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Quitting in Droves: Collective Dynamics of Smoking Behavior in a Large Social Network

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Abstract

Background—The prevalence of smoking has decreased substantially in the U.S. over the past 30 years. We examined the extent of person-to-person spread of smoking behavior and the extent to which groups of widely connected people quit together.

Methods—We studied a densely interconnected social network of 12,067 people assessed repeatedly from 1971 to 2003 as part of the Framingham Heart Study using network analytic methods and longitudinal statistical models.

Results—Discernible clusters of smokers and non-smokers were present in the network, and the clusters extended to three degrees of separation. In spite of the decrease in smoking in the overall population, the size of the clusters of smokers remained the same across time, suggesting that whole groups of people were quitting in concert. Smokers were also progressively found in the periphery of the social network. A spouse quitting decreased a person's chances of smoking by 67% (95% CI: 59%-73%). A sibling quitting decreased the chances by 25% (95% CI: 14%-35%). A friend quitting decreased the chances by 36% (95% CI: 12%-55%). Among those working in small firms, a co-worker quitting decreased the chances by 34% (95% CI: 5%-56%). Friends with more education influenced one another more than those with less education. Residential neighbors did not exhibit these effects.

Conclusions—Network phenomena appear relevant to smoking cessation. Smoking behavior spreads across close and distant social ties; groups of inter-connected people quit in concert; and smokers are increasingly marginalized socially. These findings have implications for clinical and public health interventions to reduce and prevent smoking.

Roughly 44.5 million adults were smokers in the U.S. in 2004,[i] and smoking remains the leading preventable cause of death,[ii] accounting for 440,000 deaths annually.[iii] Nevertheless, the prevalence of smoking has declined from 45% to 21% over the past four decades.[iv]

Past work has documented the impact of dyadic social ties on the initiation and cessation of smoking, primarily in youthful populations,[v,vi] but the extent to which smoking depends on people's broader embededdness in a social network and the extent to which smoking behavior transcends direct dyadic ties is not known. Since diverse phenomena can spread within networks,[vii,viii,ix,x,xi] we explored whether smoking cessation also does.

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Using a network of 12,067 people in whom smoking and social network ties were repeatedly assessed over 32 years, we examined: (1) the existence of clusters of smokers and non-smokers within the network; (2) the association between an individual's smoking behavior and the smoking behavior in their social contacts; (3) the dependence of this association on the type of social ties (i.e., siblings, spouses, friends, co-workers, neighbors); (4) the influence of education and smoking intensity on the spread of smoking; (5) the extent to which smoking cessation occurs in large sub-networks of people at once; and (6) the extent to which smokers move to the periphery of the social network across time.

METHODS

Source Data

The Framingham Heart Study (FHS) was initiated in 1948 when 5,209 people were impaneled into the "Original Cohort."[xii] In 1971, the "Offspring Cohort," composed of 5,124 children of the Original Cohort, and their spouses, was impaneled.[xiii] In 1994, a voluntary, minority over-sample known as the "OMNI Cohort" of 508 people was initiated, and in 2002, the "Third Generation Cohort" of 4,095 children of the Offspring Cohort was started. We analyzed data that originated in physical examinations and written questionnaires obtained during three-year time windows centered in 1973, 1981, 1985, 1989, 1992, 1997, and 1999 (see supplement). Validated measures of cigarette consumption were collected at each point.[xiv,xv]

Network Ascertainment

We used the Offspring Cohort as the source of 5,124 subjects to study (known as "egos" in network science). Any persons to whom these subjects were linked – in any of the FHS cohorts – can, however, serve as social contacts (known as "alters"). There were 12,067 subjects and contacts who were connected at some point during the study period (1971-2003) (see supplement), and connections were identified longitudinally.[11] As a person's family changed due to birth, death, marriage, or divorce, and as their contacts changed due to residential moves, new employment, or new friendships, this information was captured.

Overall, there were 53,228 observed family and social ties to the 5,124 subjects, yielding an average of 10.4 ties per subject within the network (not including ties to neighbors). For example, 83% of subjects' spouses were in the network and 87% of subjects with siblings had at least one sibling in the network.

Importantly, 45% of the 5,124 subjects were connected via friendship to another person in the network at some point; and there were 3,542 unique friendships for an average of 0.7 friendship ties per subject. Because friendship identifications are directional, there were three kinds: a "subject-perceived friend" wherein a subject nominates a contact; a "contact-perceived friend" wherein a contact nominates a subject; and a "mutual friend" in which the nomination is reciprocal. We hypothesized that the strongest inter-personal influence upon subjects should occur between mutual friends, followed by subject-perceived friends, followed by contact-perceived friends.

For 39% of the subjects, at least one coworker was captured in the network at some point. For 10% of the subjects, an immediate (non-relative) neighbor was also present (more expansive definitions, such as living within 100 meters, resulted in more subjects having identifiable neighbors but yielded similar results).

We included only persons 21 or older. At inception, 53% of the subjects were women; the subjects' mean age was 38 years (range, 21 to 70); and their mean education was 1.6 years of college (range, 0 to 17+ years of education). Measures of occupational prestige at each wave were available (see supplement).[xvi] Smoking in the FHS mirrored national trends; for example, among those aged 40-49 at each wave, the prevalence of smoking declined from 65.9% to 22.3% over the study period (see supplement).

Network and Statistical Analysis

We treated smoking as a continuous variable in some analyses (number of cigarettes per day), but mainly conducted analyses with dichotomous cut points of 0 versus ≥1 cigarettes per day.

We graphed the network using the Kamada-Kawai [xvii] algorithm and created an animation using SoNIA [xviii] (see supplement). The Kamada-Kawai algorithm positions nodes so that they and the ties connecting them overlap the least amount possible, thus producing interpretable images.

We measured subjects' *centrality*, which captures the extent to which people are positioned near the center of the network. One measure of centrality is simply the number of a subject's ties; people who have more contacts tend to be more central. Eigenvector centrality, used here, takes this a step further by weighting each contact based on how many other contacts they have. People who have "popular" contacts are more central, and have higher centrality, than those who have less popular contacts (see supplement).[xix]

We studied the *clustering* of smoking behavior as follows: we compared the whole observed network to simulated networks with the same network topology and the same overall prevalence of smoking as the observed network, but with the incidence of smoking randomly distributed across the nodes ("random smoking networks").[xx] If clustering is occurring, then the probability that a contact is a smoker given that a subject is a smoker should be higher in the observed network than in the random networks. What we defined as the "reach" of the clusters may be appreciated by identifying the point, in terms of a contact's degree of separation from any given subject, at which the probability of a contact being a smoker is no longer related to whether the subject is a smoker.

There are three explanations for clustering: (1) subjects might choose to associate with contacts exhibiting similar smoking behavior (*homophily*);[xxi] (2) subjects and contacts might jointly experience unobserved contemporaneous exposures that cause their smoking behavior to covary (omitted variables or *confounding*); and (3) contacts might influence subjects (*induction*). Distinguishing the inter-personal induction of smoking from homophily is easier when longitudinal information about both people's ties and attributes (*i.e.*, smoking behavior) is available.[xxii]

Hence, we specified longitudinal logistic regression models wherein the subject's smoking status (0 versus ≥1 cigarettes per day) at time t+1 was a function of various attributes of subjects such as age, gender, and education, their smoking status at time t, and, most pertinently, the smoking status of their contacts at times t and t+1.[22] We used generalized estimating equations to account for multiple observations of the same subject across waves and across subject-contact pairings.[xxiii] We assumed an independent working correlation structure for the clustered errors.[23,xxiv]

The time-lagged dependent variable (lagged to the prior exam) eliminates serial correlation in the errors (evaluated with a Lagrange multiplier test [xxv]) and also helps control for subject's genetic endowment and any intrinsic, stable predilection to smoke. The lagged independent variable for a contact's smoking status helps account for homophily.[22] The key variable of interest is a contact's smoking behavior at time $t+1$. We found no statistically meaningful difference between the processes of quitting and starting in subjects depending on quitting or starting among their contacts, and so our models here evaluate concordance in change in smoking behavior between subjects and contacts (*i.e*., contact starts smoking and subject starts, or contact stops smoking and subject stops). Since cessation predominated in our time period, however, we phrase our results in terms of cessation.

We estimated these models in varied subject/contact pair types. We evaluated the possibility of unobserved exposures explaining the associations by examining how the type or direction of the relationship between subject and contact affected the association between subject and contact smoking and by exploring the role of geographic distance between subjects and their contacts.

We computed 95% confidence intervals by simulating the first difference in contact contemporaneous smoking (changing from 0 to 1) using 1,000 randomly drawn sets of estimates from the coefficient covariance matrix and assuming all other variables were held at their means.[xxvi] All tests are two-tailed.

All subjects provided informed consent. Our IRB approved. Both authors designed the study, gathered the data, analyzed the data, wrote the paper, and decided to publish it.

RESULTS

Network Analysis

Figure 1 depicts part of the social network in 1971 and 2000. There is substantial change in the prevalence of smoking and the social life of smokers. In 1971, there were many more smokers than in 2000, and they occupied the center of their circles of friends and family to the same extent that nonsmokers did. However, by 2000, most people had quit smoking, and those who had not were more likely than nonsmokers to be at the periphery of the network. Moreover, there is an increased tendency for smokers to be connected primarily to other smokers, and for there to be relatively separate clusters of smokers and non-smokers.

Figure 2a characterizes the clusters within the entire network more formally. Across all the exams, the risk of smoking in contacts who are connected to a subject who is a smoker (one degree of separation) is about 61% higher in the observed network than in a random network. The risk of being a smoker is also about 29% higher for contacts' contacts (two degrees of separation) and about 11% higher for contacts' contacts' contacts (three degrees). By the fourth degree of separation, there is no excess relationship between a subject's smoking behavior and the contact's behavior. Hence, on average, smoking clusters have a reach of three degrees. Socioeconomic factors do not explain this clustering (see supplement).

Figure 3a shows how the average size of a fully connected cluster of smokers has changed over time. It also shows the average size of these clusters that would have been observed if we kept the network topology and smoking prevalence the same and then randomly reassigned who smokes and who does not. Notice that the observed cluster sizes are much larger than those expected due to chance, and they remain relatively stable compared to the random networks, which decline sharply in size when prevalence falls. This evidence suggests that people are not gradually quitting at the fringes of clusters of smokers. Instead, it appears that whole clusters of connected smokers convert to nonsmokers together, causing the average cluster size to remain high even while overall prevalence declines (see also the online animation).

Moreover, Figure 3b shows that the observed centrality of smokers has declined over the 32-year period: smokers are more and more peripheral within the network, and non-smokers progressively more central. Additional analyses indicated that neither the excess mortality of smokers (and hence the severing of ties) nor differences in education between smokers and non-smokers are driving these results (see supplement). Moreover, we find that smoking tends to decrease a person's centrality, not the other way around (see supplement).

Interpersonal Models

We evaluated the extent of inter-personal association in smoking behavior using regression analysis. Figure 4 summarizes the associations.

With respect to friends, if a subject stated that a contact was a friend, the contact quitting was associated with a 36% decreased chance of a subject smoking (95% CI: 12%-55%). The effect was perhaps stronger among mutual friends at 43% (95% CI: 1%-69%). The effect of a contact-perceived friend quitting was not significant (15%, 95% C.I. −35% - 50%).

Educational status was important among friends. When the *subject* had at least one year of college, smoking cessation in a contact decreased the risk of the subject smoking by 57% (95% CI: 29%–75%). When the *contact* had at least one year of college, the effect was similarly strong at 55% (95% CI: 26%–74%). Hence, those with more education were both more influential and more influenceable. Among friends who *both* had at least one year of college, when one stopped smoking it decreased the chance the other smoked by 61% (95% CI: 28%–81%). Conversely, among pairs of friends in which at least one had a high school diploma or less education, the association was not significant. A model with an interaction term denoting high-education friend pairs shows that the association is significantly stronger (p=0.049) than other kinds of friend pairs (see supplement). Thus, the spread of smoking cessation among friends appears to be stronger through networks of high-educational-status individuals. Educational status also appears to play an important role in peripheralization. The gap in centrality between smokers and nonsmokers has widened more for high-education than for low-education individuals over the 32-year period (see supplement). This evidence suggests that educated individuals experience greater social peripheralization for smoking than less-educated individuals.

Among pairs of coworkers, the effect of one person quitting was not generally a significant factor in the other person quitting. However, coworkers at large firms who may not know one another make up the majority of our observations. When we restrict the analyses to smaller firms (those with up to 6 employees who participate in the FHS) we find that a coworker quitting increases the likelihood of subject quitting by 34% (95% C.I. 5%-56%). Moreover, the effect gets stronger as firm size decreases, as one might expect since it is more likely the subjects know one another.

Among married couples, when a spouse quit, the subject was 67% (95% CI: 59%–73%) less likely to smoke; husbands and wives affected each other similarly. Among siblings, one quitting increased the chance the other quit by 25% (95% C.I. 14%-35%). Immediate neighbors had no effect.

We controlled for a number of other factors in additional models, including size of family and friend groups, prevalence of smoking in the subject's workplace, and occupational prestige. In all cases, the association of contact and subject smoking remained similar to the foregoing results (see supplement).

We also examined the impact of geographic distance between subjects and contacts on the foregoing associations and found that distance does not modify the intensity of the effect of contact smoking behavior upon a subject. That is, smoking behavior was related between subjects and their contacts regardless of how far apart they were geographically (Figure 2b).

Finally, we examined the spread of different intensities of smoking, changing the categorization of “smoker” in our models from those who smoke at least 1 cigarette per day (casual smoking) to those who smoke at least 5 (moderate smoking) or 20 (heavy smoking). The association in smoking behavior between siblings and spouses remains strongly significant at all intensity levels. However, the association ceases to be significant between friends at heavy smoking intensities, and it also ceases to be significant between coworkers at both moderate and heavy intensities (see supplement). Thus, it appears that neither friends nor coworkers influence heavy smoking as much as they do casual smoking.

DISCUSSION

Person-to-person spread of smoking cessation appears to have been a factor in the population-level decline in smoking seen in recent decades. Moreover, there appear to have been local smoking cessation cascades since whole connected clusters within the social network quit roughly in concert. This suggests that decisions to quit smoking are not made solely by isolated individuals, but rather reflect choices made by groups of individuals connected to each other both directly and indirectly up to three degrees away. Individuals appear to act under collective pressures within niches in the network. As a further reflection of this phenomenon, individuals who remained smokers were observed to move to the periphery of the network,[xxvii] and the network became progressively more polarized with respect to smokers and nonsmokers over the period 1971-2003, with relatively fewer social ties between these groups.

We also found that the educational background of connected individuals matters. The higher their educational level, the more likely friends were to emulate each other with respect to smoking. In this regard, the diffusion of smoking cessation is in keeping with prior studies of diffusion of diverse “innovations.”[xxviii,xxix] This finding is also consistent with the idea that local social niches may arise within the network and that this may in turn contribute to the well known socioeconomic gradient in smoking. That is, groups of individuals may develop self-reinforcing norms that augment individual decisions to quit and this may lead to macro-socioeconomic patterns, similar to the adoption and spread of fashions first among high-status individuals in society.[28]

While connected persons might share an exposure to common environmental factors (e.g., cigarette taxes), the experience of simultaneous events (e.g., workplace smoking cessation campaigns), or other common features (such as genes or socio-demographic attributes) that cause them to start or quit smoking simultaneously, our observations nevertheless suggest an important role for a process involving group dynamics and person-to-person spread. The group-level cessation of smoking is not solely due to people in the same household or workplace quitting together since even contacts who were geographically separated evinced inter-personal effects and since workplace effects seem to depend on workplace size in a way that suggests that actual interpersonal contact is important. Moreover, the fact that immediate neighbors do not affect subjects helps exclude joint exposure to local environmental factors (such as tobacco marketing, local taxes, or cigarette availability) as an explanation for the observations. Our models control for a subject’s prior smoking status, which helps to account for sources of confounding that are stable over time (such as childhood exposures, personality, or genetic endowment). Finally, our models also control for contacts’ prior smoking status, thus helping to account for a possible tendency of smokers to form ties among themselves.

Based both on social theory and on our previous work on obesity,[11] we expected that people would be more likely to emulate the behavior of people they nominated rather than people who nominated them as friends. The results suggest such a pattern. Moreover, such a pattern provides suggestive evidence against the role of confounding since any confounding factor would not respect the directionality of social ties.

Smoking in contacts might influence smoking in subjects by diverse biopsychosocial means, including (1) changing subject's norms about the acceptability of smoking, (2) more directly influencing subject's behaviors (*e.g*., a contact asking the subject not to smoke, or, conversely, a contact sharing cigarettes), or even (3) fostering dependence through the inhalation of second-hand smoke. Our data are not capable of distinguishing these. Yet, the lack of geographic variation in the impact of contact behavior on subjects suggest that social norms may be an important factor -- since they may spread more easily over geographic distance than behaviors.

It is possible that a change in the smoking behavior of more than one contact may be required for a subject to change, and there may be additive or even threshold effects whereby a subject's probability of quitting depends on having not one contact, but two or more, quit.[xxx] This may be especially likely in the case of smoking which is very often deemed an explicitly social -- and hence shared -- behavior. Consequently, when a smoker runs out of easily available contacts with whom he or she can smoke, he or she may be increasingly likely to quit. This possibility is also consistent with the group-level quitting we observed.

Network phenomena might be exploited to spread positive health behaviors.[xxxi,xxxii,xxxiii,xxxiv] Indeed, smoking and alcohol cessation programs that provide peer support – that is, that modify the social network of the target – are more successful.[32,34] People are connected, and so their health is connected.[xxxv,xxxvi] Collective interventions may be more effective than individual interventions. Moreover, medical and public health interventions to get people to quit smoking might be more cost-effective than initially supposed since health improvements in one person might spread to others.[35,xxxvii,xxxviii] Finally, the isolation of smokers within social networks suggests that blanket policy approaches (e.g., advertising, taxation) may be usefully supplemented by interventions targeting small groups. In the case of smoking cessation in the last three decades, there is evidence of a cascade of salubrious behavior, and cessation of smoking in one person appears to be highly relevant to the smoking behavior of others nearby in the social network.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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References

i. CDC. Cigarette Smoking Among Adults – United States, 2004. Morbidity and Mortality Weekly Report 2005;55(44):1121–1124.

ii. U.S. Department of Health and Human Services. Reducing the Health Consequences of Smoking — 25 Years of Progress: A Report of the Surgeon General. U.S. Department of Health and Human Services, CDC; Atlanta, GA: [Accessed: February 2004]. 1989 p. 89-8411.DHHS Pub. No. (CDC)

iii. CDC. Health United States, 2003, With Chartbook on Trends in the Health of Americans. CDC, National Center for Health Statistics; Hyattsville, MD: 2003.

iv. National Center for Health Statistics. http://www.cdc.gov/nchs/fastats/Default.htm#S

v. Chen PH, White HR, Pandina RJ. Predictors of smoking cessation from adolescence into young adulthood. Addictive Behaviors 2001;26:517–29. [PubMed: 11456075]

vi. Powell LM, Tauras JA, Ross H. The importance of peer effects, cigarette prices and tobacco control policies for youth smoking behavior. Journal of Health Economics 2005;24(5)

vii. Newman MEJ. The structure and function of complex networks. SIAM Review 2003;45:167–256.

viii. Bearman PS, Moody J, Stovel K. Chains of Affection: The Structure of Adolescent Romantic and Sexual Networks. American Journal of Sociology 2004;110:44–91.

ix. Fowler, JH. Turnout in a Small World. In: Zuckerman, Alan, editor. The Social Logic of Politics: Family, Friends, Neighbors, and Workmates as Contexts for Political Behavior. Temple University Press; 2005. p. 269-287.

x. Crane D. Diffusion models and fashion: a reassessment. Annals of the American Academy of Political and Social Science 1999;566:13–24.

xi. Christakis NA, Fowler JH. The Spread of Obesity in a Large Social Network over 32 Years. New England Journal of Medicine 2007;357:370–379. [PubMed: 17652652]

xii. Dawber, TR. The Framingham Study: The Epidemiology of Atherosclerotic Disease. Harvard University Press; Cambridge: 1980.

xiii. Feinleib M, Kannel WB, Garrison RJ, McNamara PM, Castelli WP. The Framingham Offspring Study: design and preliminary data. Preventive Medicine 1975;4:518–52. [PubMed: 1208363]

xiv. Patrick DL, Cheadle A, Thompson DC, Diehr P, Koepsell T, Kinne S. The validity of self-reported smoking: a review and meta-analysis. American Journal of Public Health 1994;84:1086–93. [PubMed: 8017530]

xv. Vartiainen E, Seppälä T, Lillsunde P, Puska P. Validation of self reported smoking by serum cotinine measurement in a community-based study. Journal of Epidemiology and Community Health 2002;56:167–70. [PubMed: 11854334]

xvi. Treiman, DJ. Occupational Prestige in Comparative Perspective. Academic Press; New York: 1977.

xvii. Kamada T, Kawai S. An algorithm for drawing general undirected graphs. Information Processing Letters 1989;31:7–15.

xviii. Moody J, McFarland DA, Bender-deMoll S. Visualizing Network Dynamics. American Journal of Sociology 2005;110:1206–41.

xix. Bonacich P. Factoring and Weighing Approaches to Clique Identification. Journal of Mathematical Sociology 1972;2:113–120.

xx. Szabo, G.; Barabasi, AL. Network Effects in Service Usage. http://lanl.arxiv.org/abs/physics/0611177

xxi. McPherson M, Smith-Lovin L, Cook JM. Birds of a feather: homophily in social networks. Annual Review of Sociology 2001;27:415–444.

xxii. Carrington, PJ.; Scott, J.; Wasserman, S. Models and Methods in Social Network Analysis. Cambridge University Press; 2005.

xxiii. Liang KY, Zeger S. Longitudinal data analysis using generalized linear models. Biometrika 1986;73:13–22.

xxiv. Schildcrout JS. Regression analysis of longitudinal binary data with time-dependent environmental covariates: bias and efficiency. Biostatistics 2005;6:633–652. [PubMed: 15917376]

xxv. Beck N. Time-Series–Cross-Section Data: What Have We Learned in the Past Few Years? Annual Review of Political Science 2001;4:271–293.

xxvi. King G, Tomz M, Wittenberg J. Making the most of statistical analyses: improving interpretation and presentation. American Journal of Political Science 2000;44:341–355.

xxvii. Strauss RS, Pollack HA. Social Marginalization of Overweight Children. Archives of Internal Medicine 2003;157:746–752.

xxviii. Pampel FC. Diffusion, cohort change, and social patterns of smoking. Social Science Research 2005;34:117–139.

xxix. Rogers, EM. Diffusion of Innovations. 4th ed. The Free Press; New York: 1995.

xxx. Centola D, Eguiluz V, Macy M. Cascade Dynamics of Complex Propagation. Physica A 2007;374:449–456.

xxxi. Wing RR, Jeffery RW. Benefits of recruiting participants with friends and increasing social support for weight loss and maintenance. Journal of Consulting & Clinical Psychology 1999;67:132–8. [PubMed: 10028217]

xxxii. Malchodi CS, Oncken C, Dornelas EA, Caramanica L, Gregonis E, Curry SL. The effects of peer counseling on smoking cessation and reduction. Obstetrics & Gynecology 2003;101:504–10. [PubMed: 12636954]

xxxiii. Bruckner H, Bearman PS. After the promise: the STD consequences of adolescent virginity pledges. Journal of Adolescent Health 2005;36:271–278. [PubMed: 15780782]

xxxiv. McKnight AJ, McPherson K. Evaluation of peer intervention training for high school alcohol safety education. Accident Analysis & Prevention 1986;18:339–47. [PubMed: 3741584]

xxxv. Christakis NA. Social networks and collateral health effects – have been ignored in medical care and clinical trials, but need to be studied. British Medical Journal 2004;329:184–185. [PubMed: 15271805]

xxxvi. Christakis NA, Allison PD. Mortality After the Hospitalization of a Spouse. New England Journal of Medicine 2006;354:719–730. [PubMed: 16481639]

xxxvii. Rosen M. On Randomized Controlled Trials and Lifestyle Interventions. International Journal of Epidemiology 1989;18:993–994. [PubMed: 2621039]

xxxviii. Cutler DM, Glaeser EL. Social Interactions and Smoking NBER Working Paper No. W13477. October;2007

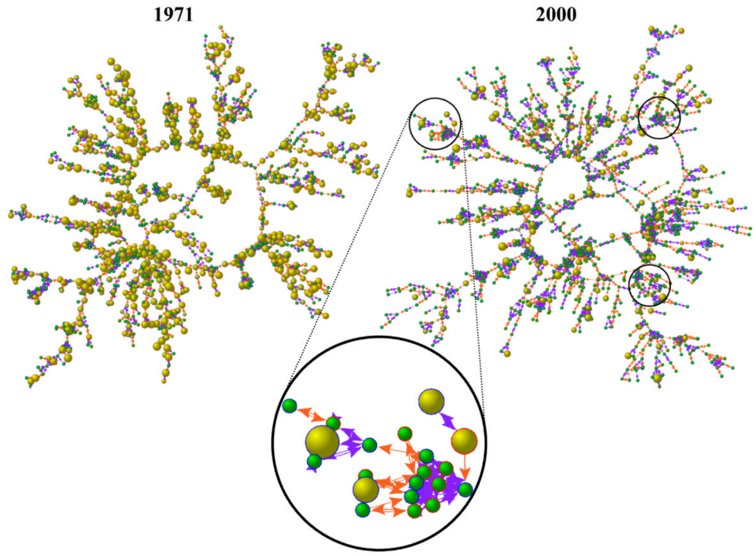

Figure 1. Smoking in the Framingham Social Network

This is a random sample of 1000 subjects in the FHS social network chosen from the largest connected subcomponent at exam 1 (left) and exam 7 (right). Node border indicates gender (red=female, blue=male), node color indicates cigarette consumption (yellow is for ≥1 cigarettes per day), node size is proportional to number of cigarettes consumed, and arrow colors indicate relationship (friends and spouses = orange, family = purple). By 2000, it is apparent that smokers are more likely to occur at the periphery of their networks. And smokers are usually in smaller subgroups than nonsmokers. The circles in the panel for 2000 identify densely connected clusters of green circles where there are no smokers at all or where the smokers sit at the edge of the subgroup.

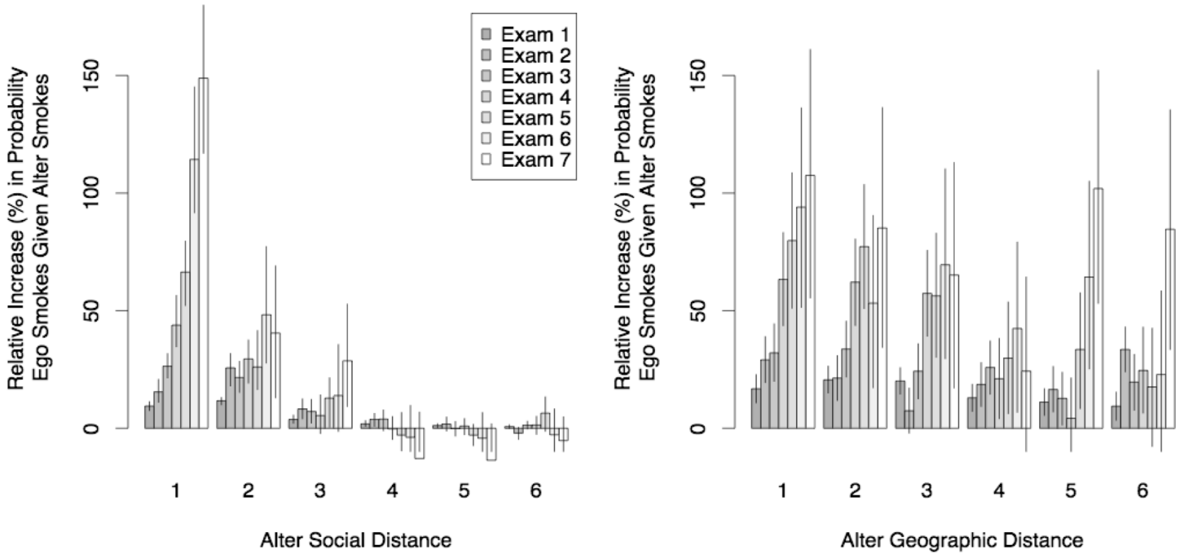

Figure 2. Effect of Social and Geographic Distance from Social Contacts Who Smoke on the Probability that a Subject is a Smoker in the Framingham Heart Study Social Network

(a) Mean effect of social proximity to a contact. This is derived by comparing the conditional probability of being a smoker in the observed network with an identical network (with topology preserved) in which the same number of persons who smoke are randomly distributed. Contact social distance refers to closest social distance between the contact ("alter") and the subject ("ego") (a direct contact = distance 1, contact's contact = distance 2, *etc*.). Within any given social distance, the effect of the smoking behavior in a social contact upon subject's smoking behavior increases across the exams from 1971 to 2003. (b) This figure shows the effects observed between directly connected persons (social distance 1) for six groups, ordered by distance between residences. The average distances in each group are as follows: group 1 = 0 miles, group 2 = 0.27 miles, group 3 = 1.46 miles, group 4 = 3.48 miles, group 5 = 9.37 miles, and group 6 = 471.9 miles. Error bars in both panels show 95% confidence intervals based on 1,000 simulations. Both panels exclude neighbor and co-worker ties.

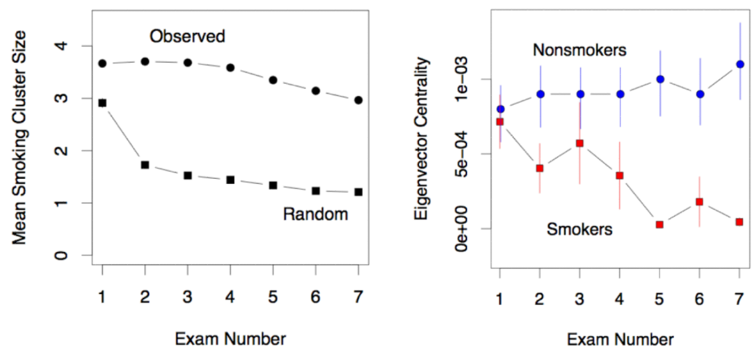

Figure 3. Cluster Size and Centrality of Smokers Across Time

(a) Smokers remained in tightly-knit groups, even as the incidence of smoking sharply declined. Marginal smokers are not leaving smoking groups; instead, whole clusters are quitting and those that are not maintain their previous size. (b) Eigenvector centrality computed at each wave for smokers and non-smokers. While the centrality of non-smokers remains roughly stable across all waves, smokers become increasingly less central, and more peripheral, in the social network. Bars in both panels show 95% confidence intervals. In the left panel, confidence intervals are too small to see (the largest is slightly larger than the height of the dark squares). Both panels exclude neighbor and co-worker ties.

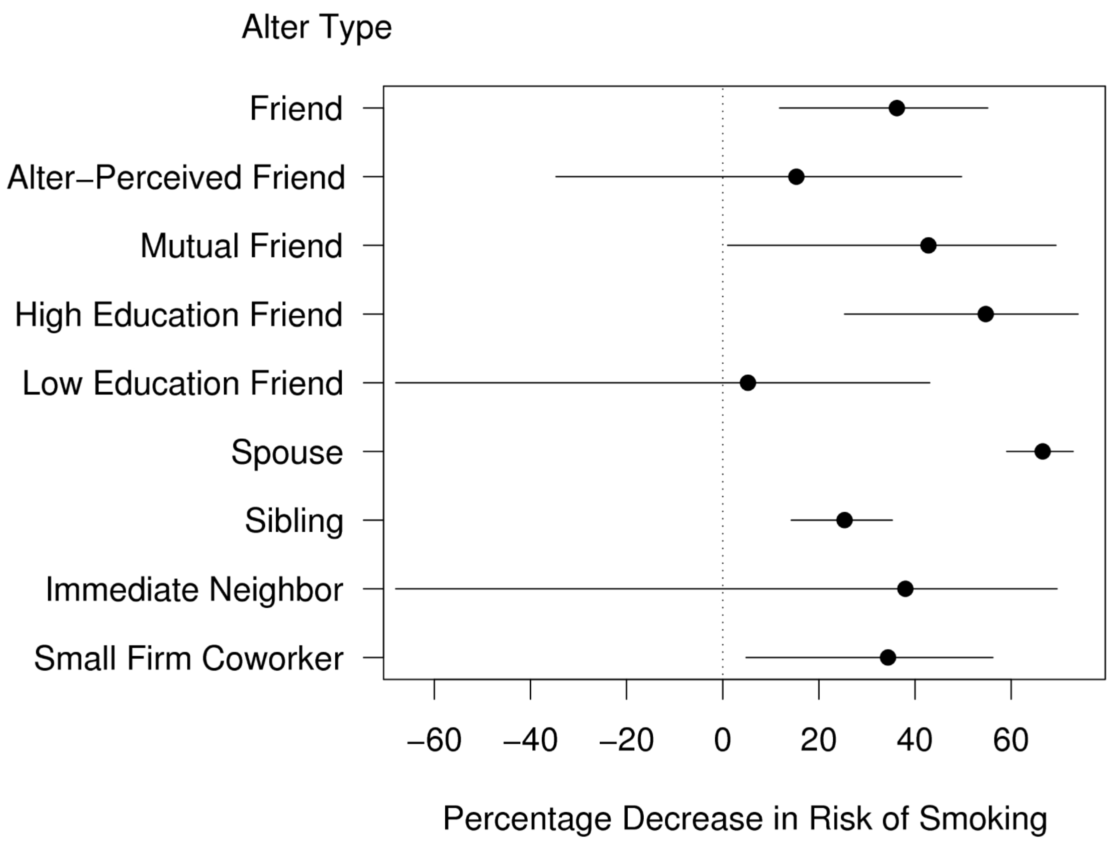

Figure 4. Association of Smoking Status Between Subjects and Their Social Contacts
The figure shows the probability that a subject (an "ego") smokes given that their social contact (an "alter") quits smoking, for generalized estimating equation logit models of smoking on several different sub-samples of the Framingham Heart Study Social Network. The dependent variable in each model is subject smoking and independent variables include lagged subject smoking status, contact smoking status, lagged contact smoking, subject age, gender, and education, and fixed effects for each wave. Full models and equations are available in the supplement. Mean effect sizes and 95% confidence intervals calculated by simulating first difference in contact contemporaneous smoking (changing from 1 to 0) using 1,000 randomly drawn sets of estimates from coefficient covariance matrix and assuming all other variables are held at their means. "Small firm coworkers" are those where six or fewer FHS participants work at the same physical location.