Multiplex network analysis for complex governance systems using surveys and online behavior

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Abstract

Text analysis, web scraping, and other computational techniques enable policy network researchers to efficiently obtain objective measures of network connections. However, the extent to which these observational methods differ from traditional survey instrument-based measures remains an open question. Focusing on a large regional policy network of 221 organizations, this study compares a measure of collaboration generated via survey instrument to two different measures based upon internet hyperlinks and Twitter interactions between network actors. We address two questions: (1) To what extent do objective network measures based upon observed online interactions and subjective measures based upon self-reported relationships reveal the same inter-organizational partnerships and structural network dynamics? and (2) How useful are online network measures for supplementing survey-based network measures? We find a significant ,but substantively small, correlation between survey-based measures and online interactions. Thus, online network measures may complement survey-based measures, but likely reflect different aspects of the overall policy network. We conclude by discussing the potential for multiplex measures of policy networks that draw upon multiple measures to more fully understand policy network landscapes. These results bridge and help to contextualize prior work on policy network measures and virtual policy networks within the broader context of complex governance systems.

Keywords: policy networks, multiplexity, collaborative governance, surveys, hyperlinks, social media

Introduction

The concept of polycentric governance, in which there are many relevant centers of decision-making that are formally independent of one-another (Ostrom et al. 1961), undergirds modern policy theories concerning the dynamics of complex policy systems (Lubell 2013; Feiock 2013; Andersson and Ostrom 2008). General recognition that each stage of the policy process thus plays out within decentralized networks of public and private actors is not new (e.g., O'Toole 1997; Heclo 1978; Provan and Milward 1995). However, ongoing advances in field methods for measuring networks (Yi and Scholz 2016; Leifeld 2013; Ulibarri and Scott 2016; Henry et al. 2012) and analytical methods for testing network theories (Lubell et al. 2012; Berardo 2014; Smaldino and Lubell 2011; Sandström and Carlsson 2008) continue to facilitate new ways of understanding network dynamics and assessing the effectiveness of network governance strategies.

Survey instruments have long been the tool of choice to measure networks of policy actors. Much empirical work testing theories of policy network and inter-organizational collaboration relies upon data derived by asking network actors to report data such as frequent network contacts, prominent collaborative partners, participation in inter-organizational forums, and other types of network ties (e.g., Schneider et al. 2003; Berardo and Scholz 2010; Calanni et al. 2015; Scott 2016; Ingold and Leifeld 2016; Leifeld and Schneider 2012). Recent advances in the use of surveys has allowed researchers to solicit more complete and reliable responses, and online and email surveys lower the cost of disseminating surveys (Henry et al. 2012). However, it still requires a significant investment in time and money to develop a survey and collect responses which increases with network size, and online surveys tend to suffer from lower response rates, partly offsetting the cost savings associated with online survey data collection (Shih and Fan 2008). As network size becomes large, so too does the number of possible network ties, increasing the burden on the survey respondent's recall. Perhaps most problematically, resource constraints and the unwillingness of institutional actors to engage in repeated surveys also reduces the capacity of researchers to study how networks change over time. These factors limit the ability to scale of survey methods to larger, more complex emerging institutional environments, and have prompted calls for (Lubell et al. 2012), and methodological explorations of (Yi and Scholz 2016), alternative measures of policy networks.

This article investigates the potential for using revealed online behavior to unobtrusively observe a large, directed policy network. While organizational actors in the governance process have increased their online presence in recent years, the study of online behavior among actors in an environmental governance context and the extent to which online network ties reflects meaningful policy-oriented relationships remains nascent in the institutional and governance literatures. This study builds upon the foundational work of Yi and Scholz (2016) by directly comparing online network measures to self-reported collaborative ties measured via survey instrument. Specifically, the purpose of this study is to investigate the correspondence between inter-organizational network ties coded based upon two objective, online measures, *hyperlinks* and *Twitter*, and subjectively reported network ties generated via survey instrument. Using survey data from 221 unique organizations active in a regional environmental policy network in conjunction with data from organizational websites and Twitter accounts, we address two primary questions: (1) To what extent do objective network measures based upon observed online interactions and subjective measures based upon self-reported relationships reveal the same inter-organizational partnerships and structural network dynamics? and (2) How useful are online network measures for supplementing survey-based network measures?

In what follows, we first provide background on the online interactions used to code network ties, specifically hyperlinks and Twitter activity. We then describe the advantageous circumstances of our case, in which we are able to pair survey data that have been used to support several studies of policy networks (Citation Redacted, Citation Redacted) with online network data in order to directly compare the different field methods for measuring a large-scale network. Then, we detail how these data are collected, and specify the quadratic assignment procedure (QAP) and exponential random graph model (ERGM) techniques used to model and compare each network measure. We conclude with a discussion of the implications of this work for future policy research.

Online Measures of Collaborative Networks

Because a considerable amount of governance processes and coordination activities now take place online, the study of policy networks has expanded to include network measures based purely within an online context (Rayner et al. 2013; Craft et al. 2013; Shumate and Lipp 2008). Advances in online data collection and the expansion of potential avenues for online communication and representation have created new opportunities to observe networks through direct collection of primary data rather than relying on self-reported network ties collected via surveys. Not only are these online network ties directly observable, but they can be observed unobtrusively and repeatedly over time, offering a clear advantage over survey measures in this respect. Online network measures do not necessarily provide a representational sample of all network organizations, since organizations with more resources or that more strongly emphasize public engagement are expected to be be more likely to design and maintain a custom website or be active on social media. Of course, survey instruments exhibit non-response bias as well; the intent of this paper is to examine how, in light of the known potential shortcomings, offline and online network measurement strategies compare in terms of how each portray the underlying collaborative network.

Online interactions enable social structure between network actors to be inferred on the basis of observed behavior (Park 2003). Whereas surveys generate subjective assessments of network connections, observed connections between network actors on social media and webpages are an objective representation of inter-organizational connectivity. Thus, online behaviors represent a publicly-observable affiliation between actors in the network (Shumate and Lipp 2008). For this study, we choose two online network measures: webpage hyperlinks and Twitter mentions, both of which are described in detail below. These particular measures are chosen because they reflect different aspects of interorganizational relationships. A webpage is the most prominent external digital presence an organization maintains; along with providing internal information about an organization, webpages also allow organizations to affiliate themselves with other entities or sources of information by linking to these other websites. For our second online network measure, we desired to use a social media platform; Twitter was chosen on account of its vast user base and the extent to which public, private, and nonprofit organizations use it to promote their activities.

Hyperlinks are the primary means by which users navigate through the Web, and the presence of hyperlinks in conjunction with the decision of the Web user concerning which links to follow shapes user experience of Web content. Each node in the network represents a webpage and each network tie is a hyperlink - a text or image the user can select in order to transfer to another webpage. Because a hyperlink is directional from one webpage to another, the network is also directed: that is, a network tie between node i and j does not necessarily imply a tie between j and i. Each hyperlink represents a conscious communicative choice by the website manager, and are not generated automatically. As a result, hyperlinks represent a purposive choice and can therefore be considered strategic in some sense (Jackson 1997). Communication researchers have focused on hyperlinks as an extension of social and professional affiliations (Adamic and Adar 2001) as well as extensions of other communication methods (Olesen 2004).

Policy scholars have focused on hyperlink networks as representing or extending other forms of political communication or affiliation. Of particular interest for this study, previous work has shown an actor's links within a policy network to be correlated with links in a hyperlink network, and hyperlink networks to share structural patterns with other policy-relevant networks (Yi and Scholz 2016). Similarly, substantive collaboration between non-governmental organizations has been found to be a strong driver in the formation of hyperlink ties (Pilny and Shumate 2012). Hyperlink network data between online policy actors within a policy subsystem was used in a test of the theoretical expectations of the advocacy coalition framework (Elgin 2015). While some support was offered for the methodological appropriateness of using hyperlink activity to study policy networks, it was also found the meaning and significance of hyperlinks varied according to context. Previous studies have also found that hyperlink activity may be aspirational in order to legitimate the linking organization by implying an affiliation with a more respected peer organization (Rogers 2008; Carpenter and Jose 2012).

Twitter is an online social network service that allows users to publish and read short messages, limited to 140 characters, called 'tweets' that are usually publicly visible to anyone on the Twitter social networking website. Each node in the Twitter network represents a distinct Twitter account. The key feature of Twitter that we use to construct a network is the ability to embed mentions of other Twitter users within the text of tweets. A network tie is defined as a mention of one user within a Tweet produced by another user. Like hyperlink networks, Twitter networks are directed because a mention is 'sent' from the user producing the Tweet to the user who is mentioned.

While the use of Twitter data specifically for recording policy and political networks has been limited thus far (Jung et al. 2014; Yoon and Park 2014), more generally Twitter is increasingly recognized as providing fruitful user-generated information for policy research (Shelton et al. 2015; Auer 2011). Specifically, research has found that Twitter provides a useful medium for constructing and disseminating policy narratives that shape policy information (Merry 2015). Furthermore, linking behavior of political actors in a Twitter network is strongly influenced by substantive political differences (Yoon and Park 2012), and popularity of politicians on Twitter is indicative of electoral outcomes (Digrazia et al. 2013). Together these results suggest actors' political communication and affiliations on Twitter reflect their interactions in the policy process.

Case and Data Collection

The nodes selected as the basis for this network analysis are organizations who participate in one or more of 57 collaborative institutions related to ecosystem restoration and recovery in the Puget Sound region of Washington State. In 2012-2013, a survey request was sent as a direct email from the coordinator of each group to group members on the official group email list. Respondents were asked to report on their network activities using the "hybrid name generator" technique proposed by Henry et al. (2012) to prompt respondents to identify up to five different organizations with whom they jointly implement policies or programs (this includes activities such as permitting assistance, as many network organizations act to provide funding, information, or administrative support rather than delivering public goods and services), coordinate plans and develop strategies, and informally consult. This means that each respondent could potentially list up to 15 other organizations with whom they engage in some form of collaboration. The final survey data consists of 400 responses from affiliates of 221 unique organizations,[1] with a response

[1] In order to aggregate responses to the organizational level, we first combine all ties associated with a given organization. Then, we remove duplicate entries (when two respondents from the same organization both report collaboration with the same external organization). Finally, we then control directly for the number of

rate of 40%. More information regarding the survey, including response rate, questionnaire wording, and descriptive statistics, are provided in Citation Redacted (2015) and Citation Redacted (2016).

It is important to note that the analysis is restricted to just ties between the 221 organizations that responded to the survey. Obviously, the policy network likely extends well beyond the 221 nodes that are the focus of our study (as do ties reported via the survey or recorded based upon online network measures). However, we limit our analysis strictly to to survey respondents because only surveyed organizations are able to have both ingoing and outgoing ties in the survey network measure (which is necessary for the basic ERGM framework).[2] The format of each network measurement then is a 221 by 221 matrix that reflects the observed value of a tie from one respondent to another. Ties are coded as directed ties, meaning that a tie originates with one node and end at another (and thus that a tie from actor A to actor B can take on a different value than the reciprocal tie from actor B to actor A). Directionality allows for a more detailed perspective and provides more information than network measurement methods that code undirected ties based upon project team co-membership or co-mentions in media reports.

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respondents from each organization in the ERGM in order to account for the fact that organizations with a higher number of respondents had more opportunities to name collaborators.

[2] Restricting to this network subset also has the advantage of reducing the risk of incorporating 'false positive' nodes. When link-tracing or other forms of snowball sampling of organizations is incorporated into online network data collection process, there is a risk that nodes with no collaborative ties to organizations in the original survey sample may inadvertently be included in the online network (Carpenter and Jose 2012).

Hyperlink Network Data

Hyperlink network data was collected using the internet software Issuecrawler (https://www.issuecrawler.net/). Issuecrawler is a common hyperlink network data-gathering tool that has often been used in studies of hyperlink networks (e.g., McNutt and Wellstead 2010; Pilny and Shumate 2012; Yi and Scholz 2016). From an initial set of 'seed' webpages, the web-crawling software automatically gathers all hyperlinks between web domains represented by the seed webpages up to up to two levels removed from the seed webpage. In other words, starting with a single web page associated with each organization, the program visited all the web pages within that website that a Web user could navigate to using two clicks or fewer within the same website. The program gathers hyperlink data for each web page the crawler visited, and the hyperlink connections that comprise the network links between organizational websites are reported automatically in matrix form.

The webpages serving as seeds for the webcrawling program were the home pages associated with organizations in the original survey-based network. The Google search engine was utilized in order to match the 221 organizations from the original survey to their institutional websites. It is indicative of the increasing importance of maintaining an organizational web presence that 186 (84%) of the 221 focal organizations maintain their own website with distinct hosts or domains (e.g., Huxley College of the Environment at Western Washington State University corresponds to the website huxley.wwu.edu) from which hyperlinks to other webpages can be gathered and matched to other organizations in the network. An additional 27 (12%) of the organizations in the sample have a web presence that is not distinctive, rather it is nested as a directory or individual web page within another organization's website. As these organizations do not necessarily control the content associated with these websites, they are treated as missing nodes in the hyperlink network along with the eight organizations that have no discernible web presence. The final hyperlink data crawl was completed May 29, 2016.

Twitter Network Data

The nodes of a Twitter network correspond to Twitter user accounts. Search engines as well as organizational websites were used to identify the Twitter accounts corresponding to each organization. 121 (55%) of the surveyed organizations were identified as having an official Twitter account. The Twitter application programming interface (API) was queried in order to pull all publicly available tweets from the timeline for specific user accounts, including other Twitter users mentioned in each user's Tweet. While the Twitter API limits data access to the last 3200 public tweets posted on a user's timeline, most users have not reached this limit over the lifetime of the account. The Twitter mentions that constitute the links in the Twitter network were identified by matching the Twitter account that 'received' the mention to the list of Twitter accounts associated with the organizations. This enabled us to define a directed Twitter network link as existing from the organization doing the mentioning to the organization that was mentioned.

In order to avoid conflating different network relationships, the Twitter network excludes network ties that are based solely on 'retweets'. A retweet represents content that is acknowledged and passed on by the Twitter user, but is not generated by them. As such, the relationship between the retweeter and the retweet's content is less direct. While the mention of one user in a tweet by another user may be representational, the mention of a user in a retweet can be more akin to a more disconnected 'friend-of-a-friend' (or, 'friend-of-a-friend-of-a-friend', etc.) relationship through a chain of other actors in the Twitter network.

Analysis and Results

Table 1 presents basic descriptive characteristics for each network. Because the nodes in the two online network measures represent a subset of the nodes in the original survey, the number of observations is lower for each online measure. Both online network measures have a higher density than the survey-based network, though each of the three networks appear to resemble the others in many respects.

TABLE 1 ABOUT HERE

Correlation Between Networks

We first turn our attention to the question of the degree of correlation between each network observation. Correlation between networks is tested using a quadratic assignment procedure (QAP) test in to control for structural processes that may violate the assumption of dyadic independence (Krackardt 1987; Lusher et al. 2013). Instead of simply computing the correlation across all dyads (potential pairs of actors), the QAP test uses a Monte Carlo simulation procedure to generate a distribution of Pearson correlations in order to test the observed network correlations against a null distribution while controlling for network structure. Each correlation statistic is based upon pairwise matching; thus, a sub-sample of the networks involved in each QAP test was taken that included only the nodes present in both networks involved in the QAP test. For instance, in comparing the Twitter mentions network and the survey-based network, the survey-based network was restricted to only include nodes also contained in the Twitter network.

In order to compare the online collaborative networks to the respondent-reported collaborative network, it is also important to consider how each network tie should be coded. Hyperlink and Twitter networks contain count data as well as directionality. It is possible for one organization's website to hyperlink to another's multiple times, or for an organization to mention another multiple times on Twitter. While the survey-based network can be analyzed as an ordinal network, with joint implementation ties as the strongest form of tie and informal consultation ties as the weakest form (as is done in Citation Redacted (2016)), for comparative purposes the most straightforward approach is simply to treat all reported ties as a collaborative tie, thus assigning each potential tie a value of 0 (no tie reported from organization A to B) or 1 (reported tie from organization A to B). Count data for each of the online network measures can be similarly transformed into the presence or absence of a tie. If any hyperlink is found to exist between one website and another or if an organization makes any mention of another organization on Twitter, the potential tie is assigned a value of 1 for the hyperlink and Twitter network, respectively, and 0 otherwise[3].

Table 2 presents the final QAP correlation estimate. Each correlation estimate is positive and highly statistically significant, thereby supporting the idea that organizations that self-reported collaborative relationships are more likely to hyperlink to those same organizations and mention those organizations on Twitter. Moreover, it is clear that the Twitter and hyperlink network measures are not correlated with each other a great deal more than either is correlated with the survey network measure. This suggests that survey and Twitter networks do not observe identical ties, and may each provide a unique measure of the collaborative network, largely independent from each other.

TABLE 2 ABOUT HERE

More generally from a substantive perspective, although statistically significant the correlation figures between these networks are relatively low. In other words, the online network measures appear to capture a different aspect of the collaborative network than does the survey-based measure. This suggests that these observational measures are not a very efficient proxy for self-reported, subjective survey measures of collaboration. However, the issue of greater theoretical interest is whether the different network

[3] In a sensitivity analysis we found a small uptick in correlation between the self-reported collaborative network and each of the online network measures when the threshold for defining a network tie for hyperlink and Twitter is two or more hyperlinks or Twitter mentions, respectively. However, the correlation is strictly decreasing for every subsequent threshold. Thus, we choose to code any hyperlink or Twitter mention between organizations as a tie in the hyperlink or Twitter network, respectively, in the analysis.

measures observe different specific ties but reveal similar overall network dynamics, or whether these metrics reveal different network characteristics or reflect certain sub-components of the collaborative network. QAP does not evaluate underlying structural differences (Butts 2008), and so in the next section we use a different modeling approach to evaluate this question.

Structural Characteristics

To model the structural characteristics observed with each network measure, we use exponential random graph models (ERGMs). ERGMs essentially function like a generalized linear regression logit model, as they estimate a binary tie variable (0 or 1) between each possible pair of actors. However, network data exhibit a property known as hyper-dyadic dependence, wherein the state of each dyadic relationships depends upon the states of other relationships (Cranmer and Desmarais 2015). An easy example of this is network transitivity, in which organizations A and B might be more likely to be collaborative partners if they both share a third collaborative partner, C. Thus, just as QAP is necessary to test correlation between network measures, ERGMs use a Markov chain Monte Carlo (MCMC) maximum likelihood estimation (MLE) approach to provide an analytic framework that is appropriate for modeling complex relational dependencies (Lusher et al. 2013; Koskinen and Daraganova 2013). We discuss the statistical mechanics of ERGMs in greater detail in appendix A.

While each network measure results in a different number of observed nodes (e.g., only 121 of the 221 organizations that responded to the survey have a Twitter account), we fit each ERGM to set of 221 nodes observed via the survey measure. In lieu of fitting ERGMs to network observations with different node sets, this allows us to incorporate a common node set while still accounting for the reality that a tie of no value between two organizations who are both active on Twitter represents a much different concept than the fact that there are no ties to or from organizations who do not use Twitter. To address the fact that an organization that is not active on Twitter cannot possible have a tie to or from another network actor, we use a technique that accounts for structural zeros (i.e., impossible ties) developed by Heaney and Leifeld (2015). This approach models the observed Twitter or hyperlink network using the entire 221 organization node set while fitting an edgewise covariate that denotes any dyad that must have a value of zero since a given organization does not have a website or is not on Twitter. The parameter for this covariate is not estimated, but rather is constrained to be infinitely small, essentially serving to downweight these dyads such that these structural zeros do not factor into other parameter estimates.

To further compare online and offline network measures, additional ERGM terms were chosen to evaluate structural characteristics identified in the policy networks literature as being important for solving different types of collective action problems. Particular arrangements of network ties foster different forms of social capital, and thus are useful for solving different types of collective action challenges (Berardo and Scholz 2010). Bridging capital is associated with low-risk coordination dilemmas where information sharing is a priority; Information dissemination tends to occur most efficiently via diffuse structures that span otherwise disconnected actors (Berardo and Lubell 2016). Following the conceptualization introduced by Berardo and Scholz (2010), we represent bridging capital through two ERGM terms: *two-path* and *in-degree*.

In a directed network, the *two-path*[4] term adds a network statistic equal to the number of organizations that are connected via an intermediary organization. Thus, a two-path allows for the increased coordination by connecting two previously disconnected nodes through a common partner. *In-degree* models the extent to which incoming network ties are evenly distributed as opposed to centralized on popular actors. Concentrating information flow through a relatively small number of well-connected actors in the policy network reduces the number of connections necessary for coordination among network actors and improves rates of information flow in the policy network (Berardo 2014). We use a geometrically weighted in-degree (GWID) term, which adds a network statistic equal to the in-degree distribution in the network that is weighted so that each additional in-link has a declining marginal effect on forming additional network ties (Morris et al. 2008).

Actors in networks with high levels of bonding capital tend to arrange in tight-knit clusters. This allows for preservation of the network flow if a link is compromised and allows relatively independent verification of network information flow (Berardo and Scholz 2010). However, robust linking patterns come at the expense of network efficiency, as more links are required to spread information among the same number of actors. Bonding

[4] A two-path exists connecting organization i and organization j through organization k if $Y_{ik} = Y_{kj} = 1$ (for $i \neq j$) (Morris et al. 2008).

capital is represented through the *transitivity* and *mutuality* terms. *Transitivity* refers to the tendency for two-paths to close; for 'friends-of-friends' to become friends themselves. This process creates clusters of redundant ties in the network characteristic of networks with higher levels of bonding capital (Berardo and Scholz 2010). Specifically, here *transitivity* is represented by a geometrically-weighted edgewise shared partners statistic (GWESP) that models the number of triangles incident on each tie[5] (Goodreau et al. 2009).[6] *Mutuality* is used to model network reciprocity, or the tendency for a tie from one organization to another to be reciprocated in the other direction.[7] Repeated reciprocal interactions increases the potential value of cooperative network ties thereby decreasing the incentive to defect in high-risk cooperative network contexts (Friedman 1971; Axelrod and Hamilton 1981).

In addition to endogenous structural terms, the model also includes key actor attributes that may affect network tie formation. The *assortative mixing* parameter models the change in log odds of a tie when both organizations in the dyad are of the same type. This controls for a common network observation known as homophily, in which organizations of a similar type are more likely to link to each other (Gerber et al. 2013). The next three coefficients represent node factor in-link effects for three organizational types: local

[5] For instance, node k is a shared partner of nodes i and j when $Y_{ik} = Y_{jk} = 1$, and the GWESP statistic would increase by 1 if $Y_{ij} = Y_{ik} = Y_{jk} = 1$.

[6] Both the GWID and GWESP statistics incorporate an additional, fixed shape parameter that determines determines the marginally decreasing weight given to each additional degree or shared partner. The general idea is that changes to lower degree nodes are more important than changes to higher degree nodes (e.g., going from an indegree of 0 to 1 rather than an indegree of 5 to 6), and likewise that the strength of the triad closure process should marginally decline with every additional shared partner (Levy et al. 2016). We return briefly to this issue in the results presented below, since the choice of a particular shape parameter bears on the estimated GWID and GWESP coefficients.

[7] Mutuality is estimated as the predicted change in log odds of tie Y_{ji} given that tie $Y_{ij} = 1$.

governments (including county governments, city governments, and special districts), state agencies, and university/research organizations, respectively. These three organizational types are called out specifically because local governments and state agencies have been identified as central network actors in similar policy network cases (Berardo and Scholz 2010; Schneider et al. 2003; Lubell and Fulton 2008), and university extensions are shown to be key conduits for information sharing in local environmental policy networks (Hoffman et al. 2015). Specifically as relates to the case of Puget Sound, local governments implement major environmental programs related to shoreline management, permitting, and nonpoint source pollution, and state agencies factor prominently as lead entities for the federal Clean Water Act and salmon recovery under the Endangered Species Act.

Finally, every ERGM includes an *edges* term, which acts as a model intercept controlling for baseline network density (simply the number of observed edges), and an *isolates* term that controls for the number of nodes that have no observed ties whatsoever.[8] We use the statnet package (statnet.org) in R to implement to estimate a separate ERGM for each network with identical terms for each model and the ties for each network serving as the respective dependent variables. Both GWESP and GWID shape parameters (which determine the marginally decreasing weight given to changes in higher order degree or shared partner values) were fixed at different values for the survey, hyperlink, and Twitter models in order to achieve a better model fit. Sensitivity analyses[9] varying the shape

[8] Specifically, *isolates* estimates the unlikelihood of a tie connecting a node to the graph through just a single tie. In other words, the parameter represents the change in log odds of $Y_{ij} = 0$ if $Y_{ik} = 0$ for all $k \neq j$ *and* $Y_{ki} = 0$ for all k.

[9] Sensitivity tests used fairly standard fixed shape parameter values between 0.5 and 2.5 (Levy 2016). When the shape parameter equals 0, only changes from 0 to 1 degree (or 0 to 1 shared partner) are counted, and when the shape parameter equals ∞, all changes are given equal weight.

parameter revealed that the choice of a particular shape parameter value does not substantially affect parameter estimates. Appendix A presents goodness-of-fit statistics for each ERGM model presented.

If online and survey network observations are largely driven by the same underlying network processes, we would expect our model results to reveal similarities in structural patterns of tie formation across network modes. The estimation results in figure 1 indicate many structural similarities between online- and survey-based network observations, but with a few notable divergences. All three network estimates suggest a similar bonding capital for the policy network. The estimated values for *transitivity* across all models suggest a similar propensity across both online and survey-based network measures for triadic closure. In the context of bonding capital, this represents similar levels of clustering, with the implied potential for cohesion and development of trust and social norms.
FIGURE 1 ABOUT HERE

While the parameter estimates for the *mutual* term are positive and highly significant for all three modes. This is matches the strong tendency for reciprocity often exhibited in policy networks (Berardo and Scholz 2010; Isett 2005; Park et al. 2009); in general, norms of reciprocity are key in maintaining collaborative ties in any policy network, making it non-reciprocal dyadic relationships unlikely (Henry et al. 2011). What is most notable for the problem at hand, however, is that the magnitude of reciprocity is considerably greater in the survey-based model. We posit that because the survey instrument was designed to elicit information on particular collaborative relationships (e.g., two organizations that jointly develop plans or policies), and this specificity of measurement induces relatively high observed reciprocity. Collaboration inherently implies mutual participation, and thus reciprocity should be the expected outcome a survey instrument that effectively measures collaborative ties. In contrast, hyperlinks and Twitter mentions are less narrowly contextualized; unlike collaboration, these other functions imply a lesser degree of mutual engagement.[10]

While the estimate of network processes associated with bonding capital is consistent across all three network measures, bridging capital structural characteristics are more disparate. All three model results indicate a negative coefficient for the *two-path* term, indicating actors tend to avoid maintaining sparse linkages that share information or facilitate coordination more efficiently across all three network measures. However, the estimated results of the *in-degree* term diverge across network measures. The *in-degree* term is negative for the survey model, which indicates a tendency for in-links to be centralized on popular actors (Levy 2016). Both online network measures exhibit the opposite tendency, with more evenly dispersed in-links among network actors. This contrasts with previous work finding that online links tend accrue to particular highly-influential organizations (Pilny and Shumate 2012; McNutt and Wellstead 2010). One possibility is that the relatively low transaction cost of forming additional online linkages caused the observed pattern of relative diffusion. Perhaps more likely, however, is that response burden plays a role in survey responses, such that on a survey instrument

[10] Eagle et al. (2009) also raise the possibility of bias in the survey instrument with respect to disproportionately measuring recent interactions, as well as more salient ties, which could serve to bias the reciprocity estimate upwards

respondents are more likely to name a few highly visible organizations as particularly salient linkages.

Estimates of the non-structural terms indicate similar linking behavior to specific actor types in all three networks. There is a propensity for organizations to disproportionately link to state agencies across all networks, perhaps indicating a similar role in each network in providing information or support to other organizations. Surprisingly given previous research, there is not a tendency for organizations to link to either local governments or universities, though this is a pattern that is likewise common to all network measures. One notable difference across networks is the assortative mixing term, which indicates a tendency for homophily in both online network measures but not in the survey-based network. If homophily links are disproportionately considered routine or perfunctory, it is possible survey respondents would not recall them (Eagle et al. 2009; Marsden 1990).

Multiplex Relationships

An additional ERGM for each network was conducted to estimate the association between each network measure and the other two network measures. While QAP was used to estimate the correlation between each of the network measures independently, an ERGM can be used to estimate the joint association of two networks with tie formation in a third network while controlling for the network processes of the dependent network. These models thus provide an additional way of gauging the strength of the association between alternative measures, and further test the extent to which each network independently contributes unique information predictive of tie formation in each of the other network measures.

INSERT FIGURE 2 ABOUT HERE

The results in figure 2 are from models that contain all terms present in the models presented in figure 1, with the addition of covariates for the presence of a tie between two actors in one or both alternative network measures. Full model results are shown in table B2; figure 2 shows the subset of coefficients that are of substantive interest. Figure 2 demonstrates a strong positive relationship among all three networks. Each network's relative predictive power can be assessed by comparing the estimates in figure 2 to the magnitude of the structural characteristics measured previously.[11] We find that each network observation method independently predicts ties in each of the other networks with roughly the same efficiency as *mutuality* or *transitivity*. Thus, all else equal, we would assess the probability of a tie in one network given the presence of a tie in either of the other networks as roughly equal to the probability of the formation of a reciprocal tie or of a tie to a 'friend-of-a-friend', both of which have previously been used as possible indicators of, or to make corrections to, cognitive errors in survey responses (McCarty et al. 2007; Marsden 1990; Huisman 2014). We explore the potential of such predictions in the following section.

[11] Because estimated probabilities of network tie formation are nonlinear, the estimated marginal effect of each network tie on the probability of predicting the same tie in another network varies according to the context.

Online Interactions For Predicting Self-Reported Collaboration

Previous results pertaining to overall graph correlations (assessed using QAP) address the general relationship between the three network measures, and the ERGM results in the preceding section speak to structural similarities in the three measures. It is also relevant to consider how well network measures are able to approximate the actual location of edges in the other networks. Because surveys represent the current state-of-the-art in measuring policy networks, we focus this section particularly on exploring how well models fit to online network measures are able to reproduce the edges observed in the survey-generated network. To do this, we repurpose the idea of precision-recall curves as a way to test not just goodness-of-fit (in terms of how well a model fits the data to which it was fit), but as a way to compare how well different models (fit to offline and online network measures) are able to predict the subjective offline collaboration patterns reported by survey respondents.

Precision-recall (PR) curves are often used to test ERGM goodness-of-fit by assessing the extent to which a model is able to successfully simulate networks that resemble the observed network (Heaney and Leifeld 2015). While goodness-of-fit statistics that assess the number of certain network structures that occur in simulations are useful for gauging whether the ERGM reproduces topologically similar networks, a PR curve compares the actual location of edges in the simulated graphs to the observed graph. Recall refers to the extent to which a model is able to predict edges that were observed (i.e., to avoid false negatives by recalling existing network ties). One way for a model to achieve perfect recall would be to predict a complete network in which every edge exists; such a model is of course not desirable, and so there must be a penalty for false positives (edges predicted that are not in fact observed). The ability of a model to minimize false positives is referred to as precision, which is calculated as the proportion of predicted edges that are observed in the data over the total number of predicted edges. By plotting recall (ability to avoid false negatives) against precision (ability to avoid false positives), we can gauge the extent to which a model successfully predicts observed network structures. The intuition behind this comparison is precision will decline as recall increases, since a model that simply generates more ties will have a higher recall rate, but precision will decline since more false positives are a natural consequence of reducing the rate of false negatives. A well-fitting model, however, should perform better in this regard by improving recall without sacrificing a great deal of precision. Specifically, instead of just increasing the number of predicted ties (thereby increasing recall and decreasing precision), a model with useful structural and exogenous covariates should be able to accurately predict more observed edges while avoiding false positives.

FIGURE 3 ABOUT HERE

Figure 3 presents precision recall curves generated from each model with respect to predicting edges from the original survey-based network measure. In addition to using models fit to each of the three network measures, we also examine a fourth model fit to the survey-generated network that includes as covariates a series of indicators for whether or not two organizations have an observed hyperlink tie, twitter tie, or both.[12] Figure 3 also

[12] These models also control for whether or not each organization has a website and and an active Twitter account, so that the estimated effect for having an online network tie is conditioned on whether or not each organization could possibly have such a tie.

includes a precision-recall curve for a random graph model (i.e., an ERGM with just an edges term) for reference. To fit each curve, we simulate 10,000 hypothetical networks based upon each fitted ERGM, and for each simulation, record the level of precision and recall with respect to the survey-generated network. Each path in figure 3 thus summarizes the relationship between precision and recall of the survey-generated network across the 10,000 simulations generated from a given model.

Turning to the items of interest (how well the hyperlink and twitter network-based models are able to predict surveyed edges), we observe that both online network measures alone do a reasonably strong job of predicting offline ties compared to random networks. One would not expect either model to perform quite as well as the survey-based model, given that the "Survey" curve reflects the ability to generate the dependent variable to which it was fit as opposed to predicting an out-of-sample network. Nonetheless, both online measures strongly outperform the random edges model in precision and recall, evidencing that readily observable online network measures can offer insights into offline collaborative behavior prior, or in addition to, survey-based data measures.

Perhaps more important is the improvement of the "Survey with online tie covariates" curve compared to the "Survey" curve. This suggests a survey-based network model that includes hyperlink and Twitter network data as additional covariates will perform considerably better at predicting network ties identified by a survey than a model based solely on structural and actor parameters within the survey-based network. In cases of missing network data, simulations of the complete network based on ERGMs or use of simple network processes can help to recover a distribution of possible full network states (Goodreau et al. 2008; Huisman 2014). Our results suggest using a data recovery method that includes hyperlink and Twitter network covariates could recover the unobserved network more precisely, leading to more accurate imputations of the full network when missing links occur in the data.

To better illustrate this, we can summarize the area under each PR curve, as shown in figure 4. Figure 4 more clearly shows the differences between each model, in particular that while the precision-recall curves for the hyperlink-based ERGM and twitter-based ERGMs diverge in figure 3, overall the two models perform similarly with respect to predicting the survey-based network (and that both models far outperform the random network graph). Figure 4 also shows the survey model that includes hyperlink and Twitter edge covariate terms clearly outperforms the model that does not include these terms.

FIGURE 4 ABOUT HERE

Discussion

The three sets of results above (overall network graph correlation, parameter-based inferences from ERGMs, and predicting survey-reported ties) collectively evidence that online measures of collaborative behavior can approximate subjective reports of interorganizational collaboration. To be sure, the QAP correlation and PR curve results clearly demonstrate that neither online measure used in this study (webpage hyperlinks and Twitter mentions) is able to perfectly replicate the survey-based results on its own.

However, to focus on this aspect of the results would be to miss the potential for alternative online network data to complement survey-based network data collection methods.

The original survey instrument used to collect data on offline collaboration took several months and thousands of dollars to develop and implement. Even then, it could only be used to collect data at a single cross-sectional instance. In contrast, measures of online collaboration were collected freely, within about a day (not factoring in time spent learning the appropriate field methods and developing the code). The expediency and minimal cost of online network data collection methods thus hold great potential for ongoing research of policy networks and collaborative governance. In particular, survey-based longitudinal analyses of policy networks have typically been limited to very few, or even just two, periods (e.g., Berardo and Scholz 2010). This is not just due to the time and effort required to design and implement surveys, but also because the intrusiveness of surveys can make it difficult to collected repeated measures from sample subjects. Online network measures obtainable via passive data collection methods offer an unintrusive alternative that can be collected frequently, if not constantly, in order to measure ongoing changes in policy networks and assess collaboration in near-real time.

One future possibility, given the demonstrated divergence we observe between offline and online network measures, might be to supplement a limited number of surveys with more frequent online data collection. This would provide a way to gauge the extent to which online measures reflect meaningful policy interactions (which are typically of primary interest both to policymakers and researchers) while enabling a frequency and volume of network data that would otherwise be unobtainable. As demonstrated herein and by Yi and Scholz (2016), other forms of affiliation data such as membership in interorganizational forums can also provide a supplementary metric to understand offline collaboration. Group membership data are often also readily obtainable, and can help researchers to further triangulate policy networks. This analysis suggests it would prove fruitful to explore both forms of alternative network measurements, group co-membership and online interactions, as possible covariates for more accurate or precise imputation methods for handling missing network data, as well as exploring possible limitations of surveys to capture all policy network linkages.

An additional issue of salience is why the inter-measure correlation estimates produced in this analysis are so much lower than the correlations that Yi and Scholz (2016) observe. Yi and Scholz (2016) do not examine subjectively reported collaborative partners; the offline measures used by Yi and Scholz (2016) are co-membership in collaborative governance partnerships (e.g., a regional planning forum) and co-mentions in media outlets (e.g., both organizations being mentioned in the same newspaper article). These types of ties likely exhibit different tendencies than self-reported survey measures, both for methodological and conceptual reasons. First, the survey measure is directed, whereas co-membership and co-mentions are not, which means that there are far more potential ties in the survey-based network. Second, the survey instrument asked respondents to report on up to five organizations with which they partner to implement projects or programs, participate in joint planning, or regularly share information, respectively. These are more specific, narrowly defined metrics that likely result in a more restrictive set of identified network ties. Although the nature of the metrics differ, there might also be additional technical reasons why inter-network QAP correlation estimates were so much larger in their analysis. While Yi and Scholz (2016) consider node-level characteristics of a large-scale network, their QAP and ERGM analyses of network structures focus on a 'core' network of 25 actors. Larger networks are inherently less dense simply because the potential number of ties each actor can have is so large, but the number of ties any one actor has does not necessarily change (Bodin and Prell 2011). By the same token, one would expect correlation to decrease as network size increases, because the number of possible ties increases much more rapidly than the number of actual ties. Thus, these results help bridge the findings of Yi and Scholz (2016) to large-scale policy networks often observed in practice. As the boundaries applied to a policy network are expanded, the network is likely to appear to be much less dense and more segmented than when viewing that same network with a narrower, more restrictive lens.

While both online network measures have been shown to correspond to subjective self-reported collaborative activities, there is a challenge in interpreting the meaning of the online network linkages. Surveys, though costly to administer, are also more precisely interpretable than online network methods. Network linkages depend on the purpose they serve for the organizations that utilize them. For example, different organizations may treat Twitter primarily as a communication tool or as a symbolic network used for purposes significantly different than the collaborative activities elicited by the survey, to the extent that they use it at all (Segerberg and Bennett 2011). Actors in a political environment may often link to their opponents as well as their allies, indicating an adversarial relationship rather than a collaborative one (Elgin, 2011). As mentioned previously, absence of cost associated with sustaining internet linkages can also result in a proliferation of symbolic or diffuse links. While most of these considerations are beyond the scope of the present analysis, they must be taken into consideration when interpreting network measures based upon online behavior. They also provide avenues for further research. Qualitatively coding the context associated with online linkages could help more precisely identify those that represent collaborative ties, although this would come at a cost of reduced speed and ease of network analysis.

Conclusion

While technical advances have created new avenues to measure collaboration among organizations in a policy network, new methodologies to exploit these new opportunities are still in the process of being developed. This study helps to extend previous work on alternative network measures to explicitly compare a survey-based network measure to online network measures constructed using hyperlink and Twitter data for a large policy network. Our results indicate that online measures generate broadly similar network-scale conclusions (e.g., similar estimates for structural ERGM parameters), but that the online measures capture tie patterns that are not observed via survey (and vice versa). Our results show that each of the network ties (both survey-based and web activity-based) are strongly indicative of tie formation activity in each of the other networks, simulation-based measures of correlation indicate highly significant correlation between survey-based and online network observations, and the inclusion of online network measures as covariates greatly improved tie-prediction in a model of the survey-based network.

However, the low level of correlation measured by the QAP test, and relatively small area under the precision-recall curves associated with each of the online network's estimations of survey ties suggests online behavior does not precisely replicate the results of survey instruments which are a current standard practice for collaborative network data collection. From the standpoint of supplanting survey-based network measures, online measures are an efficient (given ease of collection) but perhaps not very effective substitute. Rather, online methods of network observation show great promise in complementing existing survey methods rather than supplanting them.

While it may not be feasible to repeatedly administer surveys in order to dynamically measure network change, nor to measure network ties for a policy network involving thousands of actors, online measures make such network observations within the realm of possibility for the researcher. Although using online network methods alone to measure these policy networks would likely be erroneous in many contexts, future research that focuses on how best to use these methods in concert could open up many new opportunities to investigate how networks change in response to policy or how different network characteristics affect policy outcomes across many networks. Combining multiple measures of a policy network offers potential benefits both for making comparisons across policy networks and for understanding collaborative dynamics within a given network. The fact that the online and survey-based measures generate similar network-level inferences from divergent graph patterns indicates potential for jointly using online and offline metrics to triangulate key inter-network differences. Moreover, given that organizations interact with one another in numerous ways, developing a suite of metrics for more holistically assessing network ties will allow for a more nuanced understanding of governance processes that account for the various forms that collaborative relationships can take.

Finally, just as modern computational field methods allow for collecting online network measures, text analysis methods enable new and better ways of measuring offline network ties on a large scale. For instance, automated text analysis of meeting minutes can provide a more nuanced assessment of ties within inter-organizational collaborative groups than can simple membership rosters. Coupling these types of methods offers the potential to measure policy networks with greater frequency and detail, even without the use of surveys.

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Appendix A: ERGM Goodness-of-Fit

ERGM fitting

In brief, an ERGM assumes that the observed network is one possible realization of the underlying "true" network, wherein the set of possible realizations is defined by a multivariate probability distribution (Desmarais and Cranmer 2012; Cranmer and Desmarais 2011). After simulating a distribution of possible networks (weighted in accordance with similarity to the observed network), an ERGM is able to compare the observed network to this distribution and assess whether particular network structures are more or less prevalent than would be expected at random. The MCMC MLE technique is needed because the number of potential configurations for a large network is computationally intractable. An ERGM generates a graph at random, and "toggles" one tie at a time, then compares the likelihood of the prior and current graph. If the likelihood of the new graph is higher, the new graph is selected and the procedure continues. If the likelihood of the new graph is lower, the new graph is only accepted at a given rate (e.g., 50% of the time), and then the process continues (see Koskinen and Daraganova 2013). Model parameters are estimated by solving for the set of parameter values with the maximum likelihood given the observed network and distribution of hypothetical networks (Geyer and Thompson 1992).

Adequate MCMC Mixing

Exponential random graph models (ERGMs) are a tool for inferential network analysis intended to facilitate conclusions about key drivers and structural tendencies in an observed network. Standard generalized linear models (e.g., logit and probit models) are inappropriate for estimating network ties, since these dyadic statistical designs do not account for hyperdyadic relationships present in networks, such as how the value of edges from A to B and from A to C might influence the value of the edge between B and C (Cranmer and Desmarais 2015). Instead, ERGMs assume that that the observed network is one realization from the distribution of possible network graphs, and that by comparing the observed graph to the distribution of potential graphs (weighted in accordance to structural similarity to the observed network), we can make inferences regarding key network drivers and structural tendencies in the network (based upon the relative prevalence of particular structures as compared to the simulated distribution) (Lusher et al. 2013). For any network of non-trivial size, the sheer number of possible graph configures is prohibitively large; thus, ERGMs use a Markov chain Monte Carlo (MCMC) maximum likelihood estimation strategy that samples from the distribution of hypothetical networks, and then solves for the set of parameter values that make the observed network most likely (Morris et al. 2008).

A poor fitting ERGM can become degenerate, a condition wherein the sampling chain cascades to either a completely full (all ties realized) or complete empty (no ties realized) network (Snijders et al. 2006). The MCMC traceplots presented in figure A1 demonstrate that the models presented in this paper do not become degenerate, and rather that the MCMC process sufficiently mixes throughout the relevant parameter space. Note that we present traceplots only for the three primary models presented in figure 1; Diagnostics for figure 2 models (multiplex edges) were also sound.

FIGURE A1 ABOUT HERE

Parameter Convergence

Along with demonstrated sufficient MCMC mixing, it is also important to demonstrate model convergence, namely that the procedure identifies a unimodal estimate distribution for each parameter (Goodreau et al. 2008). Figure A2 presents density plots for the each model shown in figure 1.

FIGURE A2 ABOUT HERE

Approximating Observed Network

Further, in order to provide a suitable basis for comparison on which to draw inferences, an ERGM must be able to generate a distribution of networks that reasonably approximate the observed network (otherwise, parameter significance is largely meaningless) (Goodreau et al. 2008). Figure A3 compares the distribution of simulated statistics to the number of each structure occurring in each empirical network. The fact the each observed statistic is generally centered within each distribution evidences goodness-of-fit.

FIGURE A3 ABOUT HERE

Appendix B: Tabular Model Results

TABLE B1 ABOUT HERE

TABLE B2 ABOUT HERE

Table 1: Descriptive Network Statistics

	Survey	**Hyperlink**	**Twitter**
n	221	186	121
density	0.02	0.03	0.05
isolates	21	21	18
edges	1045	1051	691
mean degree*	4.73	5.65	5.71
**Term equals both mean in-degree and mean out-degree of network*			

Table 2: Graph Correlations Estimate With QAP

	survey	hyperlink	Twitter
survey	1.00 (221)		
hyperlink	0.23 (186)	1.00 (186)	
Twitter	0.17 (121)	0.23 (115)	1.00 (121)

Table B1: Full ERGM results for survey, hyperlink and Twitter models

	Survey	**Hyperlink**	**Twitter**
Structural Terms			
edges	-4.63 (0.09)***	-4.98 (0.10)***	-4.58 (0.01)***
mutual	2.02 (0.13)***	0.90 (0.13)***	0.68 (0.01)***
isolates	1.51 (0.31)***	1.57 (0.37)***	2.14 (0.00)***
transitivity (GWESP)$^{+}$	1.30 (0.06)***	1.67 (0.07)***	1.51 (0.01)***
two-path	-0.07 (0.01)***	-0.04 (0.00)***	-0.06 (0.01)***
In-degree (GWID)$^{++}$	-0.80 (0.18)***	0.28 (0.22)	0.34 (0.01)***
Node Terms			
assortative mixing	0.12 (0.10)	0.61 (0.07)***	0.60 (0.01)***
local govt in-links	-0.09 (0.06)	-0.02 (0.05)	-0.14 (0.03)***
state agency in-links	0.65 (0.08)***	1.19 (0.08)***	0.50 (0.01)***
university/research in-links	-0.08 (0.11)	0.14 (0.10)	0.03 (0.03)*
# resp (webpages, tweets)	0.11 (0.01)***	5e-4 (1e-4)***	8e-5 (2e-5)***

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

+ To improve goodness of fit, weight parameter is fixed at 0.625 for the survey model, 0.550 for the hyperlink model, and 0.700 for Twitter model

++To improve goodness of fit, decay parameter is fixed at 0.95 for the survey model, 0.80 for the hyperlink model, and 1.10 for the Twitter model.

Table B2. Full ERGM results for network multiplexity models

	Survey	Hyperlink	Twitter
Network Multiplex Terms			
Survey Network Edge	-	1.70 (0.11)***	0.93 (0.00)***
Hyperlink Network Edge	1.48 (0.09)***	-	1.33 (0.01)***
Twitter Network Edge	1.08 (0.14)***	1.05 (0.08)***	-
Both Network Edges	-1.14 (0.06)***	-1.22 (0.03)***	-0.96 (0.00)***
Structural Terms			
edges	-4.60 (0.09)***	-5.00 (0.05)***	-4.73 (0.02)***
mutual	2.07 (0.15)***	1.03 (0.09)***	0.64 (0.01)***
isolates	1.60 (0.05)***	1.87 (0.01)***	2.25 (0.01)***
Transitivity (GWESP)	1.25 (0.06)***	1.68 (0.05)***	1.43 (0.04)***
two-path	-0.06 (0.00)***	-0.04 (0.00)***	-0.05 (0.01)***
In-degree (GWID)	-0.73 (0.16)***	0.43 (0.05)***	0.48 (0.02)***
Node Terms			
assortative mixing	-0.09 (0.11)	0.68 (0.09)***	0.56 (0.01)***
local govt in-links	-0.13 (0.06)	-0.02 (0.07)	-0.17 (0.04)***
state agency in-links	0.31 (0.11)**	0.85 (0.10)***	-0.09 (0.01)***
university /research in-links	-0.11 (0.13)	0.25 (0.10)*	0.06 (0.01)***
# resp (webpages, tweets)	0.10 (0.01)***	5e-4 (2e-4)***	1e-4 (2e-5)***
Multiplex Sender Terms+			
# sender responses	-	-0.04 (0.02)***	-0.02 (0.02)
# sender webpages	-6e-4 (4e-4)	-	-1e-3 (3e-4)***
# sender Tweets	-5e-5 (4e-5)	-1e-4 (3e-5)***	-

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$
+Inclusion of these terms slightly improves model fit according to AIC and BIC but does not substantially impact the results. They are used to control for the total number of responses (and webpages/tweets) of each 'sending' node in the dyad associated with the two non-dependent networks in each of the models. The terms help capture the potential for overall out-degree behavior (including structural zeros) in the dyads of the two non-dependent networks.