

Can Random Friends Seed More Buzz and Adoption? Leveraging the Friendship Paradox

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Abstract. A critical element of word of mouth (WOM) or buzz marketing is to identify seeds, often central actors with high degree in the social network. Seed identification typically requires data on the relevant network structure, which is often unavailable. We examine the impact of WOM seeding strategies motivated by the friendship paradox, which can obtain more central nodes *without knowing network structure*. Higher degree nodes may be less effective as seeds if these nodes communicate less with neighbors or are less persuasive when they communicate; therefore, whether friendship paradox–motivated seeding strategies increase or reduce WOM and adoption remains an empirical question. We develop and estimate a model of WOM and adoption using data on microfinance adoption across village social networks in India. Counterfactuals show that the proposed strategies with limited seeds are about 13%–30% more effective in increasing adoption relative to random seeding. These strategies are also on average 5%–11% more effective than the firm’s leader seeding strategy. We also find these strategies are relatively more effective when we have fewer seeds.

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1. Introduction

Firm-initiated and consumer-driven word of mouth (WOM) marketing (often referred to as buzz marketing) has received a lot of attention and has proven effective in increasing adoption across a wide range of products and services. WOM has been examined both theoretically and empirically using a wide range of modeling approaches to understand both the motivations to engage in it and its various impacts (Godes and Mayzlin 2009, Iyengar et al. 2011, Berger and Iyengar 2013, Cai et al. 2015, Campbell et al. 2017).

An important question in WOM marketing is how to choose appropriate seeds. There are a few broad approaches considered in the literature. The first approach uses network data on connections to identify central individuals (e.g., degree or eigenvector centrality) to obtain the most WOM (Tucker 2008, Goldenberg et al. 2009, Libai et al. 2013). Recently, researchers have tried to combine multiple networks among the same individuals to identify seeds with specific relationship types that can lead to higher adoption (Chen et al. 2017). The second approach uses individual characteristics to identify how opinion leaders can be used to seed networks (Iyengar et al. 2011). But opinion leaders are often

highly context specific and may not span multiple categories; for example, an opinion leader in fashion might not be an opinion leader for consumer electronics or healthcare (King and Summers 1970). Another approach is to identify seeds based on local network properties and community characteristics to achieve higher diffusion (Yoganarasimhan 2012). But there might be trade-offs in that network structures that enable high diversity of content might not be efficient at accelerating the flow of information (Aral and Van Alstyne 2011).¹

Broadly, the emphasis in the recent literature has been to improve seed identification using more comprehensive network data. However, even with easier access to online social networks, data on the *relevant network for a particular purpose* is often unavailable. For example, even if one had access to the Facebook (or similar) social networks of everyone including physicians, the *relevant* physician-to-physician network data for seeding a new drug may be unavailable. Even within a specific context, there are many challenges in gathering accurate network data, including the time and effort required to obtain this data (Stark 2018). Moreover, the dynamically evolving nature of connections and relationships requires frequent updating of such data. Social media data, which

are relatively easier to access, also have the challenge that activity there maybe more of a substitute than a complement to offline or other social interactions and may not be effective in high-involvement applications (Borgatti et al. 2009). Given all the above, a theoretically grounded seeding approach that can be used in the absence of complete data on network structure can be valuable.

The friendship paradox suggests such just such an approach to obtain higher degree seeds, by choosing among random friends of an initially chosen set of individuals. We empirically investigate whether the friendship paradox can indeed be leveraged to choose seeds and generate higher WOM and adoption *when the relevant network structure information is unavailable*. Specifically, we address the following research questions:

1. Can friendship paradox based seeding strategies improve WOM and adoption relative to random seeding? Can it improve on an opinion leader-based strategy chosen by the firm?
2. Can hybrid approaches leveraging the friendship paradox along with leadership characteristics lead to higher adoption?
3. How does the extent of initial seeding (proportion of the network seeded) impact *absolute and relative performance* of the strategies?

1.1. Friendship Paradox–Motivated Network Seeding Strategies

The friendship paradox statement “On average, your friends have more friends than you do” is based on a mathematical result that holds independent of network structure, because popular people are always over-represented in the set of friends (Feld 1991, Kumar et al. 2024). This strategy has been suggested for immunization of networks and sensors on networks (Cohen et al. 2003, Christakis and Fowler 2010). The basic intuition is simple: suppose we choose an initial node at random (so each node has an equal probability of being selected) and then choose one friend of that node at random. This is termed the ego-based or Local Friend strategy. The chosen friend of the initial node is likely to be more highly connected than average, because, by selection, a highly connected node will be in the friend set of more people and therefore more likely to be nominated as a friend. For intuition, consider two extreme examples: (i) *a simple hub-spoke network* with a central node and several peripheral nodes, all connected *only* to the central node. Each node has equal probability of being initially selected, so we are very likely to get a peripheral node. When asked to nominate a friend, each of the peripheral nodes can only suggest the central node, who is their only friend; (ii) *an isolated node* without any connections. That node would never be chosen by anyone on the network as a friend.

The friendship paradox thus suggests potential strategies for sampling higher degree individuals (those with more friends) in any network, without knowing network structure. For example, one could select a random friend each for a set of randomly chosen individuals. This strategy only requires access to a set of randomly sampled individuals, and the ability to obtain a random friend from them. Further, one can easily obtain the relevant network, by choosing the list of relevant friends from which to sample for the particular seeding problem at hand; for example, for physician influence networks, we might ask a doctor to suggest the contact of a random physician friend with whom they discuss professional matters.

The theoretical results on the friendship paradox guarantee that individuals with a higher-than-average degree are obtained *in expectation* no matter what the underlying network, allowing for potentially better seeds (Kumar et al. 2024). However, even though the sampled individuals have higher expected degree, their use as seeds cannot guarantee greater WOM or product adoption, because the extent to which higher degree individuals communicate with friends in their network about the product is an empirical question. For instance, Kim et al. (2015) found that selecting the highest degree nodes did not always yield greater adoption than with random seeding.

1.2. Challenges in Evaluating Network Seeding Strategies

A seemingly straightforward approach to empirically evaluate the effectiveness of alternative seeding challenges is to conduct a field experiment where different seeding strategies are assigned at random to different networks. However, it is a challenge to obtain credible, robust answers on the effectiveness of various seeding strategies using standard experimental approaches because effective matching of treatment and control groups at the level of network structure is not typically feasible through randomization.² Network structure plays a crucial role in diffusion processes, and even small changes in structure can make contagion cascades possible (Centola 2010, Katona et al. 2011). Therefore, merely comparing adoption differences across seeding strategies, without appropriate controls for how network structure impacts communication and adoption within each network, would not be credible or robust.

Kim et al. (2015) conducted a field experiment by randomizing seeding treatments for two health-related interventions across 32 Honduran villages and compared the average adoption performance of random seeding and friend of random individual seeding. They found mixed results about the effectiveness of friendship paradox-based seeding in two health-based interventions—adoption of multivitamins and chlorine-based water purification. Beyond

the challenges in assessing differences in treatment and control groups (discussed earlier), there are important differences in empirical contexts. First, target seeds in Kim et al. (2015) received an intervention (a product along with education), whereas in our case, the seeds only decide whether to adopt the product. Second, seeds received tickets to distribute to their friends and the outcome measure was ticket redemption. Because of the focus on ticket redemption, WOM communication beyond neighbors of nonticketed households and the role of nonadopters in information diffusion is ignored. But these aspects of communication that we model and account for are typically important in new product adoption.

Relatedly, the issue of better control and precision to detect differences in effectiveness of stochastic seeding strategies using field experimental data treated at the network level has been considered by Chin et al. (2022) using the potential outcomes framework (Rubin 2005). This is a useful approach, but there remain important practical challenges. First, the approach only works for stochastic seeding, while our approach works for both deterministic and stochastic seeding. In fact, for the data we use from Banerjee et al. (2013), the approach would not be applicable, because leaders are chosen deterministically as seeds in all villages. Further, it is unclear if the technique can be adapted to answer the richer set of questions around leader and hybrid seeding strategies. Second, because of the nature of the algorithm, the improvements in precision occur only with relatively small seed sets (<5), which is unrealistic for many marketing settings except with very small network sizes. Substantively, unlike our results, they detect no difference between random friend and random strategies. This difference could be because the networks they consider have relatively small degree range—a factor that is known to make random friend strategies less effective (Kumar et al. 2024).³

1.3. Our Approach

Our approach involves estimating a structural model of diffusion of WOM and product adoption over networks, leveraging variation arising from seeding strategies across networks and the temporal trajectory. The modeling follows a flexible parametric approach and allows us to incorporate different elements of the diffusion process. The method combined with multiple networks also allows us to overcome practical challenges in randomization when conducting network-based field experiments involving seeding. This aspect allows us to assess robustness of the results to differences in networks and features of the data generation and WOM communication process. Specifically, the model allows for a flexible relationship between degree and WOM—a critical ingredient to evaluating the benefits of increasing degree through the friendship paradox. Further, unlike typical

diffusion models, which *assume* that all WOM arises from adopters, the model allows WOM from both adopters and nonadopters. We also provide a novel nonparametric identification argument that leverages the feature that leaders were chosen as seeds, along with the shape of the adoption trajectory to identify differential effects for leaders versus nonleaders.

Estimating such a WOM diffusion model is challenging in practice because the necessary multinet network data are typically unavailable. Most diffusion models are estimated based on one product's time series of adoption through one market (or social network). Further, the original seeding is typically unobserved, and even if observed it is often not possible to identify the effect of different seeding without multiple diffusion paths across similar networks. Finally, the impact of WOM might be misidentified in the presence of advertising (Van den Bulte and Lilien 2001), attributing to WOM what was actually achieved by advertising.

We address these challenges using data on one product (microfinance) adoption across several independent and relatively isolated village social networks. The firm's seeding across the different villages leads to exogenous variation in network position and characteristics of seeds, which aids in identifying the impact of seeding. Also, there was no advertising or promotion activity by the firm that would confound WOM effects, which is known to bias estimates of impact (Van den Bulte and Lilien 2001). Based on the estimates, we simulate counterfactuals on WOM and product adoption across these villages as a function of alternative seeding strategies. Finally, we compare the effectiveness of the friendship paradox-based ego-based or Local Friend strategy (Kumar et al. 2024) and hybrid seeding strategies relative to Random and Opinion leader seeding strategies. We use the term "Local Friend" for simplicity to refer to the ego-based strategy.

1.4. Findings

We find that higher degree nodes are less likely to communicate WOM among adopters and nonadopters. However, despite this negative correlation between degree and WOM, we estimate that the friendship paradox (ego-based) local friend strategy provides a substantial improvement over the random strategy. It also improves effectiveness over a leader seeding strategy used by the firm. When the local friend strategy is used in conjunction with the leader strategy, the hybrid provides a further marginal improvement. We find that informationally more demanding strategies like top degree and top diffusion perform better than other strategies, obtaining a much higher improvement, but at the cost of requiring information on network structure. Finally, we find that when the proportion of seeds is lower, the relative effectiveness of the local friend strategy is greater.

1.5. Contributions

Our paper makes a number of contributions to the literature on seeding strategies and diffusion. The present paper is among the first to empirically demonstrate the potential value of seeding a random friend over random nodes for WOM communication in a robust manner. We do so with a micromodel of household decision to adopt and communicate that is flexible enough to permit higher degree nodes to communicate less per capita with friends and distinguish WOM from leaders and nonleaders. Second, we compare leader seeding chosen by the firm to the proposed Local friend seeding. To estimate differential effects of leaders from nonleaders, we develop a novel nonparametric identification strategy that uses the temporal trajectory of adoption diffusion. Finally, we evaluate counterfactual hybrid strategies using both friendship paradox ideas and leadership characteristics and detail which types of hybrid strategies obtain greater adoption. Overall, we demonstrate that our results around the superiority of informationally light random friend seeding is robust to various specification checks.

2. Data

We use panel data collected by Banerjee et al. (2013) on the diffusion and adoption of microfinance across households belonging to 43 rural villages in southern India in combination with rich network data on the social connections among the households within each village.

The microfinance firm identified opinion leaders based on leader and social criteria in each village prior to entry and seeded information about the microfinance product among these individuals first. Table 1 provides the summary statistics of the village household networks. Households have an average of more than four individuals. Averaged across villages, 61% of households have private electricity, but only 28% of households

have private latrines. There is relatively lower variation in the number of people relative to rooms or beds across the households.

We use the union of all undirected network relationships detailed in the data.⁴ There is considerable variation in the extent of relationships among households. Each village contains on average 212 households. Across villages, the mean degree (connections) of households is around 9, and the mean of the standard deviation of degree for households at the village level is large at around 7.1, with the minimum and maximum reflecting wide variation. The mean degree of opinion leaders is higher than the average and close to the maximum of average degree across villages (34% more). We illustrate the network for Village 1 in Figure 1 as an example.

The primary performance comparison in our study is the adoption of microfinance by households across the villages. Table 2 summarizes adoption across household types. We find that 19.4% of households adopt microfinance, with significant variation across the villages. Opinion leaders are more likely to adopt than followers, perhaps a feature of the information propagation chosen by the firm, which targeted these leaders in each village. Adoption is correlated with household characteristics; electrified households are less likely to adopt compared with nonelectrified, and households with a latrine are less likely to adopt than those without. Broadly, these statistics reflect the reality that microfinance is used by poorer households in emerging markets.

3. Model and Estimation

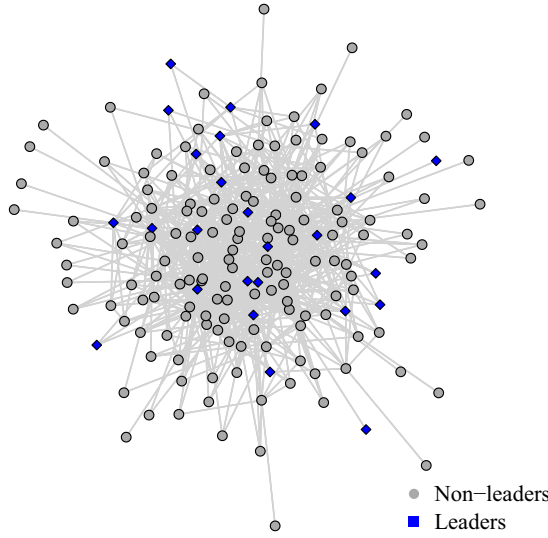
We use a model of WOM and product adoption across a social network. Using network terminology, households are *nodes* and connections between them are *edges* and friends are network neighbors. Households need to be informed about the product in order to adopt. Households who are informed communicate with their neighbors

Table 1. Village Network Statistics

Statistic	Mean	Standard deviation	Minimum	Maximum
Household characteristics				
Number of Households in Village	212.23	53.54	107.00	341.00
People in Household	4.77	0.37	4.20	5.69
Rooms in Household	2.31	0.41	0.75	2.94
Beds in Household	0.88	0.45	0.29	2.27
Proportion of Households with Electricity	0.61	0.16	0.11	0.89
Proportion of Households with Latrines	0.28	0.15	0.02	0.90
Proportion of Households with Leaders	0.13	0.03	0.07	0.21
Degree				
Mean	9.66	1.64	6.82	13.59
Standard deviation	7.09	1.32	5.18	11.02
Minimum	1.00	0.00	1.00	1.00
Maximum	39.72	13.01	23.00	90.00
Mean of leaders	12.93	2.59	8.88	18.82

Note. Unit of analysis is a village network ($N = 43$).

Figure 1. (Color online) Social Network of Households in Village 1



probabilistically, even if they have not adopted. We build on the model of Banerjee et al. (2013), with key adaptations required to study our research question related to the friendship paradox. First, we allow the WOM probability from a node to differ by degree, reflecting the idea that WOM propensity may depend on this factor. Second, we allow the WOM probability from a node to differ for those identified as leaders by the firm. Banerjee et al. (2013) allow the probability of WOM to depend on adoption status but not on the number of connections (degree) or leader status. Our extensions are specifically motivated by the strategies examined here. Recall that our approach based on the friendship paradox obtains higher degree nodes than average. Thus, we chose a conservative approach, allowing for the idea that whereas high degree nodes may be better due to their degree, they *might* also be less likely to communicate with their friends or network neighbors. If we did not account for that, then we could be biasing the results *in favor of the friendship paradox strategy*. Similarly, accounting for differences in WOM among firm-designated “leaders” is critical to assess the effectiveness of leader strategies.

Table 2. Adoption Across Household Types (%)

Statistic	Mean	Standard deviation	Minimum	Maximum
All Households	19.38	8.16	7.66	45.08
Leader Households	24.71	12.64	3.57	53.85
Follower Households	18.68	8.19	7.30	43.71
Nonelectrified Households	23.68	10.48	6.94	55.46
Electrified Households	15.87	7.52	4.76	34.43
Nonlatrine Households	21.74	9.87	7.03	51.25
Latrine Households	14.68	9.30	0.00	36.36

Note. Unit of analysis is a village network ($N = 43$).

3.1. Baseline Model

3.1.1. WOM Communication. We provide an overview of the WOM model that occurs separately over time in each network. Further details are provided in Section EC.3 of the Online Appendix.

We model households as belonging to uninformed (U), informed (I), adopter (A), and nonadopter (NA). Initially, all households are uninformed. The initial seeds become informed (I) due to the firm’s communication. In each period, all informed nodes communicate probabilistically with each of their neighbors, and the probability of such communication is $p^s(D)$, defined below. Such communication occurs at all time periods, motivated by in-person interactions that households have with their friends (network connections). We model these events as being independent draws across the set of network neighbors of a household. Households become fully informed following a WOM communication received from any neighbor. Once a household becomes newly informed (transition from U to I state), they make a decision on adoption, and they do not revisit the adoption choice in subsequent periods.

WOM in the model occurs in the network when a household receives information (only) from its *informed* neighbors. We allow WOM probability $p^s(D)$ to depend on adoption status s and degree D .

$$p^s(D) = q_{min}^s + (q_{max}^s - q_{min}^s) \left[\frac{D - D_{min}}{D_{max} - D_{min}} \right] \quad (1)$$

The WOM probability $p^s(D)$ refers to the probability that a node with degree D and adoptions status s (either adopter or nonadopter) communicates with each of its network neighbors. Thus, q_{min}^s represents the WOM probability for a node with minimum degree ($D = D_{min}$), whereas q_{max}^s represents the WOM probability for the highest degree node ($D = D_{max}$) and adoption status is denoted s . These quantities are based on the minimum and maximum degrees across all networks. Both parameters depend on the adoption status $s \in \{NA, A\}$ of the node, with NA indicating “not adopted” and A indicating “adopted.” The specification in Banerjee et al. (2013) is a special case of this model when $q_{min} = q_{max} = q$, such that WOM is independent of degree. Nodes continue communicating with neighbors in periods after they become informed.

3.1.2. Adoption. When a household becomes aware of the product at time t , the household’s decision of whether to adopt, $y \in \{0, 1\}$, is modeled as a standard logit choice with observed heterogeneity. The utility of household i from adoption and nonadoption is

$$\begin{aligned} u_i(y = 1) &= \beta_0 + \beta X_i + \epsilon_{i,1} \\ u_i(y = 0) &= \epsilon_{i,0}, \end{aligned} \quad (2)$$

where X_i represents the vector of leader characteristics

of household i , β the vector of coefficients, and $\epsilon_{i,s}$ are distributed as type I Extreme Value random variables.

After a node becomes *informed* either as an initial seed or through a neighbor, further WOM from others does not impact the likelihood of adoption. Thus, WOM is purely informational rather than persuasive in this baseline. Although the baseline model provides a useful benchmark, it leads to the question of whether there are more complex or sophisticated decision processes for communication and adoption, which we examine and model below.

3.2. Endorsement or Persuasion

In the endorsement or persuasion model, (termed “complex contagion” by Centola and Macy (2007)), likelihood of adoption varies based on whether WOM is received from more friends. We model endorsement as a factor that impacts word of mouth communication, incorporated into the WOM model. In Banerjee et al. (2013), the utility of adoption is

$$u_i(y = 1) = \beta_0 + \beta X_i + \lambda F_{it} + \epsilon_{i,1}, \quad (3)$$

where F_{it} is the fraction of neighbors who have informed i about microfinance, and λ is the endorsement parameter. The utility of nonadoption remains unchanged.

3.3. Leader Effects

Leaders selected as seeds by the firm may have unobserved individual characteristics (leadership) that lead to higher probability of WOM relative to nonleaders, over and above their higher degree. Further, firms may have provided specific information to their selected leader seeds, which may make their WOM more effective.⁵ To capture such differences, we extend the baseline model to allow for differential probability of WOM for leaders:

$$p_i^s(D) = q_{min}^s + (q_{max}^s - q_{min}^s) \left[\frac{D - D_{min}}{D_{max} - D_{min}} \right] + q_\ell \mathbf{1}[i \in Leaders]. \quad (4)$$

Thus, if leaders are especially effective in spreading WOM, we would find the parameter q_ℓ to be positive, whereas a negative value would indicate leaders are less effective than nonleaders.⁶

3.4. Nonlinear Effect of Degree

Finally, we allow WOM likelihood to be nonlinear in degree by allowing a quadratic effect, which can also

capture potential nonmonotonicity with respect to degree:

$$p^s(D) = q_{min}^s + (q_{max}^s - q_{min}^s) \left[\frac{D - D_{min}}{D_{max} - D_{min}} \right] + q_Q \left[\frac{D - D_{min}}{D_{max} - D_{min}} \right]^2, \quad (5)$$

where q_Q represents the parameter corresponding to the quadratic term.

We examine a number of models, combining these modeling elements, as summarized in Table 3. Overall, we have eight specifications. The first four models have no endorsement or persuasion effect (denoted by superscript $E = 0$). In $M_1^{E=0}$, the WOM probability does not depend on degree. This model is identical to the model in Banerjee et al. (2013). In $M_2^{E=0}$, the WOM probability depends on degree; $M_3^{E=0}$ incorporates a differential effect for leaders to the prior model specification, and $M_4^{E=0}$ allows for a nonlinear relationship between WOM probability and degree with a quadratic function. The next four models are identical to the first four, but with an endorsement effect (denoted by superscript $E = 1$).

3.5. Estimation

The model estimation proceeds in three steps similar to Banerjee et al. (2013), with specific differences. The estimation procedure is detailed in Section EC.3 of the Online Appendix. Note that we use optimization algorithms for estimation rather than grid search. Here we provide a high level description of the three steps.

3.5.1. Step 1: Adoption Process. We estimate the adoption process parameters β with a logistic regression using the adoption decisions of only the initially seeded individuals based on Equation (2).

3.5.2. Step 2: WOM Process. We estimate the WOM process parameters $(q_{min}^{NA}, q_{max}^{NA}, q_{min}^A, q_{max}^A)$, as well as endorsement (λ), leader effect (q_ℓ), and quadratic effect (q_Q) using the simulated method of moments (SMM). We use the same set of cross-sectional moments used in Banerjee et al. (2013), supplemented by time series moments, all listed in Table 4. Overall, the moments capture key aspects of diffusion within a network, both globally over the entire network and locally across

Table 3. Summary of WOM Model Components

Model element	Model							
	$M_1^{E=0}$	$M_2^{E=0}$	$M_3^{E=0}$	$M_4^{E=0}$	$M_1^{E=1}$	$M_2^{E=1}$	$M_3^{E=1}$	$M_4^{E=1}$
Endorsement	×	×	×	×	✓	✓	✓	✓
Degree-dependent WOM	×	✓	✓	✓	×	✓	✓	✓
Leader differential WOM	×	×	✓	✓	×	×	✓	✓
Nonlinear effect: WOM and degree	×	×	×	✓	×	×	×	✓

Table 4. List of Moments

No.	Description
1.	Proportion of seeds adopting
2.	Proportion of households with no adopting neighbors who have adopted
3.	Proportion of neighbors of adopting seeds who have adopted
4.	Proportion of neighbors of nonadopting seeds who have adopted
5.	Covariance between a household's adoption and average adoption of its first-degree neighbors
6.	Covariance between a household's adoption and average adoption of its second-degree neighbors
7,8,9	Cumulative adoption up to time $t = 1, 2, 3$ (time series moments)

connections. The first moment is global, matching overall adoption levels in the network. Moments 2–4 are local moments that fit household level adoption as a function of adoption characteristics of their neighbors and help identify communication probabilities for nonadopters and adopters respectively. Moments 5 and 6 are also local moments in that they capture covariance in adoption between a household and its first- and second-degree neighbors respectively.⁷ Next, we include time series moments that have not been used in Banerjee et al. (2013). Moments 7–9 characterize the temporal trajectory of adoption within villages, which helps us in the identification of the leader fixed effect, as detailed in Section EC.2 in the Online Appendix. We detail how each moment informs the estimation of each parameter, that is, the sensitivity of parameter estimates to each of the cross-sectional and time series moments based on the approach of Andrews et al. (2017) in Section EC.5.6 of the Online Appendix.

The objective function for the parameter vector θ is defined as in Banerjee et al. (2013):

$$S(\theta) = \left(\frac{1}{S} \sum_{s=1}^S [m^S(\theta) - m^D]' \right) W \left(\frac{1}{S} \sum_{s=1}^S [m^S(\theta) - m^D] \right), \quad (6)$$

where $m^S(\theta)$ represents the vector of model simulated moments, and m^D denotes the vector of data moments. W is the weighing matrix, which can either be estimated with a two-stage approach or be set to be the identity matrix to obtain consistent estimates. The estimator is then defined as

$$\hat{\theta} = \arg \min_{\theta} S(\theta). \quad (7)$$

3.5.3. Step 3: Standard Errors. We estimate the standard errors using a block-bootstrap resampling procedure of sampling with replacement, treating each network as a block.

4. Results

We use data from the villages where microfinance was introduced to estimate the proposed models. We first detail the results from the adoption model in Table 5. The number of beds in the household and the rooms per

person are negatively associated with adoption probability and access to a private latrine in the home and rooms per person has a negative impact. The estimates are consistent with the idea that microfinance is used by relatively poor households without access to traditional banking services.⁸

Table 6 reports the estimates for the eight WOM models.

We use the model specifications $M_2^{E=0}$ (without endorsement) and $M_2^{E=1}$ (with endorsement) as our primary specifications for discussion, although the results are provided for all models. We note that our primary results of interest continue to hold qualitatively across all the model specifications. For some models, it might be more relevant to use the temporal variation.⁹

We note that this communication is a one-on-one process. We first interpret the parameter estimates of the preferred model specifications M_2 . We begin with the case of no endorsement, $M_2^{E=0}$. First, the WOM probability for adopters is greater than that of non-adopters ($q_{min}^A > q_{min}^{NA}$ and $q_{max}^A > q_{max}^{NA}$). Next, we examine degree dependence. For low-degree households, the WOM probability is significant, whereas for high-degree households, it lacks significance ($q_{min}^{NA} > q_{max}^{NA}$). Thus, although low-degree non-adopter households are open to communicating with their neighbors without adopting the product, their more connected neighbors are not.

For adopters, the WOM magnitude for both low-degree and high-degree households is more comparable, with the same ordering. Despite this, high-degree households communicate more overall because they have more connections.

Table 5. Adoption: DV: Microfinance Adoption (1 = Yes, 0 = No)

Variable	Estimate	Standard error
Constant	−1.210***	(0.322)
Rooms	0.007	(0.085)
Beds	−0.283**	(0.143)
(No) Electricity	0.156	(0.123)
(No) Latrine	0.179**	(0.080)
Rooms per person	−1.023***	(0.392)
Beds per person	1.147*	(0.656)
Log likelihood	−603.093	

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6. Model Estimates

Parameter	Symbol	Model specification: Estimates (standard errors)							
		No endorsement				With endorsement			
		$M_1^{E=0}$	$M_2^{E=0}$	$M_3^{E=0}$	$M_4^{E=0}$	$M_1^{E=1}$	$M_2^{E=1}$	$M_3^{E=1}$	$M_4^{E=1}$
Nonadopter lowest degree	q_{min}^{NA}	0.186 (0.075)	0.177 (0.0845)	0.123 (0.0866)	0.157 (0.0865)	0.016 (0.111)	0.211 (0.124)	0.137 (0.0592)	0.136 (0.078)
Nonadopter highest degree	q_{max}^{NA}	0.186 (0.075)	0.030 (0.113)	0.116 (0.122)	0.078 (0.0958)	0.016 (0.111)	0.054 (0.109)	0.078 (0.0423)	0.084 (0.0639)
Adopter lowest degree	q_{min}^A	0.297 (0.0921)	0.382 (0.113)	0.345 (0.0876)	0.389 (0.0992)	0.351 (0.0703)	0.387 (0.0846)	0.375 (0.0728)	0.352 (0.0693)
Adopter highest degree	q_{max}^A	0.297 (0.0921)	0.305 (0.104)	0.383 (0.0787)	0.271 (0.0859)	0.351 (0.0703)	0.275 (0.0944)	0.315 (0.0831)	0.249 (0.0844)
Leader effect	q_ℓ	–	–	–0.091 (0.0907)	0.046 (0.0814)	–	–	0.054 (0.0554)	0.067 (0.0612)
Quadratic effect	q_Q	–	–	–	–0.010 (0.0407)	–	–	–	–0.108 (0.0396)
Endorsement	λ	–	–	–	–	0.417 (0.0281)	0.312 (0.0419)	0.134 (0.0206)	0.157 (0.048)

Note. In Models $M_1^{E=0}$ and $M_1^{E=1}$, bold out parameters are not estimated.

From $M_3^{E=0}$ and $M_4^{E=0}$, we find no differential effect of leaders; the parameter q_ℓ is small in magnitude and not statistically significant, implying that leaders do not communicate more than others. Similarly, for the quadratic effect, we do not find q_Q to be substantial.

Next is the set of models ($E = 1$) with an endorsement effect. We find the effect to be positive and significant across all models. The other parameters are qualitatively the same as for the models without endorsement. Specifically, in all cases, for both nonadopters and adopters, lower-degree households communicate more than higher-degree households. Again, we find the leader effect to be not significant across all these models, but the quadratic effect is marginally significant in this case.

In Section EC.5 of the Online Appendix, we consider a number of other additional models of the data generating process.¹⁰ In all cases, our baseline model indeed does fit best relative to other models, so we use that as the primary specification for the counterfactuals.

5. Counterfactuals

We use counterfactuals to evaluate various seeding strategies based on local friend, Leader, Hybrid, and Network Information categories described in Table 7. Within the Friend category, we examine the impact of the Local Friend strategy, which samples on neighbors of randomly chosen network nodes (households) to obtain seeds. In Leader, we examine both the “(Firm’s) Leader” strategy, using the original leaders that were designated for seeding by the microfinance firm, and “Like Leader,” which chooses as seeds leader-like nodes who have similar network positions as leaders. We use three dimensions to measure network position: degree, eigenvector, and power centrality (Bonacich 1987). This helps evaluate whether the impact of seeding is due to the network position or due to the differential impact by individual characteristics of leaders. Hybrid strategies combine the features of sampling on friends along with information on opinion leaders. We examine two

Table 7. Seeding Strategies and Implementation

Category	Strategy	Implementation procedure (for each of m seeds)
Friendship	Local friend (neighbor)	Select node at random from list. Obtain one randomly chosen friend of node as a seed.
Leader	(Firm’s) leader	Select node from list of leaders
	Like leader	Select leader node ℓ at random. Select the nonleader node most similar to ℓ in terms of network properties.
Hybrid	Friend of leader (weak hybrid)	Select a random leader from list of leaders. Obtain one randomly chosen friend of this leader as a seed.
	Leader friend of leader (strong hybrid)	Select a random leader from list of leaders. Obtain one randomly chosen friend who is also a leader to be seed.
Network information	Top degree	Select a seed node at random from the list of top (Top 15%) degree (most connected) nodes.
	Top diffusion	Select a seed node at random from the list of top (Top 15%) diffusion nodes (proposed by Banerjee et al. (2013), and defined in Table EC.4).

different hybrid strategies: choosing a random *Friend of Leader* household (weak hybrid) or choosing a random *Leader Friend of Leader* household (strong hybrid). The difference between them is whether the resulting seed obtain must be a leader (strong) or not (weak).

We also evaluate two network information benchmarks, Top Degree and Top Diffusion. Unlike the above strategies, these network strategies require complete knowledge on who is connected to whom (network structure) or the degree distribution, that is, the number of connections of each node. If highly connected nodes are likely to be better in accelerating adoption, the idea is to choose from the set of highly connected nodes in the Top Degree strategy. Top Diffusion is an approach proposed by Banerjee et al. (2013) to identify nodes with high centrality for the purpose of information diffusion. It requires the social network structure (adjacency matrix) but does not require knowledge of the parameters of the diffusion process. Seeds are randomly chosen from the set of top 15% of nodes for both top degree and top diffusion strategies. Further details about the strategies, including informational requirements, are provided in Section EC.4.2 of the Online Appendix.

We use the estimated parameters from $M_2^{E=1}$ for the counterfactual simulations below. In the Online Appendix, we provide a comparison of the counterfactual results of all the different model specifications summarized in Table 3. We set seeding level as a percentage of households in the village, so the number of households seeded varies across villages as a function of village populations. We examine the sensitivity of the results to different seeding levels (0.5%, 1%, 5%) in Section 5.1.

We evaluate seeding effectiveness in terms of proportion of informed households and adoption generated by the seeding strategies as the performance measure. We start with a higher level of seeding (5%) to be conservative, since the advantage of the proposed strategies is greater with fewer seeds. Table 8 reports the aggregate statistics on the proportion of households informed

about the microfinance service and the proportion adopting microfinance. The improvement for Local Friend over Random is about 13.1%, whereas the improvement over Random for Leader is about 9.1%. We also find that the Hybrid strategy Friend of Leader performs the best with a 15.7% improvement over Random, suggesting that the two broad approaches of leveraging network structure (using friendship paradox) and leadership or other demographic characteristics (using Leader indicator) can be combined to achieve higher performance. However, we note that using the Local Friend strategy alone without any information about the network structure or leader information can generate much of this performance benefit. However, there is a risk in applying a strict criterion requiring the friend to also be a leader, with performance worse than local friend. Overall, the Local Friend and Hybrid strategies do better than the Leader strategy without data on the full network structure, suggesting that they are viable approaches to seeding WOM with unknown networks.

As we might expect, the network information strategies, which require global knowledge of the network structure lead to much greater adoption than the above strategies. Interestingly, the top degree approach performs better than the diffusion centrality-based approach, although the difference is minimal. It's likely that for these relatively small village networks, the overlap in seed sets among the top degree and top diffusion strategies is quite high, hence the similarity. In larger networks, for example, Twitter, we might see larger differences between them. Overall, we observe that the Local Friend strategy is able to obtain about 88.7% (and the weak hybrid achieves about 91%) of the performance of the best informationally demanding network information strategy. This finding characterizes the tradeoff between the amount of information required and the effectiveness of the strategy in driving adoption. In cases where it is impractical to obtain the *relevant* network information, the Local Friend or hybrid strategies could be profitably used as an alternative.

Table 8. Comparison of Strategies (5% Seeding)

Strategy	Informed (%)		Adopted (%)		Δ Informed (%) over random	Δ Adopted (%) over random
	Mean	Standard deviation	Mean	Standard deviation		
<i>Random</i>	38.77	42.19	7.56	25.58	—	—
<i>Local Friend</i>	42.98	43.28	8.54	27.12	10.86	13.08
<i>(Firm's) Leader</i>	41.70	43.03	8.25	26.70	7.54	9.13
<i>Like Leader</i>	41.57	42.96	8.20	26.60	7.21	8.48
Hybrid strategies						
<i>Friend of Leader</i>	43.75	43.52	8.74	27.42	12.85	15.67
<i>Leader Friend of Leader</i>	40.85	42.73	8.08	26.39	5.37	6.91
Network Information Strategies						
<i>Top Degree</i>	47.37	44.65	9.62	28.78	22.18	27.28
<i>Top Diffusion</i>	46.78	44.35	9.51	28.56	20.65	25.91

Note. Parameter estimates from model $M_2^{E=1}$ used for counterfactuals.

Table 9. Pairwise Comparison of Strategies (5% Seeding)

Strategy	Local	Leader	Like leader	Friend of leader	Leader friend of leader	Top degree	Top diffusion
Random	97.67	86.05	81.40	93.02	65.12	100.00	100.00
Local Friend		32.56	30.23	55.81	27.91	90.70	90.70
(Firm's) Leader			53.49	67.44	41.86	100.00	100.00
Like Leader				74.42	39.53	95.35	97.67
Friend of Leader					20.93	90.70	88.37
Leader Friend of Leader						97.67	97.67
Top Degree							37.21

Note. Number in cell indicates % of villages where column strategy achieves higher adoption than row strategy.

We report the pairwise comparison between strategies (Table 9). The Local Friend strategy is better than Random and leads to improved adoption in most of the villages. The Local Friend strategy also outperforms the Leader strategy across a majority of villages. The (Firm's) Leader strategy does worse than Random in about 14% of the villages. The weak hybrid Friend of Leader strategy is also better than random in about 93% of villages, but the strong hybrid Leader Friend of Leader actually performs worse than random in about 35% of the villages. This implies that *it matters how the hybrid strategy is implemented* and whether the condition of leadership is required for not just the initial node but also for the nominated friend. The results suggest reduced effectiveness of seeding when we require that the nominated friend also be a leader. Finally, and as expected, the Like Leader strategy is the most similar in performance to the Leader strategy.

5.1. How Does Extent of Seeding Impact Performance of Strategies?

The idea of WOM marketing is to choose a small number of seeds to help spread information about a product or service. We summarize in Table 10 how the performance of the seeding strategies varies with the proportion of nodes seeded, at 0.5%, 1%, and 5% of nodes seeded. For full results across all model specifications, see Section EC.4.3 in the Online Appendix.

We define the performance metric as leverage in terms of how well a proposed seeding strategy s performs relative to the Random strategy (whose leverage is one by

definition):

$$\text{Leverage}(s) = \frac{\# \text{ Households Adopting under Strategy } s}{\# \text{ Households Adopting under Random Strategy}}.$$

The following observations are noteworthy. First, the (Firm's) Leader strategy always outperforms the Random strategy, and the Local Friend strategy always outperforms the Leader. Thus, our main results hold across the range of seeding proportions examined for models with and without the endorsement effect. Second, the weak hybrid strategy dominates across most model specifications, whereas the strong hybrid broadly underperforms the Local Friend strategy. Third, Like Leader performs very similar to leader, indicating that performance of the leader strategy is not driven by the differential leader effects but rather the network position of leaders. Fourth, although the full information network-based strategies perform the best, we also find that the friendship paradox based strategies get up to half of the differential benefit without requiring network structure. Finally, leverage for all strategies decreases as the number of seeds increases, implying that their performance benefit is greater under more constrained circumstances, for example, when product samples are limited or expensive, or the seeding process requires intensive education or interaction.

6. Conclusion

We estimate a model of network-mediated WOM and product adoption and evaluated the effectiveness of alternative seeding strategies that leverage the friendship paradox. The proposed friendship paradox-based strategies, which are *informationally light* and require little knowledge of network structure, significantly improve WOM seeding and product adoption relative to not just random seeding but also relative to the firm's opinion leader seeding. Specifically, we find about a 13% average improvement with Local Friend seeding in both information spread and adoption compared with Random and about 5%–10% improvement over the Firm's Leader seeding, which is based on preselected occupations. Further, Local Friend seeding is typically better

Table 10. Leverage for Counterfactual Strategies

Strategy	No endorsement			With endorsement		
	0.5%	1%	5%	0.5%	1%	5%
Local Friend	1.14	1.064	1.008	1.315	1.307	1.131
(Firm's) Leader	1.094	1.045	1.005	1.186	1.178	1.091
Like Leader	1.08	1.038	1.002	1.188	1.126	1.085
Hybrid strategies						
Friend of Leader	1.145	1.071	1.012	1.355	1.303	1.157
Leader Friend of Leader	1.089	1.049	1.006	1.208	1.216	1.069
Network-based strategies						
Top Degree	1.241	1.108	1.012	1.713	1.621	1.273
Top Diffusion	1.242	1.1	1.01	1.675	1.618	1.259

than Random across multiple villages with varying network structures, whereas we find that the Leader strategy can be worse than Random in a significant number of village networks. We note that this result is based on expected performance and can vary based on network structure. Further, it should be expected that seeding strategies that use detailed network information can improve adoption relative to the Local Friend strategy, with the tradeoff that much more information is required.

We find that the relative advantage of both Local Friend and hybrid strategies relative to the Random strategy is inversely related to the proportion of nodes seeded. Thus, when we have fewer seeds, these strategies become even more advantageous in expectation. This result is practically useful in cases where the target population is large, and seeding is either financially costly or practically challenging due to time constraints or other operational limitations. The combination of the battery of robustness checks and the monotonic improvement in performance with greater network information provides consistent evidence of effectiveness. This adds to the literature by providing a mechanism and suggests follow up studies to detect robust gains from using friend seeding strategies with field experiments (Kim et al. 2015).

The data used here from multiple village networks and explicit knowledge of who were chosen as initial seeds have many advantages for studying the current seeding problem. Yet, common with much research on diffusion, a limitation is that communication is unobserved. Although we model communication as a latent process and show that our key counterfactual claims about friend based seeding are robust to many alternative models of communication, it would be useful to study this problem in setting where communication is directly observable. Further, even though the seeding process is observed, the firm always seeded on “leaders” based on a certain set of occupations.

Methodologically, we also provide a novel nonparametric identification argument for leader fixed effects that does not depend on specific functional forms to estimate the leader fixed effect with our current data where only leaders are used as seeds. The approach relies on the shape of the temporal trajectory, and its impact on the area under the trajectory.

We suggest some broader issues to explore in future research. Future work could evaluate the effect of leaders on adoption by randomizing seeds with leaders in some villages and nonleaders in others. It would also be useful to explore whether the benefits of seeding using the friendship paradox generalize to other contexts and different network structures. Microfinance has certain adoption and WOM communication features that may differ from other products. For example, the poor need microfinance and may be more persuaded about its

benefits than the rich; the poor may also have systematically different social network structures. Hence it would be valuable to assess whether the benefits of friend-based seeding remain robust for other products. Future research should also evaluate how network structural characteristics may systematically impact friend based seeding effectiveness. It would also be useful to consider the potential tradeoffs in cost and time in using our informationally light seeding strategies relative to investing in identifying (even limited) network information prior to seeding. In some cases, rather than use opinion leaders, it may be useful to seed individuals nominated by others as “gossipers” to assess their impact on diffusion and higher overall adoption (Banerjee et al. 2014, Stephen and Lehmann 2016). Finally, it would be useful to consider whether seeding approaches proposed here need to be adapted for highly asymmetric networks, where directional ties are significant (Ben Sliman and Kohli 2018).

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Endnotes

¹ There is a complementary literature in computer science inspired by Domingos and Richardson (2001) on approximate seeding algorithms for influence maximization with performance guarantees. These algorithms differ in the level of network information used. For example, Kempe et al. (2003) use full network information, Eckles et al. (2019) use partial network information, and Wilder et al. (2018) consider algorithms when network information is unknown.

² The number of possible networks structures grows exponentially in the number of nodes; for example, if $N = 100$ nodes, there are $2^{\frac{N(N-1)}{2}} \approx 10^{1490}$ possible undirected network structures and even more for directed networks.

³ The data used in Chin et al. (2022) are from the studies by Cai et al. (2015) and Paluck et al. (2016). Cai et al. (2015) include 185 village networks and state the following (with the exception of two villages): “The social network survey asked household heads to list five close friends, either within or outside the village, with whom they most frequently discuss rice production or financial issues.” Similarly, Paluck et al. (2016) asks participants to list a maximum of 10 friends.

⁴ We use the union since communication can happen during any type of interaction. Similarly, we convert directed ties (e.g., survey questions about borrowing items like rice or fuel oil) to undirected ties since communication about the product can be bidirectional during any such asymmetric interaction.

⁵ Our model does not distinguish between incidence of WOM and its effectiveness, but as long as both those effects do not change in the counterfactual, the strategy comparisons remain valid.

⁶ We note that, because all initial seeds are “leaders,” it aids the leader fixed effect identification as any impact of leader fixed effect will be stronger in the initial periods and can be therefore identified off the adoption trajectory. More details about the identification of

the Leader Fixed Effect is detailed in Section EC.2 of the Online Appendix.

⁷ We provide precise specification of the moments and the rationale for using them in Section EC.3 of the Online Appendix.

⁸ We report a variety of adoption models in Section EC.5.5 of the Online Appendix; the results presented here is for the best fitting (lowest AIC) model.

⁹ We estimate various other models to test different specifications of the data generating process. We mention a few here. First, we allowed a “broadcast process” to consider the effect of an initial village meeting by seeds to communicate to all households. Second, we allowed for a “leader certification” effect to test for an incremental effect of leader endorsement on adoption. Third, we allowed opinion leader seeds to be chosen by occupation, where leader effects are conferred on all members with that occupation. These specifications do not fit the data better than $M_2^{E=0}$. The counterfactual performance under all the models are provided in Section EC.4.3 of the Online Appendix.

¹⁰ We consider a benchmark where there are only broadcasts (Section EC.5.1 of the Online Appendix), but no communication through networks. In Section EC.5.2, we consider a model where there is an initial broadcast by seeds, to model an initial village meeting described in Banerjee et al. (2013). We also consider the case where leaders may be present outside the initial seed set (Section EC.5.3), and where leaders may have specific certification ability (Section EC.5.4). Specifically, we show in Figure EC.3 that there is reasonable probability that seeds chosen by any of our counterfactual strategies overlap with the seeds chosen by the firm.

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