Advice Networks in Public Organizations: The Role of Structure, Internal Competition, and Individual Attributes

Abstract: Interpersonal networks are increasingly important for organizational learning and performance. However, little is known about how these networks emerge. In this article, exponential random graph models are employed to explore the underlying processes of advice network formation in 15 organizations. The author examines the influence of (1) structural effects (reciprocity, transitivity, multiplexity), (2) actor attribute effects (job function, tenure, education, self-efficacy), and (3) peer competition. Results suggest that employees rely more on reciprocity, closure, and similarity in job function than on peer expertise or status when seeking advice. In addition, employees who perceive greater levels of competition with peers are significantly less likely to both seek and provide advice. As public organizations look to private sector strategies that promote internal competition to improve efficiency and accountability, public managers need to be aware of the negative implications those strategies can have on interpersonal networks and organizational learning.

Practitioner Points

• Personal interaction through advice networks is a primary means of information and knowledge exchange in organizations.
• Employees weigh the costs and benefits associated with seeking advice from a colleague.
• Employees tend to rely on friends or peers assigned to the same job function for advice rather than peers with high status and/or expertise.
• Perceptions of internal competition may reduce the likelihood of advice seeking, leading to less dense networks and hindering knowledge dissemination.
• Informal networks within organizations deserve attention from public managers, as policy, leadership style, and culture can affect tendencies to seek and provide advice.

Public organizations are increasingly characterized as knowledge-intensive settings (Willem and Buelens 2007). Success in these settings is dependent on organizational learning, a process that occurs through knowledge creation, information diffusion, and collective problem solving (Agneessens and Wittek 2012; Kim and Lee 2006; Nahapiet and Ghoshal 1998; Tsi 2001). Despite growth in technology, personal interaction continues to be the primary means of organizational learning because of the difficulty of codifying and transferring complex tacit knowledge (Hansen 1999; Zander and Kagot 1995). Learning is an inherently relational process. It is facilitated by advice networks that operate as pathways by which tacit knowledge and informational resources are exchanged (Borgatti and Foster 2003; Brass 1995; Lazega et al. 2012; Raider and Krackhardt 2001; Reagans and McEvily 2003). Research in a variety of contexts has found networks to be important determinants of both individual and collective performance (Brass et al. 2004; Burt 1992; Krackhardt and Hanson 1993; Mandell 2001). Kim and Lee state, “As knowledge is a central resource in government service, effective knowledge sharing among employees is a significant public management challenge for providing high-quality government services to constituencies at all levels” (2006, 370).

Despite the growing acknowledgment of the importance of interpersonal or intraorganizational advice networks, much of the work regarding collaboration and knowledge sharing in public administration concerns interorganizational networks (i.e., networks among organizations) (see, e.g., Agranoff 2007; Feiock and Scholz 2010; Provan and Milward 1995). Less attention has been paid to how the individuals within those organizations collaborate and build social networks (Agneessens and Wittek 2012; Borgatti and Foster 2003; Kapucu, Hu, and Khosa 2014).

This article asks a fundamental yet little-explored question: what are the processes by which interpersonal
advice networks emerge in public organizations? The major goal of the article is to explore the antecedents of networks in public organizations and to identify the conditions under which advice relations are most likely to occur. Given the importance of networks for the success of employees and organizations (Krackhardt and Hanson 1993; Meier and O’Toole 2003; Pil and Leana 2009), understanding the origins of these structures is a critical next step. This article examines the role of structural effects (e.g., reciprocity, transitivity) as well as personal attributes and beliefs in determining advice tie formation. Given the growing use of private sector strategies in public organizations (Perry, Engbers, and Jun 2009; Weibel, Rost, and Osterloh 2010), particular attention will be focused on peer competition. Many of the current managerial strategies used to drive performance and increase accountability rely on motivational incentives that promote internal competition, often through extrinsic rewards, resulting in unintended consequences for collaborative behavior (Pfeffer and Sutton 2000). This suggests that as employees perceive greater levels of competition with their peers, the informal networks that support organizational learning may begin to erode.

To provide empirical evidence of the factors influencing interpersonal network formation and the impact of peer competition, this article examines the advice-seeking relations formed among teachers in public schools. Unlike most network studies, which rely on a single case or network, this article examines the social networks that emerge in 15 different organizations. In order to assess and control for structural dependencies inherent in network data, statistical network models known as exponential random graph models (ERGMs) are used (Lusher, Koskinen, and Robins 2013). These models “support the estimation of parameters associated with variables of theoretical interest while at the same time providing an accurate characterization of the network structure in which individual relations are embedded” (Lomi et al. 2014, 439).

This article offers two primary contributions to the literature on organizational learning and network formation in public organizations. First, it provides one of the first statistical examinations of the social processes that may be at work in determining the structure of advice networks within public organizations. Second, it provides an empirical test of the behavioral mechanism espoused by critics of many private sector management strategies—that internal competition drowns out collaboration (Firestone and Pennell 1993; Kohn 1986; Pfeffer and Sutton 2000).

Antecedents of Advice Networks

As a result of the complexity and dynamics of the tasks employees are faced with and the inability for formal documents to capture tacit knowledge (Hansen 1999), individuals seek out and rely on their local colleagues for advice and information (Morrison 2002). Because advice networks are informal organizational structures, individuals faced with uncertain job tasks have the freedom to choose whom they seek advice from. Nebus (2006) developed a theory of advice network generation that builds on individual choice models and suggests that individuals trade off expectations of knowledge value against the costs of obtaining that knowledge. This suggests that advice seeking is not solely driven by the demand for information.

In viewing advice seeking through the lens of value expectation, Nebus (2006) suggests that individuals consider the expertise, responsiveness, preexistence of friendship ties, and similarity of the advice provider when determining whom to seek advice from. In addition, both psychological and social costs are important. Despite the perceived value of the information sought, psychological costs may deter advice seeking as individuals inherently want to save face and avoid feeling incompetent (Lee 1997; Morrison 2002; Nebus 2006). Social costs arise through the expectation of reciprocity, such that the information provider will accrue future benefits from the provision of advice now (Cook and Whitmeyer 1992).

Empirical research on social networks suggests that existing models of advice seeking need to be augmented by endogenous factors associated with the structure of the network. According to Robins and Lusher (2013b), the structures observed in social networks are influenced by two broad patterns. First, as noted in the theoretical work of Nebus (2006), Morrison (2002), and others, the attributes of the individuals who compose the network affect the likelihood that certain ties will emerge (Robins and Daraganova 2013). These effects are often referred to as actor covariate effects, as they capture the tendency for individuals with certain attributes to be more active in seeking advice and/or providing advice. Second, the structure of the network itself is important, as endogenous network effects or structural effects can also influence the propensity for tie formation (Robins 2011; Robins et al. 2007). Therefore, given a set of possible connections in a network, the likelihood of an advice tie forming between two particular actors depends both on the traits of each of those actors and on the social structure surrounding them. As illustrated in figure 1, this article brings together theory and empirical evidence to develop and explore a model that captures both attribute-based and structural effects as they relate to the costs and benefits of advice seeking.

At a foundational level, individuals seek advice from peers to help them overcome a problem or clarify what needs to be done.

Actor Attribute/Covariate Effects

At a foundational level, individuals seek advice from peers to help them overcome a problem or clarify what needs to be done. When making decisions about whom to seek advice from, individuals weigh the potential costs against the benefits (Ashford and Cummings 1983; Lee 1997; Morrison and Vancouver 2000). Costs and benefits are determined, in part, through the attributes and beliefs of the advice seeker and advice provider (Nebus 2006). Salient attributes and beliefs include status, self-efficacy, and perceptions of competition with coworkers.

Status/expertise. With respect to maximizing benefits, seeking advice from peers with recognized status, such as experts or senior members of the organization, may be the most efficient approach, as these individuals tend to carry legitimacy and novel information (Morrison and Vancouver 2000). In public organizations, such as schools, status signals may be driven by one’s tenure in the organization, one’s formal position, and one’s level of education.

Hypothesis 1: Individuals are more likely to seek out high-status peers for advice.

Homophily. The psychological costs associated with embarrassment or feelings of incompetence when seeking advice (Lee 1997;
Morrison (2002) may lead individuals to look for help from peers with whom they have shared characteristics rather than seek out those in the organization most capable of addressing their needs (Lazega et al. 2012). The tendency for similarity to lead to social connectivity is termed homophily. Shared traits or characteristics are potentially important facilitators of social interaction because individuals equate similarity with trust and congruent expectations (Brass 1995). Similarity, therefore, may reduce the transaction costs associated with interaction or collaboration (Feiock and Scholz 2010; McPherson, Smith-Lovin, and Cook 2001) and strengthen existing social bonds between individuals (McPherson, Smith-Lovin, and Cook 2001; Reagans 2011). A number of studies have found strong tendencies for homophilous relations to form at the interpersonal level in organizations. This includes homophily based on age, race, and gender (Lomi et al. 2014; Reagans 2011), as well as homophily based on shared job duties or job tasks (Reagans and McEvily 2003).

**Hypothesis 2:** Individuals are more likely to seek advice from peers who have similar attributes and job duties.

**Self-efficacy.** In addition to the influence of homophily and status, individuals with certain characteristics or beliefs may be more active in a social network. One’s sense of self-efficacy, defined as the belief in one’s capacity to successfully perform one’s job (Bandura 1977; Tschannen-Moran, Hoy, and Hoy 1998), is likely to affect advice-seeking behavior. The existing literature on the relationship between self-efficacy and advice networks is mixed, with empirical evidence showing connections to both more and less advice seeking (Bamberger 2009). The mixed effect of self-efficacy on one’s likelihood of seeking advice may be a result of variation in organizational context and culture. As discussed by Bamberger (2009), when high-self-efficacy individuals have the ability to reciprocate assistance, they seek advice more frequently. Bamberger (2009), citing work by Nadler (1986, 1991), notes that the potential for reciprocation allows the advice seeker to reduce concerns about appearing incompetent and thus lessen the perceived costs of advice seeking. Given the potential for reciprocating ties in public organizations, the following exploratory hypothesis is offered:

**Hypothesis 3:** Individuals with higher self-efficacy are more likely to seek advice from peers.

**Peer competition.** Generating internal competition in organizations remains a commonly accepted means to promote innovation, efficiency, and performance (Pfeffer and Sutton 2000). Internal competition can arise through a variety of means. According to Pfeffer and Sutton (2000, 179), common management practices that generate internal competition include (1) performance evaluations with forced distributions, so that only some employees can earn the highest evaluation; (2) individual recognition awards; (3) contests between units or among individuals within units; (4) published rankings of unit or individual performance; and (5) merit raises. As the authors note, these practices are so widespread that they appear unremarkable.

However, the use of competitive strategies may have unintended implications for an employee’s propensity to seek and/or provide advice. For instance, research suggests that the introduction of extrinsic rewards can shape individuals’ perceptions of the work task and shift their motivations away from more altruistic, socially driven behavior (Heyman and Ariely 2004). Yang and Maxwell (2011) note that when strategies are not specifically designed to support or encourage collaboration, incentive systems can actually reduce knowledge exchange because employees will often compete with coworkers to obtain performance goals. This causes individuals to...
protect information and avoid seeking coworkers for help as they perceive their peers as competitors. Therefore, the management approaches listed by Pfeffer and Sutton (2000) may not only generate internal competition but also influence the social structures of the individual employees.

Morton Deutsch’s (1949) theory of social interdependence provides a theoretical connection between competition and collaboration that links goal structure with individual behavior. As discussed by Johnson and Johnson, “the basic premise of social interdependence theory is that the structure of the goals of the people in the situation determines how participants interact and the interaction patterns determine the outcomes of the situation” (2005, 292). Social interdependence can range from positive to negative. Positive interdependence exists when individuals believe that they can only obtain their goals when others with whom they are interdependent obtain their goals (Johnson 2003). Alternatively, negative interdependence is present when individual action hinders the pursuit of joint goals because in order for one individual to succeed, another must fail. Within public organizations, employee relationships could be characterized as positively interdependent or negatively interdependent depending on the leadership style, management policies, and reward systems in place. As organizations implement reforms that affect internal competition (either intentionally or unintentionally), the increase in negative interdependence may reduce social interaction and advice-seeking behavior.

**Hypothesis 4:** Individuals who perceive greater levels of competition will be less likely to seek advice from peers.

While Deutsch’s model suggests behavioral changes on part of the advice seeker, it is likely that advice providers may also be affected by their perceptions of peer competition. Research suggests that it is natural for individuals to withhold knowledge when that knowledge provides them with a competitive advantage (Ghobadi and D’Ambra 2011). Nebus (2006) identifies the previous responsiveness of the advice provider as one of the factors affecting the probability of contacting that person for advice in the future. Therefore, to the extent that individuals with higher perceptions of peer competition limit the quality and quantity of the advice they provide, peers may avoid relying on them for help.

**Hypothesis 5:** Individuals who perceive greater levels of competition will be less likely to be sought for advice from peers.

**Structural Effects**

While individual traits and attitudes can influence network formation, the dependencies that exist between ties lead to self-organization in social networks (Robins and Lusher 2013b). Endogenous structural effects play an important role in the formation of social networks from both a theoretical and an empirical perspective. Research has shown that ignoring structural dynamics and assuming independence among the relations in a network can lead to spurious findings (Krackhardt 1987). This article will examine several common structural effects found in social networks.

**Reciprocity.** Many interpersonal relations are directional, such that actor \(i\) may choose to seek advice from actor \(j\). Reciprocity refers to the tendency for the relation to be reciprocated such that \(j\), in turn, seeks advice from \(i\). According to Rivera, Soderstrom, and Uzzi (2010), there are three main reasons for the prevalence of reciprocity in social networks. First, reciprocity, especially with regard to affective ties, may be attributable to the human inclination to like those who like us (Newcomb 1956). Second, and related to social exchange theory, individuals are more inclined to reciprocate a tie as the likelihood of being refused is reduced or because there is an implicit expectation of reciprocity. Third, reciprocity in networks may also result from the tendency for individuals to dissolve unreciprocated ties (Hallinan 1978). These processes suggest that reciprocal relations are more likely to be found in social networks than would occur by chance alone. Recent empirical research by Schulte, Cohen, and Klein (2012) and Agneessens and Wittek (2012) finds positive reciprocity effects in advice networks. While the tendency toward reciprocity likely diminishes the size of the effects related to hypothesis 1 (suggesting that individuals seek out high-status peers), both status seeking and reciprocity are possible in advice networks (Lazega et al. 2012).

**Hypothesis 6:** Advice-seeking relations will tend to be reciprocated.

**Transitivity.** While reciprocity focuses on dyadic relations, the concept of transitivity emphasizes groupings of three individuals, known as triads. As with unreciprocated ties, certain structural patterns among three actors are often unstable as individuals perceive imbalance attributable to cognitive inconsistency (Harary, Norman, and Cartwright 1965; Heider 1958). For instance, if both actors \(j\) and \(j\) have positive relations with another, then they are likely to have similar evaluations of a third actor \(k\). However, if \(i\) feels negatively toward \(k\) while \(j\) feels positively, then \(i\) and \(j\) would attempt to reduce the resulting cognitive inconsistency and produce a more balanced triadic structure, either by adjusting their views toward \(k\) or by changing their views of each other (Monge and Contractor 2003, 204). Consequently, closed triads, or transitive relations, often arise in social networks.

**Hypothesis 7:** Advice relations will tend to be transitive.

**Friendship.** In addition to reciprocity and transitivity, networks are also characterized by the coexistence of multiple types of relationships (Kadushin 2012, 35–37). For example, the members of a dyad could be neighbors as well as teammates, or they could be good friends as well as coworkers. The propensity for relations to co-occur in networks is referred to as multiplexity. Multiplexity is an important concept in the literature on intraorganizational networks given the tendency for formal roles (e.g., status, position) to overlap with informal roles. Network relations are thus frequently interdependent, and changes in the structure of relations in one network can influence the structure of relations in other networks (Lee and Monge 2011). Research on multiplex relations and advice tie formation has found that friendship ties often lead to the
formulation of advice ties (Lazega and Pattison 1999). This suggests that coworkers who are friends feel more comfortable with each other and have greater access to one another in times of need. This reduces the costs of advice seeking and allows for advice relations to form more easily.

**Hypothesis 8:** Individuals are more likely to seek advice from a coworker whom they consider to be a friend.

**Methods**

Standard statistical models are generally ill suited for analyzing network data because of the dependency among the ties in a network (Butts 2008). Exponential random graph models are tie-based models that allow for multiple hypotheses regarding network-generating processes to be examined simultaneously while making no assumptions about independence among the dyads (Goodreau 2007; Robins et al. 2007; Wasserman and Pattison 1996).

ERGMs have the following form (Robins et al. 2007, 178–79):

$$
Pr(Y = y) = \left(\frac{1}{k}\right) \exp\left\{ \sum_{A} \eta_A g_A(y) \right\}
$$

where (1) the summation is over all configuration types $A$ (structural effects and actor covariate effects); (2) $\eta_A$ is the parameter corresponding to configuration $A$; (3) $g_A(y)$ is the network statistic corresponding to configuration $A$, such that $g_A(y) = 1$ if the configuration is in the observed network $y$ and $g_A(y) = 0$ otherwise; and (4) $k$ is a normalizing constant to ensure a proper probability distribution. Simply stated, "the probability of the network depends on how many of those configurations are present, and the parameters inform us of the importance of each configuration" (Robins and Lusher 2013b, 9). For instance, hypothesis 6 states that advice relations are likely to be reciprocal, and therefore the sign of the coefficient on reciprocity in the model is believed to be positive.

A positive and significant parameter estimate indicates that, controlling for the other parameters in the model, reciprocal ties are more likely to form than by chance alone. In other words, the distribution of ties in the observed network suggests a tendency toward reciprocity. The ergm package of the statnet suite (Handcock et al. 2008) in the R programming environment was used to estimate the models.

Because the range of potential advice providers was bounded by the school roster provided by the district (see discussion on data collection in the next section), a separate ERGM was run for each school. When networks in multiple organizations or contexts are modeled, meta-analysis can be used to combine the independent results (Krackhardt and Kilduff 1999; Lubbers 2003; Lubbers and Snijders 2007). The results for each school were combined using a weighted least squares approach for network data, as outlined by Krackhardt and Kilduff (1999), and Fisher’s method was implemented to test significance (Becker and Wu 2007; Borenstein et al. 2009).

**Data Collection and Measurement**

The network and demographic data utilized in this study came from an online survey of teachers in the Riley School District (a pseudonym) along with administrative records provided by the district. The district was in the midst of developing a new five-year strategic plan and was interested in the level of interpersonal communication and professional dialogue that existed in its schools. To this end, the study was coordinated with district and school leadership to explore the underlying social structures and the factors affecting advice network formation in each of 15 elementary schools in the district.

In spring 2011, teachers in the elementary schools were invited to respond to a survey and social network questionnaire. Response rates in the schools varied from 47 percent to 100 percent, with an overall response rate of 74 percent. In total, 231 of 311 teachers participated in the survey. Additional data were gathered through the district’s administrative offices, which housed information on the teachers’ formal position, time served in the district, sex, race, and level of education.

**Advice network.** The outcomes of interest in this study are the advice ties that make up the networks in each of the 15 schools. The networks were measured using the roster method. Advice ties were determined by asking each teacher to indicate which coworkers he or she sought advice or information from concerning the practice of teaching, ideas on lesson planning, classroom management, or other work-related problems or activities. A roster of all coworker names within a school was presented to the participant along with five options for rating the frequency of interaction: never, a few times a year, monthly, weekly, or daily. An advice tie was coded to exist between teacher $i$ and teacher $j$ if interaction occurred at least monthly. This threshold eliminated weak ties occurring only a few times a year, which are more prone to measurement error (Butts 2003) and less effective in supporting knowledge flow within organizations (Friedkin 1982). Research has found that weak ties, characterized by infrequent interaction, hinder the transfer of information (Hansen 1999; Reagans and McEvily 2003). Descriptive statistics for the schools, teachers, and advice networks are provided in table 1.

**Structural effects.** Structural effects are different configurations found in the network that are not dependent on the characteristics of the actors. The structural effects included in the model of the teacher advice networks are edges, two-paths, reciprocity, transitivity, multiple two-paths, popularity spread, activity spread, and multiplexity. The edge term represents the overall tendency for ties to form in the network, and it functions much like an intercept term in a standard regression model. Two-path was included in the model to control for the correlation between in-degree and out-degree, and, as noted by Robins and Lusher (2013a, 174), it tends to be negative. Reciprocity refers to the likelihood of ties to be reciprocated. A measure of transitivity was used to determine the amount of closure that occurs in advice networks. The term used in the models is a geometrically weighted edgewise shared partner distribution, GWESP. GWESP is preferred over a standard triangle term, which simply counts the number of transitive triads in a network, as it tends to avoid issues of model degeneracy that are common with ERGMs. (For a detailed discussion of GWESP see Hunter [2007]). To improve inferences regarding the effects of transitivity, a parameter capturing nonclosure of triadic structures, referred to as multiple two-paths or multiple connectivity, is also included in the model (Robins, Pattison, and Wang 2009). Popularity spread and activity spread are common parameters in ERGMs used to control for variation in the in-degree and out-degree distributions of the network (Robins and Lusher 2013a). Finally, multiplexity was included by using the friendship network in the school as a
predictor of advice seeking. The friendship network was measured by asking teachers to indicate which of their coworkers they perceived as being close personal friends.

**Actor covariate effects.** The actor covariates included in the model were perceived competition, self-efficacy, organizational tenure (number of years teaching in the district), job function (grade level taught), and education (binary variable indicating a bachelor’s or a master’s/doctoral degree). While both race and sex are often important contributors to tie formation, especially with regard to homophily, the vast majority of teachers in the district were white females. Such demographic homogeneity is especially common among elementary school teachers. Because of the lack of variation on race and sex, these variables were not included in the model.

Based on Deutsch’s social interdependence theory, a five-item scale measuring an individual’s perceived competition with peers was developed ($\alpha = 0.81$). Deutsch states that “cooperation implies the positive attitude that ‘we are for each other,’ ‘we benefit one another’; competition, by contrast, implies the negative attitude that ‘we are against one another,’ and in its extreme form, ‘you are out to hurt me’” (2006, 25). The latter attitudes are the result of negative interdependence. Therefore, teachers who perceive greater levels of internal competition will (1) believe that other teachers are only concerned with their own students’ performance (rather than all of the students in the school); (2) feel as though they are in competition with their coworkers; and (3) lack the feeling that their peers look out for one another. Based on Deutsch’s conceptualization, five items were used to capture a teacher’s perception of competition in his or her school: (1) “How many teachers in this school help maintain discipline in the entire school, not just their classroom?” (2) “How many teachers in this school feel responsible to help each other do their best?” (3) “How many teachers in this school feel responsible that all students learn (not just those in their classroom)”; (4) “Teachers in this school feel as though they are in competition with fellow teachers”; and (5) “Teachers in this school typically look out for each other.” These items were derived from a broader set of items used by the Chicago Consortium on School Research. A maximum likelihood factor analysis using varimax rotation was used to produce factor scores for perceived competition. The same approach was used to produce self-efficacy scores.

**Self-efficacy** ($\alpha = 0.88$) was measured using the teacher self-efficacy scale developed by Tschannen-Moran and Hoy (2001). The scale combines three aspects of teacher efficacy: instructional strategies, classroom management, and student engagement. Nine items were chosen from Tschannen-Moran and Hoy’s (2001) scale, three items from each of the three dimensions. Representative items include the following: (1) “How much can you do to get children to follow classroom rules?”; (2) “To what extent can you provide an alternative explanation or example when students are confused?”; and (3) “How much can you do to control disruptive behavior in the classroom?”

When entered into an ERGM, actor covariate effects can take several forms (Robins and Daraganova 2013), including sender effects, receiver effects, and homophily effects. Sender effects account for variation in advice-seeking behavior and indicate whether an individual with a particular trait is more or less likely to seek advice. Receiver effects account for variation in advice-providing behavior, and thus the variable captures whether individuals with certain traits are more or less likely to be recipients of others’ advice-seeking behavior. Homophily effects, measured through difference scores for continuous variables and matching attributes for categorical variables, capture the increase in the likelihood of an advice tie forming between two actors given that both actors share or are similar on a given attribute. In the models analyzed here, four sender effects and four receiver effects were added for (1) years in district, (2) education, (3) self-efficacy, and (4) perceived competition. Two homophily terms were also added: (1) teach same grade, indicates whether both individuals in a given dyad teach the same grade, and (2) years in district (difference), which indicates the absolute size of the tenure difference between two individuals. Table 2 provides a graphical representation of the actor covariate and structural effects used in the models along with an intuitive definition.

**Results**

The meta-analysis of the ERGM results is presented in table 3. The first column contains the weighted estimate of the population parameter, or the combined effect, and the second column contains the associated $p$-value. Results of the models for each individual school along with goodness-of-fit diagnostics are available in a supplementary appendix in the online version of this article.

Table 1 Descriptive Statistics for Schools, Teachers, and Networks

<table>
<thead>
<tr>
<th>Elementary School Site</th>
<th>Number of Students</th>
<th>Total Number of Teachers</th>
<th>Number of Complete Responses</th>
<th>Response Rate</th>
<th>Percentage of Teachers with a Master’s or Doctoral Degree</th>
<th>Average Years Served in the District</th>
<th>Advice Network Density</th>
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Note: Network density is simply the total number of ties present in the network divided by the total number of possible ties.
A significant and positive coefficient estimate on a structural effect indicates that the particular configuration (e.g., reciprocity) is found in the network more often than would be expected by chance given the other effects in the model. Despite the complex estimating procedures, the parameter estimates in ERGMs can be interpreted as conditional log-odds ratios (Goodreau, Kitts, and Morris 2009). For reciprocity, the results suggest that the odds of an advice-seeking tie from $i$ to $j$ are 5.9 times more likely ($\exp[1.7820] = 5.9$) if a tie from $j$ to $i$ already exists, holding constant the other features in the network.

The negative coefficient on two-path indicates a small negative correlation between in-degree and out-degree. Thus, those actors who send a lot of ties tend to receive fewer, and vice versa. Like reciprocity, transitivity has a positive and significant effect. This effect, coupled with a negative coefficient for multiple two-paths, indicates that two-paths tend to be closed, and thus there is a tendency toward transitivity (Robins and Lusher 2013a). With regard to popularity spread, there does not appear to be a tendency toward centralization with respect to in-degree. The negative and significant coefficient on activity spread suggests that most teachers have similar levels of advice seeking. Finally, multiplexity, as measured by having a friendship tie with a coworker, increases the odds of an advice tie with that coworker by a factor of more than three ($\exp[1.1758] = 3.2$) compared with the odds of a tie when no friendship is present. As found in previous research by Lazega and Pattison (1999),...
friendship ties may be an important precondition for the formation of advice-seeking relations. Overall, the results provide support for each of the three structural effects hypotheses (hypotheses 6, 7, and 8) related to reciprocity, transitivity, and multiplexity through friendship.

**Actor covariate effects.** The actor covariate effects include both homophily effects and the main effects of teacher attributes. For the homophily effects, there is a positive and significant coefficient for teaching the same grade. The result supports hypothesis 2 and indicates that a teacher is nearly two times more likely (exp[0.5968] = 1.82) to seek advice from a coworker who has the same formal position than from someone in a different position. The effect on teacher difference in the number of years served is negative but not significant. These results provide evidence to support homophily effects based on job function but not job tenure.

The main effects for years in district are mixed. There is no effect for receivers of advice ties, indicating that teachers do not seek out more tenured coworkers for advice. However, there is a positive effect for senders, suggesting that teachers with more experience are more inclined to seek advice. For education, the coefficients for both receiver and sender are negative, but only the sender effect is significant. Teachers with a master’s or doctoral degree are nearly 20 percent less likely (exp[–0.2012] = 0.82) to seek advice compared with teachers with a bachelor’s degree, controlling for the other effects in the model. Combining the lack of receiver effects for years in district and education level, there is little evidence of a status effect in schools. Consequently, hypothesis 1 is not supported. The lack of an effect based on status or prestige may be driven by the fact that schools, at least with respect to teachers, are more horizontally organized. While some teachers have served longer, their formal positions in the hierarchy are the same. The main variation is in the grade level taught, not in the type or complexity of their work. It appears that teachers seek help from those who may be dealing with similar students (i.e., same grade level) rather than the most veteran or well-educated peer.

In terms of self-efficacy, there is no indication of either a receiver effect or sender effect. This suggests that teachers do not seek out their high-self-efficacy peers for advice, and teachers with higher self-efficacy are not any more likely to seek advice. These findings disconfirm hypothesis 3.

For the sender effects of perceived competition, the coefficient is negative and significant. The result provides support for hypothesis 4 and suggests that as perception of competition increases, a teacher is less likely to engage in advice-seeking behavior. Here it is important to revisit the wording of the questions in the competition scale. The questions measure how competitive one perceives his or her work environment to be, not how competitive that person is. Thus, aligned with social interdependence theory, the focus is on the relationship between situational competition (i.e., the competition perceived to exist in one’s environment) and the likelihood of seeking others out for professional advice and assistance. The competition variable has a standard deviation of 1; therefore, controlling for the other structural and actor covariate effects, a one-standard-deviation increase in perceived competition decreases the odds of seeking advice by nearly 25 percent (exp[–0.2549] = 0.77).

The receiver effect is also negative and significant, supporting hypothesis 5, although it is roughly two-thirds the size of the sender effect. Because the measure of competition is situational and advice seeking is initiated by the sender, the negative receiver effect may be an indication of a reactionary process on the part of one’s peers. Teachers with a high perception of internal competition may be much more likely to protect rather than share information (Yang and Maxwell 2011). If a teacher reduces the amount or quality of information provided to his or her peers, the costs of seeking advice from that individual increases, potentially making future interactions less likely (Nebus 2006). Over time, those with higher perceptions of internal competition may both seek and be sought for advice less than others. Overall, the parameter estimates on the actor covariate effects for perceived competition provide tentative support to suggest that competition may erode collaboration.

**Discussion**

This article has examined several structural, cognitive, and attribute-based processes that may influence the formation of advice networks in public organizations. Meta-analysis of the ERGMs across the different elementary schools found strong structural effects for reciprocity, transitivity, and multiplexity through friendship. Homophily effects based on formal job function were also found. The results suggest that teachers rely on mutual relations, closure, friendship, and work function similarity in determining advice-seeking behavior more so than peer status. This may mean that there is expertise in the network that is not being fully accessed or utilized. The meta-analysis also suggests that perceived competition may have a negative effect on the likelihood of being both a sender and a receiver of an advice tie. This is a potentially worrisome result, as reductions in collaboration may be particularly harmful in organizational settings, such as public school systems, that are dependent on shared knowledge (Resnick 1991; Spillane, Halverson, and Diamond 2001).

Collaboration and knowledge exchange are critical components in schools because much of what teachers learn about being good teachers is socially derived (Bryk et al. 2010). The results have implications for how principals, public managers, and policy makers shape the culture and norms of an organization through their leadership and managerial approaches and highlight how employees could react to those approaches by shifting their motivations away from socially driven behavior when internal competition increases. An interview with a fourth-grade teacher in another district provides a useful anecdote for the observed effects of competition on advice seeking.

The teacher described the strong collaboration that existed between the members of her grade level team. The level of help and advice seeking displayed within her group earned them the moniker “Team of Love.” However, this year in particular, teachers were strongly
challenged by the principal to achieve high growth and to outperform their coworkers regarding student performance on the state exams. At grade-level and school meetings, many inappropriate and highly competitive comments were made, such as “your kids won’t pass the exams,” “your kids won’t score as high as my kids,” “I had the second highest growth in the school last year,” and “I’m getting first this year.” The internal competition and emphasis on individual teacher performance ultimately divided the previously highly collaborative “Team of Love.” Two veteran teachers stopped sharing ideas with the other members. Other teachers implemented motivational tactics and test-taking lessons without offering any of the material to their peers. One of the teachers continuously tried to bring in the sole teaching assistant assigned to the team to aid only her class. As a result of her peers’ behavior, this teacher stopped seeking her colleagues out for advice and assistance. The teacher voiced her frustration with the situation and noted how competition harmed the team’s collective capacity and, ultimately, student learning. This one example of internal competition, as structured informally by the principal, highlights the potentially detrimental effects of heightened competition on collaboration and the complex social dynamics of advice seeking in public organizations.

Conclusion
The purpose of this article was to statistically explore the processes influencing advice tie formation in public organizations and to empirically test the hypothesized effect of competition on collaboration. Understanding the processes influencing network formation is important because the advice relations that form among coworkers affect an organization’s capacity to learn (Senge 1990), improve outcomes for clients (Pil and Leana 2009), and implement reforms (Daly 2010). The results suggest that advice networks are not the simple consequence of individual information needs but are affected by personal attributes, beliefs, and structural effects. Advice seeking is also likely influenced by the leadership, culture, and policies of an organization (Coburn and Russell 2008; Daly 2010), especially, as suggested by this article, in regard to how those factors alter internal competition. The findings raise important questions about the role of public managers in shaping their employees’ informal networks. Consequently, future research in two areas would be fruitful.

First, research that connects the types of policies and cultures that exist within public organizations to the underlying advice relations is needed. This will require longitudinal research designs that gather data on managerial approaches as well as network evolution to provide a clearer understanding of how certain performance strategies and leadership styles do or do not influence advice seeking. A longitudinal research design would also overcome inherent limitations in this study, with regard to directionality and causality, attributable to the cross-sectional nature of the data. Second, more in-depth, qualitative research on the individual’s decision to seek advice and on the type of and quality of information that flows across particular advice ties is needed. Such research can help clarify the costs and benefits perceived by employees when deciding to seek advice and capture variation in the value of certain ties.

More broadly, additional research utilizing statistical network methods to explore intraorganizational networks should be conducted in public administration (Kapucu, Hu, and Khoza 2014). As public organizations continue to become more information intensive, a knowledge base on the processes of interpersonal network formation and the consequences of network structure is needed. It is critical for policy makers and public managers not only to be aware of the importance of informal relations within organizations but also to understand how certain strategies can facilitate or constrain the development and structure of those relations.

Supporting Information
A supplemental appendix can be found in the online version of this article at http://onlinelibrary.wiley.com/journal/10.1111/ISSN1540-6210.

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Notes
1. The combined or summary effect, \( \beta^+ \), is a pooled measure of the overall parameter estimate. It is calculated as follows:

\[
\beta^+ = \frac{\sum_{i=1}^{k} \beta_i}{\sum_{i=1}^{k} 1/\sigma_i^2}
\]

where \( k \) is the number of parameters being combined, \( \beta_i \) is the parameter estimate from study \( i \), and \( \sigma_i^2 \) is the weight for study \( i \) (Becker and Wu 2007). Fisher’s method was used to determine the overall level of significance of the combined effect. Fisher’s method of combining \( p \)-values is calculated as follows:

\[
X^2 = -2 \sum_{i=1}^{k} \ln(p_i)
\]

where \( p_i \) is the one-sided \( p \)-value from study \( i \) and \( k \) is the number of studies (Borenstein et al. 2009). This fixed-effects meta-analysis approach is used because the schools analyzed in each ERGM are functionally identical (i.e., same researcher, survey instrument, recruitment procedures, etc.) and therefore are expected to share a common effect size (Borenstein et al. 2009). The \( Q \)-statistic was calculated (Krackhardt and Kilduff 1999; Borenstein et al. 2009) to examine heterogeneity in results across the schools (Borenstein et al. 2009). The \( Q \)-statistic is calculated as follows:

\[
Q = \sum_{i=1}^{k} \left( \frac{(\beta_i - \beta)^2}{\sigma_i^2} \right)
\]

where \( \beta \) is the study effect size, \( \beta^+ \) is the summary effect, \( \sigma_i^2 \) is the study weight, and \( k \) is the number of schools (Borenstein et al. 2009). No significant heterogeneity was found for 14 of the parameters. A random-effects meta-analysis, conducted under the assumption of effect heterogeneity, was also run, and the results did not alter the findings.

2. The Consortium on Chicago School Research (CCSR) was created in 1990 to study the long-term effects of the school restructurings that occurred in the
If you are working on a rigorous review that critically assesses a body of theory and empirical research, articulates what is known about a phenomenon and ways to advance research about it, and identifies influential variables and effect sizes associated with an existing body of empirical research, please contact Michael McGuire, the Research Synthesis Editor, at mcguirem@indiana.edu.