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

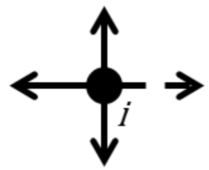
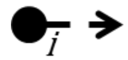
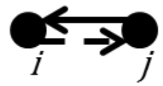
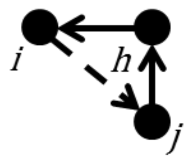
In addition to the convergence tests, we apply the following two approaches to guide the model selection and test the goodness of fit: (1) a generalized Neyman-Rao score-type test for each covariate proposed by Schweinberger (2012); and (2) a test of the fit of the simulated networks in terms of the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

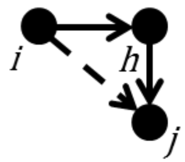
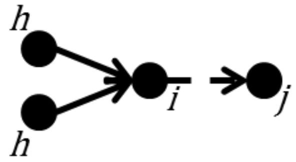
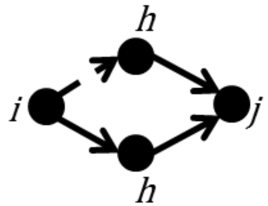
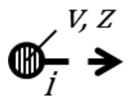
These methods are applied in combination with a forward model selection approach, starting with a trivial model including only the outdegree (the tendency to create and maintain ties) and reciprocity effects (the preference to link to alters who link to ego). Covariates are then gradually added. In each 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.

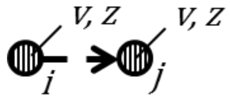
For every new specification, we test the model's goodness of fit by examining the simulated networks' fundamental characteristics that are not directly estimated by the methods of moments. We focus on the following three important properties of graphs: (1) indegree distribution; (2) outdegree distribution; 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 $\Delta = max|v_i - v_j|$