LA, the 57 respondents generated 38 and 24 unique nominees, and in NYC the 69 respondents generated 43 and 22 unique nominees. Again following Coleman, Katz, and Menzel (1966), we excluded physicians who were nominated by survey respondents but who were not part of the original network boundary (e.g., a Stanford University professor cited by an SF physician but based outside the SF 5-digit ZIP codes). Physicians who were within the network boundary but did not respond to the survey, in contrast, were included in the network. We then built separate "discussion" and "referral" network matrices for each of the three cities, with respondents as rows and all network members as columns and with the (i,j)th cell being 1 when i cited j and 0 otherwise. We also constructed "total" network matrices by adding the referral and network matrices in each city. The three SF matrices were of size 67 × 150, the LA matrices were 57 × 197, and the NYC matrices were 69 × 284. Including all physicians who were part of the network boundary as columns allows us to take into account the contagion emanating from prior adopters within the network boundary even if they did not respond to the survey.

Prescription data

For each physician within the network boundary (not only respondents), the time of adoption is measured using monthly individual-level prescription data purchased by the pharmaceutical company from IMS Health, a data provider whose role and reputation in the pharmaceutical industry is similar to that of ACNielsen and IRI in consumer package goods. For the focal drug, the data start from the month the drug was introduced. Prescriptions were tracked for the next 17 months—incidentally, the same duration as that in *Medical Innovation* (Coleman, Katz, and Menzel 1966). Data on postadoption prescriptions are available as well.

Of the 193 doctors across the three cities who responded to the survey, 68 adopted within 17 months. This adoption rate of 35% is markedly lower than the 87% rate for tetracycline in *Medical Innovation* over the same length of time, consistent with the notion that the present drug poses greater risk to physicians than tetracycline did.

We also have prescription data for the two other drugs in the category for two years prior to the launch of the focal drug. This allows us to identify physicians who were heavy prescribers in the category before the focal drug was introduced. This not only is the key variable to test hypothesis H5 but also avoids an endogeneity problem that could have occurred if the local sales offices believed that heavy prescribers of the incumbent drugs were more likely to adopt the new drug early, and therefore exposed them to a higher level of detailing (Lexchin 1989; Manchanda, Rossi, and Chintagunta 2004). By including the variable available to the decision maker directly in the model, we avoid such an endogeneity bias in the effect of detailing.

Sales call data

From the company's internal records, we obtained data on the number of sales calls (detailing efforts) pertaining to the focal drug for each of the physicians and in each of the 17 months we track. The company did not distribute any free samples, and the product's price did not vary over the observation window.

Data Analysis Approach

H2, H3, and H5 can be tested using simple correlation analysis. For H3 and H5, however, such tests may be subject to confounds and should be complemented by multivariate analyses. Moreover, H1, H4, and H6 require relating exposure to prior adopters, something that varies over time, to the probability of adopting early. We therefore use hazard modeling as the main statistical approach to analyze the data and test the hypotheses.

We operationalize the time of adoption as the time of first prescription (see, e.g., Coleman, Katz, and Menzel 1966). For each physician-month, we create a binary adoption indicator variable $y_{i,t}$, which is set to 0 if physician i has not adopted by time t and is set to 1 if he or she has. The discrete-time hazard of adoption is then modeled as:

$$P(y_{i,t} = 1 \mid y_{i,t-1} = 0) = F(x_{it}\beta), \tag{1}$$

where x_{it} is a row vector of covariates, β is a column vector of parameters to be estimated, and F is a cumulative distribution function (e.g., logistic or standard normal). This modeling approach allows one to include covariates that vary over time.

Covariates

Opinion leadership

Indegree Centrality. This is the number of nominations a particular physician has received and is computed for each physician separately in the referral, discussion, and total network (indegree in the total network is the sum of the indegrees in the referral and discussion networks). Indegree centrality is the most basic measure of status or prestige in a network (e.g., Wasserman and Faust 1994). Because we measured social ties as pertaining to patient referral and discussion of the treatment of a medical condition, physicians with high indegree are, in the parlance of Goldenberg et al. (2006), both "social connectors" with many ties and "recognized experts" with expertise and good judgment.

We do not have information about the ties sent by all physicians in each city but only about those sent by physicians responding to the survey. This generates some measurement error in the indegree of the physicians whose adoptions we study. The amount of error, however, is negligible because indegree in human networks is a robust metric as long as response rates are higher than 10%–20% (Costenbader and Valente 2003), a hurdle our data pass in all three cities.

Self-reported Leadership. The reliability of the six-item scale closely following that of Childers (1986) was quite high (Cronbach $\alpha = .88$), and a factor analysis confirmed the presence of only a single dimension underlying the items. We construct the Self-reported Leadership variable by taking the average of the six items.

Category-level prescription volume

To test H5, we use the number of prescriptions for each of the other two oral antivirals, Drug 1 and Drug 2, during the 12 months prior to the launch of the focal drug.[3]

Social contagion

We operationalize exposure to prior adopters through social ties by using lagged endogenous autocorrelation terms (Strang 1991). The extent to which physician i is exposed at time t to prior adoptions is captured through the term $\Sigma_j w_{ij} z_{j,t-1}$, where w_{ij} captures how relevant each physician j is to i, and $z_{j,t-1}$ is a variable capturing the behavior of j at time $t-1$.[4]

The social network weight w_{ij} can be constructed in various ways. Because we do not have complete network data, we limit our attention to influence operating over direct ties (or "social cohesion" [Burt 1987]). The weights are then unaffected by having a less-than-perfect response rate because they rely only on nominations sent by people whose adoptions are being modeled, all of whom are respondents. We use a simple weighting scheme: in both the referral and the discussion network, w_{ij} equals 1 if i nominates j and equals 0 otherwise. In the total network, the weights are simply the sum of the referral and discussion weights. Because $Indegree_j = \Sigma_i w_{ij}$, the number of colleagues that a physician can influence directly through social contagion over network ties equals his Indegree. The number he or she can influence indirectly is of course greater.

We capture the behavior of fellow physicians in three different ways:

1. Adoption. In this variant, $z_{j,t-1} = y_{j,t-1}$, i.e., the lagged adoption indicator. The resulting contagion variable assumes that people start influencing once they have adopted and that they continue doing so. This operationalization is the one commonly used in models of network contagion in the adoption of innovations.

2. Use. In this variant, $z_{j,t-1} = s_{j,t-1}$, where $s_{j,t-1}$ is set to 1 if j wrote at least one prescription at time $t-1$ and is set to 0 if he or she

did not. The resulting contagion variable assumes that only recent prescribers exert peer influence (e.g., for reasons of enthusiasm or credibility).

3. Volume. In this variant, $z_{j,t-1} = q_{j,t-1}$, i.e., the number of prescriptions written by j at time $t-1$. The resulting contagion variable assumes that one's influence is proportional to one's recent prescription volume (e.g., again, for reasons of enthusiasm or credibility).

Having operationalized both the social network weights w_{ij} and the various kinds of behavior $z_{j,t-1}$, we calculate the extent of social network exposure a physician i is experiencing and create the following lagged network variables: Adoption Contagion, Use Contagion, and Volume Contagion. To assess to what extent sociometric and self-reported leadership moderate the effect of these contagion variables, we also create the necessary interaction terms.

Marketing effort

We use monthly physician-level detailing (sales calls) as our measure of marketing effort. To allow for effects spanning multiple months, we construct a depreciation adjusted stock measure, in which D_{it} is the amount of detailing (number of sales calls) received by physician i in month t. The Detailing Stock of physician i for month t (DS_{it}) is then defined as follows:

$$DS_{it} = D_{it} + \delta DS_{i,t-1} = \sum_{\tau=1}^{t} \delta^{t-\tau} D_{i\tau}$$

where δ is the monthly carry-over rate bounded between 0 and 1, and *DS* in month 1 is the amount of detailing in that month. To control for a potential confound in the interaction between contagion and the leadership variables (H4), we allow the effect of marketing effort to be moderated by Indegree and Self-reported Leadership.

Control variables

Physician Characteristics. We control for several physician characteristics which industry experts and prior research suggest may be associated with early adoption (e.g., Coleman et al. 1966; Rogers 2003). Identifying systematic heterogeneity in adoption time is also of practical interest to managers seeking to identify and target likely early adopters. University Hospital is a dummy variable indicating whether the physician works in or is affiliated with a university or teaching hospital. Solo Practice is a dummy variable capturing whether the doctor is in solo practice or not. While this variable was important in the original *Medical Innovation* (Coleman, Katz, and Menzel 1966) reports, it is not clear a priori whether practicing solo is a useful predictor once one takes into account actual network exposure to previous adopters. Early Referral is a dummy variable taking the value 1 if the physician reports sometimes referring patients to other doctors before initiating any treatment, and 0 otherwise. A doctor referring patients even before starting any treatment is less likely to adopt the focal drug early. Primary Care is a dummy variable capturing whether the doctor is a primary care physician rather than a specialist (in, e.g., internal medicine, gastroenterology, infectious diseases), who is more likely to focus on the relevant medical condition. Patients Managed is the number of patients with the medical condition that the physician reported clinically managing in the last 6 months. Physicians with many patients may adopt sooner.

Outdegree is the number of nominations given by a specific physician to others and is computed for each physician separately for discussion, for referral, and in total. Given the importance of out-of-town contacts in the study by Coleman, Katz, and Menzel (1966), Outdegree includes nominations given to both in-town and out-of-town colleagues. Unlike Indegree, Outdegree is not a measure of status or prestige. Simply connecting to many people may be related to being an opinion leader, but it may also indicate a lack of expertise and confidence (Van den Bulte and Wuyts 2007; Wasserman and Faust 1994). Hence, we include Outdegree as a control variable allowing a sharper interpretation of the Indegree effect. If Indegree is associated with early adoption but Outdegree is not, one can be more confident in the interpretation of Indegree as a measure of status. Because Outdegree is based on the respondents' own answers, the measurement quality is never affected by the response rate.

City Dummies. We control for city-specific differences in the propensity to adopt early by including dummy variables for LA and NYC, treating SF as the reference.

Time Dummies. We include a dummy for each period. This has two advantages. First, it captures the effect of any marketwide time-varying factor, such as changes in disease prevalence or the appearance of new clinical evidence. The dummies capture all cross-temporal variation in the mean tendency to adopt, leaving only variance across physicians within particular months to be explained by contagion. As a result, including the dummies provides a stringent test for the presence of network contagion. The second advantage of including monthly dummies is that it provides a nonparametric control for unobserved heterogeneity creating spurious negative time dependence in the observed adoption rates (see, e.g., Han and Hausman 1990).

Final sample size and descriptive statistics

Data on past prescription of the two other oral antivirals (Past Drug 1, Past Drug 2) are missing for 8 doctors, 3 of whom had adopted the focal drug. We dropped these 8 physicians from our dataset. Thus, our analyses are based on data from 185 doctors, 65 of whom had adopted the focal drug after 17 months.

We organize the data set as a panel from which all postadoption observations are deleted because they do not contribute to the likelihood function of hazard models. Table 2 presents the descriptive statistics for these data. In this unbalanced panel, physicians' weight in computing the means and correlations equals the number of months until they adopt or are right censored. Table 3 reports the descriptive statistics for the time-invariant covariates using equal weighting.

Preliminary Data Analyses

Analysis of non-response

We tested whether survey respondents differed from nonrespondents on those variables that we observe for both groups: City, Indegree, amount of Detailing received in the first 6 months after launch, amount of prescription of two other drugs in the category for 12 months prior to launch, and time of adoption. After controlling for city, none of the variables was significantly associated with the probability of responding ($p > .05$).

Graphical analysis

Figure 1a shows the diffusion curve, i.e., the cumulative proportion of physicians who adopted, and Figure 1b shows the empirical hazard rate, i.e., the number of adopters divided by the number of those who had not adopted before. The diffusion curve does not have a pronounced S-shape, and the hazard rate does not exhibit an upward trend, suggesting the absence of contagion. However, the average monthly detailing efforts targeted toward physicians who had not yet adopted (called physicians "at risk" of adopting) has a clear downward trend. That the marketing effort toward at-risk physicians decreases over time while the empirical hazard rate does not suggests that—controlling for marketing effort—the hazard rate might actually be increasing, which would be consistent with contagion being at work.

Figure 2 shows how the three contagion variables for the total network evolve over time among the physicians at risk. Both Adoption Contagion and Use Contagion increase for the first 9 months and tend to level off afterward.[5] Put simply, the exposure to both adopters and prescribers stopped growing after 9 months.

Table 2

Descriptive Statistics and Correlations among All Covariates for All At-Risk Physician-Months Observations

Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1. Adoption (yit)	.025	.16	0	1	1.00																										
2. Detailing (Sales Calls)	.29	.83	0	9	.23	1.00																									
3. Indegree - Referral	.11	.59	0	17	.23	.21	1.00																								
4. Indegree - Discussion	.25	.78	0	19	.25	.27	.82	1.00																							
5. Indegree - Total	.36	1.31	0	36	.25	.26	.94	.97	1.00																						
6. Outdegree - Referral	1.37	1.39	0	5	.00	–.02	.00	–.04	–.02	1.00																					
7. Outdegree - Discussion	2.36	1.54	0	6	.03	.03	.04	.02	.03	.37	1.00																				
8. Outdegree - Total	3.73	2.43	0	10	.02	.00	.02	–.01	.00	.81	.85	1.00																			
9. Self-reported Leadership	4.25	1.29	1	7	.11	.18	.19	.25	.23	–.17	.19	.02	1.00																		
10. LA Dummy	.31	.46	0	1	–.01	–.02	.00	–.04	–.02	–.05	.00	–.02	.15	1.00																	
11. NYC Dummy	.37	.48	0	1	–.02	.04	–.02	–.03	–.02	–.07	–.11	–.11	.02	–.52	1.00																
12. Solo Practice	.39	.49	0	1	.00	.13	–.06	–.14	–.11	–.03	–.19	–.14	–.12	–.01	.09	1.00															
13. University/Teaching Hospital	.21	.41	0	1	.00	–.09	–.06	–.04	–.05	–.13	.00	–.07	.07	–.12	.03	–.41	1.00														
14. Primary Care	.13	.34	0	1	–.05	–.10	–.08	–.08	–.08	.11	–.05	.03	–.24	.13	–.14	–.06	–.01	1.00													
15. Patients Managed	36.36	109.42	0	1200	.04	.12	.08	.12	.10	.03	–.07	–.02	.02	–.14	.20	.14	–.13	–.08	1.00												
16. Early Referral	.35	.48	0	1	–.07	–.16	–.05	–.13	–.09	.21	–.02	.11	–.44	–.17	.00	–.05	.13	.15	.00	1.00											
17. Past Drug 1	10.89	25.76	0	265	.25	.50	.38	.55	.50	–.09	–.06	–.09	.24	–.07	.15	.02	–.07	–.09	.22	–.16	1.00										
18. Past Drug 2	10.45	24.86	0	510	.25	.32	.32	.42	.39	–.02	–.06	–.05	.05	–.11	.09	.09	–.06	–.05	.46	–.04	.53	1.00									
19. Contagion - Referral, Adoption	.57	.91	0	5	.02	.05	.01	–.03	–.01	.62	.30	.55	–.08	–.14	–.11	–.08	–.11	.02	.03	.13	–.02	–.02	1.00								
20. Contagion - Referral, Use	.54	.90	0	5	.03	.03	.02	–.02	–.00	.61	.29	.54	–.07	–.15	–.09	–.09	–.09	.00	.03	.13	–.04	–.02	.98	1.00							
21. Contagion - Referral, Volume	4.03	10.45	0	104	.05	.02	.02	–.00	.00	.39	.21	.35	–.06	–.16	–.09	–.07	–.11	–.03	.02	.11	–.04	–.02	.72	.76	1.00						
22. Contagion - Discussion, Adoption	.65	.97	0	6	.04	.07	.04	.00	.02	.31	.36	.41	–.06	–.04	–..21	–.11	–.06	.02	–.03	.09	–.04	–.05	.65	.62	.47	1.00					
23. Contagion - Discussion, Use	.57	.89	0	5	.04	.03	.06	.02	.04	.31	.35	.40	–.07	–.08	–.19	–.12	–.06	.03	–.03	.09	–.05	–.03	.63	.64	.49	.96	1.00				
24. Contagion - Discussion, Volume	3.85	9.64	0	89	.06	.00	.05	.05	.05	.20	.21	.25	–.06	–.13	–.15	–.08	–.08	.00	–.01	.09	–.05	–.03	.47	.49	.69	.67	.71	1.00			
25. Contagion - Total, Adoption	1.23	1.71	0	9	.04	.06	.03	–.01	.01	.51	.37	.53	–.08	–.11	–.18	–.11	–.09	.01	.00	.12	–.04	–.04	.90	.87	.66	.91	.88	.63	1.00		
26. Contagion - Total, Use	1.11	1.63	0	9	.04	.03	.04	.00	.02	.51	.36	.52	–.08	–.14	–.16	–.11	–.08	.02	.00	.13	–.05	–.04	.89	.90	.68	.87	.91	.66	.97	1.00	
27. Contagion - Total, Volume	7.88	18.49	0	178	.06	.01	.04	.02	.02	.33	.23	.33	–.07	–.16	–.14	–.08	–.10	–.02	.00	.11	–.05	–.03	.65	.68	.93	.66	.65	.91	.71	.73	1.00

Note: Values computed on all physician-month observations for which physician was at risk of adopting, $N = 2{,}575$. All correlations equal or larger than .04 are significant at $p \leq .05$.

Table 3

Descriptive Statistics and Correlations among Time-invariant Covariates

Variable[a]	Mean	SD	Min	Max	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
3. Indegree - Referral	.37	1.57	0	17	1.00															
4. Indegree - Discussion	.58	1.90	0	19	.95	1.00														
5. Indegree - Total	.95	3.42	0	36	.98	.99	1.00													
6. Outdegree - Referral	1.34	1.43	0	6	–.12	–.14	–.13	1.00												
7. Outdegree - Discussion	2.40	1.58	0	8	–.09	–.11	–.10	.41	1.00											
8. Outdegree - Total	3.74	2.54	0	12	–.13	–.15	–.14	.82	.86	1.00										
9. Self-reported Leadership	4.46	1.34	1	7	.29	.34	.32	–.21	.13	–.04	1.00									
10. LA Dummy	.31	.46	0	1	–.09	–.13	–.11	–.02	.00	.00	.09	1.00								
11. NYC Dummy	.36	.48	0	1	–.09	–.07	–.08	–.13	–.08	–.12	.02	–.49	1.00							
12. Solo Practice	.38	.49	0	1	–.09	–.14	–.12	.03	–.12	–.06	–.17	.00	.04	1.00						
13. University/Teaching Hospital	.22	.41	0	1	–.06	–.02	–.04	–.15	–.06	–.12	.12	–.09	.05	–.41	1.00					
14. Primary Care	.11	.32	0	1	–.08	–.09	–.09	.09	–.06	.01	–.27	.13	–.12	–.04	–.02	1.00				
15. Patients Managed	44.67	109.82	0	1200	.26	.28	.28	–.02	–.09	–.07	.09	–.16	.21	.08	–.11	–.09	1.00			
16. Early Referral	.3	.46	0	1	–.12	–.17	–.15	.21	–.02	.11	–.48	–.16	.00	–.01	.08	.17	–.06	1.00		
17. Past Drug 1	21.36	47.11	0	265	.54	.62	.59	–.21	–.21	–.25	.37	–.11	.09	–.02	.00	–.13	.29	–.22	1.00	
18. Past Drug 2	21.44	56.55	0	510	.57	.62	.60	–.12	–.12	–.14	.21	–.12	–.04	.03	–.05	–.09	.31	–.14	.71	1.00

[a] The numbers in front of the variables match those in Table 2.

Note: Values computed on a single observation for each physician, $N = 185$. All correlations equal or larger than .15 are significant at $p \leq .05$.

Under such conditions, the firm's strategy to decrease the sales effort over time might have been inappropriate to drive late adoptions. Instead, increasing detailing once the effect of word of mouth had stalled (i.e., after 9 months) might have been more suitable. But consider how Volume Contagion trends upward throughout the entire 17-month observation period. If contagion based on peers' prescription volume is more important than that based on their adoption or user status, then the firm's detailing strategy may have been quite appropriate. This simple analysis shows how the precise nature of the social contagion process may be quite relevant to marketing policy.

Results

To test hypothesis H2 on the association between sociometric and self-reported opinion leadership, we use correlation analysis. To test all other hypotheses, we use discrete-time hazard models with a logit link function estimated using standard maximum likelihood. Because models using the total network tended to fit slightly better than models using only the referral or discussion network, and because using the total network follows the re-analyses (e.g., Burt 1987; Strang and Tuma 1993) of the *Medical Innovation* study (Coleman, Katz, and Menzel 1966), the results reported here are from models using the total network, unless noted otherwise.

Correlation results

The correlations reported in Table 2 between Self-reported Leadership and the various Indegree measures are all significantly positive ($p < .001$), supporting H2. However, the correlations are low: .19 in the referral network, .25 in the discussion network, and .23 in the total network. The results are similar if one

Figure 1a
Cumulative Proportion of Physicians Having Adopted

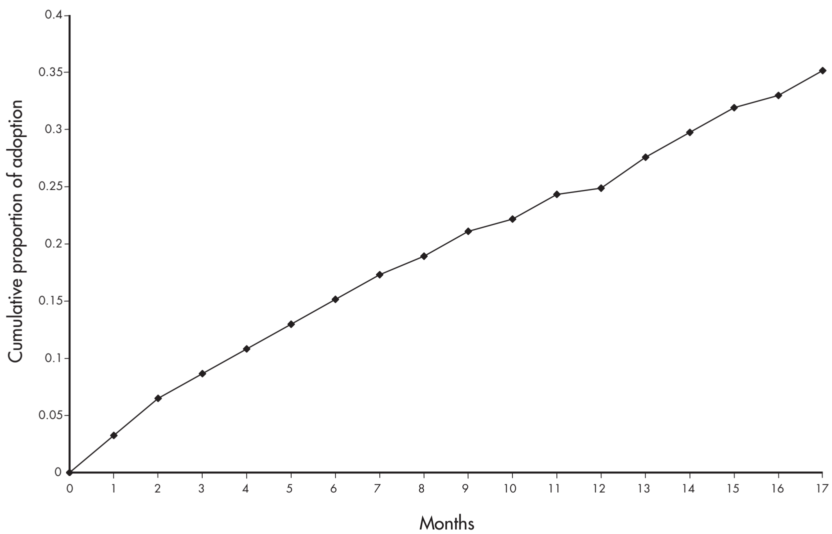
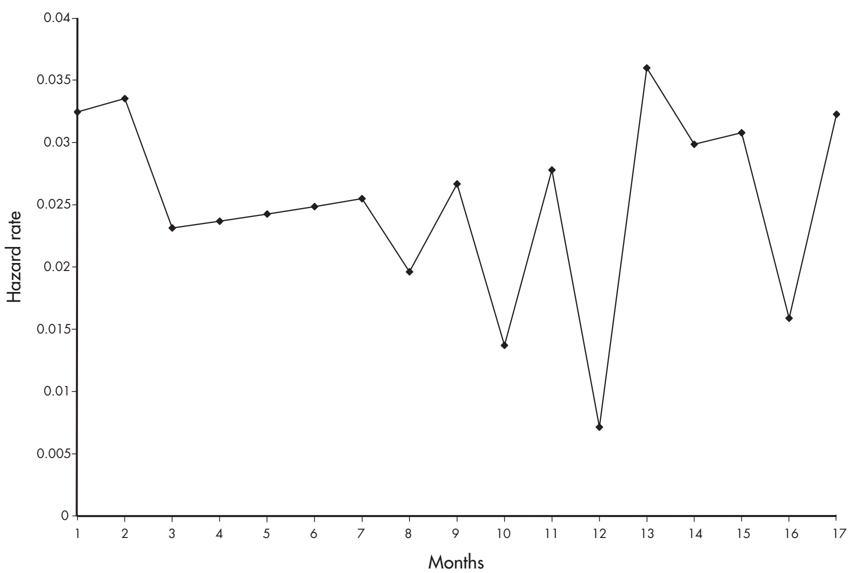


Figure 1b
Empirical Hazard Rate of Adoption



weighs all physicians equally, as reported in Table 3. For instance, the correlation between total Indegree and Self-reported Leadership in Table 3 is only .32 (p < .001). Analysis by city shows that the correlations do not vary markedly with the response rate (SF: r = .45, response rate λ = 44.5%; LA: r = .32, λ = 28.9%; NYC: r = .41, λ = 24.3%). Hence, the low correlation between Indegree and Self-reported Leadership cannot be attributed to measurement error in Indegree stemming from survey nonresponse.

The positive correlations in Tables 2 and 3 between the Indegree variables and past prescription of other two drugs (Past Drug 1, Past Drug 2) indicate that high-status physicians were heavy prescribers in the category. The positive correlations in Table 2 between the three Indegree variables and Detailing received suggest that high-status physicians were targeted by the firm. Also, there is a strong positive correlation between detailing and prescription of past drugs, indicating that the firm targeted heavy prescribers of the closely related drugs.

Finally, adoption (y_{it}) correlates more highly with referral, discussion, and total Indegree (r = .23, .25, and .25, respectively, p < .001) than with Self-reported Leadership (r = .11, p < .001) in Table 2. This indicates that sociometric leaders tend to adopt earlier than self-reported leaders in this study. However, antecedents of adoption are better identified using a hazard model.

Hazard model results

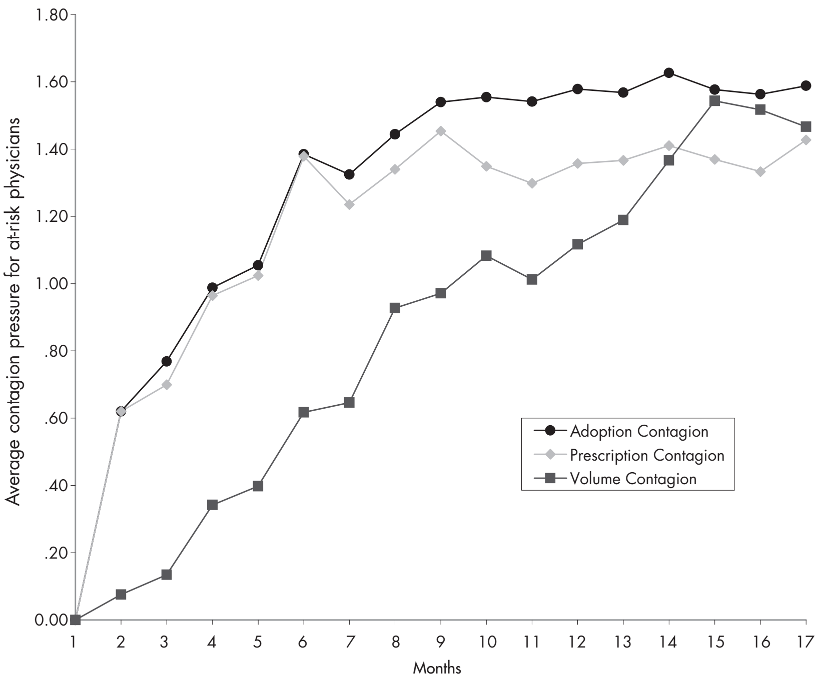
Table 4 shows models for Adoption, Use, and Volume Contagion. For each, we present models with and without interactions between the opinion leadership variables on the one hand and detailing and contagion on the other. The Indegree and Self-reported Leadership variables are mean centered, so the linear effects of Contagion and Detailing Stock are the effects pertaining to the average physician.

Physicians with high Indegree adopt sooner, and this result is robust across all model specifications. So, H3a is strongly supported. Self-reported Leadership, in contrast, has no significant effect on time of adoption in the main-effects-only models. But the models with interactions indicate that Self-reported Leadership indeed was associated with early adoption.[6] Therefore, H3b is supported as well, but not as strongly as H3a.

Figure 2

Contagion Pressure Operating over the Total Network

(Average across At-risk Physicians)



Note: Volume Contagion is divided by 10 in this figure. Adoption Contagion decreases at times because the set of physicians at risk varies over time. Use Contagion decreases at times for the same reason and because adopters need not use the product every month after adoption.

Indegree has a strong main effect, but does not affect how sensitive physicians are to Contagion or Detailing. Self-reported Leadership behaves differently. In the models without interactions, it is not significantly associated with early or late adoption. This, however, is the result of two counteracting effects. As the models with interactions show, physicians with high self-reported leadership have a higher intrinsic tendency to adopt early but are less sensitive to contagion from peers. In Model 6 with Volume Contagion, which fits markedly better than Models 4 and 5, this interaction is significant at the 5% level. Therefore, the models with interactions, especially the model that fits best, support H4.

Physicians' prior prescription level of Drug 2 has a robust effect on their speed of adoption, corroborating H5. Physicians' Outdegree has no significant impact at the 5% level. Additional analyses indicate the absence of interaction effects of Outdegree with either Contagion or Detailing Stock ($p > .10$). Physicians who sometimes refer patients before starting treatment have a slight tendency to adopt later, but this effect appears only in the models with interactions and is significant only at the 10% level. None of the other physician characteristics has an effect.

Detailing has a very significant effect that is robust across model specifications and exhibits a carry-over rate of about 45%. Physicians' responsiveness to sales calls does not vary as a function of their Indegree or Self-reported Leadership.

The contagion effects require careful interpretation. In the models without interactions (1–3), only Volume Contagion shows a significant effect. The model with Volume Contagion (3) fits better than the other two models (1–2), be it only slightly. Among the models with interactions (4–6), the model with Volume Contagion (6) fits markedly better than the other two (4–5). The difference in deviance ($-2LL$) between the model with Volume Contagion and Use Contagion equals 7.32, which is strong evidence of superior fit since the models have the same number of covariates (Raftery 1995). That the model with Volume Contagion fits better than the one with Use Contagion indicates that the volume effect stems from differences in peers' prescription volume and not simply from whether one's peers are prescribing or not. In none of the three models with interactions does contagion have a significant effect for the average physician, but the effect is moderated by physicians' Self-reported Leadership. In the model with Volume Contagion, which is favored by the data, that interaction is significant at the 5% level. Additional analysis indicates that contagion has a significant positive effect (at 5%) for physicians with a Self-reported Leadership score of 4.25 or lower, which corresponds to physicians at the bottom 43% percent of the distribution. The conta-

Table 4

Main Results Using the Total Network and Flexible Baseline

	Basis of Contagion			Basis of Contagion		
	Adoption (1)	**Use (2)**	**Volume (3)**	**Adoption (4)**	**Use (5)**	**Volume (6)**
Intercept	–3.35**	–3.43**	–3.92**	–3.27**	–3.41**	–3.88**
	(.68)	(.68)	(.69)	(.71)	(.71)	(.74)
LA Dummy	–.11	–.09	.19	–.18	–.14	.09
	(.38)	(.43)	(.40)	(.39)	(.39)	(.42)
NYC Dummy	–.54	–.49	–.24	–.57	–.51	–.27
	(.41)	(.42)	(.42)	(.42)	(.42)	(.43)
Solo Practice	.04	.07	.11	–.01	.01	.01
	(.34)	(.34)	(.35)	(.35)	(.35)	(.35)
University /	.58	.59	.72	.55	.56	.69
Teaching Hospital	(.40)	(.40)	(.41)	(.41)	(.41)	(.41)
Primary Care	–.64	–.65	–.61	–.60	–.59	–.57
	(.76)	(.76)	(.76)	(.76)	(.76)	(.77)
Early Referral	–.63	–.62	–.64	–.69	–.68	–.77
	(.43)	(.43)	(.43)	(.43)	(.43)	(.44)
Patients Managed	.001	.001	.001	.001	.001	.001
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Past Drug 1	.003	.004	.003	.004	.003	.002
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
Past Drug 2	.01**	.01**	.01**	.01**	.01**	.01**
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
Detailing Stock	.36**	.36**	.37**	.39**	.39**	.41**
	(.14)	(.14)	(.14)	(.13)	(.13)	(.14)
Carry Over Effect	.48*	.47	.43	.44**	.44*	.44*
	(.25)	(.25)	(.26)	(.20)	(.20)	(.20)
Contagion	–.03	.01	.01*	–.02	.02	.01
	(.09)	(.09)	(.006)	(.10)	(.10)	(.007)
Indegree	.15*	.15*	.15*	.31*	.32*	.30*
	(.07)	(.07)	(.07)	(.14)	(.15)	(.15)
Outdegree	.12	.10	.07	.12	.11	.08
	(.07)	(.07)	(.06)	(.07)	(.07)	(.06)
Self-rep. Leadership	.19	.19	.19	.37	.38*	.42*
	(.14)	(.14)	(.14)	(.20)	(.19)	(.18)
Indegree x Contagion				.01	.01	.001
				(.04)	(.05)	(.005)
Indegree				–.05	–.05	–.05
x Detailing Stock				(.04)	(.04)	(.04)
Self-rep. Leadership				–.09	–.09	–.01*
x Contagion				(.07)	(.07)	(.005)
Self-rep. Leadership				–.02	–.02	–.05
x Detailing Stock				(.07)	(.07)	(.07)
LL	–231.22	–231.28	–229.40	–229.08	–229.14	–225.48

Note: The numbers in parentheses are the standard errors for the parameters. * indicates $p \leq .05$ and ** indicates $p \leq .01$. All models include 16 monthly time dummies and so have a flexible baseline hazard rate.

gion effect is never significantly negative. So, H1 is corroborated for Volume Contagion in the main-effects model, and is also corroborated for Volume Contagion in the model with interactions for physicians in the bottom 43% of the Self-reported Leadership distribution.[7] Adoption Contagion and Use contagion effects are not significantly positive or negative at any level of Self-reported Leadership. So, Volume Contagion has a significant effect whereas the other two types of contagion do not. This is consistent with the notion that social interaction with heavy users is more effective in driving adoption than social interaction with light users (H6).

Robustness checks

Our results are quite robust. Table 5 shows the results for some variants of Model 6 in Table 4, the one best supported by the data. The first column in Table 5 just repeats the information of Model 6 in Table 4. The second column shows the results for the same model specification, but with Indegree, Outdegree, and Contagion based only on referral ties. The third column shows the results for a model using only discussion ties. The fourth column is again based on the total network, but uses normalized social network weights w_{ij} such that $\Sigma_j w_{ij}$ equals unity (or zero for physicians nominating no peers at all), implying that physicians react to the proportion rather than the number of their peers who have adopted or are prescribing. The coefficients of these three alternative models are quite similar to those of the original model, and none fits better than the original. The one slight deviation worth noting is that, in the referral-only model, the coefficient of the interaction between self-reported leadership and contagion is very similar to the one in the total network but its standard error is slightly bigger, which pushes the significance level slightly above .05. The fifth column in Table 5 pertains to the original model, but without time dummies. That model has a lower fit, but the loss in fit is small compared to the gain of 16 degrees of freedom ($\Delta - 2LL = 10.56$, $p = .84$). Unlike the original, the model without flexible baseline hazard exhibits a significant contagion effect for the average physician. Otherwise, the results are again very robust.

Our results are also robust to distinguishing between in-town and out-of-town contacts. Splitting the Outdegree into these two components did not improve model fit ($\Delta - 2LL = .04$) or affect the coefficients of substantive interest. Approximating Volume Contagion from out-of-town contacts by multiplying the number of out-of-town contacts by time (which is reasonable because Figure 2 shows that the Volume Contagion variable (capturing only within-city contagion) increases linearly over time) and adding that new covariate to the model did not significantly improve fit ($\Delta - 2LL = .38$) or affect the results. Finally, allowing the effect of approximated out-of-town volume contagion to vary as a function of Indegree and Self-reported Leadership by adding the two relevant interaction terms did not improve model fit ($\Delta - 2LL = 2.54$) or affect the results either. In short, our findings are robust to distinguishing between in-town and out-of-town contacts.

Since time dummies control for much but not necessarily all of the unobserved heterogeneity, we also estimated models with a normally distributed intercept and models with both a normally distributed random intercept and time dummies (see, e.g., Meyer 1990). For hierarchical Bayes (probit) hazard models without time dummies, the estimated variance of the heterogeneity distribution tended to be determined entirely by the prior distribution of that variance (indicating there is no information in the data), and comparisons using Bayes Factors confirmed that unobserved heterogeneity was not a concern. For the hierarchical Bayes models with time dummies, the convergence of the parameters within the Markov chain Monte Carlo (MCMC) routine was extremely poor, suggesting overparameterization. Similarly, empirical Bayes (logit) hazard models estimated using adaptive Gaussian

Table 5
Robustness Checks for Network Weights and Time Dummies

	Total Network (1)	Referral Network (2)	Discussion Network (3)	Total Network, Normalized (4)	Total Network, No Time Dummies (5)
Intercept	–3.88**	–3.70**	–3.88**	–3.72**	–4.62**
	(.74)	(.70)	(.74)	(.73)	(.45)
LA Dummy	.09	–.01	.09	.02	.18
	(.42)	(.41)	(.42)	(.42)	(.43)
NYC Dummy	–.27	–.33	–.31	–.23	–.15
	(.43)	(.42)	(.43)	(.44)	(.43)
Solo Practice	.01	–.01	–.01	–.11	.01
	(.35)	(.35)	(.35)	(.36)	(.34)
University /	.69	.64	.54	.63	.74
Teaching Hospital	(.41)	(.42)	(.40)	(.41)	(.41)
Primary Care	–.57	–.48	–.65	–.48	–.52
	(.77)	(.77)	(.78)	(.76)	(.77)
Early Referral	–.77	–.86	–.52	–.73	–.75
	(.44)	(.47)	(.42)	(.44)	(.44)
Patients Managed	.001	.001	.001	–.001	.001
	(.001)	(.001)	(.001)	(.001)	(.001)
Past Drug 1	.002	.004	.002	.003	.001
	(.004)	(.004)	(.004)	(.004)	(.004)
Past Drug 2	.01**	.01**	.01**	.01**	.01*
	(.004)	(.004)	(.004)	(.004)	(.004)
Detailing Stock	.41**	.38**	.41**	.41**	.37**
	(.14)	(.14)	(.13)	(.14)	(.12)
Carry Over Effect	.44*	.47*	.42*	.42*	.53**
	(.20)	(.24)	(.19)	(.21)	(.18)
Contagion - Volume	.01	.01	.01	.04	.01*
	(.007)	(.02)	(.01)	(.03)	(.007)
Indegree	.30*	.51	.52*	.32*	.22
	(.15)	(.34)	(.25)	(.15)	(.12)
Outdegree	.08	.12	.10	.10	.06
	(.06)	(.12)	(.08)	(.06)	(.05)
Self-rep. Leadership	.42*	.36*	.44**	.39*	.39*
	(.18)	(.18)	(.19)	(.18)	(.18)
Indegree x Contagion	.001	–.02	.002	–.003	.003
	(.005)	(.03)	(.01)	(.03)	(.005)
Indegree x Detailing Stock	–.05	–.02	–.11	–.05	–.03
	(.04)	(.09)	(.07)	(.04)	(.03)
Self-rep. Leadership	–.01*	–.01	–.03**	–.05*	–.01**
x Contagion	(.005)	(.008)	(.01)	(.02)	(.005)
Self-rep. Leadership	–.05	–.06	–.03	–.05	–.04
x Detailing Stock	(.07)	(.07)	(.08)	(.07)	(.06)
LL	–225.48	–227.59	–225.99	–226.02	–230.68

Note: The numbers in parentheses are the standard errors for the parameters. * indicates $p \leq .05$ and ** indicates $p \leq .01$. Models (1)-(4) include 16 monthly time dummies and so have a flexible baseline hazard rate.

quadrature in SAS NLMIXED led to variance estimates of 10^{-8}, the boundary value. All these results indicate the absence of detectable effects of unobserved heterogeneity.

Managerial calculus

Since both social contagion and detailing affect adoption, the concern arises whether focusing one's marketing efforts on opinion leaders is an effective marketing strategy. Our analysis can provide some guidance on this issue.

We assume a network marketing approach enabling the company, in each city, to have the physician with the greatest following (Indegree) not only adopting in the first month after launch but also endorsing the product more strongly in his interactions with colleagues who turn to him for discussion or referrals. In terms of our model, we operationalize this increased word-of-mouth activity as a persistent increase of prescription volume by 10 units, though in practice it may (also) take the form of engaging the opinion leader in medical education efforts (see, e.g., Dorfman and Maynor 2006; Valente et al. 2003).[8] Using our model, we can then compare the expected number of adopters following the intervention and compare it against that in the base scenario, where nothing is changed. Such a network-based intervention is of course not costless, but no cost data is available. So, as a benchmark, we compare the expected effectiveness of the intervention against that of another intervention, in which each physician in the sample receives one additional detail in the first month. Using the model and taking into account the carry-over effects of detailing, one can again compare the expected number of adopters with and without the intervention. Assuming both interventions are equally costly, their relative effectiveness reflects their relative efficiency. The procedure is easily adapted if managers believe that the network intervention requires less or more effort than the equivalent of 185 details.

We apply this logic by using the volume-based contagion models both with and without interactions. In both models, the effect of a general detailing impulse declines smoothly over time (due to the partial carry-over), whereas that of the network intervention is very small at first but increases steadily over time. The effect is more muted at first in the model with interactions, because of the negative interaction between Self-reported Leadership and Volume Contagion, but the dampening disappears as more and more self-reported leaders adopt over time and drop out of the "at risk" set. Comparing the effects of the two interventions by using the model without interactions, we find that after 8 months, the expected cumulative number of physicians who adopt due specifically to the network intervention exceeds the number who adopt due specifically to the detailing intervention. In the model with interactions, the cross-over happens after 12 months. Because more than two-thirds of all physicians still have not adopted by that time, the network intervention is the more attractive of the two.

The procedure just outlined provides a model-based assessment of the likely effectiveness of different interventions. The illustration assumes that the cost of having the top 3 leaders double their effective network influence is the same as the cost of one additional detail to 185 physicians. Depending on managers' beliefs, one might use different inputs and come to different conclusions.

Discussion

We conducted a modified replication of the classic *Medical Innovation* study by Coleman, Katz, and Menzel (1966) on the impact of social networks in the adoption of a new drug by physicians. There are four important differences between the present and the original study. First, the decision to adopt is more risky because the new drug studied here, unlike tetracycline, is used to treat a potentially lethal medical condition, and its benefits cannot be observed quickly. Second, we explicitly control for marketing efforts. Third, we operationalize opinion leadership both as physicians' indegree in their professional network based on peer nominations and as physicians' self-reported opinion leadership. Fourth, we investigate whether contagion is driven not simply by peers' prior adoptions but by their current usage behavior, including usage volume. The first difference between the two studies makes it more likely that contagion truly is at work, whereas the second increases the confidence that any evidence of contagion is not simply an artifact due to confounding contagion with the effect of marketing effort (Van den Bulte and Lilien 2001). The third and fourth differences allow us to gain deeper insights into the nature of the contagion process and the role of opinion leaders in that process, an issue that has become controversial again (Becker 1970; Godes and Mayzlin 2009; Thompson 2008; Valente and Pumpuang 2007; Watts and Dodds 2007).

Our main findings are as follows. First, we find evidence of contagion operating over network ties, even after controlling for marketing effort and arbitrary marketwide changes. Second, contagion was affected by peers' usage volume rather than by whether peers had adopted or were prescribing. Third, physicians describing themselves as opinion leaders were less responsive to their peers' behavior, whereas physicians who were often nominated by their peers were not differentially responsive. Fourth, heavy use at the category level before the focal product's launch was associated with early adoption. Fifth, both self-reported leaders and sociometric leaders tended to adopt earlier than the average physician, but the tendency to adopt early was more pronounced for sociometric than for self-reported leaders. Finally, self-reported leadership and sociometric leadership were only moderately positively correlated.

Since these findings stem from a very detailed study of a single product in three cities, the results cannot be considered to have high external validity until they are corroborated by other studies. Yet they already suggest several implications for diffusion theory and research as well as for marketing and market research practice.

Implications for diffusion theory and research

Our evidence about the presence of contagion for a risky product, contrasted with the lack of evidence of contagion for the simple antibiotic tetracycline in the earlier analysis by Van den Bulte and Lilien (2001), corroborates the latter's point on the need to take contingencies in diffusion theory seriously. Depending on the product, the target audience, the amount and effectiveness of traditional marketing communications deployed, and other facets of the specific situation identified in prior research, contagion is or is not likely to be at work (e.g., Rogers 2003; Valente 2005; Van den Bulte and Stremersch 2004). These nuances have not always been attended to in empirical research, leading to seemingly contradictory results.

The finding that self-reported and sociometric leadership are only moderately correlated and behave differently within the nomological network of constructs may be somewhat surprising to our discipline, in which the great bulk of the research has used only self-reported leadership. As we argued, the two measures most probably tap into different facets of an overarching leadership construct. This issue needs to be delved into. Recent research on a distinction between expertise and social connectivity (Goldenberg et al. 2006; Locock et al. 2001) is a step in the right direction, and more research is needed.

We found that people who perceived themselves to be opinion leaders responded less to peer behavior. This finding is consistent with standard perceived risk arguments as well as status maintenance mechanisms (see, e.g., Van den Bulte and Joshi 2007). However, it may also be consistent with social identity considerations in which people react positively to adoptions by people like them and negatively to those by people unlike them (see, e.g., Berger and Heath 2007, 2008; Lieberson 2000). Studies that differentiate between mechanisms involving risk mitigation, "vertical" status, and "horizontal" social identity have the potential to provide a deeper understanding of contagion and new product diffusion processes than we currently have.

The finding that indegree is informative in understanding the diffusion process whereas outdegree is not indicates that the relevant network ties are asymmetric. This suggests that spatial distance, by definition symmetric, may be a poor proxy for the relevant ties in the contagion process. This raises concerns about the insights about contagion that can be gained from spatial data (e.g., Bell and Song 2007; Manchanda, Xie, and Youn 2008). Even so, spatial distance data are more easily, and more cheaply, obtained than actual network data. Therefore, the net benefit of using spatial rather than true network data to understand and predict new product adoption remains an empirical question. Answers would be of both scholarly and practical value.

We found that contagion was affected less by peers' adoption or use status than by their prescription volume. This may stem from a source credibility mechanism. Physicians who prescribe a lot are a more credible source of information: not only do they act in accordance to their own recommendation, but they also have a larger experiential base to found their recommendations on. Research documenting in greater detail the sources of relevance and credibility in word-of-mouth communication would be valuable (Goldenberg et al. 2006).

It is also possible that usage volume is important in contagion because it correlates not with the persuasiveness of the source but with the valence of their outcomes and recommendations. Because people who use a product extensively are more likely to be satisfied with its performance, it is possible that volume contagion acts as a proxy for vicarious learning about postadoption outcomes (see, e.g., Haunschild and Miner 1997; Lee and Strang 2006). Research on the role of postadoption outcomes and satisfaction in contagion dynamics could further our understanding of contagion processes and of how marketers can use them to their benefit.

Our results on volume-based contagion corroborate the argument by Godes and Mayzlin (2009) that heavy users are likely to be more influential than light users when contagion fosters adoption by operating at the evaluation stage rather than at the awareness stage. Our finding complements Godes and Mayzlin's finding of a larger effect of light users for a product that did not benefit from standard marketing communication and that presented little perceived risk such that potential buyers needed little additional information to make a positive evaluation once they were aware. Further research on the role of usage behavior in word-of-mouth and contagion dynamics could enhance our understanding of contagion processes and provide useful guidance to managers on whether heavy users or light users are the more attractive seeding points for viral marketing campaigns.

Implications for marketing research practice

As in earlier network diffusion studies, indegree based on others' nominations was found to be an informative way to measure opinion leadership—or at least one facet of it. This suggests a way for market researchers to assess the opinion leadership of customers even if they do not respond to a survey. But our findings also indicate that there is additional information to be gained from self-reported leadership scores.

We found that much—though not all—of the relevant network information can be obtained from patient referral ties. This is quite promising for applications of network marketing in health care. Because some secondary data on patient referral are commercially available (e.g., the longitudinal patient data provided by Surveillance Data Inc.), it might be possible to measure relevant networks without collecting network surveys. Using secondary data might lead to lower costs and more complete observation of the entire network. Such secondary patient referral data, however, are not complete or cheap, so the net benefits of using them remain an empirical question. Some kind of data-fusion approach may prove the most attractive option.

Implications for marketing practice

Our results support the use of network-leveraging campaigns hinging on central influentials exerting above-average social influence on other customers, an idea about which doubts have arisen recently (Thompson 2008; Watts and Dodds 2007). Our evidence, it should be noted, pertains to a product for which one would a priori expect contagion to matter and does not invalidate the warning that contagion cannot simply be taken for granted in every situation. Another managerial caveat is that our study documents that well-connected people are more influential than others but does not take into account the marketing cost of identifying and converting them. Still, by combining model results and their own judgments, managers can assess the attractiveness of a network marketing approach and compare the expected results with those of more traditional marketing.

Our study suggests the existence of hitherto neglected benefits of targeting sociometric opinion leaders. The standard argument for targeting them is that they influence more peers than less-centrally located people do. Our results are consistent with this, but suggest two additional benefits. First, the "stand-alone" customer lifetime value (CLV) of opinion leaders may be higher than that of other people because opinion leaders tend to be early adopters and heavy users. Second, their "network" value may be higher not only because they reach more people but also because, by being early adopters and heavy users, they start influencing others sooner and more effectively then less-connected people. Here again, some caveats are due. First, if opinion leaders tend not only to adopt but also to disadopt sooner than others, and if the firm's discount rate is low, then the "stand-alone" CLV of an opinion leader need not be systematically above average. Second, a customer's heavy use may boost his "network" value only if the product is perceived to be risky and heavy users are more credible or otherwise more influential than light users (Godes and Mayzlin 2009). Third, when the new product challenges the power base or norms of the opinion leaders, the product is likely to be resisted by them and to be adopted first by members at the fringe of the network (Becker 1970; Leonard-Barton 1985; Valente 1995).

Managers should also take note that heavy prescribers of the last drug launched in the category tended to adopt the new drug early and also tended to be opinion leaders. It suggests that the industry practice to overweight one's marketing efforts at launch on heavy prescribers is sound not only to gain quick trial sales but also to generate a larger contagion effect.

Conclusion

Just as marketing practice is rediscovering the idea of leveraging customer networks to accelerate new products' market acceptance, some network research has emerged challenging the basic premises of this practice (Van den Bulte and Lilien 2001; Watts and Dodds 2007). Network and diffusion researchers as well as practitioners will find it encouraging that we were able to document contagion effects operating over social networks, even after controlling for targeted marketing effort and arbitrary marketwide changes. Similarly, our findings about sociometric versus self-reported opinion leadership and about contagion being moderated by usage volume suggest not only venues to gain richer theoretical understanding of social contagion dynamics but also ways through which one might ultimately increase the effectiveness of network marketing.

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Glossary

Hazard rate of adoption

Probability that someone who has not adopted earlier does so at the present time (under the technical assumption of "discrete time").

Indegree

Number of incoming ties. In this study, the number of nominations one has received from others as someone they discuss medical treatment with or refer patients to.

New product diffusion

Process of a new product's gaining acceptance in a population or market. May but need not be affected by social contagion.

Opinion leader

Person with high opinion leadership.

Opinion leadership

The degree to which an individual influences others' attitudes or behavior without having formal authority over them and without being formally directed to do so.

Outdegree

Number of outgoing ties. In this study, the number of others one has nominated as people one discusses medical treatment with or refers patients to.

Self-reported opinion leadership

Opinion leadership measured by self-reports. In this study, people rated themselves on a six-item scale.

Sociometric opinion leadership

Opinion leadership measured in network terms. In this study, operationalized as indegree.

Social contagion

Phenomenon of people's behavior being influenced through exposure to others' knowledge, attitudes, or behavior. This study investigates only direct exposure.

Tie

Link or connection between two nodes in a network.

Viral marketing

Marketing strategies or programs aimed at leveraging social contagion.

Word-of-mouth

Social contagion by talking or writing to others (rather than by exposure through visual observation or through mentions by salespeople, ads, and other paid-for commercial materials, or publicity from media reports).

Notes

1. For reasons of anonymity agreed upon to gain the cooperation of the company, we do not report its identity or the drug's name, treatment category, and launch date.

2. In consultation with industry experts, we excluded one item from the seven-item Childers scale, as it was not relevant to our research context. The six items in our survey included the questions below, in which "——" stands for the medical condition treated by the focal drug:
In general, do you talk to other doctors about ——? (Never/Very often.)
When you talk to your colleagues about —— do

you . . . (offer very little information/offer a great deal of information)?
During the past 6 months, how many physicians have you instructed about ways to treat ——? (Instructed no one/Instructed multiple physicians.)
Compared to your circle of colleagues, how likely are you to be asked about ways to treat ——? (Not at all likely to be asked/Very likely to be asked.)
In discussions of ——, which of the following happens more often? (Your colleagues tell you about treatments/You tell your colleagues about treatments.)
In general, when you think about your professional interactions with colleagues, are you . . . (not used as a source of advice/often used as a source of advice).

3. We also used the number of prescriptions over the 6 months prior to launch and over two years prior to launch. The model fit (in log likelihood) of the model using the one-year window was marginally better than that of models using the shorter and longer window, but there were no substantive differences in the results.

4. Lagging avoids endogeneity problems, unless (1) people are forward-looking about not only their own behavior but also that of others *and* (2) social ties over which influence flows are symmetric. The first condition is quite unlikely in large networks, and the second condition does not hold in our data.

5. Adoption Contagion and Use Contagion level off after 9 months (Fig. 2), even though the total number of adopters keeps growing roughly linearly (Fig. 1a), because those adopting after month 9 tended to have very low indegree and hence not to exert any contagion on colleagues.

6. In the model with Volume Contagion, the total effect of Self-reported Leadership becomes significantly negative only for levels of Volume Contagion above the 99th percentile. In the models with Adoption and Use Contagion, the total effect of Self-reported Leadership never becomes significantly negative.

7. The volume-based contagion model with (without) interactions fits better than the two competing models with (without) interactions. Whether it is desirable to include the interaction terms in the volume-based contagion model is a more subtle issue. The presence of a significant interaction suggests that the main-effects-only model is misspecified.

8. The scenario of this intervention is quite realistic. In SF and LA, the physician with the highest indegree adopted in month 1, and in NYC he adopted in month 2. Upon adoption, the average prescription volume per month of the 3 leaders was 10 units. Thus, we simply assume doubling the average prescription volume of leaders.

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