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Essays on Networks of Influence - Discovering Insight through Social Network Analysis

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DEDICATION

This work is dedicated to my wife Heather and daughter Sydney.
I would not have accomplished this without their love and support.

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I would like to express my sincere gratitude to my advisors Dominique Haughton, M. Lynne Markus, Heikki Topi, and Anne Washington. I recognized that I challenged the status quo at times when it would have been easier to just go along, and they have each been extremely patient with my journey.

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Abstract

Essays on Networks of Influence – Discovering Insight through Social Network Analysis

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Social network analysis (SNA) is a set of methods used for the examination of the relations found in social structures. While SNA has been used to study business for over 100 years, with early work showing the structure of organizational charts, it has experienced resurgent interest recently with the advances in computing power that allow for much more complex examination of these networks.

This research demonstrates how the use of SNA yields novel insights in three different situations. In study 1 we apply SNA to take a fresh look at U.S. State gubernatorial power. We introduce and implement a weighted network model by which state agency appointments can be examined. Instead of taking a governor-centric approach, as has been the practice, we construct and examine the whole appointment network. Our work shows that continuing with the existing practices will yield misleading results; we propose an alternative and more holistic view of these networks which better illustrates the changing nature of the structure of state government. In study 2 we explore and compare interlocked corporate boards in the U.S. and Europe over a period of 10 years (2001-2010). This longitudinal study examines, through the lens of the interlocked board network, whether the Mizruchi hypothesis, according to which the power of the corporate elite is disintegrating, holds. In study 3, we continue with the theme of interlocked boards but now consider the problem of how to test for statistical significance in network change over time. Our proposed model extends a Bayesian model beyond a pairwise analysis and allows for testing over a multi-year period. We apply and test our model with the interlocked director network in the U.S. over a period of 10 years (2001-2010), but this model is domain independent and can be applied anywhere a network is being examined longitudinally.

Table of Contents

List of Figures

List of Tables

1 Introduction

1.1 Overview

Business Analytics is the combination of data and the tools and techniques that provide insight into that data. This insight is in the form of new understanding gained through the results of the analytics process. This insight could be at a very low level, such as discovering that your customers don't care for a particular color scheme of your product, or at an industry-wide level which may challenge a widely-held sentiment that has been driving the industry. New contributions to academic knowledge and practical insights can be gained through the introduction of new data or applying new analytical techniques to existing data. This dissertation is an exploration of what new knowledge and insights could be gained through one such toolset, social network analysis.

Scholars working in the area of analytics are well familiar with the speed and frequency at which new tools and techniques become available. These tools are being applied in a cross-disciplinary fashion, and analytics researchers frequently support analysis as members of research teams in a broad area of domains. The analytics researcher needs to be comfortable with picking up new tools and applying them to existing context to see if new knowledge emerges.

Social network analysis (SNA) is a set of methods used for the examination of the relations found in social structures. While SNA has been used to study business for over 100 years, with early work showing the hierarchical nature of genealogy (Hobson, 1919), it has experienced resurgent interest recently with the advances in computing power that allow for a much more complex examination of these networks (Barabási & Albert, 1999). Always building on a foundation of empirical data, SNA uses statistical and computational techniques to produce insights through measurements of the structural nature of actors and their relations as well as through graphical imagery (Freeman, 2004).

As highlighted through the editorial criteria for the journal Social Networks, contributions to social network analysis "range from abstract, formal mathematical derivations to concrete, descriptive case studies of particular social networks." Insights through SNA can be gained either through the analysis of the myriad of measures that are available, such as node centrality and network density, or through the visualizations that can be obtained by graphically displaying the social network.

Figure 1-1 Research Map

My work is divided into three papers, which are all connected in several ways, as highlighted in Figure 1.1. All of the work applies SNA in a domain specific context. This has allowed me to explore SNA, as used in social sciences, in depth, whether it was justifying a weighting scheme for a weighted network as in paper 1, or finding statistical significance in longitudinal studies of networks as in paper 3. My journey has been circuitous in nature. I begin by looking at geographically diverse networks as applied to U.S. States in paper 1. I then expanded the geographic context by comparing interlocked board networks in the U.S. to those in Europe in paper 2. Building on the move to interlocked boards, I then expand this work to look at the implications of studying those networks longitudinally in paper 3. This leads to a need to address a recognized limitation, resulting in a novel method for studying time series of networks. I then demonstrate that future work could include bringing that novel method back into the gubernatorial power context of paper 1.

Looking more closely at this work, I begin in paper 1 by testing the idiom “A picture is worth a thousand words.” Using a dataset that has not yet been explored through social network analysis, namely the index of formal powers of U.S. state governors, I create visualizations to better understand the administrative changes occurring within state government. I show that the existing weighting method is inadequate and needs to be adjusted in order to convert the data to a social network. This brings a new weighted dataset into the Social Network domain. Not only am I able to replicate knowledge that had been gained previously not using this toolset, but the study also highlights that some states are adopting structures that the legacy model would have mis-identified as a move away from centralization of power.

Visualizations alone are only part of the story. A strong component of social network analysis is the set of various statistical measures available to the researcher. These could be at the individual level, which I explore in paper 1 as I apply measures to gubernatorial power, or at the network level as I do in paper 2 when comparing whole network characteristics of networks of boards of directors. Paper 1 highlights that measures used at an individual level may not work in today's complex government environment. Paper 2 shows that whole network measures can bring insight when comparing international networks.

Limitations of existing social network tools led to an important methodological contribution. These limitations emerged when analyzing networks longitudinally. In paper 3, I make a methodological contribution by introducing a new Bayesian model for measuring statistical significance of change to a social network over a multi-year period. While I apply this method to the same dataset used in paper 2, namely the interlocked board member network of the companies that make up the DOW Jones Industrial 30, this same new approach could also be applied to the state government data to rapidly detect statistically significant changes in administrative arrangements within state government. This would allow us to quickly hone in on the specific state/year combinations where change is occurring. This would be a logical follow-up study to this work.

In summary, this work reports the results of a multi-study research program on SNA through an interdisciplinary perspective using real network data. This dissertation empirically examines data from the domains of interlocking boards of directors and gubernatorial power in the U.S. states. It proposes and tests a network weighting scheme for appointment power while at the same time expanding the network to include all actors involved in the process. Methodologically, it proposes a new model that allows us to determine if network change in the longitudinal analysis of a network is statistically significant.

The key contributions of this dissertation are as follows:

1) Demonstration of applicability of SNA to two new contexts;
2) Significant domain-specific findings in the areas to which the research applied SNA; and
3) The expansion of SNA with a new Bayesian model for longitudinal networks.

1.2 Background

This work explores two different domains through social network tools. In the first domain we consider gubernatorial power within U.S. state government. We introduce the novel approach of modeling gubernatorial power utilizing social network tools. In the second domain, interlocking corporate boards of directors, we look at a domain that has a long history of utilizing social network analysis; we bring new insight to this established field through the introduction of global comparisons of data, covered in paper 2, and a new model for testing for longitudinal significant change, covered in paper 3. This work thus contributes new applications to social network analysis, as well as new techniques in well-established domains.

The topic of gubernatorial power has long been of interest to the research community with the Formal Powers Index (FPI) introduced by Schlesinger in 1965 and maintained by Beyle since then. This index, which has gone through several revisions and additions, scores the power of the governor along several components including budget power, tenure potential, gubernatorial party control, separately elected officials, and appointment power. Even though the index is now 50 years old, it has had staying power and continues to drive new research. However, it has not been without criticism. Krupnikov and Shipman (2012) show that when considered longitudinally there are flaws in the FPI related to budget power and stress that all components of the index should be looked at more closely.

This work heeds the call issued by Krupnikov and Shipman (2012) by being the first to re-examine the appointment power component of the index. We show that the manner in which the components of the FPI are measured is quite similar to the way measures of centrality are defined in network analysis. This supports the idea of utilizing network analysis as a suitable tool to re-examine this measure. However, we will further show that there are issues when attempting to directly convert the FPI weighting to a social network weighting and, as a result, we propose a new weighting scheme that allows for a full network model. To this effect, we take one component of the index, namely the appointment power, and convert it to a social network.

This work is of interest to political scientists because it expands the depth of understanding about appointment power within U.S. states. This expansion is achieved through the consideration of all actors who participate in the appointment process, not just the governor, which is a limitation of the FPI. Network visualization techniques highlight changes occurring over time and demonstrate that the governor is not operating in isolation.

Those who might have dismissed appointment power in the past will also be interested in this work. This work shows that appointment power cannot be fully understood through a single value attributed to the governor. The appointments happen in an environment in which many actors participate and changes indirectly related to the governor may be at play in different states.

Finally, this work is of interest to social network researchers and will show that new life can be given to old data. It opens up a new field of study for network researchers, namely gubernatorial power, something that has seen little interest to date. While this work addresses appointment power, other components of the FPI such as budget power, are also ripe for reexamination using these same techniques.

Papers 2 and 3 both contribute to the much-researched area of interlocking corporate boards. Paper 2 explores the question of what knowledge can be gained by comparing interlocking boards in the U.S. to those in Europe. This novel study is the first that compares interlock networks for a stock market index in the U.S. directly with that of an index in Europe in an effort to understand the differences that may exist. While others have explored U.S. and European interlock networks in the past, no one has to date performed a side by side comparison to look at differences.

One of the challenges often cited when comparing different networks is the challenge of using different sized networks, which leads to incomparable measures. We sidestep this challenge by comparing trends in density of different sized networks. So while the DOW 30 is comprised of 30 different companies, each having varying size boards, and the CAC-40 is comprised of 40 different companies, also each having varying sized boards, we are able to do comparisons by looking at how a single measure, density, changes within each network over time.

This work is of interest to policy makers who are interested in affecting external pressures in order to reduce the risk of collusion through interlocked boards. While the U.S.

and European markets have experienced different institutional pressures, we can look to see if either market is realizing greater change over time.

In addition to policy makers, this work is also of interest to those who study interlocked directorates. This is a well-formed group of scholars who regularly publish special issues and run program tracks on interlocked boards at conferences.

Paper 3 addresses one of the biggest challenges facing those who study social networks, namely, how to test for statistically significant change in networks over time. Through the use of Bayesian versions of random effects extensions of the P_1 model of Holland and Leinhardt (1981), others have been able to perform pairwise comparisons of a network across two years (Adams, Carter, Hadlock, Haughton, & Sirbu, 2008; Gill & Swartz, 2004). We extend this Bayesian model to allow for multi-year comparison and show how to apply it to interlocked board networks. We provide the source code, written in OpenBUGS, which will allow other researchers to apply this same technique to their own social networks.

Frequently the nodes in the network change over time. This is true in the case of the interlock board network of the DOW 30 corporations for example and this has added to the challenge of studying the network longitudinally. We will propose the notion of a "hull" that creates a level of node stability over the time period being analyzed.

1.3 Social Network Analysis

Social Network Analysis (SNA) is the study of actors (individuals or aggregates of individuals such as organizations, departments, boards, etc.) and their connections with each other (Easley & Kleinberg, 2010). Why study networks? When we arrange our data in a network form that consists of actors (called nodes) and interactions (called edges) we are then forced to look at the relations between those actors that comprise the system (called the network) in light of the characteristics (called attributes) of the actors and interactions. When considering the relationship between two nodes, this is called a dyad. It is common for researchers to extract network variables to be used as independent variables in their models.

Modern social network analysis consists of these four features (Freeman, 2004):

1. A foundation of systematic empirical data.
2. Structural knowledge generated from social actors and the connections between those social actors.
3. Reliance on knowledge emerging through graphical imagery.
4. Established in mathematical and/or computational models.

SNA can be performed at multiple levels of analysis: at the node level, where we may evaluate the centrality level of an individual to see if they more likely to get a promotion or raise; at the dyad level, where the pair of nodes is considered and we might evaluate whether two companies, based on their attributes, might form a partnership; and at the network level, where we may look at knowledge transfer and ask whether knowledge travels more quickly in a dense (many edges and paths between nodes) versus a sparse network. Deciding the boundary edges, which nodes to include and which to exclude, is called the boundary specification (Borgatti & Halgin, 2011).

When considering theories that network analysis is built upon, two main avenues emerge. The first, and more common approach, is the consideration that network constructs are independent variables where network variable X leads to outcome Y. The emphasis in this type of research is to focus on the output available in the social network analysis and to apply that output as part of the model development process. This type of research falls under the Network Theory umbrella (Borgatti & Lopez-Kidwell, 2011). For example, Calvo-Armengol and Jackson (2004) utilize Granovetter's Strength of Weak Ties Theory (1973) to evaluate employment prospects based on their social network. While it is generally understood that job opportunities are more apt to come from weak ties (M. Granovetter, 1981), Calvo-Armengol and Jackson (2004) show that unemployment extends when those weak ties are also unemployed and therefore are less likely to pass job opportunities to others in their social network. This approach is typically based on an ego network. An ego network is one by which a key actor has been identified and all other relations are built out based on that key actor.

The second approach considers network properties as dependent variables and is called the Theory of Networks (Borgatti & Lopez-Kidwell, 2011). This latter approach considers the influence that other variables have on the structure and makeup of the network, with the primary goal being one of understanding the characteristics of the network better. For example, Miles and Snow (1978) discuss the environment in which new organizational forms emerge. They highlight that changes in organizational structure enable the pursuit of new competitive strategies. This approach is typically based on a whole network. A whole network is one by which a network is developed in order to answer research questions that are not based on any one particular actor.

1.4 Types of Networks

There is some key terminology that needs to be defined since it will be used throughout this document. We begin with terms that are used when discussing networks in general. Table 1-1 lists these terms as well as identifying the papers in this document where you will encounter that network feature. Figure 1-2 gives a graphical representation of several types of networks in order to help clarify the meaning.

	Dimensionality		**Reciprocity**		**Strength**		**# Link Types**	
	Simply	Bi-Partite	Undirected	Bi-Directional	Equal Weighted	Weighted	Single	Multiplicity
Paper 1	✓		✓			✓		✓
Paper 2		✓		✓		✓	✓	
Paper 3		✓		✓	✓		✓	

Table 1-1 Summary of Network Topics by Paper

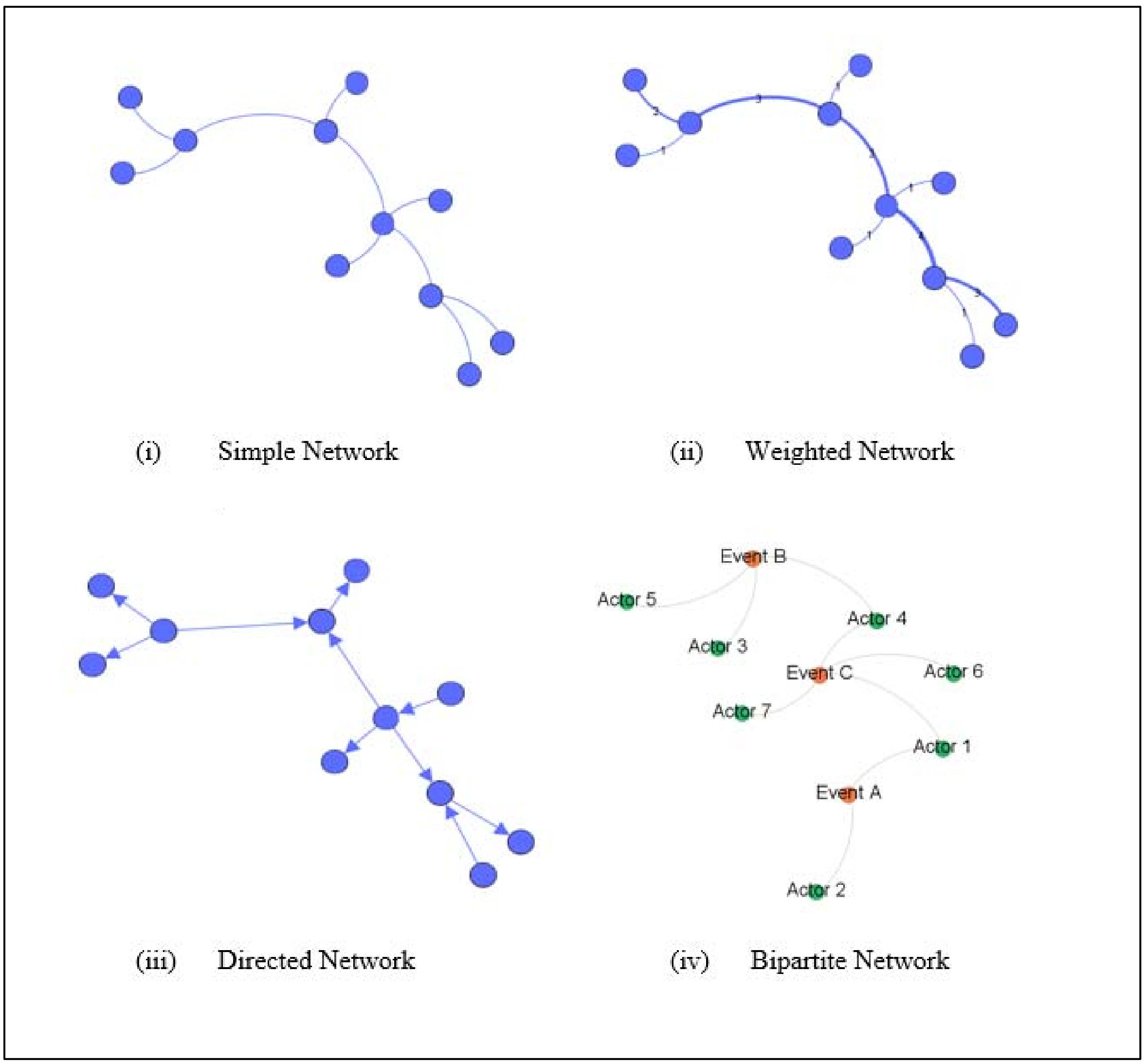


Figure 1-2 Examples of Network Types

Simple Versus Bipartite Networks: A network is considered simple if all nodes are of the same type and could potentially be connected. However, there are cases where researchers need to model more than one node type. For instance, in a situation where people who engage in conversation with other people at different events, people and events would both be nodes. However, each node type would only be connected to the other node type, that is, a person is only connected to another person through an event and one event would never be directly connected to the other event. Such networks are called bipartite networks. It is understood that when two individuals jointly participate in shared events, then that activity reinforces personal ties. This bipartite network could consist of people joined through social events (Breiger, 1974), co-authors in research papers (Small, 1973), or corporate board members who participate in multiple corporations' boards of directors (Mizruchi, 1996). This last example is that of the interlocking directorate network and is the focus of papers 2 and 3.

Reciprocity: When network researchers model two people who are connected through a kinship, the connection, or edge, is considered bi-directional or undirected. In this case the two people are related and that relationship is reciprocated. It would make no sense to say that Person A is related to Person B, but Person B is not related to Person A. However, reciprocity often does not hold. For example, researchers who study legitimate power (French Jr, 1956) often need to identify who holds the power in the relationship such as in a manager/employee relationship. These networks are considered *directed* and are drawn with an arrow on the edge indicating the direction of the power (as shown in network (iii) in Figure 1-2). Paper 1 utilizes directed graphs when modeling the appointment network in

U.S. State government, while papers 2 and 3, which look at corporate directors who share common directorships with others, employ undirected graphs.

Weighted versus Unweighted Networks: Strength within social networks refers to the weighting of the tie that connects two nodes. In simpler networks the weights are equal and set to one. However, scholars are increasingly interested in understanding more complex relations between nodes which go beyond the simple question of whether there is a connection or not, and instead looks at some weighting of each connection. In social networks these weights may measure relations such as frequency of communication, duration of activity, level of intimacy, or the amount of services exchanged (M. S. Granovetter, 1973). For example, weighted networks have been used in co-authorship studies to measure the number of publications two authors have collaborated on (Barrat, Barthelemy, Pastor-Satorras, & Vespignani, 2004).

In paper 1, we show that the legacy approach of measuring appointment power actually transfers to a weighted network quite well. In the case of appointments, researchers have claimed that it is more valuable to have the power to appoint the position than it is to approve the position. In paper 3, we utilize weighted networks as a mechanism to reduce the bi-partite network down to a unimodal one by replacing individual board members with a weighted connection directly between the two boards.

Multiplicity: Social networks may be multi-relational, where more than one type of relationship may exist between two nodes. This is called multiplicity. Multiplicity allows researchers to add additional layers of relational types to the social network analysis, which, in turn, allows the researcher to explore the important questions of how and why different types co-exist (Faust, 2011). Often grouped with multiplicity, a network is called a pseudograph when nodes can be tied to themselves. Researchers have used multiplicity to examine different social acts in animal social networks (Hemelrijk, 1990; Seyfarth & Cheney, 1986), different communication techniques in cyber-communities (Garton, Haythornthwaite, & Wellman, 1997) and power structures in government (Laumann & Knoke, 1987) to name just a few. We explore the issue of multiplicity in chapter 2 where we explore two different tie types in regards to political appointments: the power to appoint, and the power to approve. These graphs are also considered pseudographs since an agency may self-appoint their own agency head.

1.5 Common Network Measurements

In this section we will explore some of the more common measurements used in analyzing networks. The purpose is not to produce an exhaustive list, but instead highlights some of the measurements used throughout this dissertation.

Degree: The degree of a node is the number of connections that directly join this node to other nodes within the network. The degree may be as low as 0 if the node is not connected to any other nodes, or as high as the total number of nodes if the node is directly related to all other nodes. The degree of a node is often denoted as $d(n_i)$. For example, Facebook users can be considered to have a degree equal to the number of friends that they have in the social network. When an account is first created, the degree would be 0, and then the degree changes over time as friends are added and removed. When dealing with weighted networks, nodes have both a degree and a weighted degree. The weighted degree is the sum of all adjacent connections, where a link with a weight of 2, for instance, would count as 2 connections.

Centrality: One of the core sets of measurements of network analysis, centrality was originally introduced by Bavelas (1948) and Leavitt (1951) and measured the distance of each node in relation to all others within the network. They used this measurement to explain individual performance and morale within organizations. Since that time, many other measurements of centrality have been developed including *closeness centrality* (Sabidussi, 1966), *degree centrality* (Nieminen, 1974), and *betweenness centrality* (Freeman, 1979) to name just a few. In fact, the literature in the area of centrality measurements in the social sciences has seen strong growth since the 1980's (Freeman, 2008).

Density: A measure by which the interconnectedness of a network is determined, density is measured by the overall number of ties present in the network relative to the maximum number of potential ties. With a directed network, the maximum number of potential ties is $n(n-1)$ while for an undirected network it would be $n(n-1) / 2$ (Borgatti & Everett, 1997). However, when dealing with bipartite networks, this measurement is not appropriate since, by the very nature of bipartite graphs, there is no possibility for connecting between nodes of the same type. In this case, the maximum potential connections would be when all nodes of one type are connected to all nodes of the other type. Note that these equations are for an unweighted network. In the case of a weighted network, one must calculate density using the sum of all weights of all ties divided by the maximum possible weight per tie times the total number of possible ties.

Distance: While many measures, such as measures of degree, focus on the relationship between two adjacent nodes, the embeddedness of nodes within the context of the network is more complex than this. One way to measure how embedded a node is in relation to the other nodes is through the measure of distance, or how many nodes one must travel through in order to make contact with a non-adjacent node. When considered at a network level, distance is a measure used to determine how long it would take for information or resources to diffuse across all nodes. Distance is often used in heat maps to color code the farthest reachable points within the network from any given node.

Diameter: The diameter of a network is the longest distance between any two nodes in the network (Wasserman, 1994). When considering transmission within a network, if we assume that messages will travel along the shortest route, we can guarantee that the transmission between two nodes can be no greater than the network diameter.

1.6 Research Map

The next three chapters represent studies exploring SNA in the context of gubernatorial power and interlocking directorates. In this section we summarize the main direction of these studies.

Study 1 - Gubernatorial Appointment Power

Establishing quantitative measures for gubernatorial power has been of interest since Schlesinger (Schlesinger, 1965) published his index of the Formal Power of the Governors in 1965. The index scored the governor of each state on four measures (1) gubernatorial budget power, (2) appointment power, (3) veto power, and (4) tenure potential. Budget, appointment, and tenure powers were all scored on a 5 point scale and veto was scored on a 4 point scale. The result was an overall score ranking from 4-19. In 1965 the lowest scoring states, with a score of 7, were Mississippi, South Carolina, Texas, and North Dakota, while the state of New York was the state with the highest score at 19. Figure 1-3 is an example of the type of network that can be visualized when a part of the index is converted over to a social network. In this example, it is clear that the governor is at the center of this network and has direct control with most of the agencies visualized in the network.

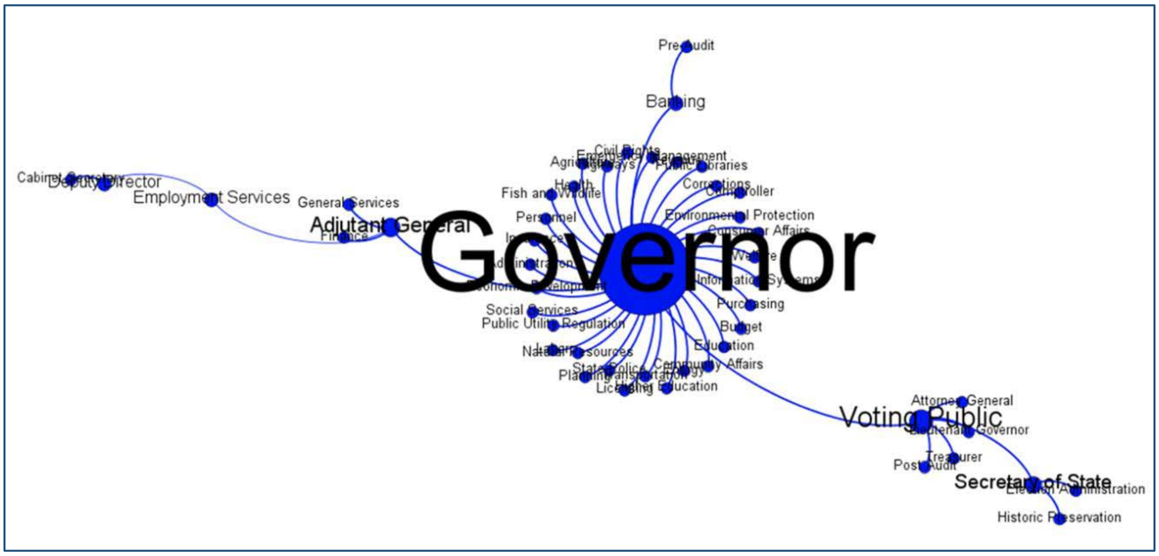


Figure 1-3 Gubernatorial Appointment Power

Over the years many have worked with this index, none more than Thad Beyle who, as early as 1968, using both the original Book of the States data along with survey data, replicated the findings of Schlesinger (Beyle, 1968). This model has been used to explain the effectiveness at which policy change can be enacted at the state level (Barrilleaux, 1999; Erikson, Wright Jr, & McIver, 1989) as well as to explain conflict between the governor and legislature (Clarke, 1998).

However the model has not been without its critics. Dometrius (Dometrius, 1987) was particularly critical of the appointment power measure, arguing that as states have evolved and become more complex, the power has shifted away from some of the early agencies however the index does not take these changes into account. He goes so far as to say that it is “problematic to include the index, or any of its components, in the analyses of contemporary governorship.” In this dissertation, we address the deficiencies and argue that more modern techniques that shed light on the entirety of the appointment network can be employed to better understand the governor's power in this network.

Study 2 - Global Interlocking Corporate Boards

While considerable work has been done testing the impact of interlocked boards, there has not been as much attention to the network structure, beyond simple averages, when viewed as a network of linked entities *over time*. This study begins by looking at the network characteristics of the interlocked boards of the companies that make up the DOW 30 in comparison with the Paris CAC 40. We show that while the level of connectedness, when measured through network density, is decreasing in the CAC 40, it appears to remain stable in the DOW 30 network. We explore the DOW in more detail by creating networks that represent the non-changing node of the network, as well as a network that includes all companies that were part of the DOW 30 at any time, over the period of the analysis. We are then able to show that the level of connectedness of the core companies is increasing over this period while at the same time the extended network connectedness is decreasing. Figure 1-4 is a visual representation of one of these networks. In this network we have color coded the nodes with green nodes representing companies that were added to the DOW 30 index in that year, red nodes represent those that were removed, and the grey nodes represent companies that remained constant.

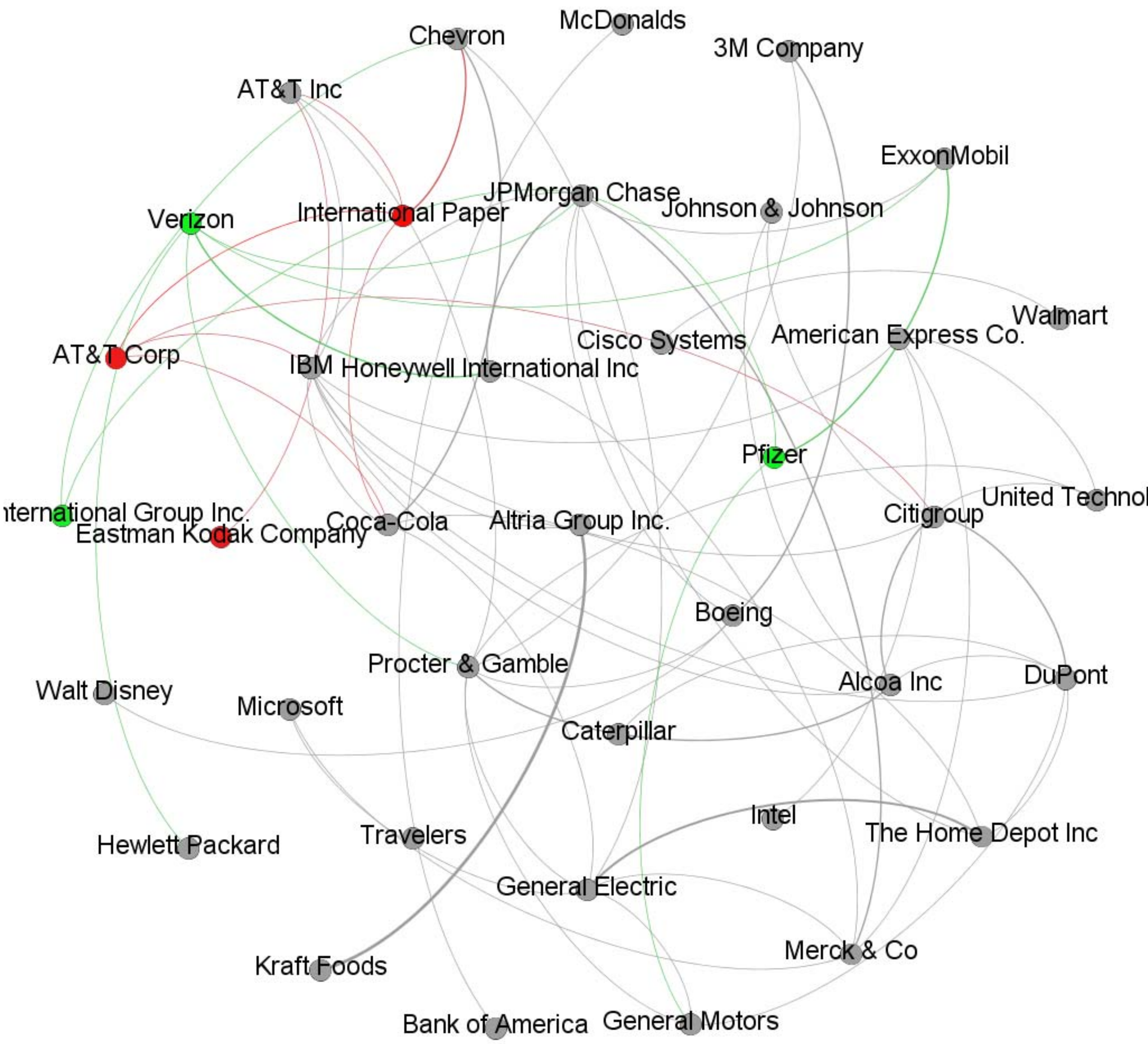


Figure 1-4 DOW 30 Interlocked Boards

Study 3 - Measuring Network Change over Time

While much work has been done with social networks, one of the primary challenges facing the research community has been the ability to detect statistical significance when examining networks over time. Using the data on interlocking directorates that was discussed in paper 2, we begin by presenting three alternative networks that represent the

DOW 30 over the period of 2001-2010. The three networks include one in which companies simply replace other companies as they are added and dropped from the DOW 30 index. This network has 30 nodes throughout the period, but over three years (2004, 2008, and 2009) some of the companies, represented by those nodes, have changed. Our second network considers just the 23 companies that remained in the DOW 30 over the entire period of study; we call this network the *core hull*. Finally, our third network includes all companies that were part of the DOW 30 at any time over the years of interest; we call this network the *extended hull*. This final network is comprised of 38 companies. While there appear to be some differing trends in these three networks, we were confronted with the question as to whether the trend is statistically significant. We therefore extend the Bayesian P_1 model to account for multiple years in order to test for significance. This work builds on prior Bayesian models of social networks (Adams et al., 2008; Snijders, 1996; Wasserman & Iacobucci, 1988) with random effects which allow for the time-sensitive dependence of edges present in the network.

These three studies provide insight into how SNA can be applied in both domains that have not had much exposure to SNA as well as domains that have a well-established SNA body of work. The studies show that the field is ripe for researchers who are looking for a fresh perspective. The next three chapters cover each of the papers while the final chapter provides a wrap-up summarizing the work and discussing the future direction for the work.

2 Gubernatorial Appointment Power

2.1 Abstract

We use social network analysis to better understand historical data on the administration of local governments. Despite advances in e-government applications, the public sector lags behind in the field of analytics because information is locked in legacy data formats. Can e-government researchers bridge the gap between legacy data and analytics? We argue that computational analytic methods, popular in big data applications, can explain patterns that have gone unquestioned in previous research on government. Specifically, we consider how explanations of state government authority can be explained using a network perspective. These data were originally designed to describe administrative differences across US territories and states. We investigate methodological challenges in building a weighted social network to confirm existing measures for calculating the power of the state governor.

This paper reports on an initial step within a broader study to cover all 50 states across multiple years and agencies. We compare the two states that experienced the greatest differences in gubernatorial appointment power between 1992 and 2012, namely Texas and Massachusetts. Our research also examines the two agencies that moved furthest away from and closest toward gubernatorial control across all 50 states, namely the Energy and Information Systems agencies respectively. Social network analysis improves upon existing measurements because it considers relationships between the governor and other top officials and agencies. This approach can uncover where power shifted across states and across time. Our computational analysis of existing government data matches findings from previous studies and yields additional explanatory power.

2.2 Introduction

This paper reports on a first step in a broader study using analytics to better understand governance. With the proliferation of public sector information, researchers interested in e-government have unprecedented opportunities to demonstrate the potential of computational analysis. While big data and computational analysis encompass a popular new technique in information systems (Agarwal & Dhar, 2014; Chen, Chiang, & Storey, 2012; Goes, 2014; Kane, Alavi, Labianca, & Borgatti, 2014; Sundararajan, Provost, Oestreicher-Singer, & Aral, 2013), their value is still debated among social scientists. Computational analysis is not uniformly accepted and many scholars question knowledge claims that emerge from analytics (Bisel, Barge, Dougherty, Lucas, & Tracy, 2014; boyd & Crawford, 2012; Lin, Lucas Jr, & Shmueli, 2013; Ruppert, Law, & Savage, 2013; Weinberg, Davis, & Berger, 2013).

To address those concerns, this study compares its findings to existing measures published by political scientists (Schlesinger, 1965). We use social network methods to analyze the administration of state governments. Specifically, we consider how organizational power is shared across multiple actors. While power has multiple dimensions, for the purpose of this paper we are focusing on the notion of power as control (Pfeffer & Salancik, 1978; Smith et al., 2014). When a person has the ability to hire, s/he is likely to hire those with similar belief structures, who in turn are more likely to enact the changes requested by the person who made the appointment. In this study, we consider the power of the chief administrative officer, the governor, in United States states. The governor has the power to appoint the leaders of executive agencies, such as Energy, Information Systems, or Education.

Networks provide novel tools to address concerns about organizations and power. Previous studies on power have been conducted as in-depth case studies, however computational methods could further reveal patterns of power within organizations (M. L. Markus, Dax D. Jacobson, Quang "Neo" Bui, Kevin Mentzer, & Olivier Lisein, 2013a; M. L. Markus, Dax D. Jacobson, Quang "Neo" Bui, Kevin Mentzer, & Olivier Lisein, 2013b; Markus & Robey, 1983; Robey & Boudreau, 1999; Salancik, 1977). The study of networks particularly lends itself to computational analysis, due to the fact that the relational aspects of large data sets enable observations across time and many groups (Sundararajan et al., 2013). This paper introduces specific methods for converting existing government data to social networks.

One way in which researchers have analyzed power within state government has been through the lens of gubernatorial power, in an attempt to find a correlation between gubernatorial powers and the ability of the governor to enact change. Political scientists measure gubernatorial power using Schlesinger's Index of the Formal Powers of the Governor (Schlesinger 1965). Called the Formal Power Index (FPI), this index quantifies governor power along four dimensions (1) gubernatorial budget power, (2) appointment power, (3) veto power, and (4) tenure potential. However, each of these dimensions looks at gubernatorial power in a vacuum, without consideration of other actors who may be involved in each dimension. For example, in the case of appointment power, the FPI gives the governor a score based on his/her direct appointments, but fails to score others involved in the appointment of key personnel. The result is a score that could mean quite different things based on whether or not someone else scores higher than the governor. For example, two governors may have the same score but in one state the remaining appointment power is dispersed among so many other parties that the governor still has the greatest power in the state. While in the other state the remaining power may be concentrated with one other party, who is viewed as having much more influence than the governor. Social networking analysis seems to be an ideal method for understanding how other actors are involved in gubernatorial power. This paper argues that power within U.S. state government can be explained using methods that extend the single stakeholder perspective (i.e. the governor) to a network perspective. Analytics is in a position to provide the holistic picture needed to understand power within state government.

We base our analysis on data on gubernatorial power taken from *The Book of the States,* which has been used in past political science studies (Beyle, 1968; Ferguson, 2012; Schlesinger, 1965). These data were originally designed to describe administrative differences between US territories and states, by identifying who had the power to appoint and approve the various heads of state agencies. However, this data were reduced down by Schelsinger for the use in the index of formal power of the governor, by converting the appointment to a score based on the ability of the governor to appoint and approve. As a result, the existing measures show observable differences that cannot be explained (Dometrius, 1987), due to either transfers of power outside of those identified in the Book of the States, or due to a lack of understanding who else, besides the governor, had these appointment powers. We compare the states that experienced the greatest differences in gubernatorial appointment power between 1992 and 2012, namely Texas and Massachusetts in an effort to explain these differences. We also consider the data from an agency perspective across all states. We do this by examining which agencies were closest to, and furthest away from, the control of the governor, specifically how the Information Systems and Energy agencies changed over time.

Through the use of social network analysis, we expand the power discussion to include other actors involved in state activities, and thereby demonstrate power dynamics within state government. The power structure within state government consists of both formal powers, such as the ability to approve budgets, appoint positions, etc., and informal powers, such as political capital and party support. This paper demonstrates how social network analysis, using one measure of Schleslinger's FPI, namely the power to appoint department heads in state agencies, can expand the discussion beyond a single numeric measure into a broader discussion of how power has shifted over time. Through specific state examples we show that measurements available through social network analysis (SNA) allow us to not only produce similar results as the FPI technique produces, but also to produce measures related to other actors in the appointment process, as well as to produce network level measures that demonstrate the overall characteristics of the entire network. We show that changes occurring within states cannot be adequately explained using the legacy technique, and that we are able to glean additional insight through SNA that clarify the changes occurring within the states.

In order to understand the changes occurring within state government we look at the states of Massachusetts and Texas, and compare those states and their changes from 1992 to 2012. These states were chosen because the formal power index in 1992 would have ranked the governor of Texas as having the least appointment power, suggesting a decentralized structure, and the governor of Massachusetts with the highest appointment power, suggesting a centralized structure. However, over the 20 year period in which the appointive power of the governor of Texas remained the lowest of all 50 states, the appointive power for the governor of Massachusetts declined the most of any of the 50 states over that same period. The FPI leaves us scratching our heads as to what is occurring in Massachusetts while, through SNA, we are able to show that the governor appears to have delegated appointive responsibilities to his/her cabinet secretary. This view displays a continued trend toward centralized power under the governor rather than a decline in power. Texas, while generally exhibiting a decentralized structure across both time periods, has still moved toward centralization under the governor. The visuals provided by the social network tools give further proof that the power structure within Massachusetts is not changing as much as could have been interpreted using the FPI.

Our findings give us the necessary evidence to support moving more of the FPI over to social networks, and we look to continued expansion of this work to help tackle the big data challenge of understanding power within state government.

2.3 Literature review

2.3.1 Index of the Formal Powers of the Governor

Establishing quantitative measures for gubernatorial power has been of interest since Schlesinger (Schlesinger, 1965) published his index of the Formal Power of the Governors in 1965. Over the years many have worked with this index, none more than Thad Beyle who as early as 1968, using both the original Book of the States data along with survey data, replicated the findings of Schlesinger (Beyle, 1968). The current version of the composite index includes personal powers (such as Ambition Ladder) and institutional powers (such as Appointment Power) (Ferguson, 2012). These individual measures are often summed or averaged into a general composite index (the FPI), or are used individually, based on the topic being studied.

This model has allowed researchers to make comparisons over a more than 60-year time period (1960 to 2012). The index has been used to explain the effectiveness with which policy change can be enacted at the state level (Barrilleaux, 1999; Erikson et al., 1989), conflict between the governor and legislature (Clarke, 1998), policy success (Ferguson, 2003), and confidence in state government (Kelleher & Wolak, 2007), to name just a few.

However, the model has not been without its critics. Dometrius (1987) was particularly critical of the appointment power measure, arguing that as states have evolved and become more complex, power has shifted away from some of the early agencies, but that the index could not address these changes. He goes so far as to say that it is "problematic to include the index, or any of its components, in the analyses of the contemporary governorship."

While others (Krupnikov & Shipan, 2012) have proposed different ways to calculate these measures, we are not aware of any who have expanded the calculations beyond the sole actor of the governor. As Smith et al. state, "power is inherently a structural phenomenon where one actor's influence over another needs to be considered within a wider network of relationships" (Smith et al., 2014). To this end, we suggest that the scope of the legacy index needs to be expanded to include the "wider network of relationships," which can be accomplished using social network analysis.

2.3.2 Social Network Analysis

A social network perspective provides a novel means of evaluating research questions through an analysis of the network structure (Wasserman, 1994). Modern social network analysis consists of these four features (Freeman, 2004):

1. A foundation of systematic empirical data.
2. A structural knowledge generated from social actors and the connections between those social actors.
3. A reliance on knowledge emerging through graphical imagery.
4. Established mathematical and/or computational models.

Social networks allow us to emphasize the relationships among actors that comprise the social system (Borgatti, Everett, & Johnson, 2013). These actors are called nodes and have attributes (for example, name, gender, age, tenure, etc.) that can distinguish each node from another. The relationship between the actors, or nodes, is called a link or edge. Edges can either be weighted or non-weighted. An example of a weighted network might employ the frequency of interaction between the two nodes, or, as we will use, the relative power of the link. Edges can also be directed or non-directed. A non-directed edge means that the link is equally valuable to each node, while a directed edge would indicate that the edge has a sender or originator, and a receiver.

A key concept in social networks is the notion of centrality. Centrality, in general, means the relative importance of one node over the other nodes in the network (Borgatti, 2005; Borgatti, Mehra, Brass, & Labianca, 2009; Wasserman, 1994). One measure of centrality is degree centrality, which is a measure of the number of nodes directly connected to the focal node. In the context of this paper we will use degree centrality as a means of mapping back to the original FPI measurements.

2.4 Methodology

We adopt a weighted network to emphasize that the power to appoint a position means more than the ability to approve that position. In fact, this weighting was inherent in the FPI, and lends itself quite well to being represented through a weighted network. We adopt directed links to emphasize that the power is uni-directional. When one party has the ability to appoint the other, they then hold the power in that activity.

We utilize the data source, *The Book of the States (The Council of State Governments, 1935-2012),* as has been used by Schlesinger, Beyle, and Ferguson (Beyle, 1968; Ferguson, 2012; Schlesinger, 1965). Published since 1935, the Book of the States identifies approximately 50 state agencies (the actual number varies on a year-to-year basis based on additions or subtractions to the table of State agencies, and will vary within states depending on whether they have such agencies), and identifies who is responsible for appointing and approving the head of each agency. This paper looks at the data over a 20 year period from 1992-2012. 1992 was the first year that Information Systems agencies were identified in the *Book of the States*. 2012 was the most recent available at the time of this study.

2.4.1 Legacy Weighting of FPI

A sample of the *Book of the States* dataset is provided in Table 2-1. In this table one can see that for each agency, by state, a code is identified. This code represents the combination of who appoints and who approves the head of that agency for that state. For example, a code of "G" means that the governor has sole responsibility for appointing and approving the head of the department, while a code of "A" means that the agency self-appoints their head.

State or other jurisdiction	Administration	Agriculture	Banking	Budget	Commerce	Community affairs
Alabama	(a-17)	CE	GS	A	G	G
Alaska	GB	A	A	(b)	GB	GB
Arizona	GS	GS	GS	(a-26)	GS	A
Arkansas	(a-16)	B	BG	CS	(a-12)	(a-32)
California	(c)	GS	GS	(a-16)	GS	G
Colorado	GS	GS	CS	G	…	CS
Connecticut	GE	GE	GE	CS	(a-12)	A
Delaware	GS	GS	G	GS	(a-2)	…
Florida	G	CE	(a-9)	G	G	G

Table 2-1 Sample Book of the States Appointment Power

Following the process employed by Schlesinger, and using the same legacy appointment power encoding (see Table 2-2), we were able to calculate the legacy governor appointment power for each state from 1992 and 2012.

2.4.2 Legacy Weighting converted to Social Network

Code	Description
5	Governor has sole discretion to appoint position
4	Governor appoints position but it is approved by others
3	Governor shares appointment power
2	Other party appoints position and governor approves the appointment
1	Governor plays no formal role in the appointment

Table 2-2 Legacy Appointment Power Encoding

The FPI appointment power scoring is, in essence, an ego network with the governor being the focal node. Because of this, we can easily take the legacy values and convert them over as weighted edges between the governor and each agency head. Figure 2-1 shows the resulting network for the states of Massachusetts and Texas. The labels have been omitted to allow for readability, but the central node is the governor and the remaining nodes are the agency heads. Three rings of circles emerge around the governor node. The inner most ring, including 7 nodes in Texas and 19 nodes in Massachusetts, represents the set of strongest connections – those agencies where the governor has sole discretion to appoint the agency head. The next ring of nodes, including 2 for Texas and 19 for Massachusetts, represents the set of agency heads that are appointed by someone other than the governor but for which the governor has approval authority. The final ring, including 33 in Texas and 8 in Massachusetts, represents the set of agency heads in which the governor plays no role in the appointment or approval. Coincidentally both Massachusetts and Texas only display 3 of the 5 potential values (from table 2-2), while other states might feature up to five rings, with the closest ring representing those connections weighted at 5 and the outermost ring representing those connections weighted at 1.

By building the network in this manner we are able to reproduce the legacy FPI figure for appointment power by using the average weighted degree for the governor node. However, while these networks are attractive in the way they appear, they do give a false sense of the governor as the central figure. This is because with the legacy weighting, even if the governor is not involved in the appointment, s/he is still given a weight of 1 in connection to those nodes. Therefore in Texas, although the governor is only involved (at any level) with the appointment of 9 of the 42 agencies, 33 agencies still surround the governor albeit at a distance.

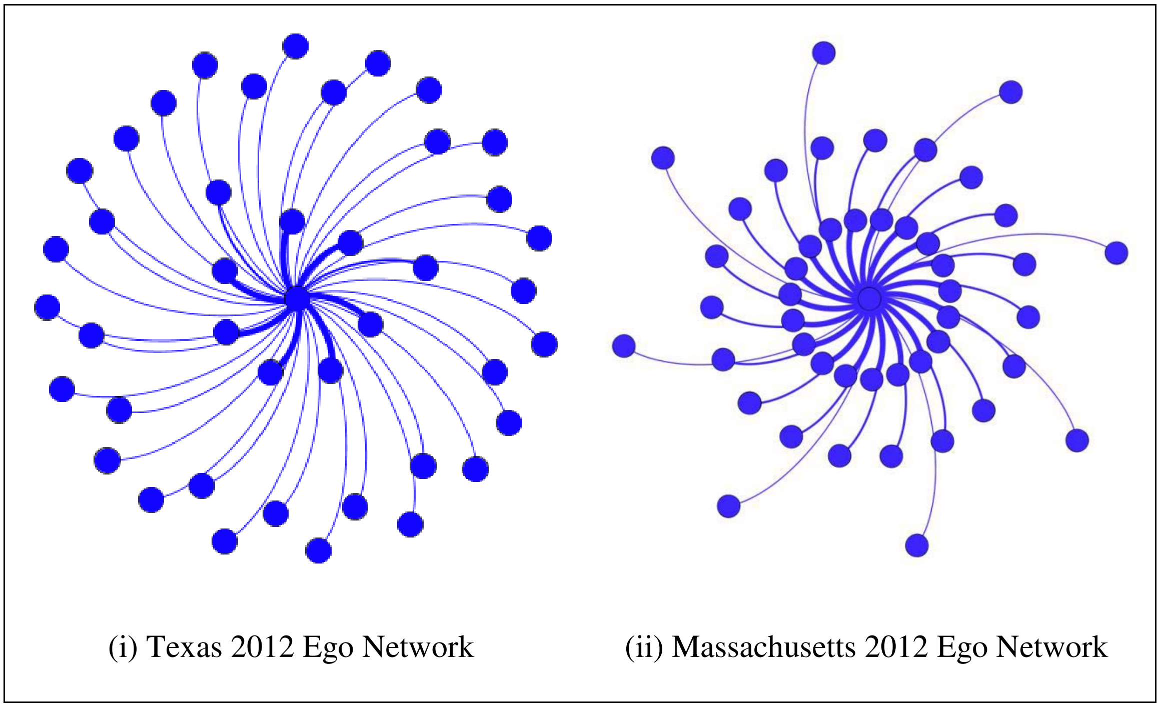


Figure 2-1 Appointment Network Viewed as Ego-Network

Next, we convert the legacy encoding into values that we could use for a whole network, rather than an ego network. Our vision here is that, in order to fully understand appointment power, we need to show that the governor does not operate in a vacuum and additional insight can be gained by including all nodes involved in the appointment process. Therefore we want to apply the legacy weighting scheme to all nodes that had either appointing or approval power. To do this we broke out each of the 5 possible combinations into their own scenario. We present the five scenarios in Figure 2-2 and cover each in depth next.

In the scenarios (see Figure 2-2) used to present this work, all nodes are the same size, while the arrows depicting the edges are sized according to their weight (so a wider arrow indicates a higher authority value, which has been interpreted as more appointment power). We started with the first scenario, in which the governor has sole appointment and approval power. In the legacy encoding this would have a weight of 5, so in our network we are able to envision it appearing as seen in Figure 2-2, where the node representing the governor is connected to the node of the Head of the Agency with an edge that has a weight of 5.

To round out the remaining scenarios, scenario 2 covers the weighting when the governor has appointment power and another party has the ability to approve that appointment. Scenario 3 yields the weighting when the appointment and approval power are shared between two parties. Scenario 4 covers the weighting when someone else appoints the position and the governor approves that appointment. The 5th and final scenario covers the situation when the governor plays no formal role in appointing or approving the position.

When we envision extending this encoding strategy to include all actors as nodes in the appointment and approval process a few issues immediately emerge. First, in scenario 1, in which a single person has both appointment and approval authority, that person has a weight of 5, while in scenarios 2, 3, and 4 the combined weighting for the appointment and approval is 6. This suggests that scenario 1 may be underweighted (or 2, 3, and 4 are over-weighted). Second, in scenario 5 we are giving a weight of 1, even in the case where the governor plays no role in the process. We highlighted this issue earlier and, along with the issue of making the governor seem more involved than s/he actually is, if we adopt this across all nodes then each will be attached to each other with at least a weight of 1, which does not seem to make sense since it would imply that all nodes participate in the appointment of every agency head. Third, there are scenarios around shared responsibilities that are not covered in this model. For example, if the governor shares the responsibility for approval, we have no direction as to how to weight that using the legacy encoding.

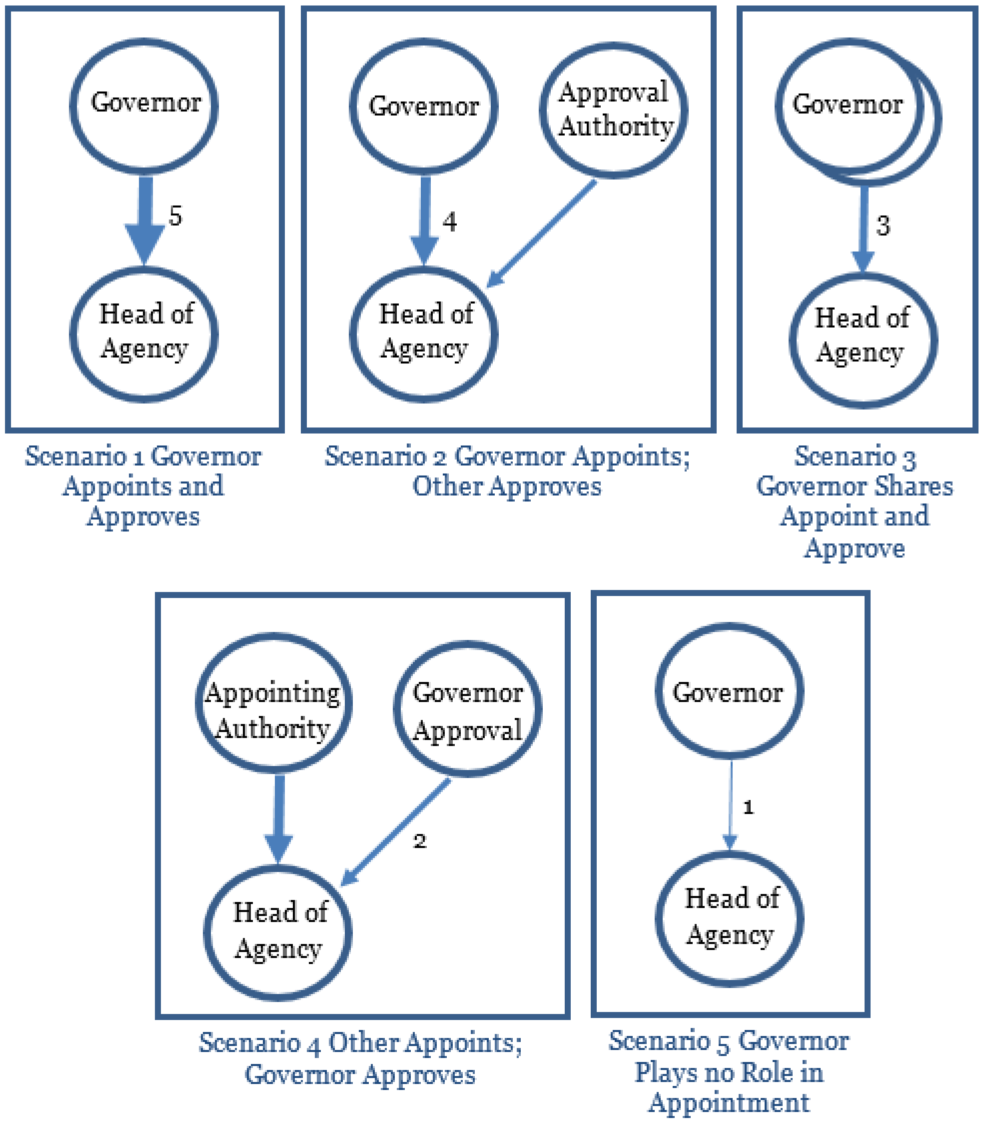


Figure 2-2 Scenarios with Legacy Weighting

2.4.3 Revised Weighting

Because of these challenges, we propose a revised weighting scheme (see Figure 2-3) that attempts to conform as closely as possible to the legacy weightings, while at the same time making sense from a social network perspective. We employ a strategy in which an appointment is afforded a weight of 3 and an approval is afforded a weight of 1. We also give no weight to nodes that are not directly involved in the process. We then apply these to all of our scenarios, and extend these scenarios to all actors involved in the appointment process. In the case of shared responsibility, we simply divided the weight by the number of individuals involved with that activity. For example, if the governor is only involved in the approval process, which is scenario 4, but shares that approval with someone else, then they would each only receive half of that weighting, in this case .5 each.

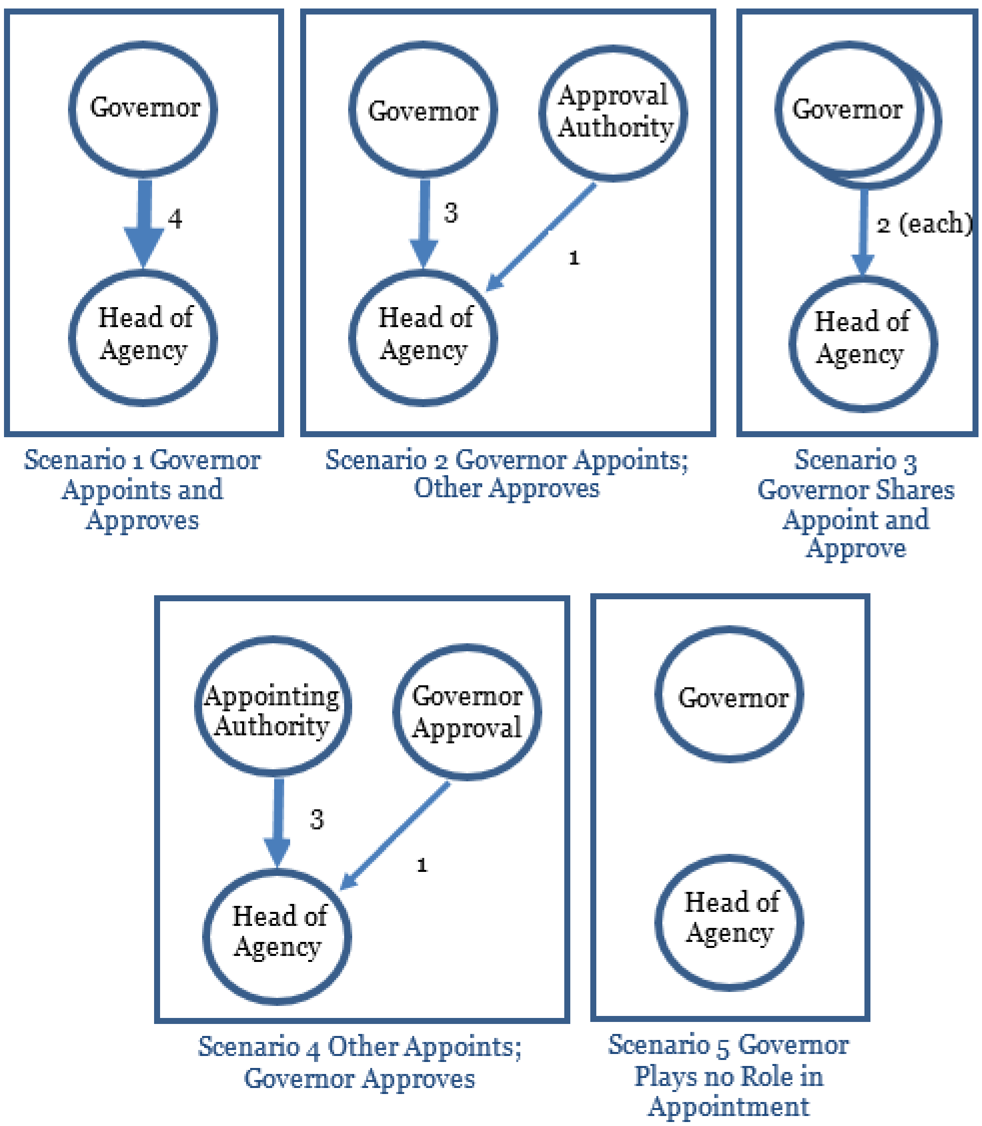


Figure 2-3 Scenarios with Proposed Weighting

2.4.4 Network Creation

Using this weighting scheme we can now create the whole network. To create the network we need the nodes and the edges. In the context of the state appointment network, the nodes will be any person, identified by their title, who is either appointed or participates in the appointment process though recommending or approving the appointment.

The edges represent the appointing or approving action. For example, if the Governor is responsible for filling the position overseeing the Energy Agency, but the appointment requires approval from the Secretary of State, then we would have 3 nodes (Governor, Head of Energy, and Secretary of State) and 2 edges (one linking Governor with the Head of Energy, and the other linking the Secretary of State with the Head of Energy).

Node	**Name**
1	Voting Public
2	Governor
3	Lieutenant Governor
4	Secretary of State
5	Attorney General
6	Treasurer
7	Adjutant General
8	Administration
9	Agriculture
10	Auditor
11	Banking

Table 2-3 Partial List of Nodes

The nodes are identified in a two-step process. First we create a node for each head of agency identified in The Book of the States. This yields 51 initial nodes. We then use the coding scheme from the Book of the States to identify any additional nodes that are not listed as agency heads, but who have appointment or approval authority. This yields an additional 7 nodes.

Finally, we have an indicator that some agency heads are neither appointed or approved, but rather are elected positions. We view the election process as an appointment and approval by the general public, so we create a final node called "Voting Public" to account for this scenario. This gives us a final tally of 60 nodes. A partial list of nodes can be seen in Table 2-3.

From Node	**To Node**	**Edge Weight**
2	11	4
2	12	4
2	13	4
14	14	4
2	15	4

Table 2-4 Partial List of Edges

To create the edges we take all the codes in the Book of the States and convert these codes to edge weightings. For the weighting value we use the "revised weightings" identified earlier. A partial list of edges can be seen in Table 2-4 in which each row corresponds to 1 edge. The first two columns refer to the nodes and the third column refers to the edge weight. For example, the first row indicates that node #2, which is the governor, has an edge to node #11, which is the head of the Banking agency, with a weight of 4, meaning the governor both appoints and approves that position.

2.5 Results

In selecting the states to analyze, we looked at their relative ranking using the appointment power of the FPI for 1992 (see Table 2-5 for top and bottom ranked states). The state with the highest gubernatorial appointive power (with a legacy score of 3.96 on a 5-point scale) was Massachusetts, while Texas was the state with the lowest gubernatorial power (with a legacy score of 1.16 on a 5-point scale). Our belief was that the state with the highest score would represent the most centralized state, while the state with the lowest score was the best candidate for a decentralized state. We chose the ranking from 1992 because we are interested in seeing how these states changed over a 20 year period.

State	**Gubernatorial Appointment Power using FPI 1992**	**1992 Rank**	**Gubernatorial Appointment Power using FPI 2012**	**2012 Rank**	**Change**
Massachusetts	3.96	1	3.07	7	-0.89
Pennsylvania	3.91	2	3.43	2	-0.48
Virginia	3.37	3	2.93	9	-0.43
California	3.15	4	3.34	4	0.19
Indiana	3.09	5	3.40	3	0.31
Missouri	1.87	45	2.09	46	0.22
Michigan	1.75	47	2.50	25	0.75
Mississippi	1.55	48	2.21	42	0.67
South Carolina	1.18	49	1.89	49	0.71
Texas	1.16	50	1.71	50	0.56

Table 2-5 States with Highest and Lowest Appointment Power

2.5.1 Massachusetts

From Table 2-5 we see that the appointment power of the governor of Massachusetts was the highest of any governor in 1992, yet also dropped the most from 1992-2012. What the FPI is not able to tell us is where that power went, only that it appeared to be taken away from the governor. We begin with the appointment network of Massachusetts in 1992 as seen in Figure 2-4. What is shown appears to tell a story of centralized power, with the governor responsible for appointing most of the agency heads. Only 5 of the 46 agencies, or 10.9% of all agencies, appointed their own head of the agency. While there are some minor actors in the appointive process, none come close to challenging the power the governor wields.

However, based on the decrease in FPI score, we suspect that significant changes occurred in Massachusetts between 1992 and 2012, with power being taken away from the governor. Figure 2-5 displays the appointment network for Massachusetts for 2012. Contrary to the notion that power is being stripped from the governor, it appears that the governor has delegated the appointment authority to his cabinet secretary, while still retaining the approval authority for almost all appointments. There is no indication of any type of power shift outside of the governor's office, nor is power decentralizing. In fact, none of the 5 agencies that appointed their own agency head in 1992 were still doing so in 2012. All 5 agencies are now appointed by the cabinet secretary and approved by the governor.

Table 2-6 presents quantitative centrality measures for key nodes in the Massachusetts appointment network for 1992 and 2012. We can see that, when you combine the average degree centrality (column 3) of the governor and cabinet secretary, the appointment power actually increased from 1992 to 2012. This contradicts the finding of the legacy FPI.

	1992			2012		
Position	**Legacy Appointment Power**	**Weighted Degree Centrality**	**Degree Centrality / # Agencies**	**Legacy Appointment Power**	**Weighted Degree Centrality**	**Degree Centrality / # Agencies**
Governor	3.96	136	2.96	3.07	99	2.15
Cabinet Secretary	n/a	0	0	n/a	58	1.26
Voting Public	n/a	24	.52	n/a	36	.78
Boards	n/a	0	0	n/a	12	.26
Secretary of State	n/a	8	.17	n/a	0	0
Administration	n/a	8	.17	n/a	0	0

Table 2-6 SNA Centrality Measures for Massachusetts

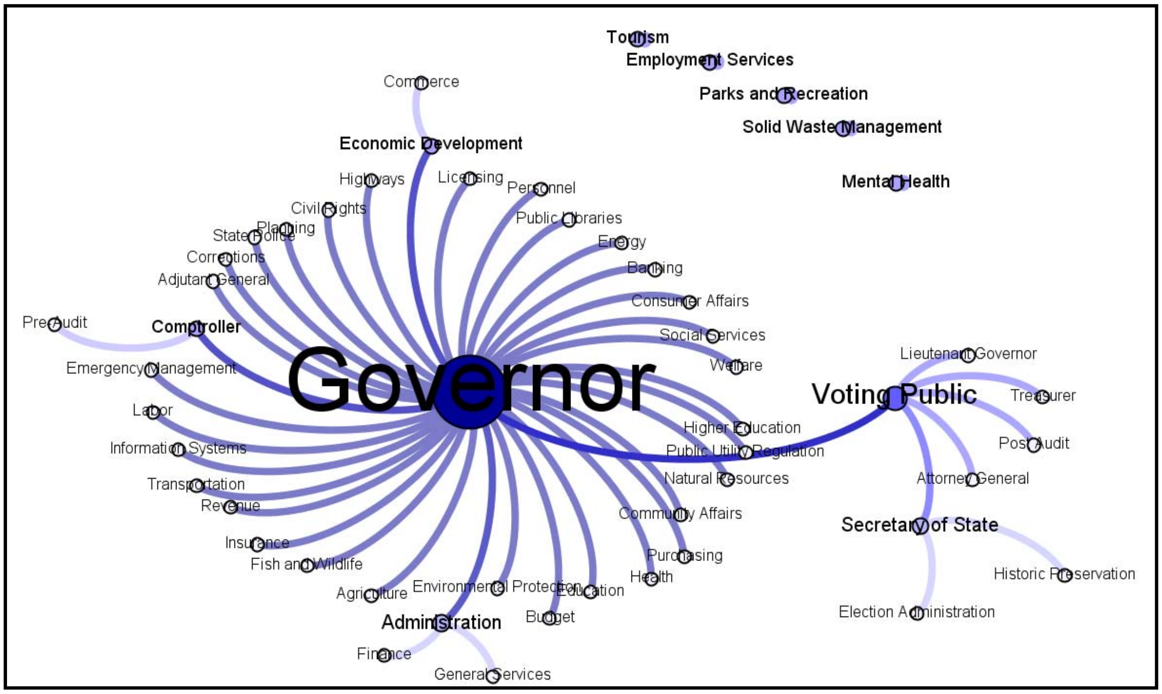


Figure 2-4 Appointment Network; Massachusetts, 1992

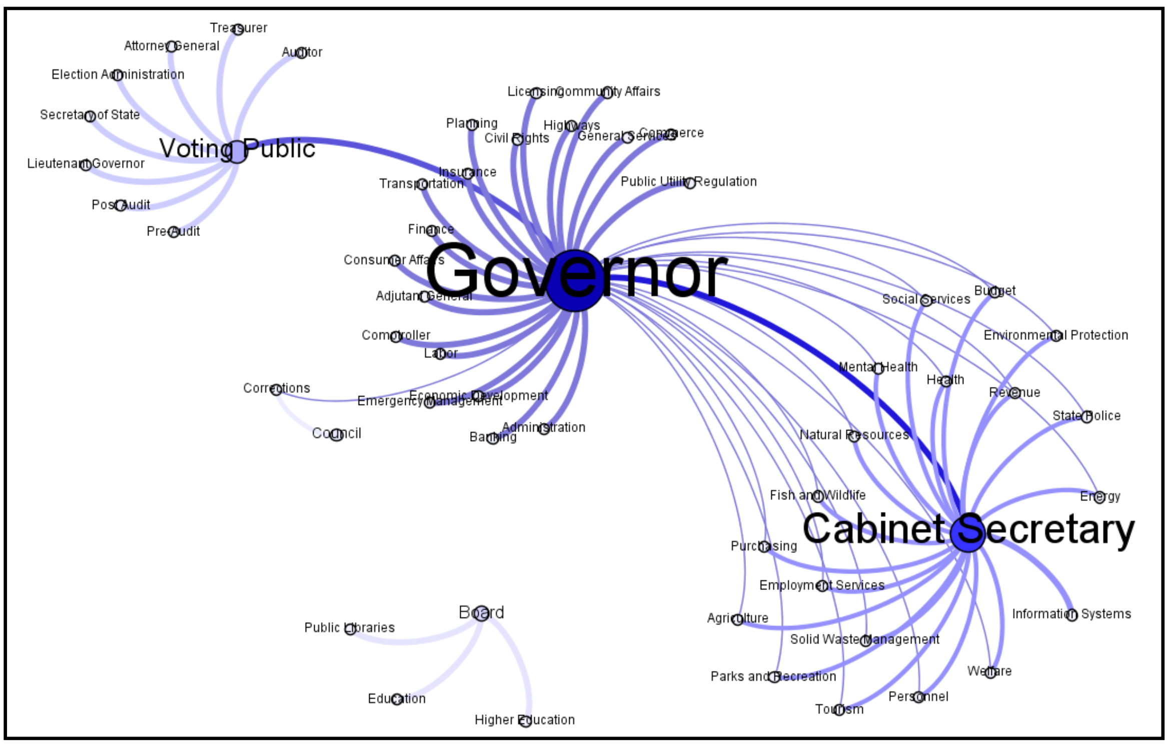


Figure 2-5 Appointment Network; Massachusetts, 2012

2.5.2 Texas

Using the FPI figures, the appointment power of the governor of Texas ranked lowest of any state in both 1992 and 2012, but the increase in governor power over that time suggested a move toward centralization in our analysis. First we look at the appointment network for 1992, which is presented in Figure 2-6. We can see that 9 agencies, representing 20% of all agencies, appoint their own head. The governor indeed does not appear to have much power, playing a role in appointing only 3 agency heads, and in each of those cases the appointment needs to be approved by the senate. By 2012 (see Figure 2-7) the governor appoints 8 positions with none needing approval. The number of agencies appointing their own agency head has decreased from 9 to 6. So, even though Texas ranked lowest in gubernatorial power over both time periods, we are seeing a move toward centralizing that power.

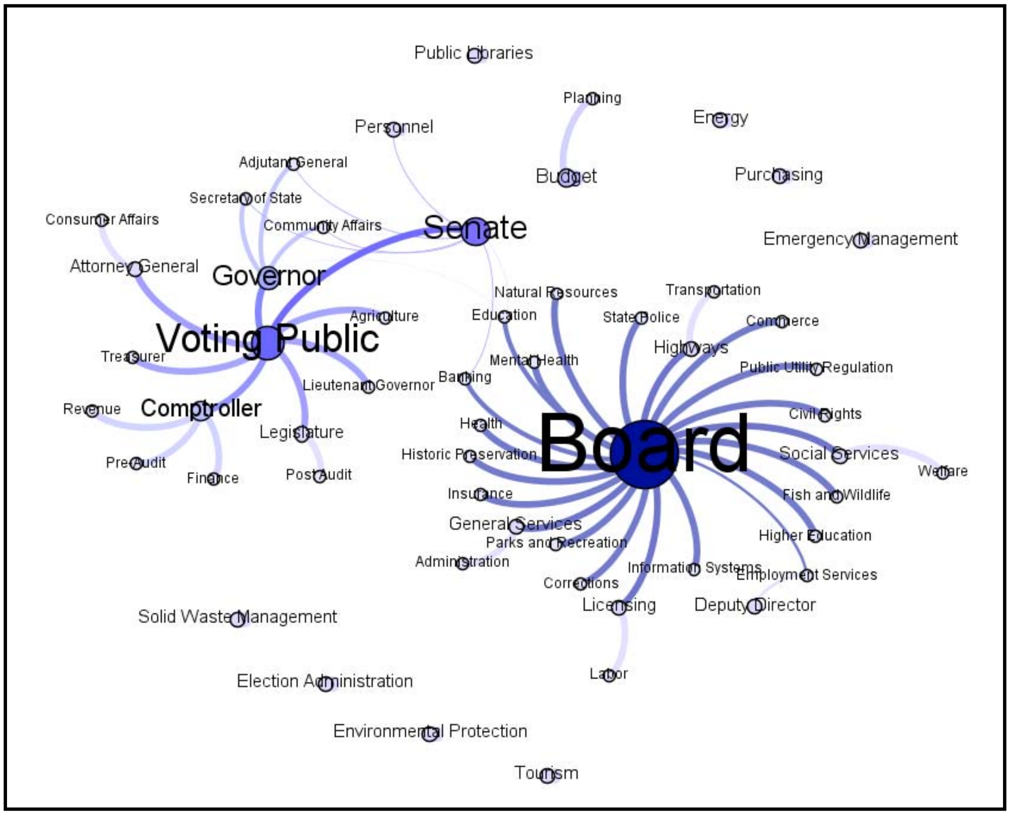


Figure 2-6 Appointment Network; Texas, 1992

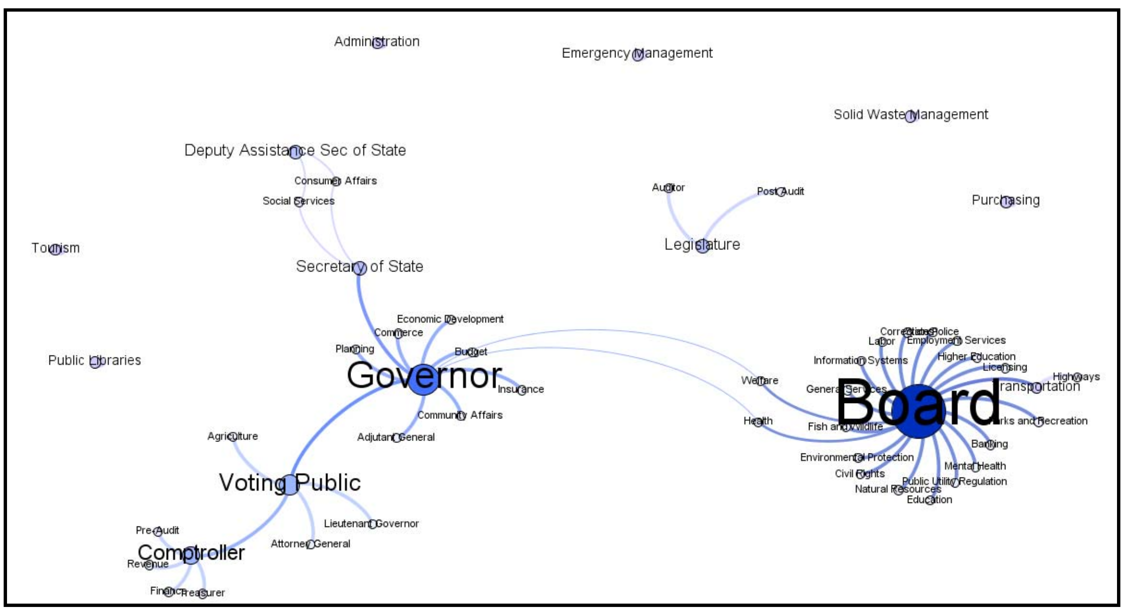


Figure 2-7 Appointment Network; Texas, 2012

2.5.3 Agencies

In selecting which agencies to analyze we followed the same process as we did with the states. We looked at the combined 50-state gubernatorial power for each agency, for the years 1992 and 2012, and selected the agencies that appear to have the strongest move toward and away from the governor. Figure 2-8 shows the 45 agencies that were identified in both the 1992 and 2012 Book of the States, ordered by the governor power to appoint values using the original FPI values. The bars represent the change between 1992 and 2012, with a green bar indicating a move toward the governor (i.e. higher appointment power in 2012 versus 1992) and a red bar indicating a move away from the governor. Overall, 12 of the 45 agencies (or 26.67%) moved away from the governor and 33 of the 45 agencies (73.33%) moved toward the governor. Table 2-7 lists the top and bottom 5 agencies, when ranked by their value change from 1992-2012. Information Systems displayed the strongest move toward the governor, while Energy displayed the strongest move away from the governor.

Agency	Governor FPI change
Energy	-0.48
Higher education	-0.29
Public library development	-0.27
Purchasing	-0.25
Election administration	-0.24
…	
Administration	0.66
Economic development	0.70
Social services	0.71
Commerce	0.89
Information systems	1.23

Table 2-7 Change in Governor Agency Appointment Power

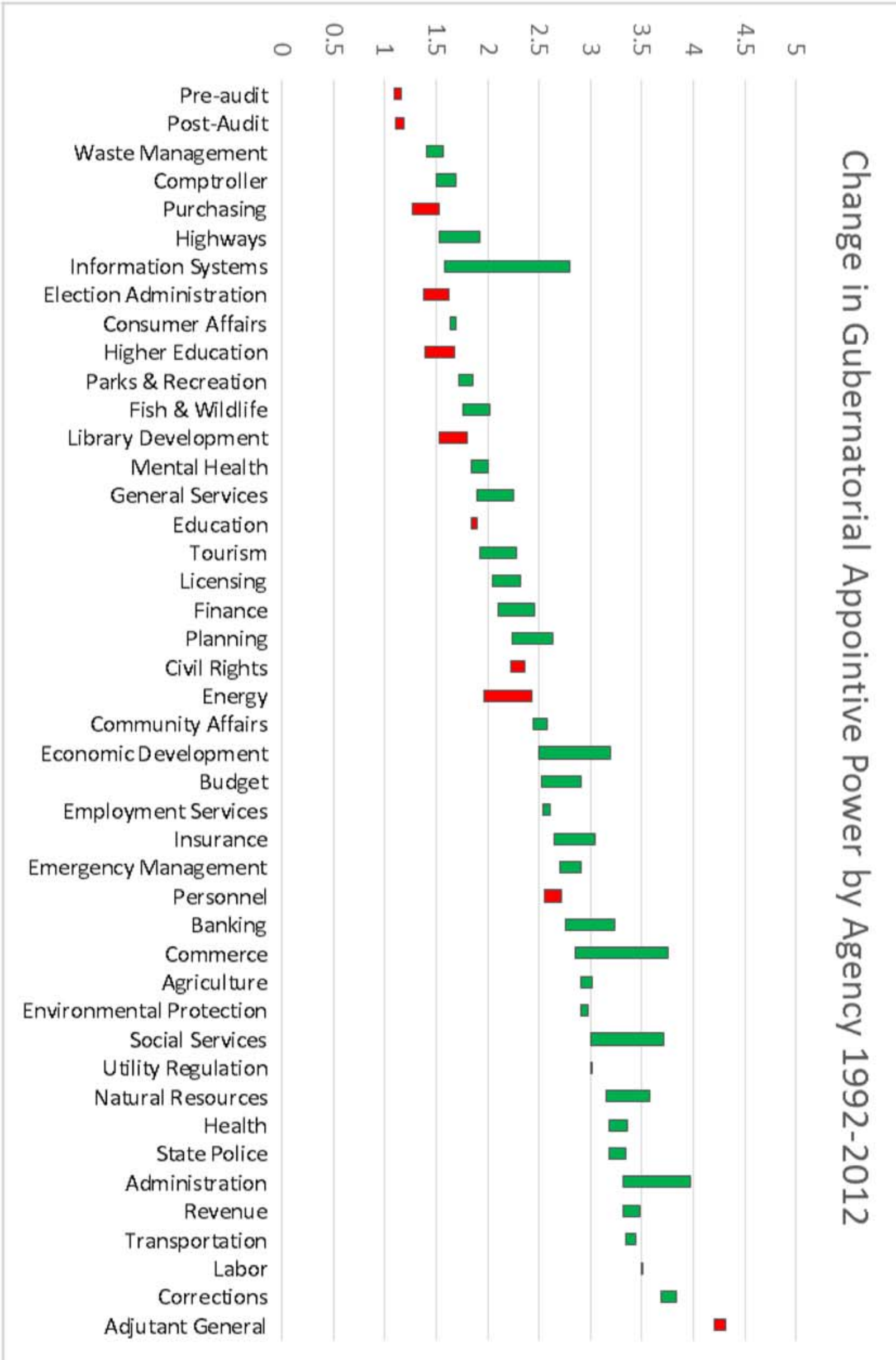
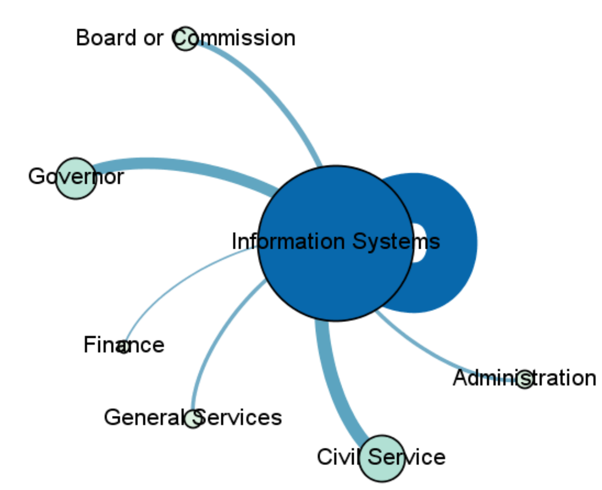


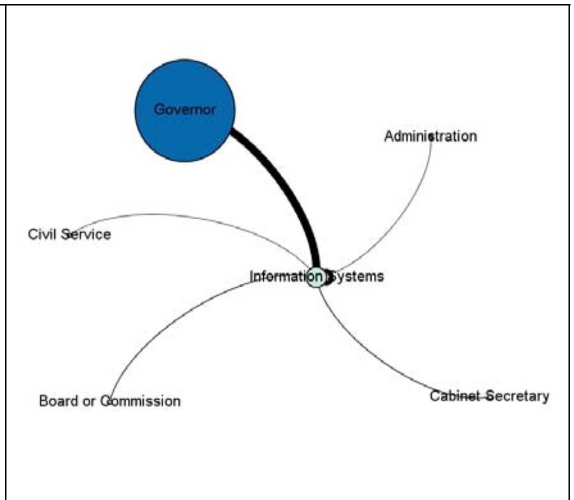
Figure 2-8 Change in Governor Appointment Power across Agencies

If we pivot the legacy appointment data to consider it by agency across all states, instead of across agencies for a single state, as we have done in Figure 2-8, we can observe a collective move toward or away from the governor, but we cannot see whom that power was taken from or whom it was given to. This highlights the limitation of looking at this data from an ego (governor) only point of view. However, by taking advantage of the full network that we created in section 2.4.4, we are able to show much more detail about changes at the agency level, including how state governments across all 50 states have changed who appoints any given agency head.

We begin with the agency that had the greatest move toward the governor from 1992 to 2012, the Information Systems agency. Figure 2-9 displays the network for appointing the head of the Information Systems agency for all 50 states in 1992 and 2012. The nodes are sized according to their appointment power, using our new weighting scheme, and represent who is responsible for appointing the agency head across all 50 states. The Information Systems node in 1992 is quite large in comparison to the other



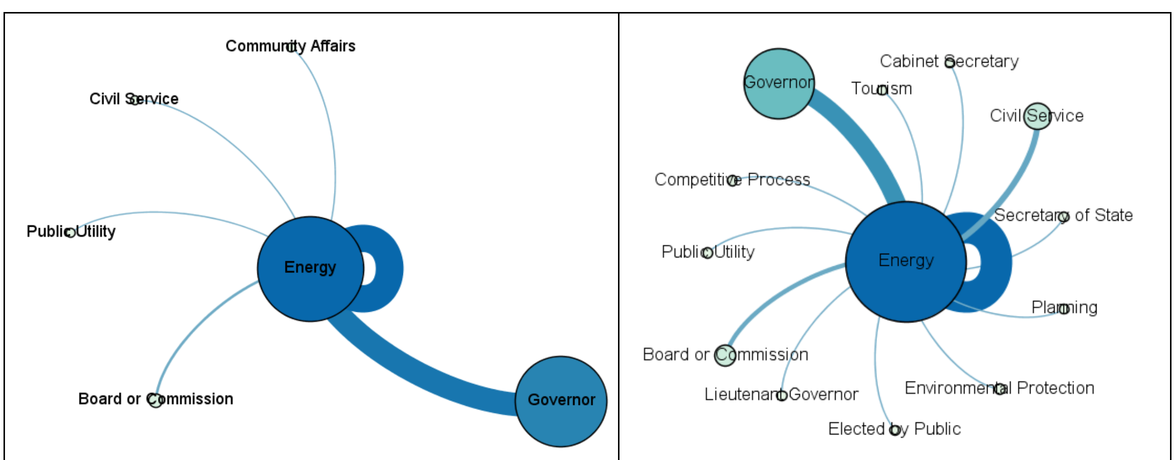
a) Information Systems Network, 1992



b) Information Systems Network, 2012

Figure 2-9 Appointment Network - Information Systems Agency nodes. This is because the agency self-appoints its own head in 26 states in 1992, while the Governor only appoints the agency head in 6 states, representing a decentralized structure. However, by 2012 the Information Systems agency only appoints its own head in 15 states, while the Governor appoints the head in 25 states.

Next we turn to the agency which had the greatest move away from the governor over our period of study, the Energy agency. Figures 2-10 displays the Energy agency in 1992 and 2012. Although we can see a slight decrease in the size of the governor node, if we consider delegated responsibility to the lieutenant governor and to the cabinet secretary, then the overall strength of the governor has actually increased over this time period. We recall that this agency appeared to have the strongest move away from the governor using the FPI. These figures show us that the appointment power move away from the governor has been transferred to a variety of other agencies such as the Planning and Environmental Protection agencies. Several states have also moved this position over to be appointed through a civil service process.



a) Energy Network, 1992 b) Energy Network, 1992

Figure 2-10 Appointment Network - Energy Agency

2.6 Discussion and Limitations

Using the legacy FPI we saw a general trend toward more gubernatorial power overall, yet there was evidence that some states who had a strong governor in 1992 were taking power away from the governor, while states with a weak governor in 1992 were giving more power to their governor. Our analysis of the state of Massachusetts contradicts this assumption, and shows that strong governor states may instead be adopting a delegated power structure in which the governor actually retains overall power. Similarly, the FPI figures based on individual agencies show a general trend toward granting the governor more power in appointing the heads of those agencies, but had some agencies moving away from the governor. When considering delegated authority as part of the governor authority we find that the agency with the strongest move toward the governor (information systems) displays an even stronger such move, and the agency with the strongest move away from the governor (energy) has actually been moving toward the governor. Valuable information can be obtained from filling out the complete appointment network within state government. We have shown through direct examples that the single node method of calculating gubernatorial power can be misleading, and we have presented a new approach for the consideration of appointment power through networks. Based on the findings from Massachusetts and the Energy agency, we recommend that researchers using the FPI should consider changes to the weighting in cases where the governor has delegated authority.

We expect that expanding on this work will provide additional insights, similar to this scenario, which could be used to recommend changes to the FPI, highlighting one of the benefits of utilizing SNA in this manner. In addition, we have shown that there is a benefit to seeing the entire appointment network across all 50 states, especially when considering the agency level trends across all states.

This method can also be used to evaluate changes in state agencies. The trend toward giving the governor the power to appoint the agency head certainly suggests that Information Systems has moved into a more prominent role over this time period. The purpose of this paper is not to make conclusions about the implications of such a change; but rather, to highlight the benefits of using network analysis in analyzing the structure of state government.

Harking back to Freeman's four features of social network analysis we have:

a) Used data from the Book of the States to populate our network, employing a uniform weighting strategy to arrive at an unbiased measurement of centrality, which is applied to all nodes in the network in the same manner.

b) Shown that, if one accepts that there is power in the appointment of key personnel, this power is shifting within states in different ways, beyond what can be accounted for by looking only at the power of the governor in isolation.

c) Provided the graphics that highlight these changes and emphasize these structural changes in ways that are harder to understand through tables alone.

d) Provided the measures that are also visually represented.

2.6.1 Limitations

This work is based on results from a few key states and agencies. A continuation of this research, including a comprehensive view across all 50 states, will help clarify whether the trend toward centralization is confirmed. Other scenarios, in which states are adopting novel administrative structures, such as in Massachusetts, may become evident when each state is considered on its own.

2.7 Conclusion

We have contributed a method by which the Index of the Formal Powers of the Governors can be recast in light of social network analysis. We have shown that the existing FPI weighting scheme is not extendable to network analysis because of deficiencies in the design. Instead we have proposed a weighting scheme that can be employed and extended to all relevant parties in state government who participate in some way in the appointment process of key state government personnel. We have shown that a measure of centrality (weighted out-degree / # of Agencies) could replace the legacy FPI for researchers who want to continue looking at this from a governor centric perspective. This gives a measure that continues to allow for a direct comparison of governors across the states. However, we have highlighted that this approach will fail to uncover other innovative changes that may be occurring within the states. We have identified at least one state, Massachusetts, that has moved beyond direct gubernatorial appointment; this indicates a limitation of the original index, but also challenges researchers to find a centrality measure that looks beyond the immediate reach of the governor to avoid an under appreciation for the move toward centralization across states and agencies.

Scoring a network, instead of an individual, can lead to such questions such as a) if an individual is losing power, where is that power going? b) how powerful is one individual in relation to all the others? and c) how is the dynamic process of power evolving over time?

This paper has shown how social network analysis can be used with legacy data. We offer a methodology for researchers and managers in the government domain who want to begin using analytics tools to understand existing data sets. The results of the social network analysis were able to explain where power shifted across states and across time. Our computational analysis of existing government data matches findings from previous studies and adds additional explanatory power.

2.8 Acknowledgements

This research was supported in part by the National Science Foundation, under grant number SES-0964909 (M. Lynne Markus, Principal Investigator).

3 Visualizing Global Interlocking Corporate Boards

3.1 Introduction

In *The Fracturing of the American Corporate Elite* (Mizruchi, 2013). Mark Mizruchi makes the argument that the corporate elite have been losing power since World War II, and the result is a lack of social direction due to this missing voice. This chapter begins to test this hypothesis. Following decades of research, which began with Mills' pivotal book *The Power Elite* in 1956, we adopt that there is an "elite" group of individuals who have historically driven not only the corporate, but also political and social agendas. It is this group of individuals that serve as CEOs, board member, leaders of churches, in local and regional political positions, etc. According to Mizruchi this cohesive group has been fracturing and, as such, their voice is no longer in solidarity to help push the corporate, political, and social agendas.

It is beyond the scope of this chapter to try to build out a social network that takes corporate, political, and social power into consideration. Instead, we posit that one way to measure the control of the elite is to examine the level of board interlockedness. Boards become interlocked when a person serves on the board of directors or in a senior role of two different companies at the same time. This interlocked network can be used as a proxy for the level of interconnectedness of those in control of the large corporations operating in our societies. We argue that if we see this level of interconnectedness decreasing, we will have evidence to support the Mizruchi hypothesis. But if there is no such decrease, and therefore no evidence that the corporate elite is diminishing, political or social elite may still be diminishing.

We begin by establishing a level of understanding of these networks by comparing the interlocked boards of the DOW 30 companies with the Paris CAC 40 companies. These two indexes were chosen since they represent the elite of the elite. If we are able to see change in these indexes, it will suggest that the core of elite power is changing. Since there are significant financial incentives for a corporation to be in a stock index, especially the DOW 30 and CAC 40, it strengthens our analysis to use these indexes due to these incentives. The elite have financial incentives to have the companies on the boards of which they serve, added to the index when openings occur. They are also incentivized to try to keep companies on whose boards they serve in the index. Consequently, we claim that if there is an elite group that is not fragmented, we should at least see stability in the level of interlockedness, if not an increase in interlockedness over time. The fact that the CAC40 and DOW are the elite of the elite is a good justification for us studying them since they are likely to be very influential.

On the other hand, it is long believed to be in society's best interest to reduce the level of board interlockedness. Interlocked boards have been of public interest for more than 100 years, since the Clayton Act of 1914 prohibited companies who compete in the same market from sharing directors. It was believed, at the time, that collusion would lead to price fixing. Therefore, in defense of the public and to limit this type of collusion, the Clayton Act was passed to reduce the level of interlockedness. In general, interlocks are viewed by policy makers as something that should be avoided since there is evidence that they lead to price fixing (Baker & Faulkner, 1993), contribute to the rapid rise in CEO pay (Hallock, 1997), and promote a lack of diversity among those controlling the elite firms of the world (Useem, 1984). As a result of these pressures, if the elite is indeed fragmenting, then we would expect to see a decrease in the level of interlockedness.

This first level of analysis, which looks at network density over time, will show that the level of interlockedness is decreasing in the CAC 40 but is remaining stable in the DOW 30. While there is stability in the interlocked network of the DOW 30, we still don't have enough clarity to understand exactly how the network is remaining stable. During the period of our analysis (2001 through 2010), there were three sets of changes in which a total of 8 companies were added and removed from the DOW 30. So we next pull in Burt's theory (Burt, 2000) on network decay to examine the DOW 30 in more detail to shed light on whether the interlock network is in fact changing at all or if it is remaining stable. Burt shows that network decay, which is the tendency of relationships to weaken and disappear, is amplified or lessened due to a) the strength of prior relationships, b) the "liability of newness," and c) the stability of embeddedness. Using this theory, we expand our analysis of the DOW 30 to encompass two adjusted networks. The first, which we have termed the *core hull*, consists of those 23 companies that remained in the DOW 30 throughout our period of analysis. The second, which we have called the *extended hull*, includes all 38 companies that were part of the DOW 30 at any time during the period of study.

Our results show that the density of the extended hull decreased over the period of study, lending support to the theory of decay. However, the core hull unexpectedly experienced a rise in density, suggesting that the strength of prior relationships among board members may play an important role. These findings suggest that the corporate elite may have the power to get themselves appointed to the boards of companies in the index, but lack power to get the non-index companies on which they serve added to the index when openings occur.

3.2 Literature review

In 1956 Mills' book *The Power Elite* (1956) described our society as one that is controlled by a small group of individuals termed the "elite." These elite are in control of not only the corporations, but also politics and society as a whole. This is a singular group whose members serve as CEOs of the major corporations, financiers of the political process which determines who can successfully run for political office, and leaders of our societal institutions such as the churches and other non-profits that provide necessary services to our society. In essence, wherever there is power and money, the persons behind those institutions are all controlled by this elite group of individuals.

One way in which these elite can be identified is through corporate boards of directors. The board of directors is a necessity of all publicly traded companies in the U.S., with a typical board consisting of 10 or more members (Bouwman, 2011), with the average director participating in three boards (Fich & Shivdasani, 2006), and the directors of larger firms participating in more boards than those of smaller firms (Bouwman, 2011; Ferris, Jagannathan, & Pritchard, 2003). *Interlocked boards*, also called *overlapping boards*, occur when a "person affiliated with an organization sits on the board of directors of another organization" (Mizruchi, 1996). Building on the work of Mills (1956), decades worth of research into the power elite has been conducted, including the inspection of the influence of board members on issues related to executive compensation and firm performance.

There are conflicting views of whether our society benefits or not from having an elite class. On one hand, there are vocal public groups, such as Occupy Wall Street (OWS), who argue against having an elite group of individuals in control of our society. They argue that this elite group (termed the 1%) has driven our society to extreme division in wealth distribution, resulting in severe economic inequality between the 1% and the 99%. On the other hand some, including Mark Mizruchi (2013), argue that much of the dysfunction we see in today's society is a result of a weakening elite class. He argues that having a cohesive group responsible for shaping society benefits society as a whole, since World War II, this elite group has, however, been fracturing and no longer retains that singular voice.

In selecting which boards to examine we turn to the various stock market indexes, specifically the DOW Jones Industrial Average index in the U.S. (DOW 30) and the Cotation Assistée en Continu index in France (CAC 40), which represent two of the most respected indexes in the world. The DOW 30 has a lengthy history beginning in 1896 when it was created by the Wall Street Journal editor and DOW Jones & Company co-founder, Charles Dow, as a way to show how 30 of the most respected U.S. companies fared on the stock market for any given trading day. Today, the 30 companies that make up the DOW 30 range in market value from approximately $34B to $554B, with a total market value of $5.43T (which is roughly $17,000 per person in the U.S.).

What can we expect when comparing U.S. companies to European ones? We will investigate this issue in light of the major causes of interlocking as identified by Bouwman (2011), which we depict in Figure 3-1.

Competition suppression occurs when two firms are able to collude while

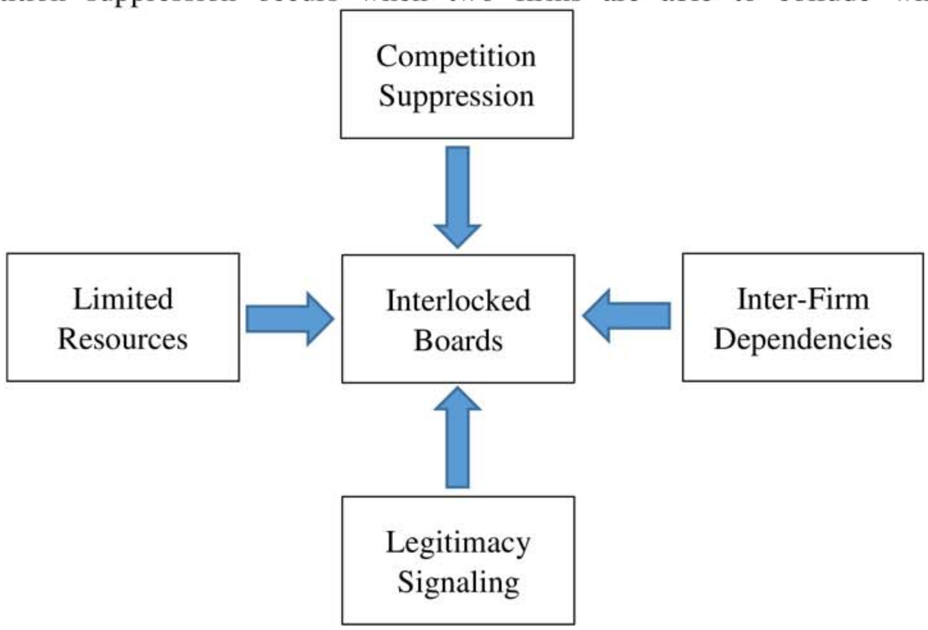


Figure 3-1 Sources of Interlocked Boards

competing in the same market. This can occur more readily when there are shared personnel resources, including at the director level (Pfeffer & Salancik, 1978). In the U.S., interlocked boards are prohibited among competitors through Section 8 of the Clayton Act of 1914, while there is no such prohibition in Europe. U.S. companies are cognizant of the Clayton Act, as evidenced by the Oct 12, 2009 Federal Trade Commission press release announcing that one board member, who also served on Apple's board, was stepping down from the Google board in order to comply with the Clayton Act. The FTC included the following in the press release: "Google, Apple, and Mr. Levinson should be commended for recognizing that overlapping board members between companies raise serious antitrust issues and for their willingness to resolve our concerns without the need for litigation" (Leibowitz, 2009).

Inter-firm dependence occurs when one firm is reliant on the other firm, and therefore the latter firm has a vested interest in keeping a close eye on the operations of the reliant firm, and is more likely to want a seat on the board of directors. Therefore the number of financial firms in any index would theoretically increase the level of inter-firm dependence due to the fact that, by their nature, firms are more dependent on the financial institutions. Legitimacy signaling occurs when a lesser known firm is trying to gain prestige by having board members from prominent firms on their board. Finally, when firms compete for board members, but there is a limited pool to draw from, the constraint of limited resources occurs. For example, Stokman, et al. (1988) found that in the Netherlands, firms were pulling board members from a limited number of available director talent.

As a result, other than legislation aimed at reducing competition suppression, which differs in the U.S. and Europe, it can be expected that each of the remaining factors presented by Bouwman would apply to both European and U.S. markets.

While much has been done in looking at the impact of interlocking directorates on issues related to the firm, there is little longitudinal research on how the interlocked network is evolving. Lluch and Salvaj (2014) examine Argentinian firms over an 80 year period. They find that the number of isolated firms increased from 23% in 1937 to 60% in 2000 while the percentage of interlockers as board members decreased from 18.6% to 8.5% over that same period. Maman (1999) looked at interlocking ties of Israeli business groups over the period of 1974-1987 and found that the level of interlocking remained relatively constant over this period. It is interesting to note that the period of most change in the Lluch and Salvaj study was between the years 1970 and 1990 which is close to the same period in the Maman study where very little change was observed.

Over time the member companies of the DOW 30 change as companies are added and removed from the index. Being added to an index has a significant positive impact on the stock price of the company, while being removed has a significant negative impact on the stock (Chang, Hong, & Liskovich, 2014). Those who benefit from changes in the stock price of these companies, therefore, have a financial incentive to try to influence which companies are added and/or removed from an index. Therefore, while there are external pressures to reduce the level of board interlockedness, there are unseen pressures being exerted to add specific companies to the index. We can hypothesize that the power elite identified by Mills (Mills, 1956) hold board positions of DOW 30 companies and have interests that would benefit financially by having other companies, on whose boards they serve, added to the DOW index. The result is a hidden pressure to actually increase the level of interlockedness, regardless of which companies actually make up the DOW 30 index in any given year.

Turning to the literature on social networks, Burt (2000) proposes the term *decay* to explain the tendency of relationships to weaken and disappear over time. He finds three primary reasons why decay occurs in one network while not in another. First, the strength of prior relationships is correlated with the level of decay. Strong prior relationships reduce decay. Second, the "liability of newness" explains that new ties are much more likely to weaken and disappear, while this propensity decreases as the age of the relation increases. Finally, embedded stability measures how stable the node is in the network; disruptions to the embedding lead to faster decay. Therefore, decay could be considered a friend to those trying to reduce the level of interlocked boards. As old interlocks are disrupted, the board members are either replaced with new board members who are not interlocked, which adds pressure on the network as a whole to reduce the number of ties, or, if they are replaced with alternative interlocking members, then those relationships are fragile due to their newness and subject to a higher risk of severing.

Therefore, it is to be expected that changes to the DOW through company additions will suffer the same liability of newness. That is, new companies are prone to rapid relationship decay. Furthermore, with the addition and removal of companies to the DOW, disruptions to embeddedness are realized, exerting more pressure for decay over the entire network. We are able to test whether this decay is occurring by looking at network density. Since density measures the level of connection between all nodes in the network, any decay should be seen through a decrease in density. This leads us to hypothesize that the DOW 30 network will experience periods of decreased density following periods in which companies are added and removed from the index.

Our evidence gives us reason to believe that there may be a higher level of interlocked boards in Europe, versus the U.S., primarily due to a) legislation in the U.S. prohibiting shared board members across competitors and b) a limited pool of resources for qualified board members in Europe.

We know from prior research that in the 1980's the average director of a median Fortune 500 board sat on 7 other Fortune 500 boards (Davis, 1996). But what about the average number of interlocks per firm for some subsets of industries? Since the Clayton Act prohibited competing companies from sharing directors, researchers have analyzed subsets of firms using their SIC codes. Pennings (1980) looked at 55 chemical firms and found 20[1] occurrences of an interlocked board[2]. Zajac (1988) looked at 43 transportation firms and found 14 occurrences. Zajac also looked at 32 primary metals firms and found 7 occurrences.

To test whether these groupings at the SIC code level were different from just a random selection of firms, Zajac (1988) created 50 random samples of 53 firms, each from the Fortune 500 group, and found an average of 16 interlocks per group or .30 interlocks per firm, and concluded that the number of interlocks occurring within an industry is the same across industries. We need to be clear here: these results are not saying that firms in general will have .30 interlocks in total, but instead will have on average .30 interlocks from a random sample of 52 other firms.

3.3 Methodology and Data

In order to measure the interlocked nature of corporate boards we use social network analysis. We treat each index as a network, in order to understand the characteristics of the network, and then compare these networks with one another.

In our comparison of the different networks we will focus on network density. Network density is calculated as the number of ties in the network divided by the number of possible ties where the number of possible ties is $n(n\text{-}1) / 2$.

The analysis compares the networks that make up the New York DOW 30 to the Paris CAC 40 over a 10 year period spanning from 2001 through 2010. We are coordinating

[1] Using the same SIC codes, Zajec (1988) found only 15 interlocks.

[2] Penning counted both firms in his analysis resulting in 40 interlocks. We halve it here to stay consistent with the way in which we count an interlock (1 board member on 2 boards = 1 interlock)

our efforts with those of researchers at the Université Paris Dauphine who are supplying the data for the Paris CAC 40 index.

For the DOW 30 we are utilizing the database supplied by BoardEx, which tracks board members from over 800,000 organizations internationally. The BoardEx "database" is a series of 66 Excel files that break out companies, individuals related to companies, and demographics. The information related to directors for a single company is spread out over dozens of files. Each of these files individually maximizes the amount of data that one can load into Excel. As such, the data needed to be trimmed down to a manageable size; we outline this process in the next section.

3.3.1 Data Selection

We have selected the DOW 30 and CAC 40 indexes as our basis on which to measure whether there is a disintegration of the elite class. We will do this primarily through the measure of network density of the interlocked networks of these companies. We believe that these 30 companies in the U.S. will provide the evidence needed to either support or refute the claim by Mizruchi that the (corporate) elite is fragmenting. These 30 companies make up the 30 of the most heavily owned and traded companies. Since we are concerned with the power of the elite, it would make sense that members of the elite would rather be a board member of one of the DOW 30 companies versus a board member of smaller and lesser known companies. As such, the elite as a whole would look to maintain control of these companies. If fracturing is occurring, and it has reached the inner core, then we will see evidence of it through the density of the interlocked network.

While the emphasis on the sectors that make up of the DOW 30 has changed over the years, with diminished emphasis on industrial sectors such as manufacturing and greater emphasis on financial and technology sectors, we argue that overall the DOW 30 have represented those most admired public companies in the U.S. regardless of sector. As such, the elite would wish to retain control of these companies regardless of the sectors they represent. As a result, the changing companies and sectors they represent provide us a healthy sample of companies to validate that the elite retain enough control to make these changes.

We bring in the CAC 40 interlocked network as a point of comparison by which to gauge the change, or lack of change, in the U.S. Through the comparison of these networks we are able to better understand the global nature of the elite and whether region specific influences (such as the Occupy Movement in the U.S.) are having an impact on these networks.

3.3.2 Preparation

Over the 128-year history[3] of the Dow Jones Industrial Average the companies that make up the index have changed 53 times. The index started in 1884 with 12 companies. This list expanded to 20 companies in 1916 and expanded again in 1928 to include a total of 30 companies where it stands today. Our period of interest was from 2001 through 2010 and included a total of 38 companies, because of additions and subtractions over this period. A full list of these 38 companies, along with their time in the DOW 30 related to this study, is located in Appendix A.

[3] http://www.djindexes.com/mdsidx/downloads/brochure_info/Dow_Jones_Industrial_Average_Historical_Components.pdf accessed 1/4/2015

Having identified the 38 companies of interest, our next step was to filter the list of directors down to just those directors who served on the boards of these companies. This allowed us to condense all of the directors of interest into a single file.

The data from BoardEX provide a row for each director who overlapped with another director in the same firm for some period of time (the overlap period). A new row is created if either director changes positions within the firm, or changes director roles. The overlap period was difficult to work with, and had to be segmented with a start and end date. Eventually we were able to get the file down to a unique list of directors for each firm during only the period of interest.

From this list we were able to create our nodes and edges. We started by creating nodes for both the companies, as well as the directors, and then creating the edges between them. This allowed us to see demographics on specific directors (age, gender, tenure, role, etc.), which allowed us to manually spot check our data using director lists found in the annual reports of these companies. We had to rely on these demographics, instead of board member names, due to the absence of names in the BoardEX database. Our network, at this stage, can be visualized in Figure 3-2 with the nodes sized on the basis of their degree centrality (note that we are displaying all 30 companies regardless of whether they had a shared board member, but we have filtered out board members that were not considered interlocked to keep the graph as easy to read as possible). This is called a *bipartite*, or *2-mode*, graph because we have two types of nodes, companies and directors.

Next, in Figure 3-3, we have stripped out the individual board members and have replaced them with weighted connections between the two companies, converting our 2-mode network into a 1-mode representation. As can be seen in Figure 3-3, General Electric and Microsoft have one common board member so an edge with a weight of 1 was created between GE and Microsoft, while GE and Home Depot share two board members, which resulted in an edge with a weight of 2 between GE and Home Depot. The final network for the DOW 30 companies in 2001 can be seen in Figure 3-3.

So how does this network compare with the European Indexes? Figure 3-4 shows the one-mode interlocked board network for the Paris CAC-40 index in 2001. We can observe that the companies that make up the CAC-40 appear to be far more interlocked than the companies comprising the DOW-30. However, it is difficult to know from these graphs whether the level of interconnectedness is greater in the CAC 40 due primarily to the increase in the number of nodes in the network. To get a deeper understanding we have to look at the network statistics, which we cover in the next section.

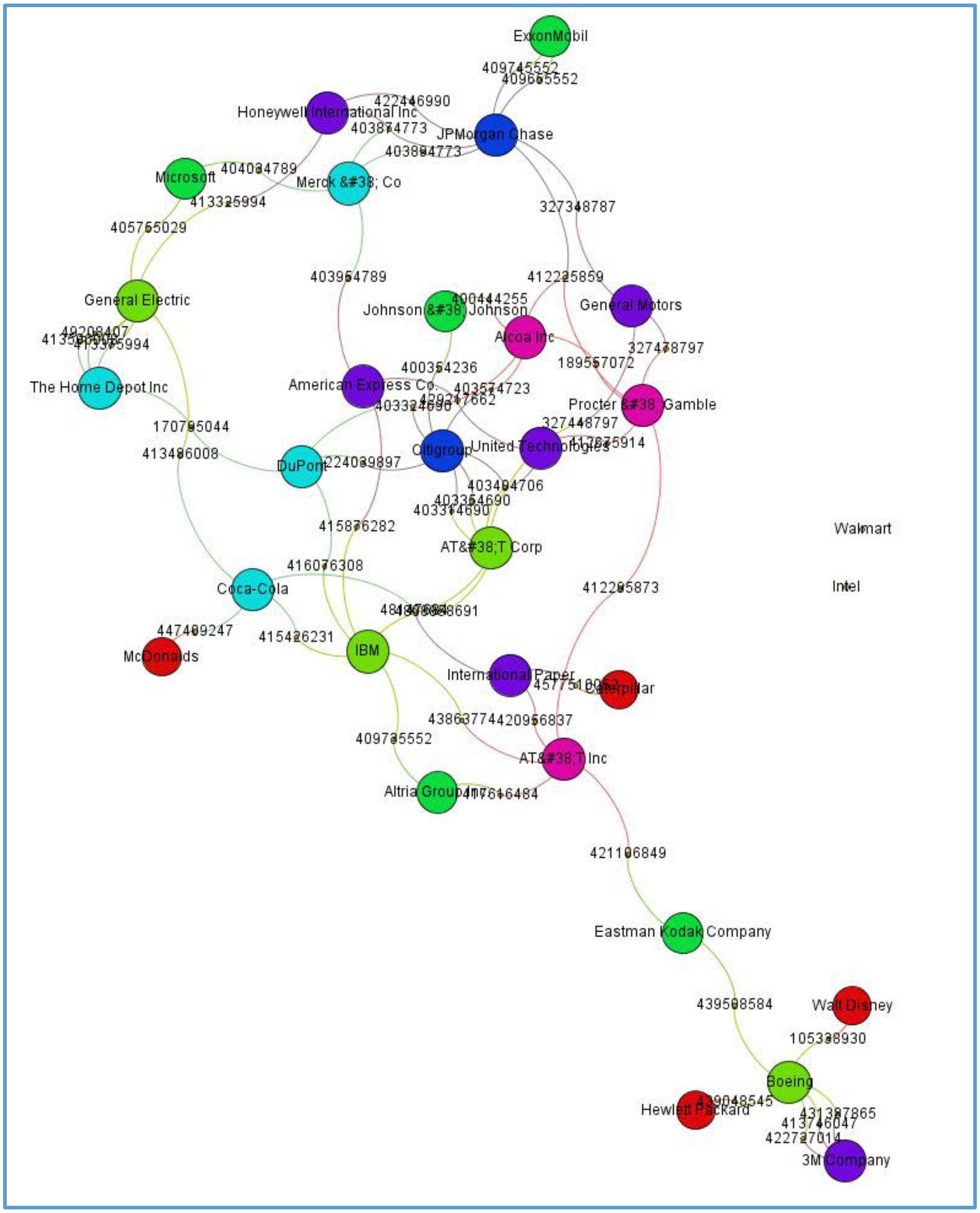


Figure 3-2 Interlocked Network showing Interlocked Board Members, 2001

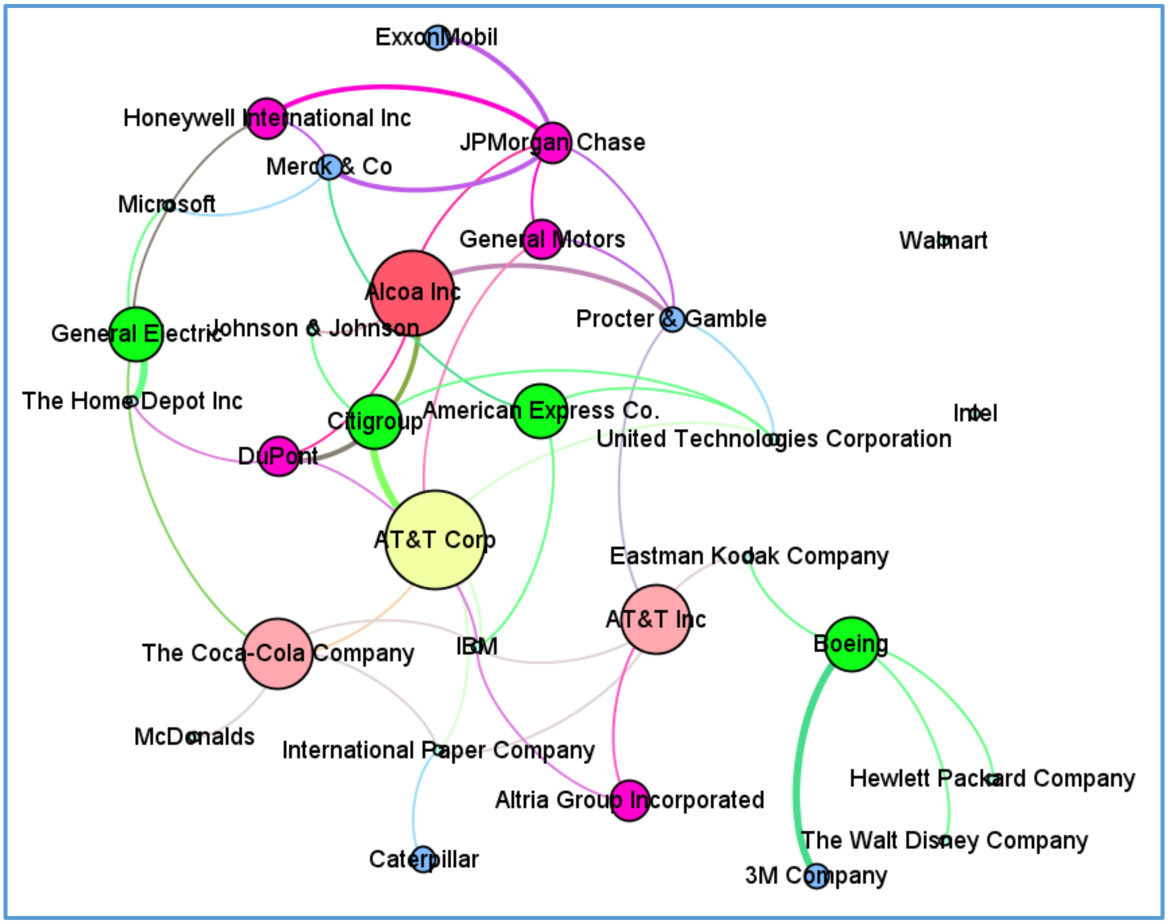


Figure 3-3 DOW 30 Interlocked Boards Network. 2001

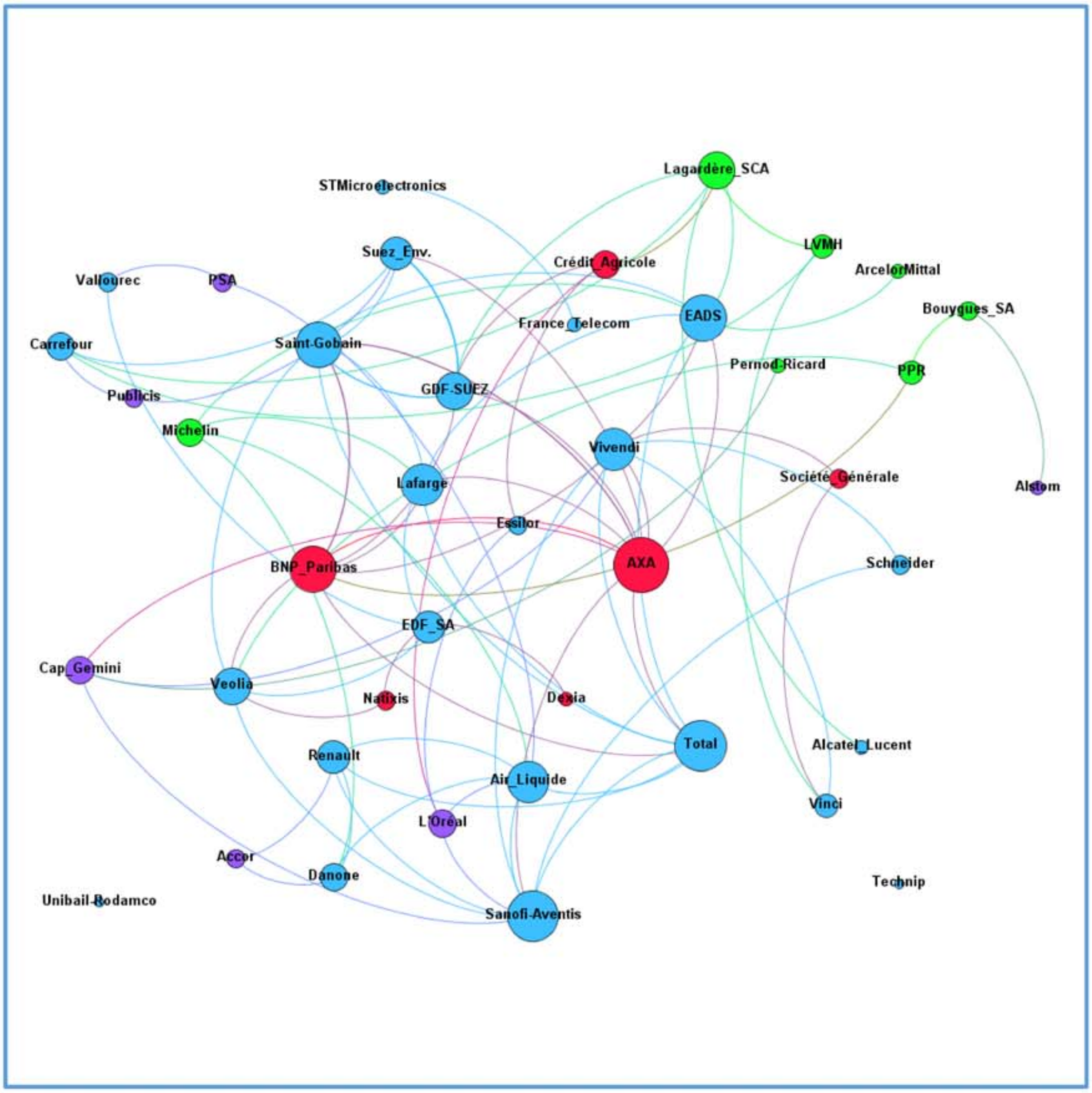


Figure 3-4 2001 CAC 40 Interlocked Board Network

3.4 Analysis and results

With the visual evidence in hand, we now turn to whole network measures to add depth to our understanding of the differences between the U.S. versus European markets. Table 3-1 provides the key network level measures for the DOW 30 network over the 10 year period, while Table 3-2 provides these same measures for the CAC-40[4]. We can see that over this period the average DOW 30 company was connected to a low of 2.667 (2009), and a high of 3.4 (2004), other DOW 30 companies through at least one interlocked member, while in the CAC-40 network the average company was connected to a low of 3.905 (2010), and a high of 6.714 (2002), companies. The average weighted degree for the DOW-30 ranged from 2.8 (2009) to 4.067 (2004), while for the CAC-40 this range was from 4.412 (2010) to 8.001 (2002). The difference in the average degree versus the weighted average degree is based on the number of interlocks that have more than one shared director.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Average
# Nodes	30	30	30	30	30	30	30	30	30	30	30
# Edges	46	46	48	51	47	46	48	44	40	50	46.6
Average Degree	3.067	3.067	3.200	3.400	3.133	3.067	3.200	2.933	2.667	3.333	3.107
Average Weighted Degree	3.933	3.867	3.867	4.067	3.533	3.533	3.467	3.200	2.800	3.667	3.593
Network Diameter	7	7	5	5	5	6	5	6	7	5	5.8
Graph Density	0.106	0.106	0.110	0.117	0.108	0.106	0.110	0.101	0.092	0.115	0.107
Modularity	0.497	0.478	0.437	0.441	0.402	0.454	0.433	0.529	0.465	0.447	0.458
Connected Components	3	3	4	3	3	2	2	1	3	3	2.7
Average Clustering Coefficient	0.226	0.169	0.324	0.336	0.168	0.212	0.197	0.292	0.263	0.235	0.242
Average Path Length	3.071	2.934	2.584	2.495	2.54	2.845	2.645	3.062	3.114	2.514	2.780

Table 3-1 Key Network Level Measures DOW-30, 2001-2010

If Companies A and B share two different directors (and do not share directors with any other companies) then the degree of A and B will be 1 while the weighted degree of A

[4] Note that the slight differences in the number of companies in the CAC 40 over time are due to the fashion in which time was recorded in the CAC 40 database; at each event of a company joining or leaving the index, rather than on December 31st of each year as was done for the DOW 30.

and B will be 2. It follows that while there is some occurrence of multiple shared directors, it does not occur frequently. Dividing the average weighted degree by the average degree results in 1.16 for the DOW and 1.15 for the CAC, indicating that the frequency by which multiple board members overlap is roughly the same for both indexes.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Average
# Nodes	40	42	42	42	43	44	43	42	41	42	42.1
# Edges	109	141	133	113	117	102	98	111	103	82	110.9
Average Degree	5.450	6.714	6.333	5.381	5.442	4.636	4.558	5.286	5.024	3.905	5.273
Average Weighted Degree	6.593	8.001	7.406	6.183	6.179	5.243	5.133	5.945	5.684	4.412	6.078
Network Diameter	5	5	4	4	5	6	6	7	7	6	5.5
Graph Density	0.140	0.164	0.154	0.131	0.130	0.108	0.109	0.129	0.126	0.095	0.129
Modularity	0.394	0.372	0.370	0.366	0.361	0.364	0.388	0.360	0.344	0.448	0.377
Connected Components	4	4	2	5	4	5	3	2	3	4	3.6
Average Clustering Coefficient	0.674	0.619	0.610	0.604	0.557	0.455	0.466	0.448	0.348	0.448	0.523
Average Path Length	2.414	2.206	2.287	2.368	2.392	2.629	2.685	2.620	2.650	2.911	2.516

Table 3-2 Key Network Level Measures CAC-40, 2001-2010

The network diameter is the measure of the longest shortest path between any two nodes in the network. In other words, for those nodes that are connected the furthest distance, when traveling the shortest route, is the network diameter. Somewhat surprisingly, even though the CAC has more nodes, the network diameter is shorter in the CAC (5.5) than it is in the DOW (5.8), suggesting that it wouldn't take as long for information to pass through this network.

Another useful measure is network density, which represents the proportion of connections to the potential number of connections. As we can see in Table 3-1, the DOW 30 network density ranged from .092 to .117, while the CAC 40 network density ranged from .095 to .164 (see Table 3-2). This suggests that while the *number* of shared directors appears to be greater for the CAC 40, (as measured by the degree), the *proportion* of boards where at least one director is interlocked is roughly the same, which answers the question as to whether the CAC had more interlocks simply due to the size of the network – it appears to be the case.

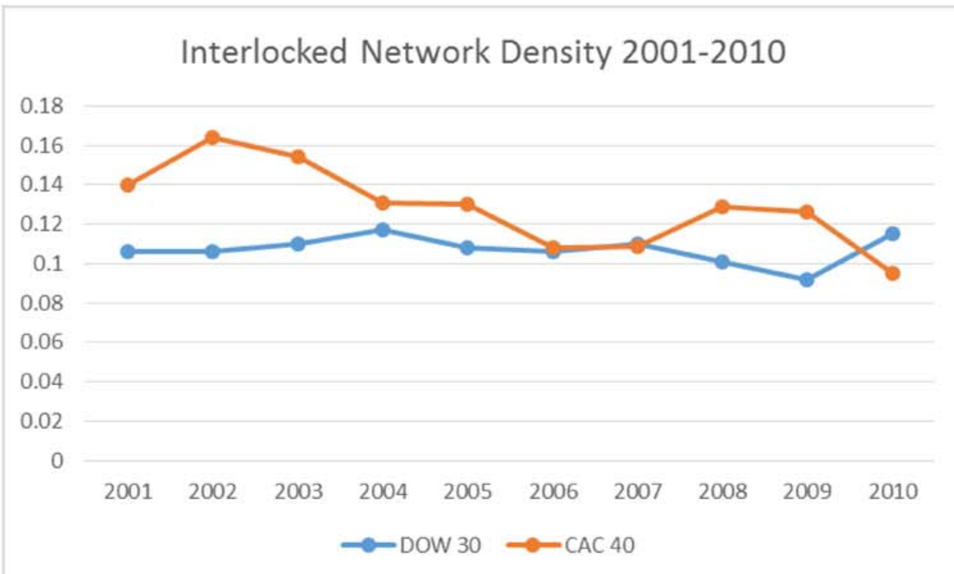


Figure 3-5 Interlocked Network Density 2001-2010

Figure 3-5 plots the density for both the CAC 40 and the DOW 30. This chart shows us that density in the CAC 40 decreased over the period of our study while the density of the DOW 30 remained flat. Using a simple regression of the densities over time we test whether a significant trend occurs within either the DOW 30 or the CAC 40. The result is non-significant change in the DOW 30 (slope=-.001, p-value=.539) and significant negative change in the CAC 40 (slope=-.005; p-value=.009). Based on the density, we see no evidence of network decay for the DOW 30 index, but there is evidence of some decay in the CAC 40.

However, Burt's theory of network decay reminds us that connections are more vulnerable when companies are added and removed from the index. There are three periods of change in the companies that comprise the DOW 30 during our period of study.

a) In 2004 AT&T Corporation, Eastman Kodak, and International Paper were all removed while American International Group Inc, Pfizer, and Verizon were added.

b) In 2008 Altria, American International Group, and Honeywell were replaced with Bank of America, Chevron, and Kraft Foods.

c) In 2009 Citigroup and General Motors were replaced with Cisco Systems and Travelers.

While we see a slight decrease in density following the changes in 2004 and 2008, we see an increase in density after the 2009 changes. Overall this doesn't lend strong support for the theory of network decay for the DOW 30 companies.

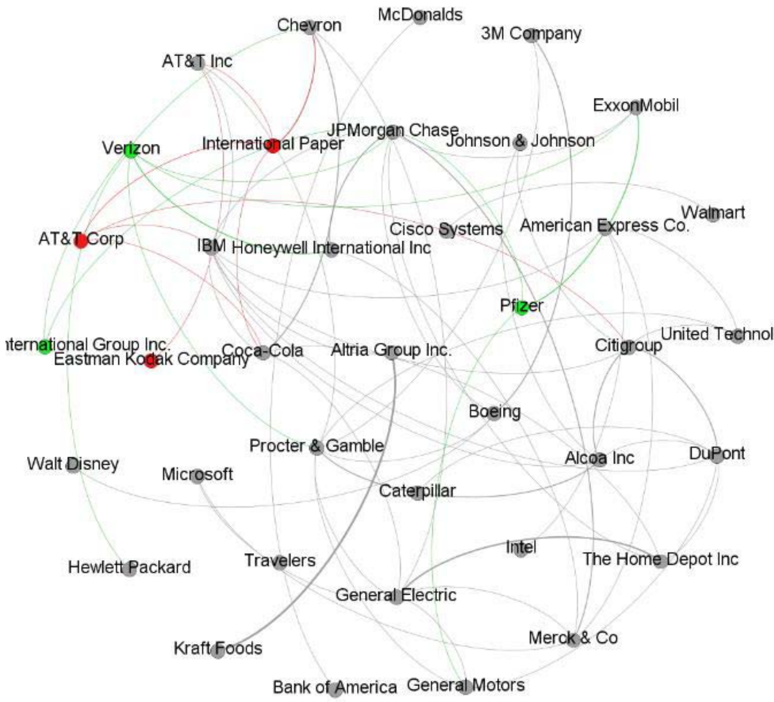
In order to dive deeper into these changes we turn to our DOW hull data in order to tease out whether network change is occurring when additions or subtractions are factored in. Throughout our 10 year period of study, a core group of 23 companies remained in the DOW 30 index. We refer to the 23 companies as the *core hull* since they represent that portion of the network that did not change at all over the period of study. We add in the companies that were added and removed over the years and call this the *extended hull*. In the next section we will dive into the analysis of the core and extended hulls.

3.5 Extended DOW Index

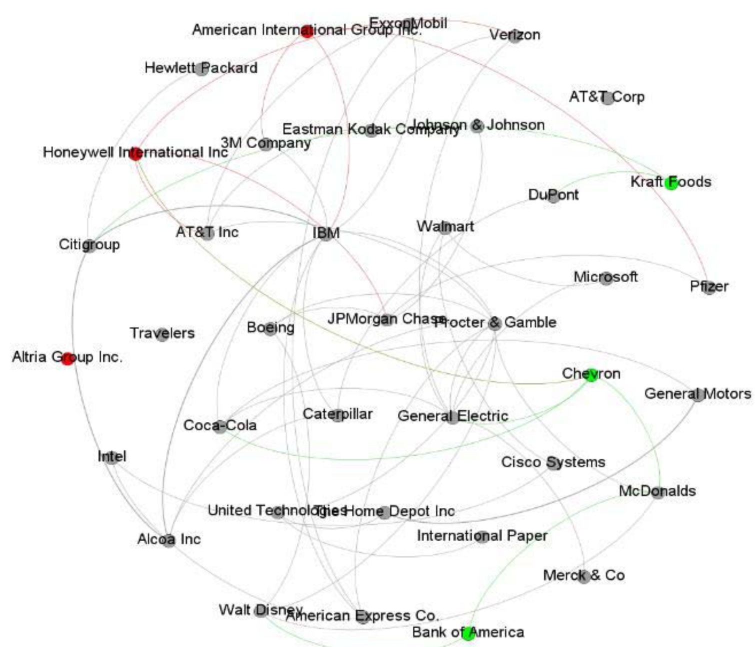
As discussed earlier, one complication in longitudinal investigations of the DOW 30 network is that corporations leave and enter this network as years pass. Up until this point we have used a network that swapped companies as they were replaced in the DOW. Next we compare those results with a network including all 38 companies that participated in the DOW 30 at any time since 2001 (the *extended hull*), as well as the 23 companies that remained in the DOW 30 throughout this 10-year period (the *core hull)*.

We begin by considering the visualizations of the extended hull network with nodes color coded according to whether they are added (green), removed (red), or remained (grey) in the DOW 30 for the visualized year. Recall that there were 3 periods (2004, 2008, and 2009) when companies were added and removed from the index; Figure 3-6 shows the network layout using the classical Fruchterman Reingold layout (Fruchterman & Reingold, 1991) for those three years.

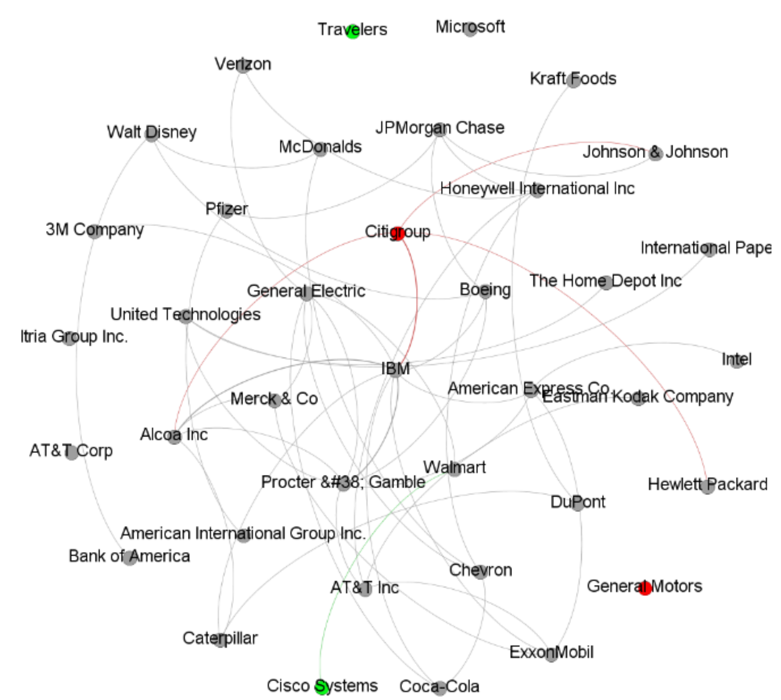
In 2004, two of the three companies that were removed were interlocked with 4 others DOW 30 companies. The third was interlocked with only one other DOW 30 company. All combined, the removed companies were interlocked with 9 companies. Of the three companies that were added, Verizon was interlocked with 5 other companies, Pfizer with 3, and AIG with 2, for a total of 10 companies.



(i) Extended Hull; 2004



(ii) Extended Hull; 2008



(iii) Extended Hull; 2009

Figure 3-6 Extended Hull with Exits in Red and Entrants in Green

It is interesting to note that from the visualizations it is not obvious, based on network connections, which nodes would be added or removed. In other words, we cannot claim that the companies that were dropped from the DOW 30 had no (or fewer) connections with the other DOW 30 components, or that the companies that were added were obviously better connected than other companies. This suggests that either a) the interlockedness of a company is not related to whether they are added or removed from the DOW 30 index, or b) as companies are replaced they are replaced with similarly connected companies to, perhaps, provide stability to the DOW through these periods of change. One item that we did observe is that the number of financial institutions remained consistent throughout the period of study, which included the years of the subprime mortgage crisis. During the crisis two financial firms (AIG and Citigroup) were replaced with two alternative financial firms (Bank of America and Travelers). We'll revisit this topic in chapter 4.

We now move beyond the visualizations to look at the core network statistics. Tables 3-3 and 3-4 report on the key network measures for the core and extended hulls, respectively. While the average degree and average weighted degree are higher in the extended hull, this is to be expected due to the increase in the number of companies comprising the network. A better measure to consider is network density.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Average
# Nodes	23	23	23	23	23	23	23	23	23	23	23
# Edges	24	26	30	31	30	29	32	30	29	34	30
Avg Degree	2.087	2.261	2.609	2.696	2.609	2.522	2.783	2.609	2.522	2.957	2.566
Avg Weighted Degree	2.696	2.783	3.130	3.130	2.783	2.696	2.870	2.696	2.696	3.217	2.870
Network Diameter	6	7	5	5	5	5	5	6	5	5	5.400
Graph Density	0.095	0.103	0.119	0.123	0.119	0.115	0.126	0.119	0.115	0.134	0.117
Modularity	0.505	0.450	0.412	0.396	0.374	0.425	0.433	0.466	0.349	0.422	0.423
Connected Components	5	4	4	4	4	3	3	2	3	3	3.500
Avg Clustering Coefficient	0.036	0.044	0.142	0.233	0.173	0.312	0.310	0.379	0.118	0.320	0.207
Avg Path Length	2.476	3.089	2.516	2.437	2.421	2.595	2.548	2.779	2.752	2.545	2.616

Table 3-3 Core Hull Network Statistics

We can see from Table 3-3 that the density is increasing over time. This is supported by the number of connected components, which represent the number of subgroups, which is decreasing, indicating that the nodes in the core hull are getting more connected over time. This is further supported when the average clustering coefficient is considered.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Average
# Nodes	38	38	38	38	38	38	38	38	38	38	38
# Edges	70	68	67	65	57	55	61	56	48	61	60.8
Average Degree	3.684	3.579	3.526	3.421	3.000	2.895	3.211	2.947	2.526	3.211	3.200
Average Weighted Degree	5.053	4.895	4.597	4.211	3.474	3.421	3.421	3.158	2.684	3.632	3.855
Network Diameter	7	6	5	5	6	7	6	6	7	5	6.0
Graph Density	0.100	0.097	0.092	0.085	0.081	0.078	0.087	0.080	0.068	0.087	0.086
Modularity	0.506	0.494	0.496	0.489	0.468	0.505	0.473	0.507	0.437	0.453	0.483
Connected Components	2	3	5	5	5	3	3	4	6	7	4.3
Average Clustering Coefficient	0.301	0.182	0.278	0.253	0.162	0.174	0.141	0.232	0.102	0.231	0.206
Avg Path Length	2.994	2.833	2.544	2.614	2.677	3.146	2.944	3.027	3.233	2.493	2.851

Table 3-4 Extended Hull Network Statistics

Table 3-5 displays the network statistics for the extended hull. In this network we see that density is decreasing, the connected components is increasing, and the average clustering coefficient is decreasing. Each of these results support the belief that the network is getting less connected over time.

Figure 3-7 displays the density over time for the core and extended hulls, along with the original DOW 30 graph we introduced in Figure 3-5. As previously discussed, the density of the DOW 30, in which companies were replaced over time, remained flat. It appears that over this period of time the density of the core hull increases, while the density of the extended hull decreases. We run a simple regression using time as our predictor and density as our dependent variable. The results show significance for both the core (slope = .003; p-value = .017) and extended (slope = -.002; p-value = .016) hulls, with density increasing and decreasing respectively.

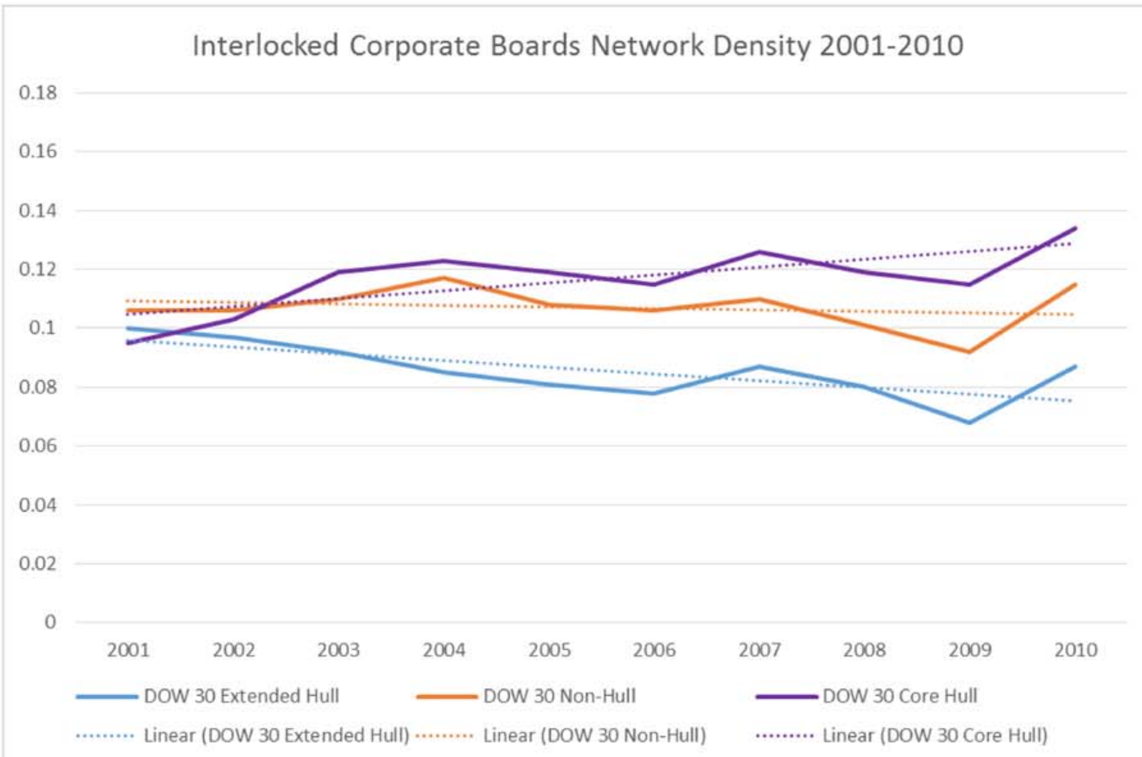


Figure 3-7 Network Density for Core and Extended Hulls

The result of this analysis leads us to conclude that the DOW 30 is stable when companies in the network are replaced, at the time they are added or removed from the index. Since we are seeing a positive trend in the core hull we conclude that there appears to be support for the theory that longevity plays a role with regards to network decay. Those companies that maintain a long-term presence in the DOW 30 are forging new interlocked connections at a faster rate than decay eliminates old connections. The decline in the extended hull supports Burt's (2000) theory that newness and disruption affect the connections.

3.6 Conclusion

Our findings show that any two elite firms are interlocked with roughly the same frequency in the CAC 40 as the DOW 30. However, when interlocks do occur, the chance for multiple shared directors is greater in the CAC 40 than in the DOW 30. The interlocks for these two index networks occur much more frequently than prior literature shows, based on either a network of companies in the same industry or a random sample of companies making up the Fortune 500 index.

While the density in the CAC 40 decreased over the period of our study, the DOW 30 appeared stable. This would suggest that a fracturing of the corporate elite may be occurring in Europe, but not in the U.S. However, by looking at the core and extended hulls, we were able to tease out that the companies that were stable throughout the whole period increased in density, while once the companies that were added and removed were added back in (the extended hull), the density decreased over the period of our study. This leads us to conclude that the DOW 30 and, more particularly, its core hull, may represent a very robust kernel of the corporate elite in the U.S. It suggests that the elite do a good job of retaining their directorships over the long-run, but may not have as much power to influence the decision of which companies to add to the DOW. Overall these findings suggest that changes to the DOW 30 index increase diversity (and decrease the power of the elite) in network composition as evidenced by an overall decrease in interlocked density, while the stability of companies making up the index decrease diversity (and increases the power of the elite) as evidenced by the increase in density. We will return to these issues in chapter 4.

3.7 Limitations and Future Research

This work begins to tease out what is occurring at the network level as changes to the DOW 30 are experienced. However, we recognize that expanded analysis needs to be done to fully understand the impact of these changes. First, while we argue that the DOW 30 represents a powerful sample of the companies the elite would want to control, there are sectors that have more representation than other sectors. Specifically, technology and finance are two sectors that are weighted heavily, while manufacturing is underrepresented. The index also excludes the utility and transportation industries since those have historically been represented through other indexes. Due to the sectors represented during or period of study, we may be missing other sectors that have received more attention from the elite. By expanding our analysis beyond the DOW 30 we would capture more sectors.

Second, we have argued that the DOW 30 represents the elite of the elite. It may be that the overall power of the elite has shrunk while at the same time retaining most of their power around their core, namely, the elite of the elite. By expanding the analysis beyond the DOW 30, we would be able to test whether decay is occurring across a wider swath of companies.

Finally, two-mode networks, such as interlocking boards, can be reduced down to two 1-mode networks. We have continued with the more common approach of reducing this down to the corporate network, but it would be quite interesting to reduce it down to the board member network. Such an approach would allow us to focus on individual directors to gain insight into who the board members are that are participating as interlocking agents.

4 Understanding the Evolution of Networks over Time – A Bayesian Analysis

4.1 Introduction

In chapter 3 we discussed the challenges of analyzing a network in which nodes are added and removed during the period of study. We developed the concept of the core hull to represent the network including just those participants that were members of the network throughout the period of study, and the extended hull to represent all participants who were part of the network at any given time. We were then able to show that trends in density can assist in understanding the impact that the additions and subtractions were having on the network. In this chapter we explore this in more depth to tease out those differences. Our analysis is motivated by the claim by Mizruchi (2013) that the "corporate elite is disintegrating."

Indeed, in *The Fracturing of the American Corporate Elite* (Mizruchi, 2013), Mizruchi makes the claim that a disintegration of power is occurring within the corporate elite. He asserts that since World War II the voice of the American corporate elite has diminished to the point where it is now ineffectual. This shift in the role of the corporate elite has had an impact not only on the corporations it oversees but on the entire business system (Scott, 1991; Useem, 1984).

We argue that if this is occurring, then there should be evidence of such change in the power networks of members of the corporate elite. One way in which to identify the corporate elite is to look at corporate boards of directors. Building on the work of Mills (1956), extensive research about the power elite has been conducted, including investigations of the influence of board members on issues related to executive compensation and firm performance. Wong et al. (2015) show that the level of board interlocking contributes to the level of executive pay.

In this paper, we focus on interlocked boards - boards that share at least one director. A premise to our study is to consider the density of an interlock network as a proxy for cohesive power within the corporate elite.

Employing a Bayesian analysis in which we test for significance in network change over time, we show that there is little evidence that degradation in the cohesiveness of the network is occurring within the elite of the elite. We use the Dow Jones 30 (DOW 30) group of corporations to represent the "elite of the elite" and our period of study is 2001-2010. This result suggests that the Dow Jones 30 forms a very robust core that is rather impervious to degradation from outside forces.

We thus demonstrate how to apply a Bayesian model to better understand changes over time in an interlocked corporate board network. This work builds on the Bayesian version of the P_1 model introduced by Wong (1987), extended by Gill and Swartz (2004), and applied by Adams et al. (2008) to changes in the density of collaborative networks over two periods of time. This extended P_1 model includes random effects allowing for some network internal dependency (see also Goldenberg et al. (2010) for a useful review paper).

In this paper, we report on successive pairwise comparisons of the hull networks defined in chapter 3, and then contribute a method to perform a full longitudinal analysis. We test this longitudinal analysis over the 10 year period of this study.

4.2 Literature review

In *The Power Elite*, C. Wright Mills (1956) discusses the structural changes occurring within the United States in the 1930's and 1940's that gave rise to the power elite. He identifies three changes that make this rise in power possible: 1. the increasing dominance of corporations, 2. the expansion of the federal government, and 3. the emergence of a large military body following World War II. However, Mizruchi, in many articles but most visibly in (Mizruchi, 2013), argues that while the corporate elite was prominent in helping to direct the public agenda through World War II, since that time its voice has become fragmented and has lost its power.

Researchers often use interlocked board membership as the identifying characteristic to represent the corporate elite. It has been argued that members of interlocked boards are able to move in and out of not only board rooms but also of civic arenas to spread their beliefs. Their board prominence also gives them the recognition to be seen as senior statesmen in their communities.

This "inner circle" thus possesses a higher level of political influence and social cohesion (Useem, 1984). This implication has led to the realization that corporations do not exist in isolation, but instead are part of a societal power establishment through individuals including interlocked board members (Carroll & Sapinski, 2011).

The similarities of powers obtained by the corporate elite are not the only similarities. Others (Stanworth & Giddens, 1975; Whitley, 1974) have shown that demographic similarities can be observed within these members as well. They found that, when considering education and social characteristics, interlocked members have become more similar over time. One might therefore expect that these elite members will express similar opinions regarding societal directions, in turn helping to contribute to the singular voice of the elite.

Board member turnover is low, with the average board member tenure being approximately 12 years (Whitley, 1974). Because of this we don't expect to see significant change in the interlocked network on a year-by-year basis. However, we would not be surprised if events related to the Clayton Act of 1914, which prohibits U.S. firms that compete with one another from sharing board members, could result in periods of disruption in the interlock network.

In this paper, we investigate interlock networks under the lens of Social Network Analysis (SNA). A link occurs between corporations when they share a board member, or between directors where they serve on the same board. Such a network is often referred to as a *bipartite network.*

4.3 Data

In this paper we use the same data source (BoardEx) that was used in Paper 2 to establish the interlocked DOW 30 network for the years 2001 through 2010. The data are then converted to an adjacency matrix for each year. Table 4-1 shows the adjacency matrix for the first year (2001) of our analysis of the DOW 30. The rows and columns of this matrix represent the set of entities (in this case, corporations), and each entry in the matrix is 1 if the companies are interlocked, 0 if not. This network is non-directional, meaning that if company i and j have a common director then there is an edge between those companies with no directionality present. This implies that the row and column pairing is the same as column and row pairing, that matrix in Table 4-1 is thus symmetric.

0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
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0	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0
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0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	0	1	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	1	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	1	0	1	1	0	0	1	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	1	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 4-1 Adjacency Matrix Interlocked Boards 2001

4.4 Model

$Y_{ij1}^{k} = 1$ if i and j are connected, 0 otherwise

$Y_{ij0}^{k} = 1$ if i and j are not connected, 0 otherwise

$$\ln P(Y_{ij0}^{k} = 1) = \lambda_{ij}^{k}$$

$$\ln P(Y_{ij1}^{k} = 1) = \lambda_{ij}^{k} + \theta^{k} + \alpha_{i}^{k} + \alpha_{j}^{k}$$

Figure 4-1 Model for Probability of Links

Our model continues the evolution of the P_1 model (Figure 4-1) introduced by Holland and Leinhardt in 1977 (1977). This model is a continuous-time model utilizing Markov chains. The goal of the model is to understand network change over time. Change in this model is assumed to be continuous, with network observations available only at discrete points in time. Therefore, the network occur at random points in time between the observed moments (Snijders, 2001). The model allows for the measurement of alphas and thetas. The alphas, measured for each node in the network, represent the propensity for that node to form a tie within the network. The thetas represent the overall propensity for links to occur within the network. The P_1 model was extended by Gill and Schwartz (2004) in 2004 to allow for the Bayesian version with random alphas and thetas. In 2008 Adams et al. (2008) extended the model to allow for pairwise years comparisons.

Our model extends the P_1 model by expanding it to allow for multiple time-period evaluation (see Appendix B for the OpenBUGS source code for our full model). This allows us to use the information from all prior time periods to estimate alphas and thetas. Testing for statistical significance over time has been of interest to the social network research community due to the complexities faced, including link dependency. In addition to link dependency, snapshots of the network over time are typically also dependent and, therefore, traditional means that require independent observations cannot be employed.

The index *k* denotes the time period and indices *i* and *j* refer to two corporations. Because each pair of corporations *(i, j)* can either share or not share a board member, the matrix Y_{ij0}^{k} is a simple opposite of the matrix Y_{ij1}^{k} in the sense that Y_{ij0}^{k} can be obtained from Y_{ij1}^{k} by replacing zeros with ones and ones with zeros. The matrix Y_{ij1}^{k} is often referred to as the sociomatrix, with its ones indicating where a link occurs. The probability $P(Y_{ij1}^{k}=1)$ represents the probability of an interlock link occurring between corporations *i* and *j*, at time *k*, and $P(Y_{ij0}^{k}=1)$ represents the probability that no such link exists. The parameter θ^{k} represents the overall propensity for links to occur in the network at time *k,* and the parameters α_{i}^{k} represent the propensity for corporation *i* to share board members with other corporations in the network at time *k*. Prior distributions are defined on each parameter, making the model Bayesian.

The advantage of this approach to modelling links in a sequence of networks is that it allows for links to not be independent (via the random effects α_{i}^{k}) at a given point in time and also allows for parameters to exhibit a timewise correlation: for example, it is quite likely that the θ^{k} and the α_{i}^{k} are correlated over time. In Adams et al. (2008) this approach was used successfully to examine changes in network parameters over two time periods.

Our DOW 30 components change over time, which presents a unique challenge to modeling the network. We have several years of stability where the same 30 companies are present, but in other years some companies are replaced with others. Over the 10 year period under study the following changes to the DOW 30 have occured:

a) In 2004 AT&T Corporation, Eastman Kodak, and International Paper were all removed while American International Group Inc, Pfizer, and Verizon were added.

b) In 2008 Altria, American International Group, and Honeywell were replaced with Bank of America, Chevron, and Kraft Foods.

c) In 2009 Citigroup and General Motors were replaced with Cisco Systems and Travelers.

It follows that using the technique in Adams et al. (Adams et al., 2008), we could compare years within each group 2001-2003, 2004-2007, and 2009-2010, but since the companies within the network have changed, comparisons across these time periods would present a challenge.

4.5 Analysis and Results

We begin by employing our Bayesian model to investigate whether the trends in chapter 3 are confirmed through an examination of the posterior distribution of the difference in cohesiveness between 2001 and 2002, and then between all other successive pairs of years, ending in 2009-2010. Table 4-2 presents posterior descriptive statistics for the first pairwise comparison (2001 – 2002).

	Mean	Std Dev	MC Error	2.5% Value	Median	97.5% Value
Diff	-0.0774	0.1716	0.003	-0.253	0.075	0.426
Rho	0.9169	0.0329	0.000	0.837	0.923	0.964

Sigma[1,1]	0.9185	0.2629	0.002	0.527	0.878	1.456
Sigma[1,2]	0.8935	0.2585	0.002	0.508	0.854	1.508
Sigma[2,1]	0.8935	0.2585	0.002	0.508	0.854	1.508
Sigma[2,2]	1.0360	0.3050	0.003	0.585	0.987	1.763
Theta[1]	2.3750	0.2932	0.009	2.974	-2.369	1.807
Theta[2]	2.4530	0.3209	0.010	3.122	-2.446	1.834

Table 4-2 Posterior Statistics for the first Pairwise Comparison (2001-2002)

The posterior mean of the difference between 2001 and 2002 is -0.0774, with a 2.5% - 97.5% credible interval of (-0.253, 0.426) encompassing zero. The positive value of the posterior mean of the difference indicates a decrease in the cohesiveness of the network between 2001 and 2002, but this difference is a posteriori essentially as likely to be positive as to be negative. A more pronounced difference would have its posterior density shifted away from zero. Figure 4-2 shows the posterior mean of the difference between successive year pairs for the core and extended hulls.

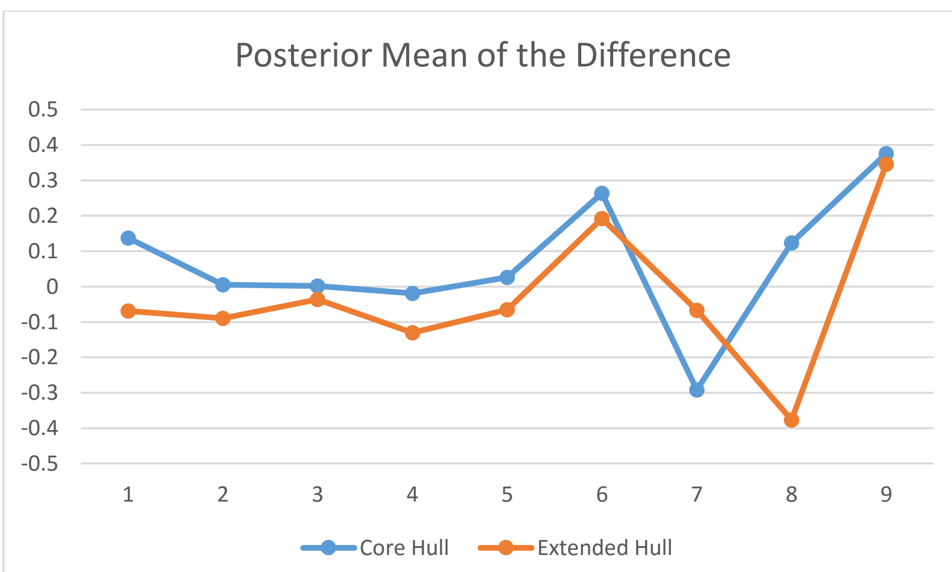


Figure 4-2 Posterior Mean of the Difference for Core and Extended Hull

Next we present the findings from the Markov Chain Monte Carlo (MCMC) analysis of the model outlined in the previous section. Appendix B includes the full results from our model for both the core hull and extended hull. These statistics were generated using OpenBUGS (Spiegelhalter, Thomas, Best, & Gilks, 1996) in which we generated 200,000 iterations of the MCMC procedure where the first 50,000 were allocated as the “burn-in” iterations[5].

One of the main advantages of our Bayesian model is to provide more reliable estimates of the variance of the model parameters, namely the propensity to form interlocks for the network as a whole and for the individual corporations, as well as an estimate of the entire covariance (and therefore correlation) matrix of the vector of these parameters over the 10 years of our study. The covariances are denoted by the sigmaa[i,j] in the output in Appendix B. The availability of these variances and covariances is what makes it possible to handle investigations of statistical significance of changes in the networks. From these estimates, we are in a position to compute the autocorrelation function for both the propensities (the thetas) to form interlocks and their successive differences, and to graph these functions in Figures 4.3 and 4.4 for the core hull and in Figures 4.5 and 4.6 for the extended hull.

For both the core and extended hulls, it is clear from the shape of the autocorrelation functions in Figures 4.3 – 4.6 that the propensity to form links is essentially a random walk, not stationary but with random differences.

[5] The model required a significant burn-in to eliminate bimodality in posterior distributions.

In paper 2 we found significant time trends for the network densities for both hulls over this period of time, but we are finding here that the overall network propensity to form links is a random walk. This would seem to imply that the trends observed in paper 2 may be coming from the movement of the individual corporations, instead of general trends in the network. Another strong advantage of our model is that it provides posterior estimates of the propensities to form links (the alphas) for the individual corporations, complete with standard deviations.

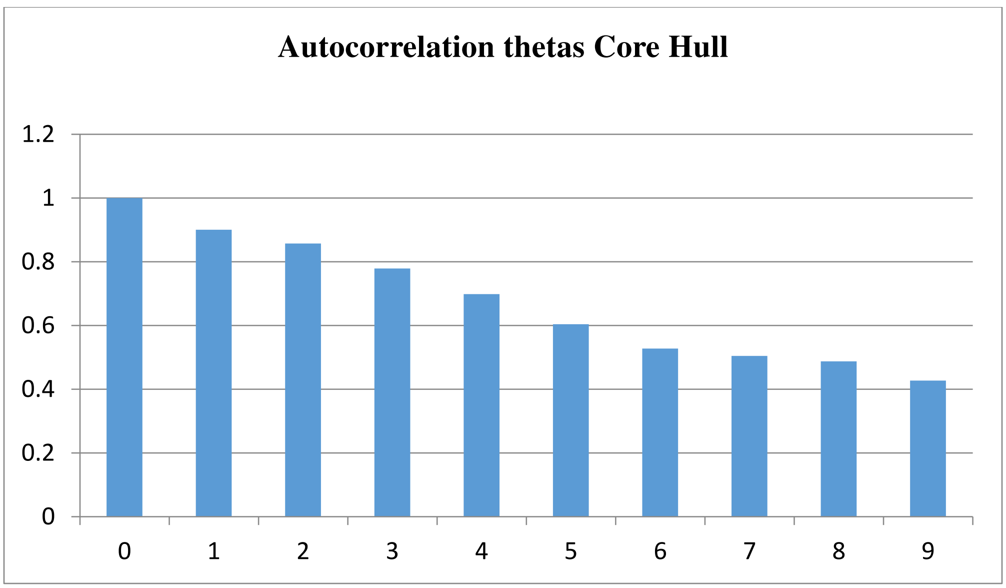


Figure 4-3 Autocorrelation of Theta by Lag; Core Hull

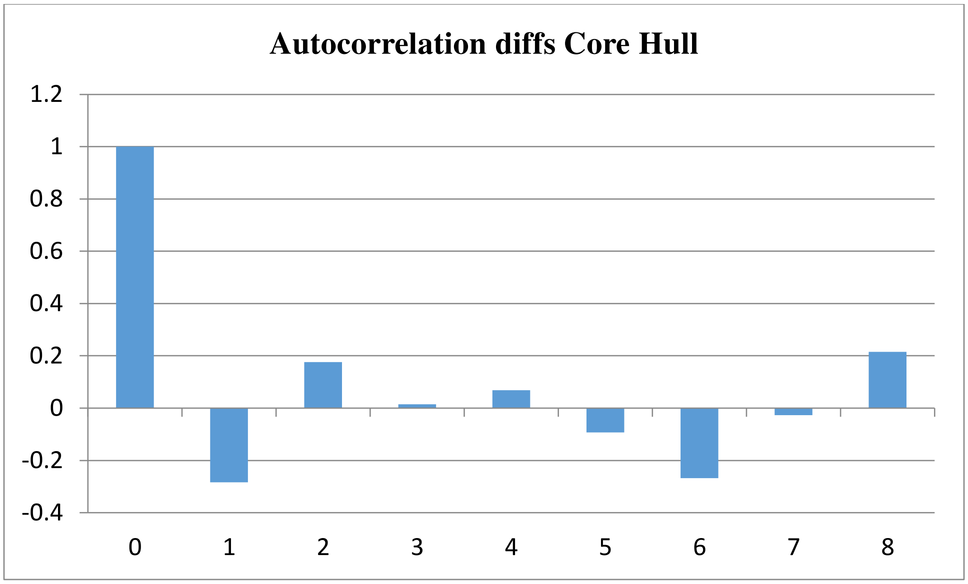


Figure 4-4 Autocorrelation of Diffs by Lag; Core Hull

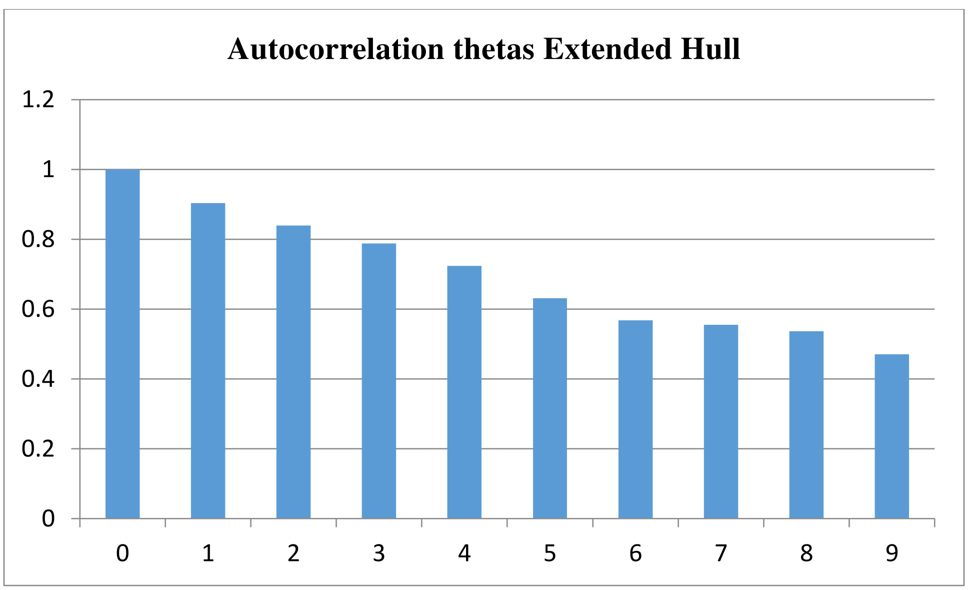


Figure 4-5 Autocorrelation of Theta by Lag; Extended Hull

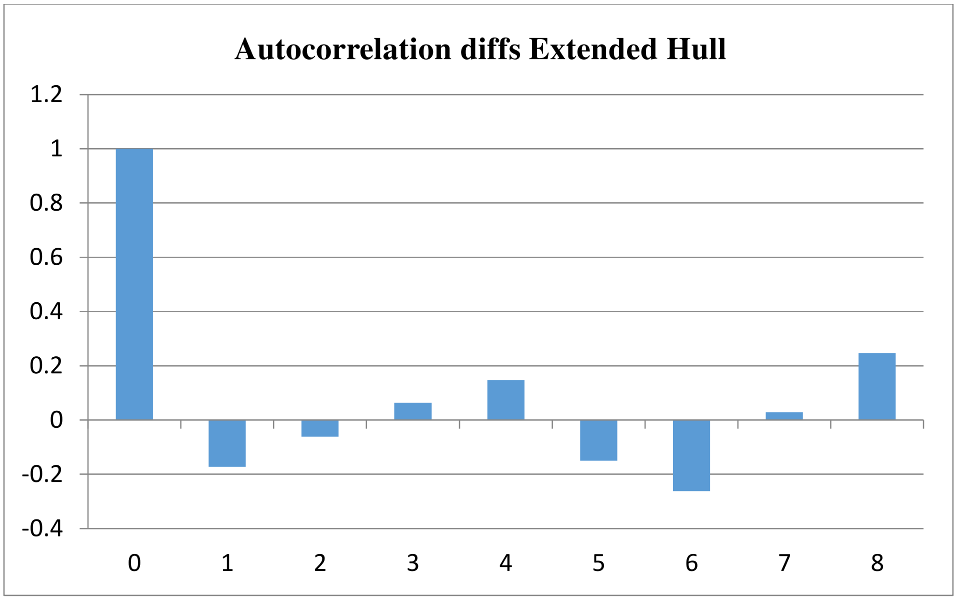


Figure 4-6 Autocorrelation of Diffs by Lag; Extended Hull

We are able to graph the alphas and their standard deviation over time for individual corporations See Appendix D for a complete set of alpha graphs for all the DOW 30 extended hull companies). The standard deviation gives us a level of confidence in the alphas by indicating the accuracy of the estimation. For example, in Figure 4-7, we can see that General Electric's propensity to form links increased gradually until 2006 and decreased a little after 2006.

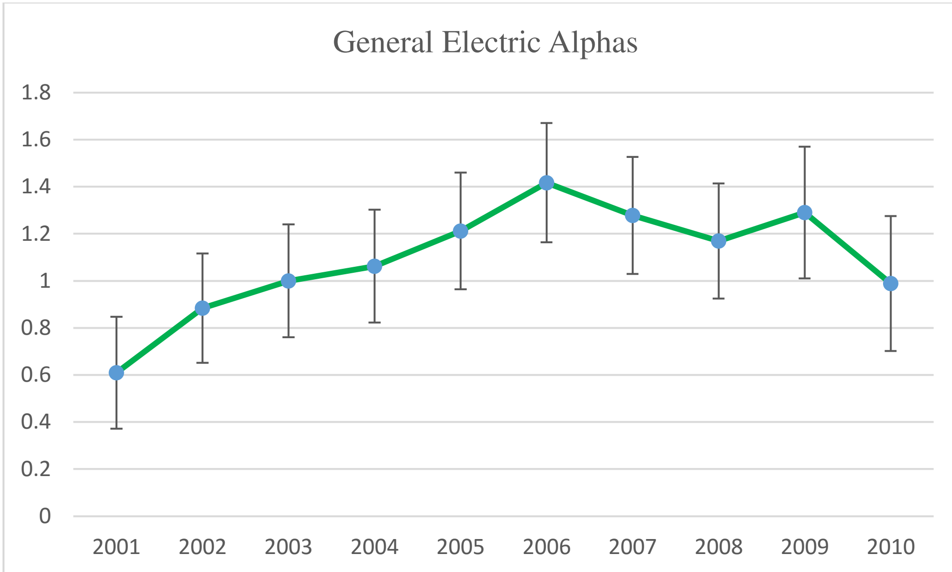
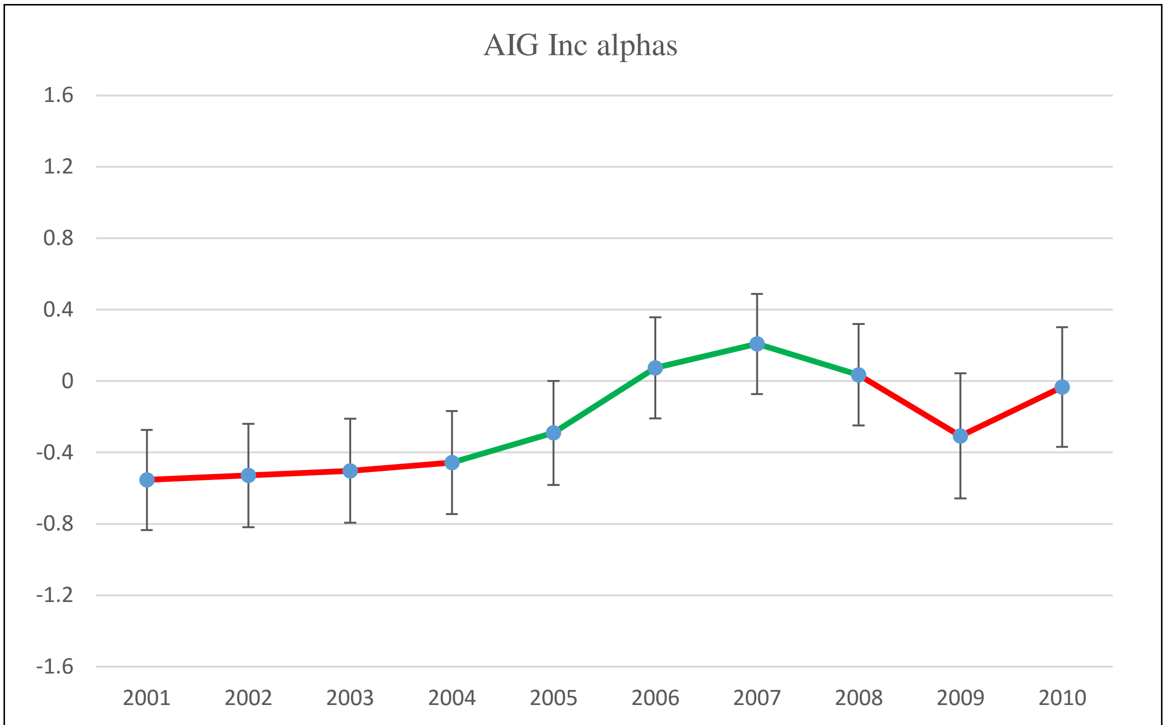


Figure 4-7 General Electric Alphas

Next we turn to those companies that were directly involved in the subprime mortgage crises that occurred in 2007-2008. Within the DOW 30 there was one insurer (American International Group) and 3 banks (Bank of America, Citigroup, and JP Morgan Chase) that were directly involved in the crisis. The alphas for each are presented in figure 4-8. Leading up to the financial crisis, it would appear that both AIG and Bank of America were increasing in their propensity to form ties within the DOW 30 network, while Citigroup and JP Morgan Chase both appear flat or slightly decreasing in their propensity to form ties. AIG and Citigroup both were dropped from the DOW 30 index after the financial crisis while Bank of America was added (along with The Travelers Group, an insurer who was not as involved in the financial crisis as AIG and Citigroup were).


AIG Inc alphas
1.6
1.2
0.8
0.4
0
-0.4
-0.8
-1.2
-1.6
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010

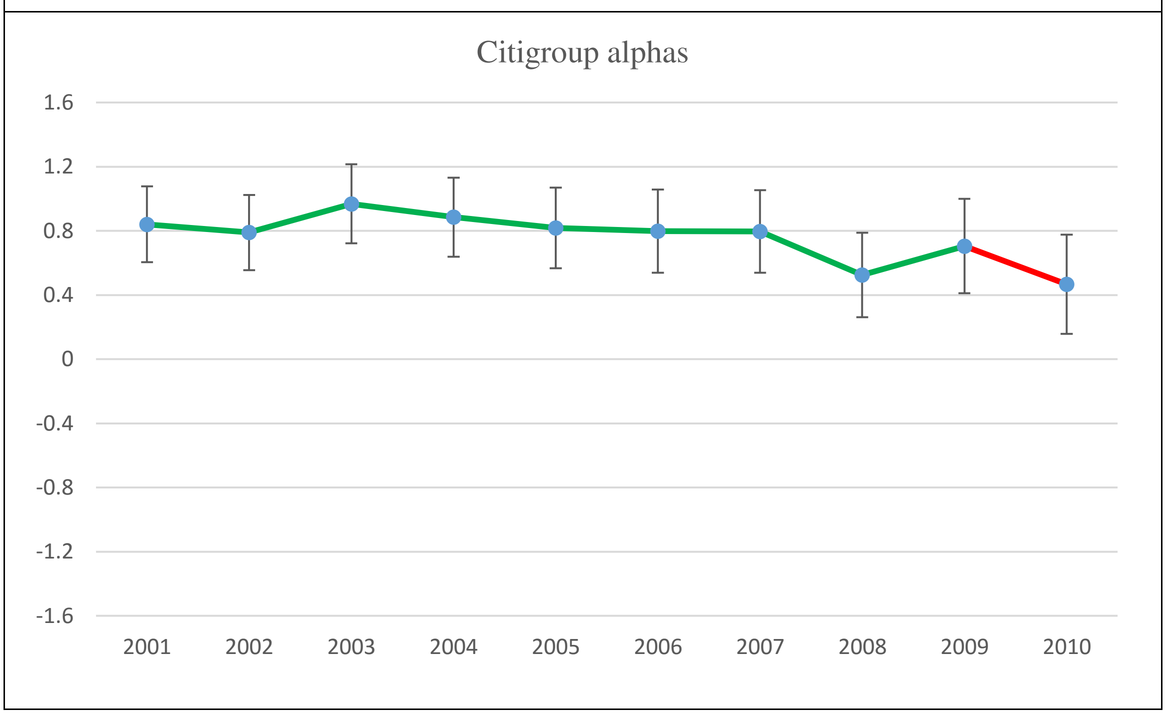
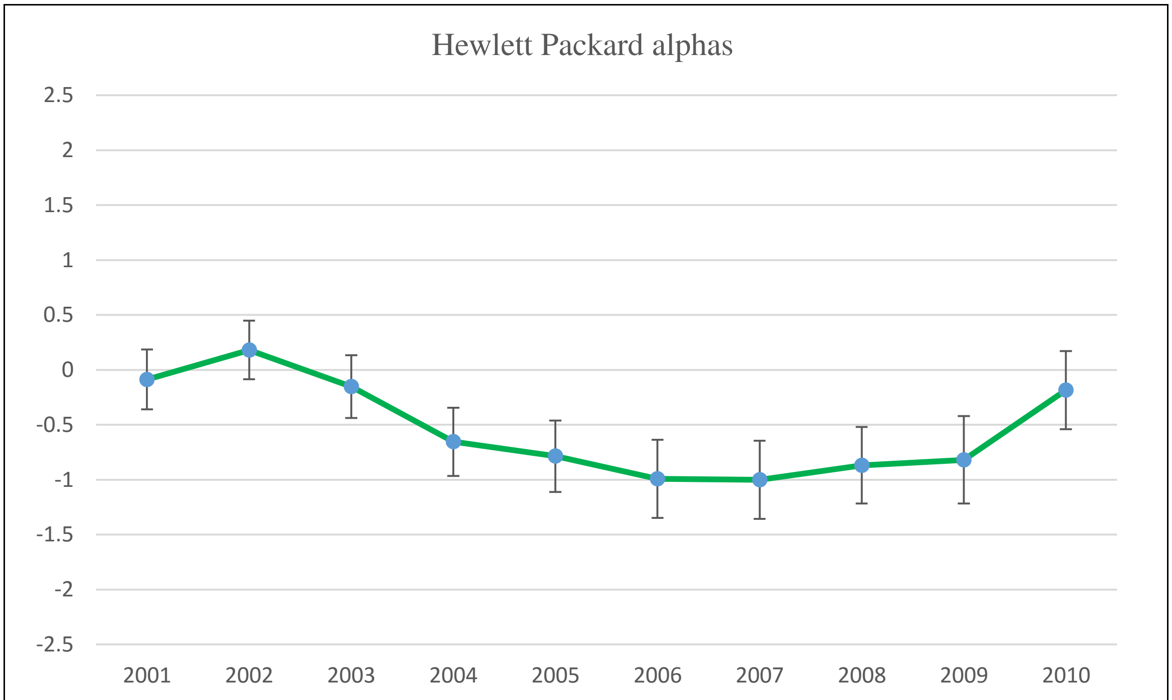
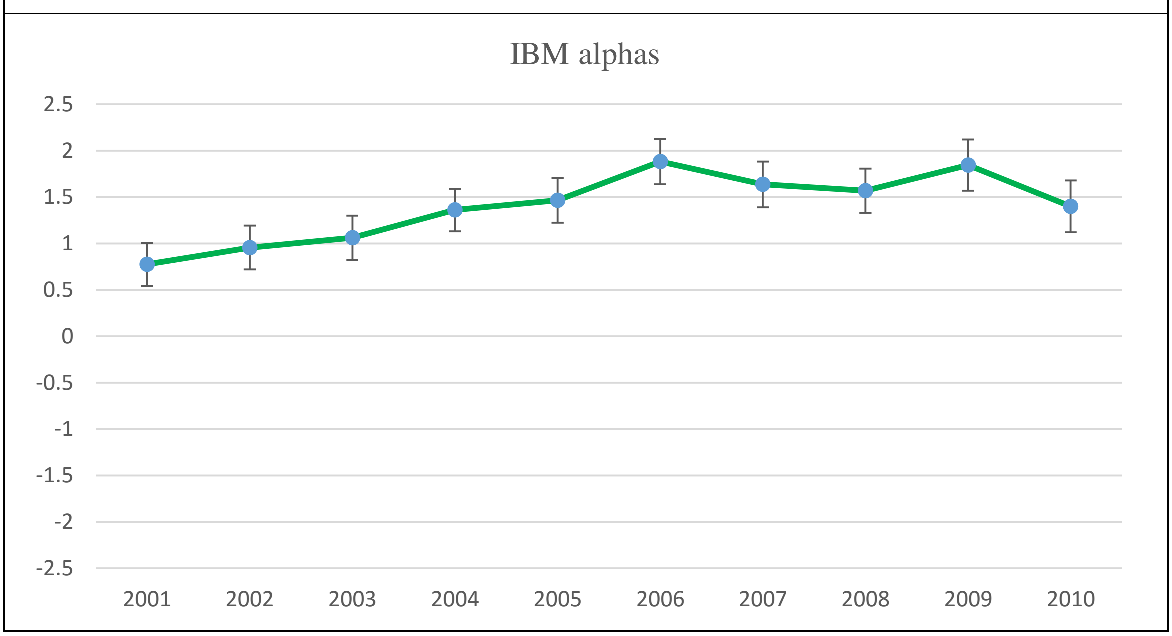

Citigroup alphas
1.6
1.2
0.8
0.4
0
-0.4
-0.8
-1.2
-1.6
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010

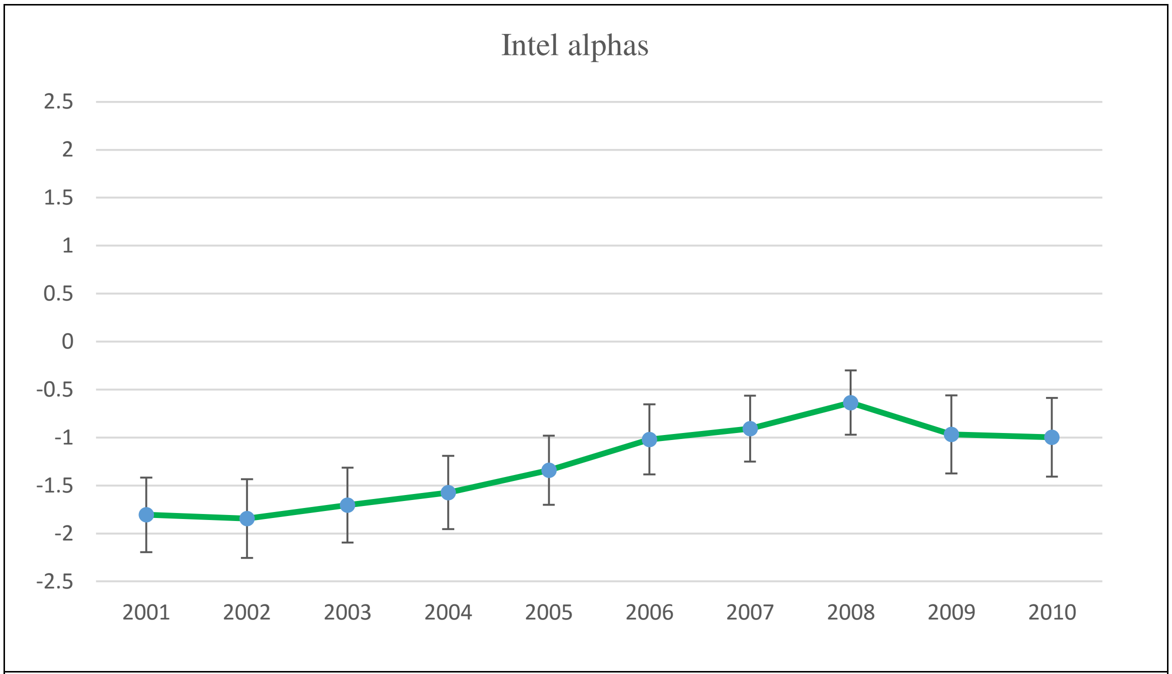
Figure 4-8 Financial Sector Alphas

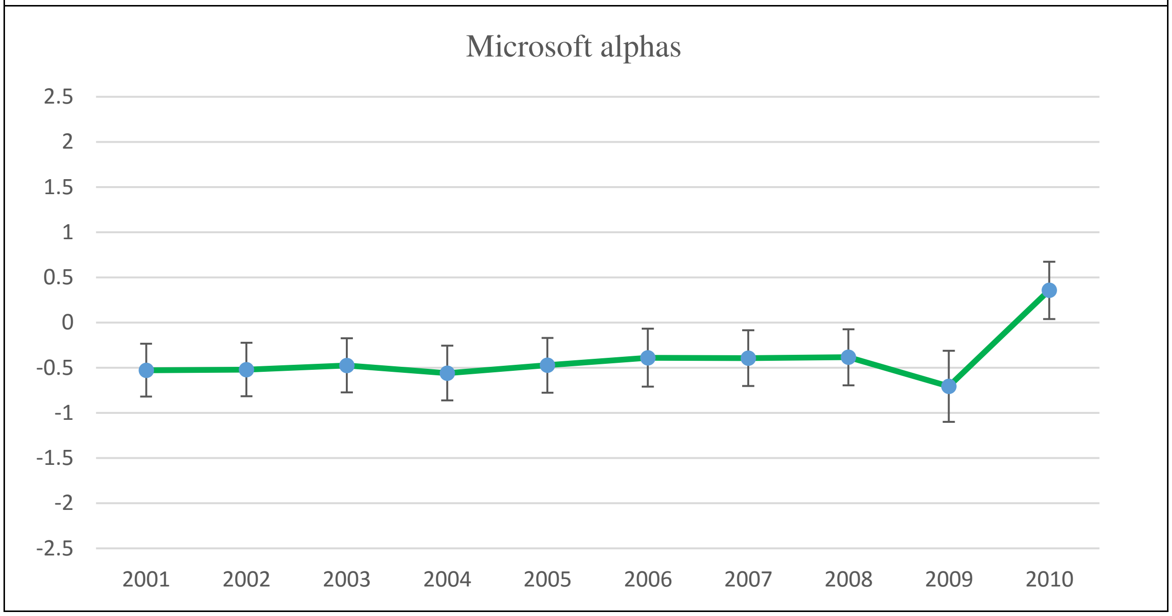
Three of the four companies had a drop in their alphas from 2007 to 2008 suggesting that interlocked board members were either self-selecting to remove themselves from the boards of these troubled companies, or the companies were actively reducing their level of interlockedness by replacing interlocked board members with non-interlocked members.

The other sector heavily represented in the DOW 30 is the technology sector. This sector had just come off of their own financial crisis of the dot com crash that occurred in 1999-2000. Five of the companies examined in our study are classified as technology companies and include Hewlett Packard, Intel, IBM, and Microsoft (see Figure 4-9) who were all present for our entire period of study, and Cisco Systems which was added in 2009.






Intel alphas
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Microsoft alphas
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010

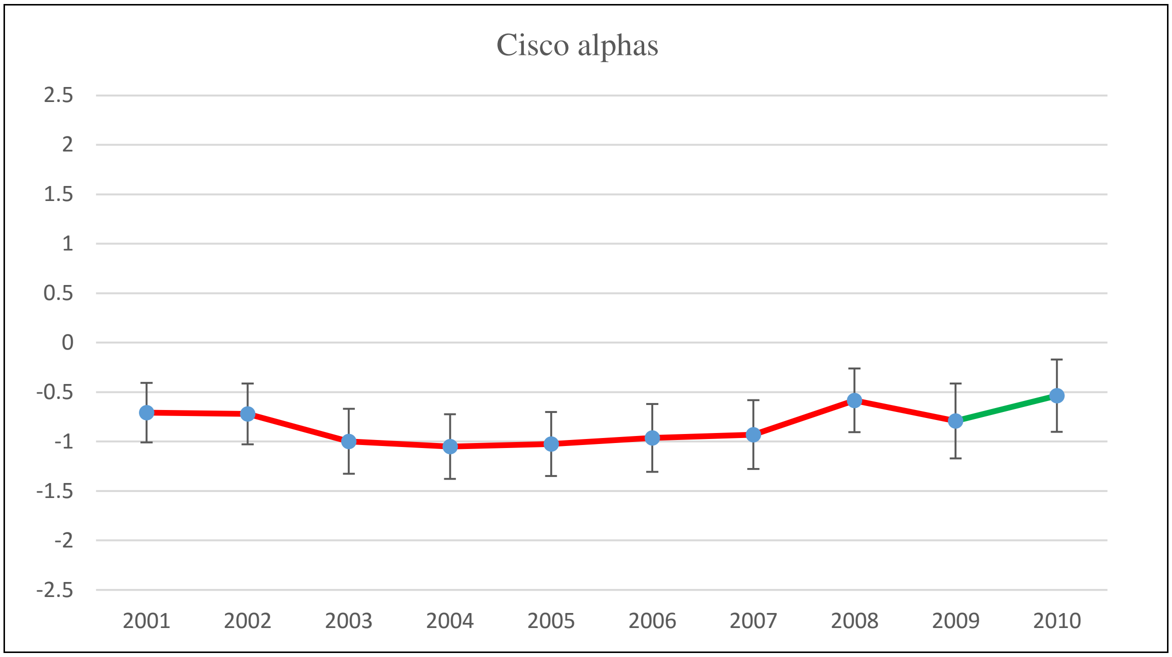


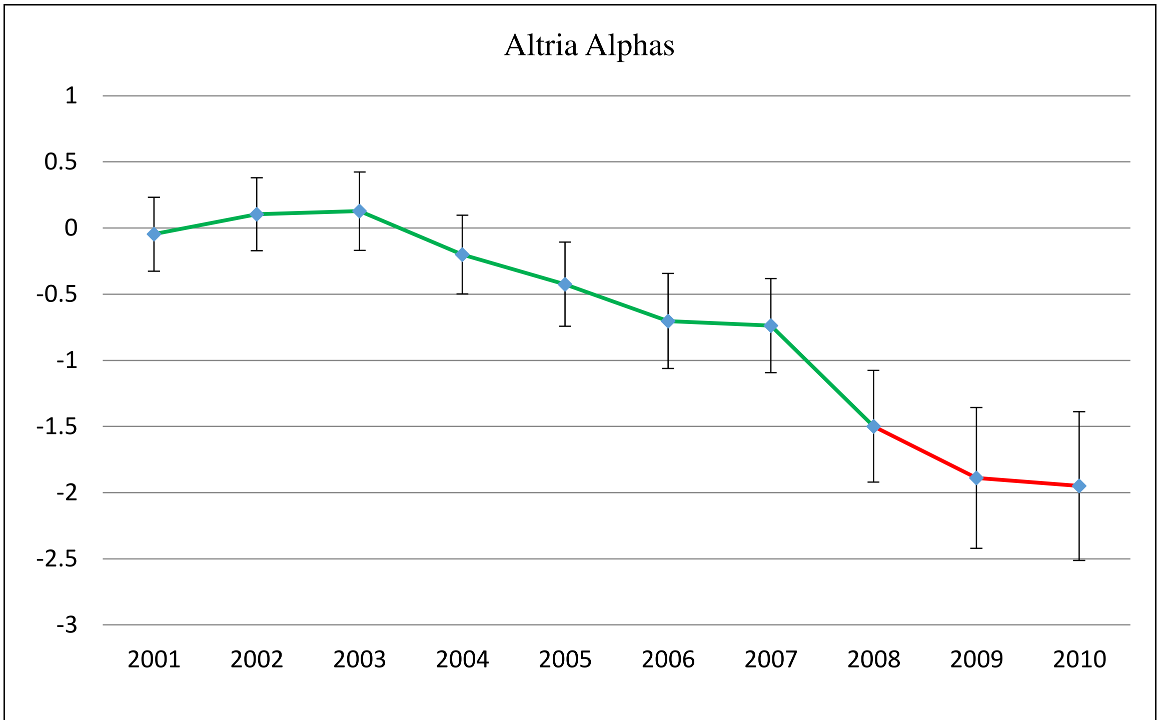
Figure 4-9 Technology Sector Alphas

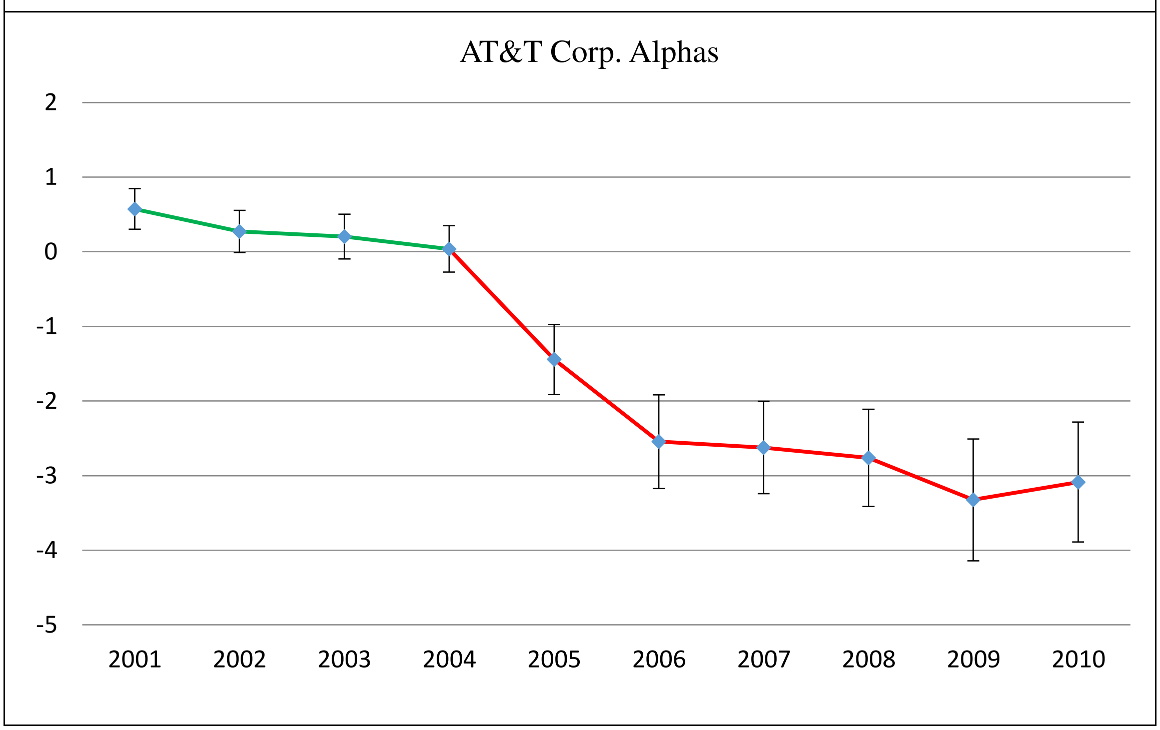
For the most part, with the exception of IBM, the technology sector stocks had a lower propensity to form interlocks in comparison to the remainder of the companies; this is evidenced by having negative alphas overall. We don't see any dramatic shifts in any of the companies over time, suggesting that the market was stable. The low propensity to form interlocks could be a result of technology firms attracting younger talent that may not be interested in serving or be able to serve, on other DOW 30 boards.

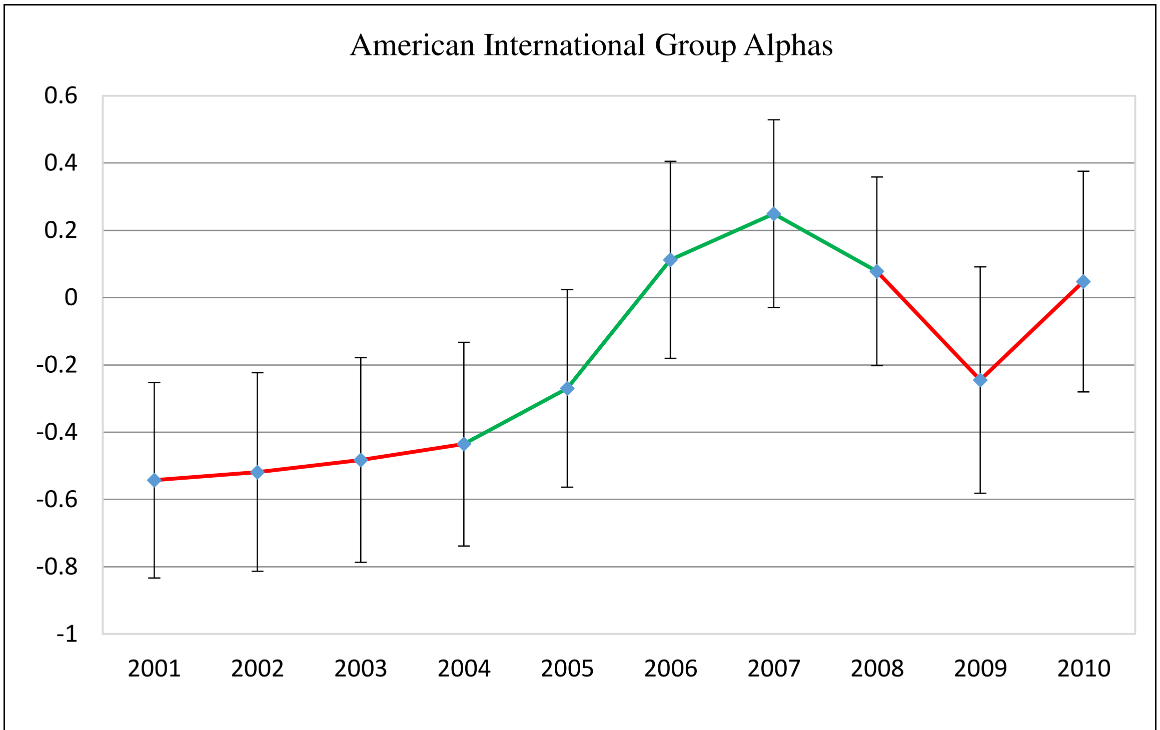
While we saw some movement with regards to the financial institutions around the time of the financial crisis, we don't see any lasting effect of the dot com bubble on technology companies. This could be due to the fact that the dot com crash impacted smaller firms much more than the well-established ones. The implication is that while the financial crisis and dot com crash were both considered significant events with regard to the economy, it would appear that the financial crisis had a broader impact on companies.

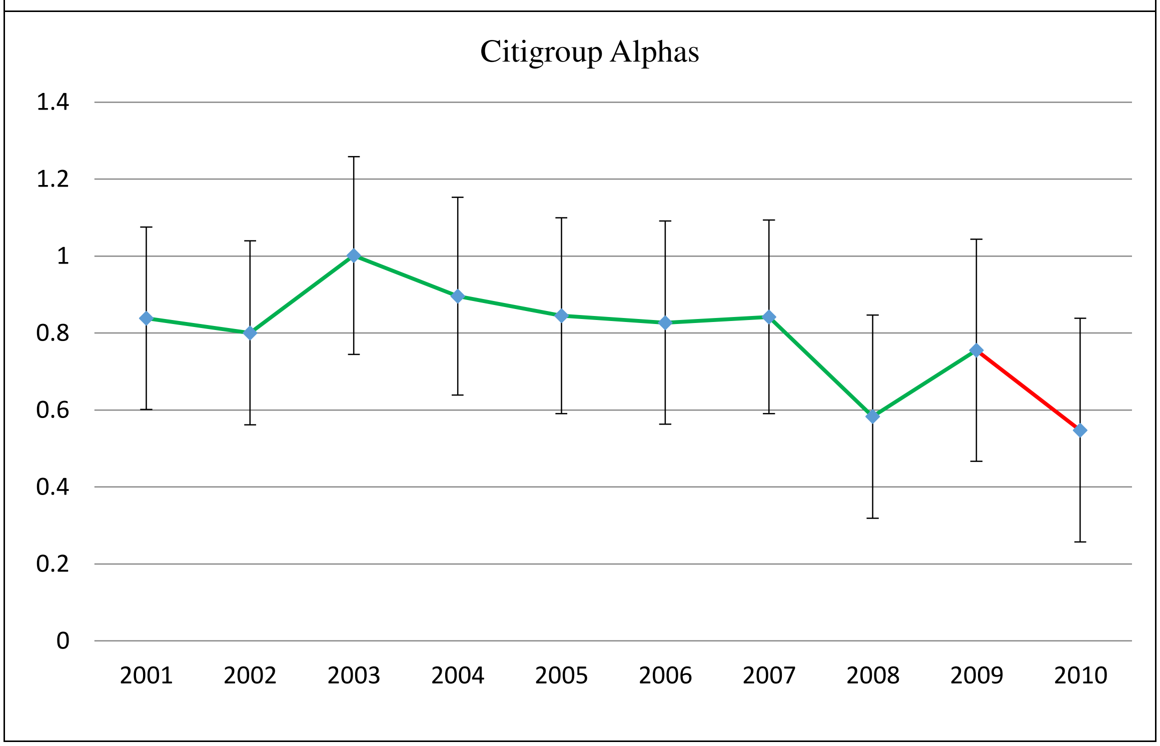
Another avenue to consider is whether being added to or removed from the DOW has an impact on the organization. Both actions have a significant impact to the stock of a company, since funds that invest in indexes would either have to sell off stock, in the case the company is removed from the index, or buy stock as in the case when a company is added to the index. Because of this financial incentive, it is reasonable to assume that those who hold stock, or whose job evaluation is tied to stock performance, have incentive to see the company either stay in, or be added to, the index.

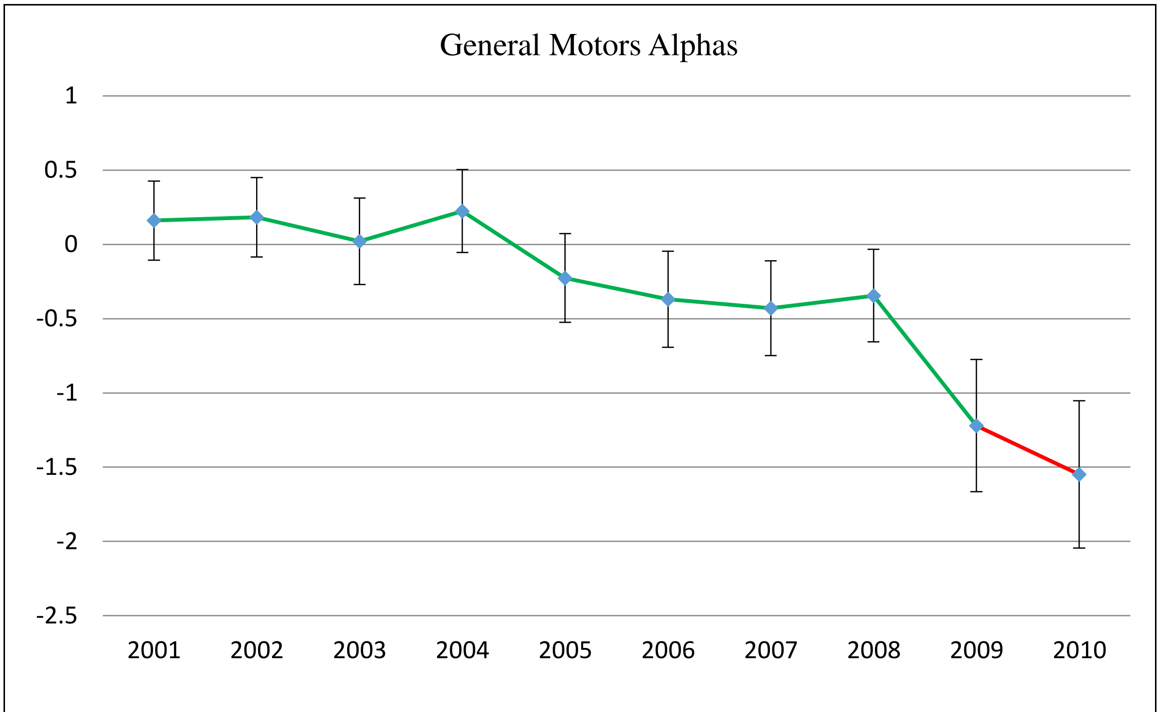
We begin by looking at the impact of being removed from the DOW 30. Figure 4-10 show the alphas for the companies that were removed from the DOW 30 index from 2001 through 2010. The charts display green for those years the company was part of the index and red for the years the company was not part of the index. During this time, 8 companies were removed from the index. In 6 of the 8 companies, the alpha shows a marked decrease in the year following their removal. One company remained relatively flat (Eastman Kodak), and one company had an increase (Honeywell). Overall, this indicates support for Burt's theory of network decay since removal from the index led to a reduction in network ties.


Altria Alphas
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


AT&T Corp. Alphas
2
1
0
-1
-2
-3
-4
-5
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


American International Group Alphas
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Citigroup Alphas
1.4
1.2
1
0.8
0.6
0.4
0.2
0
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010



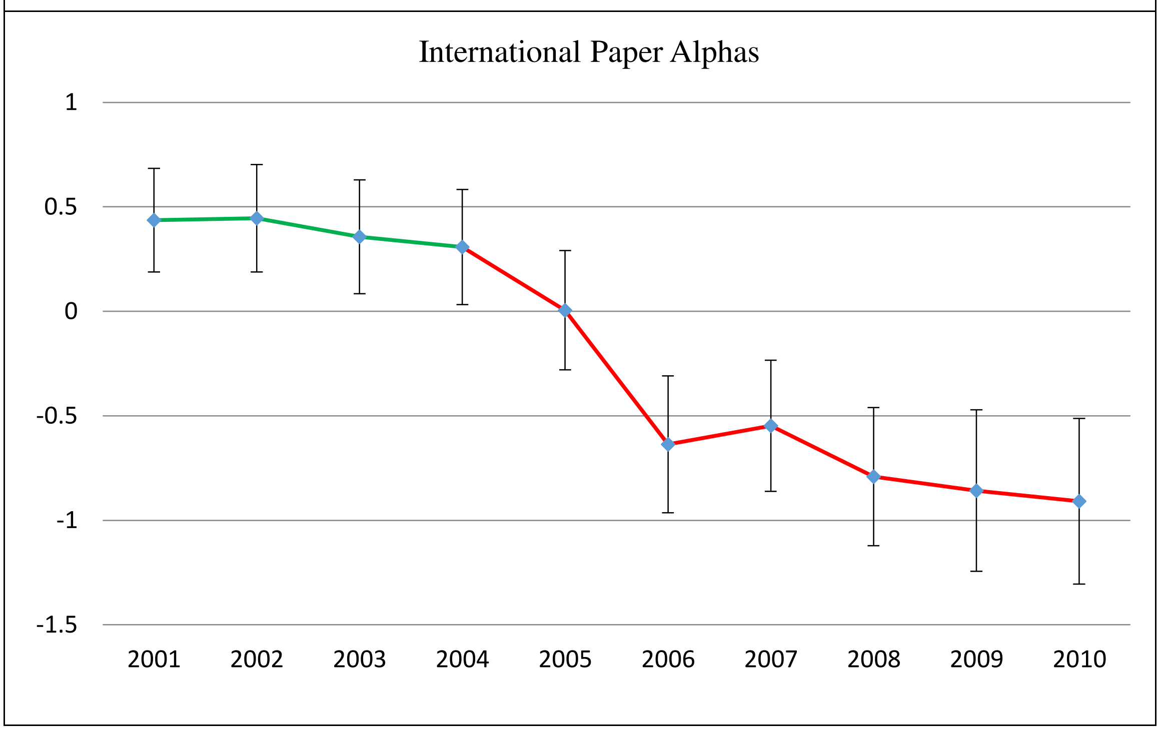
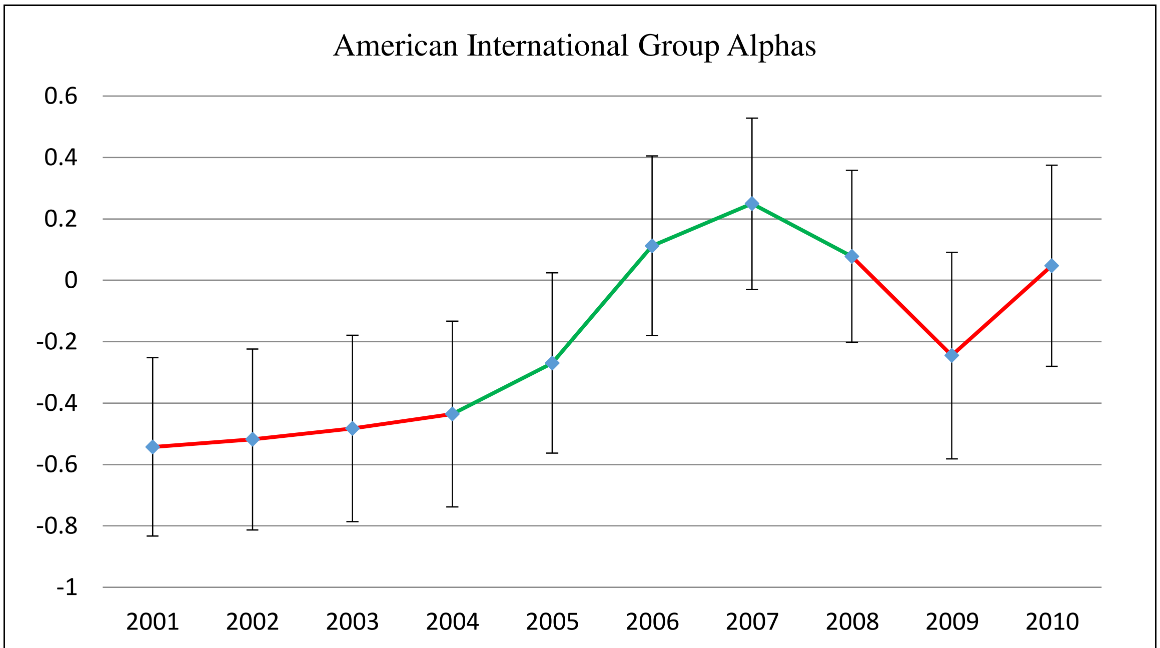
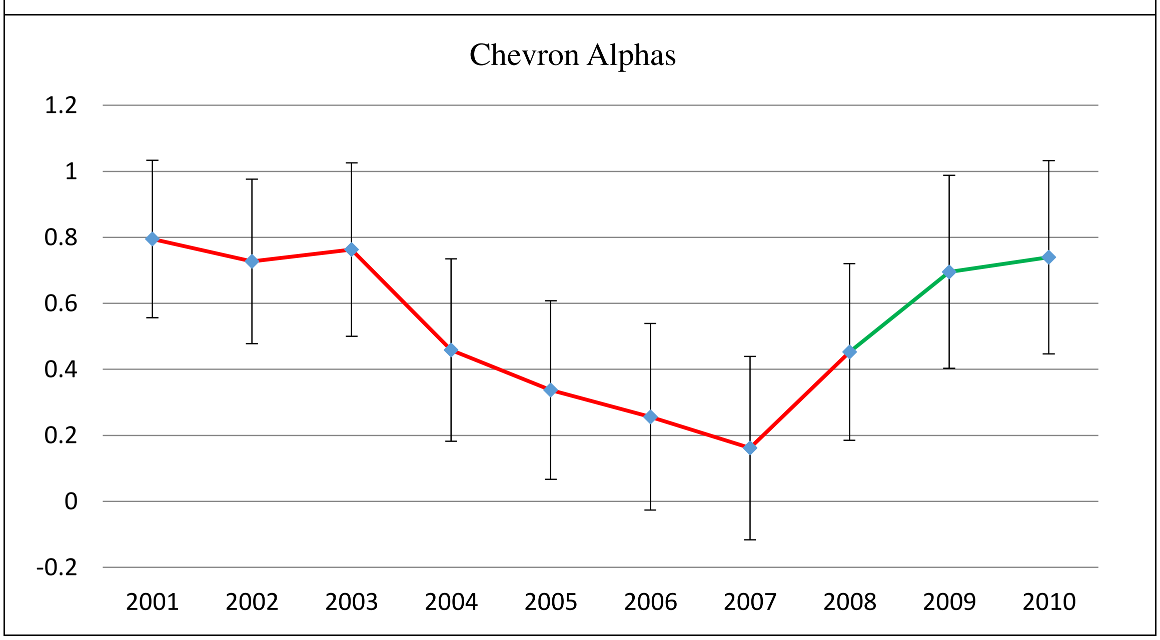
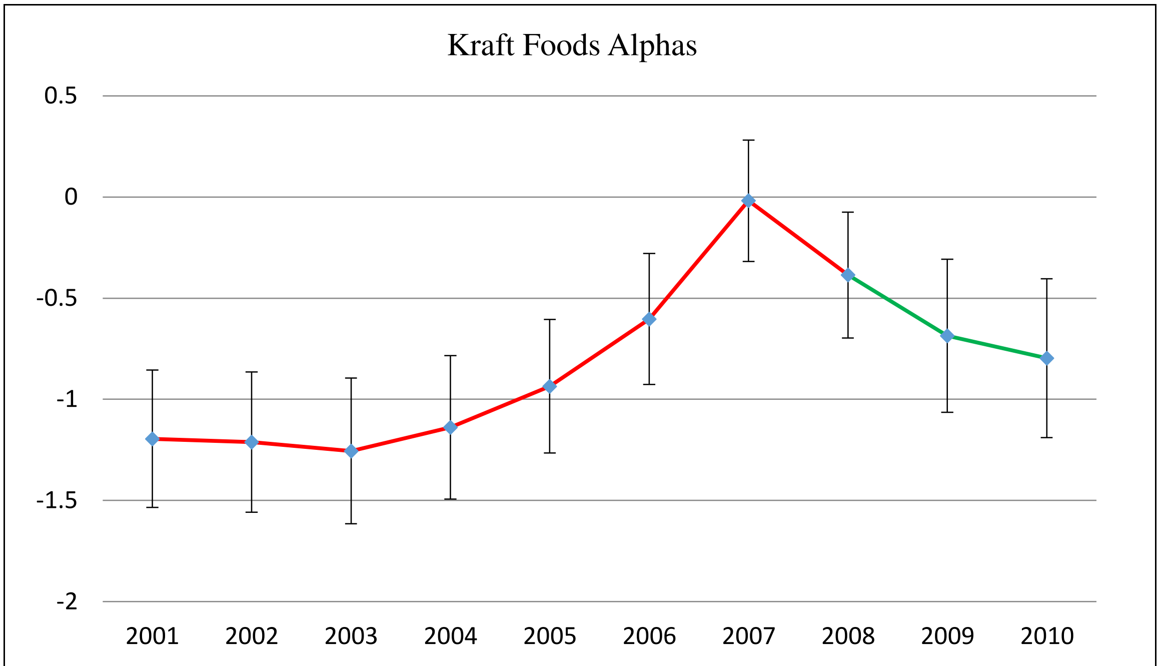


Figure 4-10 Alphas of Companies Removed from DOW 30

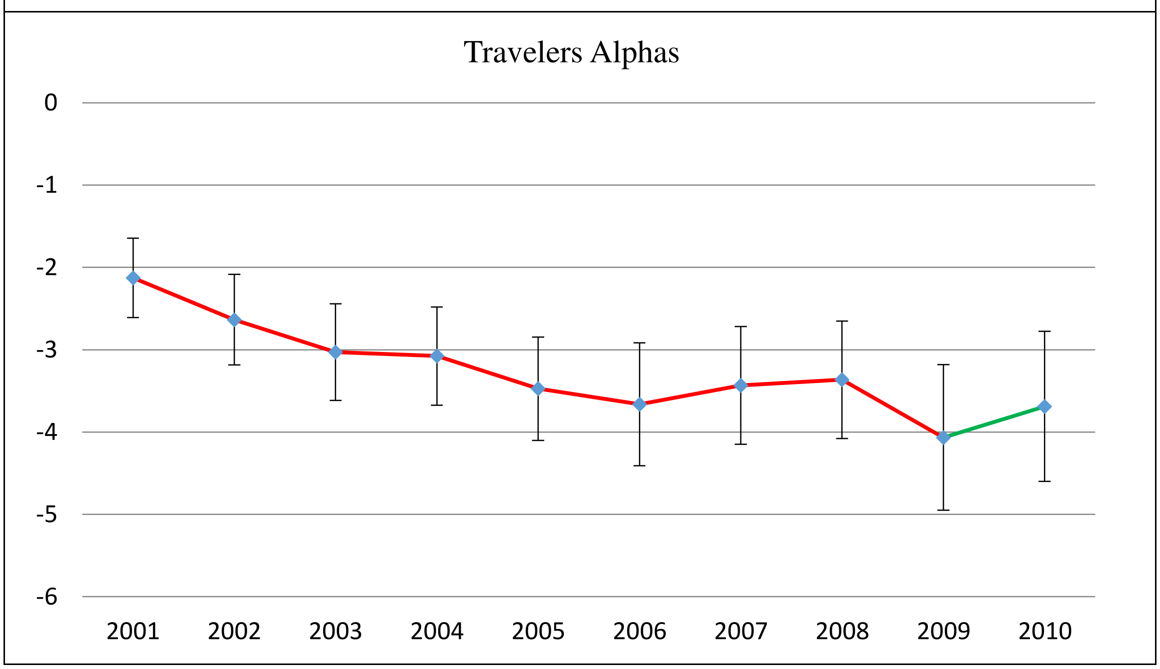
Next we look at the companies that were added to the DOW 30. Figure 4-11 shows the alpha graphs for the 8 companies that were added to the DOW 30. Again, the green periods of the charts represent the years the company was part of the DOW 30 and the red periods of the charts represent the years the company was not part of the DOW 30. When looking at these 8 charts we are focused on the period of transition from red to green indicating the year the company was added to the DOW 30. In 6 of the 8 cases, being added to the DOW 30 corresponded with an increase in the company's propensity to form links with the other DOW 30 companies.



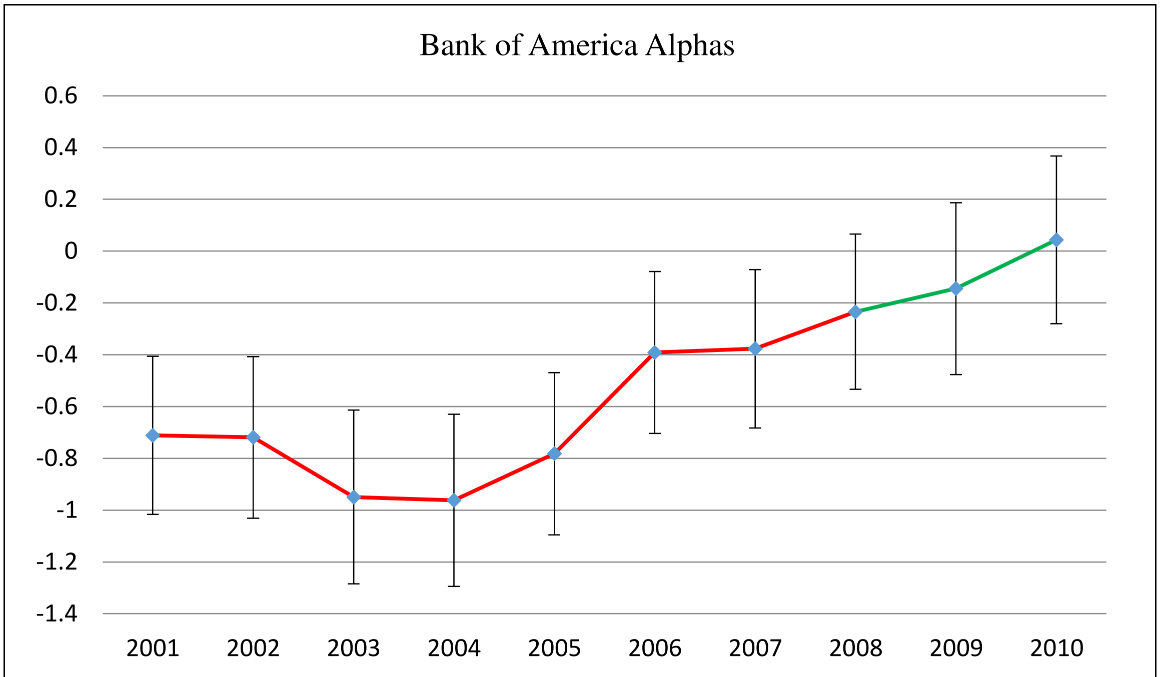


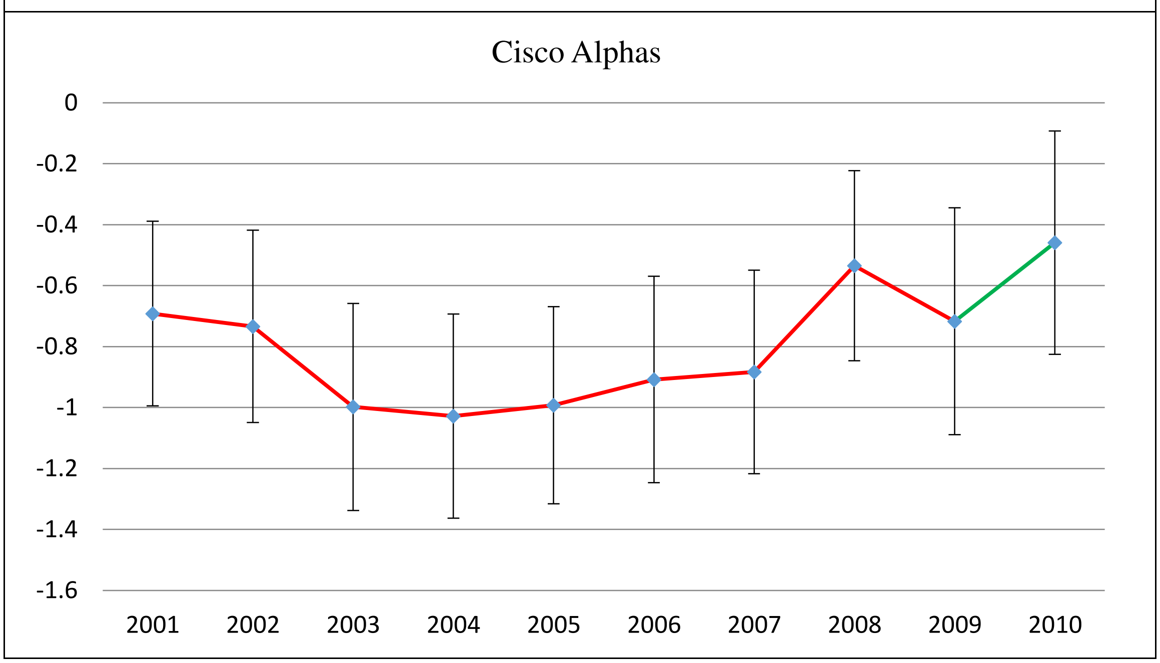


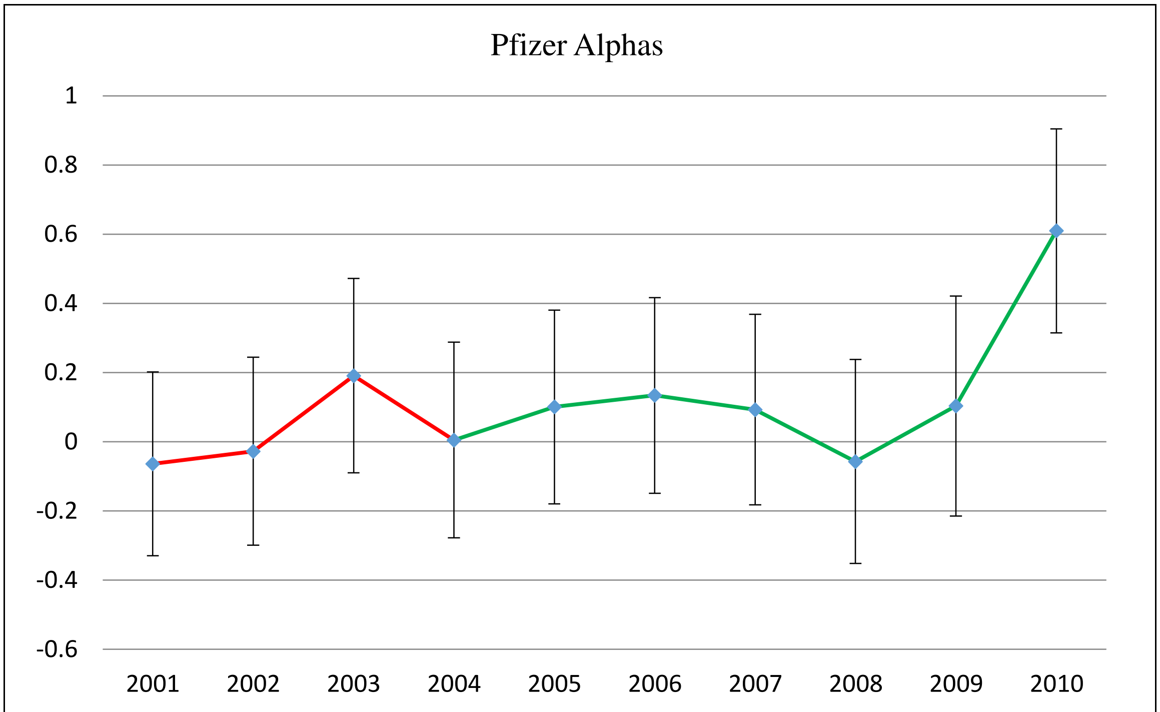
Kraft Foods Alphas
0.5
0
-0.5
-1
-1.5
-2
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010



Travelers Alphas
0
-1
-2
-3
-4
-5
-6
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Bank of America Alphas
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Cisco Alphas
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
-1.6
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010



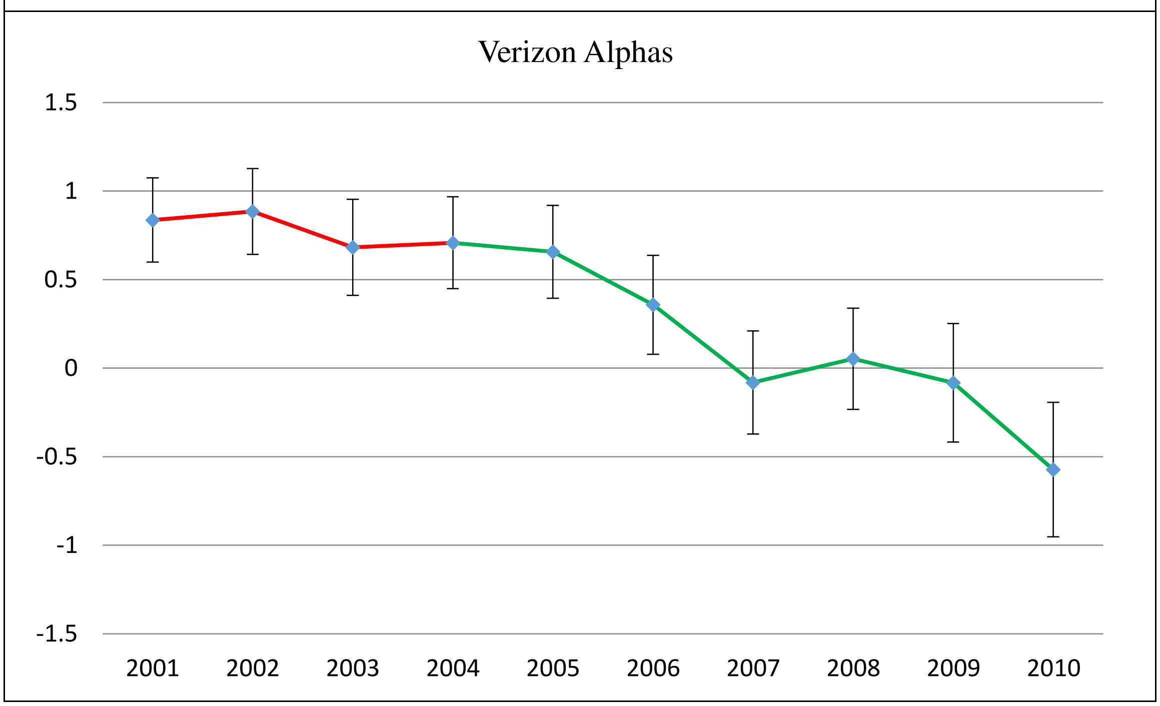


Figure 4-11 Alphas of Companies Added to the DOW 30

4.6 Discussion

This paper has introduced an approach that can be employed to compare network change over time using the interlocked board network as an example. The model allows for detecting change at the network level, through a measure of the thetas, and at an individual node level through a measure of alphas. Of particular interest is the ability to measure standard deviation of change at both the network and node levels of analysis.

Our analysis of the DOW 30 network reveals several interesting findings. First, the thetas give us no evidence that there is a general move toward or away from interlocking boards from 2001 through 2010. This finding held for both the core hull and the extended hull, which is surprising since there were shocks to the network in 2004, 2008, and 2009 as companies were added and removed from the DOW 30. Burt's theory of decay posits that these shocks should have led to a decrease in the number of interlocking boards, but we saw no such decrease. Second, being removed from the DOW 30 does tend to lead to a decrease in the level of interlockedness for that particular firm. This indicates support for the theory of decay at the individual node level. Third, being added to the DOW 30 index appears to contribute to an increase in the level of interlockedness for that firm.

We have additional findings when considering sector specific stocks that are part of the DOW 30 index. Three of the four financial sector stocks saw a decrease in their alphas from 2007 to 2008 which corresponds to the subprime mortgage crisis. The fourth firm (Bank of America) experienced an increase at that time, and also happened to be the one financial firm added to the index around the time of the crisis. What is interesting to note is that the financial firms in general were fairly stable throughout the crisis in regards to their propensity to form interlocks with other companies. We wouldn't have been surprised to see a flight away from these firms as board members tried to distance themselves away from these companies, during the mortgage crisis, but we have no evidence to support this. The firms we examined in the technology sector as a whole tended to be fairly stable and we see no evidence of any long term consequences of the dot com bubble that burst just prior to our period of study.

Overall we conclude that the elite, as measured by the level of interlockedness, appear to prefer to form interlocks with companies that are in the DOW 30 index, and will move away from those firms who are removed from the index. We see no sign of a weakening elite overall during this period.

5 Conclusion and Future Work

5.1 Overview

As a result of the above studies, we are able to contribute to the discussion on the use of social network analysis to aid researchers in the areas of state government and interlocking corporate boards. The underlying theme throughout the three studies is the concept of influence and how we conceptualize positions of power within social networks. We take the position that, in order for influence to occur, there must be some type of social connection between the two entities, and not all connections are equally successful when trying to exert influence. Through social network measures such as weighted edges, distance between nodes, measures of centrality, etc, we explore these social network structures.

We contribute to the discussion in state government by adding to the growing body of literature that is re-examining the widely used Schlesinger and Beyle technique. While others have discussed flaws in the appointment power component of the index, this is the first work to propose an alternate technique for evaluating appointment power. Our novel approach to converting the Book of the States data into a whole network, utilizing SNA, has provided new insights obtained through both graphical representation as well as providing valuable statistical results.

While we have focused on the appointment power, our research has shown that examining state government power structures through the lens of social network analysis is possible without the need to collect more data. We believe this is the first time that state government appointment power has been modeled using SNA; the result has been the ability to highlight changes occurring within state government that the existing techniques would fail to recognize. Our network weighting scheme is one that others could immediately deploy, and which has the benefit of applying to both governor-centric studies as well as studies that are looking more holistically at changes occurring within state government.

However, we caution that a straight conversion to utilizing degree centrality as a measure of gubernatorial power still exposes the research to the issue of delegated authority that we uncovered in Massachusetts and suspect is occurring in other states as well. In order to account for this we suggest that researchers either re-think their research question to be more holistic, i.e. using more than just a measure of centrality for the governor, or to consider the governor's office as a subgroup; we discuss these ideas in section 5.4.

In addition, our work has shown that changes at the agency level, across all 50 states, can also be uncovered with our weighted whole network. This allows us to highlight national trends that are occurring within state government, and policy areas that are either gaining or losing the attention of the governors' office.

Papers 2 and 3 contribute both to the literature in the area of interlocking boards and to SNA methodology. We add to this discussion through interesting and sometimes unexpected trends when comparing interlocked boards in the U.S. with those in Europe. These insights are valuable to policymakers that design policies with the goal of reducing the level of interlockedness occurring within corporate boards. In addition, we provide a valuable extension to the Bayesian model, allowing for the ability to test for significance when networks are evaluated longitudinally. This extension has far-reaching implications since it is domain agnostic. We introduce the concept of a Hull in evaluating networks that change nodes over the period of study. We have shown that comparing the core group against those who come and go can yield knowledge about how those changes are impacting the network. In this case, we conclude that changes to the DOW 30 actually bring a stability that wouldn't otherwise be the case without these changes.

5.2 Direct Contributions

Paper one contributes to the field of power studies in state government through the following:

1. A process by which the Schlesinger and Beyle measure of gubernatorial appointment power can be transformed from an Ego perspective (Governor centric) to a whole network, shedding light on how administrative structure is changing in state government
2. The identification of issues related to the transformation of the Book of the States values into a social network
3. A revised weighting scheme on the basis of which a whole network can be built
4. A discussion of how once the network is created one can then look across all 50 states by agency to understand how changes in agencies are occurring

This work has revealed that at least one state, Massachusetts, has adopted a delegated appointment authority approach that would have potentially been misunderstood as a move toward decentralization using the prior technique.

Paper 2 contributes to the discussion regarding interlocked corporate boards by highlighting differences in the U.S. versus European markets as these networks evolve over time. Key contributions are:

1. An examination of the argument by Mizruchi that the corporate elites are disintegrating..
2. The insight that density is decreasing in the European markets, while remaining stable in the U.S., when viewed through the lens of the DOW 30.
3. A concept of core and extended hulls of a longitudinal social network, in which some nodes leave and/or enter the network.
4. The insight that density increases for the core hull and decreases for the extended hull over the same time period for the DOW 30 network.

Paper 3 also contributes to the discussion regarding interlocked corporate boards, also through the lens of Mizruchi argument that the elite are losing power. The need to analyze interlock networks longitudinally motivates our extension of a Bayesian random effect model, previously employed to compare social networks at 2 points in time. Key contributions are:

1. The introduction of a Bayesian model to examine the significance of changes within a social network over time.
2. Insights about estimated time trends – with standard deviation – for the propensity to form interlocks, both for the networks as a whole and for individual corporations within the network.

5.3 Future Research

While we have shown that the Appointment Power component of Schelsinger's Index is suitable to conversion to a social network, this same process can be used to look at other components, in particular, budget power. In our work we weigh the appointment network on the basis of the level of participation to that appointment. As has been highlighted by others, this still does not address the issue that agencies gain and lose power over time. We propose that, through a combination of appointment power and budget, we can begin to shed more light on this issue. For example, our model treats the appointment of the head of a smaller agency equally with that of a larger one. To address this issue we propose sizing nodes based on their budget. This would add valuable information into the visualizations for each state. In order to gain better network statistics, we would weigh appointment power on the basis of both the level of participation as well as the budget power of that agency. We believe this would be an important next step to further our understanding of power within state government.

Part of the criticism in the analysis of the surrounding activity at the agency level is due to the fact that the Book of the State tracks only a limited number of agencies across all 50 states. It has been argued that other agencies, which are not covered by the Book of the States data, may be usurping power from those which are tracked. With the next step outlined above, we can also determine what the level of budgetary power covered by those agencies represented in the model. This would allow us to better understand how much of the overall budgetary power is accounted for within the agencies in the network. This will highlight when we need to consider adding agencies not covered by the Book of the States, either because budgets have dropped below some overall threshold (budget is slowly siphoning to agencies outside our network), or we have seen a large shift (a rapid shift of significant funds to an outside agency) that isn't accounted for in our model.

Clearly combining the work of paper 3 with the data from paper 1 could be invaluable to those studying state government. Giving researchers the ability to see when significant change is occurring within states would aid researchers performing longitudinal studies across states. Instead of the need to evaluate each state for each year of the study, researchers could focus on why change occurred at a particular time. For example, the original index includes party control as one of the measures of gubernatorial power. This measures how much of a majority the governor's party holds in the state legislature. However, we do not have a good quantitative measure by which we can identify strong governor versus strong legislature states. This is particularly important in states where the party control is very low, indicating that one party controls the governor's office while the other controls the legislature. We believe that by looking at significant change over time, and using the party control measure, we could unravel whether the state possess a strong governor versus a strong legislature. For example, let us say that one party controls both the governor's office and the legislature but that we then see a change in the party control measure. If this change is quickly followed by a change in appointment power away from the governor, this may indicate a strong legislature state. However, if we do not observe such a change then it may be an indication of a strong governor state.

In order to apply the model we developed in paper three to the Book of the States data several tasks would need to be done. First, we would convert all states, in all years, over to social networks. While the data are available, the challenge exists of codes changing year by year, and careful attention would need to be taken to convert those codes over to nodes and edges. However, this is a task that would only need to be performed once, and once available, could then be used by others in their own work. Second, we would reduce the weighted networks down to 2 non-weighted networks; one for whether the person appoints or not, and the other for whether the person approves the appointment or not. This would allow us to utilize the new model from paper 3 with no changes. This would allow us to detect major change within each state such as the one experienced in Massachusetts as the governor delegated appointment responsibility. Finally, we would extend the model to allow for weighted networks that would allow for a finer level of detail than the model currently allows. This would allow us to detect more nuanced changes occurring within states with regards to shared responsibilities.

As we have indicated, one of the limitations of this work in regards to state government is the fact that we have not presented a better measure of gubernatorial power when the governor delegates this authority. Clearly, while delegating reduces power to some degree, it is not the same as moving the power outside of the governor's office. In order to account for this, we propose the creation of subgroups within our network accounting for everyone in the governor's office, followed by the measurement of degree from the subgroup as a measure for gubernatorial power. By comparing the power of the subgroup with the power of the governor we can measure how much of that power has been delegated, which would avoid the issue of failing to detect this delegated authority.

Finally, in regards to state government, there is evidence in the literature that strong ties can promote efficiency (due to homophily), while innovation can come from weak ties. By combining the work of Markus et al. (2013a) with this work, we can begin to test whether this is the case in state government. This can lead to questions such as, in states where the governor delegates appointment authority (moving from a strong tie to a weaker one), do we see both a decrease in efficiency yet also an increase in innovation?

The work on interlocking boards has several avenues for future research as well. First and foremost would be to extend the period of study beyond the 10 years covered in these papers. To more extensively test the Mizruchi hypothesis would require building the interlocked networks going back to the 1920's. It would also be important to extend the work beyond 2010. While we have captured the years of the subprime mortgage crisis in the U.S., it is reasonable to expect its impact to boards of directors to lag a certain number of years. As such, we may not have captured the true impact of the subprime mortgage crisis in this work.

Second, the extension of the Bayesian model has the limitation of working only with un-weighted networks. In order to take advantage of the weighting from paper 1, this model will have to be extended again to allow for weighted networks. This extension, which allows for weighted networks, would be very valuable and would allow us to better model the power networks in paper 1. While such research is out of the scope of this dissertation, we outline how it could proceed here. Extending the model to directed networks is straightforward enough (see (Gill & Swartz, 2004)). To take weights into account we would need to define 8 different types of links, in each direction, and each with appropriate weight, and then model the logarithm of the probability for each of the eight types of links, as well as the probability that no link at all occurs. It would be computationally heavier than our models for paper 3 (which took 3-6 hours to run on a well-appointed laptop), but is quite feasible. The output would include graphs, such as the "alpha graphs" presented in chapter 4, displaying, for example, governor power over time – complete with standard deviations.

Finally, this work only considers the interlocked boards of a small number of elite companies. To understand trends within the market as a whole, this work would have to be extended to include many more companies. It would be interesting to compare trends within the elite companies to trends of groups of companies that compose other social groupings, such as companies in the technology sector.

We should note the challenges of working with our Bayesian model. The OpenBUGS software is resource intensive. The core hull models (23 nodes over 10 years) took approximately 2 hours to run on a well-appointed personal computer. The extended hull model (38 nodes over 10 years) took approximately 6 hours to run. As we begin exploring the use of this model with the state network data (50 states, 50+ agencies, over a 20 year period) we will have to find alternative solutions for processing capabilities. However, this is not insurmountable, as tools such as Amazon Web Services (AWS) allow researchers to purchase significant processing power at affordable rates. Such services are an attractive alternative for researchers needing to perform heavy duty computations.

5.4 Final Thoughts

This work has been an exploration of analytics in two different domains. My interest in this area grew out of my work with M Lynne Markus on the NSF funded project[6], which explores innovation in state government. In that research we applied Schlesinger's index to a model for testing administrative innovation, but were unable to find significance with the appointment power. I felt that the index was lacking a holistic view, and thought it was well suited for implementation as a social network. This began my journey of using social network analysis as a tool in my research. The initial findings of the changes occurring within Massachusetts were quite unexpected, and highlight how hard it is to examine data in tables. The visualizations in SNA made these findings leap off the page, and it quickly

[6] SES-0964909 - M. Lynne Markus, Principal Investigator

became apparent what was changing in Massachusetts. An earlier version of this work was presented at the AMCIS in Puerto Rico in the summer of 2015.

This work then led to my joining a team a researchers working on understanding interlocked boards. That team had begun to explore the European markets, while I brought in the U.S. perspective through the acquisition and conversion of the DOW 30 data. I also contributed the idea of testing the Mizruchi hypothesis using this data. An earlier version of this work was presented at the International Conference on Advances in Social Network Analysis and Mining (ASONAM) in Paris in the summer of 2015.

When presenting this work, I was challenged repeatedly with the question as to whether our findings had statistical significance. This led to the work in paper 3. I explored how to test for statistical significance in longitudinal network analysis, and discovered that this was an opportunity for me to make a contribution to the field of SNA. While pairwise comparisons had been conducted, no model was readily available to analyze more than two years of data at a time. The authors of the work by Adams et al. (2008) were gracious enough to share their WinBUGS code for pairwise year comparisons. I was able to extend that program, and hence the Bayesian model, to conduct a multi-year comparison. Earlier versions of this work was presented at the INFORMS Annual Meeting in Philadelphia in the fall of 2015 and the 12th Annual International Conference on Operations Research in Havana, Cuba in the spring of 2016.

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Appendix A - DOW Companies by Year

		DOW 30 Components at End of Year												
Company	**Years**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**Added**	**Removed**	**Notes**
3M Company	2001-2010	X	X	X	X	X	X	X	X	X	X			Minnesota Mining & Manufacturing prior to 1/27/2003
Alcoa Inc	2001-2010	X	X	X	X	X	X	X	X	X	X			
Altria Group Incorporated	2001-2007	X	X	X	X	X	X	X	-	-	-		2/19/2008	Phillip Morris Companies Inc prior to 1/27/2003
American Express Co.	2001-2010	X	X	X	X	X	X	X	X	X	X			
American International Group Inc	2004-2007	-	-	-	X	X	X	X	-	-	-	4/8/2004	9/22/2008	
AT&T Corp	2001-2003	X	X	X	-	-	-	-	-	-	-		4/8/2004	
AT&T Inc	2001-2010	X	X	X	X	X	X	X	X	X	X			SBC Communications Prior to 11/21/2005
Bank of America	2008-2010	-	-	-	-	-	-	-	X	X	X	2/19/2008		
Boeing	2001-2010	X	X	X	X	X	X	X	X	X	X			
Caterpillar	2001-2010	X	X	X	X	X	X	X	X	X	X			
Chevron	2008-2010	-	-	-	-	-	-	-	X	X	X	2/19/2008		
Cisco Systems	2009-2010	-	-	-	-	-	-	-	-	X	X	6/8/2009		
Citigroup	2001-2008	X	X	X	X	X	X	X	X	-	-		6/8/2009	Travelers Group prior ro 11/1/1999
The Coca-Cola Company	2001-2010	X	X	X	X	X	X	X	X	X	X			
DuPont	2001-2010	X	X	X	X	X	X	X	X	X	X			
Eastman Kodak Company	2001-2003	X	X	X	-	-	-	-	-	-	-		4/8/2004	

ExxonMobil	2001-2010	X	X	X	X	X	X	X	X	X	X			Exxon Corporation prior to 1/27/2003
General Electric	2001-2010	X	X	X	X	X	X	X	X	X	X			
General Motors	2001-2008	X	X	X	X	X	X	X	X	-	-		6/8/2009	
Hewlett Packard Company	2001-2010	X	X	X	X	X	X	X	X	X	X			
The Home Depot Inc	2001-2010	X	X	X	X	X	X	X	X	X	X			
Honeywell International Inc	2001-2007	X	X	X	X	X	X	X	-	-	-		2/19/2008	AlliedSignal Incorporated prior to 1/27/2003
Intel	2001-2010	X	X	X	X	X	X	X	X	X	X			
IBM	2001-2010	X	X	X	X	X	X	X	X	X	X			
International Paper Company	2001-2003	X	X	X	-	-	-	-	-	-	-		4/8/2004	
Johnson & Johnson	2001-2010	X	X	X	X	X	X	X	X	X	X			
JPMorgan Chase	2001-2010	X	X	X	X	X	X	X	X	X	X			
Kraft Foods Inc	2008-2010	-	-	-	-	-	-	-	X	X	X	9/22/2008		
McDonalds	2001-2010	X	X	X	X	X	X	X	X	X	X			
Merck & Co	2001-2008	X	X	X	X	X	X	X	X					Delisted 11/2009
Merck & Co	2009-2010									X	X			Schering-Plough prior to 11/2009
Microsoft	2001-2010	X	X	X	X	X	X	X	X	X	X			
Pfizer	2004-2010	-	-	-	X	X	X	X	X	X	X	4/8/2004		
Procter & Gamble	2001-2010	X	X	X	X	X	X	X	X	X	X			
The Travelers Companies	2009-2010	-	-	-	-	-	-	-	-	X	X	6/8/2009		
United Technologies Corporation	2001-2010	X	X	X	X	X	X	X	X	X	X			
Verizon Communications	2004-2010	-	-	-	X	X	X	X	X	X	X	4/8/2004		

Walmart	2001-2010	X	X	X	X	X	X	X	X	X	X			
The Walt Disney Company	2001-2010	X	X	X	X	X	X	X	X	X	X			

Appendix B - OpenBUGS Model

```
model {

    # This model will load 10 years worth of network/graph information and compare the years
    # to determine if the network has statistically changed over that time period.
    # Our data is defined in am adjacency matrix with the naming y00x where y00 represents
    # the positive matrix # and the x is replaced by the year. So y003 represents the positive
    # graph for 2003.
    #
    # The graphs named y11x represent the inversed matrices of the y00x matrices.
    # Since Bayesian networks cannot be weighted (need to verify this) - the data has been
    # dichotimized. In other words, any weight greater than 1 has been set equal to 1. This
    # gives us binary data to work with.
    #
    # Since our connections are undirected, the matrix is symmetric across the diagonal.

    # g1 is defined in the data file and represents the number of nodes in the network
    # In the case of the DOW 30 Hull data this equals 23 or 38 dependng on Hull
    # The outer for loop will iterate the variable i from 1 to 22 or 37 depending on Hull

    for (i in 1:g1-1)
    {
      # This inner loop will iterate variable j from i+1 to 23 (or 38 depending on Hull used)
      # The result of these two loops will be that we will traverse through the upper (lower)
      # portion of the network.

      for (j in i+1:g1)
            {
            # You can identify stochastic nodes by the presence of these three components:
            #       > The name of the random quantity is on the left hand side of the equations
            #       > The ~ symbol in the middle, and
            #       > A function name on the right representing a distribution
            #
            # You can identify logical nodes by the presence of these three components:
            #       > The name of the variable on the left hand side of the equation
            #       > The symbol <- (arrow) in the middle, and
            #       > The mathematical operation on the right hand side of the equation
            #
            # dbern is a Bernoulli distribution (anything starting with the "d" represents a
            # distribution).
            # A Bernoulli trial is an experiment with 2 and only 2 outcomes.
            # The p001[i,j] is the probability of success

            y001[i,j] ~ dbern(p001[i,j])
            log(p001[i,j]) <- lambda1[i,j]

            y111[i,j] ~ dbern(p111[i,j])
            log(p111[i,j]) <- lambda1[i,j] + theta[1] + a[i,1] + a[j,1]
```

```
lambda1[i,j] <- -log(1 + exp(theta[1] + a[i,1] + a[j,1]))
# The above block of code is then repeated 9 more times to cover the other 9
# years.

# Year 2002
y002[i,j] ~ dbern(p002[i,j])
log(p002[i,j]) <- lambda2[i,j]

y112[i,j] ~ dbern(p112[i,j])
log(p112[i,j]) <- lambda2[i,j] + theta[2] + a[i,2] + a[j,2]

lambda2[i,j] <- -log(1 + exp(theta[2] + a[i,2] + a[j,2] ))

# Year 2003
y003[i,j] ~ dbern(p003[i,j])
log(p003[i,j]) <- lambda3[i,j]

y113[i,j] ~ dbern(p113[i,j])
log(p113[i,j]) <- lambda3[i,j] + theta[3] + a[i,3] + a[j,3]

lambda3[i,j] <- -log(1 + exp(theta[3] + a[i,3] + a[j,3] ))

# Year 2004
y004[i,j] ~ dbern(p004[i,j])
log(p004[i,j]) <- lambda4[i,j]

y114[i,j] ~ dbern(p114[i,j])
log(p114[i,j]) <- lambda4[i,j] + theta[4] + a[i,4] + a[j,4]

lambda4[i,j] <- -log(1 + exp(theta[4] + a[i,4] + a[j,4] ))

# Year 2005
y005[i,j] ~ dbern(p005[i,j])
log(p005[i,j]) <- lambda5[i,j]

y115[i,j] ~ dbern(p115[i,j])
log(p115[i,j]) <- lambda5[i,j] + theta[5] + a[i,5] + a[j,5]

lambda5[i,j] <- -log(1 + exp(theta[5] + a[i,5] + a[j,5] ))

# Year 2006
y006[i,j] ~ dbern(p006[i,j])
log(p006[i,j]) <- lambda6[i,j]

y116[i,j] ~ dbern(p116[i,j])
log(p116[i,j]) <- lambda6[i,j] + theta[6] + a[i,6] + a[j,6]

lambda6[i,j] <- -log(1 + exp(theta[6] + a[i,6] + a[j,6] ))

# Year 2007
y007[i,j] ~ dbern(p007[i,j])
```

```
            log(p007[i,j]) <- lambda7[i,j]

            y117[i,j] ~ dbern(p117[i,j])
            log(p117[i,j]) <- lambda7[i,j] + theta[7] + a[i,7] + a[j,7]

            lambda7[i,j] <- -log(1 + exp(theta[7] + a[i,7] + a[j,7] ))

            # Year 2008
            y008[i,j] ~ dbern(p008[i,j])
            log(p008[i,j]) <- lambda8[i,j]

            y118[i,j] ~ dbern(p118[i,j])
            log(p118[i,j]) <- lambda8[i,j] + theta[8] + a[i,8] + a[j,8]

            lambda8[i,j] <- -log(1 + exp(theta[8] + a[i,8] + a[j,8] ))

            # Year 2009
            y009[i,j] ~ dbern(p009[i,j])
            log(p009[i,j]) <- lambda9[i,j]

            y119[i,j] ~ dbern(p119[i,j])
            log(p119[i,j]) <- lambda9[i,j] + theta[9] + a[i,9] + a[j,9]

            lambda9[i,j] <- -log(1 + exp(theta[9] + a[i,9] + a[j,9] ))

            # Year 2010
            y0010[i,j] ~ dbern(p0010[i,j])
            log(p0010[i,j]) <- lambda10[i,j]

            y1110[i,j] ~ dbern(p1110[i,j])
            log(p1110[i,j]) <- lambda10[i,j] + theta[10] + a[i,10] + a[j,10]

            lambda10[i,j] <- -log(1 + exp(theta[10] + a[i,10] + a[j,10] ))
   }
}

for (j in 1:g1-1)
{
   for (i in j+1:g1)
            {
            y001[i,j] ~ dbern(p001[i,j])
            log(p001[i,j]) <- lambda1[i,j]

            y111[i,j] ~ dbern(p111[i,j])
            log(p111[i,j]) <- lambda1[i,j] + theta[1] + a[i,1] + a[j,1]

            lambda1[i,j] <- -log(1 + exp(theta[1] + a[i,1] + a[j,1]))

            y002[i,j] ~ dbern(p002[i,j])
            log(p002[i,j]) <- lambda2[i,j]
```

```
y112[i,j] ~ dbern(p112[i,j])
log(p112[i,j]) <- lambda2[i,j] + theta[2] + a[i,2] + a[j,2]

lambda2[i,j] <- -log(1 + exp(theta[2] + a[i,2] + a[j,2] ))

y003[i,j] ~ dbern(p003[i,j])
log(p003[i,j]) <- lambda3[i,j]

y113[i,j] ~ dbern(p113[i,j])
log(p113[i,j]) <- lambda3[i,j] + theta[3] + a[i,3] + a[j,3]

lambda3[i,j] <- -log(1 + exp(theta[3] + a[i,3] + a[j,3] ))

y004[i,j] ~ dbern(p004[i,j])
log(p004[i,j]) <- lambda4[i,j]

y114[i,j] ~ dbern(p114[i,j])
log(p114[i,j]) <- lambda4[i,j] + theta[4] + a[i,4] + a[j,4]

lambda4[i,j] <- -log(1 + exp(theta[4] + a[i,4] + a[j,4] ))


y005[i,j] ~ dbern(p005[i,j])
log(p005[i,j]) <- lambda5[i,j]

y115[i,j] ~ dbern(p115[i,j])
log(p115[i,j]) <- lambda5[i,j] + theta[5] + a[i,5] + a[j,5]

lambda5[i,j] <- -log(1 + exp(theta[5] + a[i,5] + a[j,5] ))

y006[i,j] ~ dbern(p006[i,j])
log(p006[i,j]) <- lambda6[i,j]

y116[i,j] ~ dbern(p116[i,j])
log(p116[i,j]) <- lambda6[i,j] + theta[6] + a[i,6] + a[j,6]

lambda6[i,j] <- -log(1 + exp(theta[6] + a[i,6] + a[j,6] ))

y007[i,j] ~ dbern(p007[i,j])
log(p007[i,j]) <- lambda7[i,j]

y117[i,j] ~ dbern(p117[i,j])
log(p117[i,j]) <- lambda7[i,j] + theta[7] + a[i,7] + a[j,7]

lambda7[i,j] <- -log(1 + exp(theta[7] + a[i,7] + a[j,7] ))

y008[i,j] ~ dbern(p008[i,j])
log(p008[i,j]) <- lambda8[i,j]

y118[i,j] ~ dbern(p118[i,j])
log(p118[i,j]) <- lambda8[i,j] + theta[8] + a[i,8] + a[j,8]
```

```
            lambda8[i,j] <- -log(1 + exp(theta[8] + a[i,8] + a[j,8] ))

            y009[i,j] ~ dbern(p009[i,j])
            log(p009[i,j]) <- lambda9[i,j]

            y119[i,j] ~ dbern(p119[i,j])
            log(p119[i,j]) <- lambda9[i,j] + theta[9] + a[i,9] + a[j,9]

            lambda9[i,j] <- -log(1 + exp(theta[9] + a[i,9] + a[j,9] ))

            y0010[i,j] ~ dbern(p0010[i,j])
            log(p0010[i,j]) <- lambda10[i,j]

            y1110[i,j] ~ dbern(p1110[i,j])
            log(p1110[i,j]) <- lambda10[i,j] + theta[10] + a[i,10] + a[j,10]

            lambda10[i,j] <- -log(1 + exp(theta[10] + a[i,10] + a[j,10] ))

}  }
# Priors are defined here

for (l in 1:9)
{
  diff[l]<-theta[l]-theta[l+1]
}

for (i in 1:g1)
{
  a[i,1:10] ~ dmnorm(zero[],prec.a[,])
}

for (k in 1:10)
{
  zero[k] <- 0
}

prec.a[1:10,1:10] ~ dwish(b[,],nu)
nu<-10

for (k in 1:10)
{
  b[k,k] <- 1
}

for (k1 in 1:9)
{
  for (k2 in k1+1:10)
  {
            b[k1,k2]<-0
  }
```

```
}

for (k2 in 1:9)
{
   for (k1 in k2+1:10)
   {
              b[k1,k2]<-0
   }
}

theta[1:10]~ dmnorm(zero[],prec.a[,])
sigmaa[1:10,1:10] <- inverse(prec.a[,])

}   # End of Model
```

Appendix C - Hull Results

Core Hull Results

	mean	sd	MC_error	val2.5%	median	val97.5%	start	sample
diff[1]	-0.1371	0.2878	0.01325	-0.4283	0.1337	0.6837	50000	150001
diff[2]	-0.004976	0.3108	0.01448	-0.5648	-0.00705	0.6761	50000	150001
diff[3]	-0.001492	0.2985	0.01375	-0.6197	0.009119	0.5633	50000	150001
diff[4]	0.01953	0.2732	0.01261	-0.5708	-0.02601	0.5396	50000	150001
diff[5]	-0.02565	0.3339	0.01549	-0.6133	0.01342	0.737	50000	150001
diff[6]	-0.2637	0.2882	0.01348	-0.3085	0.2598	0.8355	50000	150001
diff[7]	0.2921	0.2586	0.01109	-0.8249	-0.286	0.1984	50000	150001
diff[8]	-0.1237	0.2665	0.01172	-0.3918	0.1188	0.6641	50000	150001
diff[9]	-0.3759	0.3175	0.01423	-0.2388	0.3667	0.9988	50000	150001
sigmaa[1,1]	1.443	0.5485	0.01149	0.6839	1.342	2.792	50000	150001
sigmaa[1,2]	1.219	0.4582	0.007395	0.5805	1.135	2.345	50000	150001
sigmaa[1,3]	1.371	0.5085	0.008578	0.6648	1.28	2.613	50000	150001
sigmaa[1,4]	1.363	0.5154	0.008159	0.6422	1.272	2.625	50000	150001
sigmaa[1,5]	1.307	0.5082	0.008152	0.5938	1.216	2.553	50000	150001
sigmaa[1,6]	1.068	0.4698	0.006544	0.3881	0.9894	2.203	50000	150001
sigmaa[1,7]	0.855	0.4035	0.005789	0.2587	0.7904	1.826	50000	150001
sigmaa[1,8]	0.9288	0.4461	0.00622	0.2612	0.8595	1.997	50000	150001
sigmaa[1,9]	0.8976	0.4078	0.005353	0.2958	0.8326	1.885	50000	150001
sigmaa[1,10]	0.6733	0.3181	0.004107	0.2008	0.6222	1.438	50000	150001
sigmaa[2,1]	1.219	0.4582	0.007395	0.5805	1.135	2.345	50000	150001
sigmaa[2,2]	1.303	0.4941	0.009625	0.6308	1.209	2.524	50000	150001
sigmaa[2,3]	1.247	0.4635	0.006181	0.5962	1.163	2.39	50000	150001
sigmaa[2,4]	1.197	0.4682	0.006426	0.5353	1.114	2.345	50000	150001
sigmaa[2,5]	1.118	0.4534	0.00583	0.467	1.04	2.226	50000	150001
sigmaa[2,6]	0.8928	0.4253	0.00499	0.2504	0.8265	1.92	50000	150001
sigmaa[2,7]	0.7022	0.3645	0.004009	0.1354	0.65	1.57	50000	150001
sigmaa[2,8]	0.7777	0.4088	0.004766	0.1385	0.7201	1.744	50000	150001
sigmaa[2,9]	0.774	0.3753	0.004127	0.2005	0.7177	1.666	50000	150001
sigmaa[2,10]	0.6391	0.3037	0.003705	0.1865	0.5912	1.365	50000	150001
sigmaa[3,1]	1.371	0.5085	0.008578	0.6648	1.28	2.613	50000	150001
sigmaa[3,2]	1.247	0.4635	0.006181	0.5962	1.163	2.39	50000	150001
sigmaa[3,3]	1.628	0.5978	0.01121	0.8021	1.517	3.097	50000	150001
sigmaa[3,4]	1.543	0.5657	0.008768	0.758	1.439	2.927	50000	150001
sigmaa[3,5]	1.497	0.5609	0.008695	0.7196	1.395	2.88	50000	150001
sigmaa[3,6]	1.251	0.5204	0.007379	0.5089	1.16	2.518	50000	150001
sigmaa[3,7]	1.011	0.4466	0.006402	0.3646	0.9351	2.093	50000	150001

sigmaa[3,8]	1.08	0.4892	0.006698	0.3616	1.001	2.257	50000	150001
sigmaa[3,9]	0.9984	0.438	0.00562	0.358	0.9268	2.056	50000	150001
sigmaa[3,10]	0.6849	0.3339	0.004297	0.1816	0.6343	1.478	50000	150001
sigmaa[4,1]	1.363	0.5154	0.008159	0.6422	1.272	2.625	50000	150001
sigmaa[4,2]	1.197	0.4682	0.006426	0.5353	1.114	2.345	50000	150001
sigmaa[4,3]	1.543	0.5657	0.008768	0.758	1.439	2.927	50000	150001
sigmaa[4,4]	1.829	0.6885	0.01459	0.8938	1.697	3.528	50000	150001
sigmaa[4,5]	1.707	0.6353	0.01158	0.8338	1.588	3.274	50000	150001
sigmaa[4,6]	1.561	0.6183	0.01127	0.7082	1.445	3.08	50000	150001
sigmaa[4,7]	1.271	0.5251	0.009151	0.5391	1.175	2.56	50000	150001
sigmaa[4,8]	1.368	0.572	0.009451	0.5634	1.264	2.778	50000	150001
sigmaa[4,9]	1.215	0.5021	0.007613	0.5036	1.126	2.449	50000	150001
sigmaa[4,10]	0.6964	0.3475	0.004405	0.1653	0.645	1.52	50000	150001
sigmaa[5,1]	1.307	0.5082	0.008152	0.5938	1.216	2.553	50000	150001
sigmaa[5,2]	1.118	0.4534	0.00583	0.467	1.04	2.226	50000	150001
sigmaa[5,3]	1.497	0.5609	0.008695	0.7196	1.395	2.88	50000	150001
sigmaa[5,4]	1.707	0.6353	0.01158	0.8338	1.588	3.274	50000	150001
sigmaa[5,5]	1.853	0.7219	0.0162	0.8819	1.713	3.628	50000	150001
sigmaa[5,6]	1.622	0.6375	0.01141	0.7424	1.503	3.186	50000	150001
sigmaa[5,7]	1.328	0.5438	0.009737	0.5745	1.229	2.66	50000	150001
sigmaa[5,8]	1.433	0.5986	0.01093	0.5971	1.325	2.91	50000	150001
sigmaa[5,9]	1.259	0.5196	0.008572	0.5307	1.168	2.538	50000	150001
sigmaa[5,10]	0.6936	0.3494	0.004441	0.1619	0.6416	1.529	50000	150001
sigmaa[6,1]	1.068	0.4698	0.006544	0.3881	0.9894	2.203	50000	150001
sigmaa[6,2]	0.8928	0.4253	0.00499	0.2504	0.8265	1.92	50000	150001
sigmaa[6,3]	1.251	0.5204	0.007379	0.5089	1.16	2.518	50000	150001
sigmaa[6,4]	1.561	0.6183	0.01127	0.7082	1.445	3.08	50000	150001
sigmaa[6,5]	1.622	0.6375	0.01141	0.7424	1.503	3.186	50000	150001
sigmaa[6,6]	1.905	0.767	0.01737	0.8767	1.751	3.799	50000	150001
sigmaa[6,7]	1.519	0.6017	0.01164	0.7007	1.403	3.005	50000	150001
sigmaa[6,8]	1.673	0.6539	0.01194	0.7745	1.548	3.289	50000	150001
sigmaa[6,9]	1.414	0.5503	0.008688	0.6454	1.314	2.759	50000	150001
sigmaa[6,10]	0.7668	0.3612	0.004357	0.2247	0.7107	1.628	50000	150001
sigmaa[7,1]	0.855	0.4035	0.005789	0.2587	0.7904	1.826	50000	150001
sigmaa[7,2]	0.7022	0.3645	0.004009	0.1354	0.65	1.57	50000	150001
sigmaa[7,3]	1.011	0.4466	0.006402	0.3646	0.9351	2.093	50000	150001
sigmaa[7,4]	1.271	0.5251	0.009151	0.5391	1.175	2.56	50000	150001
sigmaa[7,5]	1.328	0.5438	0.009737	0.5745	1.229	2.66	50000	150001
sigmaa[7,6]	1.519	0.6017	0.01164	0.7007	1.403	3.005	50000	150001
sigmaa[7,7]	1.489	0.5955	0.01338	0.6967	1.37	2.973	50000	150001
sigmaa[7,8]	1.519	0.5873	0.011	0.7155	1.408	2.973	50000	150001

sigmaa[7,9]	1.289	0.4929	0.0077	0.6062	1.199	2.504	50000	150001
sigmaa[7,10]	0.7487	0.3293	0.00402	0.2681	0.6939	1.542	50000	150001
sigmaa[8,1]	0.9288	0.4461	0.00622	0.2612	0.8595	1.997	50000	150001
sigmaa[8,2]	0.7777	0.4088	0.004766	0.1385	0.7201	1.744	50000	150001
sigmaa[8,3]	1.08	0.4892	0.006698	0.3616	1.001	2.257	50000	150001
sigmaa[8,4]	1.368	0.572	0.009451	0.5634	1.264	2.778	50000	150001
sigmaa[8,5]	1.433	0.5986	0.01093	0.5971	1.325	2.91	50000	150001
sigmaa[8,6]	1.673	0.6539	0.01194	0.7745	1.548	3.289	50000	150001
sigmaa[8,7]	1.519	0.5873	0.011	0.7155	1.408	2.973	50000	150001
sigmaa[8,8]	1.874	0.7304	0.016	0.8857	1.732	3.687	50000	150001
sigmaa[8,9]	1.515	0.5667	0.009213	0.7284	1.412	2.904	50000	150001
sigmaa[8,10]	0.8964	0.3773	0.004895	0.3533	0.8323	1.814	50000	150001
sigmaa[9,1]	0.8976	0.4078	0.005353	0.2958	0.8326	1.885	50000	150001
sigmaa[9,2]	0.774	0.3753	0.004127	0.2005	0.7177	1.666	50000	150001
sigmaa[9,3]	0.9984	0.438	0.00562	0.358	0.9268	2.056	50000	150001
sigmaa[9,4]	1.215	0.5021	0.007613	0.5036	1.126	2.449	50000	150001
sigmaa[9,5]	1.259	0.5196	0.008572	0.5307	1.168	2.538	50000	150001
sigmaa[9,6]	1.414	0.5503	0.008688	0.6454	1.314	2.759	50000	150001
sigmaa[9,7]	1.289	0.4929	0.0077	0.6062	1.199	2.504	50000	150001
sigmaa[9,8]	1.515	0.5667	0.009213	0.7284	1.412	2.904	50000	150001
sigmaa[9,9]	1.518	0.56	0.01038	0.7467	1.415	2.896	50000	150001
sigmaa[9,10]	0.8853	0.3513	0.004287	0.3848	0.8247	1.74	50000	150001
sigmaa[10,1]	0.6733	0.3181	0.004107	0.2008	0.6222	1.438	50000	150001
sigmaa[10,2]	0.6391	0.3037	0.003705	0.1865	0.5912	1.365	50000	150001
sigmaa[10,3]	0.6849	0.3339	0.004297	0.1816	0.6343	1.478	50000	150001
sigmaa[10,4]	0.6964	0.3475	0.004405	0.1653	0.645	1.52	50000	150001
sigmaa[10,5]	0.6936	0.3494	0.004441	0.1619	0.6416	1.529	50000	150001
sigmaa[10,6]	0.7668	0.3612	0.004357	0.2247	0.7107	1.628	50000	150001
sigmaa[10,7]	0.7487	0.3293	0.00402	0.2681	0.6939	1.542	50000	150001
sigmaa[10,8]	0.8964	0.3773	0.004895	0.3533	0.8323	1.814	50000	150001
sigmaa[10,9]	0.8853	0.3513	0.004287	0.3848	0.8247	1.74	50000	150001
sigmaa[10,10]	0.924	0.335	0.005151	0.4615	0.8629	1.748	50000	150001
theta[1]	-2.522	0.452	0.02143	1.721	2.49	3.474	50000	150001
theta[2]	-2.385	0.4018	0.01882	1.638	2.382	3.183	50000	150001
theta[3]	-2.38	0.4761	0.02284	1.485	2.371	3.352	50000	150001
theta[4]	-2.378	0.5084	0.02431	1.454	2.353	3.518	50000	150001
theta[5]	-2.398	0.4895	0.02316	1.502	2.382	3.444	50000	150001
theta[6]	-2.372	0.4909	0.02268	1.5	2.345	3.4	50000	150001
theta[7]	-2.108	0.4118	0.01933	1.342	2.094	2.948	50000	150001
theta[8]	-2.4	0.4626	0.02143	1.545	2.372	3.34	50000	150001
theta[9]	-2.277	0.4153	0.01937	1.493	2.265	3.139	50000	150001

theta[10]	-1.901	0.3421	0.01557	1.229	1.898	2.595	50000	150001

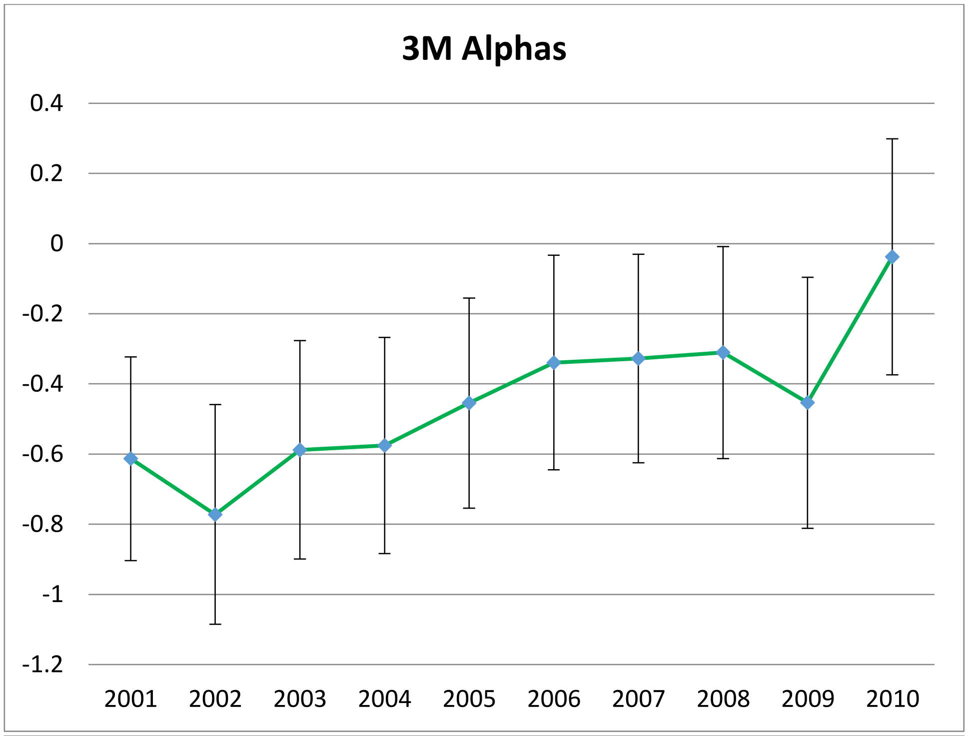
Extended Hull Results

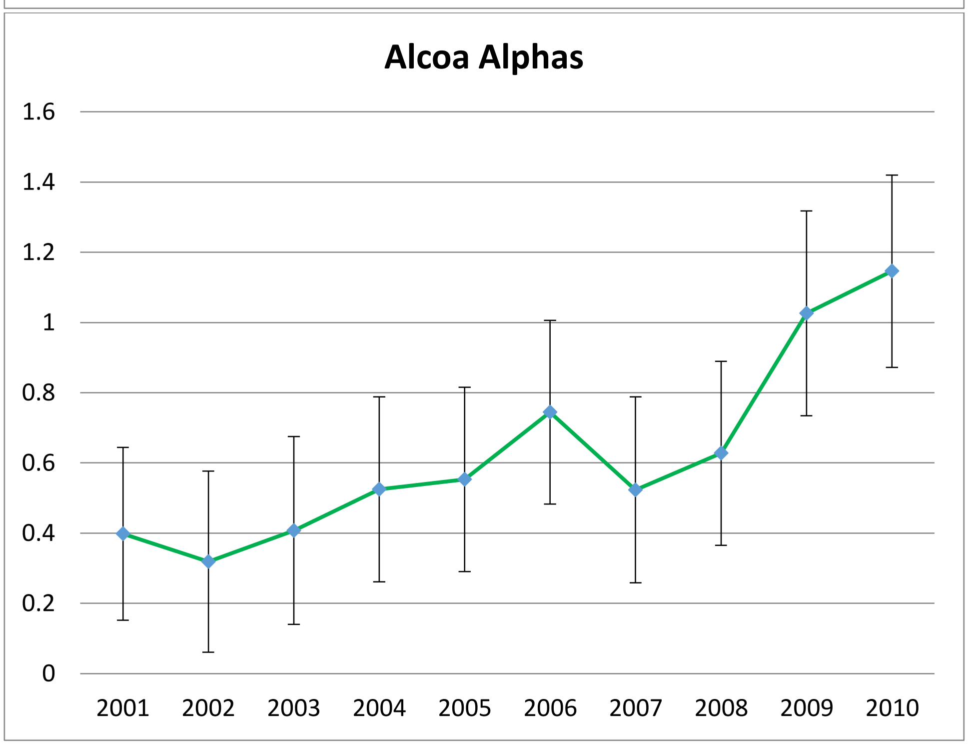
	mean	sd	MC_error	val2.5%	median	val97.5%	start	sample
diff[1]	0.08786	0.1619	0.007245	-0.218	0.08525	0.4151	50000	150001
diff[2]	0.1343	0.1821	0.008417	-0.2088	0.1287	0.4994	50000	150001
diff[3]	0.003791	0.1936	0.008508	-0.3862	0.003696	0.3799	50000	150001
diff[4]	0.1474	0.1828	0.008416	-0.193	0.1421	0.514	50000	150001
diff[5]	0.06878	0.2388	0.01121	-0.3991	0.0693	0.5464	50000	150001
diff[6]	-0.1609	0.1977	0.00906	-0.538	-0.1678	0.2424	50000	150001
diff[7]	0.0802	0.209	0.009336	-0.3226	0.07759	0.5004	50000	150001
diff[8]	0.3916	0.219	0.009953	-0.0153	0.3866	0.8496	50000	150001
diff[9]	-0.2961	0.2432	0.01093	-0.7784	-0.2881	0.1807	50000	150001
sigmaa[1,1]	0.8893	0.2413	0.003634	0.5239	0.854	1.461	50000	150001
sigmaa[1,2]	0.8671	0.2379	0.003169	0.5055	0.8321	1.427	50000	150001
sigmaa[1,3]	0.9399	0.2588	0.003514	0.5456	0.9018	1.55	50000	150001
sigmaa[1,4]	0.9033	0.2503	0.00315	0.5239	0.8664	1.494	50000	150001
sigmaa[1,5]	0.817	0.2405	0.002954	0.4469	0.783	1.382	50000	150001
sigmaa[1,6]	0.6555	0.2308	0.002875	0.2913	0.6253	1.195	50000	150001
sigmaa[1,7]	0.5628	0.2147	0.002633	0.2195	0.5362	1.063	50000	150001
sigmaa[1,8]	0.536	0.212	0.002471	0.1913	0.5108	1.025	50000	150001
sigmaa[1,9]	0.6675	0.26	0.003236	0.2489	0.6357	1.268	50000	150001
sigmaa[1,10]	0.5862	0.2445	0.003029	0.1883	0.557	1.15	50000	150001
sigmaa[2,1]	0.8671	0.2379	0.003169	0.5055	0.8321	1.427	50000	150001
sigmaa[2,2]	1.007	0.2813	0.00473	0.5837	0.9641	1.673	50000	150001
sigmaa[2,3]	1.015	0.2814	0.00409	0.5888	0.9734	1.681	50000	150001
sigmaa[2,4]	0.9729	0.2715	0.003755	0.5617	0.9322	1.613	50000	150001
sigmaa[2,5]	0.9039	0.2646	0.003566	0.501	0.866	1.53	50000	150001
sigmaa[2,6]	0.7485	0.2546	0.0035	0.3546	0.7128	1.347	50000	150001
sigmaa[2,7]	0.6483	0.2361	0.003097	0.2777	0.6173	1.199	50000	150001
sigmaa[2,8]	0.6187	0.2332	0.003033	0.2489	0.5889	1.162	50000	150001
sigmaa[2,9]	0.7618	0.2853	0.003707	0.3106	0.7248	1.424	50000	150001
sigmaa[2,10]	0.6733	0.2694	0.003682	0.2441	0.6381	1.297	50000	150001
sigmaa[3,1]	0.9399	0.2588	0.003514	0.5456	0.9018	1.55	50000	150001
sigmaa[3,2]	1.015	0.2814	0.00409	0.5888	0.9734	1.681	50000	150001
sigmaa[3,3]	1.211	0.3392	0.006341	0.7007	1.16	2.013	50000	150001
sigmaa[3,4]	1.097	0.3048	0.004706	0.6392	1.051	1.817	50000	150001
sigmaa[3,5]	1.034	0.2972	0.004409	0.5829	0.9894	1.737	50000	150001
sigmaa[3,6]	0.8719	0.2842	0.004011	0.4341	0.8314	1.539	50000	150001
sigmaa[3,7]	0.7736	0.2675	0.003923	0.3615	0.7366	1.403	50000	150001
sigmaa[3,8]	0.7153	0.2591	0.003481	0.3082	0.6805	1.32	50000	150001

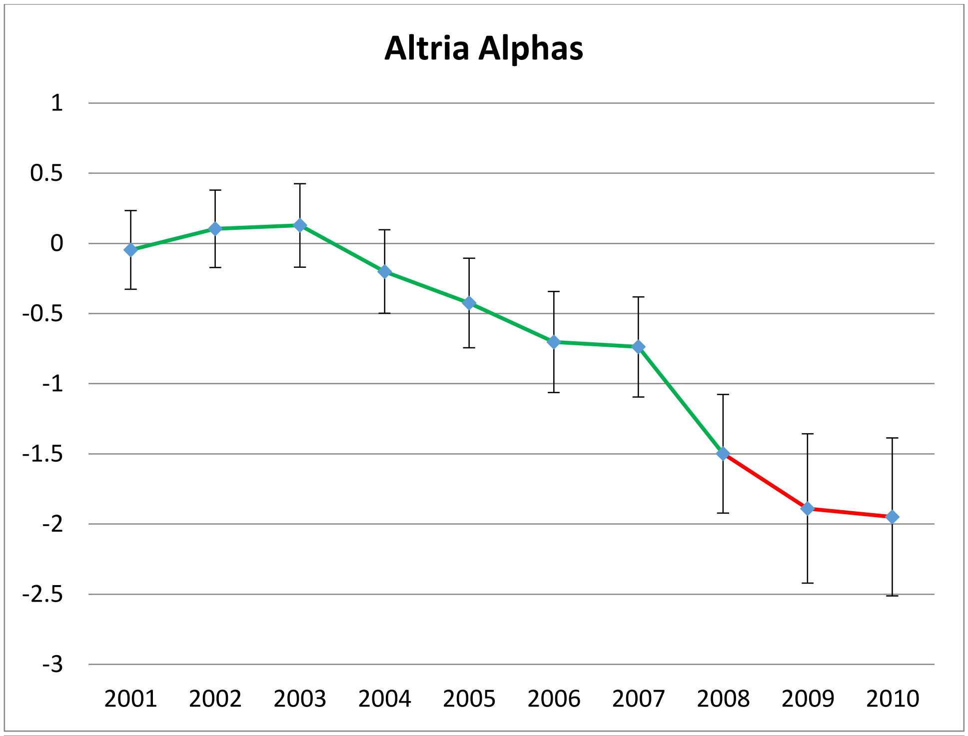
sigmaa[3,9]	0.8857	0.3167	0.004242	0.3885	0.8434	1.627	50000	150001
sigmaa[3,10]	0.8057	0.3026	0.00439	0.3312	0.7645	1.517	50000	150001
sigmaa[4,1]	0.9033	0.2503	0.00315	0.5239	0.8664	1.494	50000	150001
sigmaa[4,2]	0.9729	0.2715	0.003755	0.5617	0.9322	1.613	50000	150001
sigmaa[4,3]	1.097	0.3048	0.004706	0.6392	1.051	1.817	50000	150001
sigmaa[4,4]	1.169	0.3264	0.005712	0.6823	1.119	1.942	50000	150001
sigmaa[4,5]	1.057	0.3001	0.004604	0.6036	1.011	1.768	50000	150001
sigmaa[4,6]	0.9234	0.2915	0.004443	0.4811	0.8807	1.612	50000	150001
sigmaa[4,7]	0.8228	0.2718	0.004029	0.4078	0.7837	1.462	50000	150001
sigmaa[4,8]	0.7678	0.2636	0.003654	0.3584	0.7314	1.383	50000	150001
sigmaa[4,9]	0.9331	0.3216	0.004504	0.4358	0.8877	1.686	50000	150001
sigmaa[4,10]	0.7984	0.2973	0.004326	0.3316	0.7574	1.493	50000	150001
sigmaa[5,1]	0.817	0.2405	0.002954	0.4469	0.783	1.382	50000	150001
sigmaa[5,2]	0.9039	0.2646	0.003566	0.501	0.866	1.53	50000	150001
sigmaa[5,3]	1.034	0.2972	0.004409	0.5829	0.9894	1.737	50000	150001
sigmaa[5,4]	1.057	0.3001	0.004604	0.6036	1.011	1.768	50000	150001
sigmaa[5,5]	1.205	0.3421	0.006509	0.6954	1.153	2.023	50000	150001
sigmaa[5,6]	1.101	0.326	0.005552	0.6156	1.05	1.878	50000	150001
sigmaa[5,7]	1.005	0.304	0.004958	0.5488	0.9594	1.73	50000	150001
sigmaa[5,8]	0.9574	0.2982	0.004912	0.5106	0.9125	1.665	50000	150001
sigmaa[5,9]	1.176	0.3679	0.006376	0.6241	1.119	2.053	50000	150001
sigmaa[5,10]	1.023	0.3373	0.005591	0.514	0.9733	1.82	50000	150001
sigmaa[6,1]	0.6555	0.2308	0.002875	0.2913	0.6253	1.195	50000	150001
sigmaa[6,2]	0.7485	0.2546	0.0035	0.3546	0.7128	1.347	50000	150001
sigmaa[6,3]	0.8719	0.2842	0.004011	0.4341	0.8314	1.539	50000	150001
sigmaa[6,4]	0.9234	0.2915	0.004443	0.4811	0.8807	1.612	50000	150001
sigmaa[6,5]	1.101	0.326	0.005552	0.6156	1.05	1.878	50000	150001
sigmaa[6,6]	1.319	0.4009	0.009127	0.7339	1.254	2.283	50000	150001
sigmaa[6,7]	1.163	0.3496	0.006843	0.6486	1.107	1.999	50000	150001
sigmaa[6,8]	1.125	0.3389	0.006314	0.6222	1.072	1.928	50000	150001
sigmaa[6,9]	1.349	0.4116	0.007764	0.7342	1.285	2.326	50000	150001
sigmaa[6,10]	1.185	0.3814	0.007257	0.6167	1.126	2.094	50000	150001
sigmaa[7,1]	0.5628	0.2147	0.002633	0.2195	0.5362	1.063	50000	150001
sigmaa[7,2]	0.6483	0.2361	0.003097	0.2777	0.6173	1.199	50000	150001
sigmaa[7,3]	0.7736	0.2675	0.003923	0.3615	0.7366	1.403	50000	150001
sigmaa[7,4]	0.8228	0.2718	0.004029	0.4078	0.7837	1.462	50000	150001
sigmaa[7,5]	1.005	0.304	0.004958	0.5488	0.9594	1.73	50000	150001
sigmaa[7,6]	1.163	0.3496	0.006843	0.6486	1.107	1.999	50000	150001
sigmaa[7,7]	1.201	0.3684	0.008242	0.666	1.14	2.085	50000	150001
sigmaa[7,8]	1.074	0.3268	0.00614	0.5882	1.023	1.851	50000	150001
sigmaa[7,9]	1.282	0.3913	0.007132	0.6972	1.222	2.214	50000	150001

sigmaa[7,10]	1.134	0.3655	0.006918	0.5902	1.075	2.009	50000	150001
sigmaa[8,1]	0.536	0.212	0.002471	0.1913	0.5108	1.025	50000	150001
sigmaa[8,2]	0.6187	0.2332	0.003033	0.2489	0.5889	1.162	50000	150001
sigmaa[8,3]	0.7153	0.2591	0.003481	0.3082	0.6805	1.32	50000	150001
sigmaa[8,4]	0.7678	0.2636	0.003654	0.3584	0.7314	1.383	50000	150001
sigmaa[8,5]	0.9574	0.2982	0.004912	0.5106	0.9125	1.665	50000	150001
sigmaa[8,6]	1.125	0.3389	0.006314	0.6222	1.072	1.928	50000	150001
sigmaa[8,7]	1.074	0.3268	0.00614	0.5882	1.023	1.851	50000	150001
sigmaa[8,8]	1.205	0.3683	0.008039	0.6611	1.146	2.084	50000	150001
sigmaa[8,9]	1.351	0.4105	0.008031	0.74	1.286	2.328	50000	150001
sigmaa[8,10]	1.196	0.3778	0.007218	0.6369	1.136	2.096	50000	150001
sigmaa[9,1]	0.6675	0.26	0.003236	0.2489	0.6357	1.268	50000	150001
sigmaa[9,2]	0.7618	0.2853	0.003707	0.3106	0.7248	1.424	50000	150001
sigmaa[9,3]	0.8857	0.3167	0.004242	0.3885	0.8434	1.627	50000	150001
sigmaa[9,4]	0.9331	0.3216	0.004504	0.4358	0.8877	1.686	50000	150001
sigmaa[9,5]	1.176	0.3679	0.006376	0.6241	1.119	2.053	50000	150001
sigmaa[9,6]	1.349	0.4116	0.007764	0.7342	1.285	2.326	50000	150001
sigmaa[9,7]	1.282	0.3913	0.007132	0.6972	1.222	2.214	50000	150001
sigmaa[9,8]	1.351	0.4105	0.008031	0.74	1.286	2.328	50000	150001
sigmaa[9,9]	1.786	0.5572	0.01289	0.9655	1.697	3.116	50000	150001
sigmaa[9,10]	1.53	0.4784	0.009387	0.8231	1.455	2.674	50000	150001
sigmaa[10,1]	0.5862	0.2445	0.003029	0.1883	0.557	1.15	50000	150001
sigmaa[10,2]	0.6733	0.2694	0.003682	0.2441	0.6381	1.297	50000	150001
sigmaa[10,3]	0.8057	0.3026	0.00439	0.3312	0.7645	1.517	50000	150001
sigmaa[10,4]	0.7984	0.2973	0.004326	0.3316	0.7574	1.493	50000	150001
sigmaa[10,5]	1.023	0.3373	0.005591	0.514	0.9733	1.82	50000	150001
sigmaa[10,6]	1.185	0.3814	0.007257	0.6167	1.126	2.094	50000	150001
sigmaa[10,7]	1.134	0.3655	0.006918	0.5902	1.075	2.009	50000	150001
sigmaa[10,8]	1.196	0.3778	0.007218	0.6369	1.136	2.096	50000	150001
sigmaa[10,9]	1.53	0.4784	0.009387	0.8231	1.455	2.674	50000	150001
sigmaa[10,10]	1.623	0.5212	0.01205	0.8677	1.535	2.884	50000	150001
theta[1]	-2.423	0.2988	0.01423	-2.972	-2.44	-1.781	50000	150001
theta[2]	-2.511	0.3136	0.01507	-3.068	-2.532	-1.814	50000	150001
theta[3]	-2.646	0.3602	0.01748	-3.305	-2.663	-1.861	50000	150001
theta[4]	-2.649	0.3503	0.01653	-3.287	-2.672	-1.906	50000	150001
theta[5]	-2.797	0.3362	0.01609	-3.415	-2.809	-2.059	50000	150001
theta[6]	-2.866	0.3342	0.01609	-3.483	-2.87	-2.163	50000	150001
theta[7]	-2.705	0.318	0.01514	-3.343	-2.7	-2.095	50000	150001
theta[8]	-2.785	0.3201	0.01527	-3.38	-2.793	-2.143	50000	150001
theta[9]	-3.176	0.371	0.01781	-3.921	-3.188	-2.454	50000	150001
theta[10]	-2.88	0.3569	0.01695	-3.574	-2.859	-2.218	50000	150001

Appendix D - Company Alphas






Altria Alphas
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0
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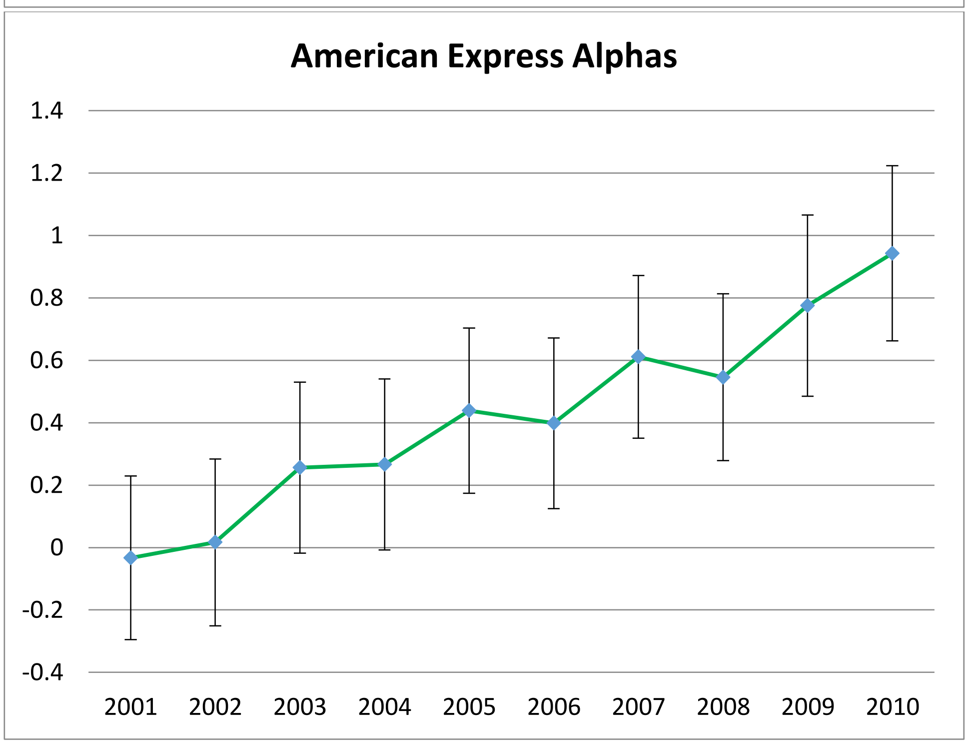
-1
-1.5
-2
-2.5
-3
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


American Express Alphas
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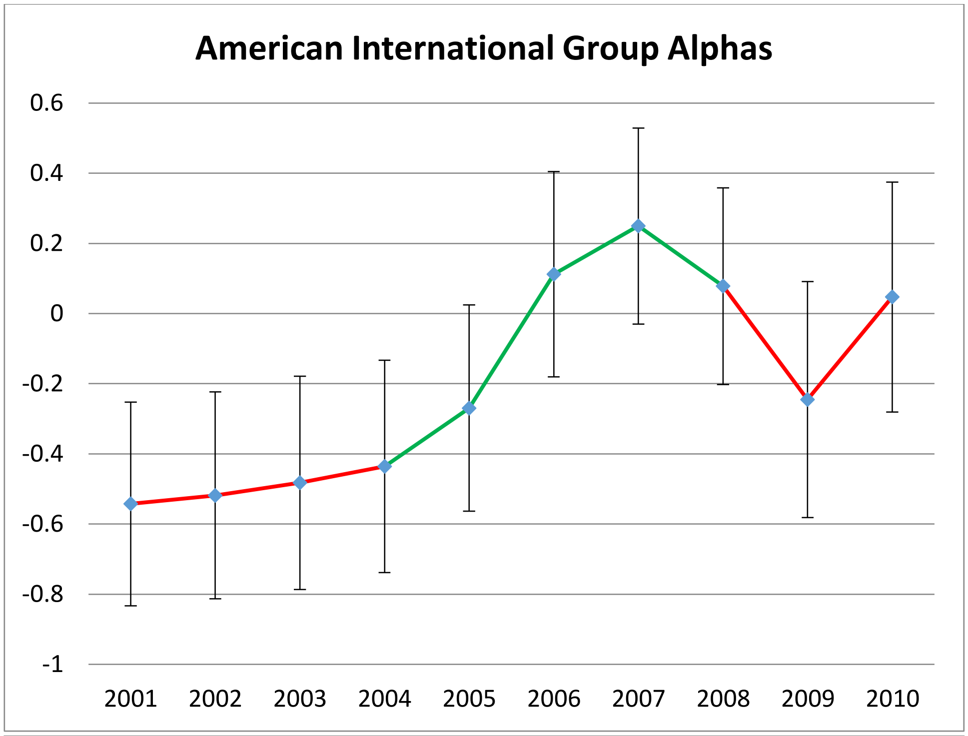
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010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-0.4
-0.6
-0.8
-1
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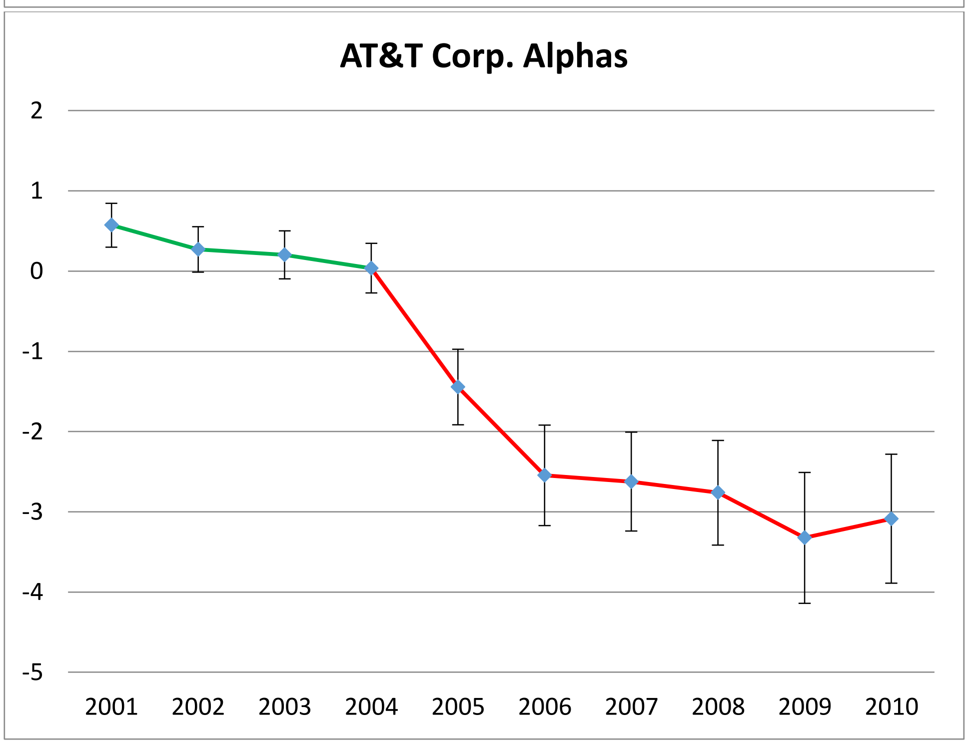
2003
2004
2005
2006
2007
2008
2009
2010


AT&T Corp. Alphas
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0
-1
-2
-3
-4
-5
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2002
2003
2004
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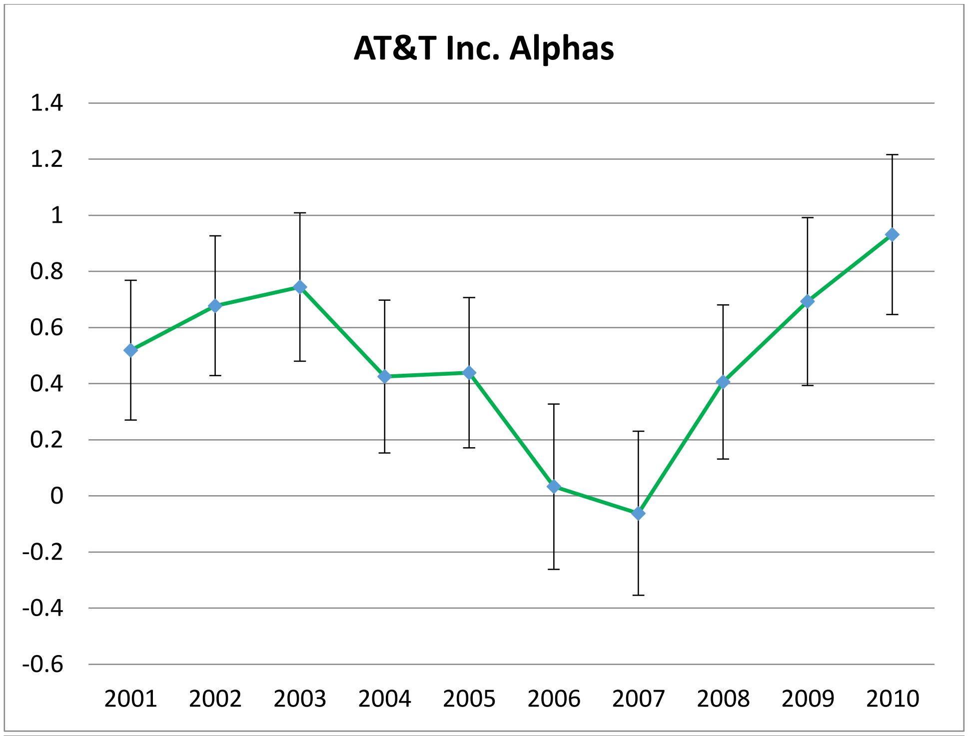
2006
2007
2008
2009
2010


AT&T Inc. Alphas
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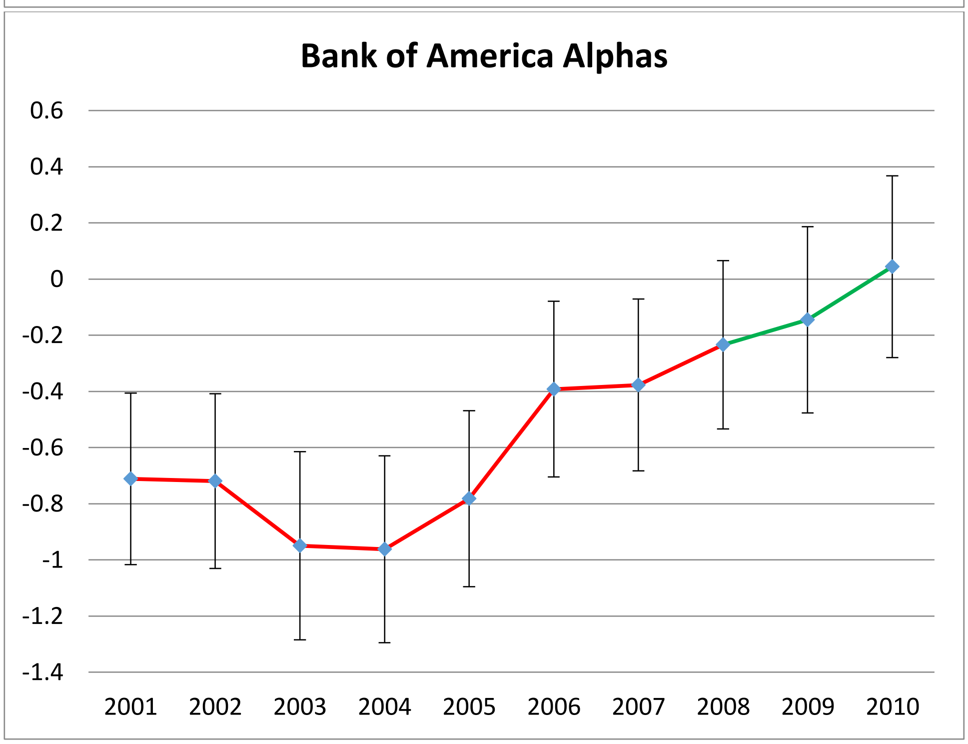
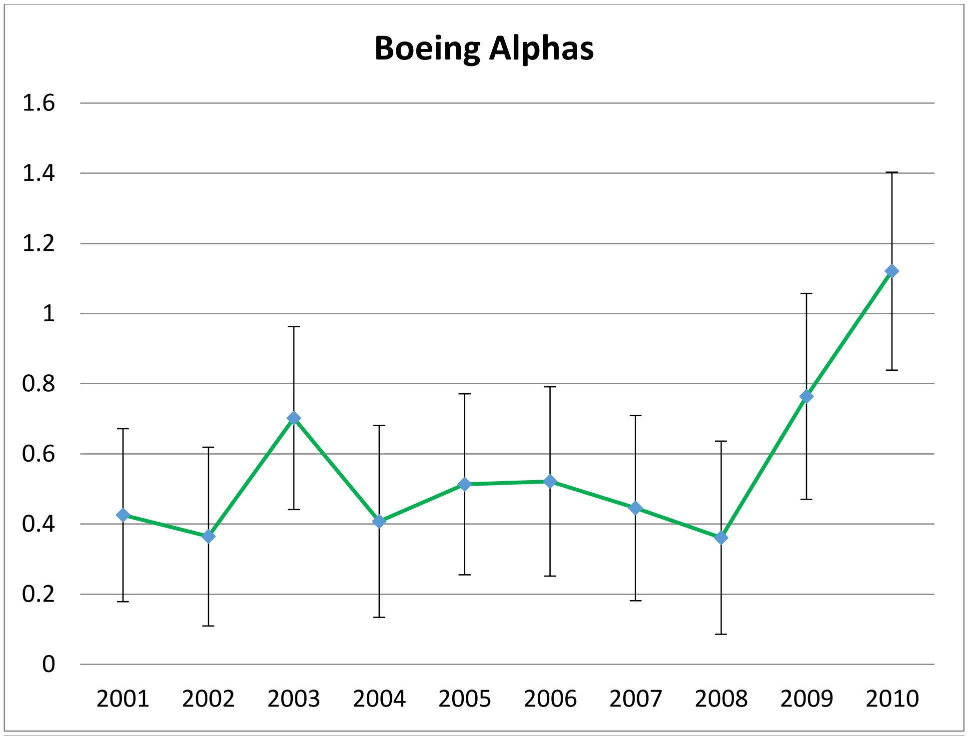
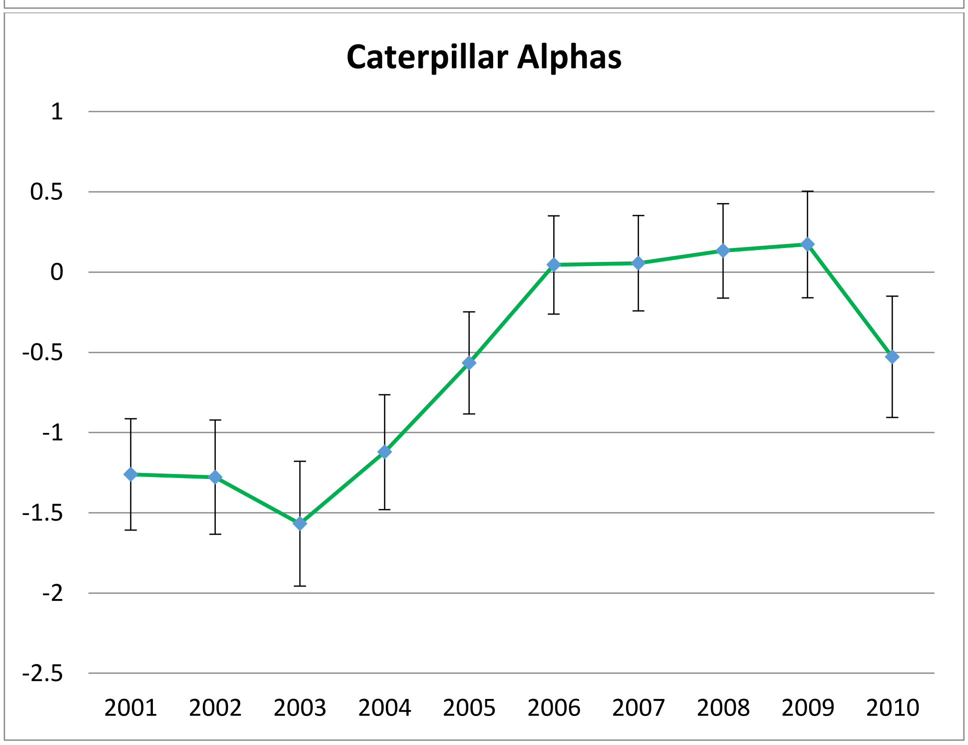
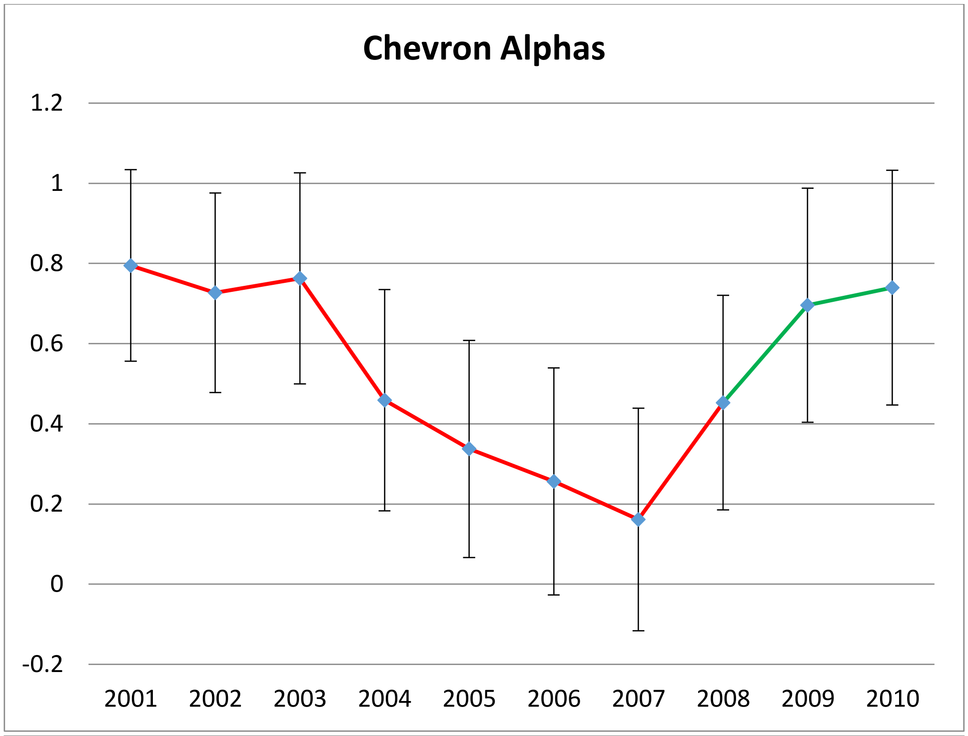
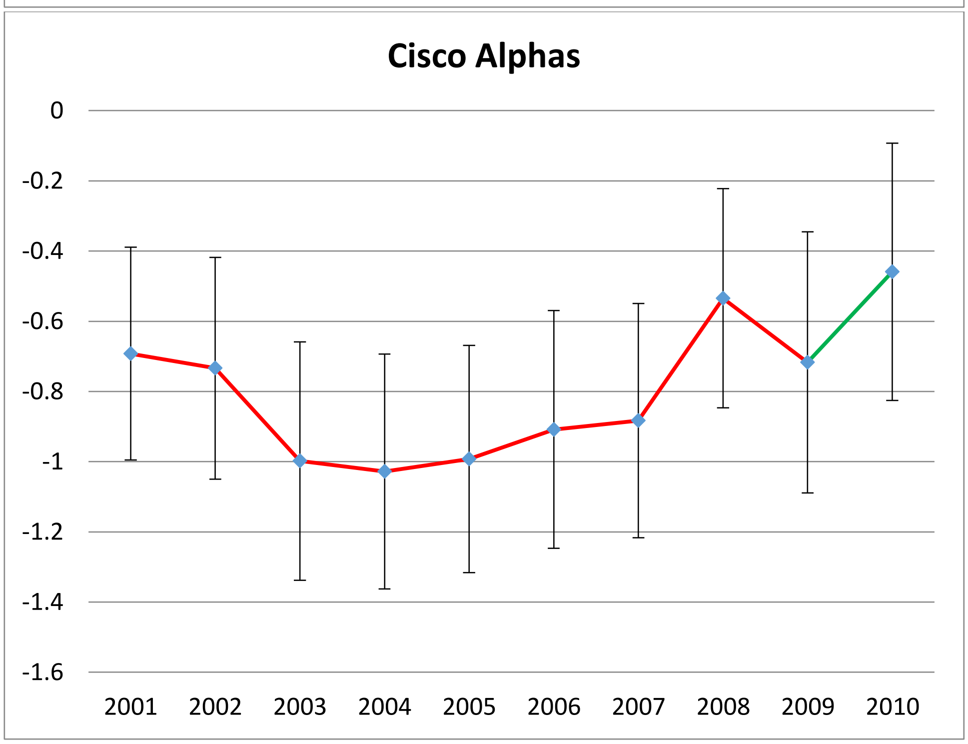
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Bank of America Alphas
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Boeing Alphas
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Caterpillar Alphas
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Chevron Alphas
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Cisco Alphas
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
-1.6
2001
2002
2003
2004
2005
2006
2007
2008
2009
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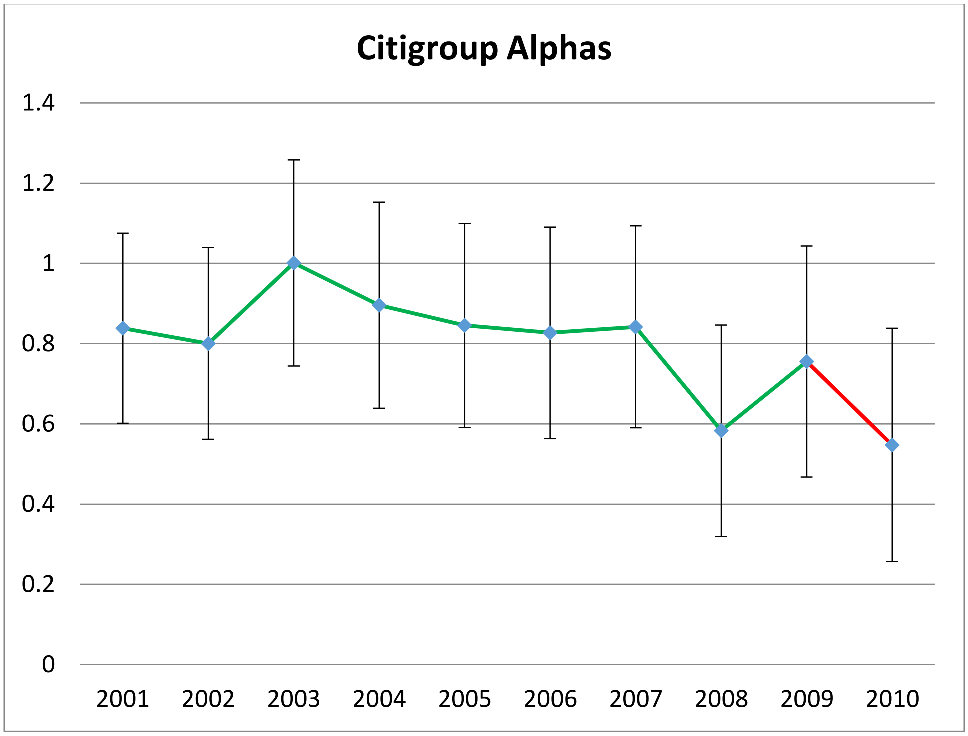
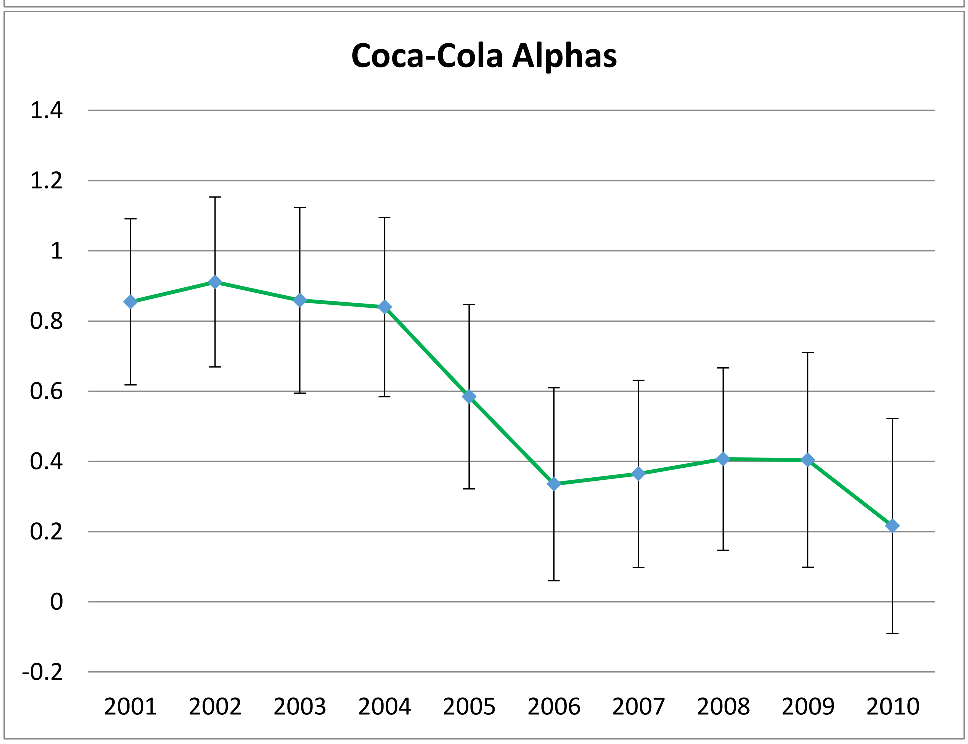
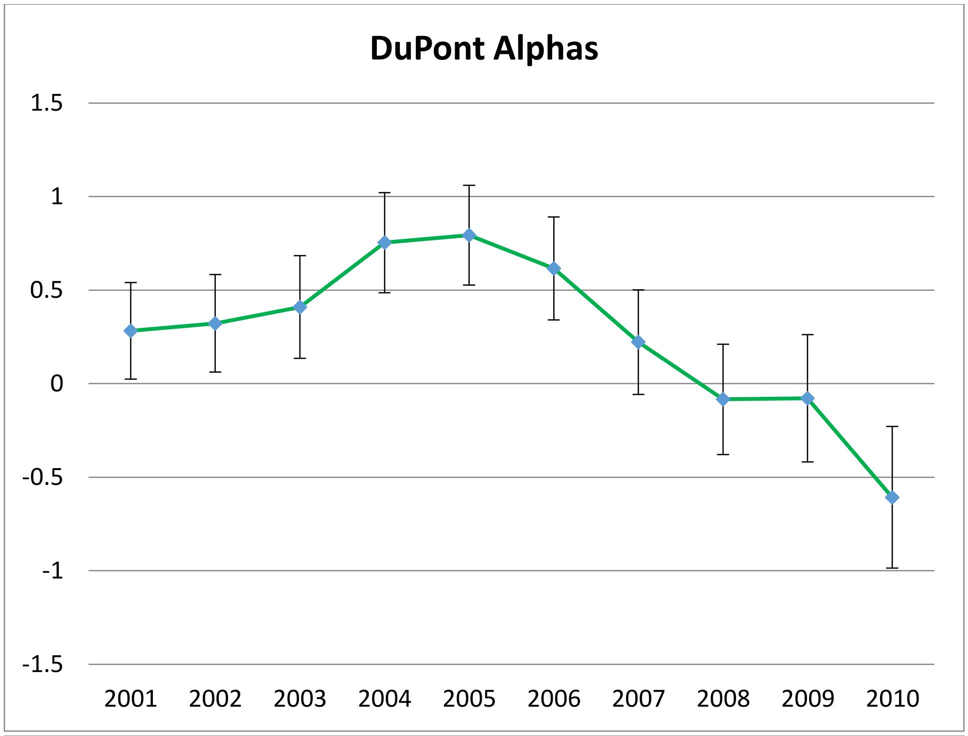
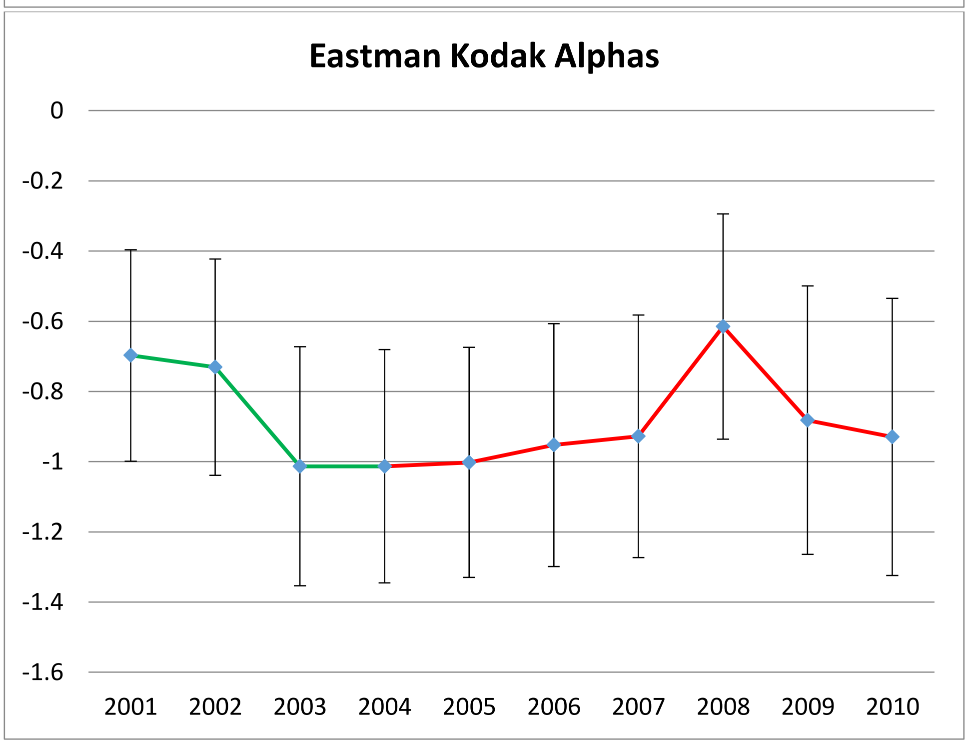

Citigroup Alphas
1.4
1.2
1
0.8
0.6
0.4
0.2
0
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010

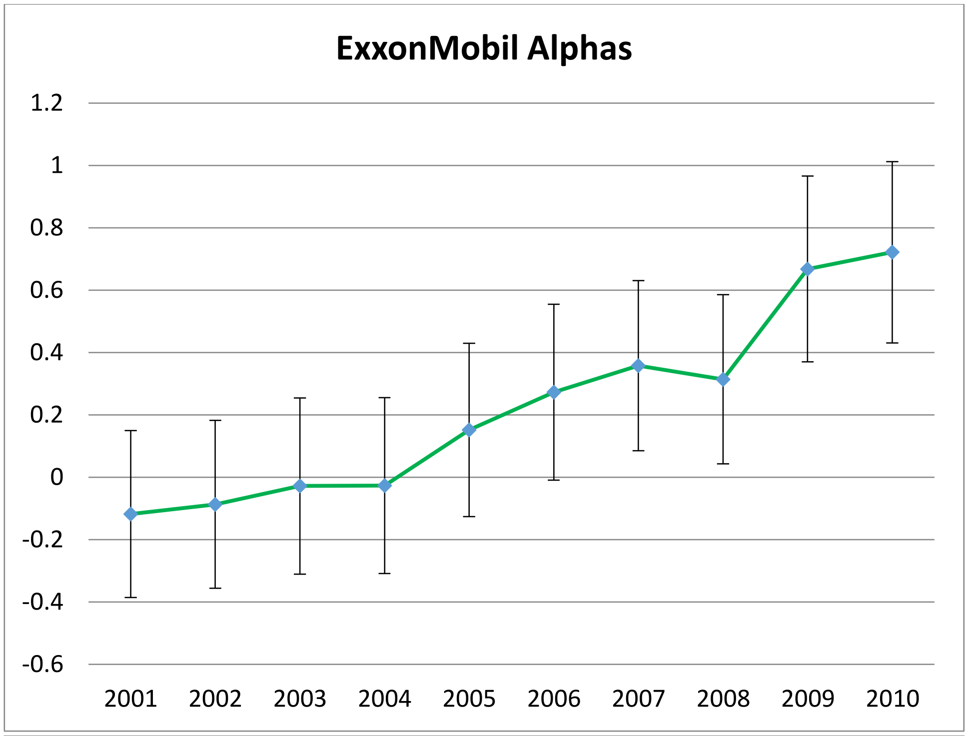

Coca-Cola Alphas
1.4
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010

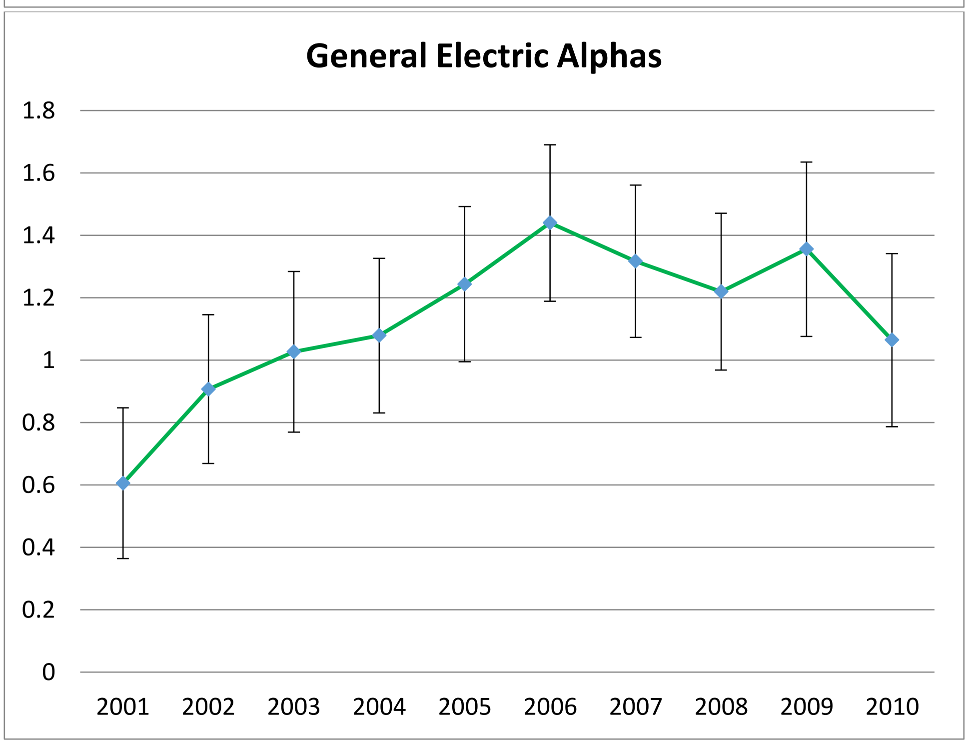


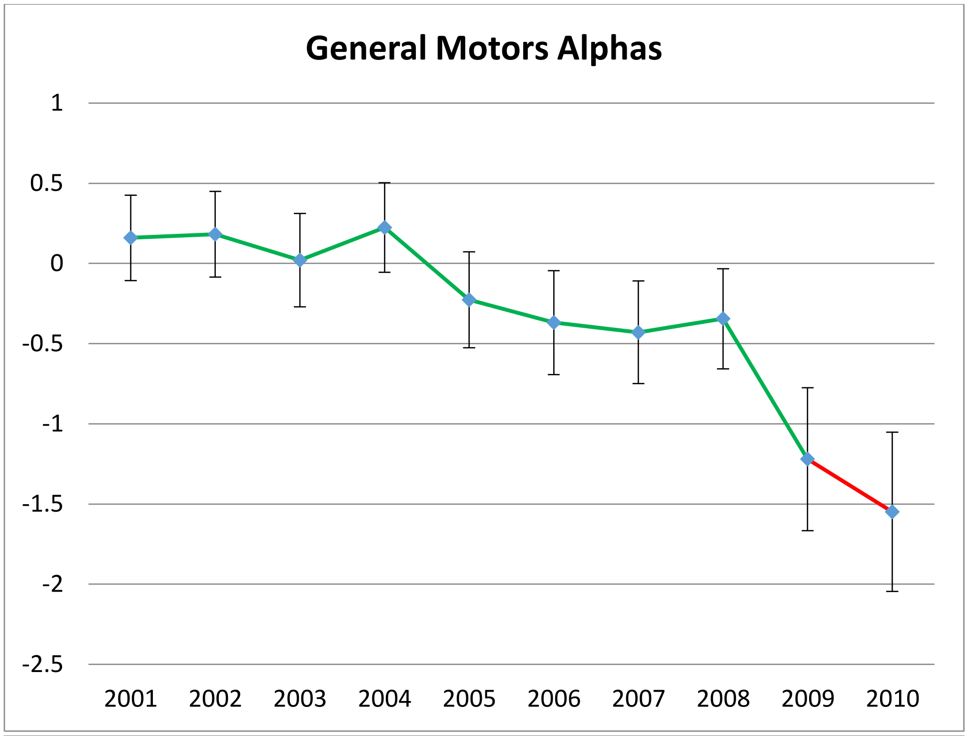
DuPont Alphas
1.5
1
0.5
0
-0.5
-1
-1.5
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010

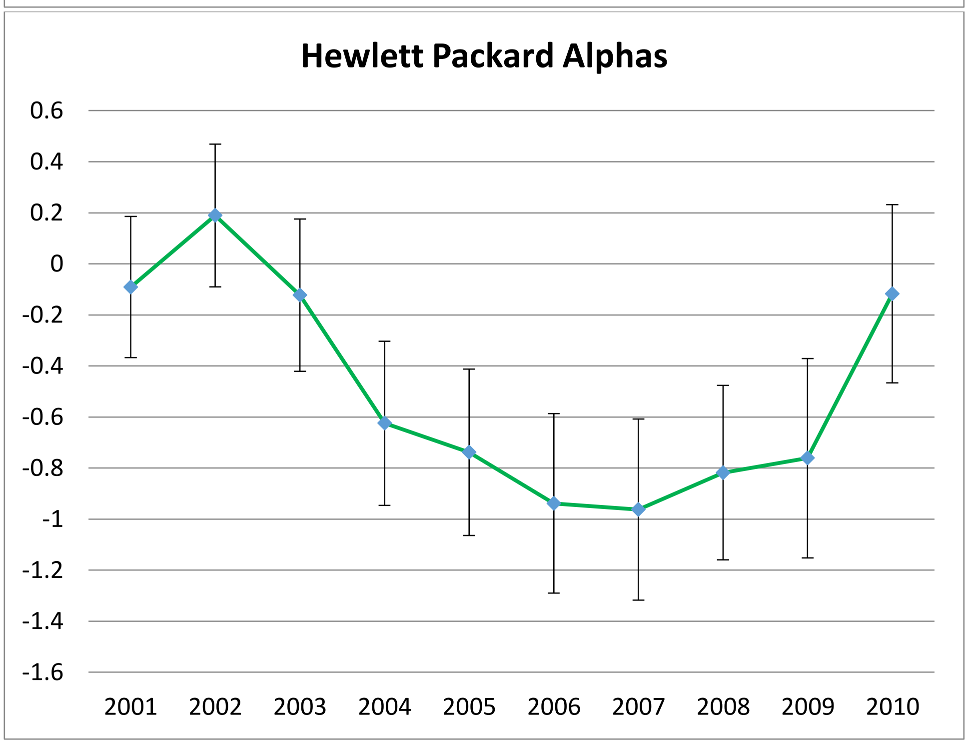


Eastman Kodak Alphas
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
-1.6
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


ExxonMobil Alphas
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


General Electric Alphas
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


General Motors Alphas
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Hewlett Packard Alphas
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
-1.6
2001
2002
2003
2004
2005
2006
2007
2008
2009
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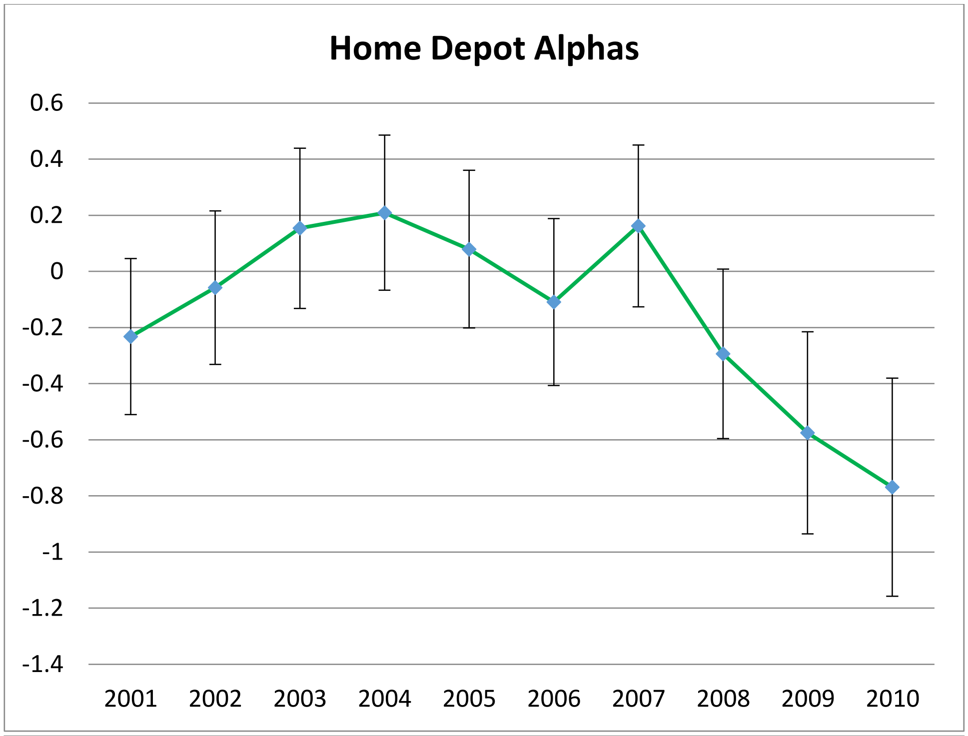
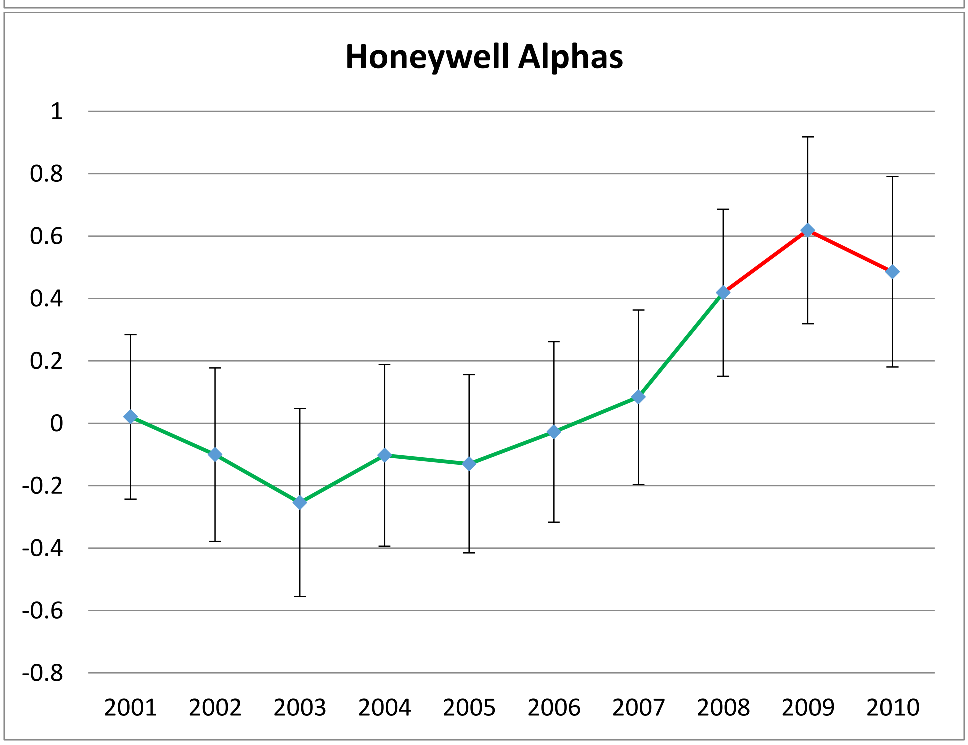
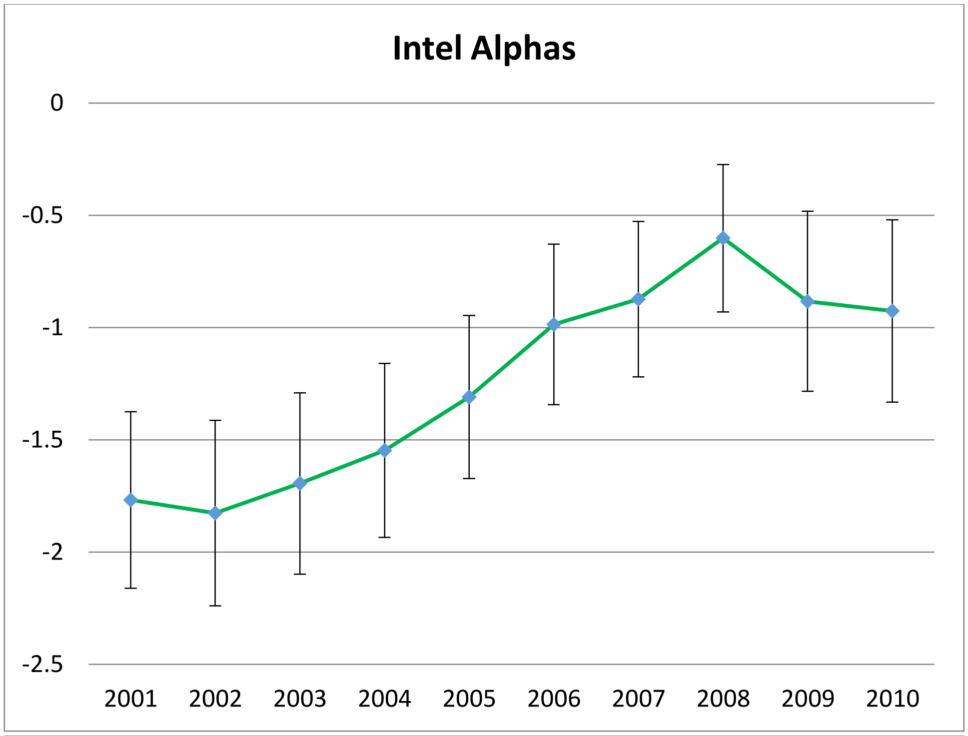

Home Depot Alphas
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Honeywell Alphas
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Intel Alphas
0
-0.5
-1
-1.5
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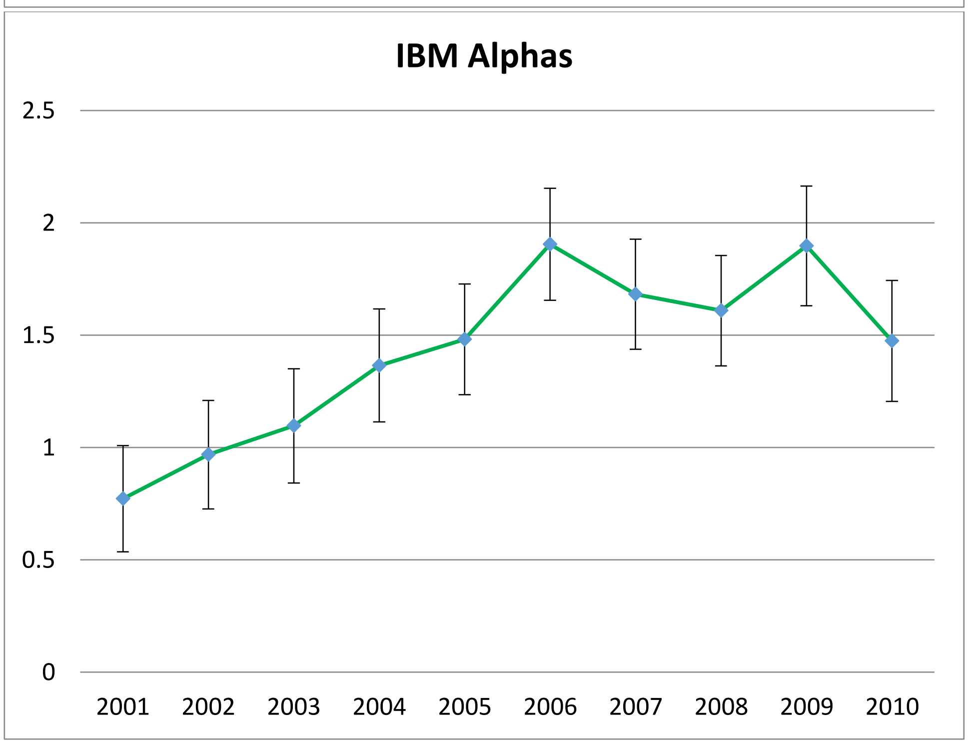
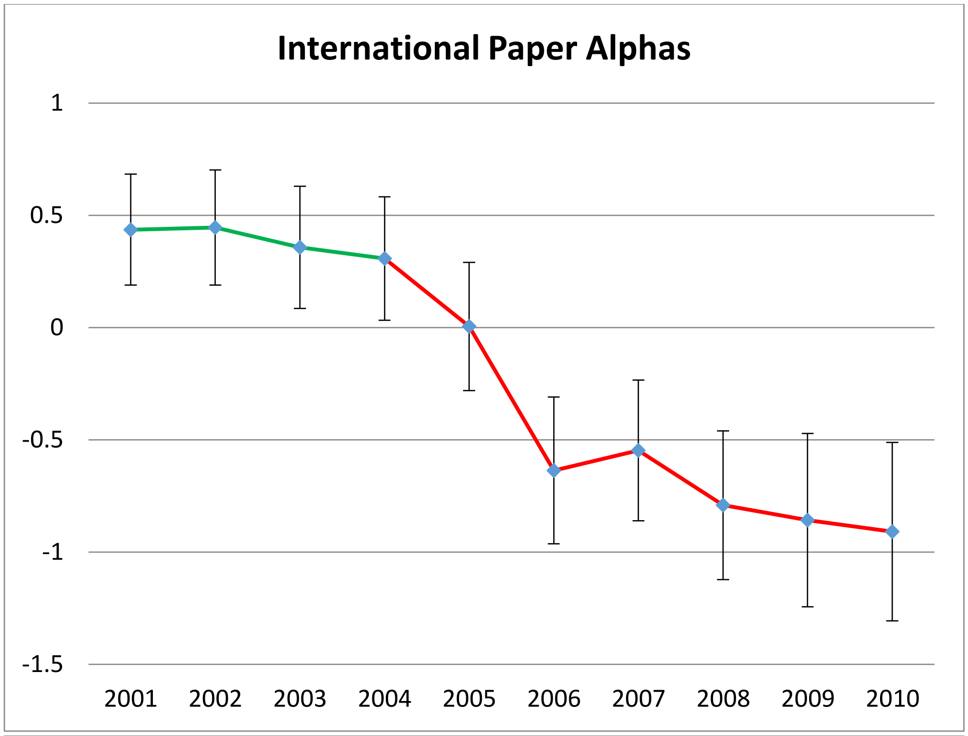
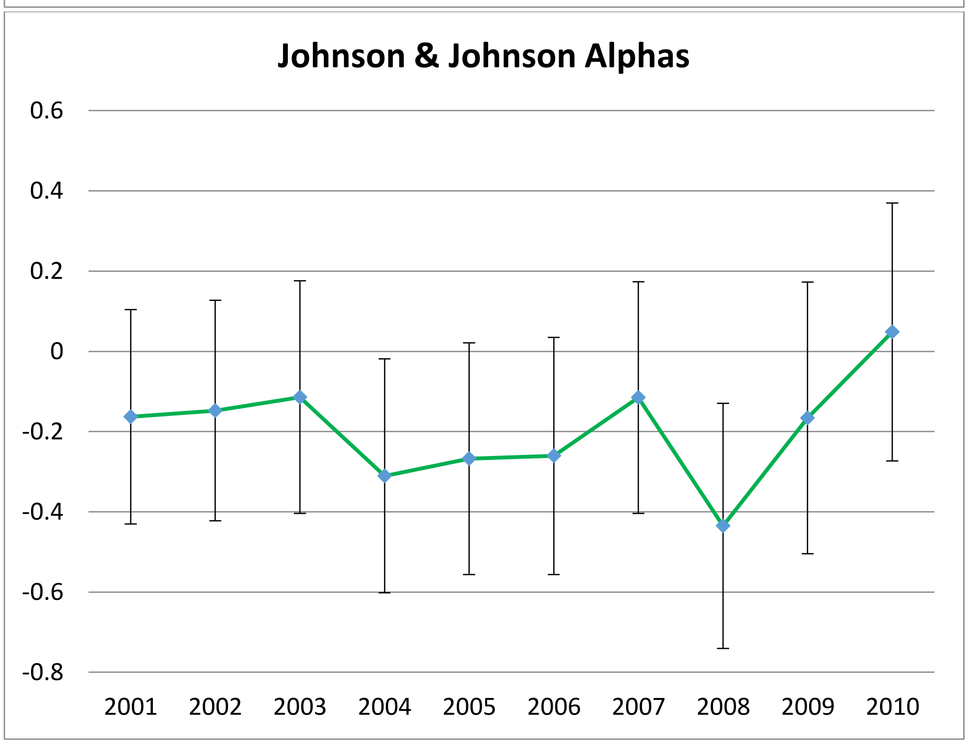
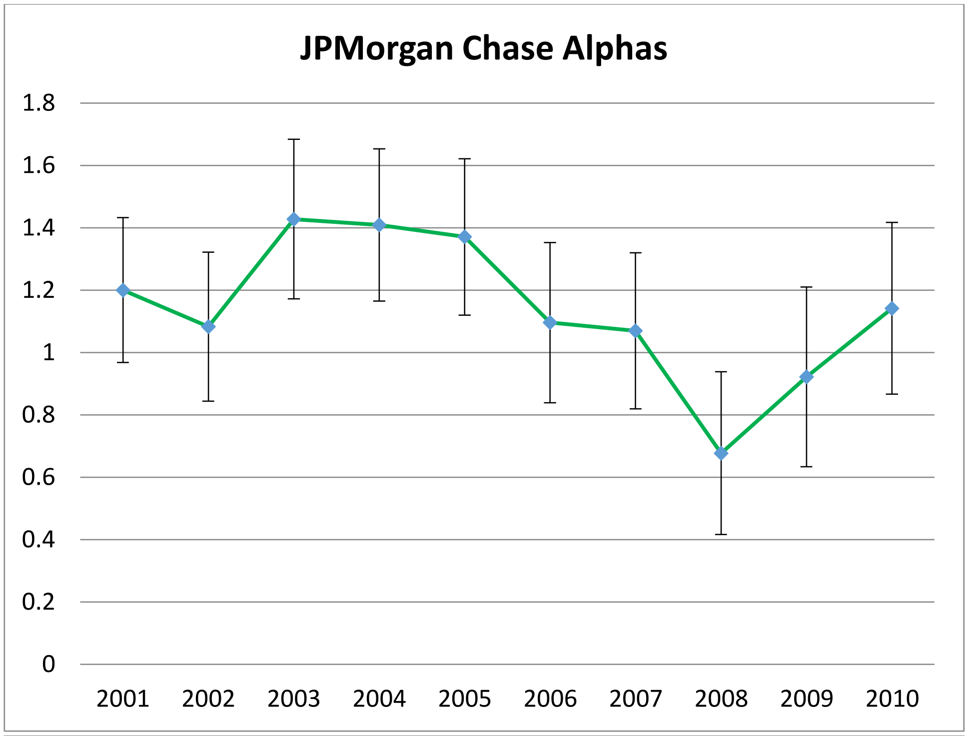
-2.5
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


IBM Alphas
2.5
2
1.5
1
0.5
0
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


International Paper Alphas
1
0.5
0
-0.5
-1
-1.5
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010


Johnson & Johnson Alphas
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010


JPMorgan Chase Alphas
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
2001
2002
2003
2004
2005
2006
2007
2008
2009
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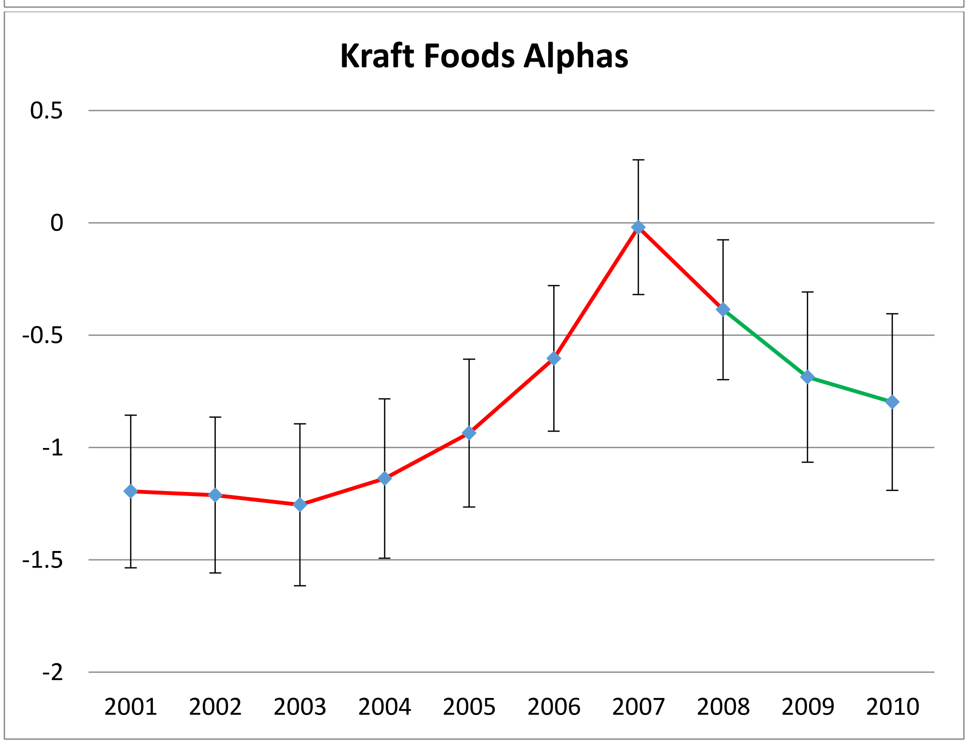
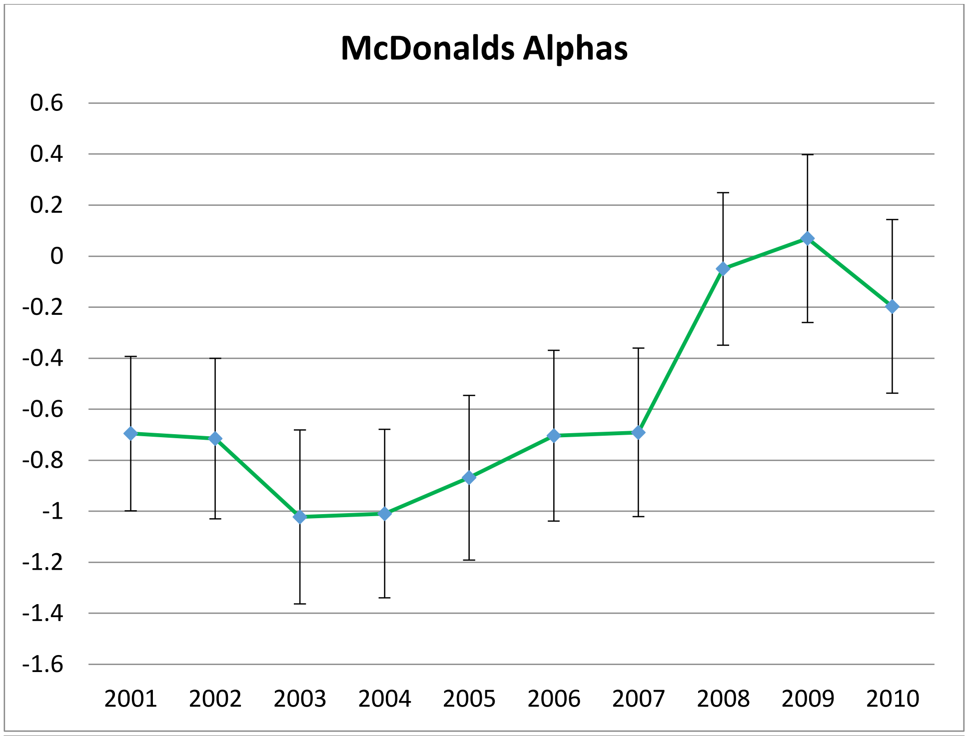

Kraft Foods Alphas
0.5
0
-0.5
-1
-1.5
-2
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


McDonalds Alphas
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
-1.6
2001
2002
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2004
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2008
2009
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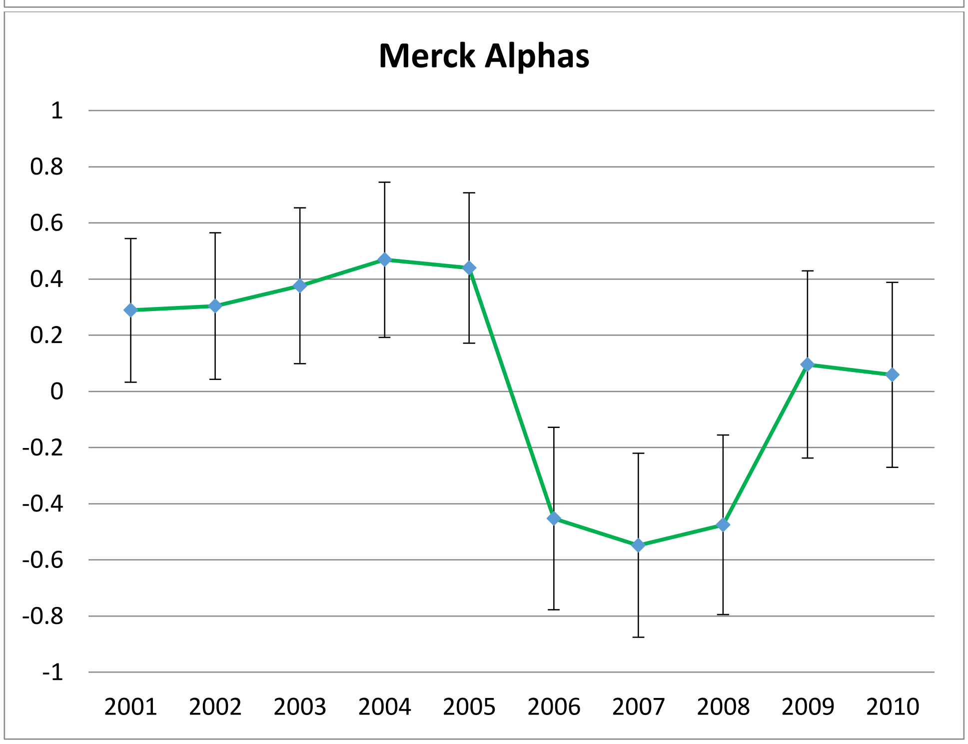
Merck Alphas
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
2001
2002
2003
2004
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2008
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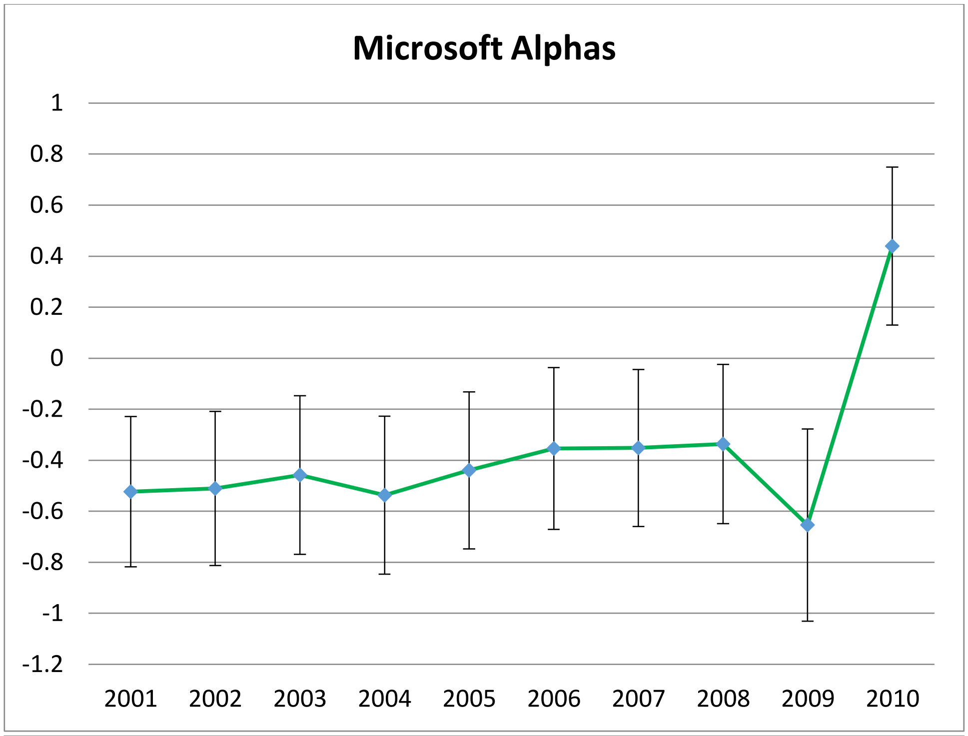

Microsoft Alphas
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
2001
2002
2003
2004
2005
2006
2007
2008
2009
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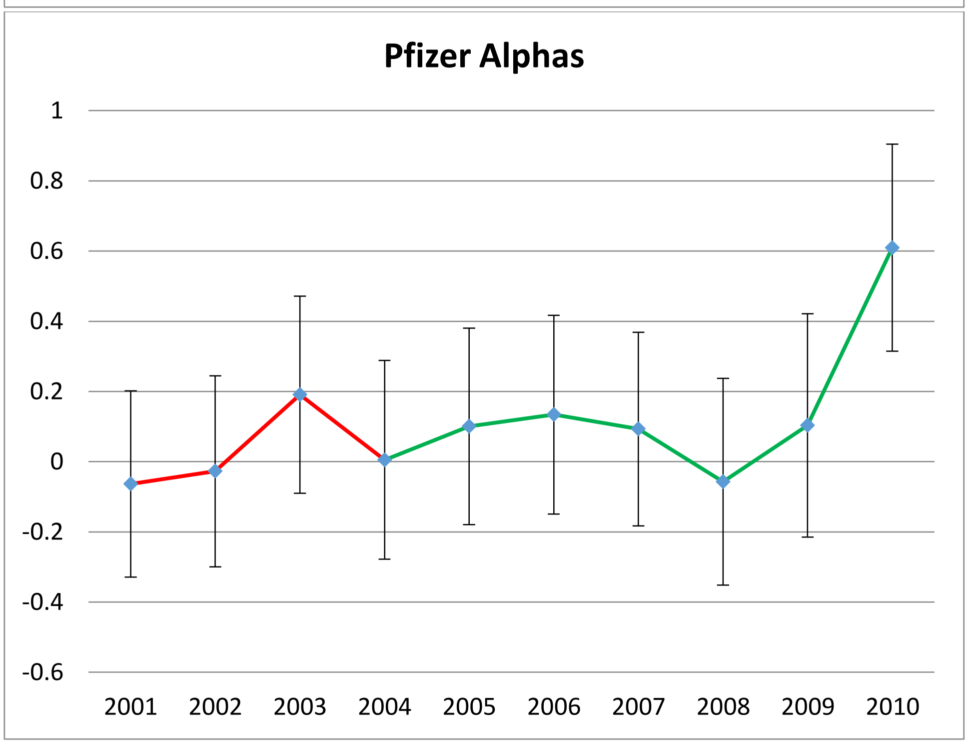
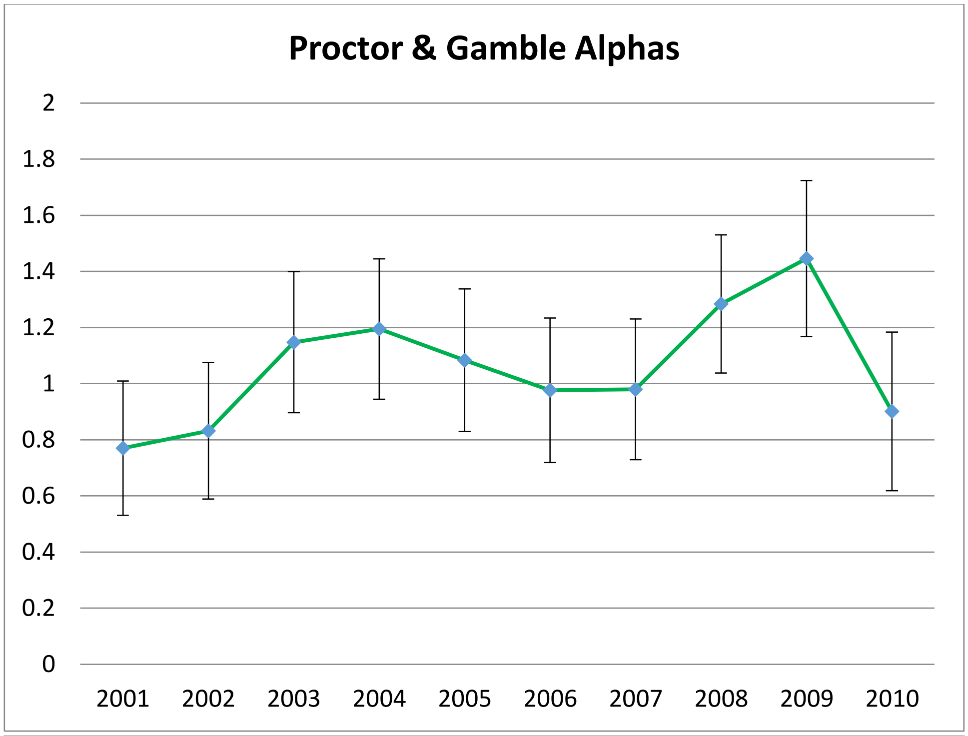


Pfizer Alphas
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Proctor & Gamble Alphas
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
2001
2002
2003
2004
2005
2006
2007
2008
2009
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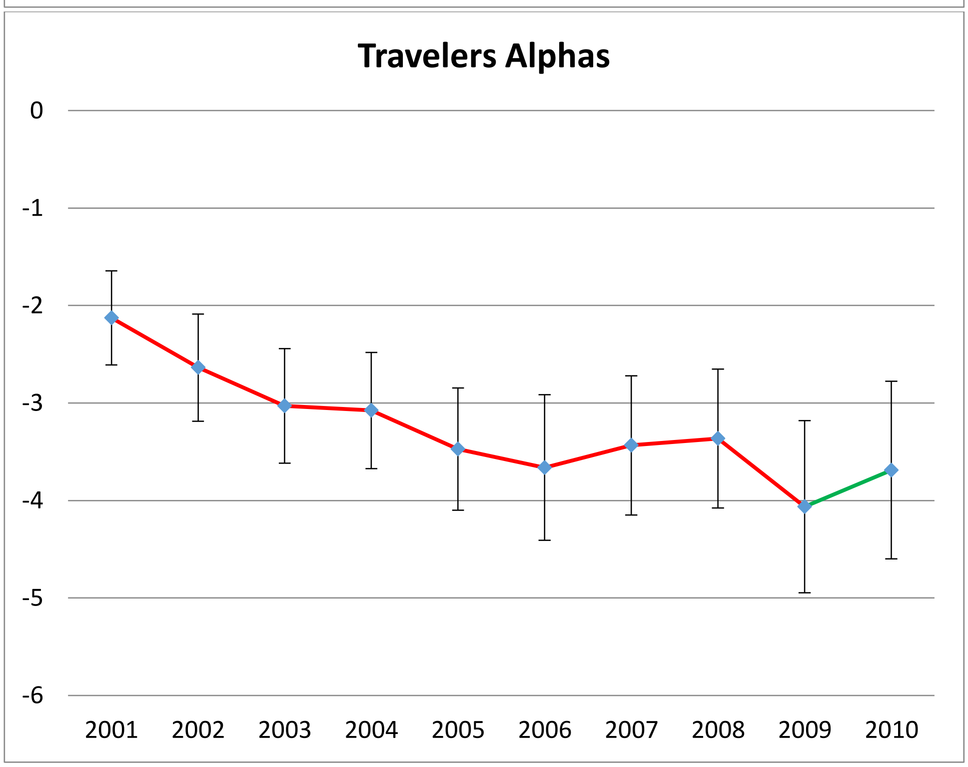
Travelers Alphas
0
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-2
-3
-4
-5
-6
2001
2002
2003
2004
2005
2006
2007
2008
2009
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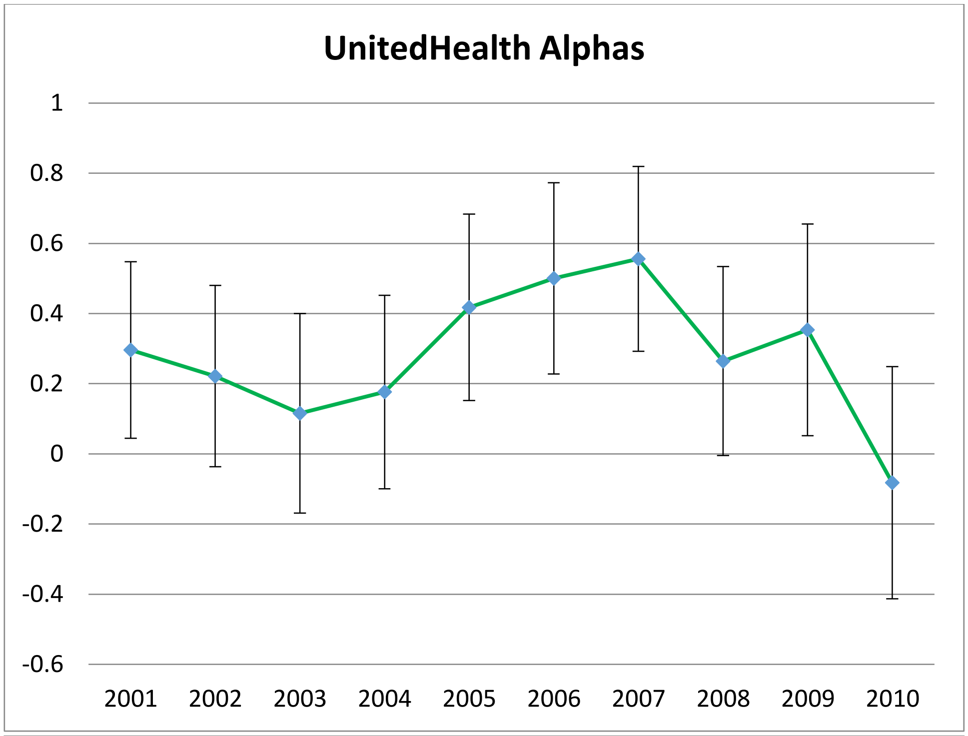
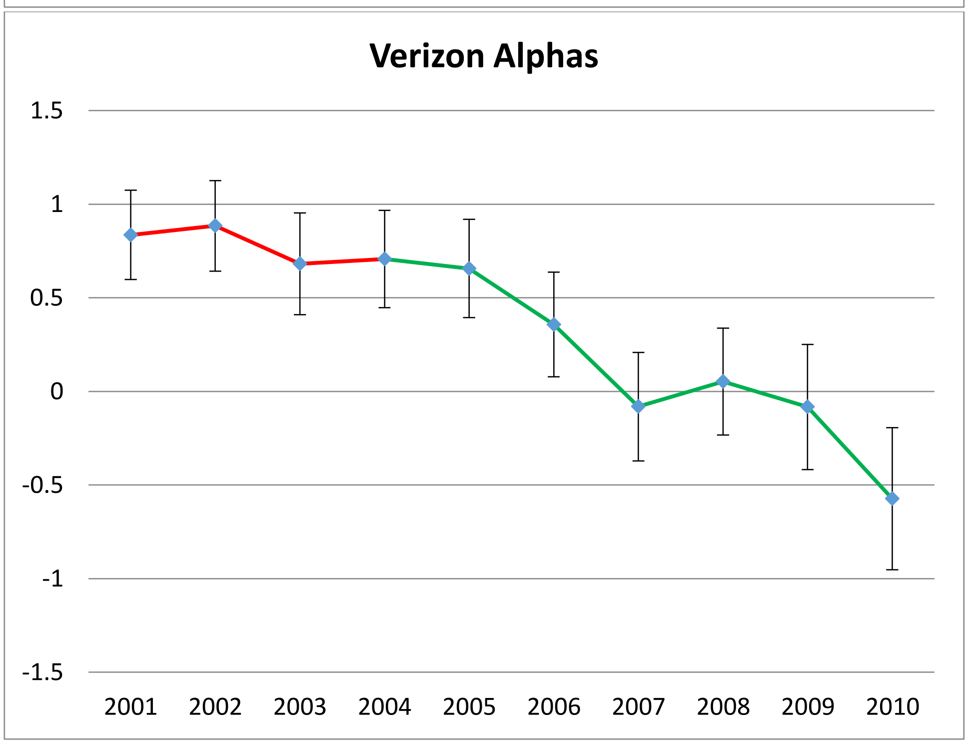

UnitedHealth Alphas
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


Verizon Alphas
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0.5
0
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-1.5
2001
2002
2003
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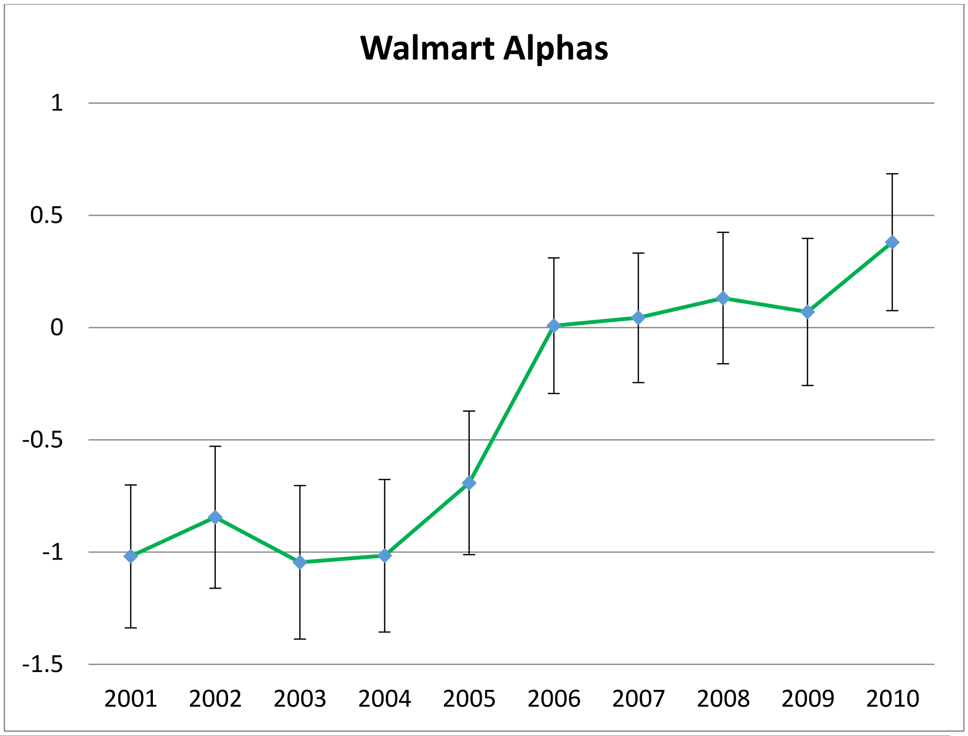
2005
2006
2007
2008
2009
2010


Walmart Alphas
1
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0
-0.5
-1
-1.5
2001
2002
2003
2004
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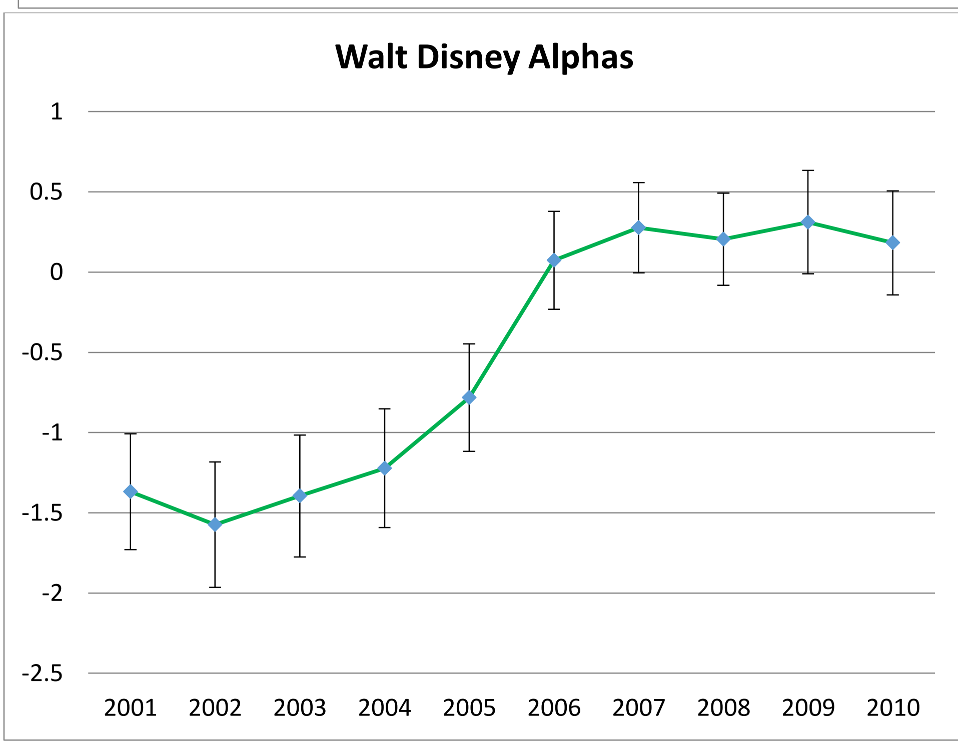
2007
2008
2009
2010


Walt Disney Alphas
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
2001
2002
2003
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2005
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VITA

Kevin Mentzer graduated from Bryant University in Smithfield, RI with a Bachelor's of Science in Business Administration. He graduated from Bentley University in Waltham, MA with a Master's of Science in Information Technology. In September, 2011 he entered the Bentley University Ph.D. Program. Kevin has significant corporate experience in the fields of insurance and energy and has served in positions as a systems analyst, consultant, project manager, director of software development, and founder and CEO of CounterPoint Technologies Corp.

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This manuscript was typed by the author.