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Algorithms for seeding social networks can enhance the adoption of a public health intervention in urban India

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Targeting structurally influential individuals within social networks can enhance adoption of health interventions within populations. We tested the effectiveness of two algorithms to improve social contagion that do not require knowledge of the whole network structure. We mapped the social interactions of 2,491 women in 50 residential buildings (chawls) in Mumbai, India. The buildings, which are social units, were randomized to (1) targeting 20% of the women at random, (2) targeting friends of such randomly chosen women, (3) targeting pairs of people composed of randomly chosen women and a friend, or (4) no targeting. Both targeting algorithms, friendship nomination and pair targeting, enhanced adoption of a public health intervention related to the use of iron-fortified salt for anemia. In particular, the targeting of pairs of friends, which is relatively easily implementable in field settings, enhanced adoption of novel practices through both social influence and social reinforcement.

social networks | network targeting | public health

Significance

A deep understanding of social networks can be used to create an artificial tipping point, changing population behavior by fostering behavioral cascades. Here, we experimentally test this proposition. We show that network-based targeting substantially increases population-level adoption of new behaviors. In part, this works by driving indirect treatment effects among the nontargeted members of the population (among people who were not initially part of the treatment group but who were affected by treatment of others in their population). The techniques we demonstrate can be easily implemented in global health (and elsewhere), as they do not require knowledge of the whole network. The novel pair-targeting technique explored here is particularly powerful and easy to implement.

Since knowledge, attitudes, and behavior can spread across interpersonal ties, and since the networks formed by such ties tend to amplify this spread, changes in one person's behavior can cascade out across a social network, producing behavioral changes in the larger population in which a person is embedded (1–3). Such cascades offer the prospect of increasing the effectiveness of public health campaigns, which could be especially beneficial in low-resource settings (4, 5). While there is a widespread interest in using social contagion to amplify the adoption of health interventions, there are currently few established network-targeting strategies available for straightforward implementation in practice. Here, we report a randomized controlled trial (RCT) of two easy-to-implement strategies designed to improve the likelihood of such behavioral cascades.

Deliberately fostering cascade effects requires the identification of a subset of potentially influential individuals among whom to launch an intervention. Simulation results suggest that targeting highly connected individuals in networks could enhance the diffusion of interventions (6–8), and other research suggests more complex methods for the selection of optimal targets (9–11). However, such methods typically require mapping whole social networks in order to identify the targets who might exercise special influence. Such sociocentric data may not be available, or certain algorithms may be simpler or more efficient than relying on whole network data.

Previous research has identified two types of seed-selection strategies that do not require knowledge of the underlying social network but that can still significantly accelerate adoption. An evaluation in India found that gossip nomination strategies (asking randomly selected people which community members are good sources of trustworthy gossip and then recruiting the gossipers for the public health intervention) can result in faster diffusion of information, driving up childhood vaccination rates (12). A study in Honduras showed that recruiting the friends of randomly selected residents can effectively accelerate adoption (13), based on the property that, on average, friends have more connections than respondents themselves (14). We refer to this approach as "friend targeting" (we use the term "targeting" as a shorthand for network seed selection more generally).

However, in many real-world situations involving public health interventions, it may be unethical or impractical to deny treatment to the original randomly-chosen informants while offering it instead to people they identify. For instance, one might not want to go into a village, ask people who their friends or gossipers are, and then proceed to offer something of value to those other people but not to the people who identified them. Here, we therefore present and evaluate the effectiveness of a seed-selection strategy, whereby both randomly chosen people and also their friends (who, in expectation, are actually more socially influential) are treated with a public health intervention. We refer to this seed-selection approach as pair targeting. The pair may reinforce each other's behavior and work in tandem (thus potentially raising their own adoption of an intervention) as

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Competing interest statement: S.G. reports being an employee of Tata. The authors declare that Tata had no influence on any part of the investigation. The authors declare that they have no other competing interests.

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well as enhance their social influence on others to whom they are connected who did not receive the intervention.

We used iron-deficiency anemia in India as our testbed. Iron-deficiency anemia can lead to cognitive impairment in childhood and in old age, physical disability and diminished work capacity in adults, and adverse outcomes of pregnancy for mothers and newborns (15–17). Prevention of anemia in childbearing women is key to preventing low birth weight and perinatal and maternal mortality (18–21). Iron-deficiency anemia among Indian women remains a key public health problem, with 53% of Indian women affected by the condition (22). Unfortunately, recent government attempts to promote nationwide use of iron and folic acid supplements have had limited reach. However, since its introduction to the market, iron-fortified salt has emerged as the major new way to help reduce the prevalence of iron-deficiency anemia in India and achieve the goals of the Anemia-Free India Initiative (Anemia Mukt Bharat), a collaboration between the Indian Ministry of Health and Family Services and UNICEF (23).

Results

Network-Based Seed-Selection Strategies. We examined the effectiveness of two different network-based seed-selection strategies (algorithms) for the delivery of health interventions, neither of which requires information about the underlying social network (although, for research purposes, we did ascertain the whole networks here without this having any effect on target selection). First, the friend-nomination targeting strategy consists of selecting a random seed (an ego), eliciting his or her relevant social connections (i.e., the people to which the ego reports being connected) using queries known as name generators, and then randomly selecting one of the ego's alters (i.e., the people to whom the ego is connected) to receive the intervention instead of the original ego. Second, the pair-targeting strategy is identical to the friend-nomination strategy, with the exception that we delivered the intervention both to the random seed and to one of the alters whom we selected randomly from the ego's nominations (therefore, the number of random seeds was half as large in the pair-targeting treatment, so the total number of people in the population who received the intervention could remain the same). Our approach for selecting alters was to select one alter at random from among all the nominated people who had not previously been selected as egos or alters by others in the community. We compared these network-based seed-selection strategies with a random targeting strategy where the intervention was delivered to the original random seeds only. Finally, all three strategies were compared with control populations, which received no public health intervention.

We used a two-stage randomization approach, which in the first stage randomized chawls (housing units) to the four conditions (three targeting methods and control) and in the second stage randomly selected 20% of the households within chawls according to the targeting strategy (in chawls assigned to the control group, no households were selected). To ensure randomization with sufficient balance of characteristics between the treated groups in the finite sample, we performed a rerandomization approach in both the first and second stages. In the first stage, this ensured that chawls assigned to the four strategies had, on average, similar chawl-level characteristics. In the second stage, it ensured that those households randomly selected as seeds and nonselected households had on average similar household-level characteristics (see *Materials and Methods* and *SI Appendix*).

Sample Characteristics. Our study sample consisted of 2,491 female heads of households living in 50 different chawls (which we call clusters). There were 49.8 households (±1.7) per chawl. The average age of the sample was 46 ± 12 (mean ± SD); more than half had high school education or higher (60%), spoke Marathi (72%), and reported Hindu as their religion (75%). *SI Appendix*, Table S1 breaks down these descriptive categories by assignment in order to illustrate balance across the treatments and control. On average, the network degree of randomly chosen seeds was 2.5 ± 1.8 (mean ± SD). From these 2,941 households, a total of 284 were chosen to target for the educational intervention in the 30 chawls receiving it.

Effectiveness of Network Targeting. Overall, network-targeting strategies resulted in higher adoption rates throughout the chawls (in the whole population, not just those targeted for the intervention), measured both by percentage of female heads of household in a cluster reporting purchase of iron-fortified salt and (as an alternative option) percentage of the cluster reported redeeming at least one coupon for iron-fortified salt that was distributed as part of the intervention (these were our two key outcomes) (Fig. 1).

Our unit of analysis was households (or, more specifically, their female heads). Coupon redemption reports showed that unadjusted adoption rates were 13.6% (SE = 1.5%) in the friend-targeted clusters, 11.2% (SE = 1.4%) in pair-targeted clusters, 9.1% (SE = 1.3%) in the randomly targeted clusters, and 0% in the control clusters receiving no intervention. This suggests the presence of social contagion. In fact, in the friend-targeted clusters, the 13.6% adoption can be broken down into 11.9% adoption by those targeted and 1.7% adoption by those not targeted (expressed as a percentage of participants residing in the friend-targeted clusters). In the pair-targeted clusters, the 11.2% rate of adoption can be broken down into 5.5% adoption by those targeted and 5.7% adoption by the nontargeted (again expressed as a percentage of participants residing in pair-targeted clusters, as illustrated by the shaded and nonshaded areas in Fig. 1). Using coupon redemption as a measure of adoption, we also observed that adoption among the nontargeted contributed relatively more to overall adoption in friend-targeted and pair-targeted clusters than

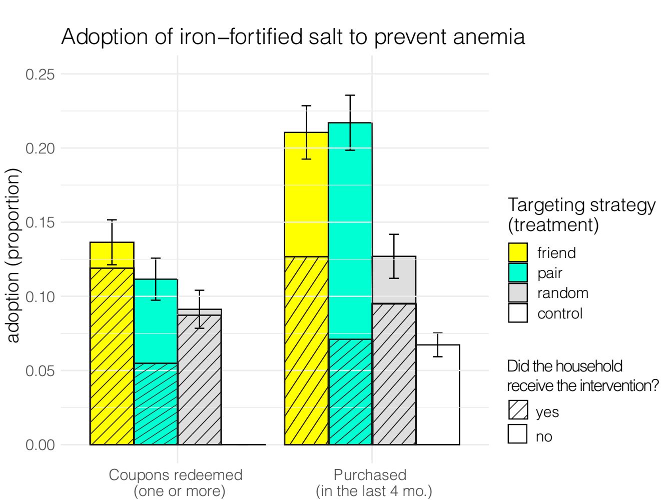

Fig. 1. Adoption of iron-fortified salt to prevent anemia, by targeting strategy. The bars represent the estimated proportion adopting the intervention, adjusted for socioeconomic factors (age, education, wealth quintile, language, and religion), mean network degree of a chawl, and chawl-level random effects, together with estimated SE. Shaded portion of the bar represents households that received the treatment and adopted the intervention, while the unshaded portion corresponds to households that did not receive the treatment but nevertheless did adopt the intervention.

it did in randomly targeted clusters, where almost all adoption was due to adoption by the targeted participants themselves (Fig. 1).

In the case of reported purchases, network-targeting strategies led to adoption levels nearly twice those in randomly targeted clusters. Purchase reports revealed unadjusted adoption rates of 21.1% (SE = 1.8%) under friend targeting, 21.7% (SE = 1.9%) under pair targeting, 12.7% (SE = 1.5%) under random targeting, and 6.7% (SE = 0.8) in the control. The friend-targeting rate of 21.1% adoption can be broken down into 12.7% by the targeted and 8.4% by the nontargeted (expressed as a percentage of households residing in friend-targeted clusters). The pair-targeting rate of 21.7% can be broken down into 7.1% by the targeted and 14.6% by the nontargeted.

The primary reason that both friend targeting and pair targeting outperformed random targeting is that the ratio of adoption by nontargeted to targeted individuals was markedly higher in these chawls subjected to these seed-selection strategies compared with random targeting (Fig. 1). More specifically, coupon redemption suggests that being in a chawl receiving friend targeting led to an average 4.5% (SE = 1.6%) higher probability of household adoption than residing in a chawl with random targeting ($P = 0.004$). As models (1) and (2) in Table 1 report, the effect was significant when adjusted for sociodemographics, chawl network structure, and cluster random effects (*SI Appendix* provides details). For reported iron-fortified salt purchases in particular, pair targeting was superior to random targeting. Specifically, our unadjusted estimate is that pair targeting led to 8.7% (SE = 4.0%) higher likelihood of adoption than random targeting ($P = 0.008$).

For neither of our two outcomes was there a statistically significant difference between the two network targeting strategies when compared directly against each other. In other words, no evidence suggests that the easier-to-implement pair-targeting strategy, presented and tested in an RCT here, was less effective than the friend-targeting strategy. It is therefore a dominant strategy, practically speaking.

Effectiveness of Network Targeting on the Nontargeted. While the effects in Table 1 report average effects of a targeting strategy on everyone in a cluster, we next estimated the effects of a strategy on those targeted by the intervention (20%) and those not targeted (80%), separately.

If a targeting strategy is to accelerate the spread of adoption of a given intervention, we would expect it to have a measurable positive effect not only on the targeted subjects, but also on those who did not receive an intervention. Both network targeting strategies had a significantly higher effect on adoption by nontargeted subjects than random targeting did (Fig. 2 and *SI Appendix*, Table S4).

In pair-targeted clusters, the adjusted average marginal effect of the intervention on nontargeted subjects reporting iron-fortified salt purchase was 13.6% (SE = 4.0%) higher than the effect on nontargeted subjects in randomly targeted clusters ($P = 0.001$). When adoption was measured by iron-fortified salt coupon redemption, the adoption was 7.5% (SE = 0.021) higher in the nontargeted in pair-targeted clusters compared with the nontargeted in the random-targeted clusters ($P < 0.001$). Chawls that received friend targeting had a 4.3% (SE = 1.7%) higher adoption among nontargeted people than chawls receiving random targeting ($P = 0.011$), as measured by coupon adoption.

Fig. 3 shows illustrative impacts of the different targeting methods in three chawls, documenting the greater spread to untreated individuals in chawls that received network targeting (Fig. 3 *B* and *C*). In each of the figures, nodes receiving targeting are colored in red. Original random seeds used for targeting algorithms are denoted with blue edges. Large circles are those who adopted the intervention.

Effectiveness of Network Targeting on the Targeted. In addition to identifying the spillover (social influence) benefits of network targeting among nontargeted individuals, we also found that network targeting may enhance the effect of the intervention on the targeted individuals themselves (Fig. 2 and *SI Appendix*, Table S5). In the chawls receiving friend targeting, the adjusted average treatment effect of the intervention on the targeted households reporting any coupon redemption was 16.6% (SE = 6.8%) higher than the same effect in randomly targeted clusters ($P = 0.016$). Of course, in addition to friend targeting identifying more central individuals by design, it may also be identifying other unobserved attributes (such as openness to innovation). This unobserved heterogeneity may explain the variation we saw not only in the degree of impact on others, but also in the likelihood of targeted individuals themselves adopting the intervention.

In pair-targeted chawls, the effect on targeted households was estimated to be lower than in randomly targeted chawls, although the estimate was not statistically significant. Based on our data, we cannot conclude that the effect on the targeted households was different in the pair-targeted versus the randomly targeted households.

Table 1. Average effects of network-targeting strategies on adoption of iron-fortified salt to prevent anemia

	Iron salt coupon redeemed		Iron salt purchased	
	(1)	(2)	(3)	(4)
Friend targeting	0.0450**	0.0456**	0.0728	0.0667
	(0.0158)	(0.0161)	(0.0411)	(0.0376)
Pair targeting	0.0216	0.0192	0.0867*	0.0815
	(0.0259)	(0.0264)	(0.0404)	(0.0424)
Pairwise contrast†				
Friend vs. pair	0.0250	0.0282	−0.158	−0.0139
	(0.0221)	(0.0226)	(0.0494)	(0.0484)
Adjusted for				
Sociodemographics‡		Yes		Yes
Network structure¶		Yes		Yes
No. of observations	1,510	1,510	1,510	1,510

Marginal effects reported for random effects probit; SEs in parentheses. *$P < 0.05$, **$P < 0.01$.
†Pairwise comparison of adjusted predictions.
‡Age, education, wealth quintile, language (Marathi, Hindi, Urdu, other), and religion (Hindu, Buddhist, Muslim, other).
¶Mean network degree.

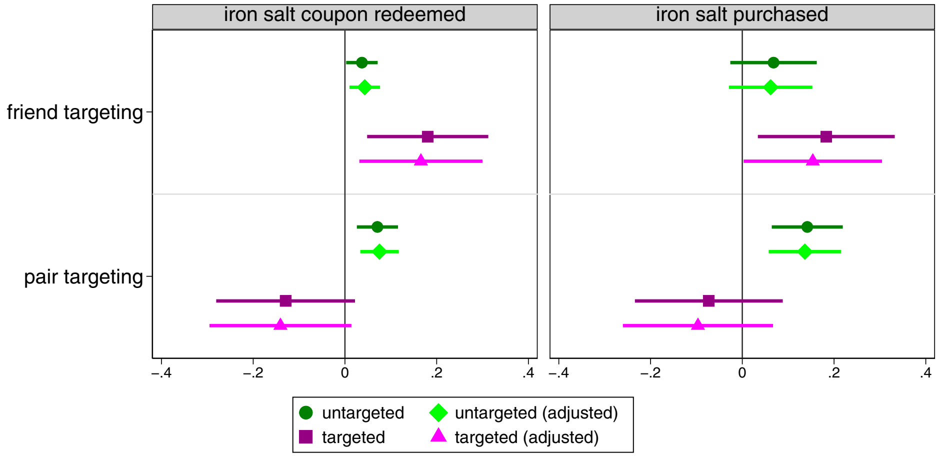

Fig. 2. Improvement over random targeting strategy by network-targeting strategy on nontargeted and targeted subjects. Random targeting is the reference. Marginal effects and CIs estimated from probit model of adoption (measured as iron salt coupons redeemed on the left, and as iron salt purchase reported on the right). The effect on the untargeted is estimated using a subsample of subjects who did not receive an intervention, while the effect on the targeted model includes only subjects who received the intervention. Adjusted results are from the model that controls for socioeconomic factors (age, education, wealth quintile, religion), mean network degree of a chawl, and chawl-level random effect. Note that the negative estimated effect is with respect to random targeting (not to control), indicating that (given its CI) we cannot tell a difference between pair targeting and random targeting in coupon redemption solely among people who were targeted.

Spillover Reinforcement Effects. If network-targeting strategies mainly work by spillover effects on the nontargeted, we may expect that the effect on the nontargeted would be proportional to the number of their connections receiving the intervention. Furthermore, the strength of the spillover effect on any one nontargeted ego may depend not only on how many of her alters are targeted, but also on whether the ego's targeted alters are themselves interconnected. Table 2 reports results showing that, in fact, the probability of adoption among the nontargeted increased the most when they were connected to a pair of interconnected targeted alters, followed by being connected to a pair of nonconnected targeted alters, followed by being connected to one targeted alter, all in comparison with the baseline case of not receiving the intervention and having no alters who received one either. Because the number of treated alters was purely exogenous only in the randomly targeted chawls, we controlled for individual degree as well as for the assignment to a targeting strategy in this analysis.

Among those not targeted, the likelihood of coupon redemption increased by 1.3% (SE = 0.55%) if they were connected to a single treated alter ($P = 0.022$), compared with no alters treated. This probability increased to 3.7% (SE = 1.9%) if they were connected to two treated alters who themselves were not connected ($P = 0.051$), and it increased even further to 6.8% (SE = 3.2%) for those connected to an interconnected pair of targets ($P = 0.033$).

Similarly, among all nontargeted people, the likelihood of reporting a purchase was 17% (SE = 6.9%) higher if connected to a targeted pair ($P = 0.015$), while the marginal effect of being connected to two unconnected targets or a single target was not statistically significant at the $P = 0.05$ level. Pairwise comparison of marginal effects did not identify a statistical

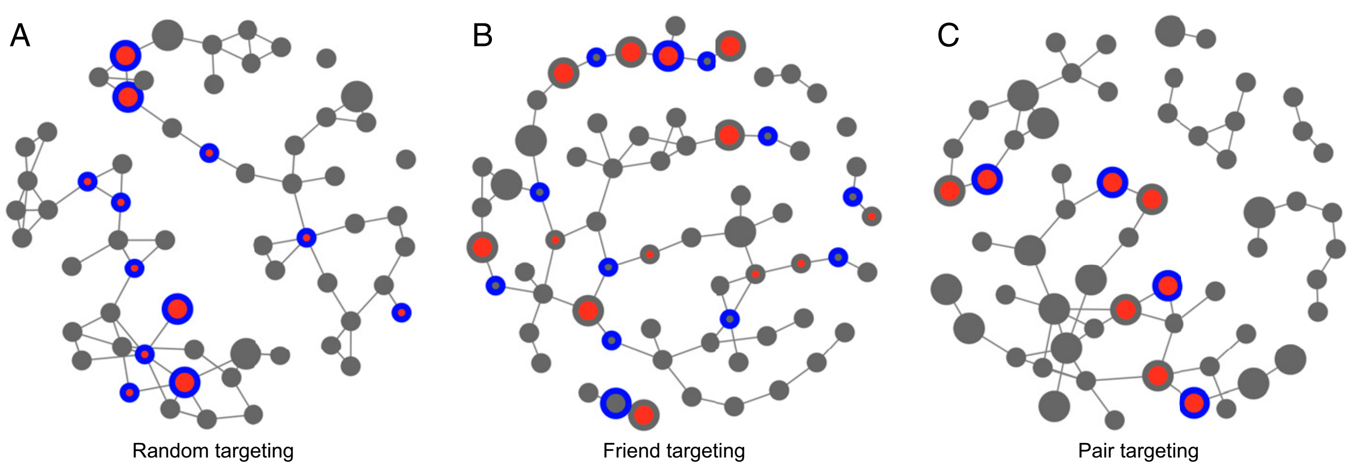

Fig. 3. Adoption of the intervention across social networks in three treatment arms of the RCT for three selected chawls. These are three illustrative social networks for chawls assigned to different targeting algorithms. Network links are defined if the ego nominated the alter in any of the five name-generator questions. Node size indicates adoption (response to treatment) using the metric of iron salt purchased. Red-colored nodes indicate participants targeted to receive the intervention. The blue perimeter indicates random seeds that form the basis for choosing targets. (*A*) In the case of random targeting, all the seeds get the treatment, and only those seeds, so all of them are also colored red; (*B*) in the case of friend targeting, none of the blue-perimeter nodes are colored red because the intervention is delivered only to a friend of the random seed; and (*C*) in the case of pair targeting, blue-perimeter seeds are also colored red and have a neighbor colored red because both the random seed and his or her friend receive the intervention. Across the three chawls, the number of total women in the networks, the number chosen for targeting, and the number of women (in the whole chawl) who adopt the intervention are as follows: 61, 12, and seven for the randomly-targeted chawl; 66, 13, and 12 for the friend-targeted chawl; and 59, eight, and 21 for the pair-targeted chawl.

Table 2. Spillover and reinforcement: The effects of targeted alters on the nontargeted

	Iron salt coupon redeemed		Iron salt purchased	
	(1)	(2)	(3)	(4)
Alters treated				
One	0.0129*	0.0129*	0.0342	0.0351
	(0.00531)	(0.00549)	(0.0182)	(0.0183)
Unconnected pair	0.0269**	0.0254**	0.0517	0.0520
	(0.00966)	(0.00915)	(0.0279)	(0.0277)
Connected pair	0.0379**	0.0371**	0.115**	0.116**
	(0.0121)	(0.0125)	(0.0367)	(0.0375)
Targeting strategy				
Friend targeting	0.166***	0.158***	0.0114	0.0122
	(0.0286)	(0.0351)	(0.0363)	(0.0364)
Pair targeting	0.182***	0.175***	0.0709**	0.0702*
	(0.0335)	(0.0396)	(0.0274)	(0.0281)
Random targeting	0.144***	0.134***	−0.0522	−0.0521
	(0.0239)	(0.0324)	(0.0374)	(0.0379)
Adjusted for				
Degree	Yes	Yes	Yes	Yes
Average degree of network	Yes	Yes	Yes	Yes
Sociodemographics†		Yes		Yes
No. of observations	2,195	2,195	2,195	2,195

Marginal effects reported for random effects probit models; SEs in parentheses. Egos with more than two treated alters are excluded. *$P < 0.05$, **$P < 0.01$, ***$P < 0.001$.
†Age, education, and wealth quintile.

difference between estimates for two connected versus two nonconnected treated alters. Table 2 also reports the results after controlling for respondents' age, education, and household wealth quintile, and all models include average degree of the chawl network and random effects.

These results are consistent with research that argues that there is a substantial and qualitative difference between a complete triad (because it forms a sociological group) and a couple of disconnected dyads, and it suggests that future experiments could include targeting of triads as a strategy (24).

Discussion

The exploitation of social contagion effects can meaningfully inform the design of public health policy and interventions (1). While different settings will require different approaches, and while policy makers should consider all available tools, one effective way to exploit contagion is to develop simple, cost-effective procedures to identify structurally influential individuals without having to map the entire networks of populations of interest. Our RCT tested two different network-targeting strategies that meet this requirement. Pair targeting, which is easier to implement than friendship targeting, was explored in detail here. Both strategies are designed to exploit structural features of social networks without the necessity of the potentially costly or otherwise infeasible process of mapping the underlying real-world face-to-face network of interactions.

We confirmed previous results obtained by our group on the effectiveness of the friendship nomination strategy in Honduras (13). The present study demonstrates the effectiveness of friendship-nomination targeting in an entirely different context, moreover one focused on new product adoption rather than promotion of a more general behavioral change with existing products. More importantly, a pair-targeting strategy was introduced and tested here in order to address cases where friend nomination may be infeasible despite its effectiveness, for instance, when it may be unethical not to offer the intervention to a random seed while delivering the same beneficial intervention to his or her friend. A further advantage to the pair strategy is that it can be implemented to select half as many seeds and thus evaluate fewer initial households. We found that pair targeting also enhanced adoption, when compared with random targeting, and that pair targeting was no less effective than friend targeting.

One may ask why the pair strategy does not do better than the friend strategy. In fact, one could argue that our results point to the possibility that pair targeting is better (pairwise comparison of adjusted marginal effects on coupon redemption: $P = 0.213$) (Fig. 1). However, further research into strategies at play in pair targeting is necessary to disentangle the role of reinforcement from the role of centrality and from other potential social-influence advantages of this seed-selection method. One area of future research could be to assess the potentially variable centrality of the recruited alters and determine if those who were more central were more effective. Also, while our analysis did not indicate that the number of alters was significantly correlated with adoption, additional experiments can design and test more advanced pair strategies that take advantage of selecting the most popular alters, for instance. Our study focused on a simple pair strategy, but a possible improvement could be to actually ask the ego who among his or her alters is more socially connected or influential. Regardless, our data do allow us to conclude that the pair strategy is just as good as the friend-targeting strategy while also being easier to implement.

Our analysis also revealed that, among those not provided the anemia intervention, their own adoption was higher if more of their social contacts were (exogenously) exposed to the intervention and also if (under some circumstances) their contacts happened to be interconnected. If a person's alters are informed of something and are connected to one another, this increases that person's likelihood of adopting the innovation. This finding may explain the higher adoption rate by unexposed individuals in the pair-targeting chawls, because more people in the pair-targeting arm than in the friendship-nomination or random arm were (by necessity and design) connected to pairs of people who were interconnected themselves.

Our results are consistent with a large body of medical and public health literature that emphasizes the role of experts, community leaders, and peer effects in promoting adoption of health interventions (1, 25–28). The effectiveness of network-targeting strategies is also consistent with the role social networks have been found to play in individual behaviors (29–31).

The simplicity of the network-targeting strategies we show to be effective means that they can be readily applied to a variety of health interventions through clear and intuitive protocols that fieldworkers can easily understand and implement. To facilitate this, we have publicly released software that can be used to identify a person's network contacts in the field (32). As such, network-targeting strategies may be able to address the growing need for increased effectiveness of public health strategies. Despite the fact that global health aid reached an unprecedented $25 billion per year in the last decade (33, 34), progress in achieving health-related UN Sustainable Development Goals has slowed (35). Prevention of anemia, which was the focus of the intervention in the present study, is just one important area where progress is insufficient to meet a set goal (set in 2012 to reduce by 50% anemia in women of reproductive age by 2025) (36).

Limitations. Our study was limited to one particular location, although the location and the intervention we used are typical of public health initiatives. Second, by design, we estimated average effects of a cluster-level intervention. On the other hand, this approach is helpful in obtaining an unbiased and consistent estimate for the effect of network targeting on overall adoption levels. We did explore the questions of spillover and treatment-effect heterogeneity in a limited way, by applying the straightforward strategy of estimating separately the cluster-level average effect on those receiving and not receiving the intervention. Third, although we measured adoption by two different instruments (knowledge about anemia and coupon redemption), they were based on self-reports. Finally, our study was of new product adoption rather than of the rates of anemia per se. While iron-fortified salt has been shown to be effective for prevention of anemia in various clinical trials, the effectiveness of iron-fortified salt interventions on raising hemoglobin levels in the real-world setting is surely dependent on a complex set of environmental, psychological, and physiological factors (37).

Conclusions. This RCT demonstrates that network-targeting strategies can enhance adoption of public health interventions at the population level, even among people not chosen to get the intervention in the first place, via spillover effects within social networks. Both pair targeting and friend targeting magnify the spillover effects of the intervention on nontargeted households, leading to adoption that exceeds the impact upon the targeted. These strategies hold promise to increase the reach and effectiveness of a range of public health interventions that currently lack the power to bring about substantial change in health-related behaviors and norms.

Deploying health interventions via network targeting, without increasing the number of people targeted or the expense incurred, may enhance the spread and adoption of those interventions and thereby improve population health at a lower cost.

Materials and Methods

Setting and Intervention. We focused on adoption of a new iron-fortified salt product for the prevention of anemia. We carried out our study in 50 chawls (identically designed residential units consisting of a four-story building) in a Mumbai neighborhood from October 2018 to March 2019. Iron supplementation is a well-recognized treatment for iron-deficiency anemia, and iron-fortified salt has been recognized by the World Health Organization and the Indian government as a promising tool to lower anemia prevalence (23, 38). Here, we exploited the circumstance of a new product introduction to a treatment-naive subject population (iron-fortified salt was not previously available for purchase in this area).

Our intervention consisted of two home visits, 60 d apart. Local beauticians were trained to provide anemia-related health education while offering optional free nail and facial treatments. In addition, one coupon for iron-fortified salt was provided for self-redemption, and three coupons were provided to be given by the egos to any of their alters. During the second visit, another coupon for self-redemption and three coupons for alters were again provided. The coupons were for a 50% discount on the price of the iron-fortified salt and were not reusable or time limited. The coupon for self-redemption included the name and details of the recipient, while the coupons to be given by the ego to his or her alters included information about both the ego recipient and the intended alter. In the final survey, the households were asked about their coupon redemption. (The coupons and the survey instrument are both included in the online *SI Appendix*.)

Study Design.

Chawl selection. Chawl selection included several phases. First, different neighborhoods organized into chawls across the city were assessed for feasibility and factors that would make them suitable for an experiment: one type of housing unit, all units identical, and roughly equal distribution of nonresidential points of interest that might affect our outcome (stores, main streets, health centers, temples, parks, etc.). In the neighborhood selected, each unit was identical and consisted of a four-story building with 20 units on each floor. The units were arranged in several lines and occupied a geographically contiguous, compact, discrete area. We identified 121 noncommercial units, and of those, after excluding hospitals and hostels, 115 units were identified as purely residential units. Preliminary interviews were conducted to assess the chawl units with respect to overall socioeconomic status, religious and ethnic composition, and distance to the main road, stores, places of worship, and hospitals. We excluded the units housing police and other government employees, as well as the units housing residents receiving government economic assistance. Fifty units were selected to ensure representation of a range of socioeconomic categories as defined in India.

Baseline data collection and network mapping. Prior to the delivery of the intervention, we collected baseline sociodemographic data and knowledge of anemia symptoms, prevention, and treatment. At the same time, we conducted a baseline sociocentric survey of the entire study population (survey provided in *SI Appendix*), using name generators to comprehensively map face-to-face social networks among female heads of households within each of the 50 chawls.

We used five name generators to map our networks, and anyone a participant listed as an answer to these questions qualified as a friend for the purposes of friend and pair seed-selection strategies:

1. Apart from people who live with you, who in this building do you visit or entertain at home?
2. In this building, who do you consider to be your closest friends?
3. In this building, aside from your doctor, who do you talk to about health issues, including when someone in your household is sick?
4. Aside from members in your household, with whom do you go shopping for groceries from the same building?
5. Do you have any relatives (mother, father, siblings, etc.) living in the building?

It is worth noting again that the collection of sociocentric networks would not be required to implement the network-based targeting strategies that we evaluated here.

Chawls were then randomly assigned to one of four groups: (1) 10 chawls to the random targeting treatment, (2) 10 to the friend-targeting treatment, (3) 10 to the pair-targeting treatment, and (4) 20 to control, receiving no intervention. In the friend and pair treatments, a "friend" refers to a randomly selected alter from the list of alters identified through the five name-generator questions above. Twenty percent of the households were targeted in each of the three targeting conditions. (A complete diagram of the study profile is provided in the online *SI Appendix*.) The inclusion criteria included being a female head of household residing in a study-designated chawl and provision of informed consent. There were no exclusion criteria. Because all female heads of household were age 18 y or older, the study did not include minors. The Yale University Internal Review Board designated this study exempt. Internal ethics review was also completed by Tata Chemicals, which funded payments to the surveyors, printed educational materials, provided coupons for its iron-fortified salt, and collected data for analysis.

At the end of the study (130 to 166 d later), we conducted a final survey of the entire chawl population, whether they received the intervention or not, collecting information on salt purchased, coupons redeemed, and the same knowledge questions asked at baseline. (Full baseline and final surveys are provided in the online *SI Appendix*.)

Analysis. Our unit of analysis was the household. We first reported raw proportions for adoption across the four different experimental conditions, and we then conducted regression analysis that also adjusted for other covariates.

Mixed generalized linear models were used to estimate the average treatment effect of being in a cluster targeted by one of the three network-targeting strategies (random, friend, and pair) (categorical treatment indicator), using a probit link function for the estimation of the likelihood of purchasing iron-fortified salt (outcome measure 1) or redeeming a coupon (outcome measure 2). Random effects were used to model unobserved heterogeneity between chawls; estimates were adjusted for any residual differences in sociodemographic characteristics despite randomization (age, education, wealth or socioeconomic status, religion, and language) as well as in chawl network structures (mean network degree), and estimated errors were clustered on chawls (39). Marginal effect estimates were compared pairwise to test for relative effectiveness between the two network-targeting strategies. We additionally estimated the effect of our targeting strategies on treated and untreated subjects by running separate analyses restricted to treated and untreated subjects, respectively.

Finally, we assessed whether having two alters targeted by chance, compared with having just one alter targeted by chance, was associated with higher likelihood of adoption by an ego, after controlling for the treatment condition. In this analysis, our explanatory variable of interest was whether, for any ego, as determined exogenously, (1) one of her alters received the treatment, (2) two of her alters received the treatment but were not connected to each other, (3) two of her alters received the treatment and were connected to each other, or (4) none of her alters received the treatment. We had to exclude those with three alters treated given that their number was too low to estimate the coefficient associated with it.

The degree variable was defined as a link of any kind in a simplified undirected graph mapped by the five name-generator questions. We use the term centrality to mean degree centrality in the underlying graph.

The analysis plan was preregistered with the Open Science Foundation (DOI: 10.17605/OSF.IO/9G7U5).

Data Availability. Anonymized (survey and experimental) data have been deposited in Figshare (https://doi.org/10.6084/m9.figshare.c.5907035) (40).

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