Modeling Information Diffusion Efficiency in a Social Network

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August 2010

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The authors thank Christophe Van den Bulte, Adam Finn, Paul Messinger for helpful comments and suggestions. We also thank Christophe Van den Bulte for providing us with the data set used in this paper. The dataset (without advertising information) was originally prepared by Ronald Burt.
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Abstract

Using social cohesion theory, we measure the timing of the adoption of a novel drug within a network of physicians. This theory suggests that innovation diffusion occurs through direct contact between neighbors within a social network.

A unique contribution of our study is to model the efficiency with which new product information is transmitted within the network. Specifically, we propose an efficiency coefficient to capture the percentage of network neighbors that an adopter can influence in a unit time period.

Analyses of the diffusion of the medicine showcase significant heterogeneity in efficiency of information transmission. Efficiency is relatively low suggesting that adopters do not transmit information to all their network neighbors within a single time period. Furthermore, adopters with a large number of neighbors will block the dissemination process, creating dissemination jams. The paper concludes with a discussion of related managerial implications and promising directions for future research.
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1. Introduction

Social contagion theory states that people may duplicate the behavior of others. An individual’s adoption of a new product depends on the adoption by those accessible others, in addition to influences from other sources such as advertising. Consumer communities and discussion groups allow consumers access to the experiences of others with respect to new products. Consumers who draw on this information may more confidently adopt a new product because the process of sharing opinions with other community members usually lowers the perceived risk associated with purchase decisions. Becker (1970) suggests that “information” may include “important data concerning cost, problems, political risks, likelihood of opposition from interest groups, efficacy of the innovation when initiated, and so forth.” Generally, such information cannot be obtained through advertising or personal selling. In the case of high involvement products, consumers are especially unlikely to make purchase decisions solely based on marketing information provided by the seller. We suggest that interpersonal information sources, such as product usage experiences of other consumers, will play an important role. Generally, social considerations such as community norms or attitudes of community members toward a new product are likely to influence a consumer’s new product adoption decisions (Godes and Mayzline, 2004; 2009; Hill, Provost, and Volinsky, 2006).

To the extent that individual consumers and business organizations are embedded within social communities, they are inter-connected by ties that characterize social networks. For this reason, the social network research perspective is especially appropriate for studying new-product adoption decisions of individuals as well as organizations. Generally, this stream of
research uses an individual’s social network position to explain the timing of new product adoption (Becker, 1970; Burt, 1987; Coleman Katz, Menzel, 1957; Van den Bulte and Lilien, 2001; Westphal, Gulati and Shortell, 1997). For example, individuals positioned in the center of a network are better connected than those placed on the network’s boundary. Our study contributes to this research stream by explicitly modeling the efficiency with which new product information is transmitted within a social network. We define this efficiency as the percentage of network neighbors an adopter can influence in a unit time period.

Our analyses of the diffusion of a new medicine (tetracycline) show significant heterogeneity in the efficiency of information transmission across four cities in the US Midwest. In most instances the efficiency is relatively low suggesting that adopters do not transmit information to all their neighbors in a network in a single time period. Furthermore, when the efficiency of information transmission is low, adopters with a large number of direct neighbors will block the dissemination process creating dissemination jams.

The next section reviews the literature on new product diffusion in social network settings. Following the literature review, we discuss our modeling approach. Next we describe our analyses and discuss the results. Finally we acknowledge the limitations and identify opportunities for future research.

2. Literature Review

In marketing, the Bass model (1969) and its extensions (e.g., Hsiao, Jaw and Huan, 2007) are the traditional approach to model the diffusion of new products. However, in this paper we focus on product diffusion in a social network, focusing on the role of social influence on the adoption of a new innovation (Baudish, 2007; Kulviwat, Bruner II and Al-Shuridah, 2009). Table 1 lists key
findings/contributions, measure/proxy of social network influence, statistical methods, description of dataset and limitations of major social network studies in marketing and sociology fields. It also highlights unique features in this study’s modeling approach.

Table 1 here.

The seminal paper by Coleman, Katz and Menzel (1957) introduces the social network approach to the literature of new product diffusion. Their pioneering study analyzes sociometric data to explain the adoption of innovations. These authors characterize new product diffusion within a social network as “a snowball process in which those who have adopted an innovation pass on the innovation to their colleagues” (p.262). This process represents a social contagion effect by which information about the innovation is transmitted through social network ties. Notably, social contagion by proximate others (or social cohesion) rests on the premise that a non-adopter can be influenced by neighboring adopters of an innovation through discussion and communication (Gruen, Osmonbekov, Czaplewski, 2006, Kulviwat, Bruner II, Al-Shuridah, 2009). Thus, network entities with more direct contacts (local centrality) in the social network are more likely to acquire new product information earlier than those with fewer direct social contacts. More formally stated, the degree of each network entity (where degree denotes the number of immediate network neighbors) influences the timing of innovation adoption.

Freeman (1977) extends the Coleman et al. (1957) study by introducing the concept of closeness (or global centrality) for a given network entity. Closeness measures the inverse of the sum of the geodesic distance to all other entities in the network. A key implication is that, for any given network member, the shorter the sum of communication paths to all other network entities, the quicker the dissemination of product information by that member.

Becker’s (1970) research examines the fit between the innovation and community norm.
Conceptually, Becker differentiates between innovations in terms of their adoptive potential. He finds that the correlation between centrality and time of adoption is higher for high adoptive-potential innovations than for low adoptive-potential innovations. This finding implies that the resistance to, or acceptance of, an innovation depends on current norms of the community.

Burt (1987), on the other hand, proposes a structural equivalence modeling approach where information dissemination depends on the similarity of network members within a social structure. That is, an individual may mimic the behavior of another holding a structurally equivalent position in a network. In contrast to social contagion via social cohesion that depends on proximity of entities to transmit information, Burt’s study demonstrates social contagion by structural equivalence that depends on similarity of entities. In other words, social influence may occur even if structurally equivalent entities remain distant from each other.

Van den Bulte and Lilien (2001) examine social contagion in the adoption of innovative products, while controlling for the effect of advertising. They do not find an effect of social contagion (either through structural equivalence or social cohesion) on product adoption. They also report that timing of new product adoption is influenced by advertising.

Recent marketing research studies in the social network area employ a dynamic modeling approach to study new product diffusion and adoption. Godes and Mayzlin (2009) demonstrate that word of mouth by less loyal consumers expands the market size. Bell and Song (2007) and Manchanda Xie and Youn (2009) use a geographic proximity measure to infer the influence of social interaction on adoption of a new drug. Finally, Goldenberg, Han, Lehmann and Hong (2009) find that early innovative adopters with many direct social network ties expedite the new product adoption process, while the followers (imitators) with many direct social network ties
increase the market size. They use a revised agent based model to capture the social contagion effect within a network.

Our study is most closely related to Goldenberg et al. (2009). A major difference is that the latter authors assume that each network entity is extremely efficient in transmitting information to other network neighbors, while our model considers efficiency as a parameter to be estimated. It is reasonable to assume extreme efficiency when information transmission requires little time and effort (for example, Goldenberg et al. studied online community members who customize homepages by posting ‘decorative’ items that are easily accessed by other members). Our approach is more valid when the adoption process is more involved such as a new drug, where physicians expend time and effort to assess the new product.

Our study is different from other work in another important respect. Although we rely on the concept of social cohesion, we use a time dependent measure of social cohesion to explicitly recognize that it takes time for information to travel within a network.

3. Modeling Approach

We propose that an individual’s adoption of innovations is influenced by social cohesion (i.e., through direct contact with proximate neighbors). As a potential adopter, a network entity has to wait until she gets reliable information from her network neighbors, who in turn receive information about the innovation from their network neighbors, and so on. As a result, it takes time for information to be transmitted from initial adopters to a potential adopter within the network. If the latter adopts the innovation, she then influences other neighboring non-adopters. The duration of the adoption process will depend on the number of entities (potential adopters),
the network structure and the efficiency with which relevant information is transmitted.

We propose a coefficient of information transmission efficiency to represent the percentage of network neighbors influenced by an adopter. A higher value for this coefficient denotes a higher probability that a non-adopter will be influenced by the information transmitted by the adopter.

Before discussing the model, it is useful to consider the illustrative social network in Figure 1 with 17 entities. Entity A is the initial adopter that can only transmit information to B, D, I and J. Entities F and G are three geodesic distances away from A, while K is only two geodesic distances away from entity A.

Figure 1 here.

Our interest centers on information transmission from the adopter -- the focal entity -- to neighboring non-adopters within her ego network (defined as the focal entity and all network members to whom the focal entity is directly connected). It is instructive to contrast low and high levels of information transmission efficiency. To exemplify low efficiency, consider the situation where the adopter can inform only one network neighbor in a given time period. The probability of information transmission from an initial adopter $j$ to its neighbor $k$ under this scenario is represented as $P_{jk} = 1/D_j$, where $D_j$ is the degree or the number of network neighbors. The probability of information transmission from non-initial adopter $j'$ to his network neighbor $k$ is similarly defined as $p_{jk} = \frac{1}{D_j - 1}$.

On the other hand, high efficiency denotes the adopter’s ability to influence all network neighbors in a single time period. Under this scenario, the probability of information transmission from adopter $j$ to its neighbor $k$ is always $P_{jk} = 1$, implying that information is
transmitted to all neighbors.

Table 2a reflects the low efficiency view by displaying the relatively lower probabilities that F, G, J and K are influenced by network neighbors at the end of time periods 1, 2 and 3 when only one of the entities in the ego network is influenced in a single time period. Similarly, Table 2b shows the high efficiency perspective with corresponding higher probabilities when all entities in the ego network are influenced in a single time period.

The preceding example points to two conclusions. First, when a network entity’s efficiency is very low, the geodesic distance between entities does not necessarily determine the speed of information transmission. Entities F and G are exactly the same geodesic distance away from A, but the cumulative probability of adoption for F is less than that of G in the third period. Moreover, although K (and K’s structural equivalent entities) is geodesically closer to the initial adopter A than either F or G, the third period adoption probability of K is lower than that of F or G. These results show that the entire network structure, rather than just the geodesic distance and the degree, may exert an important influence on an individual entity’s timing of new product adoption. Second, the network information transmission efficiency may lie somewhere between the high and low efficiency scenarios described, so it is fruitful to characterize efficiency as a parameter to be empirically estimated, as described next.

3.1 Formal Model

The information transmission efficiency coefficient $\delta$ is set to lie between 0 and 1. When $\delta = 0$, the network entity only transmits information to one of its network neighbors; when
\( \delta = 1 \), the information is transmitted to all of its network neighbors. A higher value for \( \delta \) indicates a higher efficiency, whereby a higher percentage of network neighbors are influenced by an adopter in a specific time period.

The influence of the initial adopter \( j \) on its network neighbor \( k \) at time \( t \) is formally specified as:

\[
P_{jk_t} = \frac{1}{D_j} + \delta(1 - \frac{1}{D_j})\]

where, \( 0 \leq \delta \leq 1 \).

The influence of non-initial adopter \( j' \) on network neighbor \( k \) at time \( t \) is formally defined as

\[
P_{j'k_t} = p_{j'(T-1)} * \left[ \frac{1}{D_j - 1} + \delta(1 - \frac{1}{D_j - 1}) \right] \]

where \( 0 \leq \delta \leq 1 \). This equation captures the lagged effect of social influence from an entity to a network neighbor. Moreover, this equation demonstrates the asymmetric relations between network entities as proposed by Nair, Manchanda, and Bhatia (2008). Entities with a larger (smaller) number of direct ties have a lower (higher) probability of influencing each of their direct ties (or non-adopting neighbors) due to the additional time and effort required to reach all their neighbors.

The first part in brackets in equation \((1')\) indicates that at least one non-adopter is influenced by the adopter, while the second part represents the influence on all other non-adopters. Hence we assume that an adopter influences at least one non-adopter in any specific time period.

The overall coefficient of data transmission efficiency \( \delta \) incorporates the idea that people with more (less) direct social ties could be more (less) active in networking, while the magnitude
of δ represents the percentage of influenced entities by all adopters in a social network.

The cumulative influence of adopter \( j \) on its network neighbor \( k \) by time \( T \) is represented as

\[ p_{jkT} = 1 - \prod_t (1 - p_{jkt}) \]

The cumulative influence received by \( k \) from all of its network neighbors by time \( T \) is represented as

\[ P_{kt} = 1 - \prod_j \prod_0^T (1 - p_{jkt}) \]

3.2 Measure of social network influence

Following Coleman et al. (1957), the degree is simply calculated as the total number of direct contacts for each physician. Closeness is measured as the inverse of the sum of the geodesic distances to all other physician in the network (e.g., Freeman, 1977). Finally, we used the C program language to calculate the social influence directed at each network entity in each time period for each of the four cities based on equations 1 to 3.

We set the unit of time as a single calendar month (we also tried time periods of half a month and two months, but both resulted in a significantly poorer fit). We first need to identify the initial adopters (five physicians in city 1 and six in city 2 adopted the new drug in month 1, in city 3 two physicians adopted the drug in month 2 and in city 4 two physicians adopted the drug in month 3. These 15 physicians are treated as the initial adopters disseminating influence to other entities in each city’s network. The influence values, for each non-initial adopter was calculated starting one month after the initial adopters adopted the product. Next these values are included in equation 4 presented in the next section, to determine the optimum value the information transmission efficiency coefficient \( \delta \).
3.3 Hazard Model

A discrete time hazard model is used to study the impact of social network influence on the time of adoption of tetracycline, while controlling for other variables such as the physician’s professional age, number of journals read, scientific orientation and drug manufacturer advertising. The discrete time hazard model is a type of survival analysis to examine the influence of historical events on a time-related dependent variable. A discrete time hazard model is used rather than a continuous time mode because it incorporates time-varying exploratory variables more easily (Allison 1982; Brown 1975). This approach is both important (our study employs two time-varying independent variables: social influence, and the amount of advertising) and consistent with other social network studies (Van den Bulte and Lilien, 2001; Bell and Song, 2007; Manchanda, Xie and Youn, 2008).

The hazard function of the rate of adoption of physician \( j \) at time \( t \) is represented as follows:

\[
prob(y_{kt} = 1 | y_{k(t-1)} = 0) = F(\beta_0 + \beta_1 \text{Lederle}_t + \beta_2 \text{Other}_t + \beta_3 \text{Network}_{kt} + \beta_4 \log(\text{journal})_k + \beta_5 \text{Age}_k + \beta_6 \text{Age}^2_k + \beta_7 \text{Science}_k) \]

where,

Dependent variable \( y_{kt} \) represents whether entity \( k \) adopts the innovation at time \( t \).

\( F \) is a cumulative distribution function, representing the probability of adopting the innovation.

\( \beta_0 \) is the constant.

\( \text{Network}_{kt} \) represents the social influence from network neighbors to network entity \( j \) at time.
This value is calculated according to equation 3.

\( \delta \) is the information transmission efficiency coefficient.

*Lederle* and *Other* represent, respectively, the influence of advertising by the leading tetracycline manufacturer Lederle and by other tetracycline manufacturers, at time \( t \) on every physician. The amount of advertising varies over time but is assumed to be the same across all entities. The advertising data is a count of the number of pages of tetracycline advertising by all pharmaceutical companies, obtained from an examination of each monthly issue of *Modern Medicine, Medical Economics* and *GP*, from November 1953 to April 1955.

\[
Lederle_t = \sum_{t=0}^{T} Lederle_{t} \alpha^{(T-t)} \quad \text{(5)}
\]

\[
Other_t = \sum_{t=0}^{T} Other_{t} \alpha^{(T-t)} \quad \text{(6)}
\]

A grid search identified the optimum value for the coefficient of the lagged effects of advertising \( \alpha \) as 0.75 (i.e., 75% of today’s advertising carries over to the following months).

\( \log(Journal)_j \) represents the natural logarithm of the number of journals each physician reads and demonstrates the physician’s access to professional knowledge from public media. We take the natural logarithm in order to normalize the distribution of this variable.

*Age*\(_k\) and *Age*\(^2\)_\(_k\) represent, respectively, the number of years and squared number of years that each network entity (physician) has been practicing medicine. These terms that capture the professional age may influence the rate at which the physician prescribes medicines. The quadratic term controls the effect that physicians with little experience or older physicians may be more conservative in adopting new drug.

*Science*\(_k\) is a dummy variable that represents whether the physician is science-oriented or patient-oriented. This measure is obtained through a survey. It is possible that physicians with a
scientific orientation are more likely to explore the effect of a new drug than their peers.

4. Data

The *Medical Innovation* dataset used for model estimation were originally collected by Coleman et al. (1957). These data include the monthly record of prescription of a new medicine (tetracycline) by family physicians in four cities in the US Midwest from November 1953 to February 1955. In addition, this dataset describes the friendship, advice and discussion networks of family physicians that represent potential adopters of this medicine. Other variables in this dataset include the physician’s professional age, number of medical journals read, sales force effort, the amount of advertising and the date of each physician’s first prescription of tetracycline from local pharmacist’s record.

We use the available information on physicians to construct four social networks corresponding to the four cities in the *Medical Innovation* dataset. Similar to most previous studies, the network structure is assumed to be constant across time. For each city, we combine the discussion and friendship networks into one social network because both friendship and discussion involve bilateral communication. We symmetrized the combined network data by imputing missing values in symmetric positions of the entity relational matrix. That is, if physician A reports physician B as a friend and/or discussion partner, physician B is also considered as a friend and/or discussion partner of A even if physician B did not reciprocally identify physician A as a friend and/or discussion partner. Based on this data we estimate our measure of social network influence in addition to two previously used measures: *degree* and *closeness*. 
5. Results

We estimate the hazard model in equation (4) separately for each city, by conducting a grid search for $\delta$ from 0 to 1, with an interval of 0.1, to determine the value of the information transmission efficiency coefficient that best fits the observed data. Using the Bayesian Information Criterion (BIC), this approach yielded the following optimum values for $\delta$: City One = 0, City Two = 0, City Three = 0.7 and City Four = 0.2.

The estimation results of the hazard models with the above values of $\delta$ are provided in Table 3. This table also includes two alternative models with traditional measures of social cohesion: degree and closeness. The results of the model fit, based on the BIC measure show that the model with proposed measure provides a considerably better fit, with the exception of City Three where none of the social network variables are significant.

Table 3 here.

Comparing the different results across models and cities, it is clear that degree and closeness are only significant in city four, while our measure of social influence is significant in cities one, two and four. In cities one and two, the coefficient of information transmission efficiency $\delta = 0$, indicating a very slow dissemination of information. Moreover, the parameter estimates for all three models are remarkably similar (with the exception of the advertising coefficient for the leading tetracycline manufacturer Lederle that is significantly lower in city two). The same is true for city three where network effects are not significant. Finally in city four, where $\delta = 0.2$ we do observe several differences in the results across the different models. The coefficients for age and age$^2$ of the physician and their scientific orientation are all statistically
significant in the models with the alternative network measures, but become non-significant when the model takes into account the efficiency of the information transmission.

Next we will focus on the results of our proposed model across the different cities. In city one, we observe a positive significant network effect ($\beta = 2.43, p < 0.05$). However, the information dissemination efficiency is extremely low with $\delta = 0$. In other words, on average, an early adopter only influences one non-adopter in a month. Moreover, the advertising by both leading manufacturer and other manufacturers positively influences the timing of new drug adoption. The number of journals read by physicians negatively contributes to the timing of adoption. The physician’s professional age and scientific orientation do not influence the timing of adoption.

In city two, we find a significant negative network effect ($\beta = -5.79, p < 0.05$), which suggests that negative word of mouth is transmitted in this network. Again the social influence dissemination efficiency is extremely low with $\delta=0$. Similar to the results for city one, advertising by both the leading manufacturer and other manufacturers positively influence the timing of the physician’s new drug adoption. All other variables do not significantly influence the timing of new drug adoption in this city.

On the one hand, advertising has a positive effect on the timing of the adoption. On the other hand, we also observe a negative network effect, suggesting some negative user experience with the drug in this city, leading to some negative word of mouth. However, the efficiency of the information dissemination is low, which may somewhat limit the impact of the word of mouth.

In city three, social network effects do not significantly influence the timing of new drug adoption. Thus, we did not find support for social cohesion within the physician network in city
three. Besides, advertising by the leading manufacturer does not influence the timing of adoption. However, the advertising by non-leading manufacturers has a significant effect on the timing of adoption. All other variables do not influence the timing of new drug adoption in this city.

Finally, in city four, the social network effect positively influences the timing of adoption ($\beta = 4.69, p < 0.05$). Furthermore, the social network in this city shows a somewhat faster dissemination of information ($\delta = 0.20$). This means that a physician, who has adopted the new drug in month $t$, will influence one of her social ties plus 20% of her remaining network ties the next month ($time t +1$). For example, in city four, the average number of social ties is 6.2, suggesting that on average physicians influence about 2 of their social ties [or $(1+20\% \ast (6.2-1))]$, given that the focal physician has adopted the drug in the previous time period.

Advertising by the leading manufacturer does not contribute to the timing of the adoption of this new drug, but we do observe a significant effect for advertising by other manufacturers. Physicians who read more professional journals, on average, adopt the new medicine later than those who read fewer journals. Finally, the physician’s professional age and scientific orientation do not influence the timing of adoption.

As a whole, the results demonstrate that network effects play a role in the timing of the adoption of the new drug. However, the network influence differs significantly by city. In cities one and two where dissemination of information through the network is slow, advertising seems to play a greater role. However, in city four physicians seem to depend more on network effects than on advertising. Finally, in city three the network did not influence the timing of adoption at all.

6. General Discussion
This study models a time dependent new product diffusion process in a social network, applying social contagion theory. Consistent with the results of previous research (e.g. Coleman et al., 1957; Becker, 1970 and Goldenberg et al., 2009) we find support for social cohesion, suggesting the importance of interpersonal relationships in the diffusion of new products. However, different from previous studies, we incorporate the efficiency of information transmission into our model.

While mass media are effective at creating consumer awareness for new products, interpersonal channels within a social network tend to be more capable of persuading entities to adopt an innovation (Rogers, 1995; Gosling, Westbrook and Braithwaite, 2003). Through a social network, members can transmit new product information that may reduce consumers’ perceived risks. As time passes, more people in the network are likely to adopt the new product, and social pressure to adopt accumulates for other network entities. Thus, the probability of adoption for each network entity increases over time.

In this paper we propose a novel measure of network influence, which takes the time dependence into account. We compare our proposed measure of influence against standard static measures of social cohesion, including the degree and closeness, and find that our measure of the efficiency of information transmission results in a superior model fit. Furthermore, results from four different cities suggest that the efficiency differs considerably across cities and tends to be relative low. A lower efficiency means that it takes more time for the information (influence from network members) to pass through the network.

The efficiency of the transmission of information in the social network has important managerial implications. When information dissemination efficiency is high it is important for managers to target network members with a large social circle (a large number of immediate neighbors)
who can pass on this information to all their neighboring network members. This is consistent with the results by Goldenberg et al. (2009), who find that innovative hubs facilitate the speed of new product diffusion (note that they study low involvement decisions, downloading materials from a website, where information transmission efficiency is expected to be high). However, when dissemination efficiency is low, network members with many ties may actually impede the flow of information, resulting in information jams (e.g., they may not have the time and resources to influence all their network neighbors). This is the case when a new product adoption involves significant risks, like prescribing a new drug where physicians are more likely to rely on other physicians who have already adopted the new drug, to discuss the effectiveness and the side effects. Ironically, in the case of negative word-of-mouth (WOM) these well connected members may actually block the negative WOM.

Therefore, when information efficiency is low, managers should also focus attention on network members with fewer ties, where information jams are less likely to occur. Physicians with only a few social ties are more likely to influence these ties, and may therefore act as important channels in the dissemination process.

7. Limitations and Future Research

This study focused on the efficiency of information transmission in a network, and to estimate efficiency across different cities. Future research should also identify variables that influence the level of efficiency. For example, product type, valence of WOM (Park and Lee, 2009), competing products, marketing strategies, network structure, consumers’ usage experience with similar products are candidate variables that may influence efficiency.

Our model assumes that the network structure does not change over time, as in most
previous studies in this area. While this assumption is reasonable when the dissemination of information through the network is relatively fast, the network structure may in fact change under lengthy dissemination. Future research could explore the effect on information transmission efficiency when entities and relationships are added to, and/or subtracted from, the existing network structure (e.g. Bollobás, 2001; Goldenberg, Libai, Muller and Stremerch, 2010; Kotona and Sarvary 1998).

Moreover, the algorithm developed in our study only considers bilateral relations in a network. Future research should develop an algorithm that efficiently models other relations. This approach may facilitate expanding the types of relations represented (e.g. advice network in Medical Innovation) thereby leading to more precise analyses and results.
References


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Table 1: Selected Research on the network approach to Innovation Adoption

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<td>Regression</td>
<td>The adoption of homepage building items by members of Cyworld (a social network website)</td>
<td>Treating the social influence between each pair of network relations as symmetric</td>
</tr>
<tr>
<td>Manchanta, Xie and Youn 2008</td>
<td>Both detailing and social contagion influence are incorporated into the modeling of new drug adoption</td>
<td>Geographic Proximity</td>
<td>Discrete Time Hazard Model</td>
<td>New Drug Adoption in Manhattan and Indianapolis</td>
<td>Variance of geographic proximity cannot fully represent the variance of social influences between network entities.</td>
</tr>
<tr>
<td>This Study</td>
<td>Combination of the effect of interpersonal and mass media channel; Dynamic Approach; Network transmission efficiency; Asymmetric influence between network entities</td>
<td>Discrete Time Hazard Model</td>
<td>Medical Innovation</td>
<td>Taking the initial adopters as granted. Only dealing with bilateral relations.</td>
<td></td>
</tr>
</tbody>
</table>
### Table 2a: Demonstrative Example - Information Transmission Probability When Only One Entity in an Ego Network is Influenced in a Unit Time Period

<table>
<thead>
<tr>
<th>Entity/Network Influence Probability</th>
<th>Period 1</th>
<th>Period 2</th>
<th>Period 2 Accumulative</th>
<th>Period 3</th>
<th>Period 3 Accumulative</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.13</td>
<td>0.13</td>
</tr>
<tr>
<td>G</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.25</td>
<td>0.25</td>
</tr>
<tr>
<td>K</td>
<td>0</td>
<td>0.04</td>
<td>0.04</td>
<td>0.03</td>
<td>0.06</td>
</tr>
<tr>
<td>J</td>
<td>0.25</td>
<td>0.19</td>
<td>0.44</td>
<td>0.14</td>
<td>0.58</td>
</tr>
</tbody>
</table>

### Table 2b: Demonstrative Example - Information Transmission Probability When All of Entities in an Ego Network are Influenced in a Unit Time Period

<table>
<thead>
<tr>
<th>Entity/Network Influence Probability</th>
<th>Period 1</th>
<th>Period 2</th>
<th>Period 2 Accumulative</th>
<th>Period 3</th>
<th>Period 3 Accumulative</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>G</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>K</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>J</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>City One</td>
<td>City Two</td>
<td>City Three</td>
<td>City Four</td>
<td></td>
</tr>
<tr>
<td>----------------------</td>
<td>--------------------</td>
<td>--------------------</td>
<td>--------------------</td>
<td>--------------------</td>
<td></td>
</tr>
<tr>
<td><strong>Model with</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Efficiency Coefficient</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Degree</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Closeness</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>constant</strong></td>
<td>$^{a}12.51***$</td>
<td>$^{a}12.39***$</td>
<td>$^{a}12.89***$</td>
<td>$^{a}5.65**$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$(0.00)$</td>
<td>$(0.00)$</td>
<td>$(0.00)$</td>
<td>$(0.55)$</td>
<td></td>
</tr>
<tr>
<td><strong>Network Influence</strong></td>
<td>2.34**</td>
<td>-0.09</td>
<td>-4.38</td>
<td>32.37</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$(0.03)$</td>
<td>$(0.16)$</td>
<td>$(0.56)$</td>
<td>$(0.03)$</td>
<td></td>
</tr>
<tr>
<td><strong>Delta ($\delta$)</strong></td>
<td>0</td>
<td>0</td>
<td>0.70</td>
<td>0.20</td>
<td></td>
</tr>
<tr>
<td><strong>Lederle</strong></td>
<td>50.24***</td>
<td>54.88***</td>
<td>54.41***</td>
<td>-6.14***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$(0.00)$</td>
<td>$(0.00)$</td>
<td>$(0.00)$</td>
<td>$(0.00)$</td>
<td></td>
</tr>
<tr>
<td><strong>Others</strong></td>
<td>10.90***</td>
<td>11.61***</td>
<td>11.02***</td>
<td>36.97</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$(0.00)$</td>
<td>$(0.00)$</td>
<td>$(0.00)$</td>
<td>$(0.55)$</td>
<td></td>
</tr>
<tr>
<td><strong>Log(Journal)</strong></td>
<td>-12.83***</td>
<td>-12.31***</td>
<td>-12.02***</td>
<td>2.15</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$(0.00)$</td>
<td>$(0.00)$</td>
<td>$(0.00)$</td>
<td>$(0.76)$</td>
<td></td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td>-0.09</td>
<td>-0.38</td>
<td>-0.12</td>
<td>4.69**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$(0.80)$</td>
<td>$(0.91)$</td>
<td>$(0.73)$</td>
<td>$(0.10)$</td>
<td></td>
</tr>
<tr>
<td><strong>Age^2</strong></td>
<td>0.02</td>
<td>0.00</td>
<td>0.01</td>
<td>0.04</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$(0.69)$</td>
<td>$(0.97)$</td>
<td>$(0.82)$</td>
<td>$(0.08)$</td>
<td></td>
</tr>
<tr>
<td><strong>Science</strong></td>
<td>0.08</td>
<td>0.10</td>
<td>0.76</td>
<td>16.3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$(0.84)$</td>
<td>$(0.80)$</td>
<td>$(0.83)$</td>
<td>$(0.01)$</td>
<td></td>
</tr>
<tr>
<td><strong>BIC</strong></td>
<td>146.52</td>
<td>149.18</td>
<td>150.88</td>
<td>2.15</td>
<td></td>
</tr>
<tr>
<td></td>
<td>107.77</td>
<td>110.73</td>
<td>111.69</td>
<td>$(0.76)$</td>
<td></td>
</tr>
<tr>
<td><strong>AIC</strong></td>
<td>130.18</td>
<td>132.84</td>
<td>134.54</td>
<td>163</td>
<td></td>
</tr>
<tr>
<td></td>
<td>101.10</td>
<td>104.06</td>
<td>105.02</td>
<td>$(0.16)$</td>
<td></td>
</tr>
<tr>
<td><strong>Num obs.</strong></td>
<td>427</td>
<td>427</td>
<td>427</td>
<td>117</td>
<td></td>
</tr>
</tbody>
</table>

a: Standardized Coefficient; b: p-value; * p<0.10; **p<0.05; ***p<0.01.
Figure 1: Demonstration Example – Network Structure