Published in final edited form as:
J Soc Social Work Res. 2014 December ; 5(4): 513–538. doi:10.1086/679224.

Building Service Delivery Networks: Partnership Evolution Among Children's Behavioral Health Agencies in Response to New Funding

Alicia C. Bunger,
Assistant professor in the College of Social Work at Ohio State University.

Nathan J. Doogan, and
Postdoctoral researcher in Health Behavior and Health Promotion in the College of Public Health at Ohio State University.

Yiwen Cao
Graduate research assistant in the College of Social Work at Ohio State University.

Abstract

Meeting the complex needs of youth with behavioral health problems requires a coordinated network of community-based agencies. Although fiscal scarcity or retrenchment can limit coordinated services, munificence can stimulate service delivery partnerships as agencies expand programs, hire staff, and spend more time coordinating services. This study examines the 2-year evolution of referral and staff expertise sharing networks in response to substantial new funding for services within a regional network of children's mental health organizations. Quantitative network survey data were collected from directors of 22 nonprofit organizations that receive funding from a county government-based behavioral health service fund. Both referral and staff expertise sharing networks changed over time, but results of a stochastic actor-oriented model of network dynamics suggest the nature of this change varies for these networks. Agencies with higher numbers of referral and staff expertise sharing partners tend to maintain these ties and/or develop new relationships over the 2 years. Agencies tend to refer to agencies they trust, but trust was not associated with staff expertise sharing ties. However, agencies maintain or form staff expertise sharing ties with referral partners, or with organizations that provide similar services. In addition, agencies tend to reciprocate staff expertise sharing, but not referrals. Findings suggest that during periods of resource munificence and service expansion, behavioral health organizations build service delivery partnerships in complex ways that build upon prior collaborative history and coordinate services among similar types of providers. Referral partnerships can pave the way for future information sharing relationships.

Keywords

inter-organizational relationships; service delivery systems; social network analysis; children's behavioral health; funding environment

Correspondence regarding this article should be sent to Dr. Alicia Bunger, College of Social Work, Ohio State University, 1947 College Road, Columbus, Ohio 43210, or via Bunger.5@osu.edu.

NIH-PA Author Manuscript
NIH-PA Author Manuscript

Meeting the complex and varied needs of children and youth with behavioral health problems is often dependent on a coordinated network of community-based agencies. Consistent with the *systems of care* philosophy underpinning children's behavioral health system reform efforts (Stroul & Friedman, 1986), non-profit human service agencies coordinate services by referring clients and sharing information or staff expertise with one another (Bolland & Wilson, 1994; Rivard & Morrisey, 2003). Such interagency partnerships are critical for comprehensive and seamless service delivery, and expand clients' access to available, quality treatment in their community (Sowa, 2009). However, coordinating and aligning services across multiple organizations can be demanding in terms of providers' time and resources.

The funding environment plays a key role in expanding services and agencies' capacity to deliver coordinated, partnered services. Fiscal scarcity can drive partnerships; to continue meeting basic service needs, agencies work together by sharing resources, expertise, and complementary services for their clients (Alexander, 2000; Provan, Sebastian, & Milward, 1996). However, limited service availability and time for coordination during tight economic conditions might ultimately constrain development and maintenance of strong service delivery partnerships. As Provan and Milward (1995) posited in their seminal work on network effectiveness, new funding for service expansion is needed for stimulating and strengthening coordinated service delivery networks. Little is known about how partnerships and service delivery networks evolve in the context of substantial funding fluctuations. One recent study (Park & Rethemeyer, 2014) demonstrated that under conditions of fiscal scarcity, policy networks fragmented because of conflict and competition for scarce resources. However, it is unclear whether funding munificence can reverse fragmentation. When the funding environment shifts from conditions of scarcity to munificence, do partnerships flourish? How do agencies select partners, and do agencies build the types of strong partnerships needed to deliver comprehensive and seamless services to children? The answers to these questions have potential to inform policy strategies for integrating human service systems.

Therefore, this study investigated the evolution of two types of service delivery partnerships, client referrals and staff-expertise sharing, in response to substantial new funding for services within a regional network of children's mental health organizations. Specifically, we addressed two research questions about service delivery networks evolution under conditions of resource munificence: (a) How does the structure of the referral and staff-expertise networks change? and (b) How do agencies select service delivery partners?

Building on Provan and Milward's (1995) theory of network effectiveness, we expected service delivery partnerships to grow in response to funding munificence. We argue that these partnerships are formed and maintained in somewhat predictable ways, where agency directors' partnership decisions are influenced by their motivations and resources, existing partnerships, and the larger network structure (Ahuja, Soda, & Zaheer, 2012). Thus, a whole network perspective is used in this study to account for the dynamics among the individual, dyadic, and system levels.

Quantitative network survey data about referral and staff-expertise sharing relationships were collected from the same set of children's behavioral health organizations at two time points (before and after the influx of funding). To test our hypotheses about partner selection dynamics, we used a stochastic actor-oriented model (SAOM) of network dynamics. SAOM is a relatively new approach for modeling longitudinal network data, with the capability of testing the dynamic interplay between agency characteristics and existing network structure on network evolution (Snijders, 2011). This approach enables us to move beyond descriptions of network change and begin to identify explanatory mechanisms of network evolution. To our knowledge, our study is one of the first to apply the SAOM approach to modeling longitudinal dynamics of human service delivery networks under fluctuating economic conditions. Consistent with prior evidence, our findings suggest that trust and existing relationships generally play a major role in partnership development and network evolution (e.g., Isett & Provan, 2005). However, we found that slightly different partner selection mechanisms accounted for evolution of referral and staff-expertise sharing networks. Our findings highlight the ways in which agency directors build on existing relationships to select collaborative partners as they expand services in response to environmental shifts.

Developing Service Delivery Partnerships: The Role of the Funding Environment

Human service organizations develop service delivery partnerships in response to the larger resource, social, and institutional environments. Agencies partner to access needed resources such as client referrals, complementary services for existing clients, or expertise (Pfeffer & Salancik, 2003). Agencies also partner to comply with mandates or strong institutional pressure from funders, policy makers, accrediting bodies, or other key influential system stakeholders that can influence agency resources (Reitan, 1998). The desire to create efficiencies also drives agencies to pool their knowledge, information, or service expertise (Guo & Acar, 2005). Thus, partnerships allow organizations to access, maintain, or manage key resources central to service delivery.

Dynamic funding environments can undermine the stability of relationships among nonprofit agencies (Galaskiewicz, 1985). Because nonprofit behavioral health agencies often rely heavily on public funding to support service delivery, these nonprofits are vulnerable to fluctuating resource environments, which in turn, create a high degree of uncertainty about the funding prospects for these agencies. Uncertain funding environments disrupt and spur partnerships. Agencies respond by strategically aligning and safeguarding partners that have key resources to buffer economic turbulence, and some might even benefit in the new environment (Isett & Provan, 2005; Madhavan, Koka, & Prescott, 1998). Thus, uncertainty breeds opportunities for agencies to reconsider and restructure their partnerships.

Resource munificence can also create uncertainty; however, partnerships are expected to flourish when resources are not constrained (Koka, Madhavan, & Prescott, 2006). Within human service delivery systems in particular, an influx of new funding allows agencies to expand programs, hire staff, spend more time coordinating services with other agencies, and invest more effort in identifying available services in the community and making client referrals (Provan & Milward, 1995; Purcal, Muir, Patulny, Thomson, & Flaxman, 2011). Thus, an influx of funding may not only solidify partnerships established during tight economic conditions but also stimulate new service delivery partnerships that facilitate delivery of high-quality and coordinated care. Although funding fluctuations influence partnerships and network expansion, limited research has empirically examined the specific motivations and mechanisms for forming and strengthening partnerships in the context of funding fluctuations (Isett, Mergel, & LeRoux, 2011).

How Do Networks Grow?

Networks evolve through formation, maintenance, and dissolution of partnerships between individual agencies. These interagency dynamics arise from a combination of agency motivations, convenient opportunities to partner, existing partnership routines and habits, and even random events (Ahuja, Soda, & Zaheer, 2012). Resource needs often drive interagency collaboration (Pfeffer & Salancik, 2003). Therefore, a prospective partners' funding, service array, or expertise might be a chief consideration in partnership choices. However, information about prospective partners is transmitted endogenously, through agencies' existing partners, and through the structure of the service delivery network (Gulati & Gargiulo, 1999). Therefore, agencies can also demonstrate preference for building or strengthening partnerships with convenient existing or "close" partners. In the context of service expansion supported by resource munificence, partnerships form, strengthen, or dissolve through the complex interaction of agency leaders' strategic service delivery-related decisions and existing relationships. Thus, service delivery partnership and network evolution can be explained by both agency and partner attributes.

Agency and Partner Attributes

Agencies' decisions to maintain or develop service delivery partnerships can be driven by fixed characteristics of a prospective partner. Most important to integrating service delivery systems, a prospective partners' *service array* can influence partnership development, although it is unclear whether agencies seek partners with similar or complementary services under conditions of program expansion. Agencies often seek partners who provide functionally distinct or complementary services (Bunger & Gillespie, 2014). In behavioral health, service delivery partnerships based on service complementarity are expected to expand clients' access to a range of services (Selden, Sowa, & Sandfort, 2006). However, agencies also tend to partner with agencies that serve the same population in the same sector of care (Bolland & Wilson, 1994; Rivard & Morrisey, 2003), and overlapping services have been linked to improved performance (Arya & Lin, 2007). Thus, although the existing evidence is unclear regarding how and under what conditions service similarity or complementarity drive partnership development, it is expected that the prospective partners' service arrays influence the development of service delivery partnerships in some way. Specifically, it is hypothesized that the formation or maintenance of referral partnerships is associated with the combined service array between two partners (Hypothesis 1a), and the formation or maintenance of staff expertise sharing partnerships is associated with the combined service array between two partners (Hypothesis 1b).

Agencies also seek partners that have resources to share. As a result, *agency revenue* influences partnership development, where agencies that generate large revenues are often in a better position to share resources (Foster & Meinhard, 2002). As compared with smaller, niche organizations, large agencies with more revenue have more resources to share, and are also likely to be generalists with more expansive service arrays (Wholey & Huonker, 1993). Partnership activity might also increase for agencies that bring in substantial *new funding awards* given that new funding signals programmatic expansion, with new resources or services that could benefit clients in the system. Therefore, large revenue-generating agencies and those benefitting from new funding awards are likely to play a prominent role in the expansion of service delivery networks. It is expected that as funding fluctuates, the formation or maintenance of referral partnerships is positively associated with an agency's financial revenues (Hypothesis 2a); and the formation or maintenance of staff-expertise sharing partnerships is positively associated with an agency's financial revenues (Hypothesis 2b).

Behavioral health agencies are likely to seek *trustworthy* partner organizations that can be expected to behave reliably, fairly, and with good will (Rousseau, Sitkin, Burt, & Camerer, 1998). Trust mitigates uncertainties and risks associated with partnerships (Jones, Hesterly, & Borgatti, 1997; Bunger, 2013). Therefore, as new funding facilitates service expansion, agencies are likely to maintain and strengthen partnerships with agencies perceived of as trustworthy.

Specifically, the formation or maintenance of referral partnerships is expected to be positively associated with the perceived trustworthiness between two partners (Hypothesis 3a). Further, the formation or maintenance of staff-expertise sharing partnerships is expected to be positively associated with the perceived trustworthiness between two partner organizations (Hypothesis 3b).

Network Structure

Decisions regarding strategic partnerships also depend on the availability of information about prospective partners. The time and resources associated with learning about prospective partners can be a limiting factor for partnership development. Instead, information about prospective partners' conveniently flows through existing ties and networks, which reduces the search costs associated with partner selection (Gulati & Gargiulo, 1999). Agencies with an expansive partnership portfolio generally have partnership capacity as well as experience with and knowledge of prospective partners, and thus, are likely to form and maintain service delivery relationships with new partners (Guo & Acar, 2005). In other words, the more service delivery relationships an agency has, the more likely the agency will be able to maintain existing partnerships and form new relationships when funding increases. Specifically, it is expected that the formation or maintenance of future referral relationships is positively associated with an agency's number of prior referral partners (Hypothesis 4a), and the formation or maintenance of future staff expertise sharing relationships is positively associated with an agency's number of prior staff expertise sharing partners (Hypothesis 4b).

Instead of choosing a new partner, agencies might also choose to strengthen existing partnerships through *reciprocity* or *multiplexity*. Reciprocity is the tendency to develop mutual relationships, whereby agencies share resources with partner agencies that share resources with them. Agencies that share their expertise expect their partners to share their expertise in turn, and therefore, these agencies are likely to develop partnerships in reciprocity with existing partners (Lee, Lee, & Feiock, 2012). Reciprocated relationships represent mutual cooperation and are therefore stronger than one-way relationships. As funding fluctuates and partnerships strengthen, it is expected that agencies are likely to form or maintain reciprocal referral partnerships (Hypothesis 5a), and that agencies are likely to form or maintain reciprocal staff-expertise sharing partnerships (Hypothesis 5b).

Agencies also develop stronger, multiplex relationships involving multiple collaborative activities (Isett & Provan, 2005; Provan, Nakama, Veazie, Teufel-Shone, & Huddleston, 2003). Multiplexity is the tendency to engage in multiple types of relationships or share several types of resources with the same partner. For instance, agencies might share their staffs' expertise with a referral partner. Multiple partnerships with the same partner reflect deeper levels of trust (Uzzi, 1997). As funding increases support program expansion, agencies might build upon an existing relationship by reciprocating referrals or expertise shared by a partner and collaborating in additional ways leading to two hypotheses. First, we hypothesize that agencies are likely to form or maintain referral-based partnerships with a staff-expertise-sharing partners (Hypothesis 6a). Second, we hypothesize that agencies are likely to form or maintain a staff expertise-sharing partnership with a referral partner (Hypothesis 6b).

Finally, agencies develop partnerships with agencies that are "close," that is, agencies with which they are familiar and those that have a known reputation. Agencies use prior relationships to learn about prospective partners in the system, and therefore, are likely to form a new partnership with an agency that already works with one of their existing partners. This phenomenon of agencies developing partnerships with a partner-of-a-partner creates tight clusters or triads of organizations is known as *transitivity*. Transitivity is the tendency for two agencies that have a mutual third partner, to form or maintain a relationship; transitivity is likely to contribute to partnership dynamics over time (Castro, Casanueva, & Galán, 2014; Lee et al., 2012), leading to a final set of hypotheses: We hypothesize that two agencies are likely to maintain or develop referral partnerships if they share a common referral partner (Hypothesis 7a). We further hypothesize that two agencies are likely to maintain or develop staff expertise-sharing partnerships if they share a common staff expertise-sharing partner (Hypothesis 7b).

Study Purpose

To date, although some research has examined the evolution of partnerships in human service delivery networks (Isett & Provan, 2005; Provan & Huang, 2012), the field suffers from a general lack of evidence to explain the mechanisms of change, especially in the context of funding fluctuations (Provan & Lemaire, 2012). Even though partnerships are expected to expand with funding and programs, understanding the dynamics underlying partner selection requires an approach that accounts for complex interactions between agency behavior and the evolving network structure.

This study extends prior research on network change by examining the ways in which partnership selection processes account for evolution of a regional children's behavioral health network amidst funding fluctuations. Specifically, we first demonstrate the ways in which the structure of referral and staff expertise sharing networks change over time. Second, we identify partner selection mechanisms that explain partnership evolution by testing whether agency/partner services and resources and existing network structures (e.g., tendencies toward partnering, reciprocity, multiplexity, and transitive closure) play a role in the coevolution of referral and staff expertise sharing partnerships. Understanding whether and how children's behavioral health agencies adjust their service delivery partnerships in response to funding fluctuations has implications for policy strategies aimed at integrating human service systems.

Method

Study Setting and Participants

This study was conducted in the context of an urban county coalition of nonprofit agencies serving children and adolescents with behavioral health problems that responded to an influx of $40 million in annual funding for services through a new sales tax levy. The coalition of 45 members formed in 2007 to coordinate advocacy efforts toward expanding local funding for services via a sales tax levy. The sales tax levy passed with a majority vote during the 2008 general election. After the election, coalition members voted to reorganize as a membership organization focused on promoting advocacy, collaboration, and communication. Many of these coalition members now receive funding from the new dedicated sales tax, which made the first round of awards in FY2010-2011. Funding awards were made across 10 service categories that included crisis intervention; school- and home-based prevention programs; temporary shelter; outpatient psychiatric and substance abuse treatment; individual, group, and family counseling; services for pregnant teens; and respite care. Capitalizing on this naturally occurring experiment, a pre/posttest design was used to examine how the service delivery partnership network among coalition members changed as the funding environment fluctuated from one of resource scarcity (i.e., before the first round of funding in 2009) to one of resource munificence (in 2011).

The population included a subset of 22 nonprofit organizations [formally registered with the IRS as 501(c)(3) organizations], which were paid coalition members that became funding recipients during the first year of award disbursement. This research received approval of the Institutional Review Board of the first author's prior and current institutions.

Data Collection

Data on service delivery partnerships and trust were collected via network surveys administered to executive directors of coalition members in 2009 and in 2011. At both time points, agency directors were e-mailed a link to an online survey and invited to participate. Of the 45 coalition member-agencies in 2009, 32 (89%) participated in the survey. In FY

2010, 27 coalition members received funding in the first round of county tax awards, representing 61% of all awardees. Of these agencies, 23 (85%) participated in a follow-up survey in 2011. After survey administration was complete, administrative data on agency revenue and county funding awarded to each agency were gathered from agencies' IRS 990 forms (i.e., accessible from Guidestar.org) and the county website.

Measures

Dependent variables: Service delivery partnerships –referrals and staff expertise sharing—The network survey measured two types of service delivery partnerships using two items from Van de Ven and Ferry's (1980) Resource Flows scale. Variables for *referrals* and *staff expertise sharing* were measured with one item each; agency directors used an 11-point scale ranging from 0 (none) to 10 (100%) to report the amount of referrals sent or staff expertise shared with each coalition member within the past 6 months. For purposes of analysis, responses were dichotomized to denote the *presence* (1) or *absence* (0) of any amount of resource sharing.

Independent variables: Agency and partner attributes—We measured two variables related to organizational size: *annual revenue* and *award size*. Throughout organizational research, several proxies are used for organizational size (e.g., personnel, clients, revenue, assets). Kimberly (1976) recommended measuring the specific dimensions of size with the greatest direct relevance to the research questions. Given that our study aimed to examine partnership development amid funding fluctuations, and prior evidence suggests that agencies'-ability to control financial resources influences interagency partnerships (e.g., Foster & Meinhard, 2002), we selected two direct measures of financial resources. First, data on each agency's total annual revenue were drawn from 2009 IRS 990 forms available on Guidestar.com. Second, the total amount of each organization's FY2010-2011 award was gathered from the county website.

To capture the unique mix of services potentially provided by each pair of agencies in the network, *service similarity* was measured using data about each agency's FY 2010–2011 award, which were available on the county website. Each agency reported offering one or more of 10 categories of service: temporary shelter; transitional housing; teen parent services; respite care; school-based services; home- and community-based prevention; crisis intervention; outpatient psychiatry; outpatient substance abuse services; and individual, group, and family counseling. Service similarity was defined as the number of service categories each agency dyad had in common.

We measured *perceived trustworthiness* using one item in the network survey. Agency directors rated the trustworthiness of each coalition member on an 11-point scale from *not trustworthy at all* (0) to *completely trustworthy* (10), thus providing unique assessments of each potential pair of agencies in the network. Directors responded with considerable variation in their overall mean level of trust in other agencies. This variation in mean level of trust might capture an agency-level culture of trust and sharing, general collaboration experience, a director's natural tendency to be more or less trusting, or the particular way the director read the question. Of interest is whether agencies partner with organizations that are perceived of as being more trustworthy than other agencies. Therefore, we used the relative rather than absolute measures of perceived trustworthiness. To highlight relative differences in perceived trustworthiness between each pair of agencies, scores were centered within each agency by subtracting the agency's mean trustworthiness scores from the trustworthiness score assigned to each potential partner. Mathematically, the transformation can be defined as follows. Let x_{ij} be the reported amount of trust agency *i* has in agency *j*. Let $\bar{x_i}$ be the mean of all trust responses offered by agency *i*. Then the transformation we employ is $r_{ij} = x_{ij} - \bar{x_i}$ for all *i* and *j* where $i \neq j$. Thus, trust scores r_{ij} represent the trust agency *i* places in agency *j* relative to the rest of agency *i*'s responses.

Analysis

Comparing network structure over time—The sna package in R was used to plot the changes of referral and staff information sharing networks over time (Butts, 2014). In addition, four global network metrics— density, reciprocity, transitivity, and the Jaccard similarity coefficient— were calculated and compared to indicate changes in overall connectedness, strength of referral, and staff expertise sharing networks over time (Wasserman & Faust, 1994). *Density* —defined as the proportion of all pair-wise relationships reported out of all possible relationships— measures overall connectedness in the network, with higher density scores representing more densely connected networks. *Reciprocity*, that is, the proportion of ties reciprocated, assesses the strength of the relationships within a network. *Transitivity* measures the tendency for agencies to close triadic structures (two agencies share a mutual partner), which is an indicator of network cohesion. The *Jaccard similarity coefficient*, which is the proportion of all reported ties present in both years, represents the amount of change among agency relationships (i.e., agency ties) between 2009 and 2011. The coefficient ranges from zero (no similarity; none of the 2009 ties were present at 2011) to 1 (no difference; all observed ties in 2009 and 2011 were present at both time points). Further detail on these metrics is provided in Wasserman and Faust (1994).

Testing the role of partner selection processes in network change—To explain the change observed between the 2009 and 2011 snapshots of the network, a SAOM of network dynamics (Snijders, 2011) was fitted to the network data. SAOM is a recently developed modeling approach for longitudinally observed social networks that captures the forces underlying individual tie changes that contribute to the total network change observed between two or more time points; the SAOM is a continuous time model of discretely observed data. The model contains several additive terms (called effects) that are analogous to variables in a regression model. Each of the model effects is associated with an estimated coefficient that is analogous to a regression coefficient. Coefficients in a SAOM are interpreted much like those in a logistic regression model because the outcome of a network tie change is dichotomous (i.e., a present tie is dissolved or not dissolved, or an absent tie is added or not added) (Snijders, Van de Bunt, & Steglich, 2010). SAOM models are implemented in an add-on package for the R statistical computing environment called RSiena (Ripley, Boitmanis, & Snijders, 2014).

This analytic approach has two major strengths. First, SAOM tests the role of several specified potential partner selection forces, such as reciprocal exchange and annual revenue, on network evolution. Second, because there are two networks (referral and staff expertise sharing) observed on the same set of nodes during the same period, a SAOM offers the capability to understand how each network depends on the other (e.g., does sharing referrals increase the odds of sharing staff expertise?).

The model in this study tests both endogenous and exogenous effects. Endogenous effects allow the model to capture the reciprocal relationship between structure (the network context) and agency (individual behaviors), whereas the exogenous effects allow external influences (e.g., agency attributes) to have an effect on the changing network. The difference between the two is that endogenous effects change along with the network whereas exogenous effects are fixed.

Exogenous effects (agency attributes): The exogenous effects model partnership changes depending on covariates such as fixed features of the agency or fixed dyadic features. For each of the two modeled networks, agency revenue and award size were entered as exogenous *ego covariate* effects, which model the change in odds of an agency creating or maintaining service delivery partnerships dependent on agency revenue and award size. *Trust* and *service similarity* were included in the model as dyadic covariates that model the variation in odds of Agency A forming or maintaining a partnership with Agency B based on the amount of trust, or service similarity reported between the two agencies. Notably, the service similarity of Agencies A and B is always the same as service similarity of Agencies B and A (i.e., service similarity is symmetric). However, Agency A's trust in Agency B is not restricted to be equal to Agency B's trust in Agency A.

Endogenous effects (network structure): The endogenous model effects capture structural features of agencies' local networks that influence decisions regarding tie changes. Four endogenous network effects were included in the model for both referral and staff expertise sharing networks: *reciprocity*, *transitive triplets*, *outdegree activity*, and *referrals and staff knowledge sharing*.

The most basic endogenous effect, reciprocity, is the tendency to reciprocate service delivery partnerships over time. The reciprocity effect models a change in the odds of Agency A forming or maintaining a referral partnership with Agency B depending on whether Agency B refers clients to Agency A.

The second endogenous effect, *transitive triplets*, is a tendency to close triads by forming or maintaining a partnership with a partner's partner. For example, if Agency A refers to Agency B, and if Agency B refers to Agency C, the transitive triplets effect allows for a change in the odds that Agency A will share with Agency C versus some other agency that is not shared with by Agency B. [DN10]

Third, the outdegree activity (i.e., *activity* meaning creation or maintenance of out-bound ties) effect refers to a differential tendency for agencies to create and maintain partnerships based on the number of partnerships they have at a given moment. A positive estimate for the outdegree activity effect suggests that agencies engaged in staff expertise sharing with many other agencies will tend to continue doing so, whereas a negative estimate suggests that such agencies will actively reduce their sharing to achieve an amount similar to all other agencies.

The final type of endogenous effect included in the model allows for the two modeled networks—referrals and staff knowledge sharing—to depend on one another, suggesting multiplexity. We included a main effect of referrals on staff expertise sharing, and a main effect of staff expertise sharing on referrals, to estimate the change in odds of one type of tie depending on whether the other type of tie is present. It is important to recognize that these two effects are distinct, and model whether the existence of one type of tie has an effect on a future change in the other type. Thus, these two effects could highlight a temporal dependence of one type of tie on the other, or both on each other.

The estimated model includes four coefficients that have no bearing on main study aims. The model includes an effect called *density* for each network which indicates the baseline tendency of all agencies to hold outbound sharing ties and is analogous to an intercept in a logistic regression model. The model also includes *rate* effects for each network, which allow the model to control the amount of change necessary to get from the network observed at Time 1 to the network observed at Time 2. Thus, the rate should be higher if the Jaccard coefficient measuring the similarity between two networks is smaller, indicating that the model had to allow for more tie changes in order to converge on the data.

Results

Agency and Partnership Characteristics

Descriptive statistics about the 22 agencies and their pair-wise relationships are described in Table 1.The coalition network reflects a diverse set of agencies that range from somewhat small agencies that generate less than $500,000 in annual revenue to very large, multi-million dollar organizations. During the first year of funding, 70% of agencies received awards for more than one service category. The average total award was $984,000, although awards ranged widely from $62,000 to $4.3 million.

At the dyadic level, service similarity, which was calculated in terms of the number of potentially overlapping services between 231 pairs of coalition members [(22 members × 21 potential partners) / 2 sides of a partnership = 231], ranged from 0 to 5, although the average score was low (M = 0.95, SD = .97). Directors' ratings of the trustworthiness of each coalition member (22 members × 21 potential partners = 462) varied widely from 6 points below to 7 points above an agency's average trustworthiness rating.

Change in Service Delivery Networks

Results suggest that from 2009 to 2011, both referral and staff expertise sharing networks grew denser, stronger, and more connected (see Table 2, Figure 1). The client referral network among the 22 agencies increased from 41% to 57% connected in 2011, and the staff expertise grew from 21% to 36% connected. In addition, reciprocity and transitivity increased suggesting that partnerships were stronger and more clustered in triads in 2011 than in 2009. Jaccard similarity coefficients suggest that ties changed over time; 48% of all referral ties were present in both 2009 and 2011, whereas 28% of all staff expertise sharing ties were present at both time points, suggesting that staff expertise ties changed more than referral ties.

Results From the Fitted SAOM

The influence of exogenous and endogenous forces on the formation and maintenance of referrals and staff expertise sharing partnerships is reflected by the coefficients of the fitted SOAM (see Table 3). Only one effect, outdegree activity, was significantly associated with both referral and staff expertise sharing partnership evolution; a finding that supported the fourth set of hypotheses. In the referral network, referral outdegree activity was positively associated with referral partnerships ($\beta = 0.052$, $p < .01$) suggesting that agencies with high numbers of referral partners continue to refer at relatively high levels over time. Staff expertise sharing was also associated with outdegree activity, ($\beta = 0.091$, $p < .001$), suggesting a similar pattern of partnership formation and maintenance, although to a somewhat stronger degree than that found for the referral network.

Several other effects played a significant role in the evolution of service delivery partnerships, and provided partial support for several hypotheses. In the referral network, only Hypothesis 3a was supported when trust between two agencies was positively associated with referral partnership formation and maintenance ($\beta = 0.141$, $p < .01$), suggesting that trust in an agency increases the odds of referring clients to that agency. No other effects specific to the referral network were statistically significant. Thus, Hypotheses 1a, 2a, 5a, 6a, and 7a were unsupported in the referral network.

However, several effects played a significant role in the evolution of the staff expertise sharing network. Supporting Hypothesis 1b, service similarity between two agencies was positively associated with staff expertise sharing partnerships ($\beta = 0.264$, $p < .01$), whereby the more service offerings two agencies have in common, the more likely they are to share staff expertise. In support of Hypothesis 5b, reciprocity was also positively associated with staff expertise sharing ($\beta = 0.651$, $p < .05$), suggesting that agencies preferred to share staff expertise with those agencies that shared back.

Finally, one of the two effects representing the multiplexity of the two partnership networks was significant. The main effect of referral ties on staff expertise sharing was statistically significant ($\beta = 0.912$, $p < .05$) supporting Hypothesis 6b and suggesting that if a referral tie from one agency to another is present, the corresponding staff expertise sharing tie is more likely to form or to be maintained. Notably, Hypothesis 6a was not supported: the main effect of staff expertise sharing on referral ties (the reverse effect) was not statistically significant ($\beta = 0.214$, *n.s.*) suggesting a temporal ordering for the different types of service delivery partnerships. In this case, either referral ties tend to be present before their corresponding staff expertise sharing ties appear, or when referral ties are dissolved, their corresponding staff expertise sharing ties (if they are present) will also tend to be dissolved. In other words, staff expertise sharing depends on referral sharing, but the reverse does not appear to be true. Our second, third, and seventh hypotheses were not supported by the staff-expertise sharing network.

Discussion

This study generates new insights about the evolution of service delivery systems in the context of a substantial funding increase. Over 2 years, referral and staff expertise sharing partnerships among 22 nonprofit children's behavioral health coalition members increased and strengthened. However, we found subtle differences in the reasons why referral and staff information sharing partnerships grew. An agency's number of referral partners (outdegree activity, the tendency to create or maintain referral partnerships), and the perceived trustworthiness of a potential partner seemed to drive referral partnerships. However, staff expertise sharing partnerships were driven by agencies building on and strengthening their existing relationships with coalition members, particularly with those offering similar services. Over time, agencies tended to reciprocate expertise shared by a partner and build staff expertise sharing relationships with referral partners. These findings suggest that although partner attributes matter for the development of referral partnerships, the evolution of staff expertise sharing partnerships is largely determined by pre-existing ties and network structure.

The 2-year observation period was characterized by substantial network growth, which is generally consistent with prior research on network change in the context of system reforms (Johnsen & Morrissey, 1996; Rivard, Johnsen, Morrissey, & Starrett, 1999). Both types of partnerships were prevalent within the network over the study period, which suggests a high level of service coordination existed even before the first round of funding awards. Both referral and staff expertise sharing networks grew denser, stronger, and more integrated over time, reflecting increasingly intensive service partnerships among agencies. These findings lend support to the notion that agencies reconsider and reconfigure their partnerships in response to environmental shocks (Madhavan et al., 1998), and expand partnership activity when the funding environment shifts from scarcity to munificence (Koka et al., 2006).

Despite descriptive statistics showing similar patterns of change in the global density, reciprocity, and transitivity in referral and staff expertise sharing networks, results of a more nuanced model of network change suggest that evolution of the referral and staff expertise sharing networks is explained by different dynamics. Although referral partnerships were driven by partner attributes (perceived trustworthiness) and a tendency to create or maintain referral partnerships, staff expertise sharing partnerships tended to develop between agencies that offered similar services and built on existing relationships. Specifically, staff expertise sharing relationships strengthened as agencies reciprocated staff expertise shared by a partner, and/or formed or maintained a staff expertise-based relationship with an existing referral partner. These results suggest that agencies select their partners differently depending on partnership type: although agency and partner attributes such as trustworthiness explain referral network evolution, the convenience and accessibility offered by existing ties and network structures account for evolution of staff expertise sharing networks.

These observed differences in partner selection mechanisms by partnership type builds on prior research demonstrating how network structure varies based on the tangibility of the resources exchanged (Huang & Provan, 2007; Provan & Huang, 2012). Networks based on intangible, knowledge-based resources (i.e., information or expertise) tend to be more diffuse than networks based on tangible resources (i.e., contracts or client referrals) that might be more centralized around agencies that control these resources (Huang & Provan, 2007). Together, these studies suggest that network structures, and the underlying partner selection mechanisms that give rise to network structure, vary by partnership type and reinforce the importance of gathering data on multiple types of collaborative partnerships within a single system.

In addition, Provan and Huang's (2012) work suggests that the network expansion observed in this study might be temporary, and could eventually stabilize as agencies adjust to new funding patterns, learn about newly developed programs that could benefit their clients, and settle into new collaborative routines. In a study of a network of agencies serving adults with severe mental illness, 4 years post-environmental shock (implementation of managed care mechanisms), service delivery partnerships declined and grew increasingly centralized (Provan & Huang, 2012). Thus, as the present system matures and stabilizes, some partnerships might retract and partnerships might be focused around agencies with available services and desirable expertise.

Finally, findings also highlight the importance of trust and referral relationships in developing and strengthening partnerships. Prior research on the role of network structure and performance suggested that strong, trust-based multiplex relationships were associated with knowledge sharing among mental health organizations (Huang, 2014) and better client outcomes (Provan & Sebastian, 1998). Given the risks involved, multiplex partnerships often develop among agencies with an established history of working together (Shumate, Fulk, & Monge, 2005) and become more multiplex over time (Isett & Provan, 2005). Our longitudinal findings help unpack the process by which partnerships become multiplex. In this study, the higher the level of trust between agencies, the higher the odds of those agencies forming or maintaining a referral partnership. These referral partnerships, in turn, were associated with forming or sustaining a staff expertise sharing relationship, implying a temporal order in the development of multiplex service delivery partnerships. Referral partnerships offer the opportunity for agencies to learn more about one another, reinforce trustworthiness, and establish a foundation for other collaborative activities, including staff expertise sharing. Thus, referral partnerships can mediate the process by which potential partners trust one another and develop strong, multiplex service delivery partnerships.

Administrative and Policy Implications

The current study yields several insights for directors of behavioral health agencies. Agency directors can strategically use new funding as an opportunity to expand their network of partners. As evidenced in this study, an influx of funding for service expansion was accompanied by dramatic growth in partnerships. As agencies expand services, directors should consider the capacity of their agency's existing referral network and whether existing referral partners will produce sufficient client referrals to a new program. Directors should expect that their staff will need to learn whether new services developed by other agencies in the system might be a potential benefit to clients, and thus, serve as a referral destination.

Directors should also consider testing potential collaborative partners prior to developing more intensive partnerships by first using referral or other types of time-limited or less-intensive relationships that pose a minimal risk to organizations. As compared with the relatively low-risk of referral or information sharing partnerships, joint service programming and administrative partnerships that involve shared funding or co-location require more time, effort, and resources, and therefore, can be higher risk to agencies[AB15]. Opportunities for interactions via referral exchanges or other forums allow agencies to learn more about one another, reinforce their trustworthiness, and potentially lead to stronger and more valuable partnerships (Impink, 2004; Snavely & Tracy, 2002).

Results of this study also have implications for public funders' expectations about their influence over systems. Keast, Mandell, Brown, and Woolcock (2008) noted that even though funders might be interested in having tight control over collaboration and service integration in service delivery systems, agencies operate as independent, autonomous entities. At best, funders might have indirect leverage over service delivery networks by providing enhanced resources for services and trusting that agencies will take the lead in developing partnerships on behalf of their clients. Increasing availability of funding for services by introducing new funding mechanisms or opening eligibility for agencies to bid on contracts could lead to service expansion and more opportunities for agencies to integrate service delivery. Thus, funders can exert influence over the network structure, but in an indirect way.

Limitations and Future Research Directions

The findings related to how community-based children's behavioral health agencies' partnerships evolve should be interpreted in light of several study limitations. First, the lack of a comparison group prevents us from establishing a causal relationship between the funding environment and network expansion. Other factors might explain the observed network changes, including institutional pressure for participating agencies to continue collaborating. These agencies first came together in a grassroots advocacy effort to pass a sales tax levy; once the levy was passed, agencies might experience real or perceived pressure from the new county-based funder to continue or expand interagency partnerships. This study also lacked a control period during which network change was observed over time prior to the funding increase. It is possible that the change we observed in the networks might be continuation of dynamics that were present in the network structure before the influx of funding. Future experimental studies of network interventions might capture network observations at three time points, with the intervention introduced shortly after the second observation. Using this approach, investigators could model network change during two time periods: one period in which the network was operating as it would normally, and one in which an intervention occurred. This approach might be promising for addressing questions about partner selection dynamics, rates of change, and sustainability of network growth under varying environmental conditions.

Second, this is a study of one subset of a network in one region. The same partnership dynamics might not be observed in other networks or in other regions; however, the dynamics observed within this coalition network might be applicable to other community-based nonprofit mental health agency networks fortunate to experience a substantial influx of public funding for services. New funding for services might also spur the development of service delivery partnerships with prominent agencies beyond the local region, and thus promote innovation, competitive advantage, and enhanced reputation (Whittington, Owen-Smith, & Powell, 2009). It is unclear whether our findings apply to the development of these external partnerships.

Third, the SAOM approach models the existence or absence of a partnership (a dichotomous variable). Although referral and staff-expertise sharing partnerships were measured along a scale representing the amount of resources shared, subtle changes in the intensity of these partnerships could not be modeled. In addition, the wide variation in reported agency revenue within the small study population might have been problematic in the model, masking the relationship between agency resources and partnership development observed in other studies (e.g., Foster & Meinhard, 2002). Finally, although the response rate was high (85%), survey nonresponse in network research can be problematic because of the interdependent nature of the data, which can lead to underestimation of global network metrics (Kossinets, 2006; Wasserman & Faust, 1994).

Despite these limitations, this study advances existing knowledge about the ways in which service delivery networks evolve in the context of funding fluctuations, and possibly outside of such situations. The ability of the SAOM approach to account for the dynamic interplay between agency characteristics and existing network structure provides an opportunity to move beyond descriptions of network change, and to identify explanatory mechanisms of network evolution.

The findings reported here highlight several new research questions related to the role of other environmental changes in network evolution, variation in collaborative networks, the ways in which agencies develop strong, trust-based multiplex relationships over time, and whether these partnerships really matter to organizations and their clients. In this study, service delivery networks expanded in the context of funding increases. However, funding cuts as well as other environmental shifts (e.g., emerging client needs, new standards or regulations, and innovative treatments) will also influence how agencies partner with one another and the structure of the service delivery system. Studies that investigate network evolution under these other environmental changes — that are in policy makers' control — have the potential to uncover additional explanations for partnership development or dissolution that can be leveraged by regional administrators or policy makers to further integrate local systems.

Understanding the mechanisms and under what conditions agencies develop the strong, multiplex partnerships that contribute to network performance is important for informing management decisions about partnership development. Our findings suggest that trust might inspire referral-based relationships as well as facilitate other types of collaborative relationships. Prior formal and informal interactions are likely to have shaped the observed levels of trust (Lee et al., 2011). In this study, participating agencies belonged to a coalition and engaged in policy advocacy efforts, which are often associated with other inter-organizational relationships (Mosley, 2010). Policy advocacy and coalition membership might have provided agency leaders a forum for learning about potential partners and establishing trust. Additional research examining the coevolution of several types of collaborative networks would be helpful for understanding how agency interactions around various purposes establish a foundation for trust and strong partnership.

Finally, spurring service delivery partnerships among organizations is unlikely to lead to better client outcomes unless the services being coordinated are effective (Bickman, 1997; Ridgely, Morrissey, Paulson, Goldman, & Calloway, 1996). Therefore, conducting studies focused on the formation and evolution of network substructures and on interventions that could be implemented within small, collaborative agency groups would be valuable for identifying system-level strategies for improving service coordination and client outcomes. Understanding how the evolution of the service delivery network facilitates access to effective care could help identify optimal system structures for delivering care to children and their families.

Acknowledgements

This research was supported by a National Research Service Award Predoctoral Fellowship for Dissertation Research (F31 MH088037) and Postdoctoral Traineeship (T32 MH019117) from the National Institute of Mental Health jointly sponsored by Cecil G. Sheps Center for Health Services Research, University of North Carolina at Chapel Hill, and the Department of Psychiatry and Behavioral Sciences, Duke University Medical Center.

The authors wish to thank David Gillespie for his contributions to earlier stages of this research, county administrative staff for facilitating data collection, and the agency directors who participated in this study. We also appreciate the three anonymous reviewers for their helpful feedback. A version of this paper was presented at the 2013 meeting of the Society for Social Work and Research.

References

Ahuja G, Soda G, Zaheer A. The genesis and dynamics of organizational networks. Organization Science. 2012; 23:434–448. http://dx.doi.org/10.1287/orsc.1110.0695.

Alexander J. Adaptive strategies of nonprofit human service organizations in an era of devolution and new public management. Nonprofit Management and Leadership. 2000; 10:287–303. http://dx.doi.org/10.1002/nml.10305.

Arya B, Lin Z. Understanding collaboration outcomes from an extended resource-based view perspective: The roles of organizational characteristics, partner attributes, and network structures. Journal of Management. 2007; 33:697–723. http://dx.doi.org/10.1177/0149206307305561.

Bickman L. Resolving issues raised by the Fort Bragg evaluation. American Psychologist. 1997; 52:562–565. http://dx.doi.org/10.1037/0003-066X.52.5.562. [PubMed: 9145025]

Bolland JM, Wilson JV. Three faces of integrative coordination: A model of interorganizational relations in community-based health and human services. Health Services Research. 1994; 29:341–366. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1070009/. [PubMed: 8063569]

Bunger AC. Administrative coordination in nonprofit human service delivery networks: The role of competition and trust. Nonprofit and Voluntary Sector Quarterly. 2013; 42:1155–1175. http://dx.doi.org/10.1177/0899764012451369. [PubMed: 25349468]

Bunger AC, Gillespie DF. Coordinating nonprofit children's behavioral health services: Clique composition and relationships. Health Care Management Review. 2014; 39:102–110. http://dx.doi.org/10.1097/HMR.0b013e31828c8b76. [PubMed: 23518763]

Butts CT. sna: Tools for social network analysis. R package version 2.3-2. 2014 Retrieved from http://CRAN.R-project.org/package=sna.

Castro I, Casanueva C, Galán JL. Dynamic evolution of alliance portfolios. European Management Journal. 2014; 32:423–433. http://dx.doi.org/10.1016/j.emj.2013.06.006.

NIH-PA Author Manuscript

NIH-PA Author Manuscript

Chen B. Assesing interorganizational networks for public service delivery: A process-perceived effectiveness framework. Public Performance & Management Review. 2008; 31:348–363. http://dx.doi.org/10.2753/PMR1530-9576310302.

Foster MK, Meinhard AG. A regression model explaining predisposition to collaborate. Nonprofit and Voluntary Sector Quarterly. 2002; 31:549–564. http://dx.doi.org/10.1177/0899764002238100.

Galaskiewicz J. Interorganizational relations. Annual Review of Sociology. 1985; 11:281–304. http://dx.doi.org/10.1146/annurev.so.11.080185.001433.

Gulati R, Gargiulo M. Where do interorganizational networks come from? American Journal of Sociology. 1999; 104:1439–1493. http://dx.doi.org/10.1086/210179.

Guo C, Acar M. Understanding collaboration among nonprofit organizations: Combining resource dependency, institutional, and network perspectives. Nonprofit and Voluntary Sector Quarterly. 2005; 34:340–361. http://dx.doi.org/10.1177/0899764005275411.

Huang K. Knowledge sharing in a third-party-governed health and human services network. Public Administration Review. 2014; 74:587–598. http://dx.doi.org/10.1111/puar.12222.

Huang K, Provan KG. Resource tangibility and patterns of interaction in a publicly funded health and human services network. Journal of Public Administration Research and Theory. 2007; 17:435–454. http://dx.doi.org/10.1093/jopart/mul011.

Impink RV. Leadership dimensions, the critical link for the evolution of collaboration. Social Policy Journal. 2004; 3(2):39–55. http://dx.doi.org/10.1300/J185v03n02_04.

Isett K, Mergel I, LeRoux K. Networks in public administration scholarship: Understanding where we are and where we need to go. Journal of Public Administration Research and Theory. 2011; 21:157–173. http://dx.doi.org/10.1093/jopart/muq061.

Isett K, Provan KG. The evolution of dyadic interorganizational relationships in a network of publicly funded nonprofit agencies. Journal of Public Administration Research and Theory. 2005; 15:149–165. http://dx.doi.org/10.1093/jopart/mui008.

Johnsen MC, Morrissey JP. Structure and change in child mental health service delivery networks. Journal of Community Psychology. 1996; 24:275–289. http://dx.doi.org/10.1002/(SICI)1520-6629(199607)24:3<275::AID-JCOP7>3.0.CO;2-W.

Jones C, Hesterly WS, Borgatti SP. A general theory of network governance: Exchange conditions and social mechanisms. Academy of Management Review. 1997; 22:911–945. http://dx.doi.org/10.2307/259249.

Keast R, Mandell MP, Brown K, Woolcock G. Network structures: Working differently and changing expectations. Public Administration Review. 2004; 64:363–371. http://dx.doi.org/10.1111/j.1540-6210.2004.00380.x.

Kimberly JR. Organizational size and the structuralist perspective: A review, critique, and proposal. Administrative Science Quarterly. 1976; 21:571–597. http://dx.doi.org/10.2307/2391717.

Koka BR, Madhavan R, Prescott JE. The evolution of interfirm networks: Environmental effects on patterns of network change. Academy of Management Review. 2006; 31:721–737. http://dx.doi.org/10.5465/AMR.2006.21318927.

Kossinets G. Effects of missing data in social networks. Social Networks. 2006; 28:247–268. http://dx.doi.org/10.1016/j.socnet.2005.07.002.

Lee Y, Lee IW, Feiock RC. Interorganizational collaboration networks in economic development policy: An exponential random graph model analysis. Policy Studies Journal. 2012; 40:547–573. http://dx.doi.org/10.1111/j.1541-0072.2012.00464.x.

Lee H-W, Robertson PJ, Lewis L, Sloane D, Galloway-Gilliam L, Nomachi J. Trust in a cross-sectoral interorganizational network: an empirical investigation of antecedents. Nonprofit and Voluntary Sector Quarterly. 2011; 41:609–631. http://dx.doi.org/10.1177/0899764011414435.

Madhavan R, Koka BR, Prescott JE. Networks in transition: How industry events (re)shape interfirm relationships. Strategic Management Journal. 1998; 19:439–459. http://dx.doi.org/10.1002/(SICI)1097-0266(199805)19:5<439::AID-DIA952>3.0.CO;2-2.

Mosley JE. Organizational resources and environmental incentives: Understanding the policy advocacy involvement of human service nonprofits. Social Service Review. 2010; 84:57–76. http://dx.doi.org/10.1086/652681.

Park HH, Rethemeyer RK. The politics of connections: Assessing the determinants of social structure in policy networks. Journal of Public Administration Research and Theory. 2014; 24:349–379. http://dx.doi.org/10.1093/jopart/mus021.

Pfeffer, J.; Salancik, GR. The external control of organizations: A resource dependence perspective. Stanford, CA: Stanford University Press; 2003.

Provan KG, Huang K. Resource tangibility and the evolution of a publicly funded health and human services network. Public Administration Review. 2012; 72:366–375. http://dx.doi.org/10.1111/j.1540-6210.2011.02504.x.

Provan KG, Lemaire RH. Core concepts and key ideas for understanding public sector organizational networks: Using research to inform scholarship and practice. Public Administration Review. 2012; 72:638–648. http://dx.doi.org/10.1111/j.1540-6210.2012.02595.x.

Provan KG, Milward HB. A preliminary theory of interorganizational network effectiveness: A comparative study of four community mental health systems. Administrative Science Quarterly. 1995; 40:1–33. http://dx.doi.org/10.2307/2393698.

Provan KG, Nakama L, Veazie MA, Teufel-Shone NI, Huddleston C. Building community capacity around chronic disease services through a collaborative interorganizational network. Health Education and Behavior. 2003; 30:646–662. http://dx.doi.org/10.1177/1090198103255366. [PubMed: 14655861]

Provan KG, Sebastian JG. Networks within networks: Service link overlap, organizational cliques, and network effectiveness. Academy of Management Journal. 1998; 41:453–463. http://dx.doi.org/10.2307/257084.

Provan KG, Sebastian JG, Milward HB. Interorganizational cooperation in community mental health: A resource-based explanation of referrals and case coordination. Medical Care Research and Review. 1996; 53:94–119. http://dx.doi.org/10.1177/107755879605300105. [PubMed: 10156437]

Purcal C, Muir K, Patulny R, Thomson C, Flaxman S. Does partnership funding improve coordination and collaboration among early childhood services? Experiences from the Communities for Children programme. Child & Family Social Work. 2011; 16:474–484. http://dx.doi.org/10.1111/j.1365-2206.2011.00766.x.

Reitan TC. Theories of interorganizational relations in the human services. Social Service Review. 1998; 9:285–309. http://dx.doi.org/10.1086/515760.

Ridgely MS, Morrissey J, Paulson RI, Goldman HH, Calloway MO. Characteristics and activities of case managers in the RWJ Foundation program on chronic mental illness. Psychiatric Services. 1996; 47:737–743. [PubMed: 8807688]

Ripley R, Boitmanis K, Snijders TAB. RSiena: Siena - simulation investigation for empirical network analysis. R package version 1.1-274/r274. 2014 Retrieved from http://R-Forge.R-project.org/projects/rsiena/.

Rivard JC, Johnsen MC, Morrissey J, Starrett BE. The dynamics of interagency collaboration: How linkages develop for child welfare and juvenile justice sectors in a system of care demonstration. Journal of Social Service Research. 1999; 25:61–82. http://dx.doi.org/10.1300/J079v25n03_05.

Rivard JC, Morrisey J. Factors associated with interagency coordination in a child mental health service system demonstration. Administration and Policy in Mental Health and Mental Health Services Research. 2003; 30:397–415. http://dx.doi.org/10.1023/A:1024641630430. [PubMed: 12940683]

Rousseau DM, Sitkin SB, Burt RS, Camerer C. Not so different after all: A cross-discipline view of trust. Academy of Management Review. 1998; 23:393–404. http://dx.doi.org/10.5465/AMR.1998.926617.

Selden SC, Sowa JE, Sandfort J. The impact of nonprofit collaboration in early child care and education on management and program outcomes. Public Administration Review. 2006; 66:412–425. http://dx.doi.org/10.1111/j.1540-6210.2006.00598.x.

Shumate M, Fulk J, Monge P. Predictors of the international HIV-AIDS INGO network over time. Human Communication Research. 2005; 31:482–510. http://dx.doi.org/10.1093/hcr/31.4.482.

Snavely K, Tracy MB. Development of trust in rural nonprofit collaborations. Nonprofit and Voluntary Sector Quarterly. 2002; 31:62–83. http://dx.doi.org/10.1177/0899764002311003.

Snijders TAB. The statistical evaluation of social network dynamics. Sociological Methodology. 2011; 31:361–395. http://dx.doi.org/10.1111/0081-1750.00099.

Snijders TAB, van de Bunt GG, Steglich CEG. Introduction to stochastic actor-based models for network dynamics. Social Networks. 2010; 32(1):44–60. http://dx.doi.org/10.1016/j.socnet.2009.02.004.

Sowa JE. The collaboration decision in nonprofit organizations: Views from the front line. Nonprofit and Voluntary Sector Quarterly. 2009; 38:1003–1025. http://dx.doi.org/10.1177/0899764008325247.

Stroul, BA.; Friedman, RM. A system of care for children and youth with severe emotional disturbances. Washington, DC: Georgetown University Child Development Center; 1986. Retrieved from https://www.ncjrs.gov/pdffiles1/Digitization/125081NCJRS.pdf

Uzzi B. Social structure and competition in interfirm networks: The paradox of embeddedness. Administrative Science Quarterly. 1997; 42:35–67. http://dx.doi.org/10.2307/2393808.

Van de Ven, H.; Ferry, D. Measuring and assessing organizations. New York, NY: Wiley Interscience; 1980.

Wasserman, S.; Faust, K. Social network analysis: Methods and applications. New York, NY: Cambridge University Press; 1994.

Whittington KB, Owen-Smith J, Powell W. Networks, propinquity, and innovation in knowledge-intensive industries. Administrative Science Quarterly. 2009; 54:90–122. http://dx.doi.org/10.2189/asqu.2009.54.1.90.

Wholey DR, Huonker JW. Effects of generalism and niche overlap on network linkages among youth service agencies. Academy of Management Journal. 1993; 36:349–371. http://dx.doi.org/10.2307/256526.

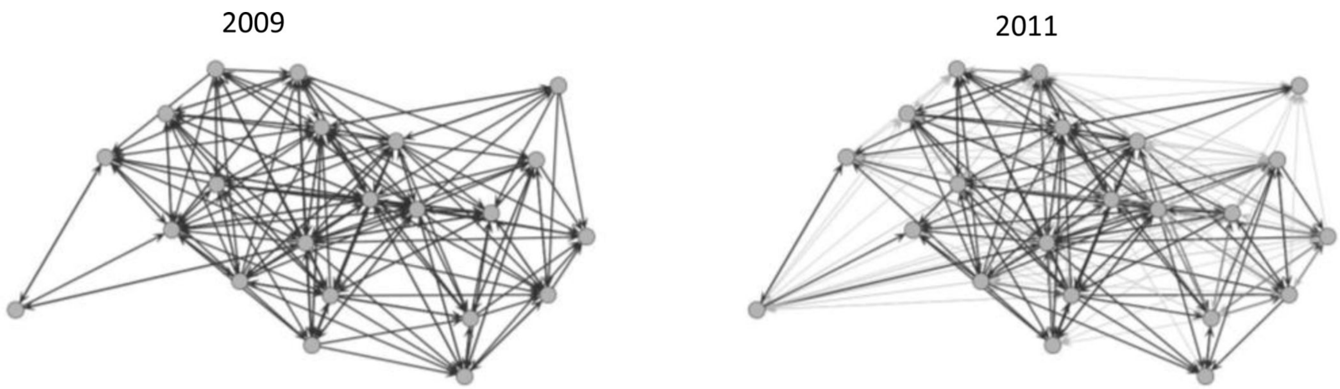

Figure 1.
Referral network in 2009 and 2011 (*N* = 22)

Note: Relationships sustained from 2009 to 2011 are depicted by dark gray lines; relationships newly formed in 2011 are depicted by light gray lines.

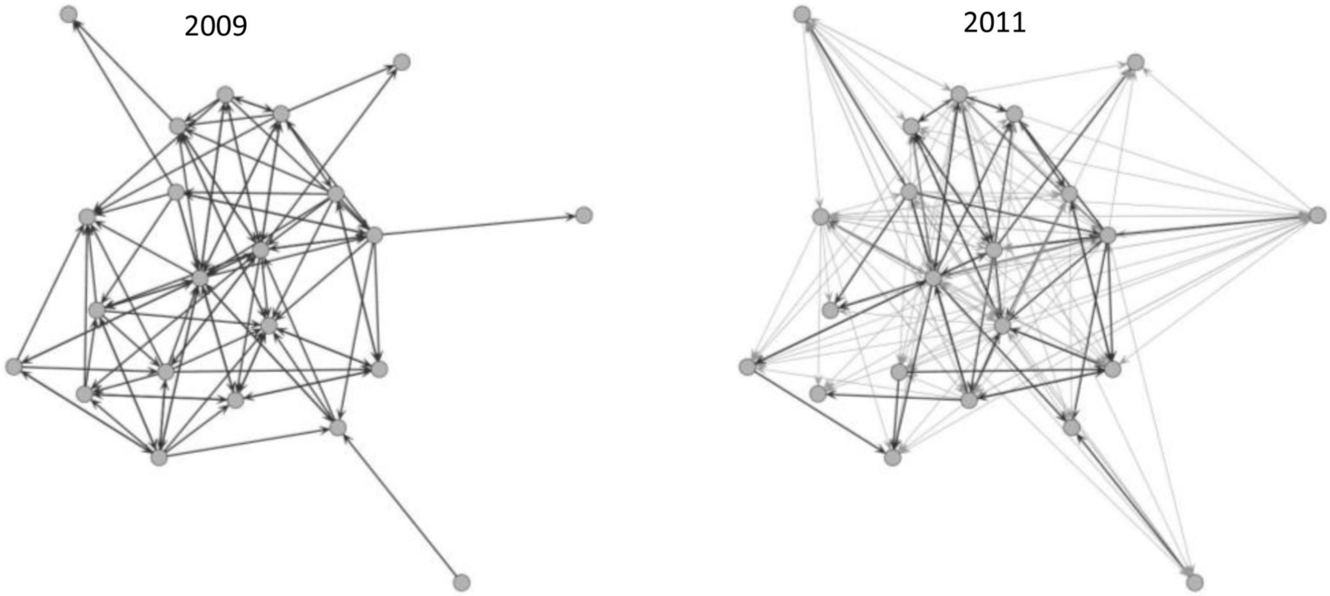

Figure 2.
Staff expertise sharing network in 2009 and 2011 ($N = 22$)
Note: Relationships sustained from 2009 to 2011 are depicted by dark gray lines; relationships newly formed in 2011 are depicted by light gray lines.

Table 1

Agency and Pair-Wise Characteristics

	N	*M*(*SD*)	Range
Organizational Characteristics			
Revenue	22	\$7.11m (\$9.63m)	\$0.04m – \$39.01m
Award size	22	\$1.00m (\$1.04m)	\$0.06m – \$4.32m
Relationship Characteristics (Dyads)			
Service similarity	231	0.95 (0.97)	0 – 5
Trust (centered)	462	0.011 (1.80)	−6.3 – 7.06

Table 2

Service Delivery Network Characteristics

	Referral		**Staff Expertise**	
	2009	**2011**	**2009**	**2011**
Density	0.411	0.569	0.212	0.361
Reciprocity	0.397	0.494	0.307	0.358
Transitivity	0.594	0.718	0.382	0.611
Jaccard Similarity	0.480		0.256	

Table 3

Service Delivery Network Evolution: Stochastic Actor Oriented Model Results

	β	SE
Referrals		
Exogenous effects		
Revenue (ego)	−0.005	0.014
Award (ego)	−0.010	0.129
Service similarity	0.163	0.138
Trust	0.141	0.052**
Endogenous effects		
Reciprocity	0.286	0.219
Transitive triplets	0.036	0.030
Outdegree-activity	0.052	0.018***
Staff Expertise-multiplexity	0.214	0.673
Staff Expertise Sharing		
Exogenous Effects		
Revenue (ego)	0.016	0.015
Award (ego)	−0.183	0.131
Service similarity	0.264	0.100**
Trust	0.076	0.053
Endogenous Effects		
Reciprocity	0.651	0.278*
Transitive triplets	0.008	0.043
Outdegree-activity	0.091	0.016***
Referrals-multiplexity	0.912	0.410*
Other Parameters		
Density (referrals)	−1.402	0.205***
Density (staff expertise)	−2.427	0.347***
Rate (referrals)	17.786	0.237***
Rate (staff expertise)	28.698	5.800***

*** $p < .001$,

** $p < .01$,

* $p < .05$