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How Correlated Are Network Centrality Measures?

Thomas W. Valente, PhD,
University of Southern California, Department of Prevention Research, Los Angeles

Kathryn Coronges, MPH,
University of Southern California, Department of Prevention Research, Los Angeles

Cynthia Lakon, PhD, and
University of Southern California, Department of Prevention Research, Los Angeles

Elizabeth Costenbader, PhD
Research Triangle Institute, Raleigh North Carolina

INTRODUCTION

Calculating centrality has been a major focus of social network analysis research for some time (Freeman, 1979). Textbooks and reference volumes on social networks include a chapter on centrality calculations and concepts (e.g., Degenne & Forsé, 1999; Scott, 2000; Wasserman & Faust, 1994). Currently, at least eight centrality measures have been proposed and made available in UCINET 6 (Borgatti, et al., 2005). These measures are: degree, betweenness, closeness, eigenvector, power, information, flow, and reach.

Perhaps the most frequently used centrality measures are degree, closeness, betweenness, and eigenvector. The first three were proposed by Freeman (1979) and eigenvector was proposed by Bonacich (1972). Centrality is important because it indicates who occupies critical positions in the network. Central positions have often been equated with opinion leadership or popularity, both of which have been shown to be associated with adoption behaviors (Becker, 1970; Rogers, 2003; Valente, 1995; Valente & Davis, 1999). Typically, investigators use only the degree measure of centrality (simply the number of links a person has), as it is the easiest to explain to non-network savvy audiences and its association with behavior is intuitive.

An often asked, yet rarely answered question has been: Are these centrality measures correlated? All centrality measures are derived from the adjacency matrix and so constitute different mathematical computations on the same underlying data. If the measures are highly correlated, then the development of multiple measures may be somewhat redundant and we can expect the different measures to behave similarly in statistical analyses. On the other hand, if the measures are not highly correlated, they indicate distinctive measures likely to be associated with different outcomes.

Previous studies have examined correlations among centrality measures. One study examined correlations between degree, closeness, betweenness, and flow, and also examined these relationships under conditions of random error, systematic error, and incomplete data (Bolland, 1988). Overall degree, closeness, and continuing flow centrality were strongly intercorrelated, while betweenness remained relatively uncorrelated with the other three measures (Bolland, 1988). In a network study of individuals connected through participation in HIV risk behaviors,

Corresponding author: Prof. Thomas Valente, Department of Preventive Medicine, School of Medicine, University of Southern California, 1000 Fremont Ave, Bldg A Room 5133, Alhambra CA 91803; tvalente@usc.edu).

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Rothenberg and colleagues (1995) examined relationships among eight centrality measures: three forms of information centrality, three distance measures (i.e., eccentricity, mean, and median), and degree and betweenness centrality. Their analyses showed these eight centrality measures to be highly correlated with a few notable distinctions. While the three distance measures were highly interrelated, they were also strongly correlated with the three information measures, although less so with degree and betweenness. The latter two measures, degree and betweenness, were highly correlated, although less so with information measures. The information measures were also highly correlated.

In another study, Valente and Forman (1998) examined correlations between measures of integration and radiality and other centrality measures and personal network density. Using data from the Sampson Monastery dataset (1969) and the Medical Innovations study (Coleman et al. 1966; Burt 1987), they found that integration was most highly and positively correlated with in-degree centrality, positively correlated with closeness, betweenness, and flow, and negatively correlated with density (Valente & Foreman, 1998). In comparison, radiality was significantly and negatively correlated with out-degree but only in the Medical Innovations dataset. Lastly, Faust (1997) examined correlations among centrality measures using a subset of the data from Galaskiewicz's study (1985) regarding relationships between CEOs, clubs and boards. Faust (1997) found correlations ranging from .89 to .99 among centrality measures including degree, closeness, betweenness, the centrality of an event, and flow betweenness for the identification of central clubs.

In this manuscript, we empirically investigate the correlation among four centrality measures, which we felt were those most commonly used by network analysts: degree, betweenness, closeness, and eigenvector. Degree and closeness are directional measures, so we calculate both in-degree and out-degree, and in-closeness and out-closeness. Closeness was calculated by inverting the distance matrix and taking the row average for closeness-out and the column average for closeness-in (Freeman, 1979). Nodes that were disconnected were given a distance of N-1 so that distances could be calculated. We also calculated closeness based on reversed distances (so called integration/radiality) but found these measures to be largely redundant with closeness based on inverting distances (Valente & Foreman, 1998). Betweenness indicates how frequently a node lies along geodesic pathways of other nodes in the network, and therefore is an inherently asymmetric measure. Eigenvector can only be calculated on a symmetric network and so matrices have to be symmetrized before eigenvector centrality is calculated. To compare eigenvector centrality to the other three measures thus requires that degree, closeness, and betweenness be calculated on symmetric data as well.

Degree, betweenness, eigenvector and closeness are all measure of an actor's prominence in a network (Wasserman & Faust, 1994). While considerable conceptual overlap exists between these constructs, they also may be conceptually distinct. For example, a node in the center of a star or wheel is the most central node in the network by all centrality measures (Freeman, 1979). In other network configurations, however, nodes with high degree centrality are not necessarily the most strategically located. One way to characterize such distinctions among these constructs is in terms of how actors who occupy positions high on each type of centrality transmit influence to other actors in a network.

We might expect that the pathway of influence transmitted from nodes high in degree and closeness centrality will be similar. Both can quickly transmit information and influence through direct or short paths to others and interact with many others directly. Closeness measures are based on the ideas of efficiency and independence (Freidkin, 1991). As a result of being situated close to others in the network, actors high on closeness measures are able to efficiently transmit information and have independence in the sense that they do not need to seek information from other more peripheral actors.

Betweenness centrality measures the extent to which an actor lies between other actors on their geodesics. Actors high on betweenness centrality, therefore, have the potential to influence others near them in a network (Friedkin, 1991), seemingly through both direct and indirect pathways. A node with high betweenness centrality can potentially influence the spread of information through the network, by facilitating, hindering, or even altering the communication between others (Freeman, 1979; Newman, 2003). Similarly, those high on eigenvector centrality are linked to well-connected actors and so may influence many others in the network either directly or indirectly through their connections.

We expect that measures of degree and closeness centrality will be more highly correlated with each other than with other measures, because they are both based on direct ties. We are unsure, however, how the other centrality measures will correlate with one another. Conceptually, each centrality measure represents a different process by which key players might influence the flow of information through a social network. In this study we examine the correlation between the symmetrized and directed versions of four centrality measures; symmetrized degree, in-degree, and out-degree, symmetrized betweenness, and betweenness, symmetrized closeness, closeness-in, and closeness-out, and eigenvector (symmetric only). We calculated these nine centrality measures for 58 existing social networks (from seven separate studies) analyzed previously by Costenbader and Valente (2003).

We correlated the 9 measures for each network and then calculated the average correlation, standard deviation, and range across centrality measures. We also calculated the overall correlation and compared it by study to assess the degree of variation in average correlation between studies. Lastly, we explore the associations between four different sociometric network properties (i.e., density, reciprocity, centralization and number of components) and the centrality correlations. This last analysis seeks to determine whether centrality measures are more highly correlated in dense or sparse networks, in reciprocal or non-reciprocal networks, in centralized or decentralized networks, and in networks with few or many components. Density is the number of ties in the network divided by the total possible number of ties (N*(N−1)). Reciprocity was measured as the percent of possible ties that are symmetric. Degree centralization was measured using Freeman's (1979) formula. The number of components in the network was determined by symmetrizing the network and calculating components.

METHODS

Data were originally collected in 7 studies, which included 62 sociometric networks in a variety of settings. All of these studies interviewed or attempted to interview every one of the members of bounded communities. Table 1 presents characteristics of the datasets. The first three studies come from the diffusion network dataset (Valente, 1995). The oldest study is the 1955 classic Medical Innovation study (Coleman et al. 1966;Burt 1987). Physicians in this study were from four Illinois communities (Peoria, Bloomington, Quincy, and Galesburg) and were asked to name three general practitioners who lived in their communities with whom they discussed medical practices, from whom they sought advice, and whom they considered friends.

Data for study two were collected in 1973 in a study of the diffusion of family planning practices in Korea (Rogers & Kincaid 1981). Women in rural villages were asked to nominate five other village residents from whom they sought advice about family planning. Data from the third study were collected in rural villages in 1966 in a study of the spread of farming practices in Brazil. Farmers were asked to name their three best friends, the three most influential people in their community, and the three most influential farmers in their community.

Data for studies four and five were collected in 1993 from women's voluntary associations, Tontines, in urban Cameroon using both nominations and roster data collection techniques (Valente et al. 1997).

Study participants initially were asked to nominate five friends who were members of their voluntary organization. In a separate question, study participants were asked to circle the names of friends on a roster, which listed the names of all members of the voluntary organization. These two questions may generate different networks and therefore were considered as two distinct datasets and centrality measures are calculated for each separately.

In these first five studies, network data were collected to study the spread of a new idea, opinion, or practice (Valente 1995; Rogers 2003). In the last three studies, network data were collected in order to assist executives in organizations to better understand the flow of information within and between organizations. Data for study six were collected in 1991 from all the attorneys, partners, and associates, employed in a law firm (Lazega & van Duijn 1997). A second distinction is that the boundary for this network was functional rather than geographic. The law firm had multiple offices throughout the U.S. and as such the network data were collected among employees working in offices located in three different U.S. cities. Data for study seven were collected in 1996 from the information technology (IT) personnel within a U.S. company (Krebs, 2002).

In the law firm, attorneys were asked in three separate questions to nominate other lawyers within the firm whom they would consider to be close coworkers, friends, and individuals to whom they went for advice. Attorneys were given a roster of names and were allowed to nominate as many other attorneys from the roster as they chose for each question. In the high tech firm, IT employees were asked seven separate questions regarding the exchange of specific types of work-related information. For each question, they were allowed to select an unlimited number of names from a roster, which listed all other IT personnel employed by their firm.

All of the sociometric networks included in this study differ in their size, the number of questions asked of respondents, the type of questions asked, and the number of nominations allowed. Table 2 summarizes these differences and shows that most of these studies collected data from more than one network. For example, the Brazilian farmer's study interviewed farmers living in 11 different villages. The total number of networks in these 7 studies is 62.

Given that our aim was to determine how well centrality measures correlated with one another, we felt it would be more difficult to make this comparison if information from a large portion of the network was not collected. Therefore, we excluded from our study any network in which less than 50% of the enumerated population initially responded to the network questions. Using this criterion, we excluded one of the Illinois communities, one Korean village, and one of the Cameroonian women's voluntary organizations, leaving a final sample of 58 networks. (Since the roster data and the nominations data for the Cameroonian women's voluntary organizations were considered as two distinct datasets, exclusion of data from one of the women's voluntary organizations resulted in the loss of two networks). Table 2 presents the average properties of the networks in the 7 studies. Since networks in the same study often shared similar attributes, it would be cumbersome to present the characteristics of all 58 of these networks. . Further information on these datasets are available in Costenbader & Valente, 2003;Valente, 1995.

RESULTS

Table 3 reports the average correlations among the measures. The overall correlation among all 9 measures and 58 datasets was 0,53 (SD=0.14). Correlations among specific centrality measures varied. For example, degree (symmetrized) had the strongest overall correlations at 0.70 with ahout the same standard deviation (SD=0.15). Eigenvector centrality had the next highest average correlation (r=0.67, SD=0.15) and in-degree, out-degree, betweenness, and symmetrized closeness all had similar correlations (average r=0.53 to 0.58). Directional closeness measures, in-closeness and out-closeness, had the lowest average correlation (0.34 and 0.44, respectively).

The correlations between measures were also quite varied. The highest correlation was between eigenvector centrality and degree (average r=0.92), perhaps because both measures are symmetrized and rely, to some extent, on direct connections. The next highest correlation was between symmetrized betweenness and degree (average r=0.85) followed by closeness-out and out-degree (average r=0.81).

The correlation between in-degree and degree is considerably higher than the correlation between out-degree and degree. In part this reflects the nature of the data analyzed in this study. Since most of these datasets involve a limited number of sociometric choices, there is comparatively less variation in out-degree than in-degree.

And since degree is calculated on both the row and column sums of the adjacency matrix, it will correlate more strongly with in-degree.

The lowest correlation between measures was between closeness-out and closeness-in (average r=0.01). This is surprising, indicating that the direction of the calculation matters more than the property being measured by the algorithm. It is also worth noting that the standard deviation of these correlations was highest (SD=0.39). The next lowest correlations were for closeness-in and out-degree (average 1=0.16) and closeness-out and in-degree (average r=0.18). This is most likely a consequence of variation in naming network partners. Someone who named only 1 person, but who was named by many others would have high closeness-in but very low out-degree.

Not surprisingly, eigenvector centrality is more strongly correlated with the symmetrized versions of the other measures than with their asymmetric versions. For example, the average correlation with degree was 0.91 whereas it was 0.71 and 0.69 for in- and out-degree.

By study

There is some variability in the overall correlation among measures between studies. Table 4 reports the total average correlation between studies and shows that the IT department and Lawyers studies had the highest average overall correlations (average r=0.89 and r=0.82, respectively). In contrast the medical innovation and Cameroon roster had substantially lower average correlations (average r=0.44 and r=0.45, respectively). Restricting the comparison to studies with multiple networks yielded a more statistically significant difference in averages between studies. The Bonferroni test showed the difference was primarily between the low average correlation within the Cameron roster data and the somewhat higher ones in the Korean Family Planning and Brazilian Farmers data. Restricting the comparison to the 2 Cameroon studies that used the same questions and populations yielded a marginally non-significant difference in average correlation, and a significant difference in variance (Bartlett's chi-square test for equal variances, χ^2=4.45, df=1, p<05).

Network properties

We tested whether network properties (e.g., density, reciprocity, centralization) affected the correlation among measures. Reciprocity was strongly associated with centrality measure correlations (β=0.89, p<.01). If there were many reciprocated relationships in the network, the various centrality measures were highly correlated. This strong correlation could be a function of the symmetry status of the various measures – networks with higher levels of reciprocity will have higher correlations between asymmetric measures than those with lower levels of reciprocity. For example, the correlation between in-degree and out-degree will be unity when the network is perfectly symmetric because the in- and out-ties are identical.

As table 5 shows, although reciprocity was always positively associated with average measure correlation, the association between reciprocity and centrality measure correlation varies by the symmetry status of the measures. Correlations between symmetrized measures are weakly associated with reciprocity (β=0.29, p<.01), those between symmetric and asymmetric measures very strongly associated with reciprocity (β=0.84, p<.01), and those between asymmetric measures also strongly associated with reciprocity (β=0.69, p<.61). The average correlation between asymmetric centrality measures increases with the reciprocity of the network. Measures based on symmetrized data are unaffected by the degree of reciprocity in the network because the reciprocity has already been forced.

Density is also associated with the average correlation. Density has a negative but not statistically significant association with the average correlation of all measures (β=−0.25, p=NS). The correlation is positive and significant for symmetric measures (β=0.60, p<.01) and negative and significant for symmetric measures with asymmetric ones (β=−0.60, p<.01). This demonstrates that the density of a network plays a role in how well different centrality measures correlate to one another. That is, symmetrizing data in low density networks adds links to the network, which changes the centrality calculations so that the symmetric and asymmetric versions diverge. Interestingly, degree centralization does not affect the correlation between measures.

Finally, the number of components in the networks was positively associated with centrality correlations among asymmetric measures only (β=0.28, p<.05). Networks with more components had stronger correlations among asymmetric centrality measures. Some caution in interpretation of these regression results is warranted as many of these structural properties are correlated. For example, density is positively correlated with reciprocity (β=0.51, p<.01) and centralization (β=0.37, p<.01); and negatively correlated with number of components (β= −0.60, p<.01). Reciprocity is negatively correlated with number of components (β=−0.53, p<01).

DISCUSSION

We find strong but varied correlations among the 9 centrality measures presented here. The average of the average correlations was 0.53 with a standard deviation of 0.14, indicating that most correlations would be considered strong. The level of correlation among measures seems nearly optimal - too high a correlation would indicate redundancy and too low, an indication that the variables measured different things. The amount of correlation between degree, betweenness, closeness, and eigenvector indicates that these measures are distinct, yet conceptually related.

Direction matters, as the correlations for the symmetrized measures were quite different than those for the asymmetric versions. Interestingly, the only network variable that was positively and significantly associated with correlations between all centrality measures (correlations between symmetric measures, asymmetric measures and between symmetric and asymmetric centrality measures) was reciprocity, suggesting that the more bi-directional information flow between individuals is, the less distinct centrality measures become. In addition, correlations between symmetrized measures were associated with the number of components and network density, while asymmetric measures were not. Thus, symmetrizing matrices before making centrality calculations should be done with caution and only if justifiable substantively. In addition, unsymmetrized centrality measures might be more distinct in densely connected networks with more components.

Correlations also varied by study, but not in obvious ways. The Lawyers and IT department studies had the highest overall correlations, perhaps because these studies used roster methods and were considerably denser than the other studies, which used nomination methods. The Cameroon roster study, however, had the second lowest average correlation and it was significantly lower than the Cameroon nomination study. Thus, network data collection methods appear to influence the correlation between centrality measures and therefore should be considered when comparing centrality measures across studies.

Network properties such as reciprocity and density correlated with average correlation in interesting ways. Density decreased the correspondence between centrality measures when comparing symmetric measures with asymmetric ones. Density increased the correspondence between centrality measures when those measures were calculated on symmetric data. In contrast, in networks with many reciprocated relationships, centrality measures calculated on symmetric data provided more unique information than those calculated on asymmetric data Perhaps this occurred because the reciprocal nature of relationships decreased the differences in centrality measures. Overall, our findings show that symmetrizing network data creates disparities between symmetric and asymmetric centrality measures.

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References

Becker MH. Sociometric location and innovativeness: Reformulation and extension of the diffusion model. American Sociological Review 1970;35:267–282.

Bolland JM. Sorting Out Centrality: An analysis of the Performance of Four Centrality Models in real and simulated networks. Social Networks 1998;10:233–253.

Bonacich P. Technique for Analyzing Overlapping Memberships. Sociological Methodology 1972;4:176–185.

Borgatti, SP.; Everett, MG.; Freeman, LC. Ucinet for Windows: Software for Social Network Analysis. Harvard, MA: Analytic Technologies; 2002.

Borgatti SP. Centrality and Network Flow. Social Networks 2005;27:55–71.

Burt R. Social contagion and innovation: Cohesion versus structural equivalence. American Journal of Sociology 1987;92:1287–1335.

Coleman, JS.; Katz, E.; Menzel, H. Medical Innovation: A Diffusion Study. New York: Bobbs Merrill; 1966.

Costenbader E, Valente TW. The stability of centrality measures when networks are sampled. Social Networks 2003;25:283–307.

Degenne, A.; Forsé, M. Introducing social networks. Sage: Thousand Oaks, CA; 1999.

Faust K. Centrality in affiliation networks. Social Networks 1997;19:157–191.

Freeman L. Centrality in social networks: Conceptual clarification. Social Networks 1979;1:215–239.

Freidkin. Theoretical foundations for centrality measures. The American Journal of Sociology 1991;96 (6):1478–1504.

Galaskiewicz, J. Social organization of an urban grants economy. New York: Academic Press; 1985.

Krebs, V. [Accessed February 2002]. http://www.orgnet.com/IHRIM.html

Lazega E, van Duijn M. Position in formal structure, personal characteristics and choices of advisors in a law firm: a logistic regression model for dyadic network data. Social Networks 1997;19:375–397.

Newman MEJ. Ego-centered networks and the ripple effect. Social Networks 2003;25:83–95.

Rogers, EM. Diffusion of Innovations. 5. New York: The Free Press; 2003.

Rogers, EM.; Kincaid, DL. Communication Networks: A new paradigm for research. New York: Free Press; 1981.

Rothenberg R, Potterat JJ, Woodhouse DE, Darrow WW, Muth SQ, Klovdahl AS. Choosing a centrality measure: Epidemiologic correlates in the Colorado Springs study of social networks. Social Networks 1995;17:273–297.

Sampson, S. Unpublished doctoral dissertation. Cornell University; 1969. Crisis in a cloister.

Scott, J. Social network analysis: A handbook. 2. Newbury Park, CA: Sage; 2000.

Valente, TW. Models and methods for innovation diffusion. In: Carrington, PJ.; Scott, J.; Wasserman, S., editors. Models and Methods in Social Network Analysis. Cambridge, UK: Cambridge University Press; 2005.

Valente TW, Watkins SC, Jato MN, et al. Social network associations with contraceptive use among Cameroonian women in voluntary associations. Social Science & Medicine 1997;45:677–687. [PubMed: 9226791]

Valente, TW. Network models of the diffusion of innovations. Cresskill, NJ: Hampton Press; 1995.

Valente TW, Davis RL. Accelerating the diffusion of innovations using opinion leaders. The Annals of the American Academy of the Political and Social Sciences 1999;566:55–67.

Valente TW, Foreman RK. Integration and radiality: Measuring the extent of an individual's connectedness and reachability in a network. Social Networks 1998;20:89–109.

Wasserman, S.; Faust, K. Social Networks Analysis: Methods and Applications. Cambridge, UK: Cambridge University Press; 1994.

Table 1

Description of Datasets

Dataset	Year Data Collected	Setting	Make up of networks	No. of network questions	Question(s) asked
1	1955	Illinois communities	Physicians	3	Name 3 physicians who you consider friends, with whom you discuss medical practices, & from whom you seek advice
2	1973	Rural villages in Korea	Married women of childbearing age	1	Name 5 people in the village from whom you seek advice about family planning
3	1966	Rural villages in Brazil	Farmers	3	Name 3 best friends, 3 most influential people in community, & 3 most influential farmers
4	1993	Urban Cameroon	Women members of a voluntary organization	1	Name 5 friends belonging to the voluntary organization
5	1993	Urban Cameroon	Women members of a voluntary organization	1	Circle names of all organization members considered friends
6	1991	Corporate law firm in	All attorneys	3	Circle names of all other attorneys considered strong coworkers, friends & individuals to whom you would go for advice
7	1996	IT department in a company in Latin America	All information technology (IT) employees	7	7 separate questions regarding information exchange at work
8	1996	IT department in a company in the US	All information technology (IT) employees	7	7 separate questions regarding information exchange at work

Table 2

Network Characteristics (N=58).

Dataset	Number of networks analyzed *	Average network size	Average response rate	Average network density	Total number of nominations possible	Average number of nominations	Range of Out-degree nominations sent	Average network centralization (symmetrized)	Average network centralization (in-degree)	Average network centralization (out-degree)
1	3	64	56%	0.06	9	2.61	0–8	24.11%	20.04%	12.26%
2	24	68	64%	0.03	5	1.64	0–5	20.02%	21.06%	5.12%
3	11	76	82%	0.03	9	1.94	0–7	27.35%	30.04%	5.77%
4	9	83	76%	0.04	5	3.13	0–5	22.08%	28.65%	2.03%
5	9	83	76%	0.49	unlimited	39.06	0–152	28.82%	16.77%	49.77%
6	1	71	100%	0.32	unlimited	22.15	2–49	33.23%	30.64%	39.46%
7	1	72	82%	0.20	unlimited	14.19	0–34	24.39%	24.34%	28.69%
8	1	45	96%	0.38	unlimited	16.62	0–40	43.45%	35.74%	54.34%

* Networks in which the response rate was less than 50% were excluded from our analysis.

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Table 3

Average correlations between centrality measures (N=58).

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	
1	Indegree												
2	Outdegree	0.3											
3	Degree	0.78	0.71										
4	Between	0.62	0.54	0.7									
5	S-Between	0.69	0.5	0.85	0.67								
6	Closeness-In	0.55	0.16	0.45	0.37	0.31							
7	Closeness-Out	0.18	0.81	0.56	0.39	0.38	0.02						
8	S-Closeness	0.4	0.64	0.66	0.37	0.44	0.42	0.65					
9	Integration	0.7	0.26	0.58	0.5	0.41	0.9	0.15	0.51				
10	Radiality	0.21	0.86	0.61	0.44	0.41	0.06	0.98	0.67	0.19			
11	S-Int/Rad	0.45	0.7	0.73	0.43	0.5	0.44	0.69	0.99	0.54	0.72		
12	Eigenvector	0.71	0.69	0.92	0.64	0.72	0.44	0.55	0.63	0.57	0.59	0.71	
Average		0.51	0.56	0.69	0.52	0.53	0.37	0.49	0.58	0.48	0.52	0.63	0.65
Standard Deviation		0.21	0.23	0.14	0.16	0.14	0.27	0.22	0.25	0.28	0.17	0.12	0.12

Table 4

Total average correlation between studies (N=58).

Dataset	Total Correlation	
Medical Innovation	0.43	
Korean Family Planning	0.57	0.57
Brazilian Farmers	0.54	0.54
Cameroon Nominations	0.53	0.53
Cameroon Roster	0.46	0.46
Lawyers	0.81	
IT Dept. Latin America	0.89	
Total	0.54	0.54
	p<.05	p<.01

Table 5

Average correlations classified by symmetry status of calculation regressed on study and network properties.

	All Measures	Symmetric w/ Symmetric	Symmetric w/ Asymmetric	Asymmetric w/ Asymmetric
Average Correlation	0.54	0.71	0.44	0.55
Cameroon Roster	−0.11	0.06	−0.16	−0.11
Brazilian Farmers	0.20	−0.04	0.16	0.23*
Korean Family Planning	0.31*	0.01	0.29*	0.31**
Density	−0.52	0.67**	−0.62*	−0.55
Reciprocity	0.85**	0.26**	0.68**	0.83**
Degree Centralization	0.02	−0.07	0.07	−0.02