A Methodology for Analyzing and Managing Complex Stakeholder Networks

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Dedication

To my family- a resilient network. To my parents, for their rebound. To my children, for their adaptive capacity. Above all, to my wife, for her graceful extensibility.

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My deep thanks to Professor Thomas Mazzuchi, for providing invaluable guidance at every turn in the development of this research, and to Professor Shahram Sarkani, for architecting such a challenging yet rewarding course of study. Special thanks also to Dr. Thomas Holzer for his coaching and assistance in crafting the final dissertation version. The formidable body of systems engineering research produced by students and professors at George Washington University has inspired and improved this dissertation, and I am proud that the faculty who taught me so well in the classroom are cited in the bibliography over two dozen times.

Abstract of Dissertation

A Methodology for Analyzing and Managing Complex Stakeholder Networks

Systems engineers, strategists and technical leaders of all stripes are tasked with the challenge of managing stakeholders in a complex environment. In the complex domain, whether an engineered system or enterprise, the relations both with and between the persons and entities affecting the survival and growth of the organization can be modelled as a stakeholder network. In such networks, relationships are valuable but costly, consuming time, mental bandwidth, and resources. Interactions with and between stakeholders must be prioritized and made more efficient. In this research, a novel graph theoretic framework was developed, based on extensive review of the complex systems, stakeholder theory, strategy, and network science literatures. This methodology analyzes and even manages stakeholder relationships, improving the reliability and efficiency of communication within the network. Real-world, complex social networks were constructed using supply chain and financial data for 100 of the largest public US firms and measured for robustness, global connectivity, and efficiency, connecting these qualities to statistics such as percolation threshold, assortativity and transitivity. A linear regression approach showed that these measures are associated with a wide range of financial and non-financial performance metrics. Practical examples of how enterprise managers could leverage these network characteristics are demonstrated. Future research directions are identified, and the research is applied to the problem of managing in a post-Covid world. The emphasis throughout is on gaining strategic advantage, by using resilient stakeholder networks to produce survivable stakeholder systems.

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List of Acronyms

DoD	U.S. Department of Defense
DSM	Design Structure Matrix
ERS	Engineered Resilient Systems
ESD	MIT Engineering Systems Division
ESG	Environmental, Social and Governance Performance Metrics
INCOSE	International Council on Systems Engineering
MAW	Mitchell, Aigle, and Wood Stakeholder Saliency Model
MBSE	Model-Based Systems Engineering
NDIA	National Defense Industrial Association
OODA	Observe Orient Decide Act Loop
OR	Operations Research
SBD	Set Based Design
SE	Systems Engineering
SEBoK	Systems Engineering Book of Knowledge
SPLC	Bloomberg Terminal Supply Chain Data Module

Glossary of Terms

Centrality	Measure of relative influence of node, or vertex, in network.
Clustering	Also known as transitivity, tendency of nodes sharing a neighbor to themselves be connected, forming a triangle. Denoted by *C*, taking values between 0 and 1. Measured as number of actual triangles in network divided by number of potential triangles.
Degree	Number of links, or edges, connecting a node to neighbors.
Degree Correlation	Also referred to as degree assortativity. Refers to tendency of nodes to connect to other nodes of similar degree. Denoted by *r*, taking values between -1 and 1, measured as Pearson correlation of neighboring nodes, with their degree being the variable of interest.
Network Density	Number of actual edges divided by number of potential edges.
Network Resilience	Ability of a system to respond or adapt when challenged by stressful events, applied to network representations of systems. Many definitions exist, but used here in terms of robustness, rebound, and adaptive capacity (Sharkey et al. 2020).
Percolation	Process of critical phase transition, or tipping-point, into connectivity. A percolating network contains a single global cluster of connected nodes.
Stakeholder	Person or entity affecting, or affected by, the survival and growth of an organization, project, or system.

Chapter 1. Introduction

1.1 Background

This research poses the question: does the resilience of an organization's network of stakeholder interactions contribute to its strategic success? Two different strains of thinking motivating this question, the first grounded in real-world observations on strategy and competition; the second in academic research on complex systems, are sketched below.

1.1.1 Informal Motivation: People, Ideas, Hardware

John Boyd, the famed USAF fighter pilot, influential military strategist and leading Pentagon reformer who revolutionized US defense acquisitions from the 1960's on (Stevenson 1993, 349-353), (Burton 2014, Prologue), was frequently known to preach "People, ideas, hardware- in that order" (Coram 2004, 354). The impetus for this line of thinking was outlined in Boyd's briefing, 'Organic Design for Command and Control', a subsection of the larger, well-known 14-hour, 400-slide briefing titled Discourse on Winning and Losing (Hammond 2012, ch.10). There, Boyd begins by reflecting on common responses to mission failures and systemic breakdowns, noting that 'the institutional response for overcoming these fiascos is: more and better sensors, more communications, more and better computers… This way of thinking emphasizes hardware" (Boyd and Hammond 2018, 219).

Boyd counseled "a different way—a way that emphasizes the implicit nature of human beings", highlighting organizational-level, human qualities such as shared orientation, harmony of effort, adaptability, and the cultivation of independent initiative (ibid, 220-22). Linkages characterized by "common frequencies", "harmony of different efforts", "correlation among multiple sources" and yet also "inversely related characteristics" are positive. Meanwhile, "compartmentation", "noncooperative centers of gravity" and "islands of disconnected effort" are negative (ibid, 227), since they force organizational participants "to look inward" and the "system comes unglued" (ibid, 238). However, Boyd also argued that explicit structures of cooperation, "disconnected from environment but connected to some formality", could be equally bad, because they similarly force participants to focus inward on internal arrangements, rather than outwards, beyond the boundaries of the system, to interact dynamically with the larger world (Hammond 2012, ch.10). As Boyd put it in other sections of the Discourse, we must pay attention to the "vulnerable, yet critical, tendons, connections, and activities that permit a larger system to exist" (Boyd and Hammond, 58), and look at "the implicit arrangements that permit cooperation in complex, competitive, fastmoving situations" (ibid, 15). "Without implicit bonds or connections," Boyd concludes, "we magnify friction, produce paralysis, and get system collapse" (ibid, 238).

Boyd's emphasis on the human element of communication and connectivity within successful systems raises the question: can resilience, measured not only as robustness, but also as "capacity to adapt", a term that appears eight times in Boyd's Discourse, explain the strategic success of networked organizations seeking "survival and growth" (ibid, 363)? Moreover, can Boydian concepts, such as the entropic effect of

competing, disconnected centers of gravity, shed light on these matters? As Boyd observed, these questions are particularly relevant to organizations operating in competitive environments made complex by virtue of their dependence on technology and global supply chains. This brief, informal excursus into Boyd's thought shows that the research program outlined below is grounded not only in the scholarly literature, but also firmly in "the uncertain, everchanging, unpredictable world of winning and losing" (Boyd and Hammond, 364).

1.1.2 Formal Motivation: Stakeholder Interaction and Complex Systems

Organizations and systems are becoming more complex, in part due to technological innovation, in part due to the fact that their stakeholders are becoming more numerous and more diverse. Here, stakeholders are defined as the key persons or entities relevant to the survival and growth of an organization or system, a definition that will be discussed at length in the literature review. Technical leaders, systems engineers, and enterprise managers consequently need more powerful formal methodological tools for managing the complexity created by expanding webs of stakeholder interaction. In fact, the importance of stakeholder interaction is not new, and has long been at the core of both complex systems research and stakeholder theory. Thus, modern socio-technical systems, according to de Weck, a former editor-in-chief of the Systems Engineering journal, become "messy" precisely because "large-scale complex systems involve many different stakeholders, who may have very different views, even on what the system's objective function should be" (de Weck et al. 2016, ch.5). Sheard and Mostashari 2009 define complex systems in the context of systems engineering as involving "disparate stakeholders creating systems that are functional for other purposes". Similarly, "the

concept of stakeholders", according to Freeman, a founder of stakeholder theory, not only "implies a two-way relationship. It is actually even more complex, because in reality stakeholders interact with each other, and the firm sits at the center of an interconnected value-creating network." (Freeman et al. 2018, ch.3). According to Snowden, the originator of the Cynefin framework for categorizing organizational complexity, a wide array of research has emphasized that "complex contexts require more interactive communication than any of the other domains" (Snowden and Boone 2007).

Stakeholder interaction is important in part because, as argued by early pioneers in administrative science and complex systems, such as Chester Barnard or Herbert Simon, no single executive, program office or systems engineer can comprehend the whole of modern socio-technical systems (Barnard 1938), (Simon 1997). As the cyberneticist Ross Ashby's famous law of requisite variety suggests, the control mechanism of an organization should be as varied or complex as the entity it controls, and management must draw on diverse and disparate resources to manage a diverse and disparate entity well (Ashby 1958). A simple management structure cannot control a complex organization (Simon 1962). Complex systems, as argued in Norbert Wiener's foundational work on cybernetics, whether nation-states or animal colonies, persist only through the inter-communication of constituent members (Wiener 1962, ch.8).

Simon argued that cognitive limitations and bounded rationality similarly require the burden of administration, or span of control, to be shared across networks of managers and stakeholders (Barnard 1938), (Simon 1962). In recent times, as the manager's span of control extends to areas formerly excluded from the narrow purview of American mid-century "managerial capitalism", such as environmental, social, and

global issues, the old model of centralized control becomes even less plausible (Freeman et al. 2007, ch.2). Interactive communication with and between stakeholders, incorporating experiential feedback, is therefore necessary to manage such complex organizations, because, according to Harrison White, an originator of social network theory, “control can only emerge from interaction between organizational schema and spontaneous responses” (Nohria and Eccles, 95).

Further, the tightly coupled, highly connected nature of modern socio-technical systems means that “failure emerges opportunistically, non-randomly from the very webs of relationships that breed success and that are supposed to protect organizations from disaster” (Dekker 2016, introduction). Healthy stakeholder interaction is necessary to prevent the complacency and maintenance of incorrect assumptions that characterize many engineering disasters (Arstad and Aven 2017), (Leveson 2015). Lack of healthy, two-way communication leads to signals of danger being missed and the “normalization of deviance”, as in the Challenger launch decision (Vaughan 2016).

Finally, in a world where firms, projects and engineered systems necessarily impact broad swathes of society, unprecedented in the scope and breadth of the populations affected, the perceived legitimacy and even legality of enterprises depends on their incorporating disparate and diverse stakeholder voices (Beierle 2002). However, many of these voices belong to unaware, complacent, marginalized or otherwise less visible, hidden populations (Bryson 2004). From both ethical and purely instrumental perspectives, new means of engagement, direct or indirect, with such “hidden stakeholders” are needed (Wood et al. 2012).

1.2 Problem Statement

The management scientist Paul Nutt found, in research conducted in the 1990's that just over half of 400 organization-level strategic decisions studied fail (Nutt, 2002). Nutt attributed many of these management debacles to a lack of attention to stakeholders and their relations, neglecting to reconcile diverse stakeholder claims and failing to manage the complexity unleashed by multi-stakeholder decision making (ibid, ch.2). Remedies suggested by Nutt include "network with stakeholders" and "create win-win situations for all stakeholders", in addition to an overall emphasis on engagement with stakeholders and attention to their needs, including their ethical claims (ibid, Table 2-1). Wood et al. 2012, building on Rowley 1997, argued that attention to stakeholder interactions modeled in network form is likely an effective antidote to the common management traps identified by Nutt. Similarly, Cameron et al. 2011 argued that poor priority-setting and self-serving behavior on the part of managers are an increasing source of concern across a range of industries, from spacecraft engineering to commodities extraction to the classic business firm and arise from lack of leadership attention to the interactions of diverse stakeholders.

Nevertheless, despite longstanding identification of the problems resulting from unmanaged, unanalyzed webs of stakeholder relations, comparatively little literature in the relevant fields has focused on analyzing and managing inter-stakeholder interactions, particularly the connectedness of such interactions, using quantitative models, and at a global scale (ibid). The 2019 Cambridge Handbook of Stakeholder Theory explicitly identifies, as one of three areas of emerging research, the question "how do the interactions between the stakeholders themselves and the differences among them

influence strategies of stakeholder management and their effectiveness?" (Harrison et al. 2019, ch.17). An earlier 2010 overview of the academic state of the art similarly concluded by identifying, as one of "10 questions on the horizon", the question of "how do we conceptualize the interaction effects of stakeholders- the jointness of stakeholder interests?" (Freeman et al. 2010, 287). Rowley, the originator of the stakeholder network concept, himself writes:

> I am puzzled by the gap between the potential of studying stakeholder networks and what we have done so far to integrate social network and stakeholder research: The connections are clear and the value of integrating are visible. What is difficult to conceive is why stakeholder network research has not gained more traction. (Rowley 2017)

1.2.1 Faulty Assumptions

Sometimes lack of attention to stakeholder interaction is intentional, merely to simplify the presentation of new material to the reader, as in Freeman et al. 2018. "While perfectly appropriate for emphasizing that managers need to consider and engage difference stakeholder groups, this perspective downplays the relationships that exist among the stakeholders themselves" (Harrison et al., 2019). More generally, however, the omission stems from faulty assumptions that actively impede attention to stakeholder interactions. These faulty assumptions, in brief, stem from the notion that stakeholder interactions can be easily mapped, managed, and predicted. This managerial perspective, however, essentially assumes away the complexity inherent in large, diverse networks. It thus obscures the difficulty, treated in the literature review, of modeling causality and making forecasts in complex contexts, where stakeholder management strategies based on optimization and forecasting typically do not succeed (de Gooyert et al. 2017).

When managers do appreciate the complexity inherent in their decision-making context, they often emphasize "involving" engagement strategies, the better to identify emerging and unpredictable stakeholder conflicts (ibid), precisely the approach advocated by Nutt 2002. However, engagement strategies often fail to appreciate that direct communications are difficult or impossible, and thus certain stakeholders can be accessed only indirectly, through other stakeholders (Cameron et al. 2008), (Cameron et al. 2011). Even if interaction *with* stakeholders should be prioritized over that *between* them, which is not necessarily so, such interactions must sometimes be pursued through third parties, and so inter-stakeholder ties become important. Additionally, the assumption of direct access ignores the likelihood, in today's tightly coupled systems, of second (and higher) order effects, that not only one's customer, but the customer's customer, the supplier's supplier, and so on, are legitimate stakeholders (Wood et al. 2012). The faulty assumptions outlined above are further addressed at length in the literature review.

1.2.2 Lack of Metrics

When researchers move beyond these assumptions and model complex networks of stakeholder interactions, there still exists the question of finding suitable figures of merit, particularly quantitative metrics. It is striking that even as the CEO's of over 200 of the largest U.S. firms signal their commitment to a stakeholder orientation, as in the 2019 Business Roundtable Statement on the Purpose of a Corporation, shifting away from longstanding notions of shareholder primacy, and the largest institutional investors such as Blackrock have declared that a stakeholder orientation will guide their allocation of trillions of dollars in savings, there are no universally shared measures of stakeholder orientation (Govindarajan and Srivastava 2020).

In fact, finding suitable metrics has been a long-standing challenge in instrumental stakeholder theory, and no definite answers exist as to how stakeholder management improves organizations, even leaving aside the complexities of stakeholder interaction (de Gooyert et al. 2017). Establishing such measures of effectiveness is frequently identified as an area needing further research (Freeman et al. 2010, 288-90), (Parmar et al. 2010). Even papers published in operations research journals typically fail to connect stakeholder interventions with empirical results (de Gooyert et al. 2017).

As will be elaborated upon in the literature review, a robust body of stakeholder theory literature has sprung up in strategic management, accounting, finance, health care management and public policy, connecting stakeholder orientation and management techniques to financial and non-financial empirical outcomes (Freeman et al. 2010, ch.4-6). However, beyond the foundational books and papers by Freeman, this strain of management literature has not been incorporated to any great extent into scholarship on the management of complex engineered systems, supply networks, and technology-driven firms. The methodology presented in Chapter 3 and results presented in Chapter 4 show how suitable metrics for stakeholder network performance can be extracted from the business management literature and applied to a technical management context.

1.2.3 Lack of Models and Data

In addition to the lack of agreed-upon metrics for characterized stakeholder management outputs, generally, there is also the problem of measuring the effectiveness of network management techniques specifically. In part, this is the larger "problem of explanation in economic sociology" discussed by Granovetter, a pioneer in social

network analysis, whereby it is hard to disentangle and analyze the effects of individual actors embedded in networked relationships (Nohria and Eccles, ch.1). Measures of overall network effectiveness are thus needed (Freeman et al. 2010, 180). While stakeholder network studies in the past have employed node-level statistics such as centrality, or simple network-level measures such as density, newer and more powerful measures to summarize graph characteristics on a global scale have been developed in the last two decades. An extensive literature review revealed that these network statistics have not been applied to the distinct topological characteristics of webs of stakeholder interaction, and the major contribution of the methodology presented here is to demonstrate how such application can be done.

Freeman suggests that we can draw on the sensemaking literature to understand the mechanisms by which stakeholder interests are coordinated (Freeman et al. 2010, 287). Gilbertson et al. 2017, and French 2013, 2015 and others draw on the systems-oriented sensemaking taxonomy called Cynefin to assert that modeling efforts in systems engineering and operations research, respectively, should match the appropriate tools with the sensemaking environment, and that, for instance, complex domains are best explored with complex tools, for instance. A review of the relevant literature showed that this Cynefin framework has been validated in the engineering management literature, but not applied to stakeholder networks. A novel contribution of this research is to show the connection between sensemaking, strategy and stakeholder networks, which is done using the Cynefin framework in Chapter 2.

Additionally, “big data” sources on the economic flows and non-economic ties between firms, on the scale necessary to construct realistic, high-fidelity stakeholder

networks, have in the past been missing (Park et al. 2018). Because publicly traded U.S. companies are required to disclose relationships with stakeholders such as suppliers, customers, shareholders and others, with this data being available computationally via the Bloomberg Terminal API, it is now possible to construct large, complex stakeholder networks, especially large publicly-traded U.S. firms, an approach which has been pursued successfully in supply chain network literature, validating it as a valuable resource for network analysis (Basole et al. 2018) (Bellamy et al. 2014), (Basole and Bellamy 2014) (Basole et al. 2016). However, this dataset has not been applied to stakeholder management, and a major contribution of the methodology in Chapter 3 is to show how this can be done. Further, a valuable database of firm non-financial performance in environmental, social and governance (ESG) measures has been created by the business intelligence provider Sustainalytics, which has been used extensively in the stakeholder theory business literature (Surroca et al. 2013), (Wolf 2013), (Francoeur 2017). However, this database too has not been employed to problems in engineering management, even as sustainability has become an increasingly important lifecycle property of socio-technical systems (Davis et al. 2012). Showing how the statistics of stakeholder networks connect to ESG performance as measured by the Sustainalytics database is an especially relevant contribution of this research, shown in Chapter 4.

By contrast, systems engineering has developed shared, standardized measures of stakeholder management effectiveness, for instance to characterize the quality of stakeholder requirements, along dimensions such as completeness, traceability, affordability, lack of ambiguity, etc. (INCOSE 2015, 59-64). Further, a multitude of studies exist connecting stakeholder management techniques to the realization of

requirements, across the system lifecycle, as in Douglas et al. 2020. However, it is inherently difficult to gather the type of massive datasets typically used to construct and evaluate complex networks for large-scale, long-lived complex engineered systems, given the heterogeneity of each program, their relatively small number, and "evaluative complexity", whereby even several years after the completion of a project such as Boston's Big Dig, it is difficult to achieve consensus on its effectiveness (de Weck et al. 2016, ch.6). Further, there is understandable unwillingness in areas such as national defense and critical infrastructure to make stakeholder and performance data publicly available, although isolated efforts such as Roberts et al. 2016 do capture such measures on a broad scale, while also noting that "almost two-thirds of the entire DoD future funding is needed to fund only 10 programs", suggesting the difficulty of gathering broad datasets on the largest systems.

Case studies are thus extremely valuable for understanding stakeholder management strategies in systems engineering, and can even incorporate second-order interaction effects, as in (Wood et al. 2012), (Garber et al. 2017). However, they do not lend themselves to the study of massive, complex real-world networks, as a qualitative approach seems insufficient to the task, with networks quickly becoming too complicated and dense to analyze visually or descriptively, due to the combinatorial explosion effect for even small networks (Park et al. 2018). As noted in Wood et al. 2012, the number of possible links *n* in a "simple" network (allowing only one edge between nodes) of *m* nodes is $\binom{m}{2}$,which is simply *m*(m-1)/2*. However, as noted in Crawley et al. 2016, the number of possible networked configurations of those *m* nodes is an exponential power

of that factorial, $2^{\binom{m}{2}}$. For if the number of *k* subsets on *n* elements is given by $\binom{n}{k}$,the total number of distinct *k*-subsets on a set of *n* elements can be derived simply as follows

$$(x+y)^n = \sum_{k=0}^{n} \binom{n}{k} x^{n-k} y^k \tag{1.1}$$

(Binomial Theorem), (Scheid 1988, 52)

Which, setting $x = y = 1$, with $n \geq k \geq 0$, means that

$$(1+1)^n = \sum_{k=0}^{n} \binom{n}{k} 1^{n-k} 1^k = \sum_{k=0}^{n} \binom{n}{k} = 2^n \tag{1.2}$$

which is also the number of possible distinct configurations for a network of *n* edges. This follows from the simple intuition that if *G* is a finite set with *n* potential elements, $\{e_1, e_2, \dots, e_n\}$, each edge *e* is either present or not present in a potential graph, and so there 2^n possible subsets of *G*. This apparently trivial calculation has profound implications for our cognitive capacity to analyze case studies requiring mentally conceptualizing, even if only informally, combinatorics on graphs. Even a small network of 10 nodes could have $\binom{10}{2} = 45$ potential edges, resulting in $2^{45} \cong 35.18\ trillion$ possible networks. A graph with only one more node would have $2^{\binom{11}{2}} \cong 36.03\ quadrillion$ potential network configurations.

Fortunately, quantitative concepts and techniques developed relatively recently in network science can be brought to bear on the area of stakeholder interaction and engagement, just as has been done in diffusion research (Centola and Macy 2007),

(Centola 2018). The framework to be presented solves exactly this combinatorial explosion problem. However, existing published academic work on stakeholder networks presents another difficulty, which is that typically the network presented has been built up through interviews with stakeholders or review of internal organization documents not publicly available (e.g. Alvarez et al. 2010). This means that every stakeholder network case study, potentially uses a different methodology for its construction (de Gooyert et al. 2017). It is therefore difficult to extract the large, consistent and, ideally, quantitative data useful for measuring stakeholder network effects, although such work has been done successfully to answer simpler research questions, such as whether stakeholder engagement generally leads to better decisions generally (Beierle 2002). The methodology presented in Chapter 3 seeks to present a paradigm for constructing real-world stakeholder networks, to solve exactly this problem, filling a significant literature gap in existing complex systems and stakeholder research.

1.3 Research Objective and Research Questions

1.3.1 Research Objective and Framework

With these considerations in mind, there is a vital yet unmet need to study the central research objective motivated above: to understand whether and how the resilience of an organization's stakeholder network explains its strategic success.

As defined in Chapter 2, the strategic success of a stakeholder system can be understood as its viability, value robustness, or survivability for stakeholders, by which is meant the organization's ability to deliver diverse kinds of values, across a range of financial and non-financial performance measures, to its diverse stakeholders, both

corporately and individually. Put this way, the research question is: can the survivability of the stakeholder network predict the survivability of the stakeholder system?

The literatures in stakeholder theory, complex systems, supply network analysis and product development reviewed in Chapter 2 argue for the importance of networked collaboration not only with, but between, stakeholders, taking network density as a first approximation of interactive communication. However, that literature also suggests that additional, complementary leverage points are available. Qualities associated with the non-functional, architectural property of resilience, such as bounce-back, adaptive capacity, elegance, and efficiency in collaboration and information-sharing, in addition to robustness or volume of communication, are also key attributes of successful systems (Neches and Madni 2012). As will be developed below, these stakeholder network leverage points are network topology characteristics treated in percolation theory such as percolation threshold; assortativity, or degree correlation; and transitivity, or clustering.

In basic research on complex networks, models of resilience have often been associated with the notion of network percolation (Dorogovtsev et al. 2008), (Newman 2003). Network percolation is essentially a generalization of the concept of percolation in a porous medium in physics, originally developed in fluid dynamics with reference to idealized lattices (Stauffer and Aharony), (Grimmett 1999), (Bollobas and Riordan 2012). As introduced in Section 2.4.4, and shown throughout the methodology in Chapter 3, percolation theory provides a novel, powerful framework for understand stakeholder system resilience and survivability.

1.3.2 Research Questions

This methodology developed in Chapter 3, and the results obtained in Chapter 4, will therefore study:

- How the density of an organization's stakeholder network influences the central entity's ability to satisfy the claims of its stakeholders.
- How greater explanatory power is achieved by supplementing or replacing density with complex network topological statistics.
- How the global connectivity and resilience of a stakeholder network, as measured by its percolation threshold, is positively associated with the central entity's ability to satisfy the claims of its stakeholder system.
- How the efficiency of a stakeholder network in achieving global connectivity, as measured by its assortativity, or degree correlation, is positively associated with the central entity's ability to satisfy the claims of its stakeholder system.
- How the inefficiency of a stakeholder network in achieving global connectivity, as measured by its transitivity, or clustering coefficient, a measure of local density, is negatively associated with the central entity's ability to satisfy the claims of its stakeholder system.

1.4 Significance and Scope of Study

1.4.1 Significance

In answering these research questions, this dissertation shows that the robustness, rebound, and adaptive capacity of an organization's stakeholder network explains its strategic success, and proposes a new methodology for analyzing and increasing the resilience of stakeholder networks. This research thus has novel and important implications for understanding and improving the structure and management of technical and scientific organizations.

The strategic management literature would likewise benefit from such work, since an influential line of resource-based strategic thought arguing that a firm's stakeholder network is a valuable source of competitive advantage (Dyer and Singh 1998), (Lavie 2006). It is even proposed that each firm's competitive advantage lies precisely in its unique web of stakeholder connections, which is where value is created (Freeman et al. 2010, ch.4), (Bosse et al. 2009). The engineering management and systems engineering communities would benefit from a big data approach to model and test the qualities of stakeholder networks, given the importance of stakeholder management in those fields along with the difficulty of collecting large, consistent data sets on complex engineered systems, as discussed above. Lastly, the emerging discipline of network science would profit from a framework, described in the next section, facilitating the application of basic research in mathematics and statistical physics to concrete problems in management science. While the network topology statistics used here have been applied individually to topics in economics networks, the only practical application of network science framework similar to the one outlined here has been in mathematical epidemiology, as in Youssef et al. 2013, Eubank et al. 2014, and Ball et al. 2012. Even in those few articles, however, the framework has been validated with simulated, rather than real-world, data.

An empirical methodology, testing hypotheses based in basic network science research, could spur continued theoretical innovation in complex networks. As Roberts wrote presciently in 1978, in Graph Theory and Its Applications to Problems of Society, "Problems of society have been a stimulus to the development of new mathematics, and should continue to be one in the future."

In addition to filling the scholarly gaps identified above, as discussed further in the literature review, this work is intrinsically important because of the central importance of understanding stakeholders in an increasingly complex, inter-connected world (de Weck et al. 2016, ch.1). INCOSE Vision 2025 states that the future of systems engineering is "comprehensively integrating multiple market, social and environmental stakeholder demands" and identifies stakeholder analysis as a core competency of the systems engineer (INCOSE 2014). The stakeholder orientation is likely both the most effective and ethical response to complexity and the increasing pace of innovation, as it forces us to quickly discard outdated assumptions and confront stakeholders as they are, rather than how we would like them to be (Freeman et al. 2007, 140-43). It is especially important, as will be discussed further in the conclusion, in the aftermath of the Covid-19 pandemic, as "managers are facing unprecedented challenges precisely because of the potential second-order network effects of doing business as usual during a global pandemic on unseen, unknown stakeholders" (Hill et al. 2021).

1.4.2 Scope

The breadth of the topics touched on above demands that the scope of research be circumscribed. A visual summary of the scope is given in Figure 1-1 below, with the

proviso that focus is on areas of overlap. The intent of this study is to bring together the literatures on

- strategy, concentrating on stakeholder theory as originally formulated in the subdiscipline of strategic management
- complex systems, with attention to the relation between stakeholders and complexity
- network science, with specific reference to the resilience of complex networks as treated in that growing body of literature.

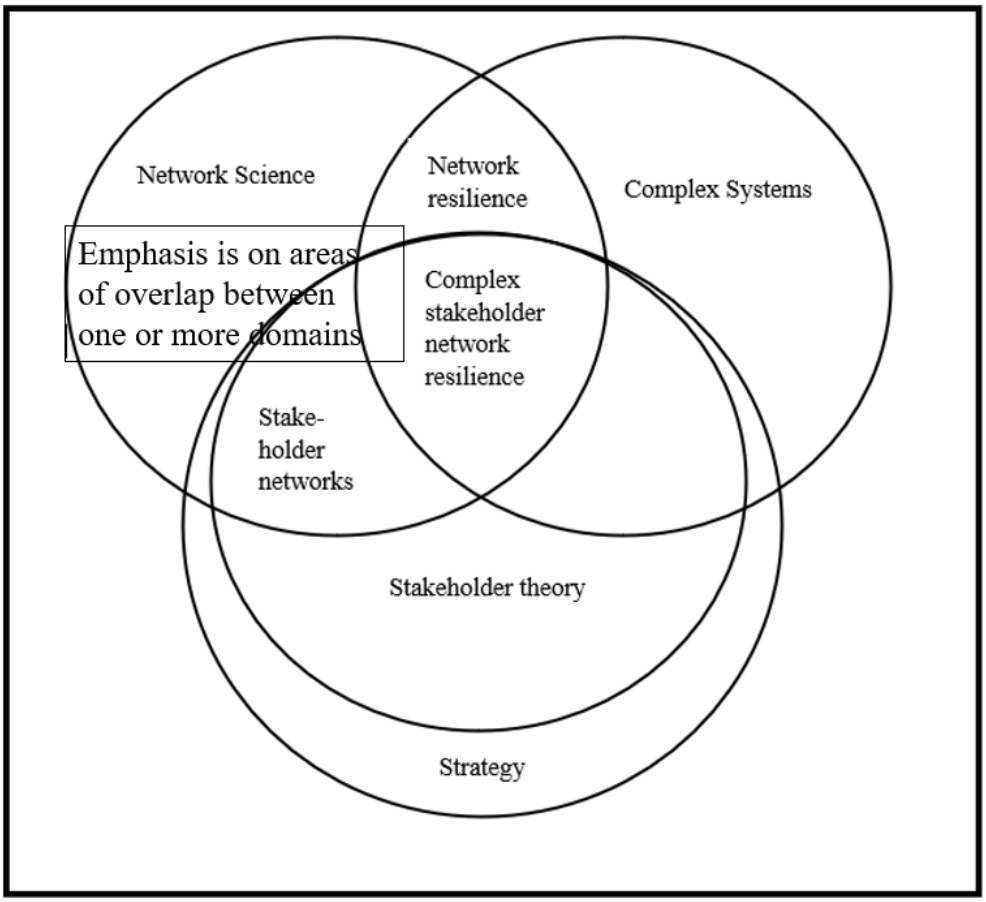

Figure 1-1: Scope of Study

The overall aim is to explain an organization's strategic advantage in dynamic, competitive, unpredictable environments, for the purposes of both stakeholder analysis and management. As will be developed in the literature review, the argument is that the resilience of an organization's network of stakeholder interactions, measured by network topology statistics correlating to qualities such as robustness, rebound, and adaptive capacity, contributes to its strategic success. As such, the target audience, the population most likely to benefit from this investigation, narrowly construed, is that of technical leaders in firms and government agencies tasked with managing for strategic advantage in a complex environment.

The focus throughout is thus on achieving competitive advantage by managing for stakeholders, rather than architecting for hardware or even organizational resilience, as stakeholder networks spread across organizational boundaries. The original impetus for this research was a desire to understand the sources of brittleness in socio-technical systems, and the causes of failure and resilience in complex engineered systems, as in (Nuss et al. 2019), (Pumpuni-Lenns 2017), (Francis and Bekera 2014). However, it was realized that the success of safety-critical organizations is, in a sense, both architectural and strategic. Resilience is an increasingly important non-functional architectural requirement and the object of growing attention in systems engineering and, in particular, systems architecting (de Weck 2016, de Weck 2018). As systems engineering techniques spread to new industries (INCOSE 2014), and firms become more dependent on interconnected technical systems and supply chains (Sheffi 2007), resilience has attracted ever broader interest, especially as the Covid pandemic has revealed how brittle many of our systems are (Hynes et al. 2020). Yet safety-critical firms and agencies that architect

more resilient systems are not only better at realizing a single stakeholder non-functional requirement. They are also better at securing their survival and growth generally. Provisioning resilience is the core mission of many safety-critical systems, such as in healthcare and air traffic control, but also provides competitive advantage in many industries (Leveson 2011, ch.2), (Sheffi 2007). The implication of this for managers is that many of the lessons learned in studying organizational resilience can be generalized to studying strategic advantage generally, even when organization boundaries are porous, as is the case with stakeholder networks. For systems engineers, this implies that their ability to architect system properties, resilience being only one of many, correlates not only with the architectural frameworks and methodologies used, but also with their strategic effectiveness (Smartt and Ferreira 2011). Resilience engineering applied to networks, as in Sharkey et al. 2020, thus has important lessons for architecting stakeholder systems for strategic advantage. In parallel to the line of thinking discussed in Section 1.1.1, the focus thus shifted from hardware, to ideas, to people.

While corporate supply-chain, financial, and ESG databases provide the empirical basis for this study, the lessons derived are applicable to firm strategists, technical leaders, engineering managers, and systems engineers generally. As argued in much of the stakeholder literature, the business firm is the paradigmatic example of a complex entity operating in a complex environment (de Weck et al. 2016), (Freeman et al. 2010), (Cameron et al. 2011). The novel framework to be described, for analyzing and managing large, heterogeneous stakeholder networks, thus has lessons for both industry and stakeholder-driven entities where such network and performance metrics are not easily available, such as engineered systems, non-profits, and intra-firm projects.

Finally, a graph theoretic methodology is used, not for its own sake, but to follow the lead of earlier, often qualitative, work on stakeholder networks, taking them seriously as networks amenable to formal analysis. While noting that engineered systems can potentially suffer from being treated as abstract graphs, prioritizing architectural form to the exclusion of engineering function (Alderson 2008), (Bounova and de Weck 2010) (Feitosa and Broniatowski 2016), the literature review will argue that many of these worries do not apply to social networks, as webs of stakeholder interaction are, since they model the "interaction of interactions" of actors in a social context (Rowley 1997).

1.5 Organization of Dissertation and Research Map

Maier 1998 identifies heuristics for analyzing re-engineering collaborative systems of systems, where architecture is associated with communication, and the interfaces facilitating communication are the leverage points for re-architecting such systems. As shown below in Figure 1-2, these range from identifying stable intermediate forms to identifying collaboration strategies. Maier 1998 specifically identifies decision-making with multiple stakeholders as a collaborative system where it is difficult to identify stable forms. Maier's influential framework can provide an informal roadmap of sorts for this research, since the aim here is to both analyze and manage collaborative systems of stakeholders, depicted graphically as follows:

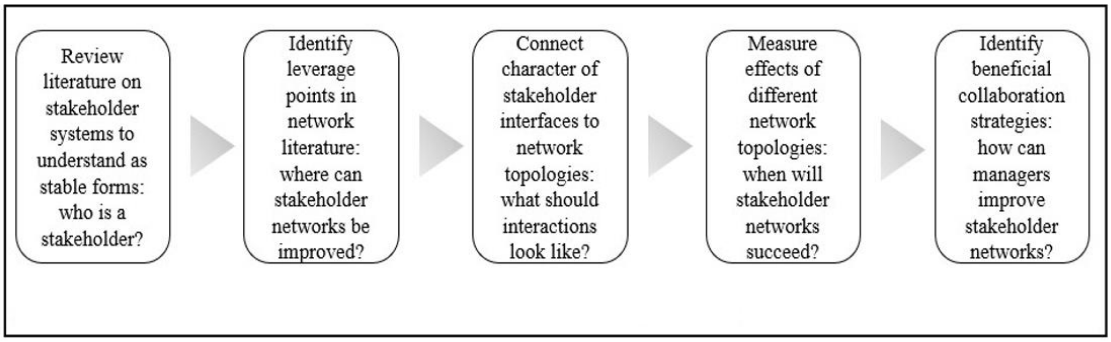

Figure 1-2: Roadmap for Research in Collaborative Systems

The first two elements above are pursued in literature review, which addresses in particular the areas of overlap in the literatures on complex systems, strategic management and stakeholder theory, and network science. These areas include the Cynefin framework for managing complexity, the Engineered Resilient Systems (ERS) approach to DoD acquisitions and systems engineering, and the extensive stakeholder management literature. The intent of the literature review is to establish a basis for understanding why stakeholder network resilience might lead to strategic advantage, in the sense of satisfying stakeholders both individually and corporately, in order to keep engaged the stakeholder necessary for the system's survival and growth. Surveys of academic work on ERS and stakeholder networks is an original contribution of Chapter 2. Further innovations include arguments linking sensemaking to strategy in a non-military context, on the one hand, and strategy to stakeholder system survivability, on the other. Also innovative is the critical view taken of network density as a useful heuristic for stakeholder networks.

The third element is pursued in Chapter 3, which establishes a novel network science framework for measuring stakeholder network resilience and connecting that with stakeholder system survivability and thus strategic advantage. While disparate elements

have been explored in some literature on economic networks and supply chains, the coherent framework for analyzing network resilience with topology measures presented here has not been presented before in a systems engineering or management science context. Exampling how massive real-world stakeholder network can be built computationally, using stakeholder saliency heuristics, is an additional original contribution of Chapter 3.

The fourth element is pursued in Chapter 4 discussing results from both simulated and real-world data, showing that more resilient stakeholder networks satisfy stakeholders more, across a wide array of financial and non-financial metrics. The identification of useful metrics for stakeholder networks is an important contribution of this chapter, as is a case study showing how stakeholder networks can be managed by leveraging network topology.

The fifth element is pursued in the conclusion, which further shows how these findings can be translated into stakeholder management techniques, by re-engineering collaborative stakeholder systems, explores future research directions, and applies this research to the problem of managing in a post-Covid world.

Chapter 2. Literature Review

2.1 Stakeholders and Complex Systems

2.1.1 Early Approaches in Administrative Science

The literatures on both stakeholders and complex systems can trace their beginning back to the years immediately preceding WWII, before growing in interest in the 1970's and exploding in the 1980's (Freeman 2018, ch.2), (Anderson 1999). This is likely no accident, given how the interplay of multiple, diverse stakeholder perspectives drives organizational complexity (de Weck et al. 2016). Both the stakeholder theorist Freeman and the historian of strategy Freedman identify the corporate executive and management theorist Chester Barnard as playing a key role in the rise of systems thinking, leading "managers to realize that their organizations were complex social structures rather than simple hierarchies" (Freedman 2015, 472-73), (Freeman 2018, ch.2). Meanwhile, Barnard 1938 is credited by Freeman as a founding document of stakeholder theory (Freeman et al. 2010, 48-49). It explicitly discusses organizational complexity in the context of the network combinatorial explosion effect discussed above (Barnard 1938, ch.8). Barnard's work played a key role in influencing Herbert Simon's thought on complex systems, with Simon explicitly naming Barnard as a major influence (Augier & March 2001), (Simon 1997).

Simon 1957, a seminal article on the architecture of complexity, noted that complexity was an object of interest from the outset of research on systems. Simon 1957 found it useful to frame complexity as arising from hierarchy, adaptation, feedback, and information, just as did Wiener 1962, the pioneering book Cybernetics (ch.8). For Wiener, as argued in his seminal article giving rise to the "cyber" sciences, feedback

requires teleology, or purpose (Rosenblueth et al. 1943). According to both Barnard and Simon, purpose is formulated at the organizational level jointly by individuals at all levels of corporate hierarchy, not only managers (Augier and March 2002). For another pioneering cyberneticist, the control of such complex organizations can only be accomplished through the "team as regulator" (Ashby 1958). Thus, although not using the word stakeholder, a clear nexus existed between stakeholder theory and complex systems thinking, a connection also made in the work of the operations researcher Russell Ackof from the 1950's on (de Gooyert et al. 2017). While Freeman argues that the link existed all along implicitly, only in his work on stakeholder management from the early 1980's on was the connection made explicit (Freeman 2018). The deep connection between stakeholders and complexity is shown by the fact that this early work on organizational science influenced the development of complexity and systems science (Anderson 1999).

2.1.2 Cynefin, Sensemaking, and Complex Systems

Simon 1957 also observed that disparate definitions of complexity abound, and different definitions are needed for different purposes. This is still the case, as a popular introduction to the subject notes that there are almost 40 measures of complexity and reviews 10 of them in depth (Mitchell 2011, ch.7). Here it will be argued that it is useful to adopt, from the vast array of potential models, Snowden's Cynefin framework (Snowden and Boone 2007), (Kurtz and Snowden 2003). Cynefin is a widely applied approach for addressing complexity in the managerial and engineering domains, as in French 2013, French 2015, Gilbertson et al. 2017, Grøtan et al 2011, Alexander et al. 2014, Walker et al. 2017, and Sprauer et al. 2016. It is a framework uniquely well-suited

for contextualizing stakeholder management strategies against the backdrop of complex systems thinking, and thus for studying the overlap between strategic management, stakeholder theory and complexity, which Snowden defines in subjective, human terms, rather than objective mathematical or computational terms.

Importantly, the Cynefin framework ties the increase in subjective perceptions of complexity to "the growth of technology and the rise of engineering-based approaches arising from the need for automation and scalability" (Kurtz and Snowden 2003). Cynefin's emphasis on group sensemaking against a background of engineered systems and technological innovation is more useful for analyzing and managing complexity in technical management than object- and process-oriented approaches based on dynamical systems or fractal dimension. Given the bounds on human rationality identified by Simon and Barnard, it is also more relevant than many information-based approaches, such as algorithmic information content, which assume idealized computational agents acting individually, rather than human beings acting in society (Mitchell 2011, ch.7). Of course, other, more quantitative information-based approaches are undeniably valid and useful, for instance Kaufman's NK model, which has also been influential in supply chain studies and industrial engineering (Giannocaro and Nair 2016).

Additionally, the Cynefin framework is uniquely suitable for this study's research agenda because sensemaking was initially formulated by Weick to explain sources of organizational resilience in a systems context (Weick 1993). An overview of complexity science summarizing the findings of an INCOSE working group in the Systems Engineering journal concludes by recommending Cynefin "to identify patterns of problems and solutions" (Sheard and Mostashari 2009), and the Systems Engineering

Book of Knowledge recommends the framework for understanding complexity in several articles (SEBoK Editorial Board 2020).

In its most basic formulation, the Cynefin framework aims to classify the different types of group sense-making by positing "five contexts defined by the nature of the relationship between cause and effect": simple, complicated, complex, chaotic and disorder, the last being simply the state where it is unclear which of the first four fundamental contexts obtains (Snowden and Boone 2007).

According to Snowden and his collaborators, in the simple context, the realm of known knowns, cause and effect relationships are stable and clear to all. This is the domain of best practices, standard operating procedures and process re-engineering. Command-and-control, reductionist managerial approaches are suitable, and "exhaustive communication among managers and employees is not usually required because disagreement about what needs to be done is rare." (ibid). The main challenge in simple contexts is categorizing phenomena correctly and avoiding complacency on the part of leadership, through continuous monitoring. Complicated contexts, in turn, are the realm of known unknowns. Here, cause and effect relationships may not be known, often because "relationships are separated over time and space in chains that are difficult to fully understand", but they are knowable, especially by experts. This is the domain of data collection, analysis, models, and methodology. Although a single right answer may not exist, teams of experts employing structured techniques usually arrive at one of the several equally good options. The danger is that such teams may be subject to groupthink, analysis paralysis or the maintenance of incorrect assumptions. Thus brainstorming, role-playing, gaming, scenario planning and the like are recommended, as the experts must

communicate not only amongst themselves, but occasionally with non-experts, to validate the decisions generated by technical expertise.

In contrast to the ordered domains of the known and the knowable are the "un-ordered" domains of the complex, the chaotic and the disordered. The complex domain is the realm of emergence, and what French calls unknown knowns, that "correspond to our knowledge in the complex space, in which we know candidates for causes and effects, but not their full relationships." (French 2013). Causality is knowable only in retrospect. We know what is happening, but not why. While predictive forecasting is impossible, patterns may emerge from the interactions of agents, although "both the number of agents and the number of relationships defy categorization or analytic techniques." (Kurtz and Snowden 2003). These patterns are potentially unstable, however, and so management approaches in the complex domain should be experimental, patient and probing, encouraging dissent and diversity. The danger in this domain is that management seeks to master ambient complexity with a command-and-control approach unlikely to succeed. Multiple solutions should be pursued concurrently, and multiple perspectives should be sought. "Complex contexts require more interactive communication than any of the other domains", and this communication should be "democratic, interactive, multidirectional" in nature (Snowden and Boone 2007). The complex, in the Cynefin framework, is to be distinguished from the chaotic, wherein there is no discernible relation between cause and effect, and even pattern formation may be missing. Here, we do not even fully know what is happening. This is the realm of crisis, emergency, and unknown unknowns. The goal of management intervention is thus to act decisively to reduce turbulence. Communication should be of the most direct, "broadcast" kind, to stabilize the situation and bring it back

towards the complex, away from the chaotic. Finally, in the realm of "disorder", per Snowden, "multiple perspectives jostle for prominence, factional leaders argue with one another, and cacophony rules" (ibid). There is, in a sense, too much communication, and the goal of management is to filter out the noise, by collaboratively establishing a consensus among key decision makers as to which of the four primary domains currently obtains.

Snowden's Cynefin framework has been usefully applied to several areas relevant to engineering management. French 2013 applies it to emergency management, human reliability analysis and, especially, the selection of decision support processes, emphasizing that "in the complex or chaotic spaces, effective decision support needs to focus on facilitating collaboration". Similarly, Alexander et al. 2014 classify decision theory research in sustainable supply chain management according to the Cynefin framework, finding the taxonomy that emerges to be a beneficial tool for supply chain managers for "the practical delivery of sustainability objectives." Sprauer et al. 2016 apply it to analyzing the performance of architect-engineer design teams in civil engineering, finding that those which adapt complex management techniques, based on team interactions and connections, to the complex sensemaking domain achieve superior performance.

Perhaps most relevant for stakeholder theory, given the importance of stakeholder management in systems engineering, Gilbertson et al. 2017 apply Cynefin to the selection of systems engineering methodologies. In their framework, simple systems are best engineered with traditional systems engineering approaches, focusing on the specification of requirements based on known stakeholder needs, the allocation and decomposition of

those requirements across subsystems, and the subsequent integration of those subsystems after the design phase. Complicated domains, in turn, are best approached with Systems-of-Systems Engineering methodologies, giving special priority to expert knowledge, to better anticipate stakeholder needs. Enterprise Systems Engineering methodologies are recommended for complex domains, given the organic, unplanned, evolving nature of enterprises, and emergent character of stakeholder needs. Meanwhile, an enterprise transformation approach is recommended in the case of chaotic systems, where we are unable to perceive cause and effect relationships, even in hindsight, due to an existing value deficiency in the enterprise, and the need to create new value propositions.

The connections between specific stakeholder management techniques and the Cynefin sensemaking domains will be explored at length in Section 2.2.3. Potts et al. 2020 note that further work on operationalizing the Cynefin taxonomy in systems engineering is needed, while also noting that complexity is often driven by both "cognitive fog" and relations between stakeholders. The strategic implications of operationalizing Cynefin management techniques for the complex domain, to improve stakeholder relations and minimize cognitive fog on one's own side, while promoting the reverse in one's adversary, is the subject of the next section.

2.1.3 Stakeholders, Sensemaking, and Strategy

The purpose of this section is to example a real-world application of resilience principles being applied to stakeholder interactions in order to gain strategic advantage. This applied framework, the DoD ERS program, largely concerns the structure,

management and operations of technical organizations designing multi-mission, multi-stakeholder systems. Examples of such systems are found, most obviously, in defense acquisition, but may also be seen in complex non-defense domains such as homeland security, cybersecurity for safety-critical industries; financial payments systems; or electronic trading markets in securities, commodities and energy (Small et al. 2017). This section builds on the author's experience as presenter and participant at the 2018 NDIA ERS conference track.

ERS is a major Pentagon research program, guiding the allocations of hundreds of billions of dollars in defense acquisitions, treated in Neches and Madni 2012, Madni 2018, Buchanan et al. 2018, Goerger et al. 2014, and Small et al. 2017. The methodologies and empirical effectiveness of this program have been validated in a wide array of systems engineering publications. This serves as a useful real-world grounding for this study, which seeks to apply network resilience principles to organizational stakeholder networks generally, not just in the defense domain on which much of systems engineering work traditionally has focused. A review of the ERS literature highlights existing approaches complementary to the one presented in this dissertation, showing the real-world demand for the methodology developed here. Identification of existing techniques for analyzing and managing stakeholders and their interactions demonstrates the robust market demand for additional tools, particularly quantitative, computational methods.

Because the ERS program is explicitly strategy-focused, this review also shows the deep linkage between stakeholder management and strategy, as other systems engineering treatments of stakeholder management typically do not (Smartt and Ferreira

2011). While corporate strategists, technical leaders and systems engineers are aware that they inhabit competitive, evolutionary landscapes, they do not typically see themselves as occupying the binary world of winning and losing they associate with national security contexts. Broader views of strategy, though, show that military conflict is not a zero-sum game either, and that there has been much crossover between strategic thinkers on both peace and war (Freedman 2015, chs.28-35).

Such a broad view of strategy was taken by the airpower tactician turned grand strategist John Boyd, whose thoughts on organic design for command and control were discussed in Section 1.1.1. Boyd applied his meditations on organic design to both the design and operational phases of system development (Boyd and Hammond 2018, 241), recognizing that even when the ultimate goal is the procurement of hardware, the focus must begin with the people who design, operate, and ultimately depend for their survival on that hardware. In fact, Boyd devoted much of an entire separate briefing, 'Conceptual Spiral', to the need for a continuous feedback loop between design engineering development efforts and operational users, characterizing this cycle, a generalization of the famous tactical-engagement observe-orient-decide-act (OODA) loop (ibid, 383-385), as essential to the system's "survival and growth" (ibid, 363-4), anticipating more recent systems engineering scholarship on 'DevOps', as in Mathieson et al. 2020.

ERS, in part, begins from an emphasis on the operational level of warfare, engineering multi-mission platforms that create flexibility and redundancy in how strategic goals are translated to the tactical level. However, the ERS program is much more profound than that, and owes much of its impetus to the thought of John Boyd, particularly his linkage of sensemaking (treated in Section 2.1.2 above) and strategy in

the context of complex engineered systems. Boyd was a trained industrial engineer, well-read in the complexity literature of the 1980's, whose strategic vision was deeply influenced by systems thinking (Freedman 2015, 198-212). Boyd's thought was in turn a formative influence on the doctrines of network centric warfare, fourth generation warfare, maneuver warfare, and the so-called revolution in military affairs, motivating concepts such as cyberwar and swarming (Osinga 2006, 243-253). These concepts play a central role in the missions carried out by ERS platforms.

Boyd is even credited with single-handedly undermining the principle of attrition warfare in US warfighting doctrine (Burton 2014, 10-11). As such, his ideas have shaped the last 40 years of US defense acquisitions policy, even contributing (Freedman 2015, 214-216) to DoD focus on the "system of systems" (Owens 1995), thus influencing the subsequent development of systems engineering as a discipline (Dahmann and Baldwin, 2008), and ultimately the rise of ERS as a concept.

It is notable that Boyd's meditations from the 1980's on the causes of "system collapse", treated in Section 1.1.1., are echoed in much of the contemporary academic literature on engineering resilience and the causes of system brittleness, as in the conceptual frameworks for resilience engineering of Woods 2015 and Madni and Jackson 2009. Resilience has become one of the most studied of system-level, non-functional requirements, or "ilities" (de Weck 2018), not least because of US Department of Defense interest in resilience, and funding for its study (Broniatowski 2018). This is in part due to the rise of agile and adaptive adversaries, from 2001 on, deploying the very same indirect approach to strategy promoted by Boyd (Goerger et al. 2014), (Haimes 2009). This is not surprising, since much of Boyd's storied, controversial military career

could be said to have focused on hardware resilience and system safety engineering *avant la lettre*, before the concepts were well defined, as in his requirements engineering work for the design of aircraft such as the A-10, F-15 and F-16 (Burton 2014), (Coram 2004).

Just as Boyd discounted hardening vulnerable or damaged targets with increased resources, calling that "supporting failure not success" (Boyd and Hammond, 80), so too has recent literature on resilience frequently gone beyond robustness, to focus on concepts such as rebound, graceful extensibility, adaptability, and capacity to maneuver (Woods 2015), (Sharkey et al. 2020). The latter-day focus on adaptive capacity over "hardening" (Lundberg and Johannson 2015) was manifestly anticipated by Boyd's Discourse, where the phrase "capacity to adapt" occurs eight times. Similarly, Boyd's thoughts on organic design have clear resonances with the resilience-enhancing properties identified in the INCOSE Systems Engineering Handbook, such as threat absorption, drift correction, humans-in-the-loop, layered diversity, cohesion, and internode interaction (INCOSE 2015, 230-31). Boyd's skepticism towards formal structures for promoting interaction and cooperation is mirrored in approaches that characterize resilience as a property of networked system architectures for which design principles and heuristics are more useful than hard requirements (Woods 2015), (Sharkey et al. 2020). The notion of a "modeler-in-the-loop", to counter fundamental surprise and maintain the ability to improvise (Eisenberg et al. 2019), is thoroughly Boydian.

It is thus suggestive to note that while many of Boyd's ideas on organic design are echoed in recent resilience scholarship, others are not, such as specific design principles for architecting cooperative systems of interaction, for example the idea that "disconnected islands of effort" precipitate "system collapse", mentioned in Section

1.1.1. Moreover, the focus of Boyd's Discourse was strategic advantage in competitive, dynamic environments writ large. Essentially, Boyd sought to apply lessons learned in the earliest days of requirements engineering for complex engineered systems, an area we are only now yet beginning to understand, as in (Douglas et al. 2020), to the management of firms, organizations and, especially, nations relying on technology to compete in harsh, evolutionary environments. Boyd did this, in large part, by applying principles of organic design for resilience not to hardware systems, but to the people managing and using them, just as contemporary resilience engineering began, according to the Systems Engineering Handbook, with an initial focus on organizations (INCOSE 2015, 229). Further, he directed his audience's attention not to organizations as seen in idealized form, in org charts and official hierarchies, but as they are in practice, in their "implicit" bonds of connection. Finally, he modeled organizations not as closed systems with hard boundaries, but as "open systems" (Boyd and Hammond 2018, 283) or multi-level living "organisms" (ibid, 80), seeking to "survive on own terms" (ibid, 27), rather than accomplish finite aims.

This suggests that Boyd's thought not only played a key role in shaping DoD focus on ERS but has vital lessons for non-military domains as well, especially technical organizations operating in complex environments. This implies that the in-depth discussion of ERS below has implications for engineering management and systems engineering generally. Boyd's OODA loop is occasionally referenced in resilience engineering literature (Sharkey et al. 2020), (Lundberg and Johannson 2015), and related areas such as crisis and emergency response (Von Lubitz et al. 2008). Yet the appeal of his ideas for modern systems engineering lies not in their scholarly grounding, but in

Boyd's profound depth of practical experience and his deep, lasting influence on national security decision makers (Boyd and Hammond 2018, Introduction, 1-7), (Osinga 2006, 255-58).

The key takeaway from Boyd's thought is that more resilient webs of human interaction facilitate more effective, more rapid sensemaking, which in turn leads to strategic advantage. The purpose of Section 1.1.1, introducing this dissertation, was to draw on the strategic thought of John Boyd to develop informal intuition on how the resilience of a human-centered system determines its survival and growth. By highlighting "the implicit bonds or connections" that ensure "an organic whole can stay together and cope with a many-sided uncertain and ever-changing environment", thus preventing "system collapse" (Boyd and Hammond 2018, 238), the lesson was that the resilience of the organizational network, broadly construed, is key to strategic success. While Boyd never used the term, the extension to stakeholder networks is obvious.

That formulation, however, does not capture the military context of Boyd's strategic thought. For Boyd's emphasis in warfare was not on ensuring the coherence of one's own side, a defensive posture he associated with Clausewitz, leading to the attrition mindset he associated with WWI and Vietnam, but on destroying that of the opponent:

> Clausewitz incorrectly stated: "A center of gravity is always found where the mass is concentrated most densely"—then argued that this is the place where the blows must be aimed and where the decision should be reached. He failed to develop idea of generating many non cooperative centers of gravity by striking at those vulnerable, yet critical, tendons, connections, and activities that permit a larger system to exist (ibid, 58).

Rather, where Clausewitz counseled decreasing the friction facing one's own side, in order to gather one's forces to mount direct frontal assaults, Boyd emphasized the need

to produce friction on the other side, by selectively destroying, not merely lines of communication, but bonds of human interaction:

> He who can generate many non-cooperative centers of gravity magnifies friction. Why? Many noncooperative centers of gravity within a system restrict interaction and adaptability of system with its surroundings, thereby leading to a focus inward (i.e., within itself), which in turn generates confusion and disorder, which impedes vigorous or directed activity, hence, by definition, magnifies friction or entropy (ibid, 237).

In practical terms, this led to Pentagon focus on using networked, technology-driven approaches to warfare tailored to produce shock and surprise and heighten the tempo of operations in the battle theater (Osinga 2006, introduction). The intent was explicitly to disrupt the opponent's sensemaking capabilities, as treated above, and thus their ability to maintain coherence and unity of effort within both their military and political institutions (Alberts et al. 2005). Special emphasis was put on agility and faster design cycles in engineering design, in order to stay ahead of near-peer competitors (ibid).

Boyd's strategic thought was thus the intellectual basis for initiatives such as "fourth-generation warfare" and "network centric warfare" (Osinga 2006). Systems produced under the rubric of these initiatives are multi-mission, and thus multi-stakeholder, engineered systems designed to operate in dynamic, unpredictable contexts, at the limits of their operational capabilities, in competitive, adversarial contexts. As such, they present special systems engineering challenges.

ERS research identified an array of factors driving "a dramatic increase in interest within the DoD to engineer systems that exhibit resilience in the face of the unexpected and the unknown" (Goerger et al. 2014). These are systems which "adapt affordably and perform effectively across a wide range of operational contexts" (Neches and Madni

2012) and are “adaptable to a wider range of mission contexts, across multiple alternative futures” (Spero et al. 2014). These factors include the “ever-increasing complexity of large-scale, ubiquitous systems” (Roberts et al. 2016); which in turn affect “larger numbers, and more diverse groups, of stakeholders” (Garber et al. 2017); and “rapid changes in missions and mission requirements, as well as the emergence of new asymmetric threats in the operational environment” (Goerger et al. 2014), underlining the complex, multi-mission, multi-stakeholder nature of ERS systems. Other challenges include impending retirements and consequent loss of institutional knowledge and increased specialization among systems and design engineers, creating “barriers to communication among and across design organizations” (Neches and Madni 2012).

A number of innovative systems engineering methodologies have been proposed to help design elegant, complex, multi-mission, multi-stakeholder ERS systems. The need for innovation in managing multi-stakeholder systems is suggested by the fact that one source reports that in the “current literature, no existing methodology could be found for evaluating engineering resilience for complex systems with multiple functions, objectives, and measures” (Buchanan et al. 2018). The major thrust of ERS initiatives pursued under DoD leadership has centered on tradespace exploration via high-fidelity physics-based virtualization. However, this was initially only one of five focus areas identified, the others being systems representation and modelling; cross-domain coupling; *collaborative design and decision support* (emphasis added); and characterizing changing operational contexts (Madni 2018). Methodologies proposed to facilitate collaborative design and decision-making include set-based design, as opposed to point-based design (Kennedy et al. 2013), (Rapp et al. 2018); values-based decision analysis, as opposed to

alternatives-based decision analysis (Small et al. 2017); heuristics for elegant system design (Madni 2012); technical storytelling and gamification to engage non-engineer stakeholders (Madni 2015); and multi-objective decision analysis (Garber et al. 2017), (Small et al 2017).

In fact, stakeholder engagement and collaboration could be said to be the ultimate goal of ERS methodologies:

> In the world of systems acquisition more so than other activities, time is money. The majority of costs stem from amortizing lengthy development and test cycles over relatively small quantity purchases. And, of course, when engineering issues arise, causing delays in a development program, the "cost meter" continues to run driving up costs and potentially reducing the quantity that can be purchased. Eventually, the amount of rework becomes unaffordable invariably leading to program cancellation. To make engineering development affordable requires up front collaboration among all stakeholders. The latter is the key to reducing the risk of schedule slips and cost overruns on acquisition programs… To effectively accomplish the above *requires significant communications among and across engineering and acquisition activities* to understand scope, identify interdependencies (that can potentially lead to undesirable outcomes), and make informed trade-offs and decisions (Madni 2018).

For example, in the ERS emphasis on high-fidelity virtualization, tradespace exploration is intended to present "a holistic view of decision impacts on required system capabilities in order to support decision making across the lifecycle by communicating to multiple perspectives and across the system hierarchy" (Spero et al. 2014). Physics-based, high performance computing-driven "tradespace exploration and analysis enable decision makers to discover and understand relationships across capabilities, gaps, and potential compromises that facilitate the achievement of system objectives", since "decision makers must have deep knowledge of the component elements of a system, which includes how these elements interact internally to the system and externally with the operational environment" (Sitterle et al. 2017). The ERS approach goes far beyond the traditional concept of operations and stakeholders' views approach, due to a belief

that stakeholder tacit knowledge concerning the full range of design possibilities and operational scenarios is of vital importance, and must be discovered via interactive, high definition tradespace exploration, rather than merely elicited.

Similarly, set-based design (SBD), which like ERS tradespace exploration seeks to flip the design-test sequence, begins from the fact that

> Different stakeholders source different constraints and requirement thresholds change over time. The relative priorities, that is, the willingness of stakeholders to relax one requirement to be able to restrict another requirement and still have feasible solutions, also change over time. SBD is an iterative process where design and requirements evolve in parallel and stakeholders restrict and relax requirements regarding feasible design space solutions. It is a concurrent engineering process that helps stakeholders understand requirement interdependencies and impact on design as they work to develop the performance specification and preliminary design (Rapp et al. 2018).

SBD sees the causes of rework as stemming from development teams learning "something critical late in the development process that invalidates prior assumptions", often from customers and users; design teams making "critical decisions too early in the project, before they have the knowledge needed to make a reliable decision"; and "development team members with one expertise inadvertently mak[ing] decisions that overly constrain those of another expertise" (Rapp et al. 2018). Many of these problems could be ameliorated simply by better stakeholder cooperation and communication, but SBD goes further and creates a tool that draws out such collaboration. SBD begins with intentionally broad bands of design possibilities, drawn from multiple stakeholders, rather than educated guesses at point estimates that anchor the project narrowly to design team choices. Where, often, "concurrent engineering efforts degenerate into simply involving representatives from other areas as advisors, to hopefully avoid the larger design mistakes", SBD enforces continued stakeholder engagement, by persisting stakeholder-derived design possibilities until they are definitively rejected (ibid).

Likewise, values-based and multi-objective decision analysis both benefit from enhanced stakeholder engagement and collaboration, to gain a comprehensive set of values and objectives and properly expand the decision context (Garber et al. 2017). Elegant design choices often dissolve conflicts in stakeholder objectives, without necessitating compromises, and are in part arrived at by imaginatively inhabiting various stakeholder roles (Madni 2012). And the power of the "two design methodologies that hold promise in the engineering of complex systems", technical storytelling and MBSE, lies primarily in their ability to engage, respectively, non-technical and technical stakeholders (Madni 2014).

This is not to say that the answer to all ERS design challenges is simply more or better communication with and between stakeholders. While Madni and Neches state that "needed cultural changes include greater collaboration and information sharing among stakeholders" and that "a key aspect of effectiveness is the frequency and quality of interaction (i.e., communication) between the different aspects of a process", they also note that "there are, however, cost implications if additional stakeholders are simply asked to stand by or are tasked to review a greater number of decisions. Furthermore, the volume of information and proliferation of alternatives is too great to assume that simply making information available will ensure that it is noticed and acted upon." Stakeholder communications can consume valuable resources of money, time and mental bandwidth, and typically have to be moderated with a specific tool, such as high definition tradespace exploration or SBD, to be effective (Rapp et al. 2018). While "information needs to be acquired from a much wider range of stakeholders than is done today", this "is not meant to imply that every individual will be communicating with every other individual about

everything, all the time. Rather, a key challenge is creating an environment which supports context-driven, targeted information exchanges" (Madni 2018). Such concerns are all too familiar to those experiencing "Zoom fatigue" during the Covid lockdown and its aftermath (Hill et al. 2021).

Further, stakeholder inputs are not always beneficial, but can themselves be key drivers of increased engineering overhead and lengthened development cycles. Pennock 2015 presents a compelling game-theoretic model attributing cost and schedule overruns in defense acquisitions to a "tragedy of the commons", whereby rational agents, in this case multiple stakeholders in a multi-mission, multi-function defense system, consume more of a public resource, in this instance engineering development work, than is efficient, in the way shepherds might allow their flocks to overgraze public pastures. Empirical evidence suggests that design and rework cycle times are largely driven by technical maturity requirements, but stakeholders in a multi-mission, multi-function system employing concurrent engineering each have strong incentives not to have less aggressive performance than their peers in other function/mission areas, since there is little private benefit to confining one's program to mature "evolutionary" technologies, when other program's stakeholders are pursuing immature "revolutionary" technologies, thus extending cycles times for the system as a whole.

For instance, if stakeholders with an interest in the anti-air capability of a proposed naval surface combatant believe that stakeholders with an interest in subsurface warfare capabilities will push for the incorporation of speculative, immature technologies, extending the development cycle, they are incentivized to do likewise, resulting in a suboptimal game-theoretic equilibrium, with excessively immature

technologies chosen. The net result is that increased direct engagement with stakeholders might contribute to the very problem that ERS methodologies seek to solve. At the same time, however, it is quite possible that *inter*-stakeholder communication and collaboration is key to solving the problem identified by Pennock, as mutual monitoring and informal enforcement mechanisms among peers are often key to solving such solving such "tragedy of the commons" problems (Ostrom 2011).

This review of the ERS literature shows how a real-world initiative guiding the allocations of hundreds of billions of dollars in defense acquisitions has recognized the importance of stakeholder interaction for establishing and maintaining strategic advantage. The national security context of ERS shows that stakeholder communication and alignment does not merely promote certain system-level architectural properties in isolation but serves as a strategic differentiator generally. Interactive communication between disparate stakeholders enables systems with multiple mission capabilities. Flexibility in tactics allows commanders to distribute decision making downwards, using mission type orders, a doctrine promoted by Boyd, based on his reading of German Blitzkrieg warfare (Boyd and Hammond, 87-90), and an increasingly influential approach in DoD acquisitions, as seen in the rise of mission engineering (Giles and Giammarco 2019). This allows operators on the ground flexibility in executing command intent, the better to raise operational tempo, sow chaos and surprise in the adversary, and generate "many non-cooperative centers of gravity" (Boyd and Hammond, 89). The net result is not so much tactical as strategic advantage, because the adversary's collective sensemaking faculties are impaired (Bezooijen and Kramer 2014).

Importantly, the approach to stakeholders in fourth generation warfare and ERS promotes quality over quantity. Collaborative overload and excessive coordination overhead are identified as dangers to be avoided, while the "capacity to adapt" is promoted time and again in Boyd's work, over "hardened resistance", suggesting that aspects of resilience such as bounce-back and adaptive capacity are more strategically relevant than robustness, implying that the density of stakeholder networks is an insufficient measure of their quality.

The cognitive, "operational" approach to war, largely developed under the intellectual influence of Boyd, driving demand for multi-mission, multi-stakeholder engineered systems, has not in practice always met with success, for a wide variety of reasons (Freedman 2015, chs.15-16). However, this excursus makes clear the deep real-world linkages between strategy, stakeholders, and sensemaking. This complex of ideas has occasionally been applied explicitly to the management of organizations, for instance by the corporate strategy guru Tom Peters, influenced by both Boyd and Weick (Freedman, ch.34). Boyd and his acolytes felt the ideas were broadly applicable and that lean production techniques innovated in the Toyota production system were "frighteningly familiar" (Coram 2004, 427-8). The emphasis on shortening decision and design cycles has obvious resonances with agile methodology (Hammond 2012, ch.9). This extension to non-military strategy makes sense, as winning in this framework was defined not as imposing one's will by force, but "survival and growth", while losing was defined as "system collapse".

More generally, the tie-up between strategy, sensemaking and stakeholders lies implicitly behind the body of scholarship most responsible for the rise of the stakeholder

orientation in technical management: the corporate strategic management literature on stakeholder theory.

2.2 Stakeholder Theory

A review of the literature on stakeholder definition in the Cambridge Handbook of Stakeholder Theory (Harrison et al. 2019) finds there to be 36 different definitions of stake-holding in important journal articles and industry documents. The survey further notes that the most influential of these articles, defining stakeholders in terms of salience (Mitchell et al. 1997), itself surveys a further 27 different sources not included in the handbook. The fact that there are well over 60 published definitions suggests the difficulty of summing up the large, influential, and complex stakeholder theory literature. The aim in what follows, therefore, is not to comprehensively review the field, but to concentrate on areas of overlap between stakeholder theory, complex systems, and network science. The major theme is that strategic edge in complex environments emerges from the survivability of the stakeholder system.

2.2.1 Early Approaches in Administrative Science

Much of the overlap between complex systems and stakeholder theory literature centers on the purposes of organizations. As discussed above in Section 2.1.1, the very fact that institutions have multiple purposes, and thus multiple stakeholders, is responsible for complexity. Sheard and Mostashari 2009 formulate a definition of complex systems tailored to systems engineering, given below in its entirety:

> Complex systems are systems that do not have a centralizing authority and are not designed from a known specification, but instead involve disparate stakeholders creating systems that are

> functional for other purposes and are only brought together in the complex system because the individual "agents" of the system see such cooperation as being beneficial for them.

This definition makes clear the connection between complexity, disparate stakeholders, and diverse purposes, making explicit what was implicit, as argued above, in pioneering work by Barnard, Simon, Wiener, Ashby and others. In such a context, according to the strategist Boyd, the aim of organizations must be "survival and growth", which means to "survive on own terms, or improve our capacity for independent action" (Boyd and Hammond 2018, 27). This same language, of "survival and growth", was used by Simon in Administrative Behavior to describe the purposes of an organization (Simon, 1947, 146). For Simon, as for Boyd, survival means not the persistence of an institution for its own sake, but success in realizing, at the same time, both the "organization objective" *and* the "diverse personal motives" of the "participants", the term Simon used for stakeholders (ibid, 14). In this, as in many other things, Simon was following the lead of Chester Barnard.

Barnard, described by Freeman and Rowley as the proto-stakeholder theorist (Freeman et al. 2010, 48-49), (Rowley 1997), made organizational survival the central preoccupation of his work (Barnard 1938). He identified it with two attributes: efficiency, by which was meant essentially the ability of a system to keep specific stakeholders engaged, by efficiently meeting their individual claims, and effectiveness, by which was meant the ability of the organization to meet the claims of its stakeholders generally, both by being effective in its meeting performance goals, whatever they may be, and in efficiently satisfying fellow stakeholders other than oneself (ibid, ch.7). Barnard, much like research performed almost 80 years later, suggests that survival is less a matter of factors such as size, age, or stock market performance (Reeves et al. 2016), (West 2018),

but rather of finding the right equilibrium between effectiveness and efficiency, satisfying stakeholders both individually and corporately. Concretely, this means that survival consists in effectiveness in satisfying stakeholder claims generally, not just in one narrow metric, such as revenue, size, or sustainability.

The practical implication of this is that, in the case of a publicly held corporation, organizational survival is ensured by effectiveness in both generating profits, which is at least part of the purpose of any for-profit organization, and in meeting the non-financial interests of stakeholders, whether financiers, employees, suppliers, customers, regulators, or community interests, thus incentivizing their continued participation. Thus environmental, social, and governance (ESG) performance is not an optional extra, but rather a core interest of the stakeholder system generally, since the interests of shareholders are not absolute. Likewise, suppliers, customers and even peers are interested not only in maintaining mutually beneficial, sustainable trading relationships or industry conditions, but that the central firm be effective in generating the profits necessary for its corporate survival.

In Barnard's view, the organization's aim is not mere institutional persistence, but survivability for stakeholders, the ongoing ability to meet their aims both corporately and individually, to keep them within the system of organizational participants interacting with each other. Barnard's emphasis was undeniably strategic, and he is discussed as a major innovator in strategy in a review of the subject, but his aim was to show the benefits of cooperation rather than value extraction (Freedman 2015, 471-73).

Another early administrative scientist promulgating a similar view was the "management cyberneticist" Stafford Beer, who coined the "Viable Systems Model",

which sought to explain how systems are “capable of independent existence”. Drawing heavily on Ashby and his “law of requisite variety”, discussed above, Beer 1984 argued that systems stay viable by “maintaining adequate control mechanisms to cope with uncertainty in the environment” (Mekdeci 2015). Following Barnard, similarly using the language of effectiveness and efficiency, what matters is not mere persistence:

> A question often asked is this: if we are dealing with an organization that exists, that is actually there to be investigated, then surely it is by definition a viable system and nothing remains to be said? This is where the pathological vocabulary becomes so useful. The fact that the societary system is there does not guarantee that it will always be there: its days may well be numbered, and many have been the 'buggy-whip' companies to prove it. The fact that it is there does not prove that it is effectively there, witness universities, nor efficiently there, witness hospitals. Monoliths and monopolistic systems in particular (such as these two) often operate at the margins of viability, creaking and choking like the valetudinarian organizations that they are. Moreover, many such are operating at such an enormous cost that they are becoming less and less viable in front of everyone's eyes (Beer 1984).

This brief review of early stakeholder and systems theory shows an emphasis on survival through both global effectiveness in meeting organizational purpose and local efficiency in inducing participants to continue to cooperate with the organization. For instance, in Simon’s example of a shoe factory, effectiveness consists in producing shoes, while efficiency is realized in the products, wages and profits accruing to, respectively, the customers, employees and entrepreneur (Simon 1947, 15), This is further put in the context of the combinatorial explosion facing managers seeking to optimize institutional interactions, discussed in 1.2.2, and consequent cognitive constraints (Barnard 1938, ch.8). This suggests that the problem facing stakeholder systems in complex environments is in part one of multicriteria analysis for satisficing with bounded rationality- precisely the area in which Simon made many of his greatest contributions (Augier and March 2002). However, the emphasis in the early literature on organizational strategy as the survival of a web of interests suggests another direction, used in the methodology presented here: network resilience.

2.2.2 Stakeholders, Survivability and Strategy

A review of more recent literature on stakeholder definition shows that survivability for stakeholders continues to be a key theme. In the systems engineering and operations research arena, this notion is captured by the complex of qualities termed variously resilience, viability, value robustness, value sustainment, and survivability. Mekdeci, Ross, and Rhodes note:

> There has been a considerable amount of research done at determining qualities that may help systems maintain value delivery in spite of change, including reliability, security, safety, survivability, resilience, versatility, and robustness. While the usefulness of these various -ilities has been established, many of them are similar and possibly redundant. Does a viable system need any or all of these -ilities? How is resilience different from survivability?... Out of all of the -ilities, the term "resilience" is probably used the most often to describe how a system maintains stakeholder value over time (Mekdeci 2015).

Elsewhere, some of these same authors (Ross and Rhodes) argue that "survivability is the ability of a system to minimize the impact of a finite disturbance on value delivery", suggesting the degree of overlap in these terms (Ross and Rhodes 2008). To complicate the matter, survivability in systems engineering is often defined in a military context, as lack of system susceptibility to mission termination or loss of life (INCOSE 2015, 240). Leaving aside the precise semantics, the intention is clear: the strategic success of a complex firm or organization lies in its ability to deliver value to stakeholders over its lifecycle both *in toto* and individually, in the face of evolution, competition and surprise. Mere perseverance, or robustness, in the manner of Beer's "buggy whip companies" cannot be the aim, as it does not result in organizational effectiveness. For example, survival of a coordinated emergency response group after the emergency passes does not deliver value, and so is not value robust. What matters at the

strategic (as opposed to operational) level is resilience, viability, value sustainment, or survivability – for stakeholders.

This is relevant because the Cambridge Handbook of Stakeholder Theory survey of stakeholder definitions notes that the earliest approaches explicitly mentioning stakeholders, from 1963-1983, universally defined the concept in terms of organizational survival (Harrison et al. 2019, ch.4). Similarly, Freeman's groundbreaking 1983 study found that survival was the central concept in stakeholder theory up through the 1980's (Freeman 2018, ch.2), with stakeholders defined as those without whom the organization would cease to exist. Later stakeholder definitions typically go beyond the original, narrow emphasis on survival, variously emphasizing legitimacy, interest, influence, responsibility, and other concepts. The Cambridge Handbook of Stakeholder Theory survey argues that the common theme in all these 60+ definitions is value creation (Harrison et al. 2019, ch.4). In fact, there is no contradiction, as a survey of strategy and systems engineering explicitly links strategic advantage, value creation, and organizational survival (Smartt & Ferreira 2011). Without understanding stakeholder concerns and needs, executives cannot formulate strategic objectives necessary for the survival of the enterprise.

Freeman himself concluded that "the more we can begin to think in terms of how to better stakeholders, the more likely we will be to survive and prosper over time" (Freeman 2018, ch.3) and "survival" even appears in the title of a later work of his (Freeman et al. 2007). Similarly, Rowley 1997 characterized the "stakeholder perspective" as arguing that "management choice and organization survival are functions of how well the organization satisfies its stakeholders". Likewise, strategic management

approaches which emphasize the role of stakeholder networks in creating sustainable competitive advantage are emphasizing qualities of endurance and persistence (Dyer and Singh 1998), (Lavie 2006), (Jones et al. 2018). Further, research on corporate survivability has highlighted stakeholder satisfaction as a key driver (Reeves et al. 2016).

Survival is a concept manifestly relevant to "unordered" domains, in the Cynefin sense where, given the difficulty of discerning cause and effect, and thus taking an optimizing approach, systems and their stakeholders must concentrate first on mere survival. In fact, survivability is called by Alderson the main objective of evolutionary complex systems, as many of today's engineered systems are (Alderson 2008).

Even if priority is placed entirely on value creation, "a possible mechanism through which the stakeholder work system creates value [is] consonance across phases, by which we mean: all elements of the stakeholder work system function effectively together" (Harrison et al. 2019, ch.4). This view would similarly imply that the strategic success of an organization operating in a complex environment relates to the survivability of its web of interests. As suggested above in 2.2.1, stakeholder network resilience is likely a useful addition to the toolkit of technical leaders in firms and government agencies tasked with managing for strategic advantage in a complex environment. To contextualize this claim, it is necessary to review existing stakeholder management techniques, with special attention to those suited to complex, chaotic and disordered domains. The Cynefin framework explored in 2.1.2 provides a useful taxonomy for this.

2.2.3 Stakeholder Management, Strategy and Complex Systems

The author's literature review found that the Cynefin framework has not been explicitly applied to stakeholder management research. A mapping of stakeholder management methods to their corresponding Cynefin domains, as Sprauer et al. 2016 and Gilbertson et al. 2017 map engineering design team and systems engineering techniques respectively, may be a small contribution to the literature. More importantly, it makes apparent the need for more stakeholder management techniques for complex and chaotic domains. A recent survey (de Gooyert et al. 2017) suggests that most stakeholder research in management science has focused on decision support methods identified by French 2013 as suitable primarily to ordered domains, the complicated and the simple, suggesting that formal methods for unordered domains are lacking. This is also true in industry, where most firms use tools suited mainly for ordered domains, even when not appropriate (Freeman et al. 2018, ch.5). Consequently, there is a manifest market demand for further techniques managing complex stakeholder networks, such as the methodology presented here, given the increasing complexity of our socio-technical systems.

Methods emphasizing the correct identification, mapping and monitoring of stakeholders would seem most applicable within the simple known domain (i.e., well defined, delimited projects and systems). So would stakeholder requirements and needs definition activities undertaken in a largely one-sided fashion, without an interactive, iterative approach, as in a serial, waterfall development process, as well as other arm's length, formally contracted approaches (Jones et al. 2018). These and similar methods constituted the majority of early approaches to stakeholder management (Rowley 1997). To the extent that quantitative methods are employed, they aim to arrive at a single optimal solution, given known stakeholder needs or interests (de Gooyert et al. 2017). In

the realm of business, Freeman et al. 2018 suggest that many firms practice a “public relations” or “implicit negotiation” approach to their stakeholders, with communication being largely one-sided (ch.5). This is a suitable approach in predictable situations, but not as a general enterprise strategy.

In turn, the complicated domain would seem appropriate for structured, interactive elicitation and engagement methods, iteratively incorporating feedback, as in agile development processes, lest experts become entrenched in their assumptions. Similarly needed are sophisticated classification schemes requiring analysis of stakeholders’ power, legitimacy, urgency, or dynamism (Mitchell et al. 1997) and stakeholder intelligence gathering (Freeman et al. 2018, ch.5). This is the domain of stakeholder needs brainstorming and affinity maps, and individual stakeholder analysis generally, undertaken with a view to discovering what is unknown, but knowable. Quantitative methods focus on balancing the disparate preferences of stakeholders through trade-off analysis and tend to assume trade-offs are unavoidable (de Gooyert et al. 2017), and that solution or design alternatives are known (Keeney 1992). The relative importance of stakeholders, considered individually, is key in this domain, as decisions must be made on how to allocate influence, power, and reward among them. The emphasis is on keeping open the lines of communication and engagement between the focal entity and its stakeholders, who can be accessed directly, forming so-called dyadic relations, as in a typical hub-and-spokes stakeholder diagram.

In the complex domain, the connections between stakeholder spokes themselves become important, as Rowley 1997 emphasized, initiating a formal, network-based line of stakeholder research tailored to the complex domain. Just as the term supply chain best

describes classical, linear, unidirectional buyer-seller relations, while supply network describes relations which are interconnected and complex (Park et al. 2018), so too may stakeholder relations be understood as networks in the complex domain (Wood et al. 2012), (Cameron 2011). Here, cause and effect relationships between an entity and its stakeholders are not immediately clear, but emerge from complex networks of relations, and so pattern identification is key.

The complex domain has been particularly emphasized in Freeman's influential body of work, which he has characterized frequently as being oriented towards the complex domain. Freeman emphasizes the need to avoid a trade-off mentality, slicing up an existing pie, and instead focuses on making the pie bigger for all stakeholders. As opposed to Porter's linear value-chain concept, Freeman argues that value is created as an emergent property of stakeholder networks, which has proven an influential line of thinking in resource-based strategic management thinking (Dyer and Singh 1998), (Lavie 2006). Stakeholder interests should be seen as joint, rather than opposed, as it is difficult to trade stakeholder objectives against each other, since there is no clear hierarchy of stakeholder importance, which is similarly an emergent property of the larger network (Parmar et al. 2010), (Garcia-Castro and Aguilera 2014).

Given the diversity of purposes characteristic of complex sociotechnical systems, as discussed above, the effectiveness of organizations and teams operating in complex contexts can only be captured with a range of financial and non-financial measures, and not by any single figure of merit. Formal methods should thus focus first on simply structuring the problem facing the stakeholder system, through "soft" operations research methods, simulation, and systems dynamics (de Gooyert et al. 2017), just as has been

recommended in the management of complex systems generally (French 2013). Garber et al. 2017 show that multi-criteria decision models may be applied, even for systems with multiple and diverse stakeholders, but with stakeholder values and objectives being the variables of interest, rather than known solution alternatives (Keeney 1992). The lack of a single objective value function, a critique of the stakeholder concept often raised by partisans of shareholder theory, is no real objection since such functions are lacking in complex domains generally (Freeman et al. 2010). To the extent that solution alternatives are put forward for subsequent trade-off analysis, they are best generated collaboratively with stakeholders, for example through distributed collaborative design (Ganguly et al. 2008), supplier associations (Dyer and Singh 1998), (Basole et al. 2018), and set-based design (Kennedy et al. 2013), (Rapp et al. 2018). Similarly, as discussed above in the ERS literature, high-fidelity system virtualization, model-based systems engineering and technical storytelling (Madni and Sievers 2018) seek to spark dynamic stakeholder interactions in the design of complex technical systems at the earliest design stages, saving engineering overhead and rework later on (Madni 2018). In all these complex stakeholder system approaches, researchers recommend a cooperative, rather than command-and-control, outlook.

The stakeholder network resilience methodology presented here complements such approaches, and similarly focuses on interactions, which are of particular importance in complex, chaotic and disordered domains. Further aspects of stakeholder interaction are treated in the next section. This review shows, however, that no existing methodologies provide a simple tool for measuring the resilience of these networked interactions, particularly one that scales easily as stakeholder systems become larger and

more complex. Additionally, there is need for further understanding of stakeholder interactions on the other side of the complex/chaotic boundary, the domain of emergency, crisis, and unknown unknowns, where the management challenge is simply to preserve the integrity of the system and create a semblance of order through a broadcast approach to communication and bring the state of the system back towards the merely complex. Such work that exists in this area has been largely qualitative and case-study oriented, focusing on keeping stakeholders merely involved in the system, rather than dropping out, due to dissent or dissatisfaction (de Gooyert et al. 2017). Finally, there is need for a model useful in the disordered domain, where it is not clear which of the four primary domains provides the relevant sense-making context, and the management challenge is to filter out noise generated by competing stakeholder perspectives, even to the extent of limiting communication.

2.2.4 Stakeholder Interaction Theory

Sections 1.1.2 and 2.2.3 above discussed stakeholder interaction in the context of complex systems. Here, stakeholder interaction theory is more fully sketched out, as a lead-in to the remainder of this dissertation, which focuses exclusively on stakeholder networks. While interactive communication is particularly important in the complex domain due to the influence of technological innovation (Snowden and Boone 2007), stakeholder interaction is also an important object of study because of perennial challenges not grounded in political and technological innovations, such as the fact that there is important tacit knowledge that stakeholders cannot express explicitly (Polanyi 2013), (French 2013). A seminal article in knowledge management argued that stakeholders often have difficulty formulating explicit product specifications, design

requirements and the like, let alone communicating these successfully with management or product developers, and group dialogue employing metaphor, analogy and other intuitive approaches is thus useful (Nonaka 2008). Communication can be especially difficult between engineers and non-technical stakeholders (Madni 2014). A broad array of tools, ranging from interviews, focus groups, gamification, and storytelling, to more traditional techniques such as trade-off analysis and simulation, has thus been developed to elicit stakeholder needs, conduct market research, and produce more meaningful forms of feedback (Madni 2018, 55). Often, these preferences only emerge through use and practice, and thus many tools in technical design, e.g. model-based systems engineering and high-fidelity, physics-based virtualization, emphasize active stakeholder interaction with not only the proposed system, but other users of the system, in the hopes that tacit preferences and design possibilities can be made explicit (Bryson 2004), (Calton and Payne 2003).

Furthermore, it is often the case that stakeholder goals or even values conflict (Keeney 1992). In such instances, conflicts need to be identified early, in order to realize joint gains, whether through brainstorming or bargaining (Beierle 2002). It is important to forestall stakeholders feeling excluded from the decision-making process, leading them to undermine the project, or seek to gain power in unhelpful ways, at a later date (Nutt 2002, ch.2, Garber et al. 2017). It is even important to include stakeholder who oppose the system, or "detractors", in establishing consensus, where possible (de Gooyert et al. 2017), (INCOSE 2015, 55). It is often stakeholder conflict that generates innovative problem-solving: "dissent and formal debate are valuable communication assets in complex contexts because they encourage the emergence of well-forged patterns and

ideas" (Snowden and Boone 2007). Inter-stakeholder communication is necessary to identify such conflicts where they exist, and even where they do not, with ritual dissent also being a useful tool for managing complex systems (ibid).

Identifying stakeholder conflicts is especially consequential in safety-critical environments, which is a central theme of Vaughan 2016. An influential school of thinking on systems safety and resilience engineering emphasizes the need for ongoing communication between disparate elements of the control systems of such complex systems and assigns much of the blame for engineering disasters to missing or defective communication links in technical organizations (Woods et al., 2006), (Dekker et al. 2011), (Rasmussen 1997). Nor has this emphasis been limited to resilience engineering. For instance, the strategic management scholar Rowley places a 1971 DC-10 crash due to a failure in a cargo door locking system 'into a network framework in which McDonnel Douglas is the focal organization falling between two stakeholders that do not share a relationship'. If these two stakeholders, in this case Convair, the fuselage subcontractor, and the FAA, had shared a relationship, vital information could have been exchanged, likely preventing a major aviation disaster (Rowley 1997).

In a similar vein, as complex engineered systems have proliferated, and been asked to take on multi-mission capabilities, and thus multi-stakeholder objectives, their impacts have become more wide-ranging and unpredictable (de Weck et al. 2016, ch.1). In part due to the need to minimize and mitigate impacts on such varied and disparate stakeholders, through testing, feedback and regulatory processes, design lead times for modern complex systems have become too lengthy and expensive, consuming too many program resources too early, limiting their extensibility and adaptability (Neches and

Madni 2012), (Madni 2018). Greater stakeholder engagement has been put forward as a promising means of shortening design cycles, moving products to market faster, spending fewer program resources up front (ibid). Lengthy development cycles drive longer system lifecycles, increasing the likelihood of the system being deployed in unforeseen and unforeseeable circumstances, exhausting or "saturating" its adaptive capacity (Buchanan et al. 2018), (Goerger et al. 2014). This means that "no single unit, regardless of level or scope, can have sufficient range of adaptive behavior to manage the risk of saturation alone, therefore, alignment, coordination, and synchronization are needed across multiple interdependent units in a network" (Woods 2018). It is no longer enough merely to satisfy existing constraints; extra slack or operational capacity must be built in (Saurin and Werle 2017). Therefore, an expanded set of risks, scenarios, and design possibilities is necessary in long-term planning, for which, as suggested above, stakeholder interaction is vital.

For these reasons, in addition to those put forward in Sections 1.1.2 and 2.2.3, stakeholder interaction is a necessary object of study, and yet has been under-theorized and underutilized in both the strategic management and technical management literatures (Rowley 2017), (Cameron et al. 2011). This literature gap may stem in great part from incorrect assumptions on the part of both practitioners and scholars. First, while it is often assumed that firms and program offices have direct access to their stakeholders, often they do not (Rowley 1997). Sometimes this is because firms do not even know who their stakeholders are, or do so only incompletely, as "one of the biggest challenges in system development is identification of the set of stakeholders" (INCOSE 2015, 54). Sometimes stakeholder relationships are involuntary, as the result of risks and externalities imposed

non-contractually, for instance in the case of ecosystems and their stakeholders impacted by pollution, or labor forces impacted by deskilling due to automation and offshoring, with no obvious transmission channel between focal organization and reluctant stakeholder (Wood et al. 2018). Other times, firms face formal obstacles to communicating with stakeholders, for instance in the form of cartel laws intended to prevent anti-competitive coordination between peer firms. Similarly, fair disclosure securities regulations require, in the case of publicly traded firms, that suppliers, customers and existing shareholders be given no privileged insight into management forecasts and planning, but only the same access as merely prospective shareholders. In all these instances and more, direct communications are difficult or impossible, and thus certain stakeholders can be accessed only indirectly, through other stakeholders (Cameron et al. 2008), (Cameron et al. 2011).

Second, models often assume stakeholder homogeneity, for instance treating the customer as a single uniform population, the supplier as another, and so on, rather than as discrete, heterogeneous individuals. In this way, rough stakeholder maps are drawn. While this approach may suffice for simple contexts, or as a starting point for further work, it is patently insufficient for today's socio-technical systems, which are complex precisely because of the heterogeneity and multiplicity of their stakeholders, with diverse objectives and goals (Calton and Payne 2003). The diversity of stakeholder perspectives is responsible for the "evaluative complexity" that characterizes modern engineered systems, and so cannot simply be assumed away (de Weck et al. 2016, ch.6).

Third, even when the distinctiveness of stakeholders is recognized, the standard bicycle wheel model, with the central entity as hub, and stakeholders as spokes, and

similar schematizations, assume that communications necessarily run through the central entity (Harrison et al. 2019, ch.17). As Rowley 1997 argued, in a paper that initiated the network analysis approach to stakeholder systems, most extant research has focused "on individual stakeholder influences and the dyadic ties between an organization and each of its stakeholders," but "since stakeholder relationships do not occur in a vacuum of dyadic ties, but rather in a network of influences, a firm's stakeholders are likely to have direct relationships with one another," and so it is necessary to examine "the complex interaction of multiple and interdependent stakeholders". This suggests that it is necessary to look at such interactions not only individually, but on a global scale, with a view to the distinct topological characteristics of each stakeholder network.

Fourth, even when complex, diverse inter-stakeholder relationships are mapped with high-fidelity models, it is typically assumed that the links are persistent and reliable, when in fact they are dynamic (Windsor 2010), differentiated in strength or weighting (Bryson 2004), and unreliable (Harrison et al. 2019, ch.17). Research recognizing the dynamic or temporary nature of stakeholder networks has emphasized the need for an iterative, continuous approach to stakeholder analysis, and sought to understand how changing stakeholder network configurations affect system outcomes (Alvarez et al. 2010). However, it must also be acknowledged that communications with and between stakeholders take place over noisy channels, with some ties more dependable, some less, due to a variety of factors.

Here, the literature on the diffusion of innovations and new behaviors is relevant (Rogers 2003), (Centola 2018), (Easley and Kleinberg 2010, ch.19). Organizations looking to spread innovative behavior, such as new, more productive agricultural

practices among farmers, or novel public health precautions among vulnerable populations, often face the problems of inherent resistance to change; limitations in resources, whether of time, mental bandwidth or otherwise, for engaging with others; cultural, educational, geographic or other barriers to engagement; and the incentives for those invested in pre-existing behaviors to sabotage, or simply drop out of, the diffusion network. Similar obstacles likely apply to complex stakeholder systems, especially given the interdependencies noted above, with each stakeholder belonging to multiple networks at once, not always willingly, and their resources for engagement with other stakeholders being finite.

2.3 Stakeholder Network Theory

A recent survey of the history of systems engineering scholarship in the 20th anniversary edition of the *Systems Engineering* journal notes the increasing prominence of networks and graphs in systems engineering scholarship (Sheard 2018), while another literature survey in that edition explains the growing importance of network methodologies by observing:

> Technical systems have network structures. Social, organizational, and technical elements of most sociotechnical systems are interconnected through exchanges of resources (information, energy, and material) and dependencies among various decision parameters in various stages of systems life cycles. Such dependencies are often not uniform and follow structured patterns that can naturally be modeled using complex networks (Heydari and Pennock 2018).

A significant way in which networks have impacted systems engineering and technical management is through scholarship on stakeholder networks, building on the argument first brought by Rowley 1997, that webs of complex stakeholder interaction are best understood through social network methodologies. Meanwhile, the literature review

below shows few areas in which systems engineering and technical management has shaped the development of stakeholder network theory, in the way these disciplines have shaped, for instance, supply chain network theory (Bellamy and Basole 2012), revealing another literature gap filled by this dissertation.

2.3.1 Antecedents of Stakeholder Networks

Rowley 2017 provides an overview of both social network analysis and stakeholder theory, and argues it "useful to outline three principles that guide and distinguish social network research":

- Organizations Exist Within an External Network of Relationships
- Networks Create Advantages for Some Actors
- Networks Evolve and are Vulnerable to Strategic Actions

This summary is striking, because the early administrative scientist Barnard similarly took an open systems view, and recognized the dynamism of such systems, writing that "if there is a change in the relationship of one part to any or all of the others, there is a change in the system… Moreover, most formal organizations are partial systems included with larger organization systems" (Barnard 1938, 78-79). Further he wrote at length about "the theory of opportunism", whereby one's position in a cooperative system can afford special power (ibid, ch.14).

However, Barnard and other early systems scientists lacked the "formal apparatus for thinking about and analyzing social structure as networks", until the trained physicist and sociologist Harrison White took a systems view of job moves and other changes in

organizational relationships, treating labor transitions as Markov chains, ultimately leading in the 1970's to a network view of organizations (Nohria and Eccles 1992, 2).

Both Rowley 2017 and Nohria and Eccles 1992 (ch.1) summarize some of the more important aspects of the social networks literature, and its influence on management thinking in terms of the three themes listed above. They observe that a well-known strategic model pivots on a firm's external network of relationships: "Consider Porter's (1980) popular five forces model. It is essentially a network model of the five key external groups that determine the organization's potential profit range—suppliers, substitutes, rivals, entrants and buyers" (Rowley 2017). Similarly, Nohria notes how the "inter-organizational" field explores how firms are connected to each other through their shared "key suppliers, resource and product consumers, regulatory agencies, and other organizations that produce similar services or products" (Nohria and Eccles 1992, 5). Nohria notes that network analysts typically use five different principles to analyze how position in the internal organizational affords power or opportunity, "cohesion, equivalence, prominence, range, and brokerage", concepts corresponding to, roughly, similarity, salience, and power, viewed in network terms (ibid, 6). Finally, it is observed that actors in network models are "active, purposeful agents who are constantly trying to wrest control for themselves or blocking others from taking control", whose actions thus shape the network, while themselves being constrained by their positions in it (ibid, 7). This means that, for instance, "Networks tend to evolve in particular ways: Network structures will often become denser over time." (Rowley 2017).

The social network literature, like the stakeholder literature, is of course too immense to review here. What Nohria's and Rowley's summaries of the social network

analysis literature make clear is that “after reading the three network principles described earlier, it might be obvious to some that there are similarities between social network and stakeholder research”, and thus “social network theories and tools should be a handmaiden to stakeholder theory” (ibid).

2.3.2 Stakeholder Networks in Strategic Management

As discussed above, Rowley 1997 initiated the network analysis approach to stakeholder systems by arguing that “since stakeholder relationships do not occur in a vacuum of dyadic ties, but rather in a network of influences, a firm's stakeholders are likely to have direct relationships with one another,” and so it is necessary to examine “the complex interaction of multiple and interdependent stakeholders”. Rowley proposed analyzing two measures, the density of firm stakeholder networks on a global basis, and the centrality (number of connections) of a firm relative to other members of its stakeholder network, hypothesizing that these explain a firm’s ability to resist stakeholder demands. While methodologically revolutionary, it will be argued that density and centrality are insufficient as stakeholder network metrics. Further, Rowley’s analysis focuses narrowly on stakeholder sources of power over the central entity.

In somewhat similar fashion, Phillips 2003 modifies the important Mitchell, Aigle, Wood (MAW) model of stakeholder saliency, based on heuristics of legitimacy, power and urgency (Mitchell et al. 1997), by reframing the moral question of legitimacy in terms of networked relations. Frooman 1999, meanwhile, frames stakeholder power as stemming not from intrinsic, node-level qualities, but from an entity’s connections in the stakeholder network. Neville and Menguc 2006 argue that the MAW model should be

extended not only to the central firm's identification of stakeholders in its own "ego network" (where it occupies the central node in a hub and spoke type network), but also to secondary stakeholder interactions, essentially weighting them according to their saliency. Freeman et al. 2007 argue that how the firm manages one particular stakeholder relationship will influence its relationships with other stakeholders.

Roloff 2008 is a useful, but challenging, rethinking of the entirety of stakeholder theory in light of the realization that firms have diverse stakeholders with diverse purposes locked in interlinking webs of connection. Henisz et al. 2014 is one of many studies exploring the financial returns to stakeholder engagement, but one of very few empirical studies to acknowledge that stakeholders themselves interact in networks.

Dyer and Singh 1998, exploring the Toyota supplier network, and Lavie 2006, examining corporate alliances, initiated an influential line of resource-based strategic thought arguing that a stakeholder network is a valuable source of competitive advantage. Following them, Bosse et al. 2009 propose that competitive advantage lies precisely in a firm's unique web of stakeholder connections, which is where value is created. Perhaps most relevant to this dissertation is Pajunen 2006, who uses social network analysis, albeit on small data sets, and using node-level measures such as centrality rather than global network statistics, to identify stakeholders most affecting organizational survival. This is applied to evaluating firm performance and strategy in the specific context of turnaround situations when the future of the organization is in question.

Despite these efforts, Rowley 2017 summarizes the current state of stakeholder network scholarship in strategic management by noting that "social network theory and

tools are drastically underutilized in stakeholder research". As argued in the introduction, this means there is a significant scholarly gap, which this dissertation fills.

2.3.3 Stakeholder Networks and Technical Management

Bounova and de Weck 2010 address the "overall difficulty with applying simple network models to engineering systems", which is that:

> often nodes and links or node relationships are not uniform and not transitive. In an acquaintance network, for example, the relation of knowing someone is reversible, thus the network is undirected. All nodes are uniform (even in modeling hierarchies, nodes are of the same type), and all links are the same. For representation purposes geometry or order is irrelevant. This is not the case for most engineering systems, where at any level of abstraction components are assembled or arranged in particular ways to work properly. Moreover, the nodes and links rarely can be put in the same category. These are hybrid networks: in other words, networks comprised of nodes (and maybe links) of different types.

Alderson 2008 echoes similar concerns. For these engineering systems scholars, the problem with applying network models developed in sociology or physics to engineering is that they prioritize form over function, and do not explain why the network came to take on the form it has. In engineering, systems evolve, whether by explicit human design or implicit evolutionary pressures, to solve a problem. Thus, Alderson asks: "can the organizational structure of the modern corporation be viewed as the solution to some type of design problem, and if so, what is it that the corporation is designed to achieve?

These concerns extend to stakeholder networks. On the one hand, they are social networks, because they concern "the interaction of interactions" (Rowley 1997). On the other hand, as is clearer in technical management than perhaps in strategic management, they are (multi-)purposive, existing both to achieve an organizational objective, and

obtain private stakeholder benefit, as argued above in 2.2.1 They cannot be rewired at random without loss of functionality. Real-world stakeholder networks are undirected, like acquaintance networks, since collaborative relationships are bi-directional (Basole 2018). Yet they are far from homogenous. Even when not explicitly designed, they should be seen as resulting from some type of planning or optimization, even if implicit. The application of network methodologies to stakeholder management in technical domains has thus been expected to incorporate constraints on form and an emphasis on functionality: what the network is capable of, rather than what it looks like. This has likely been to the good of stakeholder network literature, as network processes, such as percolation, represent a more productive path to understanding stakeholders than network form, as will be argued below.

Typically, stakeholder networks have been studied in technical management to produce better decisions. Thus Garber et al. 2017 study stakeholder networks to facilitate tradeoffs analysis on “big decisions”, regarding systems with long lifecycles and wide-ranging consequences, such as a top-level national policy process for human spaceflight. A goal programming methodology is used to apply “the satisficing philosophy of Simon” (discussed in 2.2.1) to diverse stakeholder networks with diverse objectives, to likewise improve multicriteria decision making capabilities (Jones et al. 2016). Similarly, Mok et al. 2017 develop a project management framework for eliciting concerns from networked stakeholders on major engineering projects with long lifecycles and wide consequences. De Nouy 2013 uses network methodology to study how to build trust and maintain engagement in stakeholders to natural resource management, an area where stakeholder network methodology has become popular.

Other approaches study stakeholder networks as design teams, for brainstorming, problem-solving and an expanded set of requirements. These have particularly employed categories created in the social networks literature, such as “brokers”, “connectors”, and “boundary spanners” (Wood et al. 2012). Wood et al. describe a stakeholder discovery process, to “right-size” the design team (ibid). Although not using the term stakeholder, a series of articles by personnel associated with MIT’s Engineering Systems Division (ESD) extensively applied social network analysis to design engineering teams, developing a graph-theoretic methodology upon which this study builds (Batallas and Yassine 2006), (Collins et al. 2010), (Collins et al 2009), (Parraguez et al. 2015).

Scholars associated with MIT’s ESD also found success using the design structure matrix (DSM) to model organizational architectures in design engineering (Browning 2016), (Eppinger and Browning 2016), and systems engineering (Avnet 2016), (Bonzo et al. 2016), (Sharon et al. 2013). Madni and Sievers 2018 contextualize the DSM within other systems engineering tools, in their overview of MBSE:

> DSM is an n x n matrix in which rows and columns represent the components and activities within a system. The cell (i, j) represents the information exchange and dependency patterns associated with the components i and j. The matrix enables quickly identifying which functions depend on results from which other functions.

As Eppinger and Browning 2016 write, the DSM should be seen as a network methodology:

> The DSM is a network modeling tool used to represent the elements comprising a system and their interactions, thereby highlighting the system’s architecture (or designed structure). DSM is particularly well suited to applications in the development of complex, engineered systems… Compared with other network modelling methods, the primary benefit of DSM is the graphical nature of the matrix display format. The matrix displays a highly compact, easily scalable, and intuitively readable representation of a system architecture... The adjacency matrix [of a network] is simply the binary version of a DSM (placing ones in the cells with marks and zeros elsewhere)

A DSM approach, therefore, can answer many of the issues raised by Alderson 2008 and Bounova and de Weck 2010, as it is a common tool in academia and industry to represent designed, evolved engineered systems, where function takes precedence over form. An excellent example of such a system is the simple example of a bicycle (Brady 2002, p.23). Here, in Figure 2-1, a sample DSM used at ESD was transformed easily, using iGraph software package in R, into a network representation, by translating the DSM into an adjacency matrix, as above.

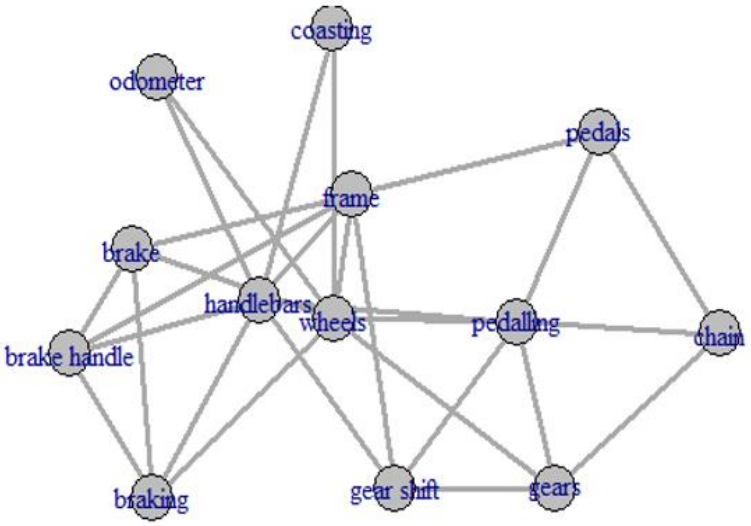

Figure 2-1: DSM of Bicycle, Translated into Network Form

This shows that organizational DSM approaches should potentially be included in the stakeholder network literature, and also that DSM's may be useful tools to architect such networks. The DSM literature demonstrates that while networks may not always be good models of generic system behavior, they are useful for designing specific behaviors into architecture,

Appendix A examples this potential methodology pictorially, further translating DSM's validated in the engineering systems literature (in Browning and Eppinger 2016)

into network representations done in iGraph. As few other sources in the systems engineering literature have demonstrated such translations, this appendix is useful in exampling how two-dimensional matrix methods can be used to assist exploratory network analysis in organizational graphs, even if only informally. Otherwise, given the combinatorial explosion problem discussed above, our cognitive capacities to process combinatorial optimization on graphs is so limited that we cannot even "eyeball" potential configurations. Thus, as shown in Appendix A, graphs too complex to consider visually become tractable when viewed in DSM form.

Another area in technical management where networks of stakeholders, albeit not using the term, but rather focusing exclusively on supplier and customer relationships, have made a substantial impact is the emerging area of supply networks, a complex networks approach to supply chain management pioneered by Basole, Bellamy, and their collaborators. This body of research is highly relevant to this dissertation, as it has been the only area in which big data, network science approaches have been used significantly. Bellamy and Basole 2012 in a review of supply networks for Systems Engineering journal, explicitly address the question of how network form instantiates system function, addressing the concerns raised by Alderson 2008. This adjacent body of research will be referenced further, as its methodology provides a model for the one used here, albeit tailored to the particulars of supply chains, which are characterized by greater hierarchy than stakeholder networks likely are.

A final area in which stakeholder networks have impacted engineering management and systems engineering is in the formulation of strategic objectives, through the analysis of stakeholder value networks by Cameron, Crawley and their

collaborators (Cameron et al. 2011 and references therein). This literature, also growing out of MIT's ESD, connects the completeness of stakeholder networks with the quality of requirements specified for the system design, like Wood et al. 2012. It goes much further than this, however, in framing value flow in the stakeholder network as the source of a system's strategic advantage, and exploring ways, both qualitative and quantitative, to analyze and maximize this flow. In this approach, as here, strategic advantage emerges from the topological characteristics of the stakeholder network, albeit analyzed with traditional operational research type models, rather than the network science statistics used here. It is thus the body of literature most conceptually relevant to this dissertation, and in suggesting an optimization approach based on flows, provides guidance on future research directions. In Eppinger and Browning 2016, this conceptual framework is deployed with a DSM methodology, tying together the technical management research strands referenced above.

2.4 Stakeholder Network Metrics and Models

2.4.1 Metrics

One of the stakeholder theorist Freeman's major concerns was to attack the primacy accorded the equity owners of the firm, under the shareholder theory of the firm. This has also been the impetus driving many other scholars to a stakeholder-based theory of the business firm (Wood et al. 2018). It is even the view put forward in the recent 2019 Business Roundtable Statement by chief executives of 200 of the largest U.S. firms (Govindarajan and Srivastava 2020). However, Freeman's attitude is not one of antipathy. He merely argues they are merely one legitimate constituency among others, financiers being necessary but not sufficient for the survival of the firm, alongside

customers, suppliers, employees, communities, and others (Freeman et al. 2010, 8). Further, they are not even the only financiers, as bondholders and banks obviously play major roles in the everyday financing needs of the modern firm. Even governments, suppliers and customers can play a finance role, using instruments such as tax deferral, trade credit and pre-payment schemes. At the same time, Freeman insists on both the central importance of financial metrics and payoffs, and management's responsibility to distribute value created by the firm meritocratically, rejecting egalitarian or anti-capitalist approaches (Parmar et al. 2010). This implies that a single financial metric, such as return on capital, let alone stock market performance, is insufficient. Other measures, such as the weighted average cost of capital, the risk premium paid by firms to issue equity, the dividend rate paid to shareholder, the riskiness of the firm's equity, etc. are important (ibid), (Freeman et al. 2010, ch.5). Henisz et al. 2014 update Freeman's work with recent scholarship on such financial measures. This further implies that there are multiple metrics, even among financial measures, by which the firm's performance is measured, and thus diverse objectives, diverse purposes, and diverse stakeholders. This in turn drives the complexity in stakeholder relations that invites network analysis.

Another concern of Freeman's has been to distinguish stakeholder theory from notions such as corporate social responsibility and the triple bottom line, and the field of business ethics, generally. For Freeman, the attention to stakeholder interests related to environmental, social or governance (ESG) issues is not an optional extra, or even essentially non-economic. Rather, he asserts that in the complex domain of management such interests are not separable from core financial interests, referring to the converse approach as the "separation fallacy" (Freeman et al. 2010, 6). For Freeman, and

stakeholder theory generally, the economic success of an enterprise hinges on its satisfaction of non-economic claims, while even non-financial stakeholders have a vital interest in its economic performance. Recent literature reviews of ESG measures of stakeholder management performance are given in Surroca et al. 2013, Wolf 2013, and Francoeur 2017. This means that, as with financial metrics, manifold measures are needed, since so one ESG measure, such as corporate governance or carbon footprint, can proxy for an organization's non-financial performance, consequently driving more "evaluative complexity", for a which a complex networks methodology is suitable.

2.4.2. Stakeholder Network Definition

In the literature on stakeholder networks, nodes or vertices are generally taken to be individual external economic partners, such as particular suppliers, customers, shareowners, bondholders, banks, public-private partnerships and so on. These are the most easily identified and analyzed shareholders, and usually the most important (Parmar et al. 2010). Other external entities with direct links might include firm peers, regulators, and various elements of government, a surprisingly overlooked constituency in much stakeholder theory (Zhang et al. 2019), although one well recognized in systems engineering literature. Secondary, less definitional stakeholder nodes include second-tier suppliers and customers, specific community constituencies, media influencers, geographic locales and environmental concerns. The links or edges are simply the relations between these nodes, whether channels of communication, collaboration, or monetary exchange. Importantly, to be of utility in the complex domain the network must be viewed in high-definition, with nodes and links considered individually, rather than as generic groups, as in low-definition stakeholder maps. Any of these node types may be

missing at a given point in an enterprise's lifecycle. For instance, a start-up firm may have no suppliers, and need pay attention only to its venture capitalist financier (Freeman et al. 2010).

Those vertices which remain, whether or not the firm accesses them directly, should be considered members of the stakeholder network, whether or not they communicate, engage in trade, or otherwise act collaboratively, since they effect the survival of the focal firm. If they cease to share this dependence, they are simply absent from the stakeholder system, rather than constituting a missing or failed node. Node failures, the original object of study of network reliability, are therefore generally irrelevant, and missing links are the objects of interest. The body of network science research most promising for a general understanding of the effect of missing links on the connectivity of the network is the mathematical modelling and simulation of so-called bond percolation, the term used in statistical physics to refer to connectivity between links, rather than between nodes, which is termed site percolation, although many results can be applied equally to both (Dorogvtsev et al. 2008), (Grimmett 1999, viii).

2.4.3 Models

Given the complexity created by the interactions of multiple stakeholders with multiple purposes, as discussed immediately above as well as in Sections 2.1 and 2.2, a framework is needed for analyzing and managing stakeholder networks in the complex domain, as well as the other "unordered" chaotic and disordered domains adjacent to it. Such a framework is provided by a network resilience approach, sometimes referred to as network reliability or survivability (Grotschel et al. 1995), (Ball et al. 1995). First

developed in the operations research literature in the 1970's and 1980's, to describe the reliability of interlinked hardware and infrastructure systems, although limited by computational constraints due to the combinatorial explosion problem (Ball 1979), (Ball 1986) to medium-sized, homogenous systems, advances in this literature were made with the introduction of concepts from physics and complexity science, particularly that of percolation, and have been extended to domains as varied as epidemiology and sociology, specifically to model large, complex systems (Dorogovtsev et al. 2008). This new approach, largely developed by trained physicists but rooted in operations research and classical graph theory, is usually referred to as network science, and often emphasizes connectivity metrics (ibid), (Alderson 2008).

Percolation theory, as will be discussed below, is particularly useful as a means of measuring global connectivity across a network. The author's literature review showed that such an approach has not, however, been applied rigorously to stakeholder analysis and management, as resilience is typically not included among social network metrics used in management (Borgatti and Li 2009). Nor have the mathematics of percolation theory, providing the framework used here, been applied to technical management and systems engineering generally, except for isolated studies focused on network reliability, (e.g. Li et al. 2015).

2.4.3.1 Density

To the extent that percolation has been used, it has been largely conceptually, in qualitative approaches, with a view to describing diffusion and cohesion by analogy with physical processes as in Wybo 2013, although a computational approach to percolation

for knowledge management is taken in Khvatova 2016, and percolation has been applied to social networks more generally in Chen et al. 2007. However, as pointed out in Basole et al. 2018, there is a close connection between network density and network reliability, which in turn is related to resilience (Li et al. 2015), and the empirical analysis undertaken in this dissertation confirms many of the findings of existing engineering management scholarship on network density.

Density has taken pride of place in the existing technical management literature on networks as a figure of merit for networks. However, this study will argue that it has serious defects as a single measure of network quality. As discussed above in 2.3.3, density describes only the form of the network, at the most abstract level, treating nodes and links as interchangeable, and does not relate to any functions or capabilities of the network. Nor does it facilitate any understanding of purpose in the network, how it evolved to take on the architecture it has. Given that stakeholder networks are both social networks and engineered networks, these deficiencies are theoretically serious, and in fact will be shown to be empirically significant.

Sharing the view that "in the complex or chaotic spaces, effective decision support needs to focus on facilitating collaboration" (French 2013), and that collaboration webs are strategic differentiators, as discussed above, scholars in systems engineering (Garber et al. 2017), strategic management (Rowley 1997), supply chain management (Basole et al. 2018), (Bellamy and Basole 2012), (Borgatti and Li 2009), and product development (Collins et al. 2010), (Collins et al. 2009), have emphasized the importance of inter-stakeholder density.

Stakeholder network density is the number of actual relationships, or edges, currently existing, *n*, between *m* stakeholders, or nodes, divided by the number of potential edges. For a network of *m* vertices, from which pairs of nodes can be combined in $\binom{m}{2}$ ways, this means that, per (Basole et al. 2018),

$$network\ density = \frac{2n}{m(m-1)} \tag{2.1}$$

Density has been identified as a performance driver of stakeholder networks because it measures a system's interconnectedness, capturing the "relational dimension of social capital", describing both the potential for information flow and the strength of shared norms and values between stakeholders (ibid). It may serve as a proxy for qualities of a system, such as concurrency (Collins et al. 2009), (Collins et al. 2010), or cohesion and lack of brittleness (Garber et al. 2017), (Borgatti and Li 2009). Importantly, it is recognized that density "is not always desirable or beneficial, especially given the added coordination burden placed on network entities as well as a great deal of unnecessary and costly redundancy that may arise" (Bellamy and Basole 2012).

Network density is thus found to have a positive effect on return to invested assets and other measures of profit margin in supply chains (Basole et al. 2018), coordination in the integration phase of product development (Collins et al. 2010), Collins et al. 2009), and innovativeness as measured by patents produced (Bellamy et al. 2014).

2.4.3.2 Beyond Density

However, these same studies found density to be less characteristic of more mature systems, being negatively correlated with long-term innovation, and lower in later

design engineering stages. It thus seems that the effects of density can be unclear, even contradictory. On one hand, greater interconnectedness yields greater control to stakeholders of a central entity, who are more likely to present a unified front, (Basole et al. 2018), while on the other the possession of a thick stakeholder network may constitute a valuable resource that allows the central entity to extract higher rents from its stakeholders (Lavie 2006). Higher density is associated with lower "brokerage", meaning that there are fewer intermediaries who extract rents from the central entity, to serve as a bridge to others, although these same brokers are helpful when there is a need for new information, as in later, more mature validation phases (Basole et al. 2018), (Wood et al. 2012), (Collins et al. 2009). A dense web of stakeholder relations may speed innovation (Bellamy et al. 2014), but also subjects the system to more complexity and, thus, uncertainty (de Weck 2006, 95). Interactive communication allows complex systems to be steered back towards order, from the brink of chaos (Snowden and Boone 2007) but risks collaborative and information overload (Neches and Madni 2012).

Further decomposition of density, into measures such as the intensity and thickness of local connectedness; efficiency and elegance in system-wide communication; and global connectivity and resilience to failure is therefore needed, building on the existing studies referenced above, which suggest but do not explore the differing effects of density in different contexts. The contribution of this dissertation's methodology is to identify alternative sources of leverage in stakeholder networks, through the application of recent scholarship in percolation theory, a field which has been increasingly applied in the last 20 years to cooperative socio-technical systems (Dorogovtsev et al. 2008).

2.4.4 Percolation Models

The methodological details of percolation theory applied to stakeholder networks will be left to Chapter 3. The percolation literature began in the 1950's, explicitly in the context of Monte Carlo modelling of "random mechanisms" in the spread of a fluid through a medium, where the interpretation of fluid spreading in a medium was intended to be extremely general, ranging from "electrons migrating over an atomic lattice" to "disease infecting a community" (Broadbent and Hammersley 1957), (Hammersley and Morton 1954). The foundational paper by Broadbent and Hammersley posited the need to study not only stochastic diffusion processes, such as Wiener Processes and Markov Chains, but also cases where the medium itself manifests randomness, coining the term percolation to describe the behavior of a random, or disordered, medium, as opposed to a disordered process. In fact, many treatments of percolation explicitly characterize it as essential to understanding the macroscopic behavior of disordered media and as one half, along with the random walk, of the study of disordered systems (Dorogovtsev et al. 2008), (Grimmet 1999), (Grimmett 2018), (Sahimi 1994).

Research at the intersection of complex systems and stakeholder has occasionally applied models based on stochastic processes, for instance employing real options analysis to model the benefits of design engineering methodologies facilitating enhanced stakeholder interactions (Rapp et al. 2018), (Neches and Madni 2012). Freeman himself suggests that financial options analysis "could be supportive of the notion that serving the interests of a broad group of stakeholders can lead to a higher value because frequently an investment in a particular stakeholder provides future opportunities" (Freeman et al. 2010, 133). Further, the relevance of unordered domains to complex stakeholder systems

was discussed above at length, as was the fact that stakeholder interactions take place in dynamic, competitive, unstable contexts, through unreliable and noisy channels. Thus, there is a plausible basis for describing webs of stakeholder interaction as instances where "the stochastic mechanism resides in the medium rather than in the particle" (Broadbent and Hammersley 1957), for which percolation is the relevant framework.

The extensive, elegant mathematical literature on percolation could thus have more general application to stakeholder analysis and will likely yield further insights beyond those derived here. The present focus however is firmly on the narrow field of percolation processes in complex networks of finite size as applied to resilience, a term which does not appear in the indices of general mathematical treatments of percolation, such as Stauffer and Aharony 2014 or Grimmett 1999. By contrast, in complex networks scholarship, resilience and percolation processes are intimately linked, as in standard textbooks such as Newman 2017 (ch.16), and Barabasi 2016 (ch.8), and the widely cited article Newman 2003. A recent textbook on mathematical methods in resilience engineering also connects percolation theory with resilience (Attoh-Okine, 2016). While the precise relation between resilience and percolation processes will be investigated at length in the literature review, it is therefore important to clarify here the relevant framework.

Within that framework, attention will be focused on a single measure, the bond percolation threshold, which as discussed in Chapter 3 is both a heuristic measure of qualities such as "rebound" and "connectedness", and a precise measure of the point at which a social network is maximally splintered between, as discussed in Section 1.1.1, "noncooperative centers of gravity" and "islands of disconnected effort" (Boyd and

Hammond 2018, 227). Two global network statistics, degree correlation (or degree assortativity) and clustering (or transitivity), will emerge as vital differentiators of network structure and performance, and thus effective levers in managing stakeholder systems. While this framework will be shown to be on firm theoretical grounding, it has found only limited real-world application in mathematical epidemiology, and has not, based on the author's literature review, previously been applied to problems in stakeholder analysis or engineering management, nor to management science generally.

Importantly, this framework is distinct from network reliability approaches, which typically emphasize all terminal reliability and as discussed in Chapter 1 suffer acutely from the combinatorial explosion problem (Ball 1979), (Ball 1986), (Ball et al. 1995). Further, it is different from operations research approaches to network survivability, narrowly defined, similarly rooted in optimization-based models, which define survivability in terms of the number of paths existing between all terminals, or a set number of terminals (Sharkey et al. 2020), (Grotschel et al. 1995). As will be discussed below, in the methodology, what matters is not whether nodes in a stakeholder network are active, but whether they are interacting. Further, what is most important is not the quantity of those interactions, but the qualities they lend to the network, specifically its ability to bounce back from disruption and its adaptive capacity, in addition to its robustness (as typically emphasized in OR optimization-based models), in sum: its resilience, as defined in Sharkey 2020.

This framework will be built on both analytic foundations and statistical findings utilizing simulation. Broadbent and Hammersley identified percolation as conceptually well-suited for being modeled with Monte Carlo methods, due to the relative simplicity

of simulating a “random maze” by randomly blocking some of the channels in which fluid, broadly defined, might flow through a medium, called an “abstract crystal”. Because “the capacity of computers is, however, insufficient for any but very small lattices”, they proposed an analytic approach, suggesting this was an area where “pen and paper might be better than machine work” (Hammersley and Morton 1954). The result of this approach, oriented to the computational constraints of the 1950’s, was a large mathematical corpus establishing analytical closed-form results on, essentially, the component structure of random subgraphs of lattice-like infinite graphs (Grimmett 1999). Network percolation is, in a sense, a generalization of percolation on lattices, since in a network all existing nodes are potential neighbors. There is no requirement that they be spatially proximate as in many lattice structures, for instance, in two dimensional square lattices where each cell would have only eight potential neighbors, although “geographic” proximity can also be taken into account in networks (Newman 2003 “Structure and Function of Complex Networks”).

As the original terminology of crystals and mazes suggests, percolation research has often been quite removed from real-world applications. However, as the methodology will make clear, applied work has been made much easier by the enormous improvement in computing power from the days of the field’s founding, facilitating the use of precisely the same simple Monte Carlo simulation methods which the mathematics of percolation on lattices was invented to replace. Given that there are as yet “few analytic results for real-world networks” (Karrer et al. 2019), simulated random graphs, where a network is randomly generated as a function of a given average degree or degree distribution are a vital means of developing intuition and testing hypotheses (Newman and Ziff 2001).

Although Poisson, or Bernoulli, random graphs lack some of the key characteristics of real-world networks, namely the significant levels of degree correlation, or anti-correlation, found in social and technological networks, respectively (Newman and Park 2003, they are useful as toy models and widely used in the published literature, as "much of our basic intuition about the way networks behave comes from the study of the random graph" (ibid.). Even more helpful are simulations run on real-world graphs. Both approaches will be used in the methodology.

The percolation literature is far too extensive to summarize here succinctly. The early analytical findings of Erdős and Rényi are most well-known, which showed how, for random graphs, "as the number of links in a network gradually increases, a global cluster of connected nodes will suddenly emerge", with small improvements in connectivity leading to large network-level effects (Houston-Edwards 2021). This critical phase change occurs at the percolation threshold, as will be discussed extensively in Chapter 3. Much of the work in the field has focused on finding such thresholds for a "mind-boggling" array of different systems (ibid), well beyond the random graph geometry first studied by Erdős and Rényi. The real "challenge in percolation", however, "lies in describing its emergent structures rather than understanding its defining rules" (Christensen and Moloney 2005, 1), meaning that at least as important as the question of "when" a connected component emerges is "what" happens when it does, shifting the focus from form to function, which will also be covered at length in Chapter 3.

The great advantage in studying percolation is that it is "arguably the simplest model that undergoes a phase transition", useful for describing phenomena ranging from earthquakes and oil recovery (ibid), to mesh cellular networks and the transmission of

Covid-19 (Houston-Edwards 2021). Percolation can even be extended to explain such disparate processes as gelation, for instance in the making of scrambled eggs, or even galaxy formation. Unlike in these latter two processes, however, percolation is also useful for understand how processes can be reversed. While eggs cannot be unscrambled, or galaxies unformed, network functionality can fail and rebound. This ability to model rebound, another important topic covered in the next chapter, is a significant differentiator between percolation and other models similarly treating phase transitions, such as rice pile and avalanche models of self-organized criticality (Christensen and Moloney 2005, ch.3). Nor are those other models readily applicable to networks (although Ising models may be both reversible and applicable to networks, and is a mathematical approach identified as a potential future research direction in Chapter 5).

These considerations are especially relevant because much of the strategic challenge facing organizations operating in complex domains is to understand how small changes in structure or function lead to large improvements, or failures, in system-level performance. The critical phenomena represented by "winner-take-all" dynamics, "platform economics", and "network effects" are essentially tipping points in "the uncertain, everchanging, unpredictable world of winning and losing" (Boyd and Hammond, 364). The unique power of percolation theory is that it offers a relatively self-contained, simple mathematical corpus for modelling and even managing such strategically important phenomena, as will be shown in Chapters 3-5.

Chapter 3. Research Methodology and Framework

3.1 Constructing Stakeholder Networks

In this section, a novel framework is developed for measuring, managing, and even improving a firm's stakeholder network, by examining its resilience, and identifying levers to improve that resilience, within the framework of percolation theory.

As discussed above, an organization's stakeholder nodes are often external economic partners, such as suppliers, customers, shareowners, other financiers and even peers, these being the most easily identified stakeholders, and usually the most important (Parmar et al. 2010). Other external entities, such as regulators, communities and environmental interests may also be relevant (Freeman et al. 2018) but are much harder to capture using business intelligence databases, as used here. Within product development, project management and the like, internal stakeholders such as users or design engineers are typically of greater importance, although data on these insiders is even harder to obtain (Wood et al. 2012). The edges are just the relations between stakeholder nodes, channels of communication, collaboration, or economic exchange, typically understood to be bi-directional, and thus undirected (Parraguez et al. 2015), as opposed to directed edges, which run in one direction only.

These channels run between the central entity and its stakeholders, yielding a core stakeholder map, with dyadic relations of the familiar hub-and-spoke type. But they also exist between the external stakeholders, who are in turn the focal point of their own stakeholder system, and so interlinked networks of relations may be established, by

finding the stakeholder map of dyadic relations for each entity in the primary firm's stakeholder system. Because second-degree stakeholders do not directly impact the central entity's survival, only links between nodes themselves linked to the central entity are typically preserved. The result is a social network, which is what stakeholder systems are since they model the "interaction of interactions" of actors in a social context (Rowley 1997), in addition to being, as discussed above, an evolving complex engineered system. The process of building such networks, elaborated below, may be introduced by exampling the case of the internet retail giant Amazon, Figure 3-1, which has the advantage, visually, of having a relatively sparse stakeholder network, using data and parameters to be discussed.

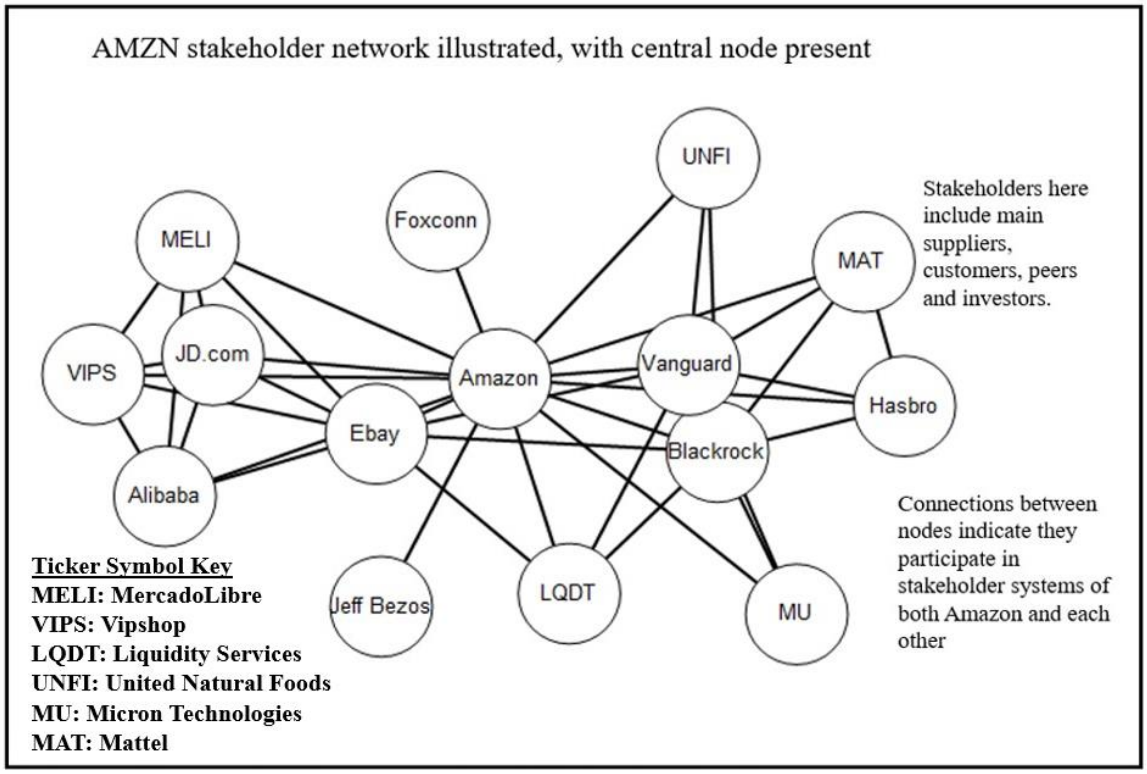

Figure 3-1: Amazon Stakeholder Network, Central Node Present

3.2 Percolation Processes on Stakeholder Networks

As percolation theory has not been applied to stakeholder networks previously, nor even to organizational science generally, it is necessary to show in detail how a percolation process on a stakeholder network can be used to predict the functionality of the stakeholder system. Percolation methodology focuses primarily on estimating, for various lattice topologies, or network configurations, the percolation threshold, the critical probability p_c. When the likelihood of a random channel being open, p, also called the occupation probability, which is also the probability of an edge being present in a network, is above p_c, there is a tipping point into connectivity. In the case of an idealized lattice, that means the formation of an infinite spanning cluster. A single, large random maze exists with a probability of 1, and a channel must be open from one boundary of the medium to the other, in size on the scale of the abstract crystal as a whole. Equally, for occupation probabilities below p_c, an infinite spanning cluster exists with probability = 0, and only small, disparate channels form, unconnected to each other, negligible in size compared to the whole. For instance, when considering fluid attempting to flow through a three-dimensional object, as in a stone immersed in water, where p is the probability that the inner passageways of the stone are wide enough to allow flow, it is useful to think of a percolating process as a volume effect, as liquid infiltrates the interior of the stone, and a non-percolating process as a surface effect (Grimmet 1999, ch.1).

In the context of a porous medium, the percolation effect can be visualized as follows, using a toy model built in Mathematica on a 9 x11 grid, using an approach suggested by the complexity scientist Steven Wolfram (Wolfram 2011). Fluid in a porous medium, such as water flowing through coffee grounds (the coffee percolation process

being the origin of the term), seeks to “percolate”, or find a channel from one boundary of the medium to another, represented here in red with one boundary being the “top” and the other the “bottom”, though the orientation does not matter, such as in the filtration of liquid through soil or bedrock. The starting point is shown in Figure 3-2.

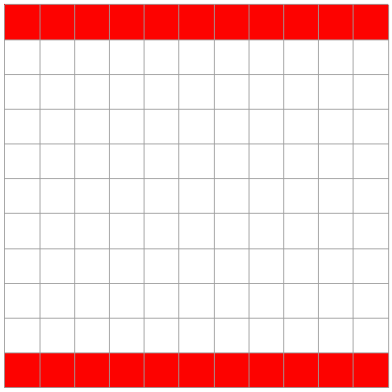

Figure 3-2: Percolation on Square Grid, Stage 1

At occupation probability p=.1, isolated clusters appear in blue, showing the presence of unconnected pores in Figure 3-3. While some cells happen to be adjacent to each other, it is clear that the flow of liquid in this medium is extremely curtailed.

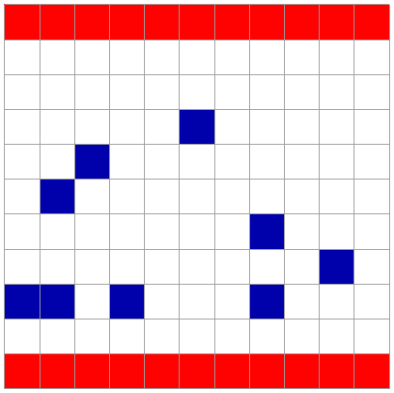

Figure 3-3: Percolation on Square Grid, Stage 2

At p=.2, some clusters are larger, some connect to one of the sides of the porous medium, but none span. No large clusters occur, and the largest are of only 3 cells in size,

or ~3% of the total, in Figure 3-4. 3 out of 17 cells are “wet”, meaning that they are in communication with a boundary of the lattice.

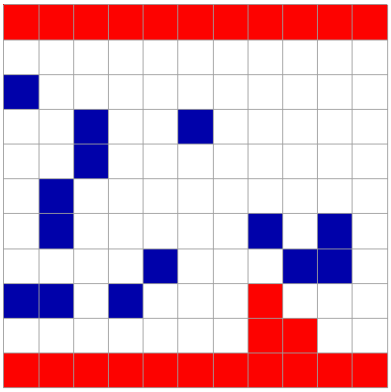

Figure 3-4: Percolation on Square Grid, Stage 3

At occupation probability p=.3, multiple large, connected clusters emerge, but do not span from one end to the other. The size of the largest cluster has gone from 3% of the total to ~16%, yet the proportion of cells that are “wet”, in communication with a boundary, has actually declined, as it is 3 out of 27. It is clear in Figure 3-5 that the tipping point towards connectivity is imminent.

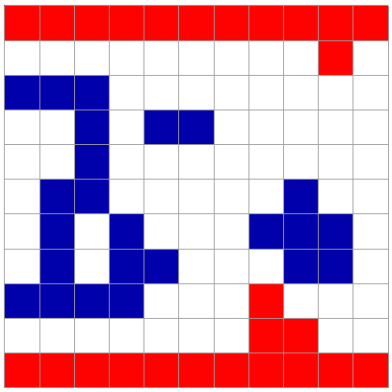

Figure 3-5: Percolation on Square Grid, Stage 4

In Figure 3-6, at occupation probability p =.4, the percolation threshold is manifestly passed, and phase transition occurs. Every occupied point on the lattice is connected, meaning that fluid is flowing through the medium. Even though the

percentage of occupied cells has only increased by about a quarter, going from ~30% in stage 4 to ~40% in stage 5, the percentage of the occupied clusters that are “wet” has skyrocketed from ~11% to 100%, almost a tenfold increase, showing the change in scale.

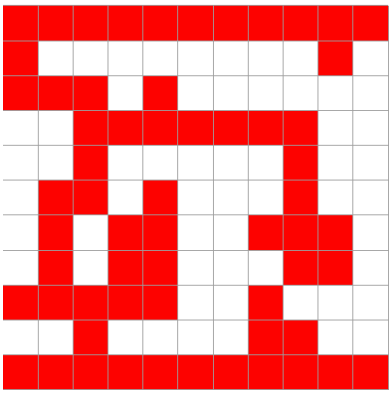

Figure 3-6: Percolation on Square Grid, Stage 5

As real-world finite networks have no boundaries, the best way to gain an intuitive understanding of the network percolation threshold is to look at the emergence of the largest connected component, the largest set of mutually reachable nodes, informally corresponding to the spanning cluster of classic percolation theory on a lattice. As the likelihood of nodes being connected increases, the network experiences a critical transition from being generally disconnected to being generally connected.

Consider a network of m=10 stakeholder nodes, represented by red dots in Figure 3-7. This is a small number, given the complexity of most real-world stakeholder systems, which in the methodology used can extend almost to 1000 nodes, and the need to treat them on an individual stakeholder basis. However, it is not completely unrealistic, as the internet retailer Amazon, exampled above in Figure 3-1, has only 14 stakeholders, as measured in the empirical methodology to be discussed below. Ten of these are either

competitors or suppliers. Five are peers in China (Alibaba, JD.com, Vipshop), the U.S. (eBay), and Latin America (Mercadolibre). Five are suppliers: Foxconn, an electronics manufacturer, the toy companies Hasbro and Mattel, the computer memory manufacturer Micron Technologies, a major supplier to Amazon Web Services, and the food wholesaler United Natural Foods, a major supplier to Amazon's Whole Foods division. Removing the four remaining nodes, for the sake of this example, would leave only 10 stakeholder nodes, excluding a single customer stakeholder, the reverse supply chain firm Liquidity Services, and the few major shareholders of the firm, the institutional investors Blackrock and Vanguard, and founder and longtime CEO Jeff Bezos.

The extremely small number of Amazon stakeholders, while striking, is intuitively justifiable: as the largest online retailer, its customer base is extremely large and diffuse and its supply chain is extremely diversified, to limit risk and maintain leverage, with supplier power and urgency thus being diffused also. Unlike older legacy firms, the founder continues to have massive, concentrated holdings in the common equity of the firm, meaning that few other financiers exercise significant influence. Having realized "network effects" unparalleled in the history of retailing, it has few true competitors. Finally, for reasons to be discussed below, it is necessary to delete the central node, Amazon itself, from its own stakeholder network. This leaves a simple model of ten stakeholder nodes, while still being a semi-realistic stakeholder system.

As discussed in 1.2.2, such a grouping would have up to 10*(10-1)/2 = 45 edges yet, as shown in equation (1.2), over 35 trillion possible network configurations. Thus a binomial graph methodology, essentially drawing randomly from those 35 trillion combinations, here using Mathematica software, can be useful to develop intuition,

studying random Erdős-Rényi graphs of the form *G(m,n)*, Here, in Figure 3-7, a random graph G(10,3) is generated with 3 edges and 3 unconnected clusters. Imagining that peers are the five nodes P1-P5 on the left-hand side, and suppliers the five nodes S1-S5 on the right-hand side, this could correspond, for instance, to two peers of Amazon having supply chain connections to two different suppliers of Amazon, and a further two suppliers having an alliance between themselves.

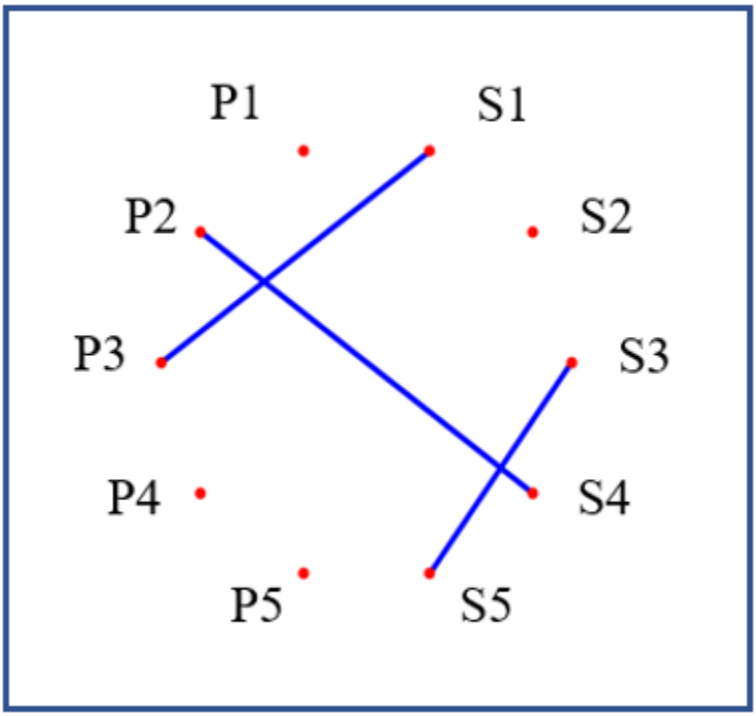

Figure 3-7: Connectivity Phase Change on a Network, Stage 1

Adding an additional edge randomly, corresponding to a new tie-up between suppliers S1 and S2, there are now 4 edges and still 3 unconnected clusters, with the largest having only 3 nodes, in Figure 3-8.

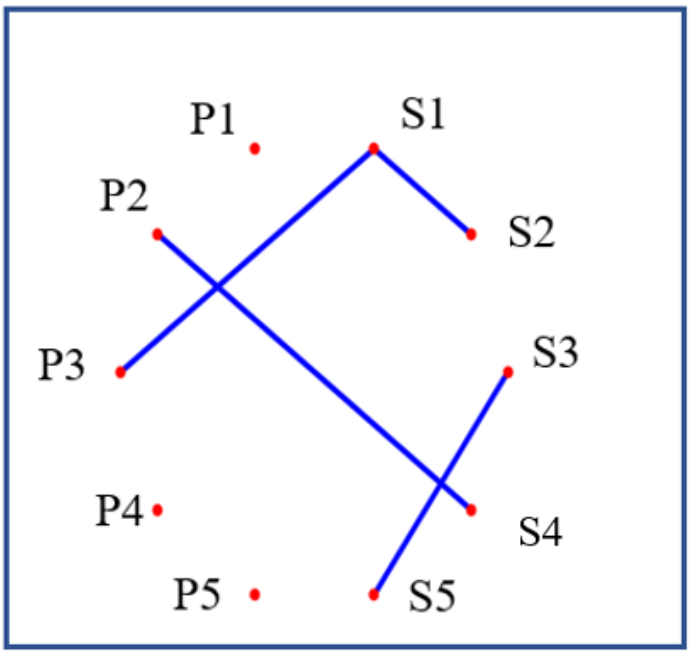

Figure 3-8: Connectivity Phase Change on a Network, Stage 2

With another edge added purely randomly, which could be interpreted in this simple model as a new supply chain relation between S2 and P1, there are now 5 edges, but still only 3 clusters, in Figure 3-9 below. The largest cluster now connects 4 nodes, {P1,P3,S1,S2}, double the size of the other two clusters. Note that this is only instantiation out of all possible combinations, and different finite random networks will behave differently.

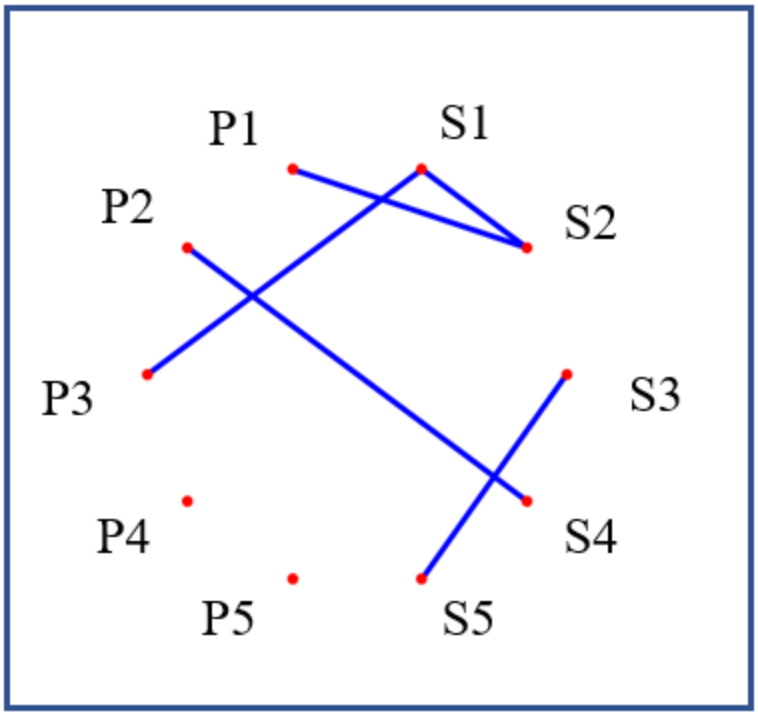

Figure 3-9: Connectivity Phase Change on a Network, Stage 3

With a single edge added randomly, corresponding to a new alliance between suppliers S4 and S5, there are 6 edges, in Figure 3-10 below. Two connected clusters emerge, of 4 nodes each: {S1, S2, P1,P3} and {S3,S4,S5,P3}. At this point, the network is broken into halves, neither communicating. This is the situation described in the introduction: there are two “noncooperative centers of gravity”, or “islands of disconnected effort”, in this model stakeholder network, as discussed in (Boyd and Hammond, 227). As introduced in Section 1.1.1, this compartmentation as lethal to strategic success, as it forces organizational participants “to look inward” and the “system comes unglued” (ibid, 238). Intuitively, there are two discrete stakeholder factions in this system, each likely jockeying for influence and power, and thus diverting the central

entity away from pursuing purposes and goals conducive to the survival of the stakeholder system as a whole.

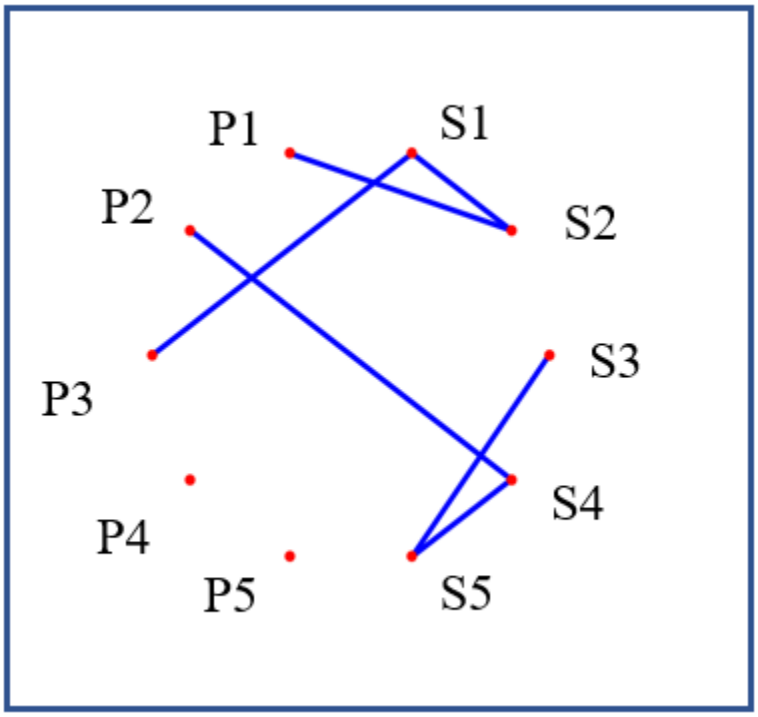

Figure 3-10: Connectivity Phase Change on a Network, Stage 4

With the addition of a single new edge, here corresponding to an alliance between suppliers S4 and S5, the situation described above changes dramatically. With only 7 edges present, out of 45 possible, the size of the largest connected cluster doubles, from four to eight. An increase in network density from ~13.3% (6/45) to ~15.6% (7/45) results in a 100% increase in the size of the large component, and the network 'tips' into connectivity. Note that while the percolation process has spread through all nodes and edges in the graph, this is not the same as all terminal connectivity, as three nodes remain disconnected. However, they are isolated, and their stakeholder interactions will exercise no influence on the central entity. Where in the previous stage in Figure 3-10 there was

maximal factionalism, now there is harmony of effort in Figure 3-11. Given the dependence of strategic success on such harmony, this stakeholder percolation process represents a critical phenomenon that has been missing from the technical management literature, yet corresponds with our intuition and experience that, on occasion, small changes in organization can initiate big differences in outcome.

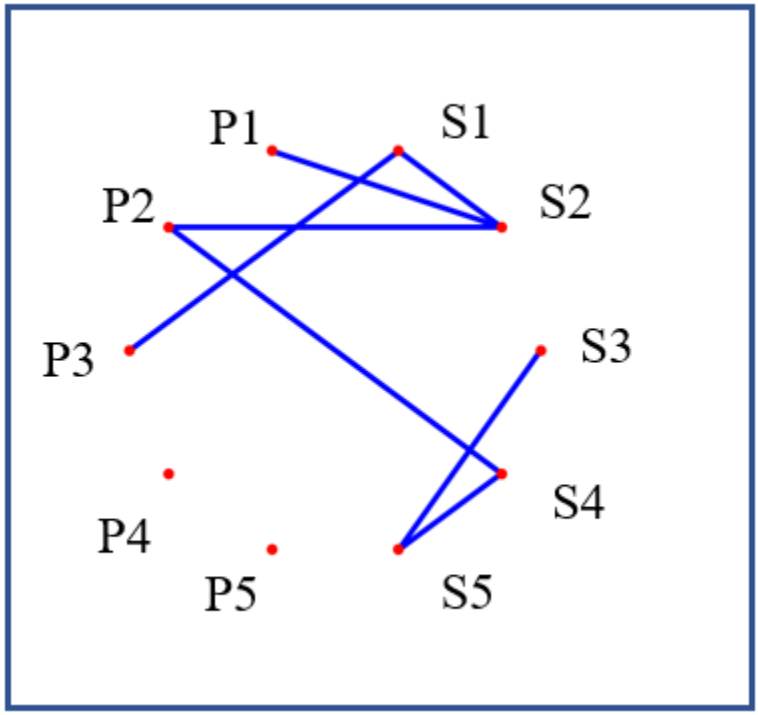

Figure 3-11: Connectivity Phase Change on a Network, Stage 5

The above visualizes only a single network. By simulating ensembles of random graphs, as discussed above, and studying how the occupation probability relates to critical behavior, one can further develop an instinctive appreciation of the tipping point into connectivity.

The below shows three arrays of 100-node Erdős-Rényi Poisson random graphs shown, simulated as above using an approach suggested by Wolfram, with .8, 1., and 1.2

edges per node, respectively. In the first, in Figure 3-12, the graphs are broadly unconnected, with islands of disconnected nodes not in communication with each other, although some are clearly more connected than others. Importantly, even when one large cluster is present, there are no competitor clusters or other independent centers of gravity.

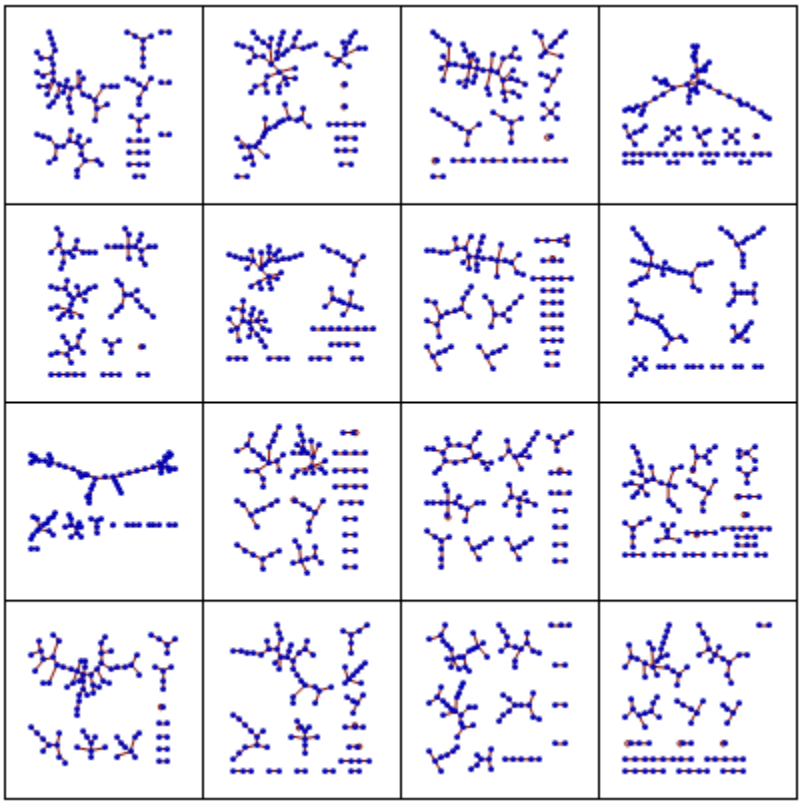

Figure 3-12: Connectivity Phase Changes in Random Networks, .8 Edges Per Node

In the limit of large *m*, Erdős showed that phase change occurs when average degree of nodes = 1, as shown in Figure 3-13. Below that level, graphs are disconnected as in 3-12; above that, as in 3-14, connected. At average degree = 1, results are mixed, as in Figure 3-13. Note that these regularities do not apply exactly to smaller, finite graphs, as encountered in the real world. In Figure 3-13, some of the networks have undergone the critical transition to connectedness, others have not. Just as in Figure 3-10, some

systems are maximally disconnected, with equally sized largest clusters. Those that have tipped into connectivity, however, are broadly speaking, connected in serial fashion, like links in a chain, with single failure points.

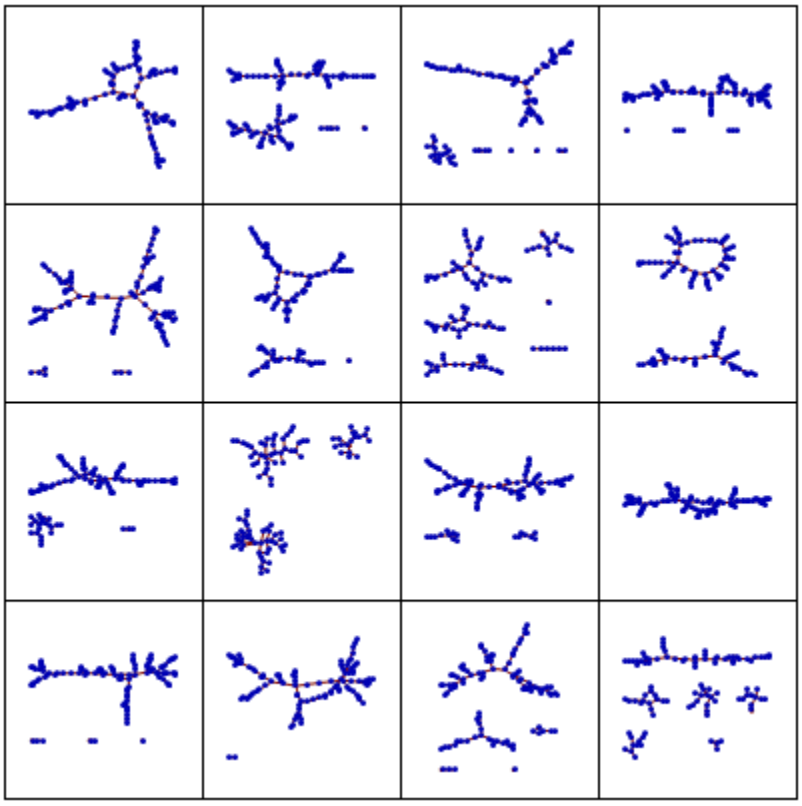

Figure 3-13: Connectivity Phase Changes in Random Networks, One Edge Per Node.

In Figure 3-14, by contrast, the clusters have formed webbed patterns of connection, with no single points of failure. These networks visually manifest the ability to be robust in the face of node or link failures, as well as to adapt by rerouting flow through the network. There is clearly a percolation process in each of the networks, but there continue to be isolated, unconnected nodes, as in 3-13, indicating that this process is not equivalent to all terminal connectivity. This is important, given the "unreliability" of stakeholder networks, discussed above, where relationships are important, but fragile.

Stakeholder interaction methodologies need to accommodate both this lack of reliability and complexity, as traditional OR all-terminal network reliability models do not.

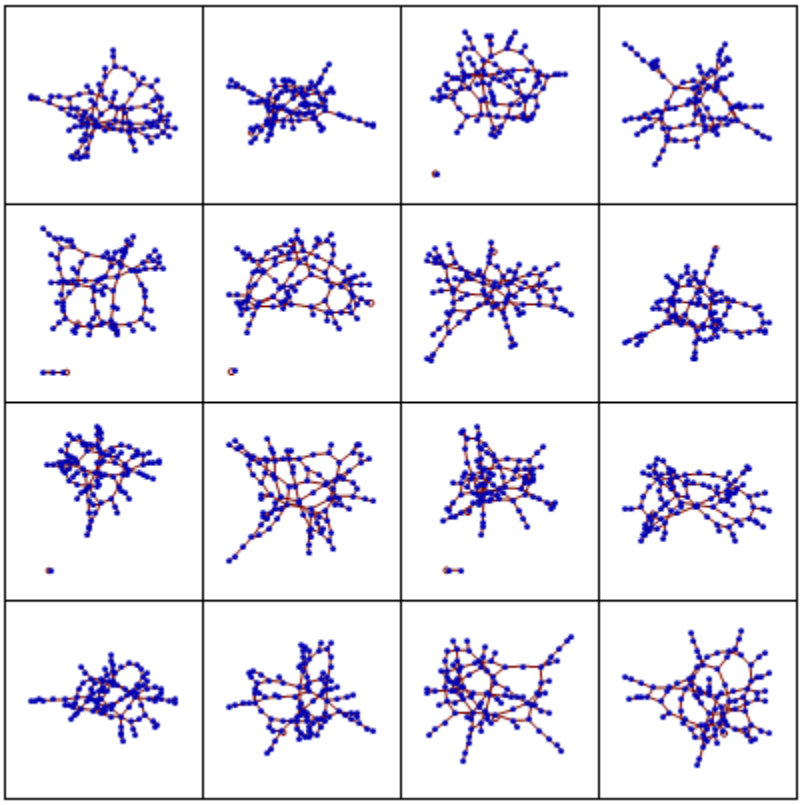

Figure 3-14: Connectivity Phase Changes in Random Networks, 1.2 Edges Per Node.

More formally, the gold standard method to measure and visualize the percolation process, as discussed further below, is to consider the size of the second largest, non-spanning cluster, which will grow before, and shrink after, the system tips into connectivity, as edge reliability increases (Karrer et al. 2014). When the size of the second largest component is at its maximum, the situation corresponds to that in Figure 3-10 above, where the network is maximally divided between independent, unconnected clusters of equal size, representing disjoint partitions of the stakeholder system. The Amazon stakeholder system, with its full complement of all 14 nodes, can again be used

as an example, in Figure 3-15. Here, it is modified using the levers of degree correlation and clustering, to be elaborated up shortly, to create two new networks differing by only two edges, with significantly different percolation thresholds, as indicated by the global maxima of the curves. This example will be returned to at greater length below.

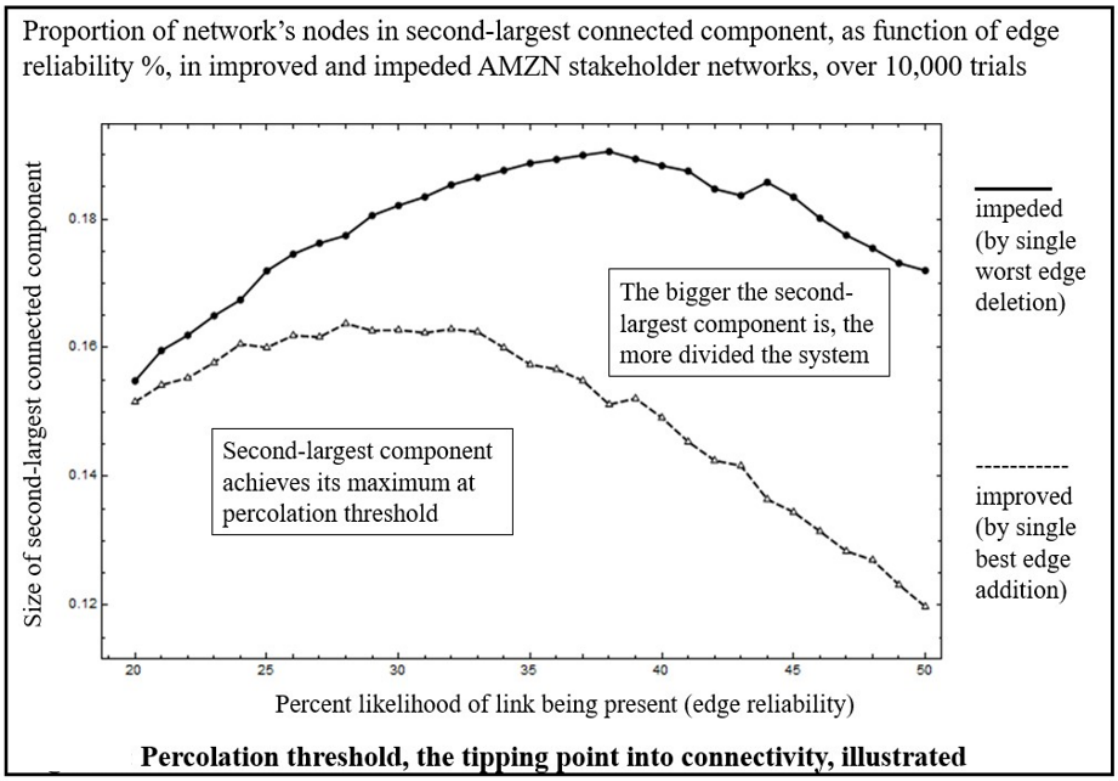

Figure 3-15: Percolation Threshold Illustrated

3.3 Percolation Theory Extensions to Stakeholder Network Methodology I

Two developments in percolation research have further made it a promising methodology for studying complex stakeholder networks. The first is the extension of research beyond p_c, establishing universal scaling laws for properties such as the percolation probability $\theta(p)$, the likelihood that for a given occupation probability p a

given vertex belongs to the spanning cluster; $\chi(p)$, the mean size of the largest spanning cluster, given p; and $\chi^f(p)$, the mean size of the finite cluster below the percolation threshold, given p. Formally, these are (Grimmet 1999, 13-23), (Sahimi 1994,12-15):

a) there exists a p_c s.t.

$$\theta(p) = \begin{cases} 0, p < pc, \\ > 0, p > pc \end{cases} \tag{3.1}$$

$$\text{b) } \chi(p) = \mathrm{E}p|\mathrm{C}|\,, where\ |C|\ is\ infinite \tag{3.2}$$

$$c)\ \chi^f(p) = E_p|C|, where\ |C| < \infty \tag{3.3}$$

Research has shown that under most circumstances, $\theta(p)$, $\chi(p)$ and $\chi^f(p)$ are all continuous, positive functions of $(p - p_c)$, the difference between the current occupation probability and the percolation threshold, regardless of the microstructure of the system, for $p > p_c$ (Christensen and Maloney, ch.2). This suggests that a lower percolation threshold represents greater network resilience in at least two of the qualities enumerated by Sharkey et al. 2020 in a review article on the subject for the 50th anniversary of the IEEE Networks journal: robustness and rebound. However, as shown below, it also relates to notions such as graceful degradation and adaptive capacity.

First, since the size |C| of the graph's largest connected cluster is a negative function of the percolation threshold p_c., scaling laws suggest that the tipping point p_c is a key metric for robustness, as a graph with a lower percolation threshold has a relatively larger connected component (Chen et al. 2007). This implies that edge or node deletions, such as a stakeholder not cooperating with the rest of the network, or ceasing relations with a specific counterparty, have less effect on the size of the large component of

cooperating stakeholders. Further, a larger connected component translates into comparatively greater capacity to adapt, in the sense of rerouting flow in the network, as shown in Figure 3-14 below. In the case of a more connected stakeholder system, there are more ways for the central entity to reach "hidden" stakeholders, or stakeholder only accessible through intermediaries (Wood et al. 2012).

Second, a lower percolation threshold translates to resilience in the sense of rebound, since it means that a single large, connected cluster emerges sooner, as the occupation probability of stakeholder interactions increases after some external shock severely curtails such relations, for instance in the wake of supply chain disruptions following a natural disaster or pandemic, or upheavals in the financial system. Further, a stakeholder network with a lower percolation threshold also exhibits graceful degradation, as each individual disruption in stakeholder relations is less likely to break apart the network.

Thus, when inter-stakeholder relations are relatively reliable and the network is connected, a lower percolation threshold p_c means a higher likelihood of a given stakeholder being connected to the largest spanning cluster. This has the positive effects of ensuring that stakeholder needs and requirements are more complete (Cameron et al. 2011); that less visible, minority viewpoints are not ignored (Mitchell et al. 1997), (Wood et al. 2012); that potential conflicts are acknowledged and dissatisfied stakeholders engaged (Garver et al. 2017), (de Gooyert 2017); and that disparate, diverse stakeholders maintain communication channels, even if indirect, avoiding groupthink, spurring innovation and creative problem-solving and scenario-planning (Bellamy et al. 2014), (Collins et al. 2009), (Neches and Madni 2012). If connections are less reliable, as in a chaotic, post-crisis

context, a lower p_c ensures that the spanning cluster contains relatively more stakeholders, and that connectivity in the stakeholder network will be lost later and restored earlier, allowing it to be steered back from disorder (Snowden and Boone 2007). Finally, when stakeholder connections are sparse, with segregated cliques and restricted communications, a lower percolation threshold p_c ensures that the stakeholder system is relatively more likely to maintain shared norms and a measure of control over the central entity (Rowley 1997), evidencing enhanced network resilience. A lower percolation threshold, measuring network connectivity and resilience, should thus correlate with better stakeholder outcomes. These effects can be illustrated, in part, by returning to the Amazon stakeholder system, in improved and impeded variants, Figure 3-16, to show how small changes, in this case a mere two edges, elaborated below, yield significant differences in the percolation threshold and thus proportion of stakeholders participating in the largest cluster, just as the universal scaling laws discussed above predict:

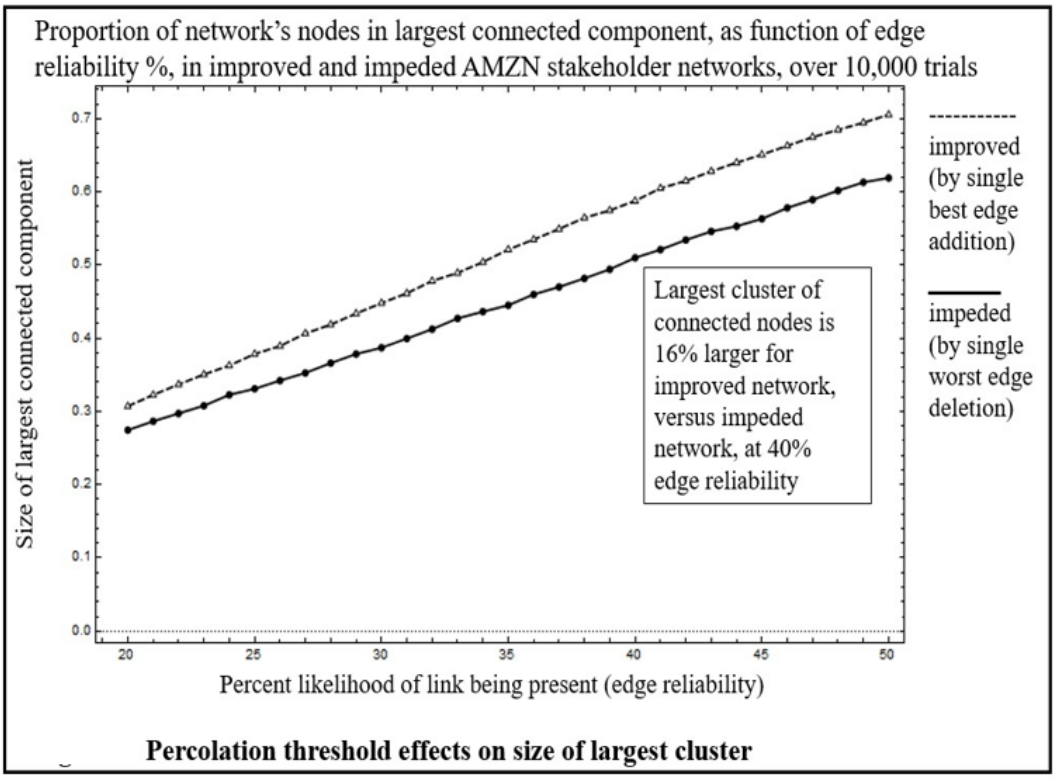

Figure 3-16: Percolation Threshold Effect on Largest Connected Component Size

3.4 Percolation Theory Extensions to Stakeholder Network Methodology II

3.4.1 Clustering

Second, it is now known that the distinguishing properties of real-world social networks are clustering and degree correlation (Chen et al. 2007), (Newman 2003), (Newman 2002), (Newman and Park 2003), (Estrada 2011). Clustering measures the tendency of vertex pairs to be linked if they share a common neighbor, where the friend of one's friend is also one's friend, in a transitive fashion, completing a triangle, providing a measure of cliquishness, or local density, in a social network (Barabas and Posfai 2016, ch.3). It is a more exact measure than density of both brokerage and the intensity of local connection, since it captures only the density of nodes already sharing a

common connection, although in practice they are highly correlated, and transitivity often plays a role similar to that of density, as in (Parraguez et al. 2015). The most commonly used definition of clustering is defined in Newman 2003 as

$$\mathrm{C} = \frac{3\ (\text{number of triangles on graph})}{\text{number of connected triples of vertices}} \tag{3.3}$$

where a connected triple can be thought of as a potential triangle, a path of length two, the sum of which, for a vertex v with k_v neighbors, is $k_v(k_v-1)/2$. The total number of triangles in the graph is then multiplied by three, since each actual triangle completes each potential triangle three times (Newman 2003). This term is equivalent to three times the number of closed cycles of length three in the graph, divided by the number of paths of length two (Estrada 2011), written as $\frac{3|C_3|}{|P_2|}$, which is relevant to the other distinguishing characteristic of real-world social networks: degree correlation, or assortativity.

3.4.2 Degree Correlation

The fact that regular lattices evidence a high degree of clustering (Watts and Strogatz 1998) suggests the results of classical percolation theory are not necessarily undermined by high degrees of clustering. This is not the case for degree correlation where, importantly, many of the results published in the percolation literature do not apply to networks showing dependence in the distribution of edges between nodes of given degrees (Cohen and Havlin 2010, ch.10), (Barabasi and Posfai 2016, ch.7). In the case where there is positive or negative assortative mixing between nodes of similar degree, as when high-degree nodes seek out, or are repelled by, other high-degree nodes, the dependence in "degreeness" (number of connections) between nodes needs to be

taken into account to model the percolation threshold. Because vertex degree is itself a property of overall graph topology, degree correlation has an important influence on network structure (Newman 2003 “Mixing patterns in networks”). In particular, it is well-established analytically, using a broad array of approaches, that greater assortativity leads to a lower percolation threshold, making the network more robust and connected (ibid), (Newman 2002), (Newman and Park 2003), (Newman and Girvan 2003), (Estrada 2011), (Cohen and Havlin 2010), (Boguna and Pastor-Satorras 2002), (Vasquez and Moreno 2003), (Noh 2007), (Goltsev et al. 2008).

This enhanced robustness is not necessarily associated with higher levels of clustering. While analysis of simulated networks often shows a negative association between transitivity and the percolation threshold (Newman 2003 “Properties of highly clustered networks”), meaning that more clustered networks are on average more resilient and connected, this association can be inconsistent, or entirely absent, when other factors are considered (Dorogovtsev et al. 2008). Moreover, the size of the giant component for $p>p_c$ is sharply curtailed for highly clustered networks, an exception to the general pattern identified above. This is intuitively because many edges in a highly transitive network are wasted, with redundant edges contributing to heightened clustering, but little to holding the giant component together, and so “the percolation properties of the network are similar to those with fewer edges” (Newman 2003 “Properties of highly clustered networks”). In fact, the positive association between clustering and resilience is likely deceptive, as it turns out that transitivity is analytically related to assortativity, as derived using a simple but clever combinatorial approach by Estrada (Estrada and Knight

2017), (Estrada 2016), (Estrada 2011), and thus the contribution of clustering to connectivity is likely due entirely to its contribution to degree correlation.

Because this result is far from obvious, with vital importance for the application of percolation theory to real-world networks, deriving this relation and building on Estrada's approach is useful. Estrada 2011's proof relies on non-intuitive algebraic combinatoric graph structures. The re-derivation that follows not only offers a simpler, more intuitive proof, with the same result. It also sharpens Estrada's proof, making the connection between clustering and degree assortativity even more pronounced. As such, it is a modest methodological contribution to the graph theory literature. Even more importantly, it demonstrates the power of algebraic combinatorics on graphs for understanding systems of collaboration.

Assortative mixing by degree was first studied by Newman 2002, establishing an assortativity coefficient based on the Pearson correlation of the node degrees at either end of a link. The coefficient *r* represents the connected degree-degree correlation function, the distribution of the number of outgoing connections of a node at the end of a randomly chosen link, divided by its maximal value, which is the variance of the distribution q_k of the remaining, excess outgoing connections for each node.

$$r = \frac{1}{\sigma_q^2} \sum_{k_i k_j} k_i k_j \left[e\left(k_i k_j\right) - q(k_i) q\left(k_j\right) \right], \tag{3.4}$$

$$q\left(k_j\right) = \frac{\left(k_j + 1\right) p_{(k_j + 1)}}{\sum_i k_i p_{(k_i)}} \tag{3.5}$$

and *e(i,j)* is the joint probability distribution of node degrees, incorporating the degree dependence. This relation can be rewritten to make it more tractable for an observed

network, summing over the edges $i,j \in E$ present in the network, instead of the vertices, where *m*=|E| (differing from the usual convention, presented above, where the number of edges is represented by *n*, in order to match the presentation of Estrada):

$$r = \frac{\frac{1}{m}\sum_{i,j\in E} k_i k_j - \left(\frac{1}{2m}\sum_{i,j\in E}\left(k_i + k_j\right)^2\right)}{\sum_{i,j\in E}({k_i}^2 + {k_j}^2) - \left(\frac{1}{2m}\sum_{i,j\in E}\left(k_i + k_j\right)^2\right)} \tag{3.6}$$

Importantly, the denominator, being a measure of variance, is guaranteed to be positive (Estrada 2011), unless the network is "regular", with the same number of degrees for each node, and thus the denominator is zero and the assortativity is undefined. Modifying significantly, but equivalently, the presentation in Estrada 2011, this entire equation can be written in terms of simple combinatorial expressions, as a function solely of the number of paths in the network of lengths 1,2 and 3, and the number of cycles of length 3. This can be done using only a few simple facts, first that, by the handshake lemma,

$$2|\mathrm{P}_1| = \sum_i k_i = 2\mathrm{m} \tag{3.7}$$

Second, as mentioned above,

$$2|\mathrm{P}_2| = \sum_i k_i(k_i - 1) = \sum_{i,j\in E} k_i + k_j = \sum_i {k_i}^2 \tag{3.8}$$

Third,

$$|\mathrm{P}_3| = \sum_{i,j\in E}(k_i - 1)(k_j - 1) - 3|C_3| = \sum_{i,j\in E} k_i k_j - \sum_{i,j\in E}\left(k_i + k_j\right) + m - 3|C_3| \quad (3.9)$$

which intuitively follows, if one thinks of paths of length three as consisting of the edge one currently is on, plus two of the edges leading from the vertices of that edge, less the number of closed cycles. Finally,

$$\sum_{i,j\in E} k_i k_j = \sum_{i,j\in E}\left(k_i + k_j\right) - m + 3|C_3| = m + 2\,|\mathrm{P}_2| + |\mathrm{P}_3| + 3|\mathrm{C}_3| \quad (3.10)$$

Using only these relations, given in (Estrada and Knight 2017), the numerator can be rewritten as

$$\frac{1}{m}(m + 2 + 2|\mathrm{P}_2| + |\mathrm{P}_3| + 3|\mathrm{C}_3|) - \frac{1}{4m^2}(2|\mathrm{P}_2| + 2\mathrm{m})^2 \quad (3.11)$$

The denominator can be rewritten, modifying Estrada's approach to use simpler graph structures, as

$$\frac{(2|\mathrm{P}_2| + 2m)^2 - 2(m + 2|\mathrm{P}_2| + |\mathrm{P}_3| + 3|\mathrm{C}_3|}{2m} - \frac{(2|\mathrm{P}_2| + 2m)^2}{4m^2} \quad (3.12)$$

Factoring, the numerator reduces to

$$\frac{3|\mathrm{C}_3|m - |\mathrm{P}_2|^2 + |\mathrm{P}_3|m}{m^2} \quad (3.13)$$

while the denominator is

$$\frac{-3|\mathrm{C}_3|m - 2m^2 + 2m^3 - 4m|\mathrm{P}_2| + 4m^2|\mathrm{P}_2| - |\mathrm{P}_2|^2 + 2m|\mathrm{P}_2|^2 - m|\mathrm{P}_3|}{m^2} \quad (3.14)$$

Cancelling the *m* terms, this means that Newman's correlation coefficient can be expressed as

$$r = \frac{3|C_3| - \frac{|P_2|^2}{m} + |P_3|}{-3|C_3| - 2m + 2m^2 - 4|P_2| + 4m|P_2| - \frac{|P_2|^2}{m} + 2|P_2|^2 - |P_3|} \tag{3.15}$$

which can be further reduced to

$$r = \frac{3|C_3| - \frac{|P_2|^2}{m} + |P_3|}{\frac{2(m-1)(m+|P_2|)^2}{m} - \left(3|C_3| - \frac{|P_2|^2}{m} + |P_3|\right)} \tag{3.16}$$

where again the denominator is positive for a normal network with degree variance > 0, which simply means it is not a very peculiar kind of network where each node has the same number of edges (Estrada and Knight 2017). Finally, letting $|P_{r/s}| = |P_r| / |P_s|$, if we divide and then multiply the term in numerator by $|P_2|$, we have

$$r = \frac{|P_2|\left(\left|P_{\frac{3}{2}}\right| + \frac{3|C_3|}{|P_2|} - \left|P_{\frac{2}{1}}\right|\right)}{\frac{2(m-1)(m+|P_2|)^2}{m} - |P_2|\left(\left|P_{\frac{3}{2}}\right| + \frac{3|C_3|}{|P_2|} - \left|P_{\frac{2}{1}}\right|\right)} \tag{3.17}$$

where, as noted above, $\frac{3|C_3|}{|P_2|}$ is just the global clustering coefficient *C*, and so

$$r = \frac{|P_2|\left(\left|P_{\frac{3}{2}}\right| + C - \left|P_{\frac{2}{1}}\right|\right)}{\frac{2(m-1)(m+|P_2|)^2}{m} - |P_2|\left(\left|P_{\frac{3}{2}}\right| + C - \left|P_{\frac{2}{1}}\right|\right)} \tag{3.18}$$

Since the sign of the assortativity coefficient only depends on the numerator, we can therefore derive conditions for the nature of assortative mixing in the network. It will be positively assortative if and only if $|P_{2/1}| < |P_{3/2}| + C$, and negatively assortative, with anti-correlation between nodes of similar degree, when $|P_{2/1}| > |P_{3/2}| + C$, where $|P_{2/1}|$ can be roughly interpreted as a measure of branching in the network, and $|P_{3/2}|$ relates to the

amount of modularity (Estrada 2011), (Estrada and Knight 2017), (Estrada 2016). Further, the form given here, differing slightly from that presented by Estrada 2011, makes clear that because the denominator is guaranteed to be positive, but will be smaller for higher C, the influence of C is further magnified.

Thus, it is conclusively shown that clustering is a positive contributor to assortativity, although Estrada's result, let alone the simpler, improved proof given here, has not been used in the engineering management literature. The implication of this is that the contribution of clustering to network robustness, rebound and connectivity is entirely captured by the assortativity measure. For a given percolation threshold and/or level of assortativity, clustering in the network may simply represent redundant density within already sufficiently connected components, wasting edges. Given cognitive constraints, on effective span of control and mental bandwidth, identified by Simon and others, redundant relationships may place a burden on the overall stakeholder system.

This means that while increased density of connections leads to higher network reliability in a supply chain generally (Basole et al. 2018), for a given percolation threshold the benefits of increased connectedness are minimal in terms of resilience measured in terms of robustness and rebound. Given the costs of collaborative overload identified in the literature review (Neches and Madni 2012), density and clustering, which as shown in the next chapter are highly correlated, thus inhibit the performance of the network. The negative effects of clustering have been extensively treated in the sociology network, for instance in Burt's works on "structural holes", and Granovetter's work on "the strength of weak ties" (Nohria and Eccles 1992). In particular, clustering makes network growth difficult, as maintaining connectivity through density, as opposed

to degree correlation, means that as the network grows the costs of cooperation grow linearly. As shown in complexity science approaches to network growth, the costs of managing an extensible network, such as the transportation system of a major city, typically scale according to a ~3/4 power law (West 2018), meaning that they decrease sub-linearly with size. Further, in the Cynefin framework, the challenge for managers in disordered contexts, where cacophony or disagreement between stakeholders hinders performance, is to filter out noise and establish consensus between key decision-makers. This is more likely to occur in a stakeholder system with relatively higher assortativity and lower clustering, facilitating connectivity between the most important stakeholders, who tend to be the most connected, without overloading stakeholders generally, with demands for collaboration. Finally, as shown in the literature on diffusion research, "thick" networks with a high degree of density are typically more resistant to change and innovation, meaning that they are less adaptive, compared to more efficient network (Rogers 2003), (Centola 2018).

Stakeholder networks with more degree correlation and less clustering, for a given level of connectivity, as represented by percolation threshold, can therefore be understood as being more resilient in the sense of adaptive capacity, as broken down into graceful extensibility and adaptability, an increasingly important way of understanding network resilience (Sharkey et al. 2020). They are more extensible, because they are able to grow more efficiently, and they are more adaptable, because dense webs of social interaction do not stifle innovative behavior, given the inherently conservative effects of "thick" social interactions. Thus, stakeholder networks with comparatively lower percolation threshold and clustering, and comparatively higher assortativity, have the

strategic advantage of having more resilient stakeholder networks, in the sense of being relatively more robust, more able to rebound, more extensible, and more adaptable.

3.5 Measuring the Percolation Threshold of Stakeholder Networks

The relations described above between clustering, degree assortativity and the percolation threshold can be shown graphically in Figure 3-17 below, using simulated random networks, confirming with simulations the analytic treatment developed above. Further simulation results will be discussed in the next chapter. Of course, to show these relations, a measure of the percolation threshold must be captured. That is not easy to do for real-world networks, as one cannot simply look at the first two moments of the degree distribution to derive an estimate, as can be done in the case of idealized networks with no degree correlation, without any need to look at the individual node and edge relations (Radicchi 2015). For real-world networks with degree correlation and clustering, there are no simple analytical formulae, and so spectral graph analysis and simulation must be used to provide a measure of the percolation threshold (ibid), and thus stakeholder network robustness and rebound capacity. In real-world networks, the topology of the network must be described at the microscopic level, which brings with it significant computational challenges. A good analytical estimate of the percolation threshold in real-world networks can be derived by building on the approach in Cohen and Havlin 2010 (ch.10). Following that, other approaches are described, but not derived.

3.5.1 An Intuitive Approach

An unconnected network, with average link reliability p, below the percolation threshold p_c, can be viewed as locally tree-like, since cycles are largely missing when no

spanning cluster exists. Such a network is a branching process, where the variables of interest are the number of surviving nodes of degree *k'* birthed by nodes of degree *k* in successive layers of the tree.

Because there are finite possible states, this is a Markov chain, with transition probabilities derived from the conditional probability of a link emanating from a node of degree *k* leading to one of degree *k'*, *P(k'|k)*. These conditional probabilities can be obtained from the matrix $\boldsymbol{E} \equiv \{e_{kk'}\}$, where entry $e_{kk'}$ for $k \neq k'$ is equal to the number of edges between nodes of degree *k* and nodes of degree *k'*, while the diagonal entries e_{kk} equal twice the number of links connecting two nodes of degree k (Latora et al. 2017).

In an undirected network, as stakeholder networks are, the matrix is symmetric, and $e_{kk'} = e_{k'k}$. Since the number of edges emanating from all nodes of degree *k* is kN_k, where N_k is the number of nodes of degree *k*, it follows that

$$P(k'|k) = \frac{e_{kk'}}{kN_k} \tag{3.19}$$

In each layer of the tree, each of N_k nodes leads to *k-1* nodes in the next, with probability *p*. The number of nodes of degree k' in the next layer is then given by

$$\sum_k (k-1)N_k p P(k'|k) \tag{3.20}$$

If N_k is a vector, where k is the index, k' is determined by a branching matrix equation, $p\boldsymbol{A}\overrightarrow{N_k}$, where the matrix $\boldsymbol{A} \equiv \{a_{kk'}\}$, with

$$a_{kk'} = (k-1)N_k\, P(k'|k) \tag{3.21}$$

which can be rewritten as

$$a_{kk'} = \frac{(k-1)}{k}\, e_{kk'} \tag{3.22}$$

The survival probability of this branching process is then determined by the largest eigenvalue of this matrix,

$$\lambda_{max} \equiv \max_{\vec{v}} \frac{A\vec{v}}{\|\vec{v}\|} \tag{3.23}$$

If $p\lambda_{max} > 1$, the branching process will continue indefinitely and the network percolates, as the size of the largest connected component in the tree-like graph grows linearly with the size of the network. If *p* times the largest eigenvalue of the branching matrix is below 1, then no giant component will exist, as the branching process dies out, so the percolation criterion is

$$p_c \lambda_{max} \equiv 1 \tag{3.24}$$

with percolation threshold defined as, per Cohen and Havlin 2010

$$p_c \equiv {\lambda_{max}}^{-1} \tag{3.25}$$

The matrix ***E*** can be found with the algorithm provided in Latora et al. 2017, and is available computationally in some network software packages, such as the iGraph package for Mathematica. Using this package to generate a large number of random graphs with fixed average degree, one hundred thousand graphs of the form $G_{(25,200)}$, and plotting their percolation thresholds, calculated as the inverse of the leading eigenvalue of the branching matrix ***A***, shows visually that network resilience is associated positively with degree correlation, and negatively with clustering. However, when average degree, the mean number of links per node, is allowed to vary, the negative correlation between

clustering and connectivity does not hold. Allowing average degree to vary uniformly by ten percent, generating one hundred thousand graphs of 25 nodes and between 180 and 220 edges, shows a positive association, in Figure 3-17. This suggests that findings associating clustering, as well as density, which correlates highly to clustering, with more connected or resilient networks, may only be capturing the effects of higher average degree. Simulated Bernoulli random graphs such as these are only toy models of real-world networks, and the patterns shown below must be verified with empirical data from systems in the wild, but they are useful for developing intuition and supplementing analytical approaches (Karrer et al. 2014), (Newman and Park 2003).

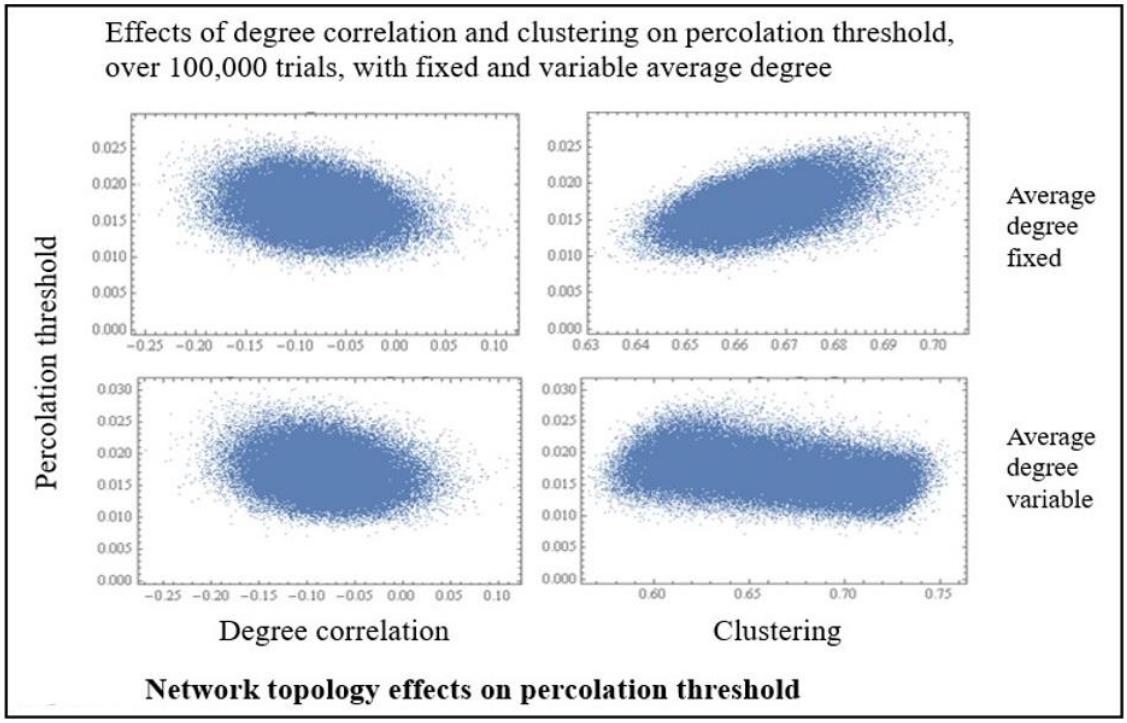

Figure 3-17: Network Topology Effects on Percolation Threshold

3.5.2 Other Approaches

The above shows that real-world stakeholder networks can be tested empirically by calculating, in addition to density, the topological properties of percolation threshold p_c, clustering coefficient C, and degree correlation coefficient r. However, while formulae for the latter two metrics are agreed upon, calculated in all standard network software packages, there are other approaches to calculating the percolation threshold, beyond the intuitive method outlined above. Of these, the Newman-Ziff Monte Carlo method is the gold standard, establishing an efficient simulation algorithm to find the occupation probability for which the second-largest component hits its global maximum, as in Figure 3-15. This approach accords with the conceptual idea mentioned in Section 1.1.1, that a system is most disjoint when it is split into two independent centers of gravity, and that when the two clusters are joined there will be a tipping point into connectivity and, thus, harmony of effort. However, the Newman-Ziff simulation approach presents significant computational challenges when analyzing large networks (>30 nodes), as is needed here (Radicchi 2015). The author of that algorithm himself suggests a numerical approach is best replaced with an analytic estimate, due to ease of computation and lack of statistical error (Karrer et al. 2014).

Thus, additional approaches based on spectral analysis of a branching process have been adopted in the literature, beyond the method outlined above, using the leading eigenvalue of the degree-degree conditional probability matrix described in Cohen and Havlin 2010, which makes the simplifying, but unrealistic, assumption that cycles and loops are largely missing in the network (Karrer et al. 2014).

The foremost analytic estimates for real-world networks are those of Bollobas and Newman, which an empirical analysis has shown are the best estimates of the percolation

threshold for, respectively, sparse and dense networks (Radicchi 2015). Using a derivation similar to, but more general and thus more complex than, the model above, the percolation threshold for high density networks $\bar{p}$ is derived as the inverse of the leading eigenvalue for the well-known adjacency matrix $\boldsymbol{B}$, which is a matrix consisting of zeroes on the diagonal, and off-diagonal entries of one, when a link exists between nodes i and j in the network, and zero when it does not. Meanwhile, the percolation threshold $\hat{p}$ for sparse networks, where the density of edges is <.5, as in most real-life networks (ibid), has been derived as the inverse of the leading eigenvalue of the "message-passing" matrix

$$\boldsymbol{M} = \begin{pmatrix} \boldsymbol{B} & \boldsymbol{I} - \boldsymbol{D} \\ \boldsymbol{D} & \boldsymbol{O} \end{pmatrix} \tag{3.26}$$

where **B** is again the adjacency matrix, $\boldsymbol{D}$ is a diagonal matrix with the node degrees k along its diagonal, $\boldsymbol{I}$ is the identity matrix, and $\boldsymbol{O}$ is the zero matrix (Karrer et al. 2014). An empirical comparison of percolation threshold estimates finds that $\hat{p}$ "represents the best measure currently on the market", and thus it is the percolation threshold metric adopted in the empirical methodology of this dissertation, although in practice $\hat{p}$ and $\bar{p}$ are highly correlated in real-world networks (Radicchi 2015).

3.6 Methodological Approaches for Building Real-World Stakeholder Networks

Recent supply chain network research (Basole et al. 2018), (Bellamy et al. 2014), (Basole et al. 2016) has utilized a curated supply chain intelligence database available computationally through the Bloomberg API, via the SPLC module. While this previous published research, validating the database as a valuable scholarly resource, has largely

focused on upstream suppliers of firms, the database provides all supplier, customer and peer relationships for firms with actively traded equity listings in US markets, derived from public filings. These relationships are particularly complete for the largest companies, such as the constituents of the OEX 100, a sector-balanced subset of the S&P 500 index designed to serve as a proxy for the performance of the largest US-listed blue-chip stocks. Given their size and scale, firms in the OEX 100 can be expected to have the largest and most diverse stakeholder systems, providing an ideal dataset for studying complex stakeholder networks generally, and were thus used as the basis for the empirical portion of this dissertation. The economic value of each supply chain relationship is calculated as the cost of goods sold (COGS) as a percentage of both the buyer's overall COGS, and the seller's overall revenue, while quantitative weights are not attached to peer relationships, which are identified by the SPLC module using its proprietary algorithm. The Bloomberg API further allows computational access to public filings regarding major shareholders, providing the percentage of firm equity held by each. Given the centrality of economic partners, such as supplier, customers and financiers, as well as industry peers, to the survival of each firm, these four groups can plausibly be said to constitute the core stakeholder system of each firm (Parmar et al. 2010). Other types of stakeholders will also be key, both external and internal, but these types vary significantly across industries, and so cannot serve as the basis for comparative study, as these "definitional" stakeholders do (Freeman et al. 2010, 25).

Supplier or customer firms were included in the stakeholder network when the focal firm spends or obtains more than 2% of, respectively, its COGS or revenue on or from them, as such firms may exercise significant power over the central firm's supply

chain. External economic partners were included when the focal firm is responsible for 5% or more of that firm's COGS or revenue, as trading partners highly dependent for their survival on the central entity possess legitimacy as stakeholders in it. Shareholders, both individuals and asset management firms, were included in the system when their stake is 4% or more, since their stake accords them both legitimacy, as owners of the firm, and potentially power and urgency, since shareholders with 5% or more of outstanding equity are accorded special legal rights and obligations. Finally, all rival firms were included, since as industry peers they possess power, legitimacy and urgency in their relations with the central firm, and even if their interests sometimes conflict with those of the central firm, as competitors, the same applies equally to other economic stakeholders also. These parameters were not experimented with, to prevent overfitting.

Following these steps for the internet retailer Amazon yields the stakeholder network depicted earlier in Figure 3-1. However, because the focus is on the quality of stakeholder interactions across the network, rather than the central entity's direct stakeholder engagement, it is appropriate to delete the focal firm node from the system. Leaving the central entity in makes sense in the context of measuring the centrality of a firm in its own network, as in (Basole et al. 2018), (Bellamy et al. 2014), (Basole et al. 2016), (Rowley 1997). Yet the inclusion of a central node connected to all others has the effect of making the network highly anti-correlated in its degree distribution, which would be unusual for a social network, as stakeholder networks are. It would make the central entity plays the role of a bus in a communications network, coordinating the relay of data between components. While such busses do play a role in engineered systems, as shown in the DSM's in Appendix 1, this is precisely what the central entity in a

stakeholder system does not do. Cognitive constraints due to the network combinatorial explosion problem discussed in Chapters 1 and 2 make such coordination and communication relay in social, as opposed to technical, networks impossible. Further, the strategic advantage to be gained by selectively withholding information make it unlikely. Finally, leaving the central entity in would have the effect of making almost all stakeholder networks quite dense, which is again unrealistic for real-world social networks (Karrer et al. 2014), (Newman and Park 2003). This last step can be depicted graphically for the stakeholder system example developed above, in Figure 3-18.

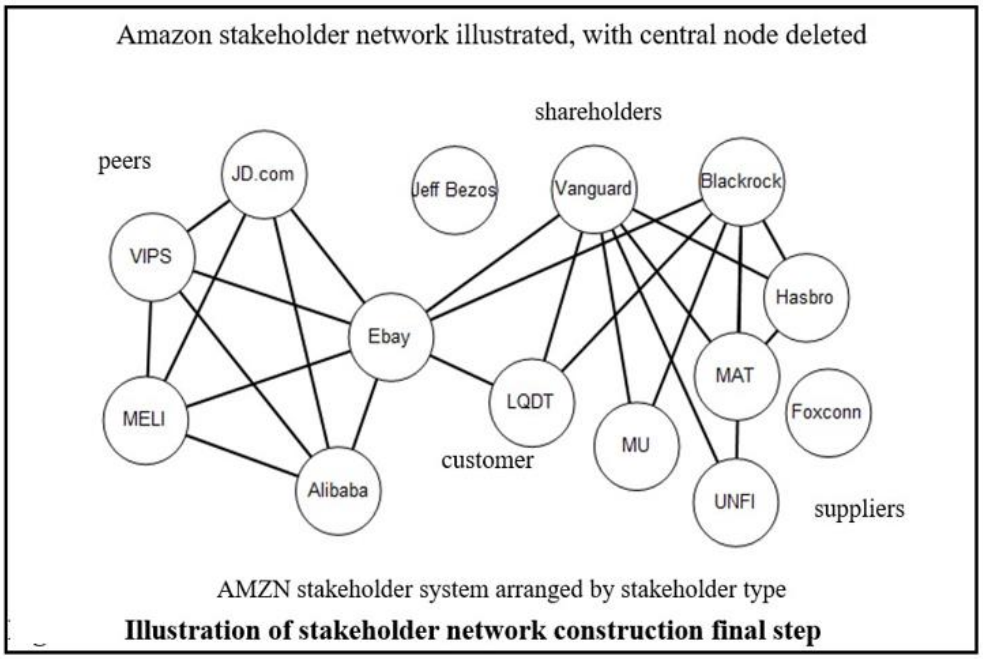

Figure 3-18: Amazon Stakeholder Network Final Form

3.7 Stakeholder Value Metrics

As discussed in Section 2.4.1, both economic and non-economics measures of stakeholder value are needed. Asset return is necessary to keep financiers, a key category

of stakeholders, engaged, but is also a requirement of the entire stakeholder system, driving the trading relationships that constitute the system (Freeman et al. 2010, 39), (Cameron et al. 2011). Historical stock performance, however, is a poor metric of stakeholder system survivability, as many shareholders have short horizons and loose ties, investing only as part of speculative, diversified, and hedged portfolios (Parmar et al. 2010). Other financiers, such as bondholders and banks, even labor unions, play a significant role. Past asset growth not only does not predict future returns but can be seen as compensation for higher risk (Penman 2011), and current shareholders are anyway forward-looking in their expectations of return (Freeman et al. 2018, ch.3).

Rather, earnings and related metrics should be the means of evaluating effectiveness, since profit, rather than speculative asset return, is a core interest of not only a firm's financiers, but the entire stakeholder system. A measure of effectiveness in generating corporate profit is thus desirable, and while return on equity is such a measure, suitable for comparing firms within the same industry, as in (Basole et al. 2018), it varies widely across industries, and is biased towards less asset-intensive sectors, such as professional services firm. The best proxy is earnings yield, the forward expected return to holding the common equity of a firm, a well-established measure long noted for its predictive power in measuring actual realized returns (Penman 2011), (Cornell 1999), (Basu 1983). Calculated as the inverse of the well-known price-earnings ratio, it does not capture short-term speculative gains, as speculators with a long interest hope to see P/E ratio go up in the short run. Rather, it is the best estimate of the future return to holding a firm's stock, and as such has long used by the Federal Reserve as proxy for comparing stock and bond yields (ibid). While the metric does vary across industries, with sectors

with higher expected growth rates having lower earnings yields, research has shown that it is a useful risk-adjusted measure of return, since high-growth firms and sectors are also riskier assets. A similar measure is dividend return, the yield on the stock price paid out in dividends to shareholders, which is often taken as a proxy of a firm's shareholder orientation (Govindarajan and Srivastava 2020), although there is of course a high correlation between dividend return and earnings yield (Cornell 1999, 122).

Measures of risk are obviously relevant to the survival of the networked organization (Basole and Bellamy 2014) and can be assessed for public firms by the risk premia paid, such as the cost of equity and rate of return demanded by investors or the weighted average cost of capital, as well as measures of financial leverage (Penman 2011). Not only do these metrics represent the market's independent estimation of the entity's survivability, they affect managers' ability to react to challenges dynamically, as more expensive financing limits the range of strategies available to them. Risk can also be thought of arising from the chance of lawsuits, regulatory fines and reputational damage due to environmental, social and governance (ESG) issues (Freeman et al. 2018, ch.4). However, ESG metrics do not represent simply potential sources of financial liability but gauge the system's success in meeting its stakeholders' non-financial expectations generally (Freeman et al. 2010). ESG performance should not be viewed as an optional extra, but as a core competency in satisfying the claims of stakeholders, since the value created by organizations is never just financial, and a minimum level of corporate citizenship is necessary for an entity's survival (ibid). While ESG metrics may not capture the whole of a firm's non-financial value creation, given the visibility of ESG issues they serve as a proxy of its commitment to broader stakeholder satisfaction (ibid).

They are easily captured in the case of publicly traded firms from Sustainalytics, another high-value proprietary business intelligence database. These metrics, consisting of absolute and relative scores estimated on a 0-100 scale by teams of analysts, are, like the others above, available computationally through the Bloomberg API and Yahoo Finance, and have been validated by many recent studies on the non-financial claims of stakeholders, which also explain the evaluation process ((Francoeur 2017).

Chapter 4. Results

The innovative methodology presented in Chapter 3 for analyzing the resilience of stakeholder networks in terms of robustness, rebound, extensibility, and adaptability, by connecting them with the network statistics of percolation threshold, clustering, and degree correlation, was rooted in the extensive literature review in Chapter 2. The methodology developed principles of stakeholder network management for strategic advantage through a reading of relevant literature in systems engineering and technical management and tied these principles to phenomena established by basic research in network science. Outside of the area of mathematical epidemiology, these network science models have found few applications, and even in that area, the literature is highly theoretical, as in Dorogovtsev et al. 2008, Ball et al. 2012, Youssef et al. 2013, and Boguna and Pastor-Satorras. Many of the authors referenced to develop this network science methodology tailored to stakeholder systems appear among a list of most-cited authors in network science, given by Alderson 2008. Rather than try to improve on their significant innovations in graph theory and statistical physics, the aim of the methodology was to adapt this highly theoretical literature to "the uncertain, everchanging, unpredictable world of winning and losing", in other words to gaining strategic advantage by managing for stakeholders. The main innovations in the methodology were to make the proof of the relation between clustering and degree correlation sharper and clearer, present an analytic estimate of the percolation threshold in a significantly more intuitive fashion (for engineers), using Markov transition matrices, than for example Bollobas et al. 2010, and tie these topological relations together in a coherent framework.

The implication of this is that the research question and methodology were formulated with a minimum of data "dredging", or "p-hacking", fashioning hypotheses to take advantage of random patterns in the data. The difficulty of capturing data for, constructing, and measuring large real-world stakeholder networks, based on high-value supply chain and financial data, is such that it would be exceedingly difficult to "cheat" by adapting one's theory to the data. While this accords with good statistical and scientific practice, as in Freedman 2012, this makes it harder to develop intuition and test ideas quickly. Interactive exploratory data analysis on massive, complex networks is, as yet, next to impossible due to computational constraints: many of the calculations performed in this analysis took hours, rather than minutes, to run on multi-core Linux servers running in parallel (using up to 16 cores, through the Wolfram Mathematica Lightweight Grid Manager parallelization tool).

Therefore, the hypothesis that more resilient stakeholder networks lead to strategic advantage, in the sense that organizations are better able to satisfy their stakeholders, was tested in three phases. In the first, simulations were run on simulated random graphs, an approach already previewed in Figure 3-17 above. This simple approach confirmed the basic ties between clustering, degree assortativity and percolation threshold, calculated as above, and helped to develop intuition. While the individual relations were not discovered by the author of this dissertation, the papers by Newman treating these relations do so only in passing, based on simulation results, as they did not have an analytic basis for the relation, until it was proved by Estrada (a result which has not been used in any management science applications), who does not tie all three measures into a coherent framework. Thus, the relations have not been influential outside

of a limited set of papers on mathematical epidemiology, cited above, let alone in management science. The simulation results thus were useful in confirming the promise of this methodology, tying network resilience to network topology in the innovative approach described here. It was subsequently discovered that a similar approach was taken in Volz 2004, likewise testing the effects of clustering and degree correlation on a phase transition (similar to, but not the same as, a percolation process) in random graphs, finding similar effects. Here, as in Volz 2004, the aim was to develop intuition, rather than to prove the relations statistically, given the inherent limitations of random graphs, results on which do not necessarily extend to real-world networks.

Second, simulations were performed on an un-simulated, real-world stakeholder network, validated in the literature (Wood et al. 2012). These showed that the percolation transition could be captured in real-world stakeholder network, that it could be analyzed for the network statistics treated here, and that it could even be re-wired to improve it, making it more resilient in the sense of robustness, rebound and adaptive capacity, as treated above.

Finally, and most importantly, empirical data from 100 of the largest U.S. firms, the constituents of the OEX 100 (N=101, because Google and its parent Alphabet Inc. have separate listings), was gathered in multiple rounds (to confirm previous findings) over the course of 2019. 101 stakeholder networks were created, many of them massive in size, based on the stakeholder saliency criteria of power, urgency and legitimacy described in Mitchell et al. 1997, as translated into quantitative criteria in Chapter 3. These stakeholder networks were then analyzed for the statistics of degree correlation, clustering, and percolation threshold, captured as described above, to provide

independent variables for the analysis. Given the computational difficulties of constructing these networks, no experimentation was done in the construction of these networks. Financial and non-financial metrics were captured, as described above, to provide the dependent variables. While there was of course greater latitude in capturing these dependent variables, only those metrics well-grounded in the stakeholder literature were explored. With these, both linear and robust regressions were done, to test the hypothesis that more resilient stakeholder networks lead to more survivable stakeholder systems. The results of all three phases are described below.

4.1 Random Graph Simulation Results

A first step in simulating random graphs and capturing their topological statistics using the functions for clustering and degree correlation built into standard graph analysis software packages, such as iGraph (Csardi and Nepusz 2006), was to recreate, independently, a method of capturing these statistics, to confirm that the theoretical understanding developed above works in practice. This was done in simple R code, shown in Appendix B. This confirmed that clustering is estimated by these packages as simply the sum of closed triangles divided by the total number of triangles, while degree assortativity is simply the Pearson correlation of the degree (number of connections) between neighboring (i.e., connected) nodes. R code was also developed to simulate random binomial graphs of the form *G(m,n)* and capture their percolation threshold estimates $\hat{p}$ and $\bar{p}$, as described above. Simulated graphs showed that, as predicted in Raddichi 2015, these measures are highly correlated. Surprisingly, no graph theory package on the market captures percolation measures. Releasing an R package to

measure the percolation threshold estimates treated above is a potential future contribution of this research.

The second step was to confirm independently the theoretical relations between percolation threshold, assortativity, and clustering. Rather than using the special percolation threshold estimate developed above, based on the inverse of the leading eigenvalue of the branching matrix, as in Figure 3-17, this simulation research used $\hat{p}$ and $\bar{p}$. As discussed above, these are the inverses of the leading eigenvalues of, respectively, the message passing and adjacency matrices of a network, and are the leading analytical estimates (Radicchi 2015).

R code to create 1000 simulated graphs with 40 nodes and 100 edges each (i.e. of the form *G(40,100))*, is given in Appendix B. Following standard textbooks such as Newman 2017 and Barabasi and Posfai 2016, random graphs were created using both an Erdős-Rényi binomial graph approach, where the degree distribution follows a Poisson distribution, and a Barabasi-Albert approach, where the degree (number of connections per node) is distributed according to a power law. The relation between percolation threshold and transitivity in random graphs was predicted to be, as posited above, strong but due to a density effect, producing connectivity by sheer volume of connection, rather than efficiency in global connectivity. This was confirmed visually in Figure 4-1, which shows a clear negative slope in the relation between percolation threshold and clustering, with lower percolation threshold equating to greater robustness:

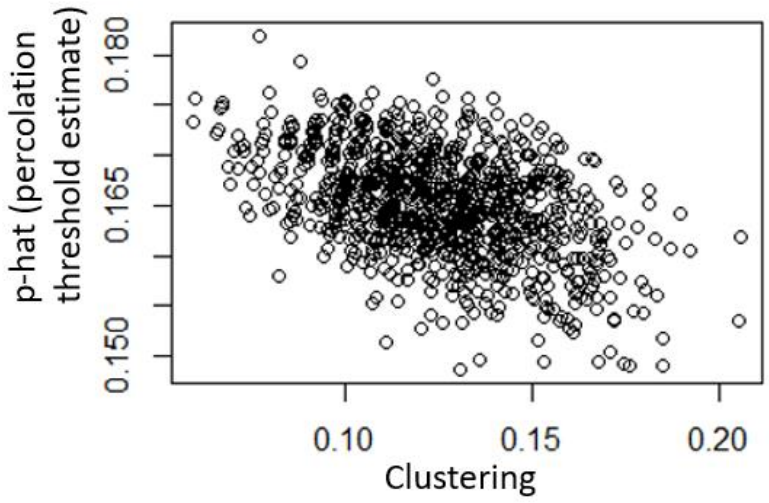

Figure 4-1: Percolation Threshold vs. Clustering in Erdős-Rényi Random Graphs

This research has purposely avoided the literature on scale-free networks, as they are quite uncommon in real-world social networks, where the number of meaningful interactions between people cannot be expected to be distributed according to a power law (Broido and Clauset 2019). However, scale-free networks play a major role in network science literature, and effects discovered in scale-free network often translate to real-world networks with truncated degree distributions. examination of scale-free networks showed that the same relations hold for scale-free networks also, as in Figure 4-2, where there is likewise a strongly negative slope in the relation between the percolation threshold estimate and the amount of clustering in the graph:

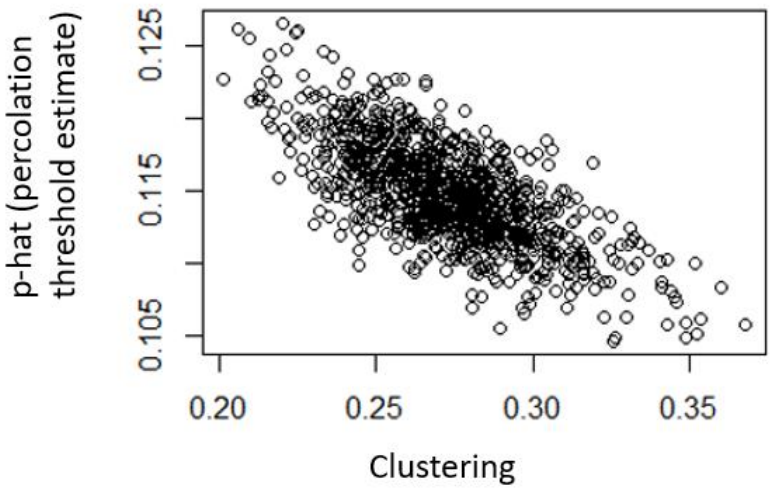

Figure 4-2: Percolation Threshold vs. Clustering in Barabasi-Albert Random Graphs

These relations were also informally confirmed with a linear regression approach, showing that the topology statistics correlate with percolation threshold, with a high degree of significance, as in Table 4-1 below.

LINEAR REGRESSION OF P-HAT AGAINST CLUSTERING (ERDOS-RENYI RANDOM GRAPHS)				
Dependent Variable	Clustering	Intercept	R^2	Adj. R^2
Percolation Threshold	-.09223***	.1776	.2166	.2158
p-value: $2.2 \, x \, 10^{-16}$				

Table 4-1: Percolation Threshold Regressed vs. Clustering (Erdős-Rényi Random Graphs)

This regression was partially validated by QQ-plot diagnostics that showed the significance of the above regression was unlikely to be illusory, because caused by deviations from normality in the residuals, as below in Figure 4-3. However, the intent of the linear regression was only to confirm the theoretical relations described above and

could not serve as proof of any statistical regularities, given the constraints on generalizing from the behavior of random graphs, as discussed above.

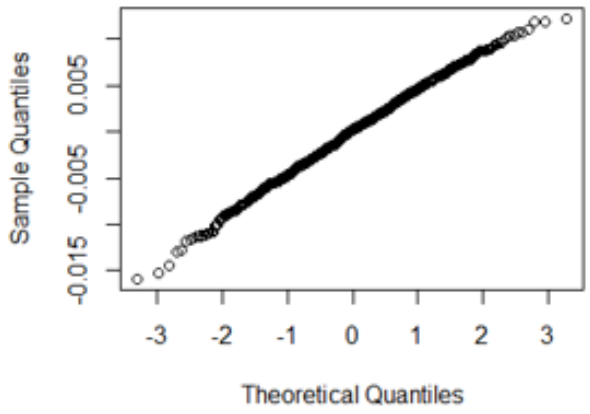

Figure 4-3: Percolation Threshold vs. Clustering (E-R Random Graphs), QQ Plot of Residuals

Further, as shown earlier in Figure 3-17, and discussed in the methodology, when keeping the distribution of degree fixed, the positive correlation between clustering and percolation threshold largely disappears. Node degree distribution is kept constant using the "configuration model", discussed in (Newman 2003. "The Structure and Function of Complex Networks"). This is shown in Figure 4-4, where there is a much more modest negative slope in the relation between the percolation threshold estimate and clustering. This is essentially because clustering and density are highly correlated, and denser networks, where each node has a higher average degree, are also more likely to "close" a triangle, a correlation confirmed in real-world networks below.

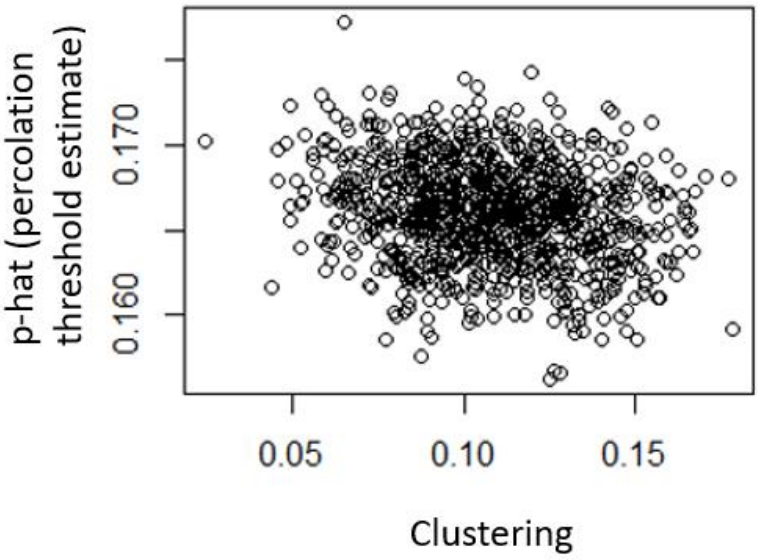

Figure 4-4: Percolation Threshold vs. Clustering in Erdős-Rényi Graphs, Average Degree Fixed

The disappearance of clustering's contribution to network robustness, when keeping degree distribution constant, was confirmed also for scale-free networks, in Figure 4-5, which shows essentially no pattern in the relation between clustering and percolation threshold at all:

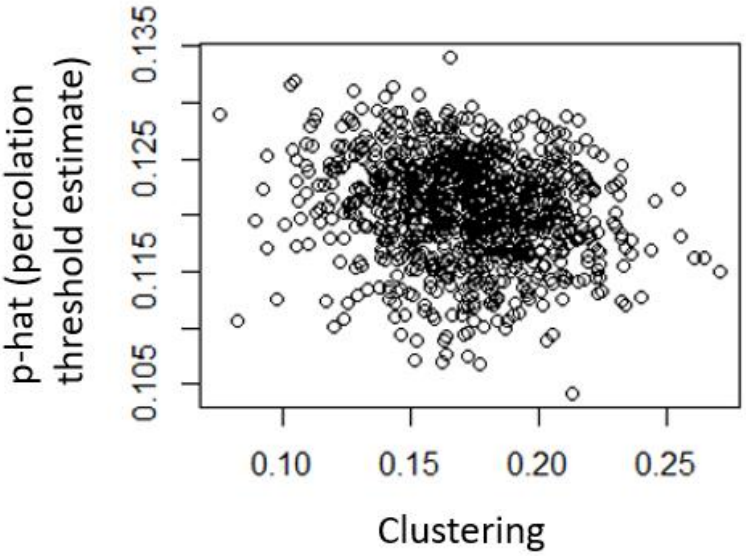

Figure 4-5: Percolation Threshold vs. Clustering in Barabasi-Albert Graphs, Average Degree Fixed

Finally, degree correlation was confirmed to have a strong association with increased network robustness, as measured by a lowered percolation threshold, especially when degree distribution is kept constant. This is partially shown in a linear regression of the percolation threshold estimate against degree correlation in Table 4-2, below:

LINEAR REGRESSION OF P-HAT AGAINST DEGREE CORRELATION (ERDOS-RENYI RANDOM GRAPHS)				
Dependent Variable	Degree Correlation	Intercept	R^2	Adj. R^2
Percolation Threshold	-.01400***	.1644	.05615	.0552
p-value: $3.14\ x\ 10^{-14}$				

Table 4-2: Percolation Threshold Regressed vs. Degree Correlation (Erdős-Rényi Random Graphs)

In the table above, it is noticeable that the R-squared is quite low, meaning that less than six percent of the variation in percolation threshold is explained by degree correlation, when not holding degree distribution constant (to limit the effects of differences in network density), although the significance of the test is quite high, as measured by a low p-value. The combination of low R-squared and low p-value typically suggests that there is a great deal of unexplained variance, which is precisely what was expected, since degree correlation does not capture the effects of network density, as clustering does, but only efficiency in global connectivity. Further, as shown in Figure 4-6 below, while there is a clear but modest negative slope in the data, the degree correlation distribution centers on zero, which is to be expected in random graphs, which unlike real-world networks do not typically have any dependence in degree between

nodes, as discussed in Chapter 3, meaning that degree correlation offers little in the way of leverage in random graphs.

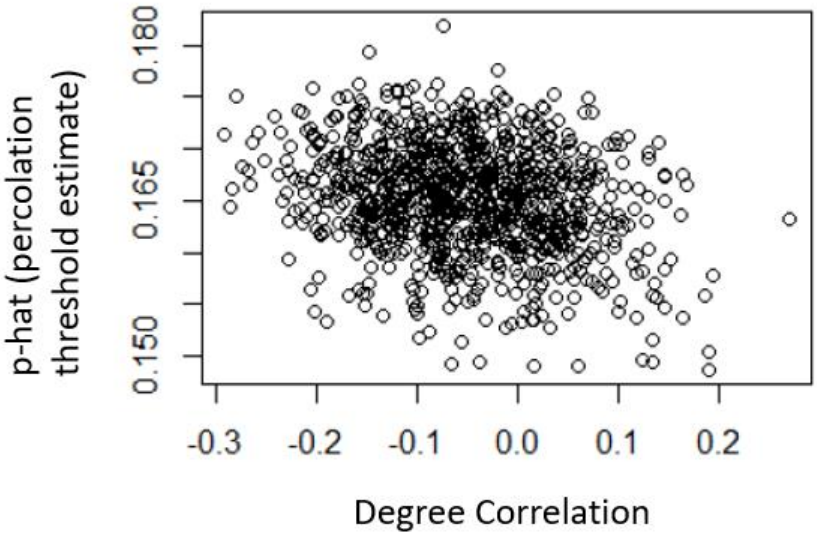

Figure 4-6: Percolation Threshold vs. Clustering in Erdős-Rényi Random Graphs

The above results suggested that attention thus needed to be directed to random graph simulations keeping degree distribution constant, to understand the effects of degree correlation in isolation from network density. This approach is shown in Figures 4-7 and 4-8, which show more markedly negative slopes in the relation between percolation threshold estimate and degree correlation for, respectively, Erdős-Rényi and Barabasi-Albert type graphs:

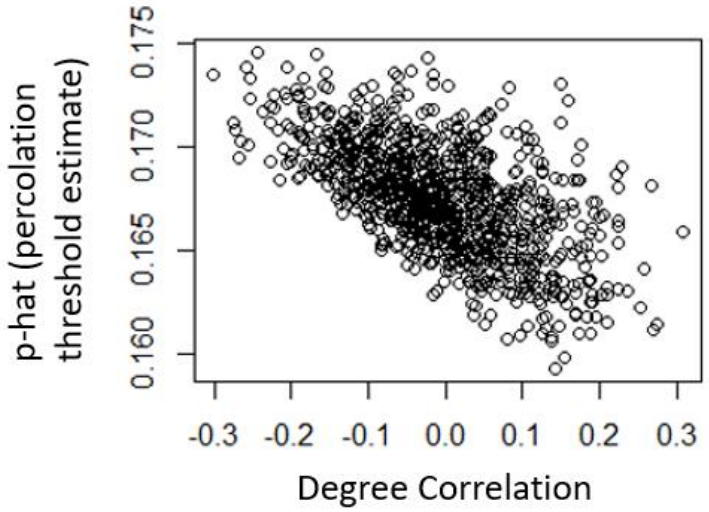

Figure 4-7: Percolation Threshold vs. Assortativity in Erdős-Rényi Graphs, Average Degree Fixed

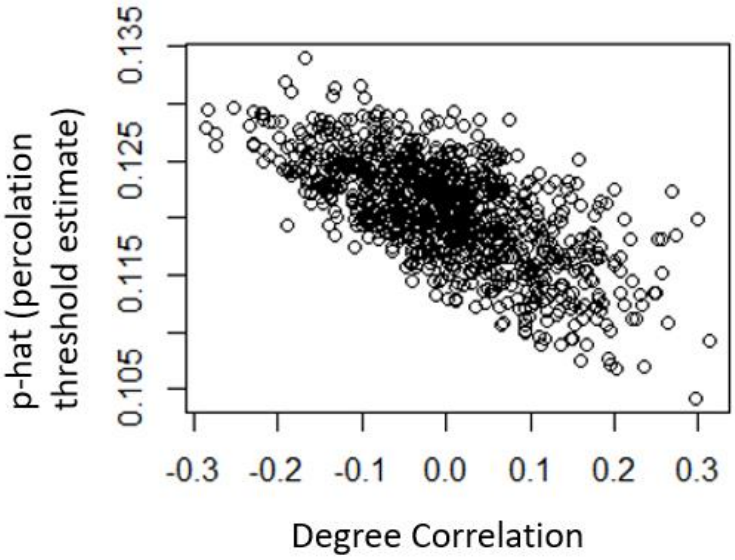

Figure 4-8: Percolation Threshold vs. Assortativity in Erdős-Rényi Graphs, Average Degree Fixed

The relations established in theory and confirmed in the simulation results above were then used as the basis for re-wiring algorithms, switching a single edge to lower clustering and raise assortativity, somewhat similar to the approach in Volz 2004. As discussed below, such re-wiring approaches must be deployed with care to engineered

systems and stakeholder networks (Zhao et al. 2019). For this reason, the details of re-wiring approaches developed during research for this dissertation are not given here but are a promising future direction. However, some significant effects on network performance are shown below, stemming from rewiring a single edge in a 100-edge simulated network, as shown in Figures 4-9 to 4-12 below.

Figure 4-9: Effects of Rewiring Strategies on Percolation Threshold in Simulated Graphs

These effects were used to rewire simulated graphs, which were then tested for robustness, following Li et al. 2015, showing that small changes in percolation threshold, by using clustering and assortativity as levers, can have big effects on robustness. Below, the improved (by a single edge) networks are in blue, the impeded in red. Networks were tested in high performance, middling, and low-performance states, corresponding to the difference between occupation probability and percolation threshold, as discussed above, ranging from occupation probability (or reliability) being significantly above the percolation threshold, to slightly above, to equal to it.

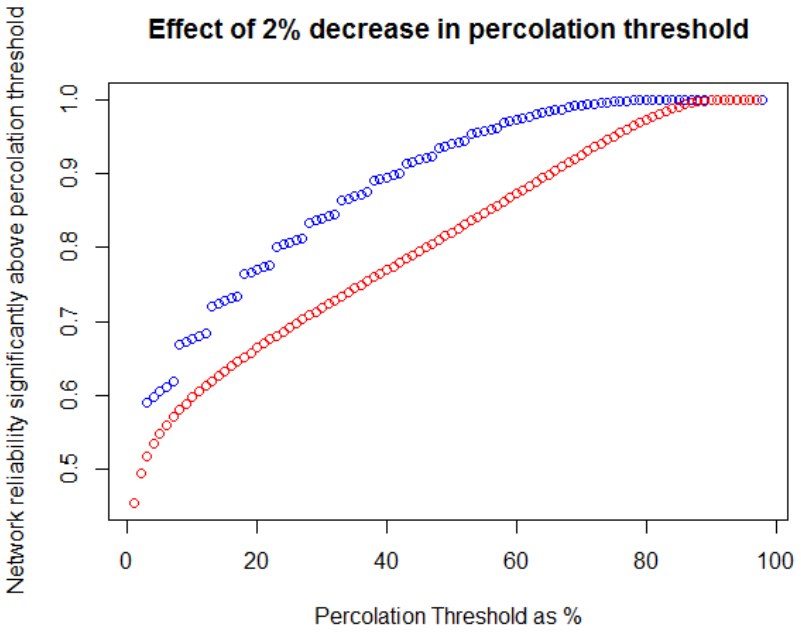

Figure 4-10: Effects of Small Improvement in Percolation Threshold, High-Performance Network

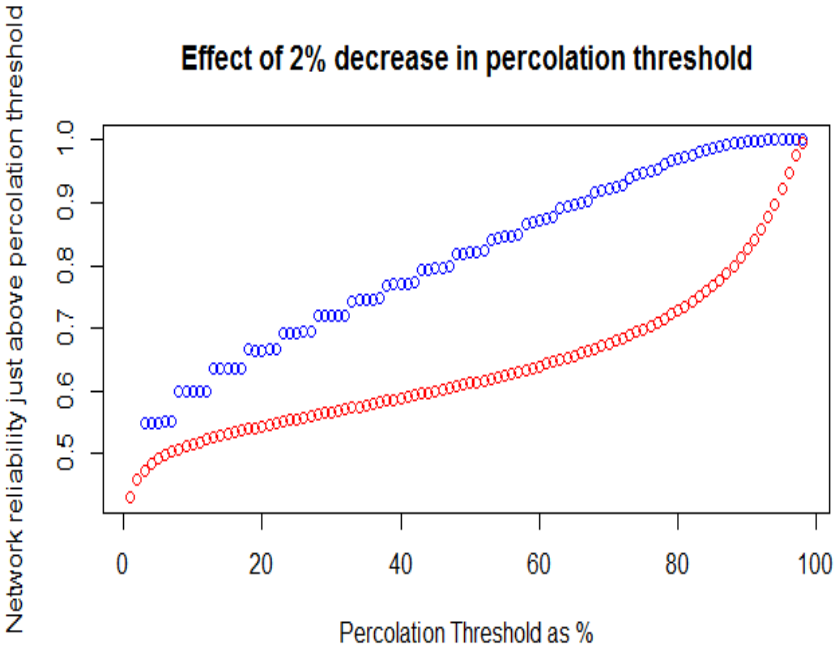

Figure 4-11: Effects of Small Improvement in Percolation Threshold, Medium-Performance Network

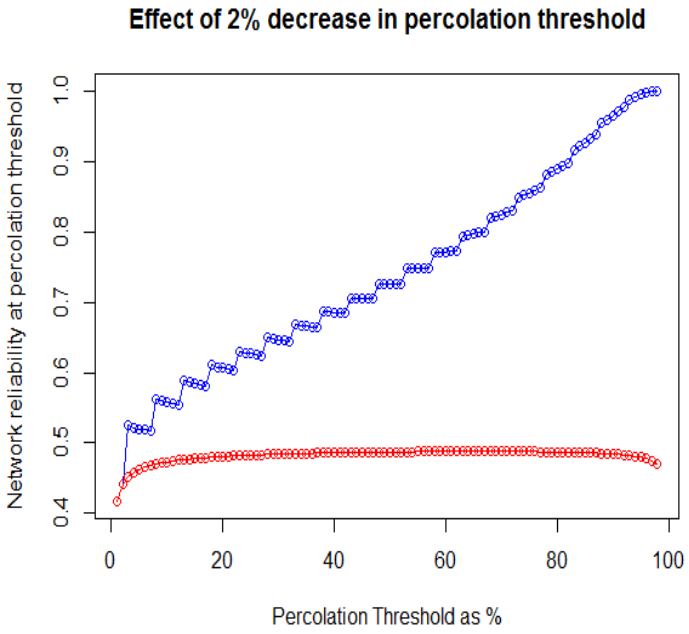

Figure 4-12: Effects of Small Improvement in Percolation Threshold, Low-Performance Network

4.2 Simulations on a Real-World Stakeholder Network

The second phase sought to validate the methodology as a useful approach for a single real-world stakeholder network, namely the DoD IT hidden stakeholder network constructed by Wood et al. 2012 in a Systems Engineering journal article. The first step was to translate the 34-node, 43-edge network into an adjacency matrix, then map that adjacency matrix to a network object in iGraph, using both R and Mathematica versions.

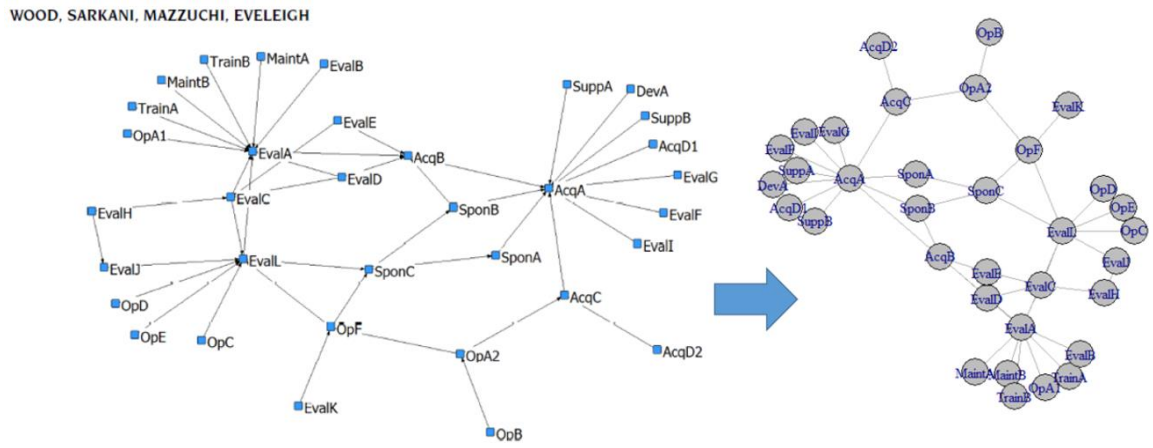

Figure 4-13: Hidden Stakeholder Network

This network case study visually confirms, in Figure 4-13, among other things, the tendency for real-world stakeholder networks to be sparse, meaning that density is significantly less than .5, thus suggesting the use of $\hat{p}$ as discussed above, based on Radicchi 2015. Further, the effects of edge reliability, when a stakeholder interaction is missing, precisely the situation addressed by Wood et al. 2012, can be shown visually by showing two variants of the above network, which is after all depicted with every stakeholder connected, assuming 100% reliability. As described above, and Wood et al. 2012 acknowledge, this often fails to be the case. In Figure 4-14, stakeholder interactions are mostly, but not completely present, and only a few isolated stakeholders stand apart.

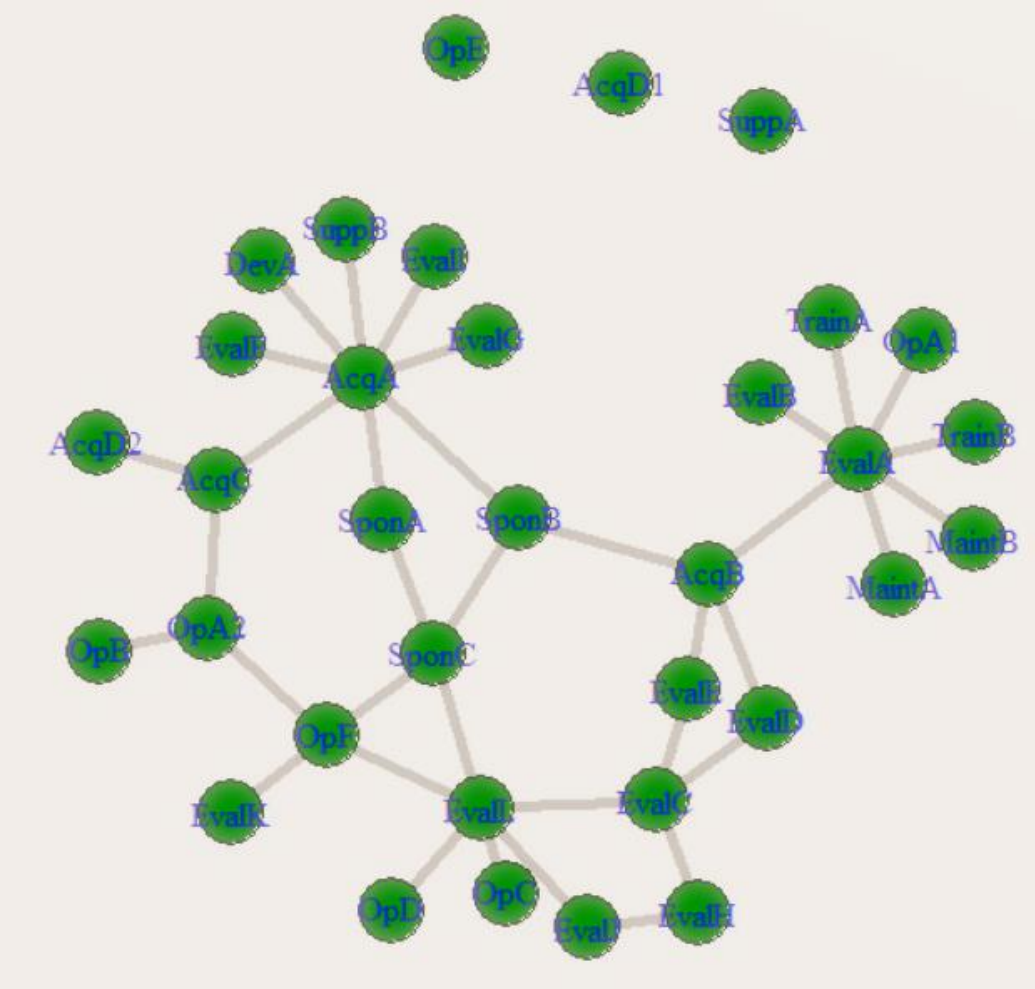

Figure 4-14: Hidden Stakeholder Network, Edge Reliability High

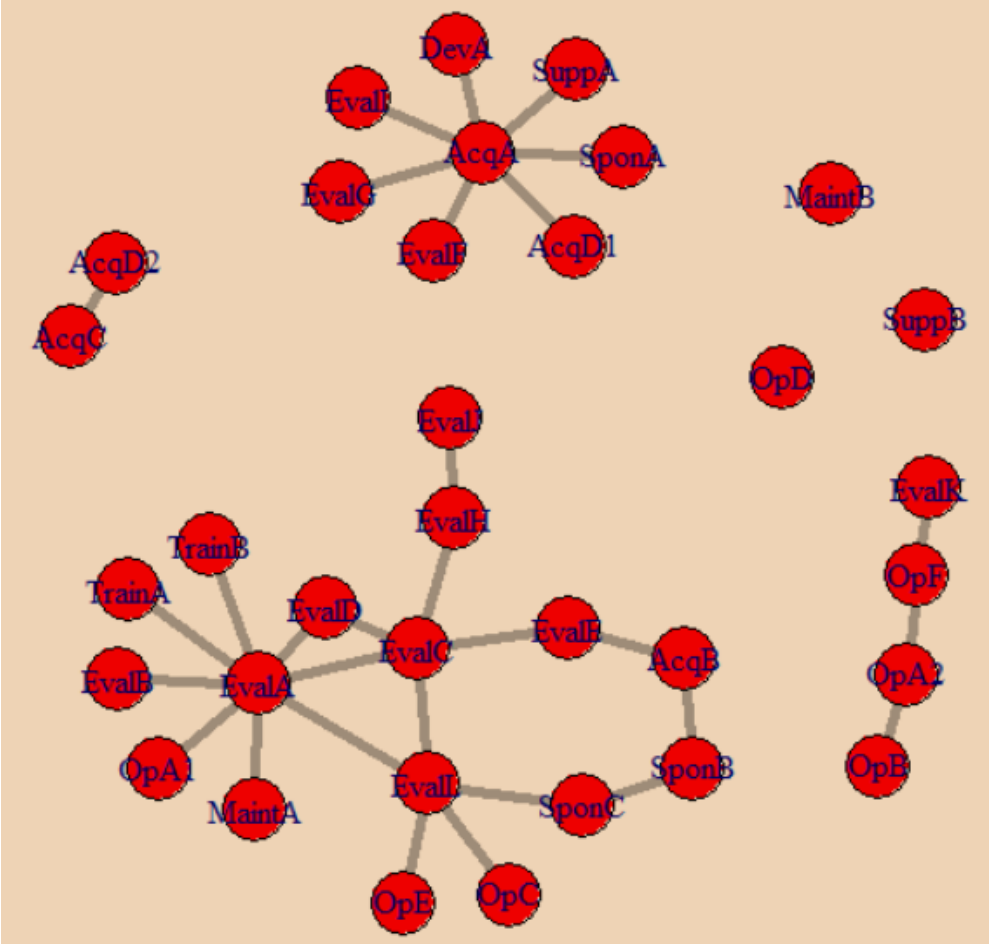

Figure 4-15: Hidden Stakeholder Network, Medium Edge Reliability

In Figure 4-15, constructed by simulating edge interruptions on the Hidden Stakeholder network, the stakeholder system is obviously plagued by disconnected islands of effort and competing centers of gravity, as discussed in Section 1.1.1. Reading the case study in Wood et al 2012 makes clear that, as Crawley et al. 2016 argue, the simulated stakeholder system in Figure 4-14, even though unfortunately excluding some stakeholders, is far more likely to formulate high-level requirements that are necessary, traceable, verifiable, complete, and consistent than that depicted in Figure 4-15, and thus more likely to succeed (INCOSE 2015, 60-63). The Hidden Stakeholder case also has the

advantage of making clearer why some stakeholder interactions, even those of DoD engineers actively engaged with system development, might be missing:

- stakeholders too busy/resource constrained to engage
- stakeholders too heterogeneous to communicate well
- stakeholders too geographically spread out
- stakeholders have differing levels of commitment
- some stakeholders may ‘sabotage’ by not participating

Taking this unreliability into account, it then becomes possible to identify which stakeholder, and which stakeholder relations, contribute most to the connectivity of the network in the face of unreliability, in other words, which stakeholders are key to the network’s resilience. Often, stakeholder prioritization approaches simply reply on number of connections. As was seen in this case study, such an approach would not have the effect of picking out the stakeholders contributing most to network resilience.

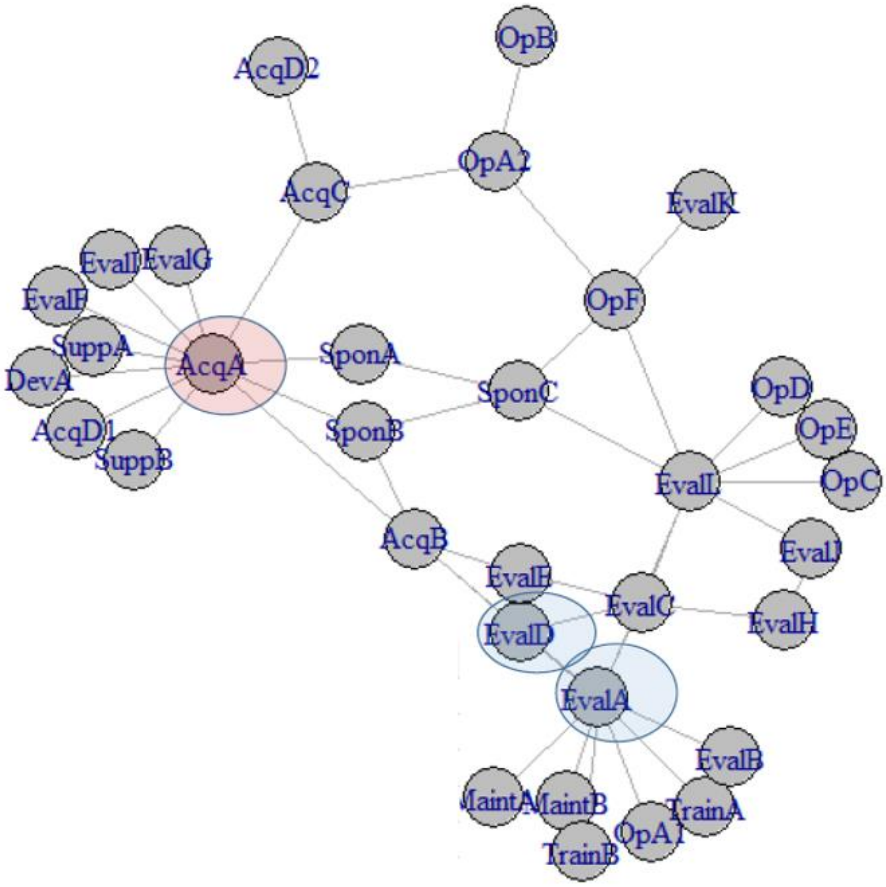

Figure 4-16: Hidden Stakeholder Network, Key Stakeholders Identified

key_vertices_df.vertex_name	key_vertices_df.delta_p_hat_pct
EvalA	0.1186518181
AcqB	0.0843986298
EvalL	0.0771243983
EvalC	0.0759756730
EvalD	0.0594753172
AcqA	0.0297603628

Figure 4-17: Hidden Stakeholder Network, Key Stakeholders Ranked

In Figure 4-16, it is obvious that the node titled AcqA, highlighted in red, corresponding to an acquisition management stakeholder in Wood et al. 2012, has the

most connections, and would thus be prioritized in many approaches. However, sensitivity analysis, capturing the network's percolation threshold after deletion of a single node, in Figure 4-17, identifies node EvalA as most contributing to the network's resilience. Counter-intuitively, even node EvalD contributes more the network's resilience than AcqA, despite having less than half the number of connections. These two evaluator nodes are highlighted in blue. Visual inspection suggests that, intuitively, these nodes play a role in intermediating between competing centers of gravity, whereas AcqA is merely the center of its own isolated circle of influence. Only the methodological framework developed here, however, formalizes such an intuition.

A similar approach may be taken to stakeholder interactions, identifying which are most key to network resilience, and thus to be defended, subsidized, or even, if possible, to be created. For while one cannot simply add stakeholders to a network, when no natural connection exists, in certain instances new connections, where appropriate, can be encouraged. Using this approach also, as above, yields powerful but non-obvious results, shown in Figures 4-18 and 4-19. A common approach in ranking edge importance is to measure the number of times an edge acts as a "bridge" along the shortest path between two other nodes, called betweenness centrality. Such an approach would identify the relation between the two acquisition managers AcqA and AcqB as most important. The method described here, however, would identify the interaction between evaluators EvalA and EvalL as key. Visual inspection shows that the AcqA-AcqB tie serves as a bridge between the rest of the stakeholder system and AcqA's own isolated circle of influence. The EvalA-EvalL interaction, on the other hand, serves to hold multiple subsystems together. Our methodology formalizes such visual impressions.

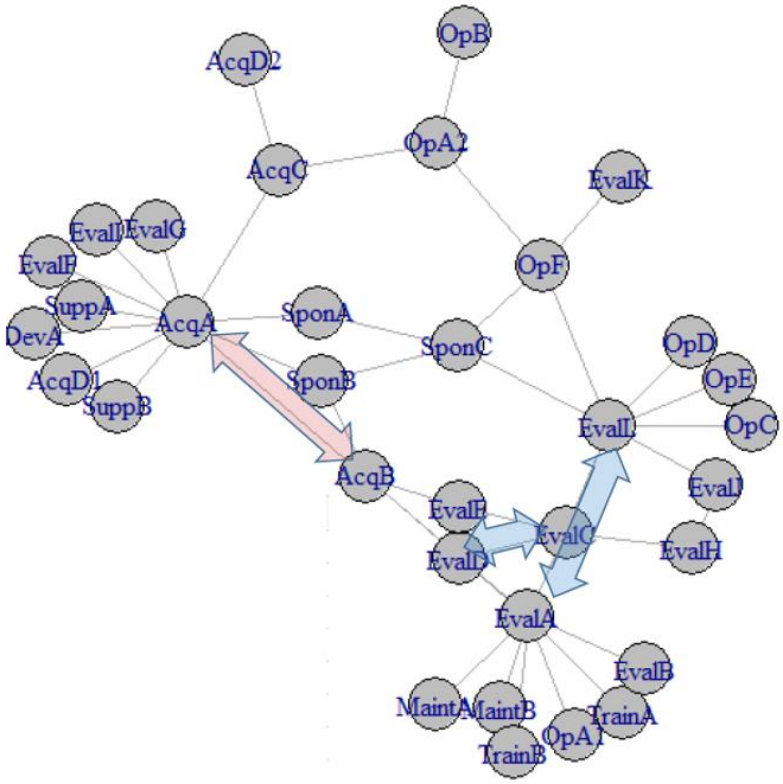

Figure 4-18: Hidden Stakeholder Network, Key Stakeholder Relations Identified

new_edge_source	new_edge_sink	new_edge	new_p_hat	delta_p_hat_pct
EvalA	EvalL	0	0.2390595	0.0548524352
EvalA	AcqB	0	0.2387630	0.0535437591
EvalA	EvalC	0	0.2376137	0.0484726649
EvalA	EvalD	0	0.2355647	0.0394312782
EvalC	EvalL	0	0.2352668	0.0381168571
EvalD	AcqB	0	0.2333406	0.0296174200
EvalD	EvalC	0	0.2331057	0.0285810464
AcqB	AcqA	0	0.2324070	0.0254982334

Figure 4-19: Hidden Stakeholder Network, Key Stakeholder Relations Ranked

Lastly, as suggested above, network resilience sensitivity analysis derived from simulations may be used to suggest new interactions to add, from the potential $\binom{m}{2}$ - n

potential stakeholder interactions not present. For instance, in the case of the Hidden Stakeholder network, it was found that a new connection between AcqA and EvalA would raise network robustness more than any other new connection, by lowering percolation threshold the largest percentage. At the same time, such a connection would increase degree correlation the most, while having an insignificant effect on clustering, as shown in Figure 4-20. Similarly, a tie-up between AcqA-EvalL would be the third-most effective in raising network robustness, while significantly lowering clustering and raising assortativity, presenting a case study confirming the relations discussed above. Meanwhile, a tie-up between AcqB and EvalL would increase network robustness, while having little effect on assortativity and clustering, showing that the relations described above are not mechanical or guaranteed.

	node1	node2	connectivity rank	deg. corr. rank	clustering rank
1	EvalA	AcqA	1.0	1.0	152.0
2	AcqB	EvalL	2.0	182.0	146.0
3	AcqA	EvalL	3.0	2.0	518.0

Figure 4-20: Hidden Stakeholder Network, Potential Stakeholder Relations Ranked

Instances of stakeholder relations being unreliable (i.e., missing), for the reasons adduced above, can be simulated on a network, and the size of the remaining largest cluster, as a percentage of all stakeholders, can be recorded. Using the top three stakeholder edge additions suggested in Figure 4-20, the performance of improved and unimproved networks can be compared with each other. The original DoD IT stakeholder network is in red, and the improved version, with the three best edges added, is in blue.

This improved network lowers the connectivity threshold by over 15%. For edge reliability in the range 1%-99%, in 1% increments, edge deletions were simulated in both networks, 1,000 times each. This resulted in 200,000 network simulations, and the recording of approximately nine million potential edge deletions, showing the computational difficulty of running simulations on even one individual medium-sized network. As can be seen in Figure 4-21, at edge reliability=40%, the average maximum cluster size about 35.5% in the original network, while in the improved network the average maximum cluster size is 44%. This case study verified the stakeholder network topology relations discussed above, and validated the approach as useful for analyzing and even managing stakeholder interactions, particularly when there are significant impediments to such interactions, as in many real-world stakeholder systems.

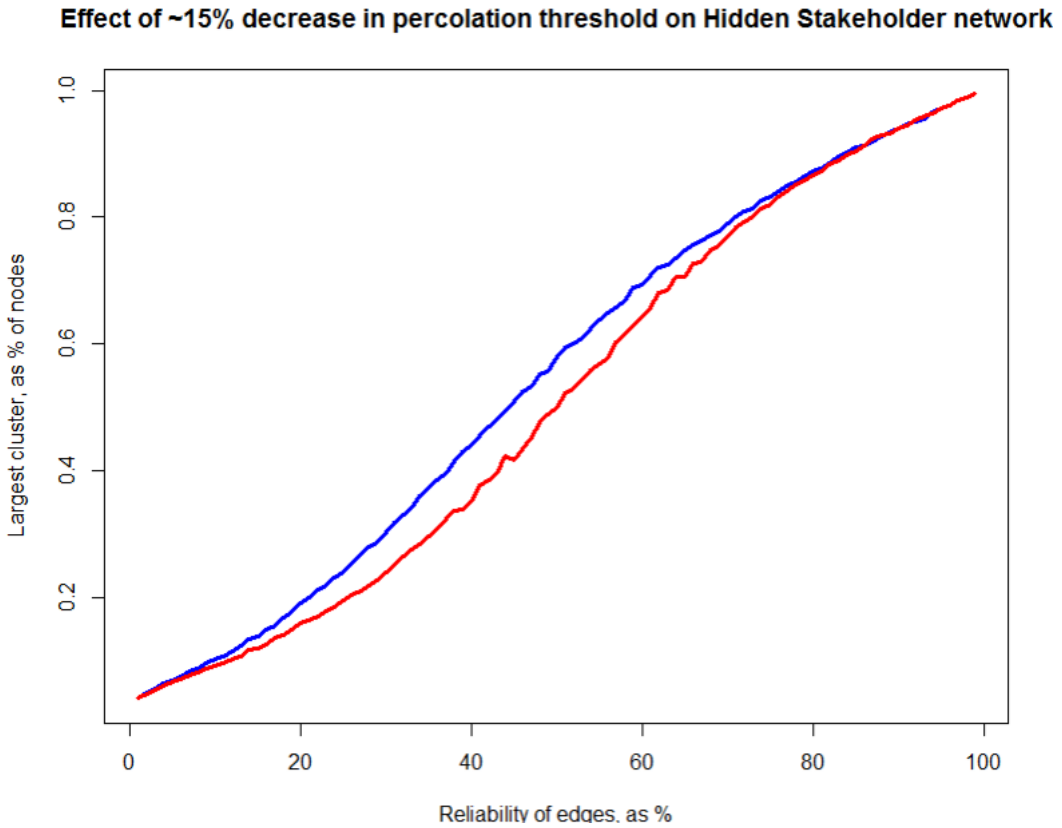

Figure 4-21: Hidden Stakeholder Network, Percolation Threshold Decrease Effects

4.3 Empirical Analysis of OEX 100 Stakeholder Networks

In this third and most important validation phase, the methodology developed in Chapter 3 was applied to 101 massive real-world stakeholder networks.

4.3.1 Independent Variables

Using the Bloomberg API, supply chain data was captured computationally using the SPLC module at the end of June 2019 for supplier, customer, peer, and investor relationships for the OEX 100. The complexity of these networks is shown by the fact that a universe of only 100 firms was found to have ~60,000 unique primary and secondary stakeholder relationships, when using a low 1% cutoff for supply chain and ownership relationships. The dynamism of these networks is demonstrated by the fact that comparison with an earlier database query in January 2019, yielding ~65,000 unique relationships, shows that ~35,000 relationships were created or ended in the SPLC database in six months. Stakeholders with power, urgency or legitimacy were then identified for each OEX 100 firm and their direct partners, using the parameters discussed above, resulting in 101 discrete complex stakeholder networks (Alphabet Inc., the parent company of Google, has two different listings). Network topology statistics were measured using Mathematica's graph theory and linear algebra functions for each of these networks, as described in the methodology, along with the number of stakeholder nodes and edges, and market capitalization at the end of the second quarter of 2019, as obtained from the Bloomberg API. These may be illustrated by examining the features of a single stakeholder network, for the retailer Amazon, in Table 4-3:

	#Nodes	#Edges	Perc. Threshold	Assortativity	Transitivity	Mkt Cap (ln)	Density
AMZN	14	24	0.30	-0.44	0.49	27.56	0.26

Table 4-3: Network Topology Metrics/Predictors for Amazon

As shown graphically above, in Figure 3-18, Amazon has a small and sparse network, which makes a sense, given the size and dominance of the firm, with relatively negative degree correlation, and relatively high percolation threshold, meaning it is less connected and resilient. Amazon's distinctiveness emerges in comparison with summary statistics for all 101 networks in Table 4-4:

N=101	#Nodes	#Edges	Perc. Threshold	Assortativity	Transitivity	Mkt Cap (ln)	Density
Mean	25.29	157.10	0.13	-0.14	0.68	25.49	0.44
SD	15.11	174.62	0.09	0.20	0.19	0.81	0.20
Min	8	12	0.03	-0.60	0.26	24.23	0.13
Max	98	790	0.38	0.33	0.97	27.66	0.96

Table 4-4: Summary Statistics for OEX 100 Network Topology Metrics/Predictors

These independent variables are given for all 101 OEX100 stakeholder networks in Appendix C. The network topology metrics in Table II show a significant spread, both in terms of standard deviation and range, suggesting that percolation threshold, degree correlation and clustering have the potential to serve as levers to improve the performance of a stakeholder network. Because these measures, unlike density, do not have a readily intuitive physical interpretation, a standardized coefficients approach to testing the research hypotheses seems useful, translating predictor and response variables into scaled versions with means zero and unit standard deviations (Chatterjee et al. 2000, 243). By showing the change, in standard deviations in the dependent variable, induced

by a one standard deviation change in the independent variable, not only statistical but scientific significance can be measured, offering managers, strategists, and systems engineers insight into the leverage they have over their stakeholder system.

Summary statistics show unexpectedly low levels of degree correlation, for social networks, suggesting that supply chain and investor networks may have characteristics of technical networks, which are characterized by negative degree correlation, and that they may be improved by making them more "social" and less "technical", raising assortativity when possible (Chen et al. 2007), (Newman 2002), (Newman and Park 2003). Some also show very high levels of density, which is notable, since real-world networks are usually sparse, with density <.5 (Radicchi 2015), which suggests that there is likewise potential for using density as a leverage point. The often-observed association between density and clustering in networks, as discussed in Newman 2003 "Properties of highly clustered networks", is confirmed by the correlations in Table 4-5:

N=101	#Nodes	#Edges	Perc. Threshold	Assortativity	Transitivity	Mkt Cap (ln)	Density
#Nodes	1.00	0.83	-0.59	0.31	0.00	0.16	-0.20
#Edges	0.83	1.00	-0.66	0.36	0.37	-0.08	0.25
Percolation Threshold	-0.59	-0.66	1.00	-0.46	-0.59	0.05	-0.40
Assortativity	0.31	0.36	-0.46	1.00	0.25	0.03	0.06
Transitivity	0.00	0.37	-0.59	0.25	1.00	-0.26	0.83
Mkt Cap (ln)	0.16	-0.08	0.05	0.03	-0.26	1.00	-0.35
Density	-0.20	0.25	-0.40	0.06	0.83	-0.35	1.00

Table 4-5: Correlations for OEX 100 Network Topology Metrics/Predictors

The percolation threshold is represented here only by $\hat{p}$, although its correlation with $\bar{p}$ was 0.996, according with predictions made in the network science literature

(Karrer et al. 2014), as does the high correlation between the $\hat{p}$ and assortativity (Chen et al. 2007), (Newman 2002), (Newman and Park 2003).

4.3.2 Diagnostics and Model Verification

The high correlation between density and clustering was a cause for possible concern, due to the risk of multicollinearity between predictors. However, the condition number κ of the 5x5 correlation matrix for the predictor variables, excluding the edge and node totals, was found to be 4.31, well below the threshold value of 15, above which the harmful effects of collinearity become strong, where

$$\kappa = \sqrt{\frac{maximum\ eigenvalue\ of\ correlation\ matrix}{minimum\ eigenvalue\ of\ correlation\ matrix}} = \sqrt{\frac{\lambda_1}{\lambda_5}} \qquad (4.1)$$

as defined in (Chatterjee et al. 2000, 245-6).

Additionally, for all linear regression hypotheses tests presented below, variance inflation factors (VIF) were calculated, with the maximum VIF found to be 2.15, also well below the threshold value of 10 implying collinearity (ibid, 240), (Basole et al. 2018). Further diagnostics performed included the Shapiro-Wilkes test to estimate the normality of residuals in the hypotheses tests and the Breusch-Pagan test of their homoscedasticity. For all 12 tests presented below, the null hypotheses of normality of error terms and constant variance of error terms could not be rejected at the .05 level. Furthermore, QQ plots of residuals were examined for each of the hypotheses tests, although in practice it was found that there was a high degree of agreement between visual inspection using QQ plots and the Shapiro-Wilkes tests.

A robust regression approach, following Maronna et al. 2019, was undertaken to confirm that the linear regression results given below were not due to outliers exercising outsized influence. This was felt to be especially important, give the wide dispersion in stakeholder network size. Analysis across a wide variety of dependent variables showed that the relationships identified by linear regressions were confirmed by robust regressions, and that the significance of the tests suffered little, as shown in Figures 4-19 and 4-20. As can be seen by comparing the R-squared metrics in Figures 4-19 and 4-20 to those in Table 4-6, greater explanatory power was gained by adding a sector dummy variable as a predictor. Robust regression on these expanded models, not shown, confirmed the results presented below.

PERFORMANCE METRICS OF OEX 100 LARGEST US-LISTED FIRMS' STAKEHOLDER NETWORKS, ANALYZED WITH BOTH LINEAR AND ROBUST REGRESSION MODELS[a]

Linear Regression/ Robust Regression coefficients & p-values	Constant	Percolation Threshold[c]	Degree Correl.	Clustering[c]	Market Cap.[b]	test p-value	test R^2
ESG rating (absolute)	76.444**	-27.847**	4.677	-13.168***	0.133	0.001***	0.145
	59.223*	-24.322**	3.742	-11.276**	0.733	0.002**	
ESG rating (relative)[c]	-1.001	-0.123	0.313*	-0.13	0.063	0.02*	0.078
	-1.373	-0.152	0.315*	-0.117	0.078*	0.018*	
5yr Avg Erngs Yield[b,c]	0.71***	-0.175***	-0.048	-0.061**	-0.015*	0.004**	0.123
	0.567***	-0.145**	-0.039	-0.041*	-0.01	0.023*	
Fwd Est Erngs Yield[b]	1.374***	-0.155*	-0.024	-0.077*	-0.036***	.000***	0.198
	1.329***	-0.156*	-0.023	-0.077*	-0.035***	0.001***	
Current Earnings Yield[b]	1.198***	-0.146*	-0.058	-0.078*	-0.03***	0.001***	0.15
	1.145***	-0.145*	-0.047	-0.08**	-0.028***	0.002**	

Figure 4-22: Linear and Robust Regressions on OEX 100 Stakeholder Networks I

Net Operating Profit[b,c]	-52.093***	-6.305*	-1.011	-3.201*	3.422***	.000***	0.571
	-55.174***	-6.183*	-0.839	-3.037*	3.543***	.000***	
Forward Est Div Yield[c]	11.925***	-2.768**	-0.317	-0.775*	-0.353***	.000***	0.168
	12.526***	-2.445**	-0.239	-0.769*	-0.38***	.000***	
10yr Tot Rate Return[b,c]	-30.194***	3.941	-3.077*	3.788**	1.367***	.000***	0.222
	-28.129***	4.978	-2.128	3.361**	1.288***	.000***	
Relative Debt Service[b,c]	38.733***	-4.159.	-2.426*	-1.18	-1.215***	.000***	0.218
	39.481***	-4.208	-2.382*	-1.173	-1.241***	.000***	
WACC[c]	-7.141*	3.766**	1.369*	0.736	0.379**	0.001***	0.149
	-6.448	3.641**	1.33*	0.771	0.353**	0.002**	

*p < .05, **p<.01, ***p<.001
[a] Linear regression results presented first, robust regression results second. R^2 is only for linear regression model. All tests fail to reject null hypotheses of normality (Shapiro-Wilkes test) and homoskedasticity (Breusch-Pagan test) of residuals, at .05 level, and do not show multicollinearity (max variance inflation factor for all tests is <2).
[b] variable is log transformed, [c]variable is power transformed, to unskew data.

Figure 4-23: Linear and Robust Regressions on OEX 100 Stakeholder Networks II

Additionally, these findings, using stakeholder networks and performance metrics gathered at the end of Q2 2019, broadly confirm initial empirical analyses undertaken at the beginning of Q1 2019. Finally, improvement in the stakeholder satisfaction categories of ESG performance, financial yield, and risk, all highlighted in the literature, were hypothesized from the outset, based on recurrent themes in the literature. The parameters for inclusion in the stakeholder system, the quantitative cut-offs determining stakeholder legitimacy, power, or urgency, were not experimented with, to prevent data dredging.

4.3.3 Hypotheses Tests

Incorporating market capitalization and sector categorical variables, to control for size and industry effects, models of stakeholder performance, without and with density, are given in Table 4-6:

Dependent Vars. (Box-Cox Trans.)	Percol. Threshold	Degree Correl.	Clustering	Mkt. Cap.	Den-sity	Raw R^2	Adj. R^2	Baseline Adj. R^2
1.ESG average	-0.37**	0.09	-0.52***	-0.08		0.46	0.39 (III)	0.24 (I)
(absolute) ***	-0.37**	0.10	-0.56**	-0.08	0.05	0.46	0.38 (IV)	0.28 (II)
2.ESG average	0.00	0.28*	-0.20	0.06		0.29	0.20 (III)	0.16 (I)
(relative) **	0.00	0.30*	-0.28	0.07	0.11	0.30	0.20 (IV)	0.15 (II)
3.ESG Soc	-0.29*	0.06	-0.32**	-0.12		0.43	0.36 (III)	0.30 (I)
(absolute) ***	-0.29*	0.03	-0.17	-0.15	-.019	0.44	0.36 (IV)	0.33 (II)
4.ESG Env	-0.06	0.28*	-0.26*	0.13		0.36	0.28 (III)	0.22 (I)
(relative) ***	-0.06	0.30**	-0.42*	0.16	0.20	0.38	0.29 (IV)	0.22 (II)
5.WACC ***	0.35**	0.10	0.33**	0.24*		0.47	0.40 (III)	0.33 (I)
	0.34**	0.13	0.17	0.27**	0.20	0.48	0.40 (IV)	0.36 (II)
6. Risk Pre-	0.22*	0.07	-0.02	-0.08		0.53	0.46 (III)	0.44 (I)
mium ***	0.22*	0.05	0.09	-0.10	-0.13	0.53	0.46 (IV)	0.45 (II)
7. Relative Cost	0.34**	0.11	0.34**	0.28**		0.47	0.39 (III)	0.33 (I)
of Equity ***	0.34**	0.14	0.15	0.31**	0.23	0.48	0.40 (IV)	0.36 (II)
8.Invested	-0.20	0.11	-0.38**	0.24*		0.45	0.37 (III)	0.31 (I)
Capital (ln) ***	-0.20	0.06	-0.13	0.20*	-0.30	0.47	0.39 (IV)	0.38 (II)
9.Est. Divi-	-0.44***	-0.14	-0.22	-0.24*		0.34	0.25 (III)	0.17 (I)
dend Yield ***	-0.45***	-0.11	-0.42*	-0.21	0.24	0.35	0.25 (IV)	0.16 (II)
10.Operating	-0.11	0.05	-0.29***	.74***		0.70	0.65 (III)	0.62 (I)
Profit (ln) ***	-0.11	0.04	-0.18	.72***	-.14	0.70	0.66 (IV)	0.65 (II)
11.EBITDA	-0.25	-0.02	-0.36**	-0.36**		0.37	0.28 (III)	0.23 (I)
Yield (ln) ***	-0.26*	-0.08	-0.06	-.39***	-0.38*	0.41	0.32 (IV)	0.31 (II)
12.Ten Year	0.24*	-0.26*	0.45***	.39***		0.46	0.37 (III)	0.24 (I)
TRR ***	0.24*	-0.25*	0.36*	.41***	0.12	0.46	0.37 (IV)	0.28 (II)

*p < .05, **p<.01, ***p<.001. All tests are significant at .00*** level, except for 2., at the .00** level.
Industry dummy variables included in all tests (8 categorical variables, for 9 sectors).
Baseline model I: $Performance_i = \beta_0 + \beta_1 \ln(Mkt\ Cap_i) + \beta_2\ Industry_i$
Baseline model II: $Performance_i = \beta_0 + \beta_1 \ln(Mkt\ Cap_i) + \beta_2\ Industry_i + \beta_3\ Density_i$

Table 4-6: Performance Metrics of OEX 100 Firms' Stakeholder Networks

Linear Regressions with Standardized Coefficients

As discussed in the methodology, Tests 1-4 measure the ability of the central entities to satisfy the non-financial claims of stakeholders, as proxied by absolute and relative ESG measures obtained from the Sustainalytics business intelligence database. Tests of absolute social and sector-relative environmental scores are shown, to highlight differences in models when looking at different aspects of ESG performance. Higher scores in these measures suggest both better ESG performance per se, and a stronger stakeholder orientation generally. Tests 5-8 are measures of risk. Firms with a higher weighted average cost of capital (WACC), higher equity risk premium, and a higher relative cost of equity, measured as the cost of equity times the percentage of firm capital held as equity, are riskier and less able to cheaply finance new projects and investments, constraining their ability to respond dynamically to new developments, hurting stakeholders. Firms with lower levels of paid-in capital, controlling for market capitalization, are less able to finance projects internally and have more leverage, also increasing risk to stakeholders (Penman 2011).

Tests 9-11 are measures of financial performance, showing expected returns to financial stakeholders as a function of both future dividend flows and earnings yield (where only firms with a positive price/earnings ratio were included in the sample), controlling for market capitalization. Expected financial yield is also important to non-financial stakeholders, and higher scores on these measures also indicate a more effective stakeholder orientation.

Finally, Test 12, measuring the total rate of return from holding the firm's equity over the preceding ten-year period, both from asset appreciation and dividends, is not, properly speaking, a measure of stakeholder satisfaction, as it is not a forward-looking

measure of yield, risk, or non-financial performance. Rather it records the firm's historical equity risk premium, and may evidence a greater shareholder, as opposed to stakeholder, orientation on the part of management (Freeman et al. 2018), (Freeman et al. 2010) as well as indicating a still-maturing organization not yet past its growth phase.

Since the slopes on the independent variables are standardized coefficients, showing the change in the response variable, in standard deviations, effected by a one standard deviation increase in the predictor, the intercept, having no variance, is not displayed. In order to show the increase in explanatory power provided by looking at complex network statistics and density, the adjusted R^2 for the complex network statistics model without density (Model III) and with density (Model IV) is compared with, respectively, a baseline model incorporating only size and industry effects (Model I), and a baseline model including size, industry, and density (Model II).

This comparison shows evidence that the density of an organization's stakeholder network influences how the central entity will satisfy the claims of its stakeholders, a common theme in the existing stakeholder literature, as discussed above All tests except for 2,4, and 9 show an increase in explanatory power from including density, adjusting for the number of predictors, comparing Model I to II for adjusted R^2.

However, even greater explanatory power is achieved by supplementing density with network statistics, as the adjusted R^2 of Models III and IV are higher than their baselines in all cases, and Model III outperforms Model II in all tests except 8, 10 and 11. These tests support findings in the supply chain network literature connecting density with increased ability to capture value in the supply chain, with a higher profit margin and return on asset base, and lower inventory levels (Basole et al. 2018). Yet here the

interpretation is different: controlling for market capitalization, entities with lower invested capital and earnings yield are riskier and have lower expected risk-adjusted future yield, and their increased market value is largely a function of financial leverage (Penman 2011).

For all relationships significant at .05 level and below, a clear pattern emerges. Firms with stakeholder networks that are more connected and resilient, as measured by a lower percolation threshold, more degree assortative, and less clustered are more effective in meeting the financial and non-financial performance requirements of their stakeholder systems, as shown by Tests 1-11. They score higher in ESG metrics, are less risky, have higher expected dividend and earnings yields, and have higher operating profits and broader asset bases, controlling for their market capitalization and sector. That said, they are not growth stocks, as indicated by Test 12, showing their lower asset appreciation over the last 10 years. Rather, they have the hallmarks of mature firms, built to last, that have emerged from the dangerous growth stage with a stakeholder orientation, becoming more resilient and connected, while seeing the nature of their stakeholder network move from being characterized by clustering to assortativity, moving from local to global connectedness. This accords with findings in the product development literature, establishing that transitivity, like density, is highest at the detailed design phase, being lower both in the initial planning and later integration and implementation phases (Collins et al. 2010), (Parraguez et al. 2015). More generally, this accords with the large literature referenced above associating increased stakeholder interaction with system survivability and shows that managers can use network topology as a source of leverage to improve outcomes.

Chapter 5. Conclusion

5.1 Applications to Stakeholder Management

This empirical research studied the business firm as the paradigmatic example of a complex, stakeholder-driven organization (Freeman et al. 2018), (Freeman et al. 2010), (Parmar et al. 2010), and thus has general application for all those charged with managing for stakeholders in complex domains. It suggests that managers should not only adopt a network-centric mentality, to understand how value is created through interlinked webs of communication and exchange between stakeholders, but also analyze those networks, by measuring the global network topological characteristics identified here, and even seek to control them. For instance, firms such as Toyota succeed by increasing the density of their supply chains, encouraging collaboration between suppliers (Dyer and Singh 1998), (Basole et al. 2018). The novel contribution of this research is to show that improved performance is similarly possible for stakeholder-driven organizations by managing characteristics of their networks other than density. Density after all may be exogenous, beyond the control of many organizations, who, lacking the market power of Toyota, cannot simply enforce enhanced collaboration between stakeholders, especially given the costs of collaborative overload (Neches and Madni 2012). Rather, managers can identify beneficial nodes and edges in their stakeholder network as those contributing positively to resilience and degree correlation, while lowering or at least not increasing clustering in the network, prioritizing their requirements or needs, deriving valuable stakeholder weightings, as in (Cameron et al. 2011), (Garber et al. 2017). Given the patterns identified here, adding any stakeholder or stakeholder relationship meeting those criteria will Pareto improve the stakeholder network, other things being equal. Likewise,

any node or edge deletion that lowers resilience and degree correlation, while raising clustering, will Pareto impede the network. This can be used as a tool to identify and even rank key stakeholders and stakeholder relations, an important goal of stakeholder management (de Gooyert et al. 2017).

Although more efficient algorithms have been developed as part of this research, not presented here, harmful node and edge deletions can be identified with a simple enumerative approach. Using the methodology outlined above, it is straightforward to measure $\hat{p}$,r and C after the deletion of the m^{th} stakeholder node, for all m stakeholders in the network, or n^{th} stakeholder relationship, for all n edges in the network. This approach was exampled in Section 4.2, modifying the Hidden Stakeholder network of Wood et al. 2012. Those deletions which raise $\hat{p}$ (lowering resilience), lower r or raise C, whether accomplishing all three or only a subset (if leaving other measures unchanged), identify stakeholders or interactions which should be targeted for reinforcement and defense. Similarly, unhelpful relationships whose deletion Pareto improves the network could be given fewer resources, targeted for removal, or even rewired, redirecting relationships where possible to promote resilience, as has been suggested in the case of supply chains (Zhao et al. 2019). Rewiring algorithm approaches using network topology measures have also been developed as part of this research, also, but are not presented here. While common in network science, such rewiring strategies must be applied with care to engineered systems, as discussed in 2.3.3 (Alderson 2008), (Parraguez et al. 2015), (Zhao et al 2019). In similar fashion, helpful edge (but not node) additions can be identified from the $\binom{m}{2}$ - n potential stakeholder interactions not present.

One practical and intuitive way for engineering managers and systems engineers to explore re-wiring their stakeholder network is through an organizational DSM, as discussed above in Section 2.3.3. Stakeholder management strategies rooted in the complex network topology analysis given here could even be translated to tools such as Excel, via Visual Basic macros, and then used to analyze two-dimensional DSM's, providing managers with little time for network science, but extensive experience with spreadsheets, a simple and familiar tool. For instance, the Hidden Stakeholder network of Wood et al. 2012, discussed in Section 4.2, would be depicted as follows in a DSM, in Figure 5-1, demonstrating its relative ease of use.

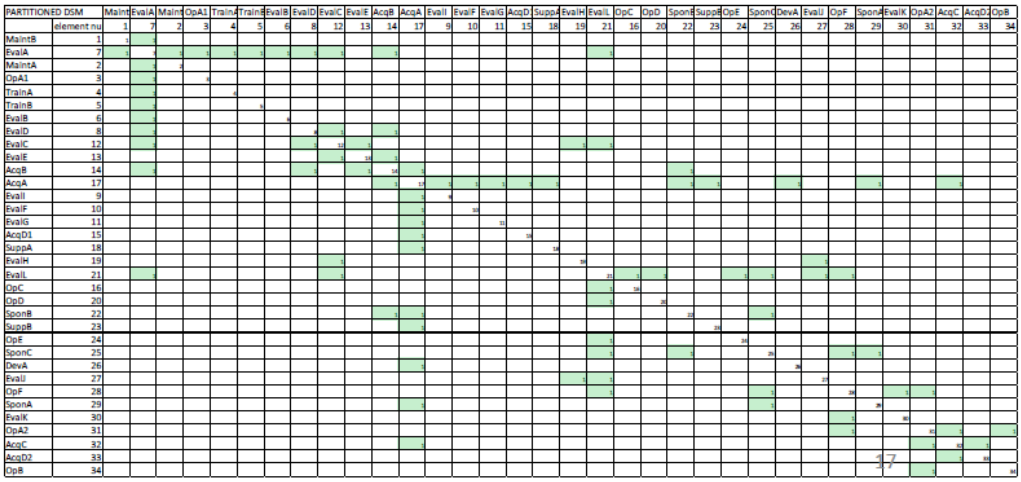

Figure 5-1: DSM Representation of the Hidden Stakeholder Network

Relative weightings between the individual network topology characteristics of resilience, degree correlation and clustering are necessary to strictly rank stakeholder management strategies and are a promising area for future research. However, as the Amazon stakeholder network example used above shows, it is often possible to identify harmful edge deletions and helpful edge additions that Pareto improve or impede the

network on all three measures. Of the 67 possible edge additions to the 14-node Amazon network, 12 potential edges can be identified that improve the network on all three measures, with, however, no single strategy Pareto-dominating the others. All are potential links between peers excluding the online marketplace eBay, such as Alibaba, and either a) Liquidity Services Inc. (LQDT), a major reverse supply chain manager and Amazon's sole customer here, with over 40% of its COGS coming from Amazon, or b) the suppliers Micron Technologies (MU) and United Natural Foods Inc. (UNFI), vendors heavily tied to Amazon's Web Services and Whole Foods divisions, respectively. On the other hand, only two existing ties, those between eBay and the institutional money managers Vanguard and Blackrock, contribute beneficially to the network on all three measures, and thus are clear candidates for reinforcement. Concretely, this might mean that the best edge-protection strategy would be for a major shareholder such as Blackrock, which has publicly committed itself to a stakeholder-centric orientation (Govindarajan and Srivastava 2020), to use its leverage to ensure that eBay remains a publicly traded company, and thus linked to Blackrock, rather than being acquired by a peer or private equity firm, since the loss of this relationship would be the single worst edge deletion. The best edge-addition strategy, meanwhile, might be to encourage LQDT to diversify its supply chain, to create tie-ups with Amazon competitors such as Alibaba.

These two stakeholder management strategies were used as the basis for the improved and impeded networks used in Figures 3-15 and 3-16 above, and are visualized in Figure 5-2, with resulting network metrics given in Table 5-1 below. This research thus demonstrates a novel methodology for analyzing and managing large, complex real-world stakeholder networks, establishing a theoretical framework for understanding and

even predicting how the character of their interactions, translated into global network topology statistics, affects their ability to deliver value, while offering to managers tangible strategies and leverage points to improve and maintain their performance.

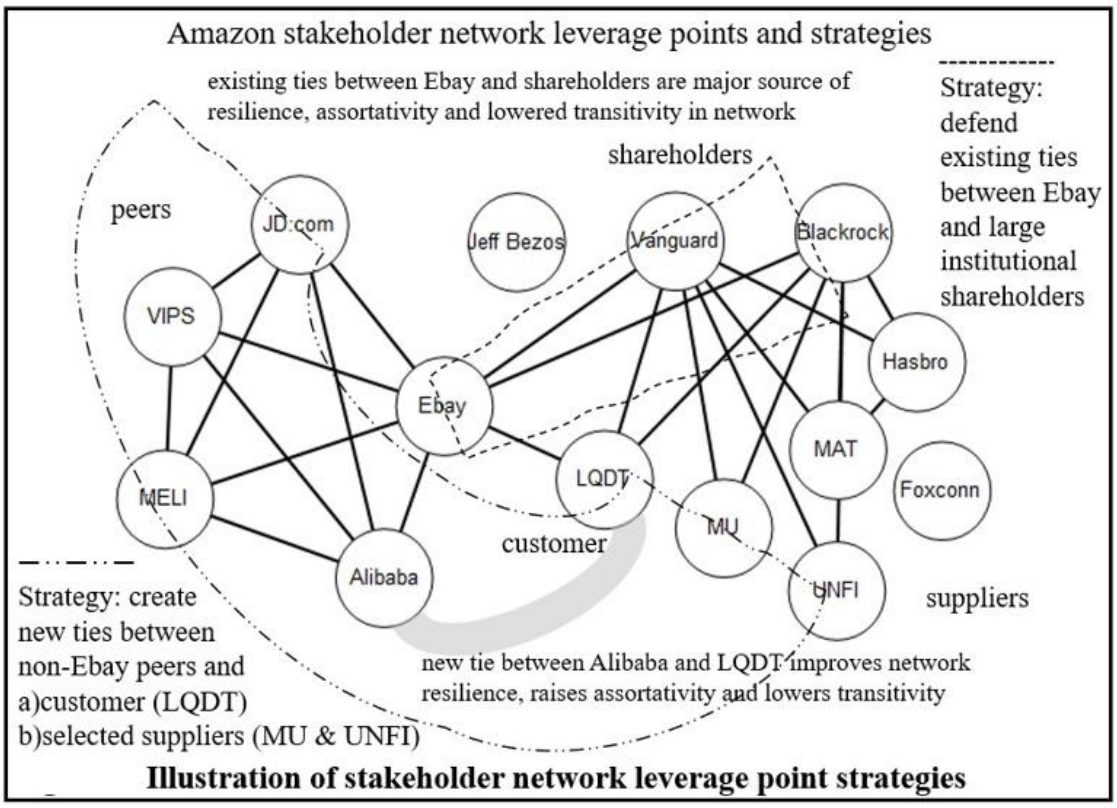

Figure 5-2: Amazon Stakeholder Leverage Point Strategies

Stakeholder network strategy	#Edges	Perc. Thresh.	Degree Corr.	Clustering	Density
Leave unchanged	24	0.30	-0.44	0.49	0.26
Improve, adding new peer (ex-eBay) link to LQDT (4 options)	25	0.28	-0.37	0.48	0.27
Improve, adding new peer (ex-eBay) link to MU/UNFI (8 options)	25	0.29	-0.42	0.46	0.27
Impede, by deleting link from eBay to Blackrock/Vanguard (2 options)	23	0.32	-0.52	0.52	0.25

Table 5-1: Topology Metrics for Improved and Impeded Amazon Networks

5.2 Future Research Directions

In the course of this research, a number of future research directions have been identified, as discussed in Hill et al. 2021. As mentioned above, further work on rewiring complex network seems promising. Applied work in mathematical epidemiology has developed rewiring algorithms, switching edges to make simulated graphs more social and less technical, and thus more likely to facilitate epidemics (Ball et al. 2013), (Youssef et al. 2013). However, additional understanding is needed to rewire real-world stakeholder systems, which are sparse, heterogeneous, weighted, and constrained by economic, legal, and other considerations. While Pareto-improving rewiring was often found possible in OEX100 stakeholder networks, raising assortativity and resilience without increasing clustering, this is by no means assured, and further research is necessary to perform trade-offs between graph topological measures.

Further, while the causes and benefits of decreased clustering in social networks are well known, going back to long-standing concepts of brokerage, structural holes, and the strength of weak ties in sociology (Nohria and Eccles 1992), (Centola 2018), this is not so for assortativity. Recent research, however, has identified a key dynamic in the rise of degree clustering within a network, suggesting another source of leverage for leaders looking to improve their organization's stakeholder network (Sendina-Nadal et al. 2016). It has been discovered that in real-world social networks, assortativity often arises from new entrants into the system who initially exhibit anti-preferential attachment, reversing the more common dynamic whereby networks grow by connecting new entrants to already highly connected nodes (Barabasi and Posfai 2016, ch.5). Preferential attachment between the most important, connected nodes was already known to be a source of both

increased resilience and assortativity (Newman 2002), meaning that leaders in the stakeholder network should be encouraged to communicate and collaborate with each other, at the expense of their relations with less important follower nodes. Sendina-Nadal et al. show that leadership itself emerges from new entrants to the system purposely connecting with less important follower nodes. Managers looking to improve the topological properties of their stakeholder networks organically should thus consider encouraging new entrants who will form links with more marginal stakeholders.

This novel finding is supported here by the fact that the empirical analysis in Section 4.3 showed significant correlation between the number of nodes in the stakeholder network and both $\hat{p}$ (ρ= -.59) and r (ρ= .31). Meanwhile, there was a complete lack of correlation between number of nodes and clustering (ρ= .00). This suggests that a way to improve a stakeholder network's topological characteristics is simply to make it larger and more inclusive, adding stakeholder nodes that would increase global connectivity rather than local density, according with the literature on the advantages of stakeholder diversity and diversification (Francoeur et al. 2017), although more must be done to understand the underlying network science.

Additionally, the effect on stakeholder performance metrics of other firm differentiators, such as innovativeness, research intensity, or capital intensity, beyond size and industry effects, could be explored, as in (Basole et al. 2018). While parameters for inclusion in the stakeholder system were not experimented with, to prevent data dredging, sensitivity analysis on these parameters could be a potential area for investigation. Other potential research avenues include expansion of the focal firm universe, beyond the large-cap stocks studied here, and the extension of this methodology to stakeholder systems

beyond those of publicly traded firms, such as non-profit and government entities, engineered systems and intra-firm or intra-agency projects. Additional mathematical approaches could be employed, for instance network optimization models from operations research, or Ising models from physics. Finally, the effects of clustering and degree correlation in real-world networks are still not fully understood (Sendina-Nadal et al. 2016). Additional properties such as modularity could be incorporated in the approach developed here. It is hoped that further advances in network science will be readily applied to the management of complex stakeholder systems.

5.3 Application to Managing in a Post-Covid World

As discussed in Hill et al. 2021, the particular challenge of the Covid-19 pandemic is three-fold. The first is one applying to epidemic contagions generally: they spread along social networks, which are robust, adaptive, and efficient, but we seek to defeat them with hierarchical, technical organizations, such as the Centers for Disease Control and Prevention or World Health Organization, which show characteristics of technological networks, and are thus inherently less resilient and more liable to break down in a crisis situation, as established above, following Newman 2002. The organizational resilience concern "is particularly salient for large and often multi-national organizations with broad mission requirements," since "such organizations with operational and organizational complexity are increasingly exposed to systemic threats, where a disruption to one component of an organization's systems can trigger losses and disruptions throughout the larger organizational body" (Linkov 2018). We thus need ways of making the collaboration networks within technical organizations more social, and less technological, in a post Covid-19 world.

Second, the extremely high transmissibility of the novel coronavirus, with the attendant social distancing requirements, means that we cannot easily architect new social networks to combat its spread. This is because innovation and diffusion of innovation initiatives are themselves "complex contagions", requiring thicker webs of personal interaction and teamwork than broadcast communication mediums such as Zoom can provide (Centola 2018), (Batallas and Yassine 2006), and so we must seek out the distinctive characteristics of successful virtual teams and innovation networks (Bellamy et al. 2014).

Third, the unparalleled breadth of the pandemic's impact means that managers must respond to an even wider range of diverse, disparate stakeholder populations than normal. Managers are facing unprecedented challenges precisely because of the potential second-order network effects of doing business as usual during a global pandemic on unseen, unknown stakeholders. Tools and methods for identifying and accessing such "hidden" stakeholders are thus necessary (Mitchell et al. 1997), (Wood et al. 2012).

The net result is that organizations need to re-think their network structure, to better serve and interact with their stakeholder constituencies, choosing configurations that are both more efficient and less dense than commonly found in social networks in real-world managerial environments. The research described above offers a path forward for this. Moreover, the complex stakeholder network perspective developed here demonstrates the need to embrace an inclusive stakeholder orientation, to better counter the pandemic's unprecedented breadth of impact, especially its second-order network effects on unseen, hidden stakeholder populations, while being mindful of the ways in which the Covid-19 pandemic has impacted our modes of group sense-making.

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APPENDIX A: Network Representations of DSM's in Eppinger and Browning 2016

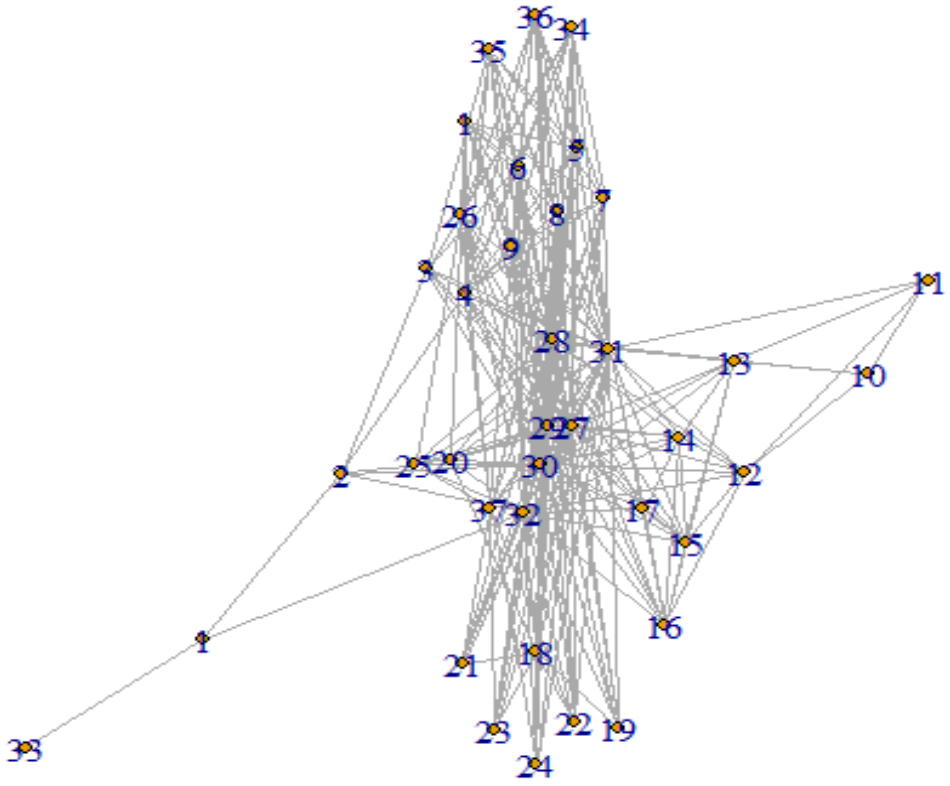

Figure A-1: Mars Global Surveyor DSM in Network Form

(DSM given in Eppinger and Browning 2016, Section 3.4, pp.49-53, based on Brady 2002)

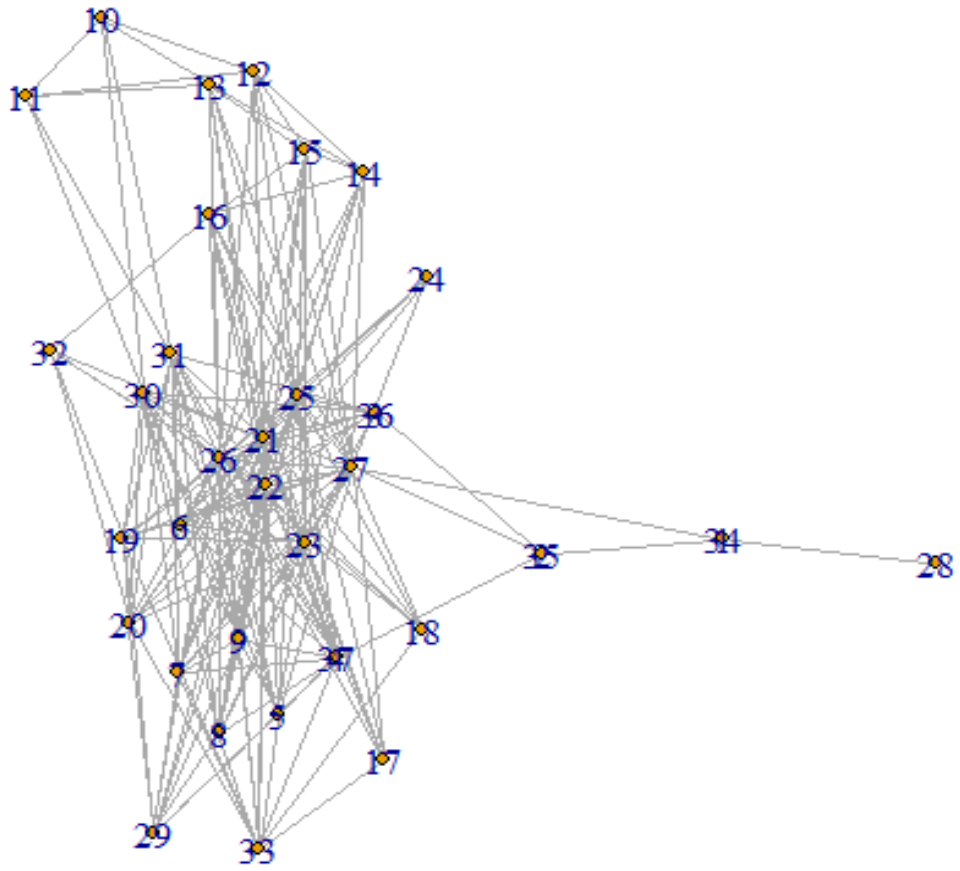

Figure A-2: Mars Climate Orbiter DSM in Network Form

(DSM given in Eppinger and Browning 2016, Section 3.4, pp.49-53, based on Brady 2002)

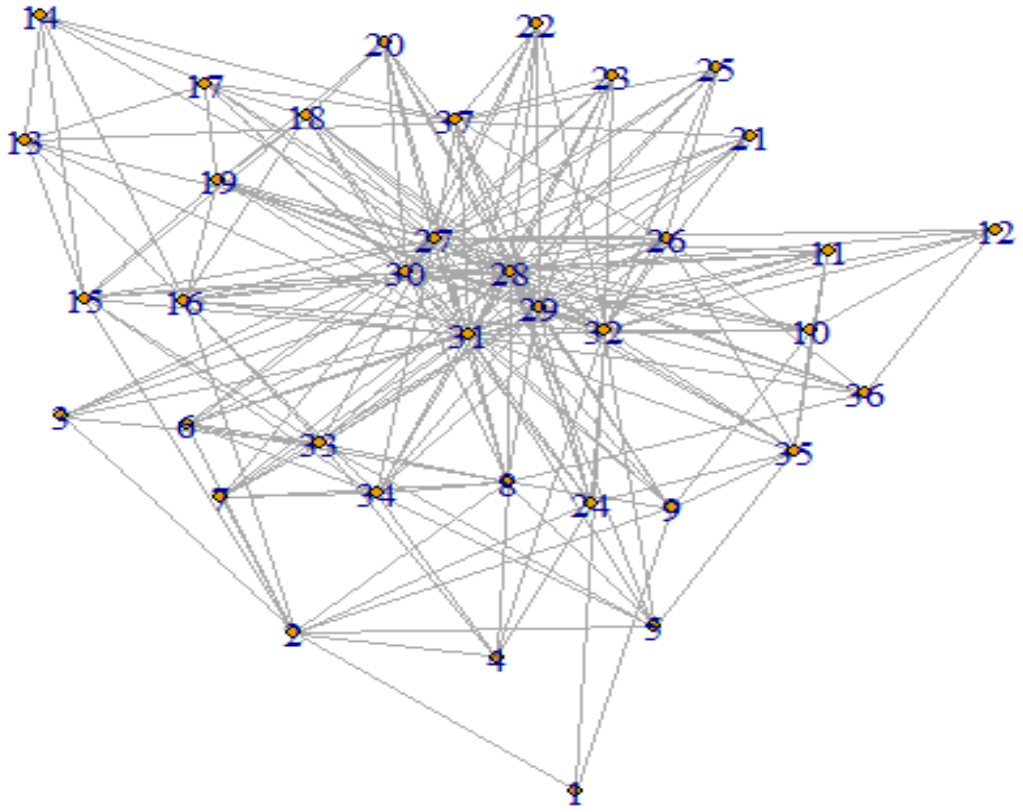

Figure A-3: Mars Polar Lander DSM in Network Form

(DSM given in Eppinger and Browning 2016, Section 3.4, pp.49-53, based on Brady 2002)

Appendix B: Code for calculating clustering and degree correlation in R

```
> library(igraph)
> vertices=20
> edges=50
> ergraph<-sample_gnm(vertices,edges,directed = FALSE, loops =FALSE)
>
> root_node<-NA
> intermediate_node<-NA
> final_node<-NA
> root_node_degree<-NA
> neighbor_node_degree<-NA
> open_triangle<-NA
> closed_triangle<-NA
> counter=0
> counter2=0
> for (i in 1:vertices) {
+   for (j in (1:length(as_ids(neighbors(ergraph,i))))){
+     counter=counter+1
+     root_node_degree[counter]=degree(ergraph,i)
+     neighbor_node_degree[counter]=degree(ergraph,as_ids(neighbors(ergraph,i))[j])
+     for (k in (1:length(as_ids(neighbors(ergraph,as_ids(neighbors(ergraph,i))[j]))))){
+       counter2=counter2 + 1
+       root_node[counter2]=i
+       intermediate_node[counter2]=as_ids(neighbors(ergraph,i))[j]
+       final_node[counter2]=as_ids(neighbors(ergraph,intermediate_node[counter2]))[k]
+       if (i==final_node[counter2]){
+         open_triangle[counter2]=0
+         closed_triangle[counter2]=0}
+       else if (are.connected(ergraph,i,final_node[counter2])){
+         open_triangle[counter2]=0
+         closed_triangle[counter2]=1}
+       else {
+         open_triangle[counter2]=1
+         closed_triangle[counter2]=0}
+     }}}
```

Figure B-1: R code for Simulating Random Networks and Measuring Network Statistics

```
> sum(closed_triangle)/(sum(open_triangle)+sum(closed_triangle))
[1] 0.2288136
> transitivity(ergraph)
[1] 0.2288136
>
> cor(root_node_degree,neighbor_node_degree)
[1] -0.1408083
> assortativity_degree(ergraph)
[1] -0.1408083
```

Figure B-2: Confirmation of Calculation Technique for Network Statistics

```
Sample R code, for generating Erdos-Renyi random graph samples and statistics
N=40
M=100
er_p_bar<-NA
er_p_hat<-NA
er_assortativity<-NA
er_transitivity<-NA
S<-NA
for (j in 1:1000) {
 er_graph<-sample_gnm(N,M,directed = FALSE, loops =FALSE)
 A<-as_adjacency_matrix(er_graph)
 A_eigen<-eigen(A, symmetric = TRUE,only.values=TRUE)[1]
 p_bar<-1/max(A_eigen$values)
 I<-diag(N)
 D<-diag(degree(er_graph))
 B<-I-D
 Z<-matrix(0,nrow=N,ncol=N)
 H<-rbind(cbind(A,B),cbind(I,Z))
 H_eigen<-eigen(H, symmetric = TRUE,only.values=TRUE)[1]
 p_hat<-1/max(H_eigen$values)
 er_p_bar[j]=p_bar
 er_p_hat[j]=p_hat
 er_assortativity[j]=assortativity.degree(er_graph)
 er_transitivity[j]=transitivity(er_graph)
 S[j]=max(components(er_graph)$csize)/N
}
er_graphstats<-data.frame(er_p_bar,er_p_hat,er_assortativity,er_transitivity,S)
plot(er_graphstats$er_assortativity,er_graphstats$er_p_hat)
plot(er_graphstats$er_transitivity,er_graphstats$er_p_hat)
```

Figure B-3: Sample R code for Generating Random Graphs

Appendix C: Table C-1 OEX100 Independent Variables

Firm	M	N	Degree Corr.	Clus-tering	pbar	phat	Sector	MKT_CAP (BN)	Density
OXY US Equity	27	106	-0.149	0.561	0.089	0.099	Energy	10.18	0.302
AXP US Equity	10	17	-0.492	0.814	0.198	0.250	Financial	71.03	0.378
MDLZ US Equity	45	664	0.095	0.918	0.029	0.030	Consumer, Non-cyclical	72.75	0.671
VZ US Equity	21	100	-0.137	0.631	0.090	0.100	Communications	223.79	0.476
BA US Equity	54	373	-0.113	0.550	0.050	0.053	Industrial	86.87	0.261
CAT US Equity	37	180	0.101	0.818	0.064	0.069	Industrial	62.92	0.270
JPM US Equity	98	790	-0.235	0.497	0.042	0.045	Financial	281.85	0.166
CVX US Equity	17	34	-0.311	0.503	0.173	0.219	Energy	136.48	0.250
EXC US Equity	43	673	0.199	0.938	0.029	0.029	Utilities	36.50	0.745
KO US Equity	31	145	0.126	0.675	0.075	0.082	Consumer, Non-cyclical	191.89	0.312
COP US Equity	21	81	-0.089	0.663	0.097	0.109	Energy	33.22	0.386
DIS US Equity	9	23	-0.416	0.853	0.167	0.202	Communications	177.06	0.639
XOM US Equity	19	26	-0.016	0.419	0.224	0.304	Energy	162.77	0.152
GE US Equity	36	101	0.077	0.556	0.103	0.117	Industrial	69.41	0.160
AMZN US Equity	14	24	-0.437	0.488	0.224	0.299	Communications	982.74	0.264
HD US Equity	32	149	-0.275	0.638	0.079	0.087	Consumer, Cyclical	203.49	0.300
IBM US Equity	25	97	0.016	0.751	0.087	0.095	Technology	99.39	0.323
JNJ US Equity	13	39	-0.325	0.663	0.137	0.161	Consumer, Non-cyclical	346.63	0.500
MCD US Equity	13	34	-0.184	0.632	0.153	0.183	Consumer, Cyclical	124.53	0.436
MRK US Equity	18	57	0.173	0.705	0.114	0.129	Consumer, Non-cyclical	194.51	0.373
MMM US Equity	14	51	0.133	0.727	0.121	0.138	Industrial	79.48	0.560
RTN US Equity	23	158	-0.149	0.699	0.068	0.073	Industrial	37.62	0.625

BAC US Equity	83	502	-0.241	0.409	0.050	0.054	Financial	191.29	0.148
PFE US Equity	19	64	-0.068	0.617	0.113	0.129	Consumer, Non-cyclical	181.85	0.374
GOOG US Equity	29	87	0.246	0.608	0.108	0.123	Communications	798.28	0.214
PG US Equity	28	121	-0.354	0.614	0.081	0.090	Consumer, Non-cyclical	272.68	0.320
ACN US Equity	23	102	-0.106	0.705	0.085	0.094	Technology	106.62	0.403
T US Equity	26	119	-0.033	0.576	0.087	0.097	Communications	211.89	0.366
CHTR US Equity	15	25	-0.334	0.459	0.191	0.247	Communications	117.88	0.238
UTX US Equity	18	76	-0.121	0.684	0.099	0.110	Industrial	83.33	0.497
WMT US Equity	26	114	-0.119	0.669	0.089	0.098	Consumer, Cyclical	325.77	0.351
CSCO US Equity	26	78	-0.425	0.318	0.123	0.146	Communications	168.70	0.240
SLB US Equity	21	43	0.157	0.408	0.162	0.199	Energy	18.72	0.205
INTC US Equity	46	297	-0.105	0.533	0.057	0.062	Technology	230.36	0.287
MSFT US Equity	38	205	0.261	0.734	0.063	0.068	Technology	1216.11	0.292
NVDA US Equity	31	183	0.018	0.698	0.065	0.070	Technology	162.25	0.394
C US Equity	79	498	-0.259	0.435	0.050	0.054	Financial	90.52	0.162
SO US Equity	45	671	0.051	0.938	0.029	0.029	Utilities	57.80	0.678
AIG US Equity	33	358	-0.138	0.939	0.039	0.041	Financial	21.63	0.678
HON US Equity	18	56	-0.249	0.553	0.128	0.149	Industrial	95.34	0.366
MO US Equity	31	229	0.059	0.812	0.054	0.057	Consumer, Non-cyclical	71.99	0.492
GS US Equity	18	71	-0.303	0.764	0.098	0.110	Financial	56.24	0.464
ABT US Equity	16	41	-0.157	0.608	0.151	0.180	Consumer, Non-cyclical	139.95	0.342
BKNG US Equity	8	12	-0.600	0.769	0.240	0.321	Communications	55.92	0.429
TXN US Equity	42	248	-0.151	0.567	0.060	0.064	Technology	93.50	0.288

KHC US Equity	44	624	-0.128	0.917	0.030	0.031	Consumer, Non-cyclical	30.14	0.660
GOOGL US Equity	28	90	0.243	0.585	0.108	0.122	Communications	798.28	0.238
NFLX US Equity	9	23	-0.491	0.809	0.170	0.208	Communications	164.48	0.639
UNP US Equity	13	41	-0.112	0.574	0.141	0.167	Industrial	96.81	0.526
UNH US Equity	13	16	-0.253	0.261	0.264	0.380	Consumer, Non-cyclical	240.94	0.205
BLK US Equity	31	356	0.068	0.957	0.039	0.041	Financial	69.89	0.766
PM US Equity	29	243	-0.038	0.798	0.053	0.056	Consumer, Non-cyclical	115.26	0.599
BK US Equity	12	18	-0.594	0.362	0.245	0.336	Financial	30.25	0.273
WBA US Equity	10	18	-0.226	0.393	0.231	0.309	Consumer, Cyclical	41.14	0.400
MET US Equity	25	191	-0.239	0.918	0.054	0.058	Financial	28.51	0.637
BRK/B US Equity	46	392	0.058	0.884	0.039	0.041	Financial	448.57	0.379
ADBE US Equity	25	216	-0.093	0.874	0.052	0.055	Technology	153.54	0.720
BMY US Equity	18	60	-0.250	0.611	0.114	0.131	Consumer, Non-cyclical	126.40	0.392
AMGN US Equity	14	39	-0.233	0.518	0.148	0.177	Consumer, Non-cyclical	119.81	0.429
AAPL US Equity	36	81	-0.234	0.401	0.149	0.182	Technology	1122.27	0.129
CMCSA US Equity	16	50	-0.186	0.572	0.129	0.151	Communications	158.83	0.417
MA US Equity	19	140	-0.153	0.964	0.063	0.067	Financial	248.37	0.819
ORCL US Equity	21	137	-0.064	0.930	0.064	0.069	Technology	154.75	0.652
CL US Equity	18	88	-0.233	0.761	0.088	0.097	Consumer, Non-cyclical	56.45	0.575
ABBV US Equity	9	25	-0.459	0.818	0.162	0.195	Consumer, Non-cyclical	113.84	0.694
COST US Equity	19	61	-0.098	0.543	0.119	0.138	Consumer, Cyclical	127.47	0.357

DHR US Equity	21	90	-0.111	0.880	0.082	0.089	Consumer, Non-cyclical	96.66	0.429
TGT US Equity	22	72	-0.114	0.562	0.108	0.123	Consumer, Cyclical	47.26	0.312
DOW US Equity	17	130	-0.156	0.968	0.065	0.069	Basic Materials	21.81	0.956
CELG US Equity	11	32	-0.115	0.568	0.160	0.193	Consumer, Non-cyclical	#VALUE!	0.582
DUK US Equity	42	671	-0.066	0.937	0.029	0.029	Utilities	60.29	0.779
EMR US Equity	18	21	-0.186	0.313	0.241	0.337	Industrial	28.62	0.137
GM US Equity	26	87	-0.361	0.572	0.101	0.114	Consumer, Cyclical	30.84	0.268
KMI US Equity	10	22	-0.300	0.643	0.186	0.233	Energy	31.17	0.489
V US Equity	19	131	-0.196	0.921	0.066	0.071	Financial	324.07	0.766
GILD US Equity	13	34	-0.365	0.575	0.152	0.182	Consumer, Non-cyclical	94.21	0.436
FDX US Equity	39	377	0.229	0.926	0.039	0.040	Industrial	31.62	0.509
FB US Equity	17	25	-0.318	0.284	0.215	0.287	Communications	480.30	0.184
F US Equity	33	180	-0.220	0.666	0.067	0.073	Consumer, Cyclical	19.79	0.341
BIIB US Equity	10	14	0.155	0.698	0.239	0.321	Consumer, Non-cyclical	54.52	0.311
NEE US Equity	13	44	-0.357	0.848	0.119	0.136	Utilities	118.09	0.564
GD US Equity	23	116	-0.144	0.639	0.083	0.091	Industrial	38.40	0.458
PYPL US Equity	19	138	-0.145	0.972	0.063	0.067	Consumer, Non-cyclical	113.84	0.807
QCOM US Equity	37	218	0.068	0.608	0.064	0.070	Technology	78.01	0.327
SBUX US Equity	39	388	0.038	0.868	0.040	0.042	Consumer, Cyclical	78.37	0.524
PEP US Equity	27	126	0.090	0.621	0.083	0.091	Consumer, Non-cyclical	171.95	0.359
USB US Equity	25	263	-0.133	0.949	0.046	0.048	Financial	53.56	0.877
AGN US Equity	19	62	0.035	0.619	0.117	0.134	Consumer, Non-cyclical	58.67	0.363
MS US Equity	18	73	-0.209	0.746	0.098	0.110	Financial	53.32	0.477

ALL US Equity	30	358	0.173	0.943	0.039	0.041	Financial	29.35	0.823
LLY US Equity	13	40	-0.145	0.845	0.126	0.145	Consumer, Non-cyclical	133.48	0.513
LOW US Equity	25	118	-0.161	0.699	0.085	0.093	Consumer, Cyclical	65.78	0.393
SPG US Equity	10	33	-0.375	0.915	0.135	0.156	Financial	16.69	0.733
UPS US Equity	35	378	0.327	0.927	0.039	0.040	Industrial	80.99	0.635
MDT US Equity	15	20	-0.127	0.407	0.250	0.348	Consumer, Non-cyclical	121.22	0.190
CVS US Equity	10	26	-0.120	0.534	0.181	0.223	Consumer, Non-cyclical	76.92	0.578
LMT US Equity	15	38	-0.454	0.472	0.153	0.187	Industrial	96.20	0.362
COF US Equity	9	18	-0.536	0.750	0.197	0.250	Financial	23.88	0.500
NKE US Equity	31	101	-0.255	0.409	0.113	0.132	Consumer, Cyclical	130.77	0.217
DD US Equity	24	146	-0.187	0.900	0.063	0.067	Basic Materials	25.81	0.529
WFC US Equity	25	246	-0.146	0.958	0.047	0.049	Financial	118.39	0.820