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Acquisition in a World of Joint Capabilities: Methods for Understanding Cross- Organizational Network Performance

24 February 2017

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Abstract

Increasingly, government managers are turning to cross-organizational networks for the acquisition and delivery of services. The use of networks is lauded as a means to eliminate service gaps, achieve synergistic benefits, and provide better buying power. Cross-organizational networks now support a large number of local, state, and federal level activities (i.e. health care, social services, emergency management, and transportation). It has long been recognized that organizations are susceptible to the vagaries of their environment and that performance is often a function of how well organizations adapt to environmental fluctuations (Ashby, 1954; Holland, 1975). Despite the popularity of networks, little is known about the unique risks they encounter and the susceptibility of cascades. The objectives of this research are to: 1) identify the exposure and vulnerability mechanisms that relate to cross-organizational network risk, contagion, and performance, 2) provide managerial recommendations on cross-organizational networks as a form of service delivery, and 3) provide a theoretical framework for conceptualizing cross-organizational networks as a service delivery option. This research models the Major Defense Acquisition Programs (MDAP) as a network of interconnecting programs and employs Contagion Modeling as a method for understanding MDAP performance.

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Introduction

Whether explicitly pronounced or implicitly performed, "jointness" has become a dominant means for modern warfare acquisition. For this research, jointness, interdependency, exchange, and partnerships all refer to a similar concept: the notion that autonomous organizations build relationships to obtain resources to provide capabilities that, when looked at in totality, form network structures. While it is true that at the individual pair-wise level, these exchanges exist as explicit transactions for the transfer of data, labor, capital, or materials, it is also true that the totality of the various dimensions, coupled with the turbulence of perturbations, influences the cost, schedule, and performance of the acquisition effort.

Organizations in the past sought to limit interdependencies to maintain control over the environment. Concerned about environmental instabilities, organizations either limited the scope of their activities, or sought to expand their domain by bringing mission critical activities internally. More recently, however, organizations have found that the costs and limitations of environmental control behaviors are both impractical and infeasible.

Typically, jointness appears in the context of shared resources, supply chains, or shared requirements. The benefits of joint activities can be great. Jointness can eliminate redundancy, streamline activities, and lead to "Better Buying Power." Jointness can also make possible what was previously improbable. Jointness has been known to result in critical synergistic opportunities, i.e. battlespace awareness.

But jointness does not come without risk. Collaborative efforts are known to experience the problems of suboptimization, moral hazard and principal-agent issues (Pfeffer and Salancik 1978). In ideal terms, the decision calculus to engage in a relationship would involve weighing the costs of lost opportunities (e.g., in terms of response time, flexibility, etc.) against the benefits of the relationship (e.g. synergy, shared resources, and economies of scale and scope). In the world of transaction costs, collaborative efforts are rarely free. Uncertainties regarding a partner's ability to commitment to a relationship for the duration of the initiative can influence the decision to engage. Transaction risk, or the probability that a loss might accrue due to a partner default, is a concern for many public managers. Recognizing that the environment of a given organization can exert powerful, and unintended, consequences on the relationship, collaboration, or jointness, is often avoided (Wilson, 1994).

Unfortunately, by and large, the literature on interdependent activities is steeped in contradictory findings. For example, some argue that tight-knit arrangements are more likely to have the social traction needed to overcome environmental difficulties (Sosa, 2011), whereas others argue that loose coupling, or weak ties, may be a better solution (Granovetter, 1973). Some claim that more information is the key to benefit attainment (Comfort, 1994), whereas others claim that more information leads to a false sense of security (Hall, Ariss & Todorov, 2007). Yet, despite the absence of consistent sage advice, resource limitations and a demand for comprehensive solutions continue to push organizations toward complex structures for the delivery of products and services.

As discussed, jointness does not occur without some degree of risk. This research examines one particular form of risk: contagion. The discussion below examines the funding interdependencies that arise from shared program elements and begs the question, are neighborhood programs contagious when it comes to cost variance? The study examines MDAP performance in light of the cost variance reports in the annual SARs from 2009 to 2014.

This report unfolds in the following manner. First we present a short overview of social network analysis. Second, we test three different modeling techniques for their ability to provide insights on the mechanisms that relate to cross-organizational network risk, contagion, and performance. Next, we provide a theoretical framework for understanding cross-organizational networks. The report then closes with managerial recommendations on cross-organizational networks as a form of service delivery.

Social Networks: A Quick Overview

This section begins with an overview of social network analysis. The section provides insight in light of the DoD MDAPs. Following the discussion, the statistical results of the examination of network cascades in MDAPs are presented.

Social Networks

A novice's glance into the field of interdependent organizational-based networks is likely to reveal a terminological jungle of abstract and obscure vocabulary. This section of the report seeks to convey many of the more common network terms and place them in the context of DoD acquisition. Table 1 provides a glossary of several of the key terms. At the onset, it is important to recognize that the term *social* is used in a specific empirical context for understanding programmatic interactions: "social systems of interaction" form the basis from which material equipment and organizational capacities get things done (Turner, 1988).

Wasserman and Faust (1994) defined the social network perspective as a focus on the relationships that exist among entities and the patterns and implications of these relationships. Overall, the vantage point is that:

- actors and their actions are viewed as interdependent rather than independent, autonomous units;
- relational ties between actors are channels for the transfer of resources; and
- network models view the structural environment as providing opportunities for, or constraints on, individual and collective action (Wasserman & Faust, 1994, pp. 3–4).

Organizations have long been viewed as resource exchanging agents. When considered in this light, each organization takes input and converts it into outputs that are then provided as inputs to another organization. Nonetheless, in the past, organizations often sought to maintain control over practices and procedures by restricting access to outside influences. Hierarchical organizational models were pursued because they provided stability. But the hierarchical approach was found to be ill-suited to situations in which needs and demands evolved. Hierarchical approaches, due to their inability to adapt, risked the obsolescence that occurred from the inability to adapt to changing needs.

Over the years, researchers have consistently found that demand uncertainty is a key contributor to the choice to forego hierarchical-based approaches in favor of organizational networks. Demand uncertainty arises when organizations lack the ability to predict near-future needs. When organizations are confronted with high levels of demand uncertainty, they require the flexibility to make rapid shifts in their service delivery and production cycles—shifts that a hierarchical approach cannot accommodate. Because networks offer an expanded set of options, they allow the ability to respond to a wider range of contingencies. For example, under asymmetric warfare conditions, the types of solutions that may be required are difficult to predict a priori. Given the uncertainty of the demands of the battle-space, warriors require a wide arsenal of alternative and complementary approaches—approaches that must be accessible at a moment's notice. When demand uncertainty is low, organizations often choose more simplistic hierarchical approaches. Under high demand uncertainty, organizations require the ability to leverage a variety of capabilities irrespective of the boundaries of a give organization's purview (Jones, Hesterly, & Borgatti, 1997).

In the work setting, network actors (or nodes) often represent people, teams, or organizations. A tie represents some form of interaction or relationship. In short, network structures provide the "plumbing" for the flow of resources through the network. Interdependent networks are complicated by the fact that they are multidimensional, and as such, understanding their behavior requires consideration of multiple levels of analysis. Typically, networks can be characterized in light of four basic levels: the individual, the subnetwork(s), the entire network, or as a multiplex network. A multiplex perspective considers the node from a multi-network consideration. For example, in this report, major defense acquisition program (MDAPs) are examined in light of the performance of the individual program as well as its resulting performance in two different networks: (1) a data-sharing network and (2) a shared budget network. Cross-level effects occur when behaviors at one network level influence behaviors at another network. Cross-level analysis involves looking at behavior across the various networks. The failure to consider cross-level effects may result in misinterpreting the full set of consequences that occur from network behaviors.

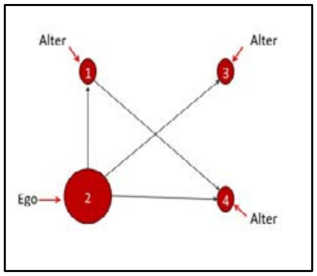

Figure 1: Network Relationships

At the individual (or node) level, an ego is the central node of interest, and those connected to the ego are known as alters (see Figure 1). A network rendering from the context of an ego is referred to as an ego-network. A dyad consists of an ego and its adjacent alter. As discussed further below, examining data in light of the dyads (or pairs) provides the ability to test the influence that one node has on another.

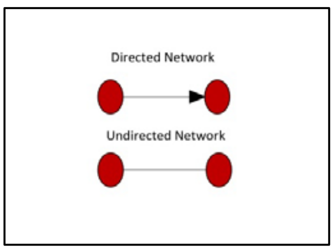

Figure 2: Directed versus Undirected Network

A directed network is one where the flow of resources moves in a specific direction, either inbound to an ego or outbound from an ego (see Figure 2). For example, the data-sharing network identified previously is a directed network because the data flow from one program to another. A directed network can be either sequential or reciprocal in nature. Alternatively, an undirected network is one that is "pooled" in nature. In other words, the nodes share a common connection (i.e., a budget), but there is no directional component to the tie. In this case, the tie indicates that the two programs share a common budget.

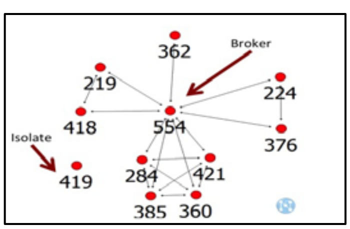

Figure 3: Network Brokers

A node is labeled as a broker when it connects two distinct subnetworks. So in Figure 3, Program Number 554 Multifunctional Information Distribution System Joint Tactical Radio System (MIDS JTRS) acts as a broker between three subnetworks. An isolate is a node with no ties. Again, in Figure 3, Program Number 419 (EA 6B

Prowler) is an isolate. In directed networks, a node can serve as a transmitter, a receiver, or a carrier. A bridge is identified when a tie spans two subnetworks. Structural equivalence occurs when two nodes are structurally similar.

Relying on matrix algebra, a number of metrics have been devised throughout the years to measure networks. Some of the metrics occur at the node or ego level, and others are at the subnetwork or whole-network levels. Nodes are often considered in light of their position, or role, in the network. Many of the ego-level metrics are calculated relative to others in the network.

The degree of a node is the number of ties that a node exhibits. These ties can be measured as inbound or outbound (or both) in a directed network. Another measure is the geodesic distance that one node may be from another. Adjacency identifies direct connections while reachability identifies whether any two nodes are capable of connecting by way of other nodes.

Degree centrality identifies the number of ties that a node possesses. The more ties relative to others, the greater the centrality. Closeness, on the other hand, indicates how close a given node is to the remaining nodes. When all of the nodes are close to all of the other nodes, the interaction level among the nodes is typically high.

Network size is often calculated as the sum of the number of nodes or number of ties. Sometimes networks (or subnetworks) are measured by their longest, or shortest, path. The bridge identified previously is often of interest because it indicates that if the tie between the two nodes can be cut, the network can be disconnected or reduced to its subnetworks. The same holds true for the broker. If a broker is eliminated, the network will be reduced to a number of subnetworks. Node connectivity identifies the minimum number of nodes that have to be removed to disconnect the network. Betweenness is the extent to which a given node lies between other nodes and, thus, could act to facilitate or block the flow of resources.

Density refers to the proportion of ties relative to the absolute total. Relational embeddedness refers to the quality and depth of a single dyadic tie. Structural embeddedness refers to the extent to which a node's alters are connected to each other. Because structural embeddedness reflects the degree of the interactions, it is often used as a proxy for understanding network actions.

In the study of networks, scholars often take either a structural or a connectionist approach. Structural approaches examine the structure of the network and its influence on key variables of interest. Connectionists, on the other hand, focus on the flows between the nodes. Those who study social capital tend to focus on the possibilities of actions that social ties provide. Others, however, tend to be more concerned with diffusion and the dynamics of network change over time. Still, other studies focus on why and how networks develop, how and why they change over time, and finally, what influences they exert. Social capital is mostly studied at the individual level, and diffusion is observed from the perspective of the entire network.

Studies of the influence of dyadic ties on performance have mixed and contradictory findings. For example, Perry-Smith and Shalley (2003) found that weak ties led to creativity, but others claim that strong ties are more advantageous (Sosa, 2011). Others claim that it is not the number of ties but rather the depth of the engagement that matters. No one would be surprised by the idea that relative to fewer ties, more ties may provide organizations with better information that might promote enhanced decision-making. At the same time, information overload and difficulties with scrubbing data to provide information at the proper specification level has become a real problem for many managers.

Similarly, studies of embeddedness are equally contradictory. According to some, the more each node knows about the others, the more constraints there are on each other's behaviors. This is often seen as a positive. Parties gather information on whom to avoid as well as potential opportunities and synergies. Structural embeddedness allows the use of sanctions since knowledge of misfeasance influences reputational value. But these constraints can backfire and actually restrict flexibility. Too much embeddedness can also create problems. It can lead to feuding, group think, and welfare support of weak members. Social aspects such as restricting access to exchanges, imposing collective sanctions, and making use of social memory and cultural processes all influence nodal behavior. Apparently, networks and ties matter, but the extent of the influence is highly debatable.

Much of the incongruity in the findings may be due to the difficulties associated with measurement and data collection. Researchers are challenged by the burden of the data collection requirements, and organizations are often frustrated by the extent of the data request. Because multilevel data are needed for each specific relationship, the data collection task can be onerous. Moreover, given that the study of networks is a fairly new phenomenon, typical organizational records often lack insights at a network level. When multilevel data are obtained, an analysis of variance statistical technique termed *hierarchical linear modeling* or *multilevel modeling* is often employed because it allows the examination of multiple units of analysis simultaneously.

Despite these contradictory findings and data collection difficulties, the examination of networks and ties that manifest as interdependencies is likely to provide substantial insights into a number of issues. First, when considering cost and affordability, examining a program in isolation of the entire value chain is likely to provide erroneous information. Second, a wealth of research illustrates the importance of risk management. Considering the risks of a given program without considering its interdependencies may underestimate the true risk level. Next, in the decision of a start-up or termination, it is essential to know how the inclusion or removal of a program will influence its n-order neighbors. Finally, network conditions may exert powerful influences over program sustainability.

The following section provides the statistical findings of the exploration of risk and MDAP networks.

Mechanisms that Relate to Cross-Organizational Network Risk, Contagion, and Performance

As alluded to above, MDAP programs often share program elements. Shared resources, i.e. program elements, are a common form of jointness. The analyses presented below test for the presence of contagion as it relates to the cost variances of neighbor programs.

The discussion below reports three different modeling techniques for understanding contagion. The three different approaches were employed to 1) cross validate the findings and 2) isolate appropriate techniques for understanding network performance. First, we evaluated the networks employing mixed effects linear regression with a modularity maximization algorithm. Second we examined the networks from a structural equation modeling perspective. We then modeled the networks from an epidemiological contagion approach. For the most part, each of the models incorporated the same measures. Below we discuss the measures employed and then turn to the results of each of the modeling attempts.

Measures

As mentioned above, the main goal of the research was to test whether the cost variance of neighborhood partners was contagious to other programs. Consequently, the cost variances reported in the annual SARs were collected. Additionally, several control variables were employed. The first was a complexity metric that measures the number of programs that share a program element. The second was a homogeneity measure that captured the number of Services that a given program element served. Homogeneity was measured by the slope of the rank abundance curve of the Services represented in each program element. A common method employed in the environmental arena, species evenness is captured in the slope of the line that fits the rank abundance. A shallow gradient indicates that the abundance of the various Services is comparable. Alternatively, a steep gradient suggests that the program element is dominated by a small number of services (or lacks diversity). Thus, a low number indicates high diversity whereas a large number reflects a high degree of homogeneity. The percent of the partners that were explicitly joint as well as the percent of the partners that were in production were included in the models as controls.

Mixed Effects Linear Regression

The modularity maximization algorithm allowed us to divide the network into groups and the mixed effects linear regression allowed us to obtain coefficients to test for the presence of contagion. With mixed effects we are able to model the random effect of the network community (j) by employing a modularity maximization algorithm.

The modularity maximization algorithm splits the network into a number of communities or groups. In other words, it tells us which MDAP programs belong together in a single cluster and which do not. Put simply, employing iteration methods modularity is the fraction of the edges that fall within the given groups minus the expected such fraction if edges were distributed at random. The benefit of using the modularity algorithm is that no single program can be identified in two groups. Hence, the groups are orthogonal.

Because we were testing the individual variance of each MDAP within each of the groups, a mixed effects model was needed (Raudenbush and Bryk 2002). The mixed effects models that were estimated are linear regressions that account for the total cost variance of all network partners, B_5 Model 1, and component cost variances of schedule, estimation, economic, and engineering that correspond with B_6, B_7, B_8, and B_9 in Model 2 respectively. The other predictors of interest in both models are β_1 which models the effect of the number of network partners that are directly connected to the MDAP program y_i. The β_2 estimator is the homogeneity of network partners based upon the rank abundance curve. The β_3 is the percent of network partners that are considered joint programs. The β_4 is the percent of network partners that are classified as in production. The δ_k is a vector of year dummies to account for the years 2010-2014, therefore, the baseline year is 2009. The network community is the random effects term (j) in the model. The α_j is the varying intercept based upon the network community upon which the MDAP program is classified.

$$\text{Model 1: } y_i=\alpha_{ji} + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \beta_4 X_{i4} + \beta_5 X_{i5} + \delta_k X_k + \varepsilon_i$$
$$\alpha_j = \mu_\alpha + \eta_j$$

$$\text{Model 2: } y_i=\alpha_{ji} + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \beta_4 X_{i4} + \beta_6 X_{i6} + \beta_7 X_{i7} + \beta_7 X_{i7} + \beta_7 X_{i7} + \delta_k X_k + \varepsilon_i$$
$$\alpha_j = \mu_\alpha + \eta_j$$

Due to the leptekurtotic nature of the untransformed y_i, the y_i was transformed using the cube root, $y_i^{1/3}$, to make the error distribution further reflect the Gaussian assumptions of the linear mixed effects model. Because the cube root equally reduces the variance of large positive and negative values, this transformation was found to be the simplest transformation possible but other transformations are also possible. The nature of the transformation does not influence the estimation of the relationship between the linear predictors. The major influence that this has upon the model is to shrink the variance of the untransformed y_i to make the model better fit the data. The interpretation of this transformation is discussed below.

The two best fitting models are presented below and they reveal that both complexity and the cost variances of the network partners influence the cost variances of the MDAP programs (see table 2). Of the two theoretical classifications of variables, we find that the complexity variable is the better predictors of cost variances in the network. First, we describe the results of the first model of the total cost variance of the network partners, which does not seem to support the hypothesis that network partners' cost variances should influence the MDAP program cost variance. Next we describe the second model that shows when we look at the component cost variances of the network partners we see modest support for the network partner to MDAP program cost variance connection at least for estimation cost variance.

Table 2: Models of Network Partner Cost Variance Effects on the MDAP Program Total Cost Variance in the MDAP Financial Network 2009 – 2014

	Model 1 - Total cost variance of network			Model 2 - Component cost variances of network partners		
Parameter	**Est.**	**Std. Error**	**Sig.**	**Est.**	**Std. Error**	**Sig.**
Number of network partners	0.0714	0.0394	0.071	0.1134	0.0449	0.015
Diversity of network partner services	5.9373	3.0053	0.049	6.3388	3.0339	0.038
Percent of network partners that are	-0.0955	0.6853	0.889	-0.2419	0.6976	0.729
Percent production of network partners	0.6047	0.6460	0.350	0.5017	0.6475	0.439
Network partner total cost variance	0.1847	0.1615	0.253	-	-	-
Network partner schedule cost	-	-	-	-0.0041	0.0029	0.162
Network partner estimation cost	-	-	-	0.0003	0.0002	0.090
Network partner economic cost	-	-	-	0.0025	0.0030	0.418
Network partner engineering cost	-	-	-	-0.0006	0.0006	0.295
Intercept	0.0240	1.0674	0.982	0.0225	1.0897	0.984
Network community (variance est.)	0.2734	0.3881	0.481	0.0760	0.1890	0.688
-2loglik	1723.35			1766.17		
BIC	1734.95			1777.75		

*MDAP program total cost variance is estimated in the model based upon the cube root of the MDAP program total cost variance. Year fixed effects are not shown in the table

The first model shows that the network partner total cost variance is not a significant predictor of the MDAP program cost variance when we account for complexity, year and network community. It is of the correct theoretical sign, which would indicate that when the network partners have greater cost variance then the MDAP programs also have greater cost variance. The fact that network partners total cost variance is not a significant predictor of the MDAP program total cost variance may be due to the fact that they are unrelated, but it may also be because there are simply too many cost variances being added together in the total network partner cost variance which creates noise in the analysis and supports the analysis of the components of cost variance as we do in the second model.

The complexity and homogeneity variables that were included in the model were significant predictors of cost variance in the model as well. The complexity variable number of network partners was significant ($p<.1$) and of the direction predicted by theory. The weak significance of this variable strengthens when we look at the second model but it is substantively significant in terms of its effect on the cost of the MDAP program. One thing to remember is that these models are based on the cube root of the total MDAP program cost variance, due to the leptekurtotic nature of the distribution. Therefore, the effect of all of these variables is nonlinear and is dependent on the current level of cost variance. Because of this, we observe that a unit change in the number of network partners is associated with a change in the cost variance of 0.214 times the square of the cube root of the estimated cost variance[1]. Given the average cost variance of the programs in the dataset is thirty eight million dollars, this means that a one unit change in the number of network partners for the average program would result in a $2.42 million increase in the cost of the program.

Likewise, the homogeneity of network partners services based upon the rank abundance curve is very strong, indicating that the greater the homogeneity the greater the cost growth. The change, therefore, from heterogeneity to homogeneity leads to an increase in the cost of the program of $201.34 million in the first model.

Overall, the first model fit better (BIC = 1734.95) than the second (BIC = 1777.75). The network community variance estimate is 0.27 but is not significant. This variable is included in the model because preliminary data analysis suggested that the network community was associated with the MDAP program cost variance. Therefore, the random effects or hierarchical model of cost variances in the network is theoretically warranted but may not be needed given the other variables included

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[1] [1] Because the linear model estimates the effect of the independent variable on the dependent variable as dY/dX and Y is to the 1/3 power, estimates of the effect must apply the chain rule of $Y = (b_0 + b_i X_i)^3$, where x is the vector of regressors. The chain rule tells us that a unit change in any of the x_i is associated with a change of Y such that $dY/dx_i = 3b_i(b_0+b_i X_i)^2 = 3b_i Y^{2/3}$. If we concentrate on just the second form of the equation, we are be able to interpret the b_i effect of a unit change on x_i given a particular level of cost variance, which we do in terms of the mean cost variance in the dataset of thirty eight million dollars.

in the model. In the conclusion, we provide suggested research approaches to further test if network communities have an influence on the cost of programs.

Interpreting the significant coefficients from the second model, we see that both the complexity and homogeneity variables are now both significant at the $p<.05$ level and the substantive effect of the variables increases. The increase in the cost to a program based upon the regression coefficients in the second for complexity and homogeneity are $3.84 million and $214.94 million respectively. In the second model the sum of the network partners estimation variances is now associated with the MDAP program cost variance ($p<.1$). This effect, like the complexity and homogeneity variables, is non-linear based upon the underlying cost variance; however, unlike the homogeneity and complexity variables this effect is not nearly as strong in practice. For example, if network partners estimation variance increased by a million dollars then the cost variance of the average MDAP program is predicted to increase by $10,172. In conclusion, this variable provides only weak evidence that network partners cost variances are associated with the MDAP program's cost variances once the models account for the year of the cost variance, the complexity of the network partners, and the homogeneity of the network partners.

Many of the variables in the model were not significant including the total MDAP program cost variance in the first model and the component cost variances with the exception of estimation cost variance. This suggests that much of the cost variance is strongly attributable to the complexity and homogeneity of the programs that are being developed.

In sum, none of the neighbor cost variance measures (nor the production or percent joint) proved instrumental in predicting individual program cost variance. However, both the homogeneity and the number of neighbors did prove instrumental and do appear correlated with cost variance growth.

Structural Equation Modeling

In spite of recent attempts to use structural equation modeling in networks (Westland, 2015; Kim et. al. 2011; Lin et. al. 2005), significant issues remain to using structural equation models with current MDAP data. The original idea behind the structural equation models is that they would allow us to combine multiple cost variances into a single higher order construct (Kline 2011) that could then be modeled in the network instead of creating separate models for each of the individual cost variances. Ultimately, it was determined that the assumptions of structural equation modeling did not sufficiently match the network data that are available. The key assumptions that are violated are that the higher order construct is not a reflective indicator (Kline 2011, p. 113) and that the underlying construct is not unidimensional (Kline 2011, p. 117) in our data. The appropriate tool for formative indicator data such as that of the MDAP networks is not structural equation models but rather a scale of the variances and earned value statistics available. Other models such as MIMIC models, may be appropriate if the data could be combined with data that is reflective of a higher order construct but at this time the data does not support this approach.

Preliminary measurement models were created on the earned value management (EVM) data with the intention of comparing the in-network to out-of-network using a multiple sample CFA approach to ascertain basic measurement invariance. However, there were only two programs that were out of network in the EVM data that we had. Therefore, construct invariance could not be tested. (Another option would have been to compare across network communities as separate sample, but the models assume that the network communities are independent (Kline 2011, p. 252). This assumption of independence is not met with the network community data and would have required further assumptions.)

Given the above concerns about the assumptions of structural equation modeling in the MDAP networks, it seems more appropriate at this time to create separate scales of variables where they are theoretically warranted. Scale reduction techniques such as principal components analysis will be tested in future work. In the short term, it seems most appropriate to continue to model cost variances separately and at the total level.

Epidemiologic Transition Model

Traditionally epidemiologic models employ a “compartmental” approach to studying communicable epidemics. The compartmental model divides the population into three distinct categories: those that are susceptible to the disease, those that are infected, and those that have recovered. In the event that the disease does not provide life-long immunity, those that are infected do not pass to a recovery mode but rather become susceptible again. Termed the Susceptible-Infected-Susceptible Model, it is this model that best captures an MDAP’s ability to encounter growth many times throughout its lifecycle. Typically, the SIS model employs differential equations that take the form of:

$$\frac{dS}{dt} = gI - \lambda S,$$

$$\frac{dI}{dt} = \lambda S - gI.$$

Where:

g = the rate of recovery

I = proportion infected

S = proportion susceptible

λ = force of the infection

More recently the compartmental model has been criticized for its simplicity and inability to model networks of contacts (Keeling and Eames, 2005). Consequently, epidemiologists have begun experimenting with network models to better understand the movement of various diseases. The network models often capture the point when transition occurs from one state to another.

The findings below examine the SARS from 2009 to 2012 time frame. CY2013 and 2014 were eliminated from the study due to the potential bias that sequestration might pose. Because of the necessity to capture the shift from susceptible to infected and back again, and the finding that there were too few observations to capture the cycling between the states, instead of analyzing the data longitudinally the cases were pooled as a cross sectional model. Where treating the cases as a pooled sample might pose a problem because any given program may be counted more than once, the findings illustrate that double counting was not a problem for this sample.

As discussed, the data were arrayed to capture those programs that transitioned from negative to positive total cost variance during the four-year period. Moreover, the data were also arrayed to capture the number of partners each program had, the number of partners that experienced positive total cost variance, as well as the individual programs cost variance. Consequently, the unit of analysis was the MDAP. To test whether partner's growth influenced individual program growth a bivariate regression was obtained.

To examine the transitional cases those cases that transitioned from "no growth" to "growth" were coded as 1 and the remaining cases were coded as zero. Following the approach set forth by Christakis and Fowler (2007), instead of measuring the sheer dollar value of the cost growth, or the sheer number of partners, the independent variable was the number of partners that experienced cost growth. We examined the data in light of the following logit equation:

$$\ln(ODDS) = ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right) = a + bX$$

where $\hat{Y}$ is the predicted probability of the event with 0 equaling no growth and 1 equaling growth.

In the logistic regression model the odds prediction is equals e^{a+bx}. Given the slope and the intercept identified in Table 3 if the subject had no growth the odds would be equal to $e^{-1.9+.22(0)}$ or 0.15. If the subject experienced growth then the odds equated to $e^{-1.9+.22(1)}$ or 0.18.

	B	S.E.	Wald	df	Sig.	Exp(B)
Number of partners that experienced cost growth	.215	.105	4.148	1	.042	1.240
Intercept	-1.908	.287	44.223	1	.000	.148

Table 3: Results of Logistic Regression Model

The probability for the non-growth group is equal to $\hat{Y} = \frac{odds}{1+odds} = \frac{.15}{1.15} = .13 \text{ or } 13\%$. Thus the non-network effects equate to 13 percent. Alternatively, for every program that transitioned, the probability of transitioning was approximately 30 percent for each partner that had growth (see table 3). In other words, programs that had partners that experienced growth were far more likely to experience growth themselves than were programs that did not have partners that experienced growth.

An additional regression was obtained measuring those that transitioned based on the sheer dollar rate of the growth. The results indicated no relationship between the sheer dollar value of the individual program's cost variance and the sum of the partners' cost variance. The fact that the sheer dollar rate was not significant, but the number of partners that had growth was, suggests a potential tipping point. In other words, because the sheer dollar value was not significant but the number of partners with growth was, the findings illustrate that there may be a significant point where the program "tips" into growth due to its partners.

In short, this section provided the results of examining the cost growth variance from the annual SARs from three different modeling perspectives: mixed effects linear regression with a modularity maximization algorithm, structural equation modeling, and from an epidemiological contagion approach. We determined that the assumptions of structural equation modeling (SEM) did not sufficiently match the network data that were available. Thus SEM did not provide a viable alternative for understanding potential cascading events.

The mixed effects modeling indicated that none of the neighbor cost variance measures (nor the state of production or the percent joint) proved instrumental in predicting individual program cost variance. However, both the homogeneity variable and the sheer number of neighbors did prove instrumental and do appear correlated with cost variance growth.

The epidemiological approach that examined the data in light of transitioning from one state to another indicated that, for every partner that experienced growth, the probability of transitioning from a “no cost variance” to “positive cost variance” is approximately 30 percent for each partner that indicated growth.

As discussed, jointness does not occur without some degree of risk. This research examined one particular form of risk, contagion, employing two statistical techniques: mixed effects linear regression with a modularity maximization algorithm and an epidemiological transition model. While the two models provided interesting results,

The results illustrate that further research will be needed to fully understand how cascades occur. Given the positive findings, the results illustrate that more research is needed on the specific measures that can yield insight. And that the additional research is likely to prove worth-while. However, the additional efforts are likely to require substantial resources given that the type of measures that may prove useful are not readily available. Field level research will be needed to identify the precise measures that prove useful to understanding the network effects. Nonetheless, the resources required to conduct field level research is likely to provide insights on how to best estimate the costs and risks of the network effects early in the lifecycle of the program.

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Theoretical Framework for Conceptualizing Cross-Organizational Networks

A theoretical framework is a conceptual model that is capable of holding or capturing the subject of a study or research. Theories are formulated to explain, predict, and understand phenomena. Often times, frameworks are built on top of existing frameworks so they tend to expand on knowledge. After providing a short description of the four common network structures, we turn to several theoretical underpinnings of network arrangements.

Network Structures

Before exploring the four major types of networks, it is important to understand that much of the literature on networks is not based on real or authentic networks. The resource demands associated with capturing authentic network data prevents the ability to conduct research on real networks in their entirety. Hence researchers depend on synthetic or hypothetical networks and simulation to garner insights. Synthetic networks tend to take one of four forms. However it is important to recognize that authentic networks may or may not reflect one of these four types, and their behavior may or may not deviate from simulated findings. Additionally, authentic networks may span many of these types depending on where the lens is focused.

Because each of these types of networks pose their own specific risks and challenges, it is important to understand how MDAPs fit, or do not fit, into these specific structures.

The following discussion focuses on the four common types of network structures. Understanding these structures is important as we move to establishing a theoretical framework.

1. Erdős-Rényi Model
2. Watts-Strogatz Small World Model
3. Barabási-Albert Preferential Attachment Model
4. Lattice Models

Additionally, the discussion below presents the structural configurations offered by Thompson (1967). Thompson's approach is offered because it often serves as a model for organizational exchanges.

One of the critical issues in examining the various types of networks has to do with "mixing," or how the nodes mix and connect with each other. In many of these models the mixing is considered random. So any node has equal probability of connecting with any other node. Assortative mixing is the tendency for nodes to connect to like nodes (i.e. "birds of a feather flock together"). Disassortative mixing reflects the tendency to mix with different types of nodes (i.e. "opposites attract"). The other key factor to consider is the number of connections each node has (or the degree distribution). Some of the networks below have nodes that all have the same degree distribution, others have "hubs" or nodes that have a larger number of connections than the other nodes. Definitions of the four common types of networks that are study by network scholars is presented below.

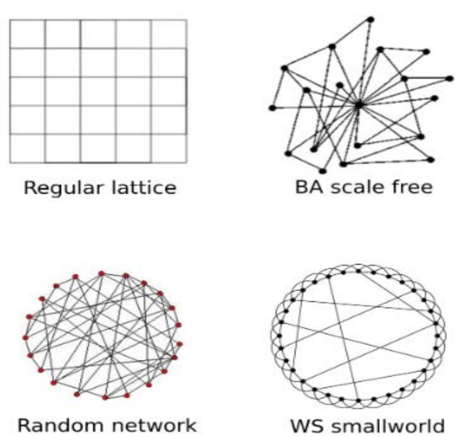

Figure 4: Types of Networks

1. Erdős-Rényi Model – These networks employ random mixing. Most nodes have the same number of connections and are paired thru a uniform probability, hence they do not account for the formation of hubs. They will have low heterogeneity and the degree distribution will be a Gaussian bell-shaped curve. They have short average paths and low clustering.

2. Watts-Strogatz Small World Model- Most nodes are not neighbors of one another, but each node can reach all of the other nodes by a small number of hops. This type of model also implies a fixed number of nodes so it cannot be used for partnership growth. It has a high average degree of clustering with a short path length.

3. Barabási-Albert Preferential Attachment Model – these networks have a high degree of hetergenity distribution that follows a power law. Typically they are scale-free, zooming in on any part of the network does not change its shape. They tend to have hubs of preferential attachment. There are a few nodes with a lot of connections with most nodes having few connections.

4. Lattice Models – In lattice models, each node is placed on the grid and is attached to each of its neighbors. These models have low heterogeneity and low randomness and they tend to have long average paths and high clustering.

Thompson (1967) offers a different perspective. He classifies the links according to the type of relationship that is established in the performance of job tasks. He argues that network exchanges can be classified in one of three ways:

1. Sequential – In sequential relationships, organizational tasks are viewed as a series of dyads. As long as the immediate upstream organization meets requirements, the chain of dyads is maintained. In this type of relationship coordination occurs through planning and scheduling. An example of a sequential relationship is automobile manufacturing.
2. Pooled – In pooled relationships organizations all pull from a central shared resource. An example of a pooled relationship is a central repository that serves many organizations. In pooled relationships coordination occurs via rules and standards. Very little coordination is needed in pooled relationships.
3. Reciprocal – reciprocal relationships are the most complicated and demanding. In reciprocal relationships, organizations work together simultaneously to produce a good or service. These relationships demand mutual adjustments as a coordination mechanism. An example of a reciprocal relationship is the MDAP network.

Note that the three configurations vary in light of the amount of coordination that is required to maintain the links. Reciprocal networks are the most complex and have the greatest number of demands.

In sum, given the difficulties of collecting real network data, researchers have developed hypothetical networks that are designed to capture various network attributes. They then employ simulation to test for behaviors or cascades. By most accounts, few of these networks represent real world networks and simulation has its drawbacks. As discussed below, the MDAP network might be better defined from the context of Supply Chain Networks.

Theoretical Underpinnings

The discussion below provides a short summary of supply chain networks, social exchange theory, transaction cost economics, and complex adaptive systems. The discussion then turns to some of the determinants of network success. With this information at hand, the section closes with a proposed theoretical framework for examining MDAP networks.

Supply Chain Networks

Traditionally, supply chains have been studied from a linear dyadic approach. Meaning that the typology or structure was viewed as a "chain" or sequence of dyads with each node connected to another. Thus, each node could be classified as upstream or downstream relative to another node. With the dyadic viewpoint there is an underlying assumption that each partner in the dyad would take care of itself and by doing so the chain was maintained. Consequently, researchers focused on the dyad, or pair, as the unit of analysis.

More recently, researchers have called for shifting the viewpoint from the dyad to the network. From a network perspective, actors may have multiple direct partners rather than simply one. And they are likely to have multiple second order partners. Hence, the call for a shift in view is not purely academic. Viewing supply chains as supply networks broadens the viewpoint and thus provides additional insights for understanding risk and performance in at least three areas. First, because all of the actors in a network bring with them their contextual factors, and because these contextual factors are likely to impose on others, failure to consider the contextual factors of all first and second order connections can result in unnecessary risk. Next, networks exhibit a host of relational dynamics that, in total, may influence other members. Again, the failure to consider the wide array of relationships is likely to create risk and reduce performance. Finally, as noted by Martin and Lee (2004) supply networks operate within environments of uncertainty, unpredictability, and vulnerability. Information improvements can help to ameliorate the uncertainty, unpredictability, and vulnerability that network members experience. In short, Hearnshaw and Wilson argue that while the dyadic view is appealing, it "grossly oversimplifies and distorts the realities of modern day supply chains" (p.442).

Yet, research on supply networks has been relatively rare. A literature review conducted by Pilbeam et al reveal that only 44 articles have been published on supply networks and most of which were in the past decade. Of these 44, twenty-one were empirical in nature. The primary focus of Pilbeam et al was governance in supply networks. They employ Grandori and Soda's (1995) definition of governance as the "set of instruments that coordinate participating organizations to deliver network outcomes" (pg 359). Per their research, the literature on supply networks can be understood in light of three constructs: context, governance instruments, and outcomes. Context can be explained in terms of two features, environmental features and actor features. Environmental features focus on globalization, change in the organization, uncertainty/unpredictability, risk, and legislation. The actor features include relationship history and partner characteristics. These contextual features are believed to provide insights on the actors in the network that are likely to have an influence on the network's outcomes.

Governance instruments are also defined in terms of two features, formal features and informal features. Formal features that actors employ are standards, processes, formal structure, and contracts. Informal features include norms, values, social structure, and information sharing. The types of outcomes networks can generate are creativity, viability, control, coordination, performance, and legitimacy.

Kim et al argue that there are two types of supply networks, firms can be material flow based (essentially non-contract based) or contract based. They then explore the different network characteristics that apply to each of the types. They also identify the various social network analysis tools and how they can be employed to better understand supply networks.

Surana et al claim that supply chains have an "overwhelming number of interactions and interdependencies among different entities, processes and resources" (p. 4235). They view supply chains as Complex Adaptive Systems and claim that supply networks exhibit self-organizing behaviors.

They argue that supply networks can be best identified by:

1) structures span several scales
2) strongly coupled degrees of freedom and correlations over long lengths and timescales
3) behaviors that are both competitive and cooperative
4) nonlinear dynamics involving interrelated spatial and temporal effects
5) a combination of regularity and randomness that results in quasi-equilbrium
6) emergent behavior that allows adaptation and evolution (p. 4239 - p.4241)

Recognizing that no model can capture all of the aspects of networks. Surana et al indicate that an important management concern is to minimize volatility by controlling lead-time ripple effects. Hearnshaw and Wilson advise managers to build in redundancy and to undertake a multi-sourcing strategy to reduce the vulnerability of supply chains to cascading failures (pg442).

The following discussion explores network theory and, thus, relates to supply networks as well.

Network Theory

Since the middle of the last century, theorists have identified organizations as open systems vulnerable to environmental flux. For example, Thompson (1967) identified that the overarching goal of an organization is to reduce to a minimum the forces that can stymie performance and outcomes. Thompson argued that all organizations seek to secure enough stability and certainty in their environments to overcome unknowns and uncertainties. To ward off uncertainty, organizations employ coding, stockpiling, leveling, and forecasting. Rules, programs, schedules, departmentalization, and hierarchy are all strategies that serve to reduce uncertainty and limit the detrimental affects of environmental flux.

Thompson (1967) then went on to argue that a firm's external environment could be understood in light of two main dimensions: heterogeneity/ homogeneity and stability/dynamism. The heterogeneity/homogeneity taps the degree to which the entities are similar or different in nature. The stability/dynamism dimension captures the rate of change that occurs within the external environment.

Shortly thereafter, Pfeffer and Salancik (1978) proposed the theory of resource dependence (RDT). RDT is predicated on the idea that organizations depend on the external environment for scarce resources. In the article "Resource Dependence Theory: Past and Future," Davis and Cobb (2010) captured the essence of RDT by noting "The basic theory might be summarized by a piece of advice to top managers: 'Choose the least-constraining device to govern relations with your exchange partners that will allow you to minimize uncertainty and dependence and maximize your autonomy'" (p. 24).

Almost by definition uncertainty is the downside of external dependencies. Additionally, given that survival is contingent on the external environment, RDT focuses on power and the tendency to attempt to exploit interdependencies to insure survival. Moreover, central to the theory is competition over the scarce external resources.

In the public sector, limited resources and increasing demands for greater accountability have caused organizations to look to external relationships to achieve goals. In the public sector, partnership arrangements can provide significant performance and economic benefits. For example, joint-purchasing arrangements can result in economies of scale. Moreover, because public problems tend to cut across organizational boundaries, without partnerships critical services may go unrealized. Without partnerships, many public problems go unresolved.

Consequently, partnership arrangements are often dictated in legislative mandates. Given the need to rely heavily on joint efforts to address mandated requirements, it is becoming more difficult to shield organizational operations from environmental disturbances. Hence, the study of the movement toward greater degrees of complexity, and the consequential vulnerabilities that ensue from environmental perturbations, is the subject of considerable attention.

Building on the ideas of Coase (1937), Williamson (1981) examined costs organizations accrue from the transactions that occur among parties. The costs of a transaction is believed to be related to three variables:

- Search Costs – determining if partners are available and if they meet the respective needs of a member.
- Bargaining Costs – are the costs associated with coming to an acceptable agreement.
- Policing and Enforcement Costs – are costs associated with making sure that your partner adheres to the agreement.

Williamson (1981) expanded on this list and argued that the determinants of transaction costs are frequency, asset specificity (how many providers are available), uncertainty, limited rationality, and opportunistic behavior. Williamson's concept of transaction cost economics is based on the exchanges between buyers and sellers – a decidedly market based approach. In this way he focuses heavily on the economic advantages and disadvantages in the buyer-seller transaction. Following the rational choice perspective, actors engage in exchanges only to the extent that they provide economic advantage. So the assumption is that exchanges have at minimum a neutral value but most often provide a net gain, else organizations would pursue other, more beneficial, tactics. Williamson's idea that net gains would pursue else organizations would not engage is not entirely true for the public sector. In the public sector external relationships are often mandated and thus the aspect of choice is absent.

Poppo and Zenger (2002) note that external exchanges are "typically repeated exchanges embedded in social relationships" (p. 710). The governance mechanisms tend to be informal and derive from the social relationships. Poppo and

Zenger go on to claim “the enforcement of obligations, promises, and expectations occurs through social processes that promote norms of flexibility, solidarity, and information exchange” (p. 710). Apparently, network success is contingent on *intentionally* adapting, coordinating, and safeguarding exchanges (Jones, Hesterly, and Borgatti, 1997). But, how one coordinates and safeguards the exchanges remains the subject of debate. Milward and Provan (2003) argue that, due to the open and permeable boundaries and the lack of a centralized command structure, management challenges are immense. They claim that managers must continuously deal with problems requiring negotiating, coordinating, monitoring, holding third parties accountable, and writing and enforcing contracts all in an inter-organizational setting in which information asymmetries and moral hazards abound.

Agranoff and McGuire (1998) state that networks demand transparency and detailed knowledge of their member affiliates. Radin and Romzek (1996) suggest that networks are likely to be more effective under low control accountability relationships rather than under high control relationships that employ legal or hierarchical authority. Yet, Isett and Provan (2005) disagree and call for formal agreements to limit opportunistic behavior. Conversely, Mandell (2001) argues that there is no evidence that any "best practice," or favored institutional form, has had any positive effect on network outcomes.

In terms of key determinants, Provan and Milward (2001) identify that system instability is the major challenge to network effectiveness. However, Hasnain-Wynia et al (2003) argue that diversity is often a significant problem because it affects the ability to steer members toward commitment. Others (Alchian and Demsetz 1972) argue that fiscal control lowers the probability of shirking and free riding – two major problems in networks. Formalization (i.e. formalized rules and standards, organized meetings, and formal decision-making procedures) predicts success (Brown, et al 1998; Crozier-Kegler et al . 1998; Jennings and Ewalt 1998). Yet, Fawcett et al 2000 identify accountability and transparency with higher rates of success in networks. Nonetheless, elements such as trust, reciprocity and norms of cooperation are considered fundamental to increasing the strength of network ties (Provan and Sebastian 1998; Provan and Milward 2001; Agranoff 2003).

Fountain (2001) maintains that well functioning organizational networks must invest heavily in social capital to build and sustain cooperation and trust. Lin (2001) argues that social relations become social capital when they mobilize resources for a collective good. Mischen (2015) claims that collaborative network success is a function of having the necessary social, knowledge, and financial capital.

Where much of the network research focuses on managing opportunistic behavior, the uncertainty associated with whether partners will prove loyal to the relationship is a major source of uncertainty. Even in the face of contracts, defection is not unusual. As the network grows in the number of partnerships, complexity (and uncertainty) increases. Moreover, it subjects the organization to ever increasing levels of environmental turbulence. Consequently, interactions between many interconnected organizations can result in emergent behavior. (More on this below).

Despite the growing body of literature, several shortcomings are noteworthy. First, much of the research is based on studying one small component of a tightly integrated network. The failure to study the entire network is problematic; it fails to capture the full complexity. In tightly integrated networks, every participant is connected to every other participant. But many organizations have strong ties with one organization, weak ties with another, and no ties with the relationships of their partners.

Second most networks exhibit what is termed multi-plexity, meaning that actors are involved in more than one network at a time. Lacking the full view, important insights might be missed. Third, no attention is given to the link, instead it focuses on the node only. While it is true that it is the node that experiences the consequences of the ties or relationships, the failure to consider the link is especially troublesome because the link (the structure of the relationship) is likely to be as important as the node. Fourth, few of the studies employ a multi – lens approach. Networks must be examined from both a micro and macro lens because macro behaviors may influence micro behaviors. Finally, few scholars have focused on the duality that confronts network members. Network members operate in two worlds, the internal world of the organization they belong to and the external world of the network. And they must learn to move seamlessly between the two worlds. Yet, the two worlds are often in opposition. For example, hierarchies strive for stability where networks demand agility. Moreover, it is not uncommon to experience both cooperation and competition. One of the most difficult issues surrounding network management, is that individual needs must often be sacrificed for the collective good. In most organizations, sacrificing individual demands for the collective good is oftentimes not rewarded or allowed.

Despite the weaknesses in the literature and the lack of congruence in the findings, few would dispute the notion that open and permeable boundaries typify network structures. It is precisely these "open boundaries" that render it difficult to coordinate and safeguard exchanges because of the uncertainty and unpredictability that accompanies environmental flux. In exchange theory, the uncertainty is often attributed to the interdependencies that exist among the organizations. The source of this uncertainty can come from suppliers, customers, competitors, regulatory agencies, unions, or financial markets (Miles & Snow, 1978).

Shirking or defection of a network member can have dire consequences on the survival and performance of the network in total and network participants in general. Because of the nature and influence of the ties that bind organizations, Levinthal's (1997) research indicates that increasing the density of the interdependencies that connect the organizations affects the complexity of the "landscape" in which it operates. Levinthal (1997) finds that these interconnections or flows yield nonlinear consequences that often involve multiplier effects based on the nature of the interdependencies in the system. The dynamic nature of the ongoing changes that occur within a network have given rise to the study of "Complex Adaptive Systems" (CAS).

Complex Adaptive Systems

According to Simon (1996) the field of complex adaptive systems provides a useful conceptual framework for studying various organizational phenomena. Many researchers hope that the field of complex adaptive systems will prove to be a useful framework for the study of networks.

The study of complex adaptive systems (CAS) is best defined as a conceptual framework capable of promoting an understanding of behavior rather than a single inclusive theory. As a conceptual framework, it is largely concerned with how complex systems relate to dynamic change, adaptation, and evolution. Simon (1996) defines a complex system as one made up of many parts that have many interactions. And Thompson (1967) describes a complex organization as a set of interdependent parts, which together make up a whole that is interdependent with some larger environment. Complexity has been used to reflect a variety of concepts including size, structure, and task environment. Despite the immaturity of the concept, there is parsimony on two important themes: complex adaptive systems are associated with emergent nonlinear adaptive properties ("self-organization") and they are vulnerable to high levels of uncertainty and unpredictability. Of central concern is how complex organizations adapt to the uncertain and unpredictable environments they encounter.

Complex adaptive systems, when defined by interdependent relationship structures, are often examined in terms of their ability to adapt to changes in the environment. As discussed in detail below, the adaptation can take a variety of forms from static on one extreme to chaotic on the other. A static state reflects the inability of the relationship to adapt requisite policies, procedures, or activities according to changes in the environment. Conversely, the chaotic state represents a hyper-turbulent response to environmental flux. Utilizing these definitions, our definition of complexity is similar to Simon's and Thompson's in that we seek to examine how interdependent cross-agency structures evolve and adapt to environmental flux. Hence the study relies heavily of concepts derived from resource dependency/exchange theory. An understanding of the adaptation patterns of these complex relationships has tremendous managerial implications. Goals and objectives, as well as capitol and opportunity costs are inherently tied to potential activities of adaptation. These secondary adaptive behaviors can cascade in unexpected ways, and thus, can have a tremendous impact on the achievement of critical goals and the final costs associated with any organizational activity. Before exploring the managerial implications of self-organization and complex adaptive systems, further elaboration of the concepts is required.

The CAS conceptual framework includes such ideas as phase changes, fitness landscapes, self-organization, emergence, attractors, symmetry and symmetry breaking, chaos, quanta, the edge of chaos, self-organized criticality, generative relationships, dissipative structures, dissipative energy, bifurcation points, punctuated equilibrium, and increasing returns to scale. CAS researchers often focus on the concept of self-organization, or the tendency for coherent and purposive wholes to emerge from the interactions of simple and sometimes non-purposive components or activities. The phenomenon of self-organization was first recognized as an important aspect of change in the physical and biological sciences (Prigogine and Stengers, 1982; Prigogine and Nikolis 1989; Bak and Chen 1991; Kauffman 1993). These researchers sought to explain unexpected aberrations in the operation of mechanical systems. Specifically, they were interested in how minor fluctuations in performance would cumulate at certain points, eventually leading to large disruptions in the operations of the total system. These minor fluctuations, or points of energy attraction, within the operation of the system were termed “strange attractors” (Ruelle, 1989). Their presence demonstrated the occurrence of an unplanned clustering of energy at specific points in the system that was *outside the prescribed plan of operations* and *occurred without external design*. The “strange attractors” shifted the pattern of energy flow within the system, eventually altering the operation of the entire system.

Complex systems are distinguished by a capacity for “self-organization”. They are capable of rearranging and reforming patterns of operation in mutual adaptation to the changing needs and capacities of their components (Comfort, 1994). They are also capable of mutually adapting to the changing demands and opportunities imposed by the environment. The distinguishing characteristic of this process is that it occurs as a result of communication, selection, and adaptation processes within the system itself and between the evolving system and its environment (Comfort, 1994; Kaufmann, 1993).

Prigogine identifies three prerequisites for the emergence of self-organization. The first condition is that a system must be open and allow exchanges of energy, matter, and information with the outside world. The second condition is that it be dynamic, far removed from a state of equilibrium. The third condition is that within the system there is feedback that enables special processes to make rapid shifts in behavior.

Kaufmann (1993) identifies 4 features of a self-organizing system. Self-organization is a continuous process that occurs in social contexts through “communicative acts”. These acts are most often forms of verbal, written, or electronic communication transmitted directly between two or more agents within the system or between the system and its environment. Second, self-organization, coupled with selective tendencies, creates the system’s capacity for adaptation to environmental conditions. Third, self-organization recognizes the influence or control that some units exert over other units in an interdependent system. Finally, self-organizing systems are massively parallel processing systems, where different components perform different functions simultaneously to achieve a goal.

The resulting self-organizing patterns are often dependent on the schema (mindset) of the involved agents. Additionally, agents do exist outside the boundaries of the CAS and their schemas also serve to determine the rules of interaction concerning how information and resource flows occur. This notion of individual schema as a locus of adaptation has tremendous implications. In human systems, self discrepancy theory (Wiggins 1987) predicts that if an individual’s current state does not match their ideal state, the discrepancy represents one of two possible states: dejection or agitation. In holding with Kaufmann’s and Prigogine’s finding, either of these states may serve as minor fluctuations capable of resulting in major transformation.

Most approach CAS from the perspective that it is a dynamical system comprised of agents at a lower level of aggregation. Each agent’s behavior is dictated by a schema (a cognitive structure or mindset) that determines what action is taken at any point in time based on the agent’s perception of the environment.

According to Levinthal (1997) each individual's payoff function depends on choices that other agents make, so each agent's adaptive landscape – mapping its behavior to its realized outcomes – is constantly shifting. Moreover complex adaptive systems evolve over time through the entry, exit, and transformation of agents. Furthermore the linkages between agents may evolve overtime shifting the patterns and strengths of interconnections. Closely tied to the concept of bounded rationality (March and Simon, 1958), agents are presumed unable to forecast the system level consequences of their individual choices, so they optimize according to their own fitness, not that of the organization. In Kauffman's adaptive landscape metaphor (borrowed from Wright 1931) agents co-evolve on a fitness landscape to a state poised between order and chaos. The landscape on which agents adapt continually shifts, because the payoffs of individual agents depend on the choices that other agents make (Levinthal 1997, McPherson and Ranger-Moore 1991).

In keeping with this line of thought Zajaak and Kraatz (1993) contend that organizations purposively adapt to environmental changes through feedback loops that result in restructuring activities. However partners are semi-autonomous, and are, thus, free to renege on prior agreed conditions.

Moreover, Senge (1990) argues that behavior patterns can emerge contrary to intention and they can produce unexpected and counterintuitive results. According to Stacey (1995) this is because the choices of agents in human systems are based on perceptions that guide behavior. Because there tends to be many outcomes for any given action, these behaviors can trigger non-proportional over or under reaction. Consequently, small changes can escalate into major outcomes. As a result, Stacy argues that group behavior is more than simply the sum of individual behaviors.

While adaptive alterations in behavior can result from voluntary/deterministic selection, many times the adaptive behaviors are emergent in nature and nondeterministic. This is commonly seen when small isolated perturbations shift the adaptive mechanisms toward an unpredictable trajectory. For example, a seemingly innocuous unpredicted citizen complaint may resonate in such a way that it takes on a “life of its own” and shifts the organization’s adaptive behaviors in a significant way. Holland (1995) notes that complex patterns can arise from the interaction of agents that follow even simple rules. These patterns tend to be emergent in the sense that new properties occur throughout the various levels of the organization.

More recently, many organization theorists are drawing managerial implications from the strides the sciences have provided to the field of complex adaptive systems (Anderson, 1999; Stacey, 1999). Seeking to use available resources efficiently and to integrate new resources into existing structures for effective action, organizations respond to environmental flux by changing operating procedures and practices in fundamental ways (Comfort, 1994). Changes occur in part through voluntary selection among alternatives for action and in part through mutual adjustment in performance among participating organizations. Order returns to the system through a creative process of reciprocal exchange, learning, adaptation, and choice among multiple participants operating at multiple levels of responsibility, experience, and knowledge.

Self-organization represents a fundamental reallocation of energy and action within a system in order to achieve a larger goal. As Comfort (1994) succinctly states “understanding when, how and where change may occur in dynamic environments is a primary and fundamental challenge for managers.” Managers attempt to dominate, control, arrange, program, and organize the disarray until it is tamed. Rules and order are constructed and maintained. Laws, rules, and regulations are erected to prevent chaos and difference from invading. Indeterminancy and uncertainty are thought of as undesirable. Lewin (1999) claims that trends toward increasing complexity require managing all the organizational levers of dissipative energy. These include allowing promoting emergent processes as self-generated sources of dissipative energy such as facilitating improvisation, product champions, and emergent strategies. Leadership styles that moderate dysfunctional tension and forestall the emergence of chaos will also be critical to adapting to the environmental demands that result from complexity.

One of the most fundamental implications emerging from the science of complexity is that order naturally emerges in systems, no matter how simple, complex, nonlinear, or chaotic the system is (Lewin, 1999). Kaufmann's research draws important, albeit controversial implications. Kauffman (1993) notes that complex systems starting in a random state evolve toward order instead of disorder. Anderson (1999) agrees by claiming that when a system is open to receive energy from the outside, it will tend to create order. According to their findings, when system boundaries exhibit permeability, natural order evolves through self-organization. Kaufmann also finds that under situations characterized by environmental flux, lacking the flexibility for spontaneous adaptation, their precise rules for operation lack reliability. Anderson concurs and claims that when a system becomes closed, it will decay into maximum disorder and chaos. He argues that systems designed for control tend to become paralyzed and can self-destruct in rapidly changing environments. Comfort (1994) argues that under extreme conditions, the desire to respond to flux with control may stifle any innovative efforts to find more effective means of functioning to altered conditions. Conversely, according to Prigogine and Stengers (1984) and Kauffman (1993) systems without sufficient structure to hold and exchange information can also disintegrate under swiftly changing conditions. According to their research, small changes in operating conditions may lead to large disruptions in performance, or avalanches of disorder.

The notion that the two extreme responses to complexity (control vs flexibility) can be counterproductive is not surprising. According to Kaufmann, creative change is most likely to occur within the narrow region on the edge of chaos. Sufficient control over the structure is required to allow participants to hold and exchange information. But sufficient flexibility to allow mutual adaptation among the participants to substantiate changes in their operating environments is also required.

In sum, in networks, participants decisions typically reflect a consideration of how others will react. Moreover, the environment in which they operate is often subject to a high degree of flux thus demanding adaptive behaviors. As a consequence, these networks tend to demonstrate emergent properties and are best described as dynamic systems with evolving structures and processes. Additionally, because they are semi-autonomous, they tend toward self-organization and co-evolution.

The problem is there are few methods, strategies, or tools that assist in understanding the risk or uncertainties that accompany these types of efforts. In essence, the emergent behavior can render the benefits of decision analysis moot thereby rendering impotent the desire for performance guarantees. Instead of proactively shaping behaviors toward desired goals and objectives, the agents are relegated to reactionary suboptimal decision choices.

MDAP Theoretical Underpinnings

Based on an understanding of MDAPs and the literature review of networks and complex adaptive systems, a synthesis of multiple theories is likely to prove instrumental in understanding MDAPs.

Where shortcomings exist, supply chain networks appear to offer the greatest insights on MDAP networks. However, it seems clear that the field of supply chains is quickly moving toward a network model. Thus, MDAPs may show the characteristics of resource dependency, and the ensuing consequences of complexity, uncertainty, and asymmetries.

Additionally, from a methodological perspective, the tools of Social Network Analysis may shed additional insights on the MDAP networks and the emergent behaviors.

The MDAP networks tend to reflect the following characteristics. The network is:

1) exchange based – typical exchanges include material, financial and information resources
2) semi-autonomous – the participants exhibit semi-autonomy
3) relatively stable but may exhibit punctuated equilibrium so tipping points may be important
4) characterized by actors that do not tend to be predatory but are expected to pursue self-interests
5) non-linear behaviors in terms of the relationship between the network and its environment
6) scale free
7) adaptive – the participants tend to be adaptive to a point. However, they are not beyond defection when resources become constrained
8) resilient – they exhibit resilience in the face of turbulence
9) duality – members are often conflicted between internal demands and network needs

Additionally the MDAP network exhibits:

10) hubs and preferential attachment
11) memory that includes positive feedback
12) actors that are intra-dependent and thus influence each other
13) uneven power arrangements
14) a high degree of heterogeneity
15) transaction costs
16) ties that are market or contract based
17) communities with overlapping boundaries for resource flows
18) multi-plexity – members are often involved in multiple networks at any given time

The last characteristic is important enough that it deserves some comments. DoD networks tend to exhibit multiplexity (or are involved in several networks simultaneously). Unfortunately, little research has been done on multiplexity and the underlying mechanisms remain poorly understood (Ferriani et al, 2013).

The other interesting characteristic is that no one body has either a full view or full control of the entire process. In interviews, program managers indicated that they knew their first order connections but that they had no knowledge of their second order connections.

The following section explores some of the management strategies that are believed to assist managers in their attempts to promote successful networks.

Managerial Recommendations on Cross-Organizational Networks as a Form of Service Delivery

In addition to the material presented above, the section below provides additional insights on managerial recommendations from the context of the entire network.

Most of the research on managerial recommendations for networks is based on small case studies. And for the most part, they tend to reflect generic management strategies that focus on the node rather than the tie or network. For example, Cristofoli et al (2014) cite much of the literature and claim:

> “network performance can be boosted by formalized coordination mechanisms such as: joint information and communication systems; shared marketing, planning or implementation structures; joint staff activities; integrated service capacities (e.g. a one-stop entity at the service of network clients); organization of meetings; definition of the network agenda; the establishment of ground rules and laying down rules for decision-making” p. 81.

They go on to say that successful managers tend to use both nurturing and steering strategies.

Agranoff and McGuire (2001) argue that network management involves activating, framing, mobilizing, and synthesizing. Activation/deactivation involves identifying network members. Framing involves establishing the network operating rules. Mobilizing involves mobilizing participation commitment and resource sharing. Synthesizing refers to creating and enhancing the conditions for productive interaction among network participants.

Many network scholars call attention to the importance of strategies and mechanisms that focus on coordination, adaptability, and agility. Again, the strategies tend to reflect tightly integrated networks. The MDAP network is characterized by a number of autonomous agents of both tight and loose ties. Where formalization may prove useful under some scenarios, it is unlikely to prove useful in the MDAP arena.

Perhaps the major issue in the MDAP network is how to strike a balance or point of equilibrium where churn in one program does not cascade to another. Or, how to limit cascades from creating whiplash affects.

In a rare study that spoke directly to network needs from a tie perspective, Valente (2012) provides a rich discussion of managerial interventions based on an extensive literature review. He highlights four overall types of interventions: identification of influential individuals or nodes, segmentation of groups of communities, induction of activation behaviors in key locations in the network, and alteration interventions that change the structure of the network.

Valente (2012) argues for the following interventions:

> *Identification of influential individuals or nodes* - the most basic intervention, this strategy is based on identifying and leveraging the most influential nodes, individuals, programs etc. He identifies two network measures that can be useful in identifying influential. "Centrality closeness" captures how close the nodes are to each other. It indicates the nodes that can reach everyone in the network in the least number of steps. Another useful metric is "closeness betweeness" it identifies gate keepers or boundary spanners that are capable of reaching many groups. Valete argues that influential nodes can be leveraged to spread desired behaviors.
>
> Valente does indicate that leaders may not always be the best change agents because they are often supportive of the status quo. Whereas bridging individuals who span non-or loosely connected groups may be more amenable to change. He also claims that low-threshold change agents may be useful recruits when the manager wants to encourage early momentum for change and accelerate the time to reach critical mass or a tipping point (p. 50).
>
> *Segmentation of groups of communities* - instead of targeting individuals or nodes for change, segmentation activities focus on targeting groups of people to change at the same point in time. Group structures can be identified with the modularity maximization algorithm. The modularity maximization algorithm identifies mutually exclusive groups where the members tend to be in close contact.

A group structure that often occurs in networks is the core-periphery structure. In the core-periphery structure, core members are densely connected to other core members and peripheral members are connected to the core but not to each other. Valente claims that understanding the core group and their distribution of success is critical to coalition success. He claims that understanding the core periphery structure can assist managers in focusing resources on the core members. He also argues that ensuring that core members have sufficient resources to achieve network goals is often critical to success.

Induction of activation behaviors in key locations in the network – induction involves stimulating or forcing peer-to-peer interactions to initially trigger cascades. Valente argues that network outreach is expected to have a large influence over behavioral change because members tend to reinforce each other. This approach is similar to the "herd" effect. For MDAPs, induction is likely to offer benefits in that military members are often steeped in loyalty and are encouraged to promote loyalty to the mission.

Alteration interventions that change the structure of the network - Many interventions deliberately seek to alter the structure of the network by adding, eliminating, or altering the nodes or links. Valente does indicate that changing network structure is probably more difficult than employing the other three strategies because networks are often formed for a myriad of individual, relational, attitudinal, and environmental reasons.

The difficulties associated with altering the network structure may be especially true for MDAPs. MDAP networks differ from traditional networks in that membership is often not voluntary. As discussed above, the networks are typically structured for the exchange of resources and are mandated to achieve higher-level goals, i.e. situational awareness.

Despite Valente's (2012) important insights on managerial interventions, he does offer two caveats. He identifies that "interventions are not agnostic or impartial but depend on the goals and objectives that initiate the intervention" (p.49). In other words, the interventions are highly contingent on the goals of the network. He also indicates that scientific theory regarding change behavior between communities is vitally important. Tested theories on how to use information to either accelerate or impede changes in social influence are developmentally nascent. Extensive empirical work is needed to fully understand the exogenous and endogenous influences under various network structures.

Finally, in a study of the Defense Logistic Agency, Schoemaker et al (2013) provide insights that might assist the performance of the MDAP network.

Conclusion

In conclusion, this report provided a short review of social network analysis. Second, we tested three different modeling techniques for their ability to provide insights on the mechanisms that relate to cross-organizational network risk, contagion, and performance.

The mixed effects linear regression indicated that none of the *neighbor* cost variance measures (nor the production or percent joint) proved instrumental in predicting individual program cost variance. However, both the homogeneity and the number of neighbors did prove instrumental and do appear correlated with cost variance growth.

The examination of structural equation modeling determined that the network data violated key assumptions. The assumptions that were violated were that the higher order construct was not a reflective indicator (Kline 2011, p. 113) and that the underlying construct was not unidimensional (Kline 2011, p. 117). The epidemiological transition model revealed that for *every partner that experienced growth*, the probability of an actor transitioning from a “no cost variance” to “positive cost variance” is approximately 30 percent.

Next, we provided a theoretical framework for understanding cross-organizational networks. Finally we provided managerial recommendations on cross-organizational networks as a form of service delivery. In short, we found that it is likely to prove instrumental to treat the MDAPs as networks semi-autonomous partners. In doing so, both the methods and instruments needed to understand networks may provide program managers with a wider perspective of the network of partners and, thus, reduce risk and enhance performance.

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References

Agranoff, R. and M. McGuire (2003). *Collaborative Public Management; new strategies for local governments*, Washington, D.C.: Georgetown University Press

Alchian and Demsetz. 1972. Production, information costs, and economic organization. American Economic Review 62 (December): 777-795.

Anderson, P. (1999). Complexity theory and organization science. Organization Science, 10(3), 216-232.

Bak, P., and Chen, K. (1991) "Self-Organized Criticality," Scientific American, 264, 46.

Brown, M.M., L.J. O'Toole, and J.L. Brudney. (1998). 'Implementing Information Technology in Government: An Empirical Assessment of the Role of Local Partnerships', Journal of Public Administration Research and Theory, 8, 4, 499–525.

Christakis, NA; Fowler, JH (26 July 2007). "The Spread of Obesity in a Large Social Network Over 32 Years." *New England Journal of Medicine*. 357 (4): 370–379.

Coase, Ronald (1937). "The Nature of the Firm". *Economica*. Blackwell Publishing. 4 (16): 386–405.

Comfort LK (1994) Self-organization in complex systems *Journal of Public Administration Research and Theory: J-PART* 4 (3), 393-410

Cristofoli Daniela, Josip Markovic, Marco Meneguzzo (2014). Governance, Management and Performance in Public Networks: How to be Successful in Shared-Governance Networks. J Manag Gov (2014) 18:77–93

Crozier Kegler, M.C., A. Steckler, K. Mcleroy and S. Herndon Malek. (1998). 'Coalitions: A Study of 10 Project ASSIST Coalitions in North Carolina Factors That Contribute to Effective Community Health Promotion', Health Education Behaviour, 25:3, 338–53.

Cyert Richard M. and James G. March, *A Behavioral Theory of the Firm*. Englewood Cliffs, NJ: Prentice-Hall, 1963. 2nd ed., Oxford: Blackwell Publishers.

Davis, G.F., & Cobb, J.A. (2010). Resource dependence theory: Past and future. In C.B. Schoonhoven, & F. Dobbin (Eds.), Stanford's organization theory renaissance, 1970– 2000. Research in the sociology of organizations, 28. (pp. 21–42). Emerald Group Publishing Limited (Ch. 2).

Fawcett, S.B., V.T. Francisco, A. Paine-Andrews and J.A. Schultz. (2000). 'A Model Memorandum of Collaborations: A Proposal', Public Health Reports, 15, May–June, 175–90.

Ferriani Simone, Fonti Fabio, and Corrado Raffaele (2013). The social and economic bases of network multiplexity: Exploring the emergence of multiplex ties. Strategic Organization 11: 1(7-34).

Fountain, Jane (2001) Paradoxes of Public Sector Customer Service. Governance 14:1(55-73)

Grandori, Anna & Giuseppe Soda. 1995. "Inter-firm Networks: Antecedents, Mechanisms and Forms." Organizational Studies 16(2): 183-214.

Hall, C, Lynn Ariss, Alexander Todorov (2007). "The illusion of knowledge: When more information reduces accuracy and increases confidence." *Organizational Behavior and Human Decision Processes*, vol. 103, issue 2, pages 277-290

Hasnain-Wynia, R., S. Sofaer, G.J. Bazzoli, et al. (2003). 'Members' Perceptions of Community Care Network Partnerships' Effectiveness', Medical Care Research and Review, 60, 4, 40–62.

Hearnshaw, Edward J.S. and Mark M.J. Wilson, (2013) "A complex network approach to supply chain network theory." *International Journal of Operations & Production Management* 33:4

Holland James (1995) "Can There Be A Unified Theory of Complex Adaptive Systems?", in: Harold J. Morowitz, Jerome L. Singer, editors. *The Mind, The Brain, and Complex Adaptive Systems* (1995). Addison-Wesley

Isett K.R. & Provan K.G. (2005). The Evolution of Dyadic Interorganizational Relationships in a Network of Publicly Funded Nonprofit Agencies. *Journal of Public Administration Research and Theory*. 15(1): 149-165

Jennings, E.T. and J.A. Ewalt. (1998). 'Interorganizational Coordination, Administrative Consolidation and Policy Performance', Public Administration Review, 58, 5, 413–21.

Jones, Candace, William S. Hesterly and Stephen P. Borgatti (1997). A General Theory of Network Governance: Conditions and Social Mechanisms. *The Academy of Management Review*. Vol. 22, No. 4 (Oct., 1997), pp. 911-945

Kim Yusoon, Thomas Y. Choi, Tingting Yan, Kevin Dooley (2011). "Structural investigation of supply networks: A social network analysis approach." Journal of Operations Management 29(3): 194-211.

Kline Rex (2011) Principles and Practice of Structural Equation Modeling. Guilford Press, New York

Mabert, V. A. and M. A. Venkataraman. 1998. "Special Research Focus on Supply Chain Linkages: Challenges for Design and Management in the 21st Century." Decision Sciences 29 (3) : 537-553.

Mandell, M (2001) Collaboration Through Network Structures for Community Building Efforts. National Civic Review 90:3

March James G. and Herbert A. Simon (1958) *Organizations.* New York: Wiley, 1958. 2nd ed., Oxford: Blackwell Publishers

Martin Christopher, Hau Lee, (2004) "Mitigating supply chain risk through improved confidence", International Journal of Physical Distribution & Logistics Management, Vol. 34 Iss: 5, pp.388 – 396

McPherson JM, Ranger-Moore J. 1991. Evolution on a dancing landscape: organizations and networks in dynamic Blau space. *Soc. Forces* 70:19–42

Miles, R. E., & Snow, C. C. (1978). Organizational strategy, structure, and process. New York: McGraw-Hill.

Milward, B.H. and K.G. Provan. 2003. "Managing the Hollow State. Collaboration and Contracting," Public Management Review, 5, 1, 1–18.

Milward, H. B., & Provan, K. G. (1998). Measuring Network Structure. *Public Administration 76*(2), 387-407.

Mischen, Pamela 2015. Collaborative Network Capacity. *Public Management Review* 17: 380-403.

Nicolis G, and I Prigogine (1989). Exploring Complexity: An Introduction. New York, NY: W. H. Freeman.

Perrow, Charles (1972). *Complex Organizations: A Criticial Essay*. Theoretical Propositions. McGraw-Hill publishers.

Perry-Smith, J. E., & Shalley, C. E. 2003. The social side of creativity: A static and dynamic social network perspective. Academy of Management Review, 28, 89-106.

Pilbeam, C, G Alvarez, H Wilson (2012). The governance of supply networks: a systematic literature review. Supply Chain Management: An International Journal 17 (4), 358-376

Poppo, Laura and Ted Zenger (2002). Do Formal Contracts and Relational Governance Function as Substitutes or Complements? *Strategic Management Journal Strat. Mgmt. J.*, 23: 707–725 (2002)

Prigogine, I. and Stengers, I. (1984) Order out of chaos: Man's new dialogue with nature. Bantam Books, New York.

Provan, K.G. and B.H. Milward. (2001). 'Do Network Really Work? A Framework for Evaluating Public Sector Organizational Networks', Public Administration Review, 61, 4, 414–23.

Provan, K.G. and J.G. Sebastian. (1998). 'Network Within Networks: Service Link Overlap, Organizational Cliques, and Network Effectiveness', Academy of Management Journal, 41, 4, 453–63.

Radin B and B Romzek (1996) Accountability Expectations in an Intergovernmental Arena: The National Rural Development Partnership. Publius 26:2(59-81).

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks: Sage Publications.

Ruelle, D. (1989). Chaotic Evolution and Strange Attractors. Cambridge University Press.

Schoemaker Paul J.H., George S. Day, Scott A. Snyder (2013). Integrating Organizational Networks, Weak Signals, Strategic Radars and Scenario Planning. *Technological Forecasting & Social Change* 80:815–824

Senge, P. M. (1990). The fifth discipline: The art and practice of the learning organization. New York: Doubleday/Currency.

Simon (1996). *The Sciences of the Artificial. MIT Press. Cambridge, MA*

Sosa M (2009). Coordination Networks in Product Development in The Network Challenge: Strategy, Profit, and Risk in an Interlinked World. Paul R. Kleindorfer, Yoram (Jerry) R. Wind, Robert E. Gunther. Upper Saddle River: Wharton School Publishing, 2009

Stacey R (1995). The science of complexity: An alternative perspective for strategic change processes. Strategic Management. 16:6(477-495)

Surana Amit, Soundar Kumara , Mark Greaves & Usha Nandini Raghavan (2005). Supply-chain networks: a complex adaptive systems perspective. International Journal of Production Research, 43:20, 4235-4265

Thompson, James (1967). Organizations in Action. Transaction Publishers: New Jersey.

Turrini, Alex; Cristofoli, Daniela; Frosini, Francesca; And Nasi, Greta (2010). Networking Literature About Determinants of Network Effectiveness. Public Administration 88:2(pg528-550).

Valente T (2012). Network Interventions. Science 337

Wasserman,S and K Faust (1994). Social network analysis: Methods and applications. Cambridge University Press

West, Richard and Turner, Lynn (2007). *Introducing Communication Theory*. McGraw Hill. p. 188.

Westland, J. C. (2015). Structural equation modeling: from paths to networks, New York: Springer.

Wiggins, J.B. (1987) Option values under stochastic volatility: Theory and empirical estimate. J. of Financial Economics 19, 351–372.

Williams, T.M. (2002), “Modelling Complex Projects”, London: Wiley.

Williamson, Oliver E. (1981). "The Economics of Organization: The Transaction Cost Approach," *The American Journal of Sociology*, 87(3), pp. 548-577

Wilson, T.D. (1994) Information needs and uses: fifty years of progress? in: *Fifty years of information progress: a Journal of Documentation review*, edited by B.C. Vickery. London: Aslib. pp. 15-51

Wright, S (1931). Evolution in Mendelian Populations. *Genetics 16 (97-159)*.

Zajaak, E and M. Kraatz (1993). A diametric forces model of strategic change: Assessing the antecedents and consequences of restructuring in the higher education industry. Strategic Management Journal. 14(83-102).

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Table 1: Common Network Terms
Node: a person, team, organization, computer, etc. in a network
Tie: a connection between two nodes
Directed Network: a network where the tie is directional in nature
Undirected Network: a network where the ties are not directional
Ego: refers to the subject of the discourse
Alter: refers to the node that the ego has ties with
Ego Network: refers to the network in light of a given ego
Dyad: two nodes linked into a pair. Networks can be decomposed into their dyads, or pairs.
Structuralist Paradigm: sees the network structure as the defining characteristic of n individual node's behavior. By extension, two nodes that share structurally similar characteristics will witness similar outcomes.
Connectionist Paradigm: The focus is on the resources that flow through the ties; the ties act as conduits for the flow of resources
Diffusion: Is a measure of the spread of an innovation or characteristic throughout the network
Social Capital: The primary focus of Connectionist paradigm is primarily concerned with the resources that are gained (or lost) via the ties, and they view success as a function of these ties.
Structural Capital: The primary focus of the Structuralist paradigm is primarily concerned with the position of nodes in a network and how this influences outcomes.
Centrality: the extent to which a given node(s) dominates the number of ties. When only a few nodes have a large number of ties compared to the others, the network is viewed as highly centralized.
Structural Equivalence: Actors (or nodes) are structurally equivalent to the extent that they are similar in their ties.
Relational Embeddedness: relates to the quality and depth of a single dyadic tie
Structural Embeddedness: relates to the extent to which a given node's alters are interconnected
Geodesic Distance: represents how far one node is from another. It is often

represented as how near or far a node is from another.
Closure : Is a measure of the number of triads (or connections among three nodes) that exist in the network
Structural Hole: A hole in the network that a node could bridge and thus act as a go-between. In this way, they can often control the two nodes that they connect.
Broker: Per the definition of *structural hole*, a broker spans two or more subnetworks.
Multiplex Ties: when a given node connects with another node in multiple networks. For example, a node may be connected to another node in both a funding network and a data-sharing network.
Homophily / Heterophily: indicates the extent to which one node is similar to another on key characteristics
Degree Distribution: the variance in the distribution of ties in a network
Network Connectivity: reflects the “size” of the network by the longest path from one node to another
Network Density: the proportion of ties in a network relative to the total number possible
Pattern of Clustering: refers to the absence or presence of subnetworks
Degree Assortativity: reflects the degree to which nodes with a similar number of ties connect with each other
Cohesion: the degree to which nodes are connected directly to each other. Under low cohesion, a number of cliques (or subnetworks) will be observed.
Bridge: a tie that is critical to the connectivity of the network. Elimination of the bridge is likely to result in a large number of factions.
Path Length: the length from one node to another. Typically measured in terms of how many nodes are in between the two.

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