SYM-AM-16-052

PROCEEDINGS

OF THE

THIRTEENTH ANNUAL ACQUISITION RESEARCH SYMPOSIUM

THURSDAY SESSIONS VOLUME II

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

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Published April 30, 2016

Approved for public release; distribution is unlimited.

Prepared for the Naval Postgraduate School, Monterey, CA 93943.

ACQUISITION RESEARCH PROGRAM
GRADUATE SCHOOL OF BUSINESS & PUBLIC POLICY
NAVAL POSTGRADUATE SCHOOL

The research presented in this report was supported by the Acquisition Research Program of the Graduate School of Business & Public Policy at the Naval Postgraduate School.

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Panel 13. Setting Requirements and Managing Risk in Complex, Networked Projects

Thursday, May 5, 2016	
9:30 a.m. – 11:00 a.m.	**Joseph Yakovac, Lieutenant General, USA (Ret.)**– Former Principal Military Deputy, Assistant Secretary of the Army for Acquisition, Logistics and Technology ***Acquisition in a World of Joint Capabilities: Methods for Understanding Cross-Organizational Network Performance*** Mary Brown, Professor, UNCC Zachary Mohr, Assistant Professor, UNCC ***Modeling Uncertainty and Its Implications in Complex Interdependent Networks*** Anita Raja, Professor, The Cooper Union Mohammad Rashedul Hasan, Assistant Professor of Practice, UNL Robert Flowe, Office of Acquisition Resources & Analysis, OUSD (AT&L) Brendan Fernes, Student, The Cooper Union ***An Optimization-Based Approach to Determine System Requirements Under Multiple Domain-Specific Uncertainties*** Parithi Govindaraju, Graduate Research Assistant, Purdue University Navindran Davendralingam, Research Scientist, Purdue University William Crossley, Professor, Purdue University

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

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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 (MPADs) as a network of interconnecting programs and employs Contagion Modeling (mixed effects linear regression with a modularity maximization algorithm) as a method for understanding MDAP performance. The presentation will provide the statistical results gained from the contagion modeling and provide insights on risk susceptibility. Understanding the nature of how exposure triggers state changes across networks levels is likely to yield new strategies on how to manage network risk.

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, that is, battlespace awareness.

But jointness does not come without risk. Collaborative efforts are known to experience the problems of suboptimization and moral hazard and principal-agent issues (Pfeffer & 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 occur 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).

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.

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 over a period of six years.

Methods

As alluded to above, MDAP programs often share program elements. Shared resources, that is, program elements, are a common form of jointness. The analysis below tests for the presence of contagion as it relates to the cost variances of neighbor programs.

To test for the presence of contagion, mixed effects linear regression with a modularity maximization algorithm was employed. 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 & Bryk, 2002). The mixed effects models that were estimated are linear regressions that account for the total cost variance of all network partners, B5 Model 1, and component cost variances of schedule, estimation, economic, and engineering that correspond with B6, B7, B8, and B9 in Model 2 respectively. The other predictors of interest in both models are β1, which models the effect of the number of network partners that are directly connected to the MDAP program yi. The β2 estimator is the diversity of network partners based upon the rank abundance curve. The β3 is the percent of network partners that are considered joint programs. The β4 is the percent of network partners that are classified as in production. The δk 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 αj is the varying intercept based upon the network community upon which the MDAP program is classified.

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

$\alpha_j = \mu_\alpha + \eta_j$

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 leptokurtic 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.

Measures

As mentioned above, the goal was to test the cost variance of neighborhood partners and contagion 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 diversity measure. Diversity was measured by the slope of the rank abundance curve. 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.

Findings

The two best-fitting models are presented in Table 1, and they reveal that both complexity and the cost variances of the network partners influence the cost variances of the MDAP programs. Of the two theoretical classifications of variables, we find that the complexity variable is the better predictor 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, which 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. Throughout all of the models, the complexity and diversity measures are significant ($p<.1$) and of the sign predicted by theory.

Table 1. 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 partners*			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 joint	-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 variance	-	-	-	-0.0041	0.0029	0.162
Network partner estimation cost variance	-	-	-	0.0003	0.0002	0.090
Network partner economic cost variance	-	-	-	0.0025	0.0030	0.418
Network partner engineering cost variance	-	-	-	-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, 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 diversity 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 leptokurtic 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 that the average cost variance of the programs in the dataset is $38 million, 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 diversity of network partners services based upon the rank abundance curve is very strong. A one-unit change that takes us from no network partner diversity to most theoretical network partners diversity has a significant impact on the cost variance. The change, therefore, from least possible diversity to most possible diversity of network partners 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 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 diversity 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 diversity 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 diversity variables, is non-linear based upon the underlying cost variance; however, unlike the diversity 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 diversity 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 diversity of the programs that are being developed.

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[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 $Y = (b_0 + b_iX_i)^3$, 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 $dY/d_{xi} = 3b_i (b_0+b_iX_i)^2 = 3b_iY^{2/3}$. 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 $38 million.

In sum, none of the neighbor cost variance measures (neither the production nor percent joint) proved instrumental in predicting individual program cost variance. However, both the diversity and the number of neighbors did prove instrumental and do appear correlated with cost variance growth.

As discussed, jointness does not occur without some degree of risk. This research examined one particular form of risk—contagion—employing one particular statistical technique mixed effects linear regression with a modularity maximization algorithm. The results did yield interesting findings in terms of size of neighborhood and diversity. Further research will test a number of different algorithms for their strengths and weaknesses in providing insights on joint activities.

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Acknowledgments

This material is based upon work supported by the Naval Postgraduate School Acquisition Research Program under Grant No. N00244-15-1-0062.

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