Influencers' Role Complexity Moderates the Benefits of Eigenvector Centrality for Diffusion in Social Networks: Evidence from the Diffusion of Microfinance in India

Abstract

Existing research on the diffusion of innovations has focused on the benefits of using central influencers to trigger adoption cascades in networks. Yet, prior work has not examined how influencers' role complexity moderates these benefits. Role complexity pertains to being embedded in complex networks with multiple types of ties, for example, co-authorship and co-patenting ties. This paper examines and offers evidence that influencers' role complexity moderates the benefits of eigenvector centrality in network-based diffusion processes. Using data from a network-based intervention seeding influencers, I demonstrate that influencers' role complexity undermined adoption among their contacts. The findings reveal important scope conditions on the benefits of using central influencers to diffuse innovations through networks.

Keywords:

networks; innovation diffusion; role complexity; eigenvector centrality

INTRODUCTION

One of the central contributions of network science to the study of innovation diffusion has been the idea that highly connected influencers promote faster and broader diffusion in a network (e.g. Borgatti and Everett 2006; Sparrowe and Liden 2005). The diffusion literature (for reviews, see Strang and Soule 1998; Wejnert 2002) has argued, and shown, that these individuals are highly effective at promoting both awareness and adoption in multi-stage diffusion processes (e.g. Centola 2015; Coleman, Katz, and Menzel 1966). This extensive literature has also argued that highly embedded actors in multiple networks are the best influencers to spread innovations, because they are positioned to mobilize information and connections across different contexts (Padgett and Powell 2012; Powell and Sandholtz 2012; Wang and Soule 2012).

Recent research has begun to examine such complex influence processes (Melnik et al. 2013; Myers and Leskovec 2012; Wang et al. 2017), and has found that complex (vs. simple) networks exhibit novel dynamical behavior not captured by existing diffusion models (Melnik et al. 2013), pointing to potential avenues for investigating how complexity affects social influence. Specifically, existing research has focused on the role of wide ties in complex diffusion (Centola 2015; Centola and Macy 2007), but has not specifically looked at the interplay between an influencer's centrality and embeddedness in multiple networks, as it affects role complexity. The concept of role complexity captures variety in influencers' positions within complex networks comprising different types of contacts, for instance, co-inventors and co-authors.

This interplay between an actor's network centrality and role complexity is important, because complexity introduces tradeoffs between social visibility in a community and constraints to being seen as legitimate and authoritative if one spans many unrelated domains (e.g. Hsu

2006; Zuckerman et al. 2003). The penalties of being the proverbial “jack of all trades,” I argue, are most salient for highly central actors in a complex network, and may undermine diffusion.

My aim in this article is to introduce the idea that role complexity affects the previously documented benefits of using central actors to diffuse innovations through networks, and further to offer an empirical test of this idea. To examine how role complexity affects diffusion processes in networks, I examine data on the diffusion of a financial service innovation – microfinance (MF) – among 43,759 people in 43 communities in India, collected as part of a prior field experiment seeding “influencers” to promote MF diffusion in these communities (Banerjee et al. 2013b, 2013a). Specifically, I examine the individual networks connecting people to their contacts, rather than the household level networks examined previously (Banerjee et al. 2013b), to uncover how influencers’ role complexity their contacts’ probability of adopting MF. Owing to the uncertain benefits of MF (Banerjee 2013; Banerjee et al. 2015), central influencers were essential to adoption, yet these influencers also played complex roles. Indeed, I find that their role complexity undermined MF adoption, and increased with centrality.

The findings provide both theoretical and practical insights for research on innovation diffusion in networks. First, they imply that influencers’ centrality in networks in not unequivocally conducive to diffusion. Specifically, the benefits of centrality decrease with role complexity, suggesting important scope conditions on the benefits of selecting central influencers to promote innovation diffusion. Second, the findings suggest that central influencers may undermine – rather than promote – diffusion when role complexity is present, such as in networks comprising multiple types of ties and multiple domains of interaction. These findings are relevant for understanding why innovations introduced in dense, interconnected networks, such as the uptake of new agricultural methods for increasing crop yields (e.g. BenYishay and

Mobarak 2016) and vaccinations and preventative healthcare practices (e.g. Burt 1973; Pagliusi et al. 2017) often fail to diffuse broadly (Assenova 2018; Burt 1973; Centola 2015). While many network-based interventions seek to trigger adoption cascades, successful diffusion may depend as much, if not more, on role complexity as on influencers' centrality.

THEORY DEVELOPMENT

Much of our understanding of how networks affect innovation adoption from a theoretical perspective comes from the literature on social influence and diffusion (for reviews, see Strang and Soule 1998; Wejnert 2002). This literature is grounded in a conception of adoption behavior that is driven primarily by the social context within which information spreads (Centola 2015; Goldberg and Stein 2016; Myers and Leskovec 2012). The dominant theories in this literature have focused on the role of network ties to socially prominent "influencers," people who adopt and spread information, opinions, beliefs, and behaviors. These ties represent interactions among people in a community, through which individuals pass word-of-mouth information and affect others' choices and behavior. Social influence, from this perspective, arises from having many ties (i.e. centrality) (Wasserman and Faust 1994:173). Actors who have many ties are thus said to be central, because they interact with many people in their community. Central actors are perceived as being more agreeable (e.g. Ibarra and Andrews 1993; Klein et al. 2004), more trustworthy and pro-social (e.g. Baldassarri 2015; Baldassarri and Grossman 2013), and more legitimate (Coleman, Katz, and Menzel 1957; Sparrowe and Liden 2005), all qualities that enable them to influence others.

People within a community who are central in networks are therefore thought to be more influential to the behavior of others and to trigger innovation adoption. The role that networks play in these diffusion processes have been documented in a number of studies examining the diffusion of management fads and fashions (Abrahamson and Rosenkopf 1999; Strang and Macy 2001), medical innovations (Friedkin 2010; Perez et al. 2008), and social practices (Curran 2015; Shropshire 2010), to name a few. Central influencers typically need not be high-status individuals (for example Kellogg (2009) found that middle-managers were the most influential in bringing about institutional change), but they do need to be visible and legitimate members of a community (Friedkin 1991; Ibarra and Andrews 1993; Rossman 2014). Two aspects of influencers' positions in networks affect this visibility and legitimacy: network centrality and role complexity.

Network Centrality. – Theories of centrality posit that having more ties to others in a community increases a person's visibility and influence through both social and psychological mechanisms. Centrality, for instance, increases exposure to and familiarity with an actor, which in turn increase perceptions of similarity, liking, and trusting another person (e.g. Friedkin 1998; Ibarra and Andrews 1993; Klein et al. 2004). These factors arguably strengthen an actor's ability to influence others. Further, central individuals often become role models to emulate, and are more often tapped as sources of information (e.g. Coleman et al. 1957). Centrality also increases a person's likelihood of engaging in pro-social behavior, thereby predisposing others to cooperation and to trust (Baldassarri 2015; Baldassarri and Grossman 2013) and providing the necessary conditions to enable diffusion through social influence.

Prior studies have found that influencers' effect on others indeed increases with network centrality. In simulations of network flows, for instance, eigenvector centrality has been shown to predict a higher probability of sending and receiving information (cf. Borgatti 2005; Brummitt, Lee, and Goh 2012). Furthermore, in empirical studies of diffusion ranging from hybrid corn (e.g. Dixon 1980; Ryan and Gross 1943), to medical innovations (e.g. Burt 1987;

Coleman et al. 1957), to social epidemics (e.g. Christakis and Fowler 2007), centrality has consistently been linked to faster and broader diffusion. That is, the behaviors, opinions, and beliefs of central influencers appear to be "contagious."

Thus, if a central agent in a network adopts a new practice, technology, or idea, she would be likely to influence her contacts to adopt also. An agent's eigenvector centrality – prominence as a function of the prominence of her contacts – is therefore thought to be highly predictive of diffusion (Bonacich 2007; Bonacich and Lloyd 2001). Recent theoretical work in this area has established that the distribution of influence among influencers in a network is asymptotically equal to their eigenvector centrality ranking (Jia et al. 2015) and holds under a variety of network topologies (Jia, Friedkin, and Bullo 2017). These theories would suggest the following prediction about how influencers' network centrality shapes network-based diffusion:

> ***Hypothesis 1:*** *Network-based diffusion will increase with the eigenvector centrality of influencers.*

This postulated relationship rests on two important assumptions about influence through network ties. The first assumption is that influencers in a network play only a single type of role (e.g. friend). The second key assumption is that ideas, behaviors, opinions, and beliefs spread upon contact, similarly to the spread of infectious diseases. Thus, having more ties is assumed to be unequivocally "better" in the sense of increasing an actor's influence.

Bringing role theory (Coser 1991; Goffman 1959; Merton 1972) into network conceptions of social diffusion necessitates a different model of influence: one involving choices and "interpretive adjustments" to the observed behavior or the recommendations shared by one's contacts (Cyert and March 1963:85). Rather than passively "infecting" others, influencers engage in purposive communication that involves the presentation of different "selves" (Goffman 1959, 1961). Further, rather than passively receiving information and recommendations, audiences form perceptions of an agent's credibility and legitimacy and adjust their interpretations (Cyert and March 1963). When social influence processes unfold over multiplex networks, in which influence can occur across multiple domains of interaction (e.g. Gould 1991; Padgett and Ansell 1993; Shipilov 2012; Smith and Papachristos 2016) and actors can be insiders into multiple groups and communities (Vedres and Stark 2010), it is important to examine how influencers' roles affect diffusion.

Role Complexity. **–** Role complexity pertains to the notion of playing different roles in a community. For example, a medical student is "student, vis-à-vis his teacher, but also an array of other roles relating him complexly to other students, physicians, nurses, social workers, medical technicians, and the like" (Merton 1957:423). Lorrain and White (1971:50) viewed these roles as being encapsulated by an actor's "total role." The concept of role complexity that I develop places the emphasis not on the sum of roles, but rather on the heterogeneity of these roles. For example, being both a co-author and co-inventor comprises a scientist's relationship to others in a scientific community but does not capture the reality that these roles place different – and sometimes conflicting – demands and expectations. Prior co-authorship may constrain the pool of potential reviewers on new scientific peer-reviewed articles, and co-invention can create conflicts of interest in who a scientist chooses as a co-author.

Figure 1 illustrates the concept of role complexity for a person and contrasts it to the concept of network centrality. In the left panel, person A has many ties to others, but a simple role-set. In the right panel, person A has many ties to others, but they are all different types of ties, so that she a complex role-set. Looking at this diagram from the traditional sense of centrality shows that person A is highly connected, i.e. "central" in the network. Network theories would therefore predict that person A will be highly influential. Yet, accounting for role complexity produces a different insight: person A's centrality is coupled with role complexity. In this specific case, person A is friends with persons B and C and is kin to persons F and E. Thus, the concepts of role complexity and centrality are distinct in the sense of pertaining to the number of ties versus the composition of roles.

When viewed from this perspective, we can begin to see that actors can have many ties – and thus be visible to others – while also playing few roles – or many ties coupled with many roles. Complexity in actors' role-sets depends on the level of embeddedness in multiple, interconnected communities within a complex network, and affects influence in this network in unique ways.

Insert Figure 1 here.

The notion that actors play "not a single associated role, but an array of associated roles" (Merton 1957:423) is invariably related to the concept of social legitimacy (Hsu 2006; Zuckerman 1999; Zuckerman et al. 2003). Playing complex roles jeopardizes credibility when audiences are not clearly differentiated (e.g. Goffman 1959, 1961; Miles 1977; Zuckerman et al. 2003). Further, actors who try to play many roles can undermine expectations about their behavior. Role complexity can also undermine legitimacy, as when a person is perceived as a "jack of all trades" and a master of none (Hsu 2006). Indeed to avoid these negative repercussions, actors often try to "segment their activities" and "behave differently at different places and at different times" (Coser, 1975: 237). Yet, in the case of complex networks, these tactics are often difficult to enact because multiple sub-communities in the network are inter-dependent. These arguments would imply the following hypothesis about the moderating effects of role complexity on actors' influence in network-based diffusion:

> ***Hypothesis 2:*** *Network-based diffusion will decrease with the interaction between influencers' role complexity and eigenvector centrality.*

DATA

The data for this study come from an intervention conducted in 2006 by Banerjee et al. (2013b) in 43 remote villages in India that had no prior access to banking (Banerjee et al. 2013a). The intervention was conducted in partnership with Bharatha Swamukti Samsthe (BSS), a local non-profit organization whose aim was to provide "microfinance services to poor women, and through them to their families, facilitating increased earnings, better money management, and life quality improvement" (company website). The intervention leveraged networks in the villages to introduce information about and encourage adoption in microfinance (MF), a method for financial inclusion to support micro-entrepreneurship among disadvantaged women. The goal of the intervention was to promote MF by using central influencers in each village.

Prior to the intervention, households in each village completed a census questionnaire asking about a variety of social and economic features of village life, such as household composition, home ownership status, ethnic composition, religious and caste composition, the presence of non-governmental organizations (NGOs), self-help groups (SHGs), and various geographic features (e.g. roads, mountains, rivers). A random sample of people, stratified by religion and geographic location, also completed a detailed demographic survey in each village asking about their contacts in the village. This survey collected information about distinct dimensions of interaction and village life. Specifically, people were asked to name others with whom they (1) exchanged money, (2) exchanged goods (kerosene and rice), (3) visited at home, (4) shared advice about difficult decisions, (5) were related to by blood or marriage, (6) assisted with medical emergencies, (7) attended social events in the village, such as marriages and festivals, and (8) prayed at temple, church, or mosque. Surveys were administered through face-to-face interviews using independent consultants, and individuals were coded using unique identifiers to preserve anonymity and linked to their demographic and household characteristics.

The design of the study unfolded in two stages. The first stage involved an initial 6-month period (June 2006 to January 2007) during which BSS identified influencers from each village and asked them to raise awareness about the benefits of MF among their contacts who were eligible to receive MF loans. BSS followed its organizational model of targeting teachers, leaders of self-help groups, and shopkeepers: people whom it believed would be effective advocates for MF. Women were eligible to participate if they met a few criteria. They had to be between 18 and 57 years old at the time when MF was introduced. They also had to be permanent residents of their village, and had to be able to work. Additionally, only women who came from poor (economically disadvantaged) households were eligible to participate. Economic need was determined through verification of being able to receive food rations from the government (by the presence and color of their ration card). Further indicators of economic need included the size of a person's house, whether this house was owned or rented, whether a person had access to electricity and a private latrine, and whether the person had savings. Adoption was limited to only one woman per household. Eligible women who decided to participate were placed in a lending group with four other women from their village. Group members had to know each other, but were not allowed to be blood relatives or kin, and were also barred from being members of more than one lending group, to prevent exploitation of the joint-liability model. The maximal initial loan amount was 10,000 rupees (about $200). Loans were uncollateralized, carried an interest rate of 28 percent per year, and were repayable over 50 weeks in small installments. By comparison, the typical loans in the villages prior to microfinance were about 50 rupees ($1) and carried annual interest rates of 40 and 200 percent (Banerjee and Duflo 2011:160). The intervention was a private meeting between BSS credit officers and selected influencers who were asked to spread information. At the meeting, credit officers explained how MF worked, who was eligible to participate, and what potential benefits MF offered for women. Influencers were then asked to advocate for MF among their contacts, yet spreading information was entirely voluntary. Neither the research team nor BSS offered financial or non-financial incentives to spread information or influence others. The provision of these incentives has been shown in other studies to increase the likelihood that influencers spread information and promote diffusion (cf. BenYishay and Mobarak 2016).

The second stage of the intervention involved a 30-month open enrollment period during which women could sign up to participate in MF (February 2007 to September 2010). BSS collected individual adoption data until there were no changes in the month-over-month enrollment rate in each village. The MF model that BSS introduced was similar to other group lending models used widely among MF organizations (cf. Armendariz and Morduch 2005). Because network data were collected independently of the selection of "seeded" influencers in the networks, eligible women's connections to influencers through network ties appear to have been as-if random and uncorrelated with economic need and social status. This feature of the intervention enables identification of how the networks affected MF adoption.

METHODS

The outcome of interest in this study is whether an MF-eligible woman enrolled in MF during the observation period (*MF Adoption*). Adoption was based on BSS's records of which eligible women in each village enrolled. To understand variation in adoption outcomes, I examine three potential mechanisms that may have affected women's MF adoption: women's economic need (A), women's social status (B), and women's social influence from contacts in the village whose family members participated in MF (C). Economic need measures factors such as a woman's eligibility for food rations, and lack of savings. Social status captures differences in a woman's social position within her village, such as her Caste and ethnic group. Social influence captures the effects of contacts' adoption on the perceived benefits of participating. The anticipated relationships among these variables and the outcome of interest are that higher economic need would increase the likelihood of MF adoption, higher social status would decrease the likelihood of adoption, and social influence from contacts would increase the likelihood of adoption.

Insert Figure 2 here.

Network Centrality. -- To measure the strength of social influence from women's contacts in the villages, I operationalize their prominence in the networks of the villages as their mean eigenvector centrality across the eight types of interactions captured by the demographic surveys (Bonacich 2007; Bonacich and Lloyd 2001). Eigenvector centrality is a widely used measure of social influence (Bonacich 2007) that captures an actor's prominence as a function of her contacts' prominence. This measure is useful for parallel flow processes, such as influence among people (Borgatti 2005). Centrality in these processes corresponds to the proportion of times that information flows through an actor to reach another actor within the network (Borgatti 2005:62).

To compute this centrality, I constructed adjacency matrices for each type of network (e.g. kinship, social, advice). Each of these adjacency matrices was denoted as $\boldsymbol{A} = (x_{ij})$, where x_{ji}=x_{ij} was a binary indicator equal to 1 if actor n_i was connected to actor n_j in the network, and zero otherwise. The eigenvector centrality $C_E(n_i)$ of a woman's contact i was then $C_E(n_i) =$

$\frac{1}{\lambda}\sum_k x_{ki}\ C_E(n_k)$ where $\lambda \neq 0$ is a constant. This equation can be represented in matrix form as $\lambda\ C_E\ =\ C_E\boldsymbol{A}$, in which the centrality vector C_E is the left-hand eigenvector of **A** corresponding to the eigenvalue λ (Borgatti 2005). I computed centralities for each type of network and then averaged them using the arithmetic mean to arrive at an overall measure of contacts' centrality. Results were similar when I examined centrality in each of these networks independently.

Role Complexity. -- I operationalized role complexity as the structural distance among contacts' involvement in different sets of roles across the multiple networks in which they were embedded in their village (e.g. advice, social, economic). Measures of structural distances in multivariate networks have been developed in social network analysis, which enable comparisons of the structural similarity among subgraphs in multiplex networks. Butts and Carley (2001) in particular have proposed two such measures of structural similarity within multivariate networks: hamming distances and graph-level product-moment correlations. Although several other methods have been proposed in the literature, including relational algebras and block models (Wasserman and Faust 1994; White, Boorman, and Breiger 1976), these approaches are harder to implement and more computationally intensive for larger networks. Butts and Carley's (2001) measures by contrast are straightforward and computationally manageable to implement.

Hamming distances capture the number of coordinate changes in Euclidean space needed to transform one set of binary elements into another (Hamming 1950). Product-moment correlations similarly examine how closely one set of binary elements correlates with another set. My approach is to use the dyadic relations between a potential participant i and her contact j in each sub-graph of the multiplex network (e.g. kinship, social, religious), and compute the hamming distance between pairs of subgraphs g_1 and g_2 as:

$$d_H\ (g_1, g_2) = \sum_{i \neq j}^{N} [A_{ij}^{(1)} \neq A_{ij}^{(2)}]$$

"Low" structural distance means that contacts played structurally similar roles. Alternatively, "high" structural distance means that influencers play structurally dissimilar roles. I code an agent's role complexity as an indicator variable based on whether the roles that an agent played were in structurally dissimilar networks.

Identification. -- I use hierarchical logistic models (cf. Wong and Mason 1985) to estimate influencers' effect on the likelihood of MF adoption among eligible women (those who met BSS's criteria) in their village, where adoption takes on a value of 1 if a woman participated and 0 otherwise. These models account for the nested structure of the data, where women are nested in different villages. Adoption is thus modeled as a function of both village-specific (u_j) and person-specific (x_{ij}) factors:

$$\Pr(y_{ij} = 1 | x_{ij}, u_j) = H(x_{ij}\beta + u_j) \qquad (1)$$

In this model, $j = 1, \ldots, 43$ is the set of independent (geographically remote) villages, where each village contributes an idiosyncratic component u_j to variation in women's adoption. The village random effects are realizations from a multivariate normal distribution with mean 0 and variance $var(u_j) = \sigma^2$. These effects absorb village-specific variation that is attributable to factors such as differences in geography and unobservable cultural characteristics that may have affected individual outcomes in idiosyncratic ways. Each village j contains $i = 1, \ldots, n_j$ person-level observations of adoption outcomes among eligible women, with $y_{ij} = 1$ denoting adoption by woman i in village j and $y_{ij} = 0$ denoting otherwise. The logistic cumulative distribution function $H(x) = exp(x)/\{1 + exp(x)\}$ maps the set of linear predictors (x_{ij}) to the probability of MF adoption ($y_{ij} = 1$). These predictors for each woman i in village j, include factors such as a woman's economic need, social status, and social influence from contacts whose family members participated in MF in her village. As in standard logistic regression, $\boldsymbol{\beta}$ denotes the vector of regression coefficients. I estimated models of this functional form with different sets of linear predictors using the `melogit` routine in Stata 15 MP.

RESULTS

Table 1 shows the effects of economic need and social status on women's MF adoption. The reported coefficients (β) represent the log-odds of MF adoption among women, and σ^2 denotes the variance attributable to the village-level random effects. As this model shows, 46 percent of the total variance in individual outcomes across villages was explained by village-specific factors, with the remaining 54 percent explained by individual differences among women. Among economic factors, only ration card, savings, and electricity predicted differences in MF adoption ($p<0.001$). As expected, eligibility for food rations ($\beta=0.25$, $p<0.001$) and no access to electricity ($\beta=0.39$, $p<0.001$) both predicted higher MF adoption. The lack of savings, however, was associated with lower adoption ($\beta=-0.34$, $p<0.001$). These results could be attributable to women's inability to repay loans if they had no savings. Among predictors of social status, everything except for the lack of education affected adoption. Having marginalized social status (OBC caste membership), for example, predicted lower adoption ($\beta=-0.52$, $p<0.001$). Meanwhile higher social status, such as having a larger house ($\beta=-0.13$, $p<0.001$) and being a member of the majority (Kannada-speaking) ethnic group ($\beta=-0.27$, $p<0.001$) was associated with lower adoption.

Insert Table 1 here.

Identification Check. -- To understand whether the intervention "worked," I first check whether the likelihood that an eligible woman was connected to "seeded" influencers was uncorrelated with her social status and economic need. One might worry that women with higher economic need or lower social status were not equally likely to be connected to seeded influencers in their community, and therefore did not have equal chances of exposure to the intervention. To check for this possibility, I estimate a hierarchical logistic regression model in which I test whether women's economic need and social status were correlated with whether she was connected to a "seeded" agent. Table 2 presents the results from these tests. As the point estimates (β) and standard errors (se) show, neither economic need nor social status appear to have been correlated with differences in the likelihood of being connected to seeded influencers (Wald χ^2 p-value=0.58). Thus, I cannot reject the validity of the identification assumption that the seeding of influence in the networks was exogenous to individual differences that predicted MF adoption.

Insert Table 2 here.

Network Centrality. -- I proceed with testing the role of social influence from women's contacts in the networks of the villages on women's MF adoption through network ties. Based on existing theories of social influence and diffusion, one would expect to observe a positive relationship between the eigenvector centrality of contacts whose family members participated in MF and women's likelihood of MF adoption (H1). Indeed, the results in Table 3 appear to support this expectation. First note that the baseline probability of MF adoption among all eligible women across all the villages was about 34 percent (=exp(-0.67)/(1+exp(-0.67)) (β=-0.67, p<0.001). The coefficients for each variable in the model can therefore be interpreted in relation to this baseline probability, as either increasing or decreasing the baseline probability of adoption. First, note that the coefficient of eigenvector centrality is positive ($\beta=77.84$, $p<0.001$). This coefficient shows that women were about 57 percent more likely to participate with every one standard-deviation increase in the eigenvector centrality of their contacts whose family members participated, relative to the baseline probability. These results are consistent with H1. Thus "central" contacts indeed appear to have predicted a higher likelihood of women's MF adoption in the villages.

Insert Table 3 here.

Role Complexity. -- I proceed with examining whether contacts' role complexity was associated with being less effective at promoting MF adoption (H2). Table 3 presents the coefficients from the interaction between contacts' role complexity and eigenvector centrality, controlling for women's economic need and social status. The coefficient of the interaction is negative ($\beta=-81.33$, $p<0.001$), meaning that role complexity was associated with 32 percent lower probability of MF adoption among women relative to the baseline probability. The interpretation of this coefficient is that contacts who were similarly "central," as measured by their average eigenvector centrality, were less likely to influence women to participate in MF if they played complex (versus simple) roles. These results support H2.

Turning to economic need, the results show that among eligible women, having a greater economic need, as measured by eligibility for food rations, was associated with 13 percent higher probability of MF adoption relative to the baseline probability ($\beta=0.24$, $p<0.001$) for every one standard-deviation increase in economic eligibility for food rations. Further, women who had greater economic need, as measured by lacking access to electricity, were 9 percent more likely to participate ($\beta=0.39$, $p<0.001$). Women who did not have the capacity to repay loans, as evidenced by their lack of savings, were 7 percent less likely to participate ($\beta=-0.34$, $p<0.001$).

Meanwhile, women with higher social status, such as those who had larger houses (β=-0.13, $p<0.001$) and were members of the majority Kannada ethnic group (β=-0.27, $p<0.001$) were also less likely to participate. Women were 12 percent less likely to participate in MF, for example, with every one standard-deviation increase in the size of their house (an increase of about 1.62 rooms). Further, women who were members of the most socially excluded Caste (OBC) were 11 percent less likely to participate relative to the baseline probability (β=-0.52, $p<0.001$). Interestingly, the gender of women's contacts in the village was not statistically associated with variation in MF adoption. The expectation would have been that female contacts might have shaped women's behavior differently from male contacts owing to gender-based homophily. The analyses, however, did not reveal any statistical differences between male and female contacts, perhaps because female contacts accounted for half (52 percent) of the contacts of MF eligible women.

Alternative Explanations. -- There are several alternative explanations for the findings. One possible explanation is that contacts who enjoyed higher social status – in terms of their Caste group and ethnicity– were both more likely to play complex roles and less likely to recommend MF. Thus, the observed effects of role complexity could have been driven by differences in contacts' status, rather than role complexity. The data, however, do not support this explanation. Indeed, contacts' social status (i.e. Caste, ethnic group) was uncorrelated with their likelihood of playing complex roles (cf. Table A2). Another possibility is that contacts whose family members participated in MF were both more embedded in multiple kinds of networks in the village – and hence to play complex roles – and less likely to promote MF to their neighbors because they perceived to be competing for loans. If this was the case, contacts whose households had greater economic need, such as those who lacked physical assets in the form of owning a house, should have been more likely to play complex roles. The data, however, do not appear to support this explanation, as greater economic need was not correlated with the likelihood of playing complex roles (cf. Table A2).

DISCUSSION

An economic development intervention in India aimed at promoting women's MF adoption through central contacts in their community presented an ideal setting for testing the notion that role complexity moderates the benefits of centrality for diffusion in multiplex networks. Analyses of women's contacts in their village revealed that contacts' role complexity moderated the benefits of centrality for influencing women's MF adoption. Nearly half the variation in MF adoption was attributable to community-specific rather than to individual factors, such as women's economic need and social status. To understand some of the key drivers behind this variation in adoption, I focused on the structure of social influence in the villages, and specifically, on the network centrality and role complexity of women's contacts whose family members participated in MF. I posited that contacts' social influence on women would increase with their eigenvector centrality (H1), but that these increases would be moderated by contacts' role complexity (H2), owing to a loss of credibility associated with playing complex roles.

The findings provided support for these hypotheses. Contacts' network centrality was indeed linked to higher MF adoption, supporting H1, and role complexity moderated these benefits, supporting H2. The moderating effects of role complexity were negative, meaning that central actors in the communities were not necessarily better social influencers when they played complex roles (e.g. Goel et al. 2016; Jia et al. 2017; Sparrowe and Liden 2005). In the villages studied here, contacts with higher centrality were less likely to increase MF adoption among women when they played complex roles. These findings reveal important scope conditions on the benefits of centrality for influence and diffusion in multiplex networks. Yet the findings also align with recent research examining complex contagion, which has shown that complex networks introduce novel dynamical behavior and deviations from established models for single-layer networks (e.g. Barash, Cameron, and Macy 2012; Myers and Leskovec 2012; Wang et al. 2017). Wang et al. (2017) have argued that appropriate selection criterion for key influencers differ across simple versus heterogeneous networks, where actors are linked by multiplex ties. Further, role complexity suggests potential reasons why having multiple information channels can produce clashes in complex contagions that decrease diffusion (Myers and Leskovec 2012).

Limitations. -- There are several limitations to this study. First, the Indian villages were highly embedded societies, in which kinship, economic, and social structures intertwined. People in these villages faced multiple areas of role complexity in navigating the economic, religious, social, and kinship structures of their small and geographically isolated community. This type of embeddedness is characteristic of rural "multiplex" societies, such as villages in developing countries (Gluckman 1955, 1962), but may less prevalent in larger and more urbanized societies with complex divisions of labor. The types of networks observed and the types of intersectionality in these networks could therefore be substantively different from the roles and social networks of individuals in other types of social organizations, especially those with clearer divisions of social and economic roles. Thus, future studies should examine the extent to which the interaction between role complexity and centrality generalizes to other settings.

Further, the data collected do not contain psychological measures of how people interpreted communications from contacts who played complex (versus simple) roles. This fact limits exploration of the psychological mechanisms undergirding the observed interaction between role complexity and centrality. Role theory would point to the benefits and constraints that actors face when they play complex roles, such as enjoying greater autonomy but also potentially being perceived as less legitimate and credible. Role complexity could produce a variety of "interpretive adjustments" in information diffusion, such as filtering information from influencers who are known to play complex roles because of their potential to skew information across their contacts. Investigating the psychological mechanisms behind role complexity and credibility through lab experiments presents an important area for future research.

Contributions. – Theories of network centrality have postulated that central people will be more influential and more likely to diffuse innovations among their contacts (e.g. Jia et al. 2017; Sparrowe and Liden 2005; Wang et al. 2017). But the findings presented here offer a cautionary tale about applying these predictions to complex networks, where central influencers play complex roles. Indeed, in the Indian villages, influencers' centrality was associated with lower – rather than higher – MF adoption when influencers played complex roles. These findings suggest an important scope condition on the benefits of centrality for network-based diffusion, namely that diffusion depends also on role complexity. Much of the prior work on centrality bypasses a key distinction between contagion models for disease spread and for socially influenced behavior. The latter involves cognition and "interpretive adjustments," which affect whether someone is "infected" by the opinions, beliefs, and behavior of another person. These interpretive adjustments appear to depend on influencers' role complexity.

Indeed, some of the most central actors – those endowed with many ties – often span multiple social milieus and play many, complex roles, which invariably affect how they are perceived by audiences (Hsu 2006; Padgett and Ansell 1993; Zuckerman et al. 2003). Role theorists have long argued that playing many roles gives actors autonomy, yet also may undermine legitimacy and credibility (e.g. Beauchamp and Bray 2001; Coser 1991; Hecht 2001). Incorporating these insights into theories of influence is paramount to understanding how influence unfolds in complex networks. Studies of influence in these networks should consider both role configurations as well as network properties such as centrality. The concepts of playing multiple roles and having multiple types of ties are often intertwined (e.g. Rudolph et al. 2016; Simpson 2015; Smith and Papachristos 2016) and present fertile ground for understanding how complex networks shape diffusion processes.

Concerning theories of diffusion in these networks, the findings show that roles and ties interact to affect the likelihood of adoption through social influence. A closer examination of role configurations – in conjunction with network positions – uncovers a richer view of diffusion, in which social practices and behaviors are not necessarily more likely to spread through the influencers with the highest eigenvector centrality. Thus, individuals in central network positions may be ineffective at promoting diffusion when occupancy of central positions is coupled with role complexity. The ability to diffuse new technologies, practices, and ideas through complex networks depends on both influencers' role-sets and connections to others. Indeed, centrality that goes hand-in-hand with role complexity may render influencers less effective. These findings inform selection criteria for the best influencers to promote diffusion. Particularly, careful selection should consider actors' embeddedness in multiple, interlocking role structures.

CONCLUSION

Existing insights about social influence in networks were derived primarily from single-role, single-relation networks. By construction, influencers in these types of networks do not experience role conflict, and are not perceived as illegitimate or untrustworthy because they span multiple roles. The notion that actors in many real settings play multiple roles across multiple types of networks introduces cognitive, agentic, and strategic dimensions to social influence in networks. Exploring these dimensions of playing complex roles is therefore an important avenue for future research. More studies, for example, can examine if and how role complexity affects perceptions of legitimacy and trustworthiness, and under what conditions influencers can avoid being perceived in these ways. Further studies can also explore whether the findings presented in this paper generalize to other types of innovation diffusion, and study how role complexity affects information discounting and information skewing. The findings from this context represent a first step towards recognizing that central influencers with complex roles face different constraints to influence than central influencers with simple roles, and that new concepts need to be introduced to account for these tradeoffs associated with playing multiple roles. When it comes to network-based innovation diffusion, the best influencers may not always be the most central, but rather the least complex in their role-sets.

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Table 1. Hierarchical Logistic Model Predicting the Likelihood of MF Adoption among Eligible Women as a Function of Women's Economic Need and Social Status

	MF Adoption			
	β	se	z	p-value
ECONOMIC NEED				
Ration card=Yes	0.25^{***}	0.05	4.99	0.00
Savings=No	-0.34^{***}	0.03	-10.93	0.00
Electricity=No	0.39^{***}	0.05	7.37	0.00
Latrine=Common	-0.14	0.28	-0.50	0.61
Own/rent=RENTED	0.06	0.07	0.89	0.37
SOCIAL STATUS				
Caste=OBC	-0.52^{***}	0.03	-18.44	0.00
Size of House (N. rooms)	-0.13^{***}	0.01	-12.34	0.00
Mother tongue=KANNADA	-0.27^{***}	0.03	-8.09	0.00
Education=NONE	-0.01	0.03	-0.23	0.81
Constant	-0.67^{***}	0.12	-5.77	0.00
σ^2	0.46^{***}	0.09	4.84	0.00
Wald $\chi^2(9)$	986.49			
p-value	0.00			
N	43929			

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed tests)

Table 2. Hierarchical Logistic Model Predicting the Likelihood of Eligible Women Being Connected to Experimentally "Seeded" Influencers through Network Ties

	Connected to Influencers			
	β	se	z	p-value
ECONOMIC NEED				
Ration card=Yes	0.16	0.14	1.19	0.24
Savings=No	0.14	0.09	1.62	0.10
Electricity=No	-0.07	0.16	-0.42	0.67
Latrine=Common	0.34	0.73	0.47	0.64
Own/rent=RENTED	-0.23	0.22	-1.06	0.29
SOCIAL STATUS				
Caste=OBC	0.06	0.07	0.84	0.40
Size of House (N. rooms)	-0.02	0.02	-1.03	0.30
Mother tongue=KANNADA	0.04	0.10	0.40	0.69
Education=NONE	0.04	0.07	0.59	0.55
Constant	-4.35^{***}	0.21	-20.73	0.00
σ^2	0.54^{***}	0.13	4.09	0.00
Wald $\chi^2(9)$	7.54			
p-value	0.58			
N	43929			

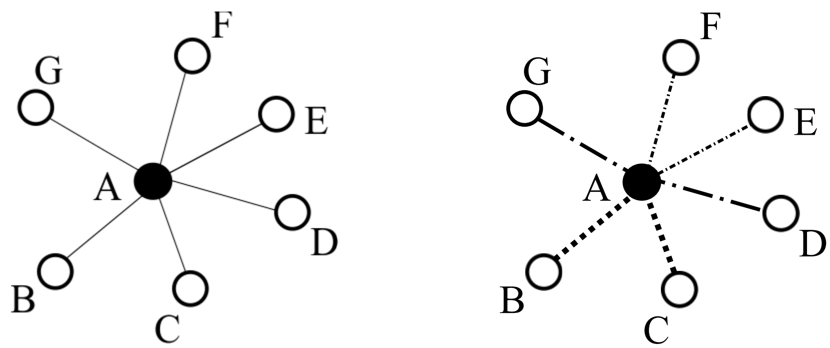
Note: Model includes constant. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed tests)

Table 3. Hierarchical Logistic Model Predicting the Likelihood of MF Adoption among Eligible Women as a Function of Contacts' Network Centrality and Role Complexity

	MF Adoption			
	β	se	z	p-value
SOCIAL INFLUENCE				
H1: Centrality	77.84***	11.57	6.73	0.00
Role Complexity	-0.04	0.03	-1.29	0.20
H2: Centrality x Role Complexity	-81.33***	19.26	-4.22	0.00
ECONOMIC NEED				
Ration card=Yes	0.24***	0.05	4.89	0.00
Savings=No	-0.34***	0.03	-11.00	0.00
Electricity=No	0.39***	0.05	7.38	0.00
Latrine=Common	-0.14	0.28	-0.48	0.63
Own/rent=RENTED	0.05	0.07	0.80	0.43
SOCIAL STATUS				
Caste=OBC	-0.52***	0.03	-18.34	0.00
Size of House (N. rooms)	-0.13***	0.01	-12.30	0.00
Mother tongue=KANNADA	-0.27***	0.03	-7.94	0.00
Education=NONE	-0.00	0.03	-0.16	0.87
Constant	-0.67***	0.12	-5.67	0.00
σ^2	0.46***	0.09	4.84	0.00
Wald $\chi^2(12)$	1027.11			
p-value	0.00			
N	43759			

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed tests)

Figure 1. Network Centrality and Role Complexity

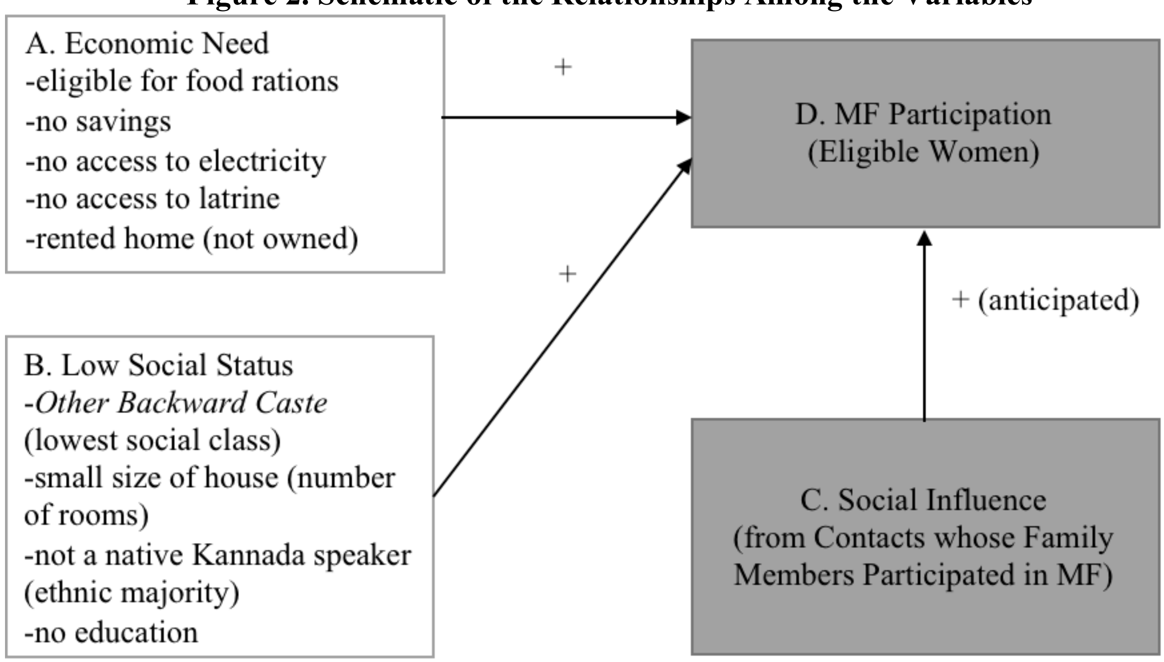


Network Centrality | Role Complexity

Set: {ab, ac, ad, ae, af, ag}
Role-relations: {1,1,1,1,1,1}

Type:	Set:	Role-relations:
friendship	{ab, ac}	{1,1,0,0,0,0}
exchange	{ag, ad}	{0,0,1,0,0,1}
kinship	{af, ae}	{0,0,0,1,1,0}

Figure 2. Schematic of the Relationships Among the Variables



APPENDIX

Table A1. Summary Statistics and Correlations Matrix

	Mean	Std. Dev.	*N*
MF Adoption	0.20	0.40	44031
Eigenvector Centrality	0.01	0.03	43860
Role Complexity	0.69	0.46	44031
Ration card=Yes	0.92	0.27	44031
Savings=No	0.79	0.41	44031
Electricity=No	0.05	0.22	44030
Latrine=Common	0.00	0.05	44031
Own/rent=RENTED	0.04	0.19	44031
Caste=OBC	0.57	0.49	43947
Size of House (N. rooms)	2.61	1.62	44031
Mother tongue=KANNADA	0.72	0.45	44014
Education=NONE	0.37	0.48	44031
Eigenvector Centrality (Money)	0.01	0.03	43967
Eigenvector Centrality (Goods)	0.01	0.03	43958
Eigenvector Centrality (Visits)	0.01	0.03	43971
Eigenvector Centrality (Social)	0.01	0.03	43948
Eigenvector Centrality (Religious)	0.01	0.03	43868
Eigenvector Centrality (Kinship)	0.01	0.03	43952
Eigenvector Centrality (Advice)	0.01	0.03	43958
Eigenvector Centrality (Medical)	0.01	0.03	43931

Correlations Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	MF Adoption (Woman)	1.00												
(2)	MF Adoption (Contact)	0.04	1.00											
		(0.00)												
(3)	Eigenvector Centrality	0.05	0.65	1.00										
		(0.00)	(0.00)											
(4)	Role Complexity	-0.01	0.05	0.01	1.00									
		(0.02)	(0.00)	(0.00)										
(5)	Ration card=Yes	0.02	0.01	-0.00	0.00	1.00								
		(0.00)	(0.07)	(0.72)	(0.97)									
(6)	Savings=No	-0.06	0.00	-0.00	-0.01	-0.00	1.00							
		(0.00)	(0.54)	(0.55)	(0.01)	(0.40)								
(7)	Electricity=No	0.06	0.01	0.01	-0.00	0.01	-0.01	1.00						
		(0.00)	(0.10)	(0.17)	(0.87)	(0.02)	(0.06)							
(8)	Latrine=Common	-0.00	0.00	0.01	-0.00	-0.02	0.01	-0.01	1.00					
		(0.74)	(0.62)	(0.29)	(0.70)	(0.00)	(0.03)	(0.02)						
(9)	Own/rent=RENTED	0.01	-0.00	0.01	-0.00	-0.07	0.01	0.07	0.10	1.00				
		(0.00)	(0.69)	(0.21)	(0.59)	(0.00)	(0.06)	(0.00)	(0.00)					
(10)	Caste=OBC	-0.10	-0.01	-0.01	-0.01	-0.03	0.02	-0.09	0.01	0.03	1.00			
		(0.00)	(0.03)	(0.02)	(0.07)	(0.00)	(0.00)	(0.00)	(0.15)	(0.00)				
(11)	Size of House (N. rooms)	-0.09	-0.02	-0.01	-0.04	-0.03	0.06	-0.13	-0.01	-0.09	0.14	1.00		
		(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)			
(12)	Mother tongue=KANNADA	-0.07	-0.02	-0.02	0.02	-0.00	-0.00	-0.02	-0.04	-0.06	0.08	0.12	1.00	
		(0.00)	(0.00)	(0.00)	(0.00)	(0.47)	(0.41)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
(13)	Education=NONE	0.04	0.01	0.01	-0.00	0.06	-0.13	0.09	-0.01	-0.00	-0.09	-0.15	-0.08	1.00
		(0.00)	(0.02)	(0.01)	(0.52)	(0.00)	(0.00)	(0.00)	(0.00)	(0.64)	(0.00)	(0.00)	(0.00)	

Table A2. Robustness Checks: Hierarchical Logistic Model Predicting Influencers' Role Complexity as a function of Influencers' Centrality, Economic Need, and Social Status

	Role Complexity	
	β	se
Eigenvector Centrality	3.434***	(0.861)
ECONOMIC NEED		
Ration card=Yes	-0.430**	(0.139)
Savings=No	0.027	(0.246)
Electricity=No	0.422	(0.418)
Latrine=Common	0.000	(.)
Own/rent=RENTED	-1.070	(0.813)
SOCIAL STATUS		
Caste=OBC	-0.116	(0.122)
Size of House (N. rooms)	-0.011	(0.027)
Mother tongue=KANNADA	-0.259	(0.165)
Education=NONE	-0.014	(0.128)
σ^2	0.090	(0.046)
Wald $\chi^2(9)$	34.65	
p-value	0.00	
N	1614	

Note: Standard errors in parentheses. Model includes constant.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed tests)