Matous, P., and Y. Todo. 2015. Exploring dynamic mechanisms of learning networks for resource conservation. *Ecology and Society* **20**(2): 36. http://dx.doi.org/10.5751/ES-07602-200236

Research

Exploring dynamic mechanisms of learning networks for resource conservation

Petr Matous[1,2] *and Yasuyuki Todo*[3]

ABSTRACT. The importance of networks for social-ecological processes has been recognized in the literature; however, existing studies have not sufficiently addressed the dynamic nature of networks. Using data on the social learning networks of 265 farmers in Ethiopia for 2011 and 2012 and stochastic actor-oriented modeling, we explain the mechanisms of network evolution and soil conservation. The farmers' preferences for information exchange within the same social groups support the creation of interactive, clustered, nonhierarchical structures within the evolving learning networks, which contributed to the diffusion of the practice of composting. The introduced methods can be applied to determine whether and how social networks can be used to facilitate environmental interventions in various contexts.

Key Words: *composting; Ethiopia; network dynamics; social learning; soil conservation; stochastic actor-oriented modeling*

INTRODUCTION

Studies of ecological and social interactions have highlighted the importance of social learning and the role of social networks in the adoption of resource-conserving practices (Solano et al. 2003, Hoang et al. 2006, Isaac et al. 2007, Atwell et al. 2008, Schneider et al. 2009, Cundill 2010, Bodin and Prell 2011*b*, Rodela 2011, Spielman et al. 2011, Isaac 2012, Matouš et al. 2013). However, little is known about the dynamic mechanism driving the emergence of relevant networks and the channels by which these networks may be used in achieving desired ecological outcomes.

The need to study the dynamic nature of socio-environmental systems has been clearly recognized but not addressed in the literature (Bodin and Prell 2011*a*, Frank 2011, Lubell et al. 2011). Although the number of relational studies on socio-environmental systems is increasing rapidly, almost all of these studies have used data from only one time point and methods that implicitly assume that the studied systems are stationary or in equilibrium conditions (see, for example, any of the quantitative network studies cited in this *Introduction*). Network evolution, if mentioned, has typically been treated in a metaphorical sense only, not explicitly measured and analyzed. This research gap has likely persisted because of the absence of longitudinal data on social networks in the context of environmental research and the complexity of analytical tools for evaluating such data.

This study aims to fill this research gap by exploring the dynamic interplay of social network evolution and the adoption of resource-conserving practices. This study was motivated by the problem of land degradation, which has been progressing in many areas, particularly in Ethiopia, because of the use of inappropriate agricultural practices (Bewket 2007, Deressa 2007, Mojo et al. 2010). Using data collected from an Ethiopian village and applying novel network analytical techniques, this study seeks to rigorously measure (1) the dynamic mechanism by which agricultural information-sharing networks are formed among the village inhabitants, and (2) the role of the network in the adoption of the practice of composting.

THE LIFE OF A NETWORK

It has been recognized that "not all social networks are created equal" (Sampson 2004, Bodin et al. 2006, Newman and Dale 2007, Bodin and Crona 2009). Different social networks have different structures with different implications for the governance of social-ecological systems. Importantly, social networks are never static, and the structural configuration in which they are observed at a given time is only a temporary outcome of their endless evolution. Social network creation is a process of continuous rearrangement of relationships by network members according to their constraints and preferences.

The process by which diverse macro network structures are created from microlevel preferences is highly complex and typically endogenous; i.e., the network structure influences its own evolution (Snijders 2001). Access to diverse social circles enables individuals and groups to gain valuable information (Burt 1995, Granovetter 1973, Erickson 2001, Lin 2001), but positions between different groups may be too demanding (Krackhardt and Hanson 1993). In some networks, actors may seek new partners who will facilitate indirect connections beyond their own clique, whereas in other contexts, actors may prefer to share information with only those who share information with them and their friends.

The combination of such microlevel preferences (i.e., the tendency to create and maintain ties, the tendency to reciprocate, the formation of triangles, and the tendency to connect different groups) determines the macrolevel structural attributes of social networks, such as density, hierarchy, clustering, or connectivity, which may have ecological implications that have been thoroughly reviewed in previous research (Newman and Dale 2005, Bodin et al. 2006, Janssen et al. 2006, Ernstson et al. 2008, Bodin and Crona 2009, Newig et al. 2010).

The process of change may also depend on static and dynamic attributes of the actors. Individuals who possess different socioeconomic attributes may have different levels of popularity and activity in forming their networks. Physical environment,

[1]University of Tokyo, [2]University of Sydney, [3]Waseda University

infrastructure, and technology may also shape social networks (Fotheringham 1981, Ellegård and Vilhelmson 2004, Knowles 2006, Ilahiane and Sherry 2012, Matous et al. 2013). Previous studies have suggested that newly available information-communication technologies may facilitate agricultural information-sharing ties, particularly in less-developed regions (Leeuwis and Van den Ban 2004, Donner 2008). Furthermore, homophily—i.e., the preference for interacting with similar actors—may also drive network evolution (McPherson et al. 2001). In some countries, agricultural and ecological learning networks form along ethnic and religious lines (Bandiera and Rasul 2006, Matouš et al. 2013).

Correctly identifying the presence of network effects on ecological outcomes is possible only after controlling for these complex endogenous and exogenous effects. The common claim that networks are important implies that the connections within these networks function as channels for exchange of relevant, tangible (e.g., money or water), or intangible (e.g., information or influence) resources. This assumption is difficult to empirically test in the case of intangible resources. If two friends practice conservation agriculture, it might not be because they influenced each other. Finding correlations between the activities of actors and the presence of a connection in cross-sectional studies does not imply a network effect. The two friends might have become friends after discovering that they have the same interests. Disentangling selection and influence in networks has been one of the greatest puzzles in social science (Aral and Walker 2012, Lewis et al. 2012).

The distinction between selection and influence may seem purely academic, but it also has potentially significant practical implications for the governance of natural resources. Where social learning effects or behavioral influences are confirmed, networks may be relied upon to disseminate ecological information or to facilitate behavioral interventions. Depending on the underlying network dynamics, one or more of four main network intervention strategies may be chosen (Valente 2012): (1) identification of key individuals for intervention targeting, (2) segmentation of the targeted population into groups, (3) induction; i.e., excitation of the existing network to catalyze desired interactions, and (4) alternation; i.e., rewiring of the network into a more effective structure. Conversely, if network selection is the main factor behind commonly observed correlations between practices and informal relational patterns, networks cannot be relied upon to disseminate such information, and costly direct formal institutional interventions across the entire population may be necessary.

Social diffusion processes were traditionally conceptualized analogically to the process by which a virus spreads, in which a single contact between two actors can lead to contagion (Rogers 2003, Centola and Macy 2007). For such diffusion processes, a centralized network structure with important hubs and long-bridging ties across distant and diverse parts of the network is most efficient (Granovetter 1973, Watts and Strogatz 1998, Barabási 2009). Such network structure of communities has been considered necessary for successful tackling of environmental and development challenges (Newman and Dale 2007). However, a single weak contact with an individual may not be sufficient to stimulate a necessary action or to cause a complex behavioral change (Centola and Macy 2007). Cliquish networks, in which friends of friends are also friends, may be more conducive to social learning, despite the limited reach of each tie, because actors are more likely to receive stimuli from multiple peers as the desired behavior diffuses through a network (Valente 1995, Centola et al. 2007, Centola 2010, Todo et al. 2013). Behavior may not transfer far from peer to peer through such localized communal networks, but once it reaches a certain critical mass in some parts of the network, the rate of adoption of that behavior will increase rapidly in those locations.

Previous research has suggested that to better understand the effects of complex dynamic processes on social networks, theoretical simulation should be conducted in addition to the ongoing static empirical studies (Bodin and Crona 2009). Owing to the recent advances in network modeling methods, conducting such dynamic analysis has become possible even on real networks, which we demonstrate.

LAND DEGRADATION AND COMPOSTING IN ETHIOPIA

Ethiopia is one of the most agrarian countries in the world, with approximately 80% of its population directly employed in agriculture (Central Statistical Agency 2004). The sector is dominated by small-scale subsistence farmers who cultivate 95% of Ethiopian crop land and account for 90% of national production (Deressa 2007). Despite the predominance of agriculture, the country is still dependent on food aid because of the use of inadequate farming practices and the progression of land degradation (Bewket 2007, Deressa 2007, Mojo et al. 2010, Van der Veen and Tagel 2011, Matouš et al. 2013).

Composting is currently one of the most frequently recommended practices to address the grave situation in Ethiopia, according to local agricultural experts. Compost is organic material, such as animal dung and crop residue, that has been fermented and decomposed as a fertilizer for soil amendment. Compost requires only renewable resources, promotes soil conservation, prevents soil erosion by wind and water, and conserves moisture. Its organic matter increases the fertility and nutrient-holding capacity of soil, which leads to higher crop production (Pender and Gebremedhin 2006). Whereas chemical fertilizers are expensive and difficult to acquire in rural regions that lack transportation infrastructure, animal dung is freely available because bullocks are commonly kept in Ethiopia for farming, meat, and milk. Moreover, compost has been found to bring greater increases in yields than chemical fertilizers in Ethiopia (Pender and Gebremedhin 2006).

Despite the benefits of composting, Ethiopian farmers have seemed reluctant to adopt the practice until recently. Animal dung has typically been considered a fuel rather than a fertilizer (Taddese 2001, Teketay 2001, Yevich and Logan 2003, Mekonnen and Köhlin 2008), particularly in areas with little access to firewood, such as the village in this study. Only approximately 25% of Ethiopian farmers were estimated to use compost in 2007 (Edwards et al. 2007). Therefore, agricultural experts in Ethiopia have been strongly recommending composting in recent years, and extension agents have been disseminating information about the practice. As a result, 98% of the farmers in the area of this study are aware of this soil conservation technique. However, most of the farmers (63%) were not interested in or capable of adopting the practice until 2011. One of the reasons may be that the process of optimal compost preparation under local conditions can be quite complex and difficult to learn without direct observation. Moreover, farmers may not be willing to change their established routines without confirming the benefits from peers whom they trust. Local agricultural extension agents teach composting in several steps. First, farmers should keep animal dung with other materials, such as animal feed leftovers or crop residue, in a hole in the ground to preserve optimal levels of humidity. These materials need to be mixed in specified proportions to achieve the optimal level of acidity. After three weeks, the materials should be transferred to another hole to allow them to react with oxygen. After another three weeks, the materials should be transferred to another hole. Local agricultural extension agents instruct farmers not to use meat, bones, fish scraps, oil, fatty materials, or dairy products as materials for compost and not to use isolated animal dung without mixing it with other appropriate materials.

Despite the complexity of composting and the initial skepticism of Ethiopian farmers toward the practice, composting has finally started to diffuse rapidly in the surveyed area. The proportion of compost users increased from 37% to 67% between 2011 and 2012, which makes the diffusion of composting an interesting success case to study.

METHODS

This analysis is based on two waves of a full network survey administered in February 2011 and February 2012 to 265 household heads in one village in Tiyo District, Ethiopia. A carefully trained team of enumerators visited each household and administered the survey questionnaires as fixed-form interviews. In addition to network questions, each interview included six pages of questions regarding the socioeconomic characteristics of the household and the household head, the owned assets of the household, the personality traits of the household head, and the agricultural production of the household. Many types of crops have been produced in the region, including wheat, barley, faba beans, maize, and potatoes, but local farmers and agricultural specialists perceive the soil quality to be degrading severely because of erosion (Mojo et al. 2010). Some farmers in the village are also involved in nonfarming activities; Wang et al. (2015) provide a cross-sectional analysis of the divergent networking strategies of these farmers. Table 1 presents the basic characteristics of the sample for the variables used in this study.

Table 1. Description of the sample.

Variable	Minimum	Maximum	Mean (Proportion)
Area of cultivated land (ha)	0.1	5.0	1.75
Education dummy (At least one year of formal education = 1; otherwise = 0)			57.4%
Religious minority dummy (Muslim = 1; Christian = 0)			17.7%
Information and communication technology dummy (Received a mobile phone from the research organizers = 1; otherwise = 0)			22.6%
Using compost in 2011			37.0%
Using compost in 2012			66.8%

To construct the learning networks between the households in the villages, all household heads were prompted to provide their sources of information as follows: “Sometimes farmers like to talk with other people to discuss farming practices, techniques, or technologies; ask for help; or observe other farmers’ practices. I will ask you now about such people. Please try to recall all people outside this household from whom you seek advice, from whom you can learn, or who can generally provide useful information about farming practices.” The respondents could name up to 20 individuals whose households were subsequently identified. These elicited networks were preserved in their directed form for the analysis. This approach enabled active information seekers to be distinguished from popular advisors nominated by many others. The former were respondents who named many information sources, conceptualized as having many outgoing ties (i.e., high outdegree) in the learning network, whereas the latter were those with many incoming ties. The direction of ties also enables unidirectional information flows to be distinguished from mutual knowledge sharing (Table 2).

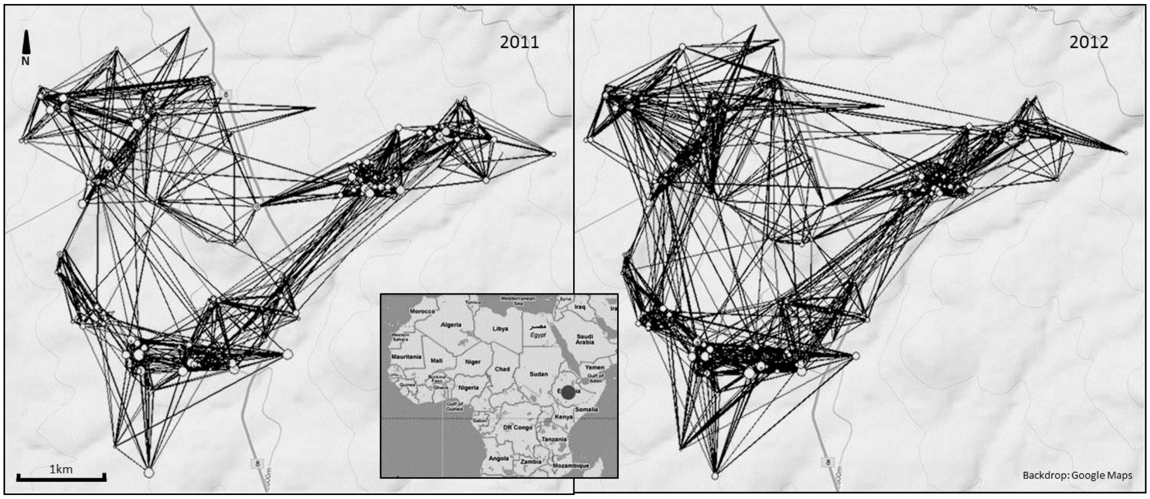
Table 2. Change in networks.

	2011	2012
Density	0.020	0.029
Average degree	5.2	7.6
Reciprocated ties	396	610
Unreciprocated ties	976	2596
Average clustering	0.13	0.15
Missing fraction	0%	3.8%

This study is a part of a larger research project that involved the donation of mobile phones to randomly selected household heads in several villages, including 60 households in this village. The main purpose of this randomized intervention was to exogenously induce a measurable change in the local social network structure in a controlled manner that could be causally attributed to this new information communication technology. The details of the intervention and the ways in which these new phones were used to share information and sentiments are described by Matous et al. (2014). In this study, this intervention enabled us to test whether this newly available communication technology in a remote rural area of a developing country can support social learning.

The dynamic network analysis was conducted through stochastic actor-oriented modeling (Snijders et al. 2007). The technical details of this method and relevant formulas and microlevel network mechanism diagrams are described in Appendix 1. As reviewed in *The Life of a Network*, actors have (not necessarily conscious) preferences regarding the type of people from whom they learn. These microlevel preferences are the building blocks of the changing shape of the entire network. The preferences may be structural; i.e., learning from a particular person may be influenced by learning from other people (a full list of the applied effects and their descriptions is provided in Appendix 1). In addition to such endogenous effects, the personal characteristics and practices of the actors may influence (1) the actors’ overall information-seeking activity (i.e., the number of information sources that a respondent names), (2) the advisors’ popularity (i.e., the number of people who name an individual as a source of information), and (3) the probability of a network tie due to homophily (i.e., the tendency to accept information from individuals with similar characteristics or practices). The farmers’ characteristics that are included in the models are education, religion, and amount of cultivated land.

Fig. 1. Learning networks in 2011 and 2012.



The test of these actors' learning preferences was conducted with the RSiena package in R, developed by Snijders and colleagues (Ripley et al. 2013). The program runs iterative simulations with varying weights of these effects (representing the strength of the actors' tendency to seek information in a way that the effect describes) and searches for combinations of these effects and their weights that recreate the observed evolution of the network. This method allows us to untangle the effects of selection and influence behind observed homophily in environmental behavior. Specifically, it is possible to distinguish whether farmers adopt practices of their advisors or select advisors with similar practices. The former would be evidence of social learning, whereas the latter would be evidence of the opposite; i.e., reluctance to learn from farmers who adopt new unusual practices.

RESULTS

Network density

On average, the farmers reported 5.2 and 7.6 other households in the village as their sources of agricultural information in the first and second survey, respectively (Table 2, Fig. 1). The increase may have resulted from the ongoing development of the area. Part of the increase in the number of elicited network partners might also be due to an increased interest of the local inhabitants in the survey. However, many network ties were also lost. Out of the 1384 ties reported in 2011, only 727 were named again the following year. This large difference in the two network measurements confirmed that learning networks are highly dynamic and that caution is necessary when working only with cross-sectional network data sets. In addition to real network changes, any social survey is subject to recall errors. Having two separate measurements on the same node set allowed us to clarify statistically what type of learning ties were perceived to be important because the ties were maintained, remembered, and named again. The results are displayed in Table 3.

Despite the overall increase in the network density, the significant negative outdegree effect indicated in Table 3 signifies that the farmers were not inclined to learn from other farmers unless other positive effects, such as having mutual friends who share information, were present. Farmers with access to few advisors were least likely to increase their learning activity (signified by the negatively significant truncated outdegree effect). This effect might be reinforced by the reciprocal and clustering tendencies reported in *Results: Clustering*. Farmers who did not contact their peers were less likely to be contacted by them and also by the peers of the peers, which further reduced the likelihood that marginalized individuals would become fully involved in the learning networks.

Hierarchy

We did not any find evidence of a hierarchy in social learning within the village. This result is in agreement with skeptics regarding traditional top-down knowledge transfer models of farmers' learning (Douthwaite et al. 2001, Leeuwis and Van den Ban 2004, Warner 2007, Spielman et al. 2009). Instead, the network was characterized by a flat structure with a tendency toward mutual learning and bidirectional interactions (signified by the significant positive reciprocity effect indicated in Table 3). The positive three-cycle effect means that providing information to the "advisors" of one's "advisors" was common, which signals a lack of hierarchy in information exchange and a preference for closed network structures, as discussed further in *Results: Clustering*.

Moreover, we did not find any tendency toward preferential attachment (i.e., learning from someone because others learn from that person) that would lead to high network centralization or the creation of high-degree hubs (i.e., extremely popular farmers connecting large parts of the network), which are characteristic of many other types of networks (Barabási and Albert 1999, Barabási 2009).

Clustering

The dominant network-forming principles seem to be clustering and disinterest in information from other cliques. To achieve a satisfactory fit of the simulations with the observed reality of network evolution, we needed to include three types of clustering effects (i.e., transitive ties, three-cycles, and double two-step paths) and a (negative) betweenness effect in the model. All these effects

Table 3. Dynamics of the network and the practice of composting.

Ecological learning network dynamics	Description	Parameter	Standard error	Significance level
Endogenous learning network effects				
Outdegree	Overall information-seeking activity	-1.90	0.31	***
Truncated outdegree	Information-seeking by less-connected farmers	-0.69	0.17	***
Reciprocity	Mutuality in information exchange	0.90	0.12	***
Three-cycles	Generalized reciprocity in information exchange	0.54	0.06	***
Transitive ties	Information network clustering	1.82	0.10	***
Betweenness	Information brokerage	-0.30	0.05	***
Double two-step paths	Avoiding unique information sources	0.18	0.10	**
Effects of individuals' attributes on learning networks				
Land				
•→	Information-seeking by farmers who cultivate large areas	0.21	0.06	***
→•	Preference for advisors who cultivate large areas	0.15	0.03	***
•→•	Preference for advisors with a similar amount of cultivated land	0.12	0.17	
Education				
•→	Information-seeking activity of educated farmers	0.37	0.15	**
→•	Preference for educated advisors	0.02	0.07	
•→•	Preference for advisors with a similar level of education	0.08	0.06	
Religion				
•→	Information-seeking activity by the Muslim minority	0.25	0.12	**
→•	Preference for advisors from by the Muslim minority	-0.27	0.10	***
•→•	Preference for advisors of the same religion	0.35	0.11	***
Effects of mobile phones on learning networks				
Information and communication technology				
•→	Information-seeking activity by those who received a mobile phone	0.53	0.12	***
→•	Preference for advisors who received a mobile phone	0.12	0.09	
•→•	Preference of phone owners toward owners and non-owners toward non-owners	0.01	0.07	
Effects of individuals' practices on learning networks				
Composting adoption				
•→	Information-seeking by farmers who practice composting	0.03	0.21	
→•	Preference for advisors who practice composting	0.06	0.15	
•→•	Preference for advisors with the same practices	0.24	0.25	
Conservation practice diffusion				
Effects of the learning network on individuals' practices				
	Baseline increase in composting	0.66	0.27	**
	Inclination toward advisors' practices	2.04	0.88	**
Learning network macro-level characteristics (The goodness of fit of the model)		Mahalanobis distance p value †		
Indegree distribution	Distribution of the information-seeking activity among farmers	0.60		
Outdegree distribution	Distribution of popularity among advisors	0.58		
Geodesic distance distribution	Learning network connectivity	0.19		

† p value for Mahalanobis distance above 0.1 indicates acceptable fit between the simulations and the observed networks.
*p = 0.1, **p = 0.05, ***p = 0.01
•→ ego effect, →•alter effect, •→• homophily effect

were significant. The actors had a strong tendency toward forming closed triangles in their personal networks and avoiding open triangles, as indicated by positively significant transitive ties, three-cycles, and the number of other actors accessed in two steps by two paths. These results indicate that the farmers preferred to exchange information with peers who also exchanged information with their other information partners and to avoid individuals who reached outside these clusters. Moreover, despite the theory that such positions provide an instrumental advantage (Burt 1995), the actors actively avoided positions between groups of information exchange (signified by the negative betweenness effect). Avoidance of bridging positions combined with clustering tendencies lead to cliquish network structures with decreased connectivity. The resulting local clustering coefficients averaged for the entire (undirected) learning networks are displayed in Table 2. The coefficients were almost three times higher than what would be expected by chance.

After network clustering had been accounted for, including straight geographical distance did not improve the fit of the model. Whereas straight distance did not seem to be an optimal indicator of informal information flows within the village, Wang et al. (2015) showed that the hamlet, or physical cluster of households, to which a family belonged was consequential. Nevertheless, the farmers may seek information from people several kilometers away on the other side of the village (Fig. 1) if they have some learning partners in common. The finding that learning inside Ethiopian villages may reach somewhat further than other everyday activities which are mostly extremely geographically constrained is consistent with findings from other villages in the region (Matous et al. 2013) and analysis of the call patterns with the donated mobile phones (Matous et al. 2014).

Homophily

The results remind us that network homophily is not omnipresent. We did not find any effects of homophily in terms of the size of cultivated land or education. Wealthier farmers with larger lands were more active information seekers and were more popular as advisors. People with formal education had higher curiosity, but interestingly, were not particularly sought out for information.

Homophily was evident only in terms of religion. The residents preferred to learn agricultural practices from peers of the same religious affiliation. This homophilous tendency contributed to the high density of ties within social groups and the lower density of ties between groups. An unequal position of the Muslim minority in this village network was apparent. Although Muslims nominated more people as their partners in the learning networks, they were less likely to be named by others (depicted by the positive information-seeking and negative advisor effects in Table 3).

Communication technologies

The farmers who received donated mobile phones showed higher information-seeking activity but were not more popular as advisors. We did not detect a specific increase in ties within the treatment and control groups (an insignificant homophily effect), suggesting that artificialities introduced by the organization of the experiment, such as summoning the treatment group farmers, did not drive the increase in activity. However, the possibility that the beneficiaries of the intervention became relatively more cooperative during the study and consequently started to volunteer more names in their interviews was impossible to test or, therefore, reject. Nevertheless, such a bias would not confound other relevant variables because the intervention was randomized.

Selection versus influence

When we controlled for the endogenous network evolution processes and homophily in terms of farmers' religion, we did not find evidence of selection of network partners based on their practices. Adopters of composting did not seem to prefer learning from fellow composters. Those who had not adopted composting did not avoid those who had. In addition, the adopters' levels of activity and popularity in the learning exchanges were similar to those of farmers who did not compost. Table 3 shows that none of the three effects quantifying the impact of composting adoption on the learning network were significant. Conversely, we found evidence of behavioral influence spreading through the learning network. Farmers seemed more inclined to adopt and continue composting if most farmers in their reference group composted. This finding statistically proves the importance of networks for the adoption of an environmental conservation practice. Presumably, some farmers needed to see how the new complex practice worked for multiple peers before changing their habits. When individual action depends on the perception of the number of individuals who adopt a practice, the diffusion process is slow until a "critical mass" is reached, and then is rapid afterward (Rogers 2003). The observed period in this study was apparently the rapid take-off in adoption after many years of slow diffusion. However, this finding should not be generalized to other cases without conducting appropriate analysis. Even for the same village and the same environmental issue, a network may have different functions or no function at all. In the present case, the function of networks was different in terms of information and behavior diffusion. Although the adoption of the practice of composting was found to be mediated through the informal farmer-to-farmer networks, 93% of the farmers reported that they gained their original knowledge of composting from official sources, specifically from agricultural extension agents operating in the area.

CONCLUSIONS AND POLICY IMPLICATIONS

The results of this research remind us of the limits of studies that implicitly assume social networks to be in equilibrium or that rely on a single observation as if no recall bias occurs in the elicitation of the social network. Even in a village with almost no population change, social networks can be highly dynamic. Despite this network volatility and the likely measurement errors inherent in all social surveys, systematic tendencies in the selection of network partners could be observed.

The implications of the uncovered network mechanisms for the promotion of conservation practices in terms of possible network intervention strategies (Valente 2012) are as follows:

First, although the identification of the most central individuals in a network is apparently the most popular strategy for network interventions (Rogers 2003, Valente 2012), it is unlikely to be the most effective strategy in contexts similar to that of the surveyed village. The way in which farmers share their experiences with each other creates decentralized learning networks comprising cliques characterized by flat structures and a lack of individuals whose influence spans across social divides. In these types of networks, the highest-degree individuals might be connected to each other in the same large, dense cluster. Moreover, for the type of diffusion mechanism identified in the present context (i.e., farmers prefer practices that most of their contacts use), it may be more difficult to persuade the better-connected individuals to change. In the early stages of new practice diffusion, high-degree individuals will have many links to other individuals who have not adopted the recommended techniques, which may render strongly locally embedded farmers more hesitant to follow external experts' advice. Such behavior of high-degree individuals has been directly observed in three other Ethiopian villages (Matouš et al. 2013). In the initial stages of field trainings, focusing on the most progressive individuals who may be identified by their other practices rather than seeking socially influential individuals, may be more effective to galvanize the process of reaching a critical mass.

Further resource conservation can be reinforced by sharing positive experiences within groups. However, common segmentation approaches in which the population is divided by external officials into target "communities" based on administrative boundaries may not reflect the ever-changing local social structures. Allowing the selected farmers to invite their friends to a demonstration on their field may be a more sensitive and effective approach. The studied village is not one homogenous community, and the farmers seem to pay little attention to information from other cliques. Therefore, educational programs should support individuals selected from across all social groups and religious affiliations and individuals on the margin of community networks.

Because of the uncovered mechanisms of network dynamics such as reciprocity and generalized reciprocity, any impetus that helps farmers overcome their reluctance to reach out and learn from others may trigger a self-reinforcing increase in knowledge-sharing through network induction. In the studied case, the experience of formal school-based education and the provision of communication technologies seemed to stimulate curiosity and information-seeking about farming practices, which may be amplified through the changing networks.

Finally, alternation of the links in a network is the only network intervention strategy that explicitly considers changes in the network structure. However, the present analysis illustrates why controlled network rewiring may be problematic. Indeed, forcing farmers to develop relationships with members of different factions or strangers to promote a certain practice might not be a realistic approach, particularly if developing such relationships goes against their innate experience-sharing habits. Moreover, when external agents attempt to mend the fragmented local social structures, the typical focus of network interventions on central individuals might not be always helpful from the viewpoint of improving network connectivity either. Depending on the context, central individuals of different factions may be more reluctant to cooperate with each other than individuals on the periphery (Krackhardt and Hanson 1993). Conversely, the lack of evidence that farming practices affect the structure of social learning networks, specifically the lack of homophily in terms of soil conservation, is promising. Farmers who have not yet adopted a conservation practice are not locked into their separate networks; rather, they have opportunities to learn from others, which is a necessary condition for educational programs that rely on social networks.

In conclusion, this study shows the importance of informal networks for the diffusion of conservation practices. However, social networks should not be assumed to always constitute the optimal learning medium a priori. Depending on the context, the network type, and the environmental issue in focus, network contagion may or may not arise. This finding has policy implications. For example, in the present case, extension agents were able to directly raise individual farmers' awareness of composting faster than information diffusion through the cliquish farmer-to-farmer learning network; however, informal sharing among peers regarding experiences with the practice contributed to the actual change in farmers' habits. By conducting a rigorous evaluation using appropriate methods, future research may identify the contexts in which social learning and network-based dissemination are suitable for environmental information and practices. For other contexts, catering to everyone in the targeted population directly may be more suitable.

Responses to this article can be read online at:
http://www.ecologyandsociety.org/issues/responses.php/7602

Acknowledgments:

The authors would like to thank to Dagne Mojo for overseeing the data gathering and the Ministry of Education, Culture, Sports, Science and Technology (Japan) for funding it.

LITERATURE CITED

Aral, S., and D. Walker. 2012. Identifying influential and susceptible members of social networks. *Science* 337(6092):337–341. http://dx.doi.org/10.1126/science.1215842

Atwell, R. C., L. A. Schulte, and L. M. Westphal. 2008. Linking resilience theory and diffusion of innovations theory to understand the potential for perennials in the U.S. Corn Belt. *Ecology and Society* 14(1):30. [online] URL: http://www.ecologyandsociety.org/vol14/iss1/art30/

Bandiera, O., and I. Rasul. 2006. Social networks and technology adoption in Northern Mozambique. *The Economic Journal* 116 (514):869–902. http://dx.doi.org/10.1111/j.1468-0297.2006.01115.x

Barabási, A.-L. 2009. Scale-free networks: a decade and beyond. *Science* 325(5939):412–413. http://dx.doi.org/10.1126/science.1173299

Barabási, A.-L., and R. Albert. 1999. Emergence of scaling in random networks. *Science* 286(5439):509–512. http://dx.doi.org/10.1126/science.286.5439.509

Bewket, W. 2007. Soil and water conservation intervention with conventional technologies in northwestern highlands of Ethiopia: acceptance and adoption by farmers. *Land Use Policy* 24(2):404–416. http://dx.doi.org/10.1016/j.landusepol.2006.05.004

Bodin, Ö., and B. I. Crona. 2009. The role of social networks in natural resource governance: What relational patterns make a difference? *Global Environmental Change* 19(3):366–374. http://dx.doi.org/10.1016/j.gloenvcha.2009.05.002

Bodin, Ö., B. Crona, and H. Ernstson. 2006. Social networks in natural resource management: What is there to learn from a structural perspective? *Ecology and Society* 11(2). [online] URL: http://www.ecologyandsociety.org/vol11/iss2/resp2/

Bodin, Ö., and C. Prell. 2011*a*. Social network analysis in natural resource governance—summary and outlook. Pages 347–373 *in* Ö. Bodin and C. Prell, editors. *Social networks and natural resource management: uncovering the fabric of environmental governance*. Cambridge University Press, Cambridge, Massachusetts, USA. http://dx.doi.org/10.1017/CBO9780511894985.015

Bodin, Ö., and C. Prell, editors. 2011*b*. *Social networks in natural resource management: uncovering the fabric of environmental governance*. Cambridge University Press, Cambridge, Massachusetts, USA. http://dx.doi.org/10.1017/CBO9780511894985

Burt, R. S. 1995. *Structural holes: the social structure of competition*. Harvard University Press, Cambridge, Massachusetts, USA.

Centola, D. 2010. The spread of behavior in an online social network experiment. *Science* 329(5996):1194–1197. http://dx.doi.org/10.1126/science.1185231

Centola, D., V. M. Eguíluz, and M. W. Macy. 2007. Cascade dynamics of complex propagation. *Physica A: Statistical Mechanics and its Applications* 374(1):449–456. http://dx.doi.org/10.1016/j.physa.2006.06.018

Centola, D., and M. W. Macy. 2007. Complex contagions and the weakness of long ties. *American Journal of Sociology* 113(3):702–734. http://dx.doi.org/10.1086/521848

Central Statistical Agency. 2004. *The Federal Democratic Republic of Ethiopia statistical abstract for 2003*. CSA, Addis Ababa, Ethiopia.

Cundill, G. 2010. Monitoring social learning processes in adaptive comanagement: three case studies from South Africa. *Ecology and Society* 15(3):28. [online] URL: http://www.ecologyandsociety.org/vol15/iss3/art28/

Deressa, T. T. 2007. *Measuring the economic impact of the climate change on Ethiopian agriculture: Ricardian approach*. World Bank, Washington, D.C., USA. http://dx.doi.org/10.1596/1813-9450-4342

Donner, J. 2008. Research approaches to mobile use in the developing world: a review of the literature. *Information Society* 24(3):140–159. http://dx.doi.org/10.1080/01972240802019970

Douthwaite, B., J. D. H. Keatinge, and J. R. Park. 2001. Why promising technologies fail: the neglected role of user innovation during adoption. *Research Policy* 30(5):819–836. http://dx.doi.org/10.1016/s0048-7333(00)00124-4

Edwards, S., A. Asmelash, H. Araya, and T. B. G. Egziabher. 2007. *Impact of compost on crop yields in Tigray, Ethiopia*. Food and Agricultural Organization of the United Nations, Rome, Italy.

Ellegård, K., and B. Vilhelmson. 2004. Home as a pocket of local order: everyday activities and the friction of distance. *Geografiska Annaler: Series B, Human Geography* 86(4):281–296. http://dx.doi.org/10.1111/j.0435-3684.2004.00168.x

Erickson, B., editor. 2001. *Good networks and good jobs: the value of social capital to employers and employees*. Aldine de Gruyter, New York, USA.

Ernstson, H., S. Sörlin, and T. Elmqvist. 2008. Social movements and ecosystem services—the role of social network structure in protecting and managing urban green areas in Stockholm. *Ecology and Society* 13(2):39. [online] URL: http://www.ecologyandsociety.org/vol13/iss2/art39/

Fotheringham, A. S. 1981. Spatial structure and distance–decay parameters. *Annals of the Association of American Geographers* 71(3):425–436.

Frank, K. A. 2011. Social network models for natural resource use and extraction. Pages 180–205 *in* Ö. Bodin and C. Prell, editors. *Social networks and natural resource management: uncovering the fabric of environmental governance.* Cambridge University Press, Cambridge, Massachusetts, USA. http://dx.doi.org/10.1017/cbo9780511894985.009

Granovetter, M. 1973. The strength of weak ties. *American Journal of Sociology* 78(6):1360–1380. http://dx.doi.org/10.1086/225469

Hoang, L. A., J.-C. Castella, and P. Novosad. 2006. Social networks and information access: implications for agricultural extension in a rice farming community in northern Vietnam. *Agriculture and Human Values* 23(4):513–527. http://dx.doi.org/10.1007/s10460-006-9013-5

Ilahiane, H., and J. W. Sherry. 2012. The problematics of the “Bottom of the Pyramid” approach to international development: the case of micro-entrepreneurs’ use of mobile phones in Morocco. *Information Technologies and International Development* 8(1):13–26.

Isaac, M. E. 2012. Agricultural information exchange and organizational ties: the effect of network topology on managing agrodiversity. *Agricultural Systems* 109:9–15. http://dx.doi.org/10.1016/j.agsy.2012.01.011

Isaac, M. E., B. Erickson, J. Quashie-Sam, and V. R. Timmer. 2007. Transfer of knowledge on agroforestry management practices: structure of informal social networks. *Ecology and Society* 12(2):32. [online] URL: http://www.ecologyandsociety.org/vol12/iss2/art32/

Janssen, M. A., Ö. Bodin, J. M. Anderies, T. Elmqvist, H. Ernstson, R. R. J. McAllister, P. Olsson, and P. Ryan. 2006. Toward a network perspective of the study of resilience in social–ecological systems. *Ecology and Society* 11(1):15. [online] URL: http://www.ecologyandsociety.org/vol11/iss1/art15/

Knowles, R. D. 2006. Transport shaping space: differential collapse in time–space. *Journal of Transport Geography* 14(6):407–425. http://dx.doi.org/10.1016/j.jtrangeo.2006.07.001

Krackhardt, D., and J. R. Hanson. 1993. Informal networks. *Harvard Business Review* 71(1993):104–111.

Leeuwis, C., and A. Van den Ban. 2004. *Communication for rural innovation: rethinking agricultural extension*. Third edition. Blackwell Publishing Ltd. http://dx.doi.org/10.1002/9780470995235

Lewis, K., M. Gonzalez, and J. Kaufman. 2012. Social selection and peer influence in an online social network. *Proceedings of the National Academy of Sciences of the United States of America* 109(1):68–72. http://dx.doi.org/10.1073/pnas.1109739109

Lin, N. 2001. *Social capital: a theory of social structure and action*. Cambridge University Press, Cambridge, Massachusetts, USA. http://dx.doi.org/10.1017/cbo9780511815447

Lubell, M., V. Hillis, and M. Hoffman. 2011. Innovation, cooperation, and the perceived benefits and costs of sustainable agriculture practices. *Ecology and Society* 16(4):23. http://dx.doi.org/10.5751/es-04389-160423

Matous, P., Y. Todo, and T. Ishikawa. 2014. Emergence of multiplex mobile phone communication networks across rural areas: an Ethiopian experiment. *Network Science* 2(02):162–188. http://dx.doi.org/10.1017/nws.2014.12

Matous, P., Y. Todo, and D. Mojo. 2013*a*. Boots are made for walking: interactions across physical and social space in infrastructure-poor regions. *Journal of Transport Geography* 31:226–235. http://dx.doi.org/10.1016/j.jtrangeo.2013.04.001

Matouš, P., Y. Todo, and D. Mojo. 2013*b*. Roles of extension and ethno-religious networks in acceptance of resource-conserving agriculture among Ethiopian farmers. *International Journal of Agricultural Sustainability* 11(4):301–316. http://dx.doi.org/10.1080/14735903.2012.751701

McPherson, M., L. Smith-Lovin, and J. M. Cook. 2001. Birds of a feather: homophily in social networks. *Annual Review of Sociology* 27:415–444. http://dx.doi.org/10.1146/annurev.soc.27.1.415

Mekonnen, A., and G. Köhlin. 2008. *Biomass fuel consumption and dung use as manure: evidence from rural households in the Amhara region of Ethiopia*. Environment for Development, Addis Ababa, Ethiopia.

Mojo, D., Y. Todo, and P. Matous. 2010. Perception of farmers and agricultural professionals on changes in productivity and water resources in Ethiopia. *World Academy of Science, Engineering and Technology* 1(66):860–868.

Newig, J., D. Günther, and C. Pahl-Wostl. 2010. Synapses in the network: learning in governance networks in the context of environmental management. *Ecology and Society* 15(4):24. [online] URL: http://www.ecologyandsociety.org/vol15/iss4/art24/

Newman, L. L., and A. Dale. 2005. Network structure, diversity, and proactive resilience building: a response to Tompkins and Adger. *Ecology and Society* 10(1)r2. [online] URL: http://www.ecologyandsociety.org/vol10/iss1/resp2/

Newman, L., and A. Dale. 2007. Homophily and agency: creating effective sustainable development networks. *Environment, Development and Sustainability* 9(1):79–90. http://dx.doi.org/10.1007/s10668-005-9004-5

Pender, J., and B. Gebremedhin. 2006. Land management, crop production, and household income in the highlands of Tigray, Northern Ethiopia: an econometric analysis. *In* J. Pender, F. Place, and S. Ehui, editors. *Strategies for sustainable land management in the East African highlands*. International Food Policy Research Institute, Washington, D.C. USA.

Ripley, R., T. A. B. Snijders, Z. Boda, A. Voros, and P. Preciado. 2013. *Manual for RSiena*. University of Oxford, Oxford, UK.

Rodela, R. 2011. Social learning and natural resource management: the emergence of three research perspectives. *Ecology and Society* 16(4):30. http://dx.doi.org/10.5751/es-04554-160430

Rogers, E. M. 2003. *Diffusion of innovations*. Five edition. Free Press, New York, USA.

Sampson, R. J. 2004. Networks and neighbourhoods. Pages 157–166 *in* H. McCarthy, P. Miller, and P. Skidmore, editors. *Network logic: who governs in an interconnected world?* Demos, London, UK.

Schneider, F., P. Fry, T. Ledermann, and S. Rist. 2009. Social learning processes in Swiss soil protection—the ‘From Farmer to Farmer’ project. *Human Ecology* 37(4):475–489. http://dx.doi.org/10.1007/s10745-009-9262-1

Snijders, T. A. B. 2001. The statistical evaluation of social network dynamics. *Sociological Methodology* 31(1):361–395. http://dx.doi.org/10.1111/0081-1750.00099

Snijders, T. A. B., C. E. G. Steglich, and M. Schweinberger. 2007. Modeling the co-evolution of networks and behavior. Pages 41–71 *in* K. van Montfort, J. H. L. Oud, and A. Satorra, editors. Longitudinal models in the behavioral and related sciences. Lawrence Erlbaum, New Jersey, USA.

Solano, C., H. León, E. Pérez, and M. Herrero. 2003. The role of personal information sources on the decision-making process of Costa Rican dairy farmers. *Agricultural Systems* 76(1):3–18. http://dx.doi.org/10.1016/s0308-521x(02)00074-4

Spielman, D., K. Davis, M. Negash, and G. Ayele. 2011. Rural innovation systems and networks: findings from a study of Ethiopian smallholders. *Agriculture and Human Values* 28 (2):195–212. http://dx.doi.org/10.1007/s10460-010-9273-y

Spielman, D. J., J. Ekboir, and K. Davis. 2009. The art and science of innovation systems inquiry: applications to Sub-Saharan African agriculture. *Technology in Society* 31(4):399–405. http://dx.doi.org/10.1016/j.techsoc.2009.10.004

Taddese, G. 2001. Land degradation: a challenge to Ethiopia. *Environmental Management* 27(6):815–824. http://dx.doi.org/10.1007/s002670010190

Teketay, D. 2001. Deforestation, wood famine, and environmental degradation in Ethiopia's highland ecosystems: urgent need for action. *Northeast African Studies* 8(1):53–76. http://dx.doi.org/10.1353/nas.2005.0020

Todo, Y., P. Matous, and D. Mojo. 2013. Effects of social network structure on diffusion and adoption of agricultural technology: evidence from rural Ethiopia. *Centre for Study of African Economies Conference 2013*. University of Oxford, Oxford, UK.

Valente, T. W. 1995. *Network models of the diffusion of innovations*. Hampton Press Inc., New Jersey, USA.

Valente, T. W. 2012. Network interventions. *Science* 337 (6090):49–53. http://dx.doi.org/10.1126/science.1217330

Van der Veen, A., and G. Tagel. 2011. Effect of policy interventions on food security in Tigray, Northern Ethiopia. *Ecology and Society* 16(1):18. [online] URL: http://www.ecologyandsociety.org/vol16/iss1/art18/

Wang, P., G. Robins, and P. Matous. 2015. Multilevel network analysis using ERGM and its extensions. *In* E. Lazega, E. and T. Snijders, editors. *Multilevel network analysis*. Springer, Berlin, Germany.

Warner, K. D. 2007. *Agroecology in action*. MIT Press, Cambridge, Massachusetts, USA.

Watts, D. J., and S. H. Strogatz. 1998. Collective dynamics of ‘small-world’ networks. *Nature* 393(6684):440–442.

Yevich, R., and J. A. Logan. 2003. An assessment of biofuel use and burning of agricultural waste in the developing world. *Global Biogeochemical Cycles* 17(4):1–40. http://dx.doi.org/10.1029/2002gb001952

Appendix 1. Stochastic Actor-Oriented Simulation

We use stochastic actor-oriented modeling to simulate the observed evolution of networks and composting adoption, accounting for normative network processes and individual characteristics (Snijders et al. 2010). The simulation is conditioned on the first observation and tests hypothetical drivers of the evolution of networks and practice adoption observed in the following period. The model assumes a continuous Markov evolution of the network and decomposes the observed changes into the smallest possible components, i.e., modifications of one tie or one person's practice at each time step between observations.

Between the observations, each actor receives several chances in a random order to change one of her outgoing ties or practices. The model includes "rate effects", which regulate how often actors receive an opportunity to modify their outgoing ties or practices. These opportunities depend on the amount of changes observed within the period. Only one actor acts at a time, and coordination is not allowed.

Each actor's decision constitutes the social context in which she is embedded, and she chooses the next move to myopically maximize her utility. Utility levels derived from the ego network and the selected practice are expressed, as in generalized linear models, as a combination of hypothetically relevant features. In the simplest form, the utility can be expressed as $f_i(\beta, x) = \sum_k \beta_k s_{ki}(x)$. For network evolution, the utility function quantifies the desirability of each possible next state of the network *x* among the fixed set of actors from the viewpoint of actor i. A Gumbel-distributed random component with a variance of $\pi^2/6$ is added to the evaluation function. This addition is made to respect the stochastic character of network evolution, which results from measurement errors and influences unrepresented by nodal or dyadic variables. Thus, the actor does not necessarily choose the state with the highest utility, but such a choice is most likely. When an actor has an opportunity to modify her network, her options are creating one new tie, deleting one existing tie, or doing nothing. When an actor has an opportunity to change her practice, which, in our case, is described by a dichotomous variable (1 = practice composting; 0 = otherwise), the actor can chose to toggle the state or stay the same. Separate utility functions are evaluated for actors' network and practice choices.

Each effect s_{ki} in the model corresponds to possible reasons why an actor might want to change a tie or a practice. These effects indicate the actors' (not necessarily conscious) preferences for optimizing their information networks; they may be related to the preferred structure of ties of the actor, the personal characteristics of the actor, the characteristics of potential advisors, and the pairwise characteristics of relationships with advisors. Behavioral effects may reflect tendencies such as a preference for the practices of alters.

The goal of the simulation is to estimate the relative weights β_k for the statistics s_{ki}. Obtained parameters can be used to compare how attractive various tie or practice changes are to the actors, while controlling for other exogenous and endogenous effects. The signs of β_k indicate the preferred directions of network or practice change, and their relative magnitudes can be interpreted similarly to parameters of multinomial logistic regression models, in terms of the log-probabilities of changes among which the actors can choose.

The simulation was executed in SIENA package version 4 in R (Ripley et al. 2012). The method of moments, which depends on thousands of iterative computer simulations of the change process (Snijders 2001), is used to estimate the parameters β_k that enable the reproduction of the observed networks. There is one target statistic for each estimated effect (for example, the number of ties in the network corresponds to the outdegree effect, the number of reciprocated ties correspondents to the reciprocity effect, the number of feed forward loops corresponds to the transitivity effect, and the amount of change in network corresponds to the rate function). The presented model converged with T-ratios, quantifying the deviations between the simulated and the observed values of the target statistics, between -0.1 and 0.1, which signals an excellent model convergence (Ripley et al. 2012). In the final stage of the simulation, the standard errors of the estimated parameters are computed by the finite difference method, based on the sensitivity of the target statistics to β_k.

Goodness of fit and model selection

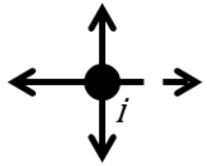
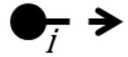
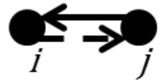
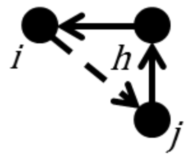
In addition to the convergence tests, we apply the following two approaches to guide the model selection and test the goodness of fit: (1) a generalized Neyman-Rao score-type test for each covariate proposed by Schweinberger (2012); and (2) a test of the fit of the simulated networks in terms of the fundamental network characteristics that are not directly estimated in the simulations (Ripley et al. 2012).

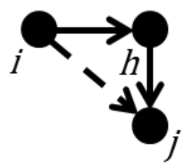
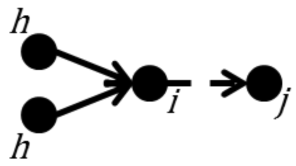
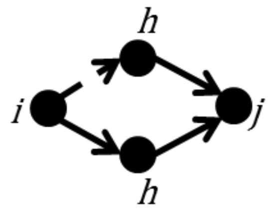
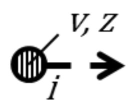
These methods are applied in combination with a forward model selection approach, starting with a trivial model including only the outdegree (the tendency to create and maintain ties) and reciprocity effects (the preference to link to alters who link to ego). Covariates are then gradually added. In each cycle of this iterative process, the values of newly included effects are first restricted to zero. The score-type test proceeds by estimating the restricted model, testing whether the restrictions increase deviations of the target statistics from the observed values. Low p-values on this test indicate that the goodness of fit of the restricted model is intolerable, and thus the tested effects should be included in unrestricted form.

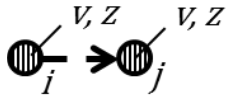
For every new specification, we test the model's goodness of fit by examining the simulated networks' fundamental characteristics that are not directly estimated by the methods of moments. We focus on the following three important properties of graphs: (1) indegree distribution; (2) outdegree distribution; and (3) geodesic distance distribution. Analogically to Wang et.al. (2009), we measure the Mahalanobis distance (Mahalanobis 1936) to quantify how far the simulated networks are from the actual observations and employ a Monte Carlo test based on this distance to compute frequentist p-values for each of the four fundamental graph parameters (Lospinoso and Snijders 2011). The whole process was repeated until a well-converged model with high p-values for the Mahalanobis distance-based tests was obtained.

During the model selection, we gradually tested the contribution of physical and social proximity, as well as the ego, alter, and behavioral characteristics to the goodness of fit. We considered the potential effects of actors' covariates on (1) the ego's overall tendency to create and maintain learning ties, (2) the alter's overall popularity as an advisor, and (3) the dyadic effect of selecting people who are similar in respect to the covariate.

Formulas for $s_{ki}(x)$ selection effects in network x for ego i and alters j, other actors h, actors' attributes v, and actors' practices z. Arrows point from information seekers to information providers; dashed arrows signify learning relationships that are likely to be created and maintained if the effect is positive.

Effect name [Represented information-network feature]	Underlying social learning tendency	Mathematical formula	Graphical representation
Endogenous learning network effects			
Outdegree [Information-seeking activity; network density]	The basic tendency to create and maintain learning relationships	$\sum_j x_{ij}$	
Truncated outdegree [Information-seeking differentials]	The information-seeking activity of less-connected individuals	$min(x_{i+}, c); c = 8$	
Reciprocity [Mutual information exchange]	Sharing information with individuals who share information with me	$\sum_j x_{ij}x_{ji}$	
Three-cycles [Generalized reciprocity in information exchange; closed information circulation]	Sharing information with individuals who share information with someone from whom I can learn	$\sum_j x_{ij}x_{jh}x_{hi}$	

Transitive ties [Information network clustering]	Seeking information from individuals who already provide information to someone from whom I learn; this behavior creates cliquish learning networks	$\sum_j x_{ij} max_h (x_{ih}x_{hj})$	
Betweenness [Information brokerage]	Aiming to position myself into brokerage positions, bridging otherwise unconnected others; seeking information from those to whom my followers do not have access increases the overall connectivity of the learning network	$\sum_j x_{ij}x_{jh}x_{hi}$	
Double two-step paths [Group formation]	Preferring individuals who do not get information from unknown information sources	$\#\{j \mid x_{ij} = 0, \sum_h x_{ij} (x_{ih}x_{hj}) \geq 2\}$	
Effects of individuals' attributes v and practices z on learning networks			
Ego attribute or practice [a]	A tendency of actors with certain characteristics or environmental practices to seek information	$\sum_j x_{ij}v_i$	
Alter attribute or practice [a]	The popularity of actors with certain characteristics or practices as advisors	$\sum_j x_{ij}v_j$	

Pairwise relational effects on learning networks			
Matching on attributes [a] [Information network homophily]	Learning from individuals with the same characteristics or practices	$\sum_j x_{ij} I\{v_{i=}v_j\}$ $\begin{cases} I\{v_{i=}v_j\} = 1 \\ 0 \end{cases}$	
Similarity in attributes [b] [Information network homophily]	Learning from individuals with similar characteristics	$\sum_j x_{ij}(sim_{ij}^{v} - \overline{sim^{v}})$	
Effects of the learning network on practice diffusion			
Overall linear growth [Baseline increase in practice adoption]	The drive of individuals to adopt a new practice that is not caused by peer imitation	z_i	
Average similarity in practices [Network diffusion]	Peer imitation, i.e., preferring practices that most of my information providers use	$x_{i+}^{-1} \sum_j x_{ij}(sim_{ij}^{z} - \overline{sim^{z}}))$	

Note: x_{ij} = 1 if a directed tie from *i* to *j* exists; 0 otherwise

[a] An analogical formula is applied for practice *z*

[b] $\overline{sim^{v}}$ is the mean of all similarity scores, which are defined as $sim_{ij}^{v} = \frac{\Delta - |v_i - v_j|}{\Delta}$ with $\Delta = max|v_i - v_j|$