MANAGING OUTSOURCING DECISIONS – GOVERNMENT POLICY, FIRM OPTIONS, AND THE ECONOMIC IMPACT

by

Youxu C. Tjader

BSEE, Dalian University of Technology, 1982

MBA, Katz Graduate School of Business, University of Pittsburgh, 2001

Submitted to the Graduate Faculty of

Joseph M. Katz Graduate School of Business in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

University of Pittsburgh

2009

UNIVERSITY OF PITTSBURGH

Joseph M. Katz Graduate School of Business

This dissertation was presented

by

Youxu C. Tjader

It was defended on

June 25, 2009

and approved by

Thomas L. Saaty, Professor of Business Administration, KGSB

Pandu Tadikamalla, Professor of Business Administration, KGSB

Shanling Li, Professor of Operations Management, McGill University

Dissertation Co-Chair: Jennifer Shang, Associate Professor of Business, KGSB

Dissertation Co-Chair: Luis G. Vargas, Professor of Business Administration, KGSB

MANAGING OUTSOURCING DECISIONS – GOVERNMENT POLICY, FIRM OPTIONS, AND THE ECONOMIC IMPACT

Youxu C. Tjader, PhD

University of Pittsburgh, 2009

In this research, we provide a comprehensive examination regarding outsourcing policies and decisions by conducting a systematic analysis from macro to micro level. At the macro level, we utilize a BOCR-based (Benefit, Opportunity, Cost, Risk) Analytical Network Process (ANP) model to find the best government policy regarding outsourcing. At the micro level, we carry out a case study to demonstrate how firm level outsourcing decisions can be made. For such, we employ a comprehensive model that consists of the "the BSC-based (Balanced Scorecard) ANP model" to assess the case firm's strategic alternatives and to identify the best option for the studied firm. After recommending the best outsourcing strategy, i.e. selective outsourcing, to the case firm, we then proposed an AHP ratings model for the firm to prioritize the various activities and identify the activities to outsource.

Understanding the economic impact of outsourcing can help firms facing outsourcing options to make a better decision. To provide firms with this guidance and the decision-support tool, in chapter 5 of this dissertation we empirically examine the relationship between outsourcing contract size, as reported in news and trade journals, and the firms' financial performance.

Using the data from Compustat for those firms that conducted outsourcing, we are able to predict firms' post-outsourcing financial performance, as measured by Tobin's q and the changes in Tobin's q. Besides predicting financial performance, our empirical models also reveal a number of important managerial implications. In the modeling process, we make use of both traditional Least Squares Regression and advanced Machine Learning techniques, such as Regression Tree and Neural Networks.

In the research front, our empirical study offers three significant findings: (1) there is a non-linear relationship between outsourcing contract value and the change in Tobin's q; (2) firm's other accounting variables do interact with the outsourcing contract size in affecting the firm's Tobin's q; and (3) outsourcing affects firms differently.

In summary, the body of this dissertation consists of the three key areas: macro- and micro-level outsourcing decision making, and financial performance evaluation and prediction.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGEMENTS

I would like to thank many people for their support, encouragement and guidance during my years as a graduate student here at KATZ.

First and foremost, this dissertation represents a great deal of time and effort not only on my part, but on the part of my advisors, Drs. Jennifer Shang and Luis Vargas. They helped me shape my research from day one, pushed me to get through the inevitable research setbacks, and encouraged me to achieve to the best of my ability. Without them, this dissertation would not have happened.

Dr. Jerry May has gone the extra mile to encourage me and play an active role to help me with my research. My deepest gratitude goes to Dr. May for being part of the driving force to push me to cross the finish line at the later stage of my dissertation.

I also thank my other three committee members, Dr. Thomas L Saaty, Dr. Pandu Tadikamalla, and Dr. Shanling Li from McGill University for valuable discussions and comments regarding my research.

I am very grateful to Carrie for her support throughout the years, and to Rozann for providing me valuable information as well as assistance with ANP software.

My family has always been, and continues to be, there for me at all times. And most of all, my husband Bill has been incredibly supportive, understanding, and encouraging as he has gone through the entire graduate experience with me.

1.0 INTRODUCTION

When we discuss outsourcing decisions, two major branches come into mind: government policy decisions and individual firm choices. As government policy makers (both federal and local), selecting the best offshore outsourcing policy options will have a direct impact on the economic and social wellbeing of the nation and of the local regions. At individual firm level, the decision of if or what or how to pursue outsourcing, may determine the success or failure of the company, which in turn, will impact the shareholders, employees, and the local communities. In this research, besides focusing our attention on finding and selecting the best options for both government decision-makers and corporate management, we also investigate the relationship between the size of the outsourcing contract and the market value of the firm as measured by Tobin's q (Tobin, 1969). Specifically, we will look into:

Chapter 3 – government policies with regard to outsourcing, particularly offshore outsourcing – we identify the best government public policy option. Specifically, should the government stay neutral (hands-off), provide displaced workers assistance programs, provide incentive for non-outsourcing, or strongly discourage outsourcing?

Chapter 4 – at the firm level, decisions of the management become whether to insource, outsource, or selective outsource certain business activities. In other words, find the most advantageous approach a firms can take when considering outsourcing. In this chapter, we study outsourcing as a general business practice by companies, where both domestic and offshore are considered.

Chapter 5 – the exploration of past outsourcing data in an effort to identify the economic impact of outsourcing. By examining the relative change in the firm's Tobin's q both pre-outsourcing and post-outsourcing together with the relative deal size of the outsourcing contract, we investigate the relationship between them. The purpose of the study is to project the possible economic performance change (as measured by change in Tobin's q) associated with outsourcing of firms' business activities (represented by the relative outsourcing contract value). Both traditional data analysis and advanced data mining techniques are applied to the outsourcing data to construct several empirical models for future prediction of likely economic impact of outsourcing.

1.1 MOTIVATION

Over the past decades, manufacturing outsourcing has been accepted as inevitable and undeniably a productivity enhancer to the U.S. economy. Recently, non-manufacturing outsourcing, especially IT related offshore outsourcing with its associated high-tech domestic job losses, has triggered intense debates among economists, business consultants, academia, politicians, and the news media. The outcome of service and IT offshore outsourcing potentially affects every one of us in the U.S. This broad impact has captured the attention of not only the business and research community, but also the general public. The negative sentiment from the general public stipulated the action from the local, state and federal government. As many as 40 states have introduced some type of bills to restrict outsourcing of government contracts by the end of 2004, and the number continued to increase to nearly all 50 states by the end of 2005. For some time now, it has become one of the primary issues that the nation's policy makers must consider. Without a doubt, choosing the best policy option is one of the most important decisions our law-makers have to make. This motivated us to conduct the first stage of this research, at the macro level of the issue at hand, in order to find a satisfactory solution for the problem. Once the best policy option is chosen, it is natural to move on to individual firm level to provide assistance to management at both the strategic and the operational level decisions with regard to outsourcing – hence in chapter 4, a case study is conducted for firm level outsourcing decisions. In order to provide further support to the management in their outsourcing decision, we present a "look into the future" – by investigating the post outsourcing changes in Tobin's q in chapter 5.

1.2 OBJECTIVES AND APPROACHES

Our primary objective is to provide a comprehensive view regarding outsourcing by conducting a systematic analysis of outsourcing from macro to micro level. At the macro level, we aim at finding the best government policy regarding outsourcing. At the micro level, we carry out a case study to evaluate and recommend the best outsourcing strategy – selective outsourcing, and then we help to identify and prioritize a list of activities to outsource. To provide further guidance as well as decision aid, empirical models are created using existing outsourcing data to forecast the firm's one and two years post-outsourcing financial performance as measured by its Tobin's q. Besides forecasting, our model can also identify other variables that interact with the relative outsourcing contract size to impact the firm's Tobin's q. The entire dissertation work takes this three-stage approach.

1.2.1 Main Questions

When studying the government policies with regard to offshore outsourcing – we evaluate and identify the best public policy option. The questions are:

(1) Should the government intervene?

(2) What is the best government policy dealing with offshore outsourcing?

In chapter 4, our focus for the case firm is finding the most advantageous approaches firms should take when considering IT outsourcing. The questions are:

(1) Should they develop them in-house (Insourcing), contract out (Outsourcing), or some in-house and some contract out (selective outsourcing).
(2) In the case of selective outsourcing, what should be outsourced first, last, or not at all?

In chapter 5 we investigate the economic impact of outsourcing by examining the relative changes in the firms' Tobin's q both pre-outsourcing and post-outsourcing. We address the following questions:

(1) Does the relative outsourcing contract size have an impact on the change in firm's Tobin's q? If so,

(2) How does it affect the change in Tobin's q?

1.2.2 Approaches

The overall approach to answering the above dissertation questions has been to “divide and conquer”. The government outsourcing policy alternatives are evaluated with a comprehensive ANP framework. The firm level decisions are carried out through a case study process. A unique framework of BSC-ANP model is developed for the case firm to identify the most beneficial approach in its pursuit of IT outsourcing. A subsequent AHP ratings model is developed to aid the case firm in prioritizing its list of possible outsourcing candidates. Finally the investigation for the possible impact of outsourcing on firm’s future financial performance is conducted via both traditional least squares regression analysis and more advanced machine learning techniques.

The issue of outsourcing has been examined at the macro level from the government policy makers’ perspective and at the micro level from the corporate management’s perspective. … The philosophy of this approach – “divide and conquer,” originated from Sun Tze’s “The Art of War.” An outline diagram of this dissertation is given in Figure 1 below.

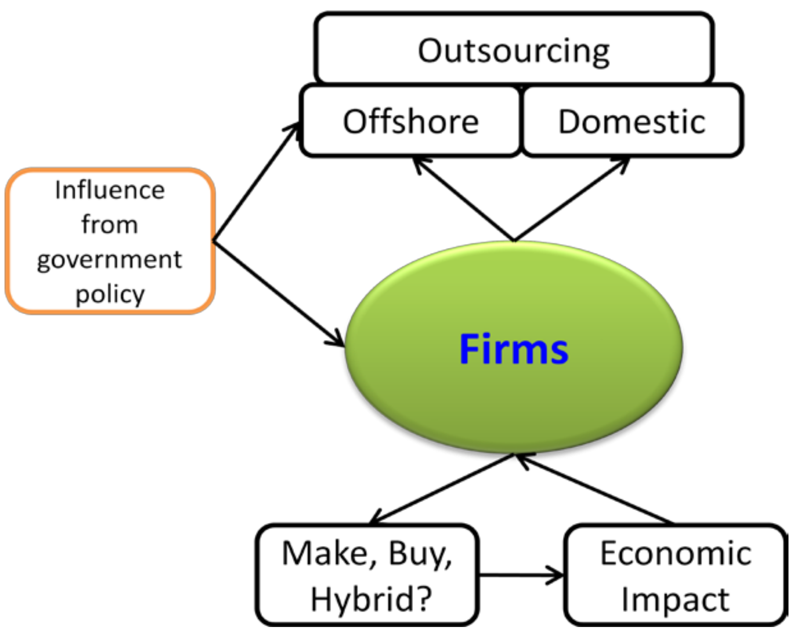

Figure 1 Dissertation Research Outline Diagram

1.3 CONTRIBUTIONS

Our contributions through this study are two folds. Next, we list the major research contributions and then practical implications achieved in this research. A more detail description of the followings can be found in chapter 6.

Research Contributions

(1) The successful adaptation of machine learning techniques to empirical outsourcing data analysis has provided a unique approach to how the outsourcing research is conducted, and enabled us to find important indications such as:

a. the relative outsourcing contract value appears to have a non-linear relationship with post outsourcing change in Tobin's q.

b. the radial basis function transferred the outsourcing variable into a significant predictor for both one year and two years post outsourcing change in Tobin's q.

c. the impact of the outsourcing on the post-outsourcing change in Tobin's q is different for some firms than it is for others.

(2) To the best of our knowledge, this dissertation is the only study that utilizes data mining tools to model outsourcing data. Our methodologies as well as the findings make this research a useful addition to the outsourcing literature.

(3) In the MCDM methodology front, we are the first to put the union of BSC-ANP into the context of outsourcing strategy evaluation rather than its traditional application of being a performance measurement tool. A BSC-ANP alternatives evaluation model is unique in that it is different from traditional ANP BOCR approach; at the same time, it is different from a traditional BSC implementation in which the main goal is to measure the firm's performance. The BSC framework contributes a comprehensive set of evaluation criteria which are widely recognized by the research community, while the ANP operationalize all criteria included in the combined decision model in a coherent manner.

Practical Implications

(1) From a policy perspective, the comprehensive approach applied in this research assures everyone affected by the outsourcing policy that the final decision is prudently made with due consideration given to every aspect of the issue.

(2) For corporate management, we assist individual firms by:

a. finding and recommending the best practice with regard to a firm's outsourcing strategy and

b. Providing assistance in the operational decision about which functions to outsource

(3) The preliminary results of our empirical data analysis support our hypothesis and also provide us with managerial implications. More specifically,

a. the relative outsourcing value does affect the post outsourcing change in Tobin's q.

b. the relative outsourcing value interacts with other accounting variable in their contribution to explain the changes in firm's future economic performance (Tobin's q).

1.4 READER'S GUIDE

To conclude the introduction chapter of this dissertation, the remainder paragraphs of this section provide a general description of the contents of all subsequent chapters as well as a summary of the relevant contribution from each chapter.

Chapter 2 consists of the introduction to the topic, and the detailed review of the currently available literature with regard to the chosen topic and methodologies.

In chapter 3 we tackle the outsourcing issue from the macro level – government policy decisions. Providing a useful analysis framework and viable solutions to an important and complex problem is the main contribution from chapter 3. The importance of the topic, the necessity for an all-inclusive analysis framework, and the urgency of deriving meaningful policy guidelines warrant our effort. The need of a resolution on this issue comes not only from the American public, but also from the business community, media, researchers and consulting groups. The general public may be reassured that the course of action taken by governments (local, state and federal) would be, first of all, for the greater good of the U.S. and benefits the global humanity.

In chapter 4, in essence, we provide the results of a case study and analyze the outsourcing decision from the micro level with an individual firm's perspective. From a research point of view, applying the union of BSC-ANP to outsourcing decision making is a new approach in outsourcing research. The practical contribution here lays in providing both strategic level and operational level decision support for our case company.

In chapter 5 we analyze the economic impact of outsourcing on firms' future financial performance potential. It is intended to provide a look into the future, post-outsourcing, for firms contemplating outsourcing. Both traditional data analysis method and the cutting edge data mining techniques are applied to the outsourcing data. More specifically, we look for the relationship between the "relative outsourcing contract amount (value) per firm's market value of equity" and the post outsourcing change in Tobin's q.

In chapter 6 we provide the overall research contribution, managerial implications, limitations, future research directions, and the conclusion.

2.0 CHAPTER 2 LITERATURE REVIEW

The broad impact of offshore outsourcing and the public interest on the issue of outsourcing government policy has compelled the author to examine not just papers from scholarly journals but also articles from the trade magazines, newspapers as well as books. The controversy regarding offshore outsourcing sparked off two very contrasting clusters of literature, those that oppose the practice of offshore outsourcing and those that support it. No matter which side the proponents or opponents are on, they often express their opinions with very high enthusiasm while citing facts and figures or anecdotal stories.

2.1 GOVERNMENT POLICY ON OUTSOURCING

The wide-spread interest and long lasting implications of outsourcing have drawn a great deal of attention and scrutiny from both researchers and practitioners. Consequently, a vast number of research and trade papers as well as books regarding offshore outsourcing are in circulation. In this section, we first examine economists' views, and then explore the social aspect of offshore outsourcing. Combining literature and discussions with business owners and other stakeholders, we present a list of possible government policy options as proposed by economists, political think tanks, and the business community.

2.1.1 The Economic Perspective – Views from Economists

Based on the classical trade theory of Ricardo (1817) and Mill (1848), Samuelson (2004) finds that free trade leaves rich countries worse off. In other words, Samuelson's analyses show that the U.S. and other developed nations suffer permanent and measurable loss from outsourcing. His results contradict the arguments given by the main stream economists: Greenspan (Berry, 2003; Ip, 2004), Bhagwati et.al (2004), Mankiw et.al (2004), Panagariya (2004), and Irwin (2004) who are the globalization supporters. The main stream economists recognize that some groups are hurt by dynamic free trade, but they argue that gains of the American winners are large enough to more than compensate the losses of the losers. Schumpeter (1950) called this “creative capitalist destruction”. The validity and applicability of Samuelson’s analysis was questioned by Bhagwati et al. (2004) and Panagariya (2004).

Mann (2003; 2004a) states that productivity gains result in significant cost savings, which in turn benefit consumers, and achieve economic growth. According to her, in the software industry, offshoring causes job loss initially, but it lowers IT costs, increases IT usage and productivity, and stimulates demand for more IT talent. Thus, outsourcing ultimately facilitates IT job creation in the long run, while limiting outsourcing of software and services will put the prospect for robust and sustainable U.S. economic performance at risk.

In essence, economists’ views are just as divided as the rest of the world with regard to the merits or perils of offshore outsourcing. This provides further evidence and serves as a confirmation to the relevance, urgency, and the importance of our research.

2.1.2 The Social Perspective

Butcher and Hallock (2005), Farber (2005), Kletzer (2005a) and Lynch (2005) point out that the main problem of offshore outsourcing is worker displacement. Kletzer (1999) notes sizeable earnings losses follow job displacement during 1975-1994. She (Kletzer, 2005b) also observes higher worker displacement rates in tradable services and decreased earnings of displaced tradable service workers. Furthermore, by examining the impact of trade/import/offshoring on the domestic labor market, Kletzer (1999; 2003; 2005a) establishes the links between U.S. jobs and imports/exports, and shows how globalization is causing job loss from manufacturing to services. The Displaced Workers Survey (DWS) by the U.S. Bureau of Labor Statistics finds that 5.3 million workers were displaced between January 2001 and

December 2003. The social impact of worker displacement cannot be ignored. While opponents of offshoring are seeking government regulations to restrict this business practice, proponents are pointing out the long term outlook of a new global economy in order to downplay the immediate problem faced by many displaced workers.

Business leaders should be held socially accountable, because the stability of the society significantly impacts business performance. Highly concentrated or large scale worker displacement has the potential of becoming the source of instability in the communities. Obviously, the elected government officials also need to consider the social impact of offshore outsourcing when making the policy choice decisions.

Atkinson (2004b; a), Kletzer (2004), Mann (2004b) and Farrell (2003) have been actively researching for ways to lessen the social impact of the domestic job loss due to offshoring. Among them, Kletzer's studies are the most comprehensive. Kletzer and Litan (2001; Kletzer, 2004) propose an insurance program for the displaced workers of offshore outsourcing. This establishes the foundation for the labor displacement program, and has been widely cited by researchers, practitioners, and leading consulting firms such as McKinsey Global Institute (Farrell, 2003). Yet, without the support of an effective governing policy, nothing can be implemented. In the next subsection, we will detail some promising policy options in order to form a realistic set of alternatives to use in our decision framework.

2.1.3 Policy Options – Alternatives for Evaluation

Atkinson (2004b) from the Progressive Policy Institute (PPi) believes that the U.S. policy toward outsourcing should: (a) help American companies become more competitive, (b) significantly reduce distortions to global free trade, and (c) do a better job of assisting workers displaced by offshoring. Mann (2003) proposes the "human capital investment tax credit" as a way to invest in people for a more competitive economy. To re-ignite American innovation and growth, Mann (2004a) also proposes to: (a) better match workers to changing jobs; (b) establish new-jobs policies for displaced workers, e.g. unemployment extension, wage insurance, entry and up-skill policies within a career-ladder; (c) establish human-capital investment tax credit through firms; (d) create movement/flexibility policies to mitigate costs of adjustment; and (e) have realistic and affordable health care and pension portability.

Atkinson (2004b) identifies four government policy options: (a) Ignore and do nothing – the market will work out for the best, which has the support of other researches (Anderson, 2005; Baker & Moore, 2005; Drezner, 2004; Corbett, 2004; Drezner, 2004). (b) Levy heavy taxes to penalize offshore outsourcing and ban any government contract from being performed overseas. Professional Engineers Groups such as NSPE, IEEE, and EIA have also favored government restriction (Boykin, 2004). (c) Provide tax incentives or subsidies to encourage corporations to keep the jobs in U.S. (d) Craft new public policies that can help firms to become more competitive and workers to become more skilled and agile (Atkinson, 2004b). The first three options are in line with those found in practice and in literature (Anderson & Cavanagh, 2004; Anonymous, 2004).

Based on the above information, we identify four policy options for the decision model in chapter 3: (a) Hands-off i.e. letting the supply and demand of human capital finds its equilibrium. (b) Discouraging the outsourcing business practice. (c) Providing assistance to domestic businesses (subsidize). (d) Providing displaced workers assistance programs to the domestic workforce. To understand the process of selecting the best option, we focus on quantitatively assessing these options in a systematic and comprehensive manner.

2.2 RESEARCHES ON MAKE OR BUY

The body of literature related to our research in chapter 4 can be divided into three groups. The first group corresponds to the most frequently used theories and methodologies for outsourcing decision (make or buy). The underlying theory of our approach: Balanced Scorecard and its applications are reviewed in the second group. In the last group, we look into applications of AHP/ANP in the context of firm-level outsourcing decision making. A selected number of the examined frameworks are summarized in Table 1 below.

Table 1 Summary of the MCDM-related (AHP, ANP, BSC) literature

Author(s)	Main Objective	Methodologies	Underlining Theory
K. Hafeez, Y.B. Zhang, and N. Malak (Hafeez, Zhang, & Malak, 2002)	Firm Capability Evaluation	AHP	BSC - firm capabilities are evaluated under 6 (3 financial and 3 non-financial) BSC measures
Hong, J-Y., Suh, E-H., Yoo K-D, Hong, D-G (2003)	Evaluating ASPs	BSC	BSC - propose a set of multi-dimensional measurement for evaluating the ASPs. No mention of how to quantify the measures
K. Hafeez, N. Malak, and Y.B. Zhang (2007)	Assessing firm competences, identify core asset	AHP	Resource based view of the firm
Udo, Godwin (2000)	Select which IT function to outsource	AHP	AHP
Yang, Chyan, Huang, Jen-Bor (2000)	Select which IT function to outsource	AHP	AHP
Yang, D-H, Kim S., Nam, Changi, Min J-W (2007)	BP Outsourcing Decision	AHP	AHP
Chen, J-R., Chou, T-C, and Lin, Y-C (2007)	IT outsourcing project evaluation	AHP	AHP
Lockachari, P, Mohanarangan, M. (2001)	Select best software development option	AHP	AHP- three alternatives, 18 criteria
Thakkar, Deshmukh, Gupta, & Shanker (2007)	Development of a BSC (Determine weights of BSC perspectives)	ANP/ISM (Interpretive Structural Modeling)	BSC
Bodin, Lawrence, Gordon, Lawrence, & Loeb, Martin (2005)	Evaluating information security investment	AHP	AHP
Yoon, Y-K, and Im, Kun Shim (2005)	Evaluating IT outsourcing customer satisfaction	AHP	AHP
Nam, Kichan, Rajagopalan, S. (1996)	Investigate the impact of organizational, environmental & economic factors on IS Outsourcing decisions	Hypotheses Testing	Transaction Cost Economics (TCE), Incomplete contracts (IC), and Power Theory
Lee, Jin Woo Kim, Soung Hie (2000)	Inter dependent IS project selection	ANP	Goal Programming (GP)
Farkasovsky & Greda in Saaty (2005, pp134-156)	Outsourcing of a firm’s application development	ANP	ANP
Leung, Lam, & Cao, (2006)	BSC performance measure using AHP and ANP	ANP/AHP	BSC
DaSilva&Santos and Vanko et.al. in Saaty & Cillo (2008)	2 examples of firm outsourcing decision using ANP	ANP	ANP

Arisoy&Wu, Sethia&Ballal in Saaty & Cillo (2008)	2 examples of firm outsourcing location selection using ANP	ANP	ANP
Our paper	Identify the best IT outsourcing strategy for a firm; prioritize firm's IT functions for outsourcing consideration	ANP/AHP	BSC

2.2.1 Theories and Methodologies for Firm-level Outsourcing Decisions

In the existing literature, transaction cost theory (TCT) is by far the most dominating theory used to conduct sourcing analysis, see Walker & Weber (1984, 1987), Ang & Straub, (1998), Ngwenyama & Bryson (1999), and Lyons (1995). It is due to the fact that cost savings is on top of the list of objectives every manager has when faced with such a decision. Even with its latest evolution, outsourcing decision made solely based on TCT is far from perfect. Its single mindedness on cost minimization draws the most criticism.

One of the departures from TCT in sourcing decision is the knowledge-based theory (KBT) (Nickerson & Zenger, 2004), evolved from resource-based theory (RBT) (Wernerfelt, 1984) of the firm. KBT/RBT views a firm as bundles of resource or sets of knowledge. Firms seek the best way to allocate existing resource and obtain new resources in order to achieve economic efficiency. Researchers and practitioners of KBT try to find the best sourcing alternative that will facilitate knowledge creation, application, and dissemination.

Besides KBT/RBT, property rights theory (PRT) (Alchian & Demsetz, 1973; Demsetz, 1967; and Grossman & Hart, 1986), agency theory (Holmstrom, 1979), and power theory (Rajan & Zingales, 1998) have all being used to compete or sometimes complement TCT in outsourcing decisions. In agency theory, the firm is viewed as a set of contracts, where assets ownership defines the role of entities as either owners (principals) or agents. All these theories have their merits in certain aspect.

However, we believe that a firm cannot be viewed as just transactions of goods and/or services, it is also a set of contracts and bundles of resources and it holds sets of knowledge and has the ability to create, exploit, apply and transfer knowledge. Furthermore, the entity we call a firm also includes groups or individuals who hold power over important strategic decisions of the firm. Some of the power holders are owners (principals) and others are agents. With this composite view of the firm, we can easily see that none of the above mentioned theories alone can give us a comprehensive and synthesized (satisfactory) solution to our outsourcing decision problem. Therefore, in chapter 4, we propose an approach to combine different perspectives of the firm into one unified framework, enabled by BSC, for the firm level outsourcing decision.

2.2.2 MCDM – AHP and ANP

Table 1 shows a list of multi-criteria decision models (MCDM) used for outsourcing decisions. It shows that AHP has been used to make outsourcing decisions by a number of researchers. Upon closer examination of the listed works, we discover gaps and limitations in them. For instance, the two models by Chen et.al (2007) and Lokachari and Mohanarangan (2001) lack strategic criteria because the alternatives they evaluated are operational level options: specific IT outsourcing projects (Chen et al., 2007) and software development options (Lokachari & Mohanarangan, 2001). In Udo (2000), Yang and Huang (2000), and Yang et.al (2007) the customer perspective and learning and growth perspective are not looked upon when selecting the determinants (decision criteria). Furthermore, Udo (2000), Yang and Huang (2000) only have a few evaluation criteria. Yang et.al (2007) present a basic AHP model to make business process outsourcing (BPO) decision. As the authors themselves point out, the criteria in the model are not complete and the model is still rudimentary. In particular, criteria interaction is not considered.

One good example of firm IT application development outsourcing decision making using ANP is given by Farkasovsky & Greda in Saaty (2005, pp134-156). Their model used the prescribed BOCR structure with a brainstorm approach to come up with a large number of decision criteria. Our framework in the case study differs in the utilization of BSC indicators as decision criteria. Two other smaller scale ANP outsourcing decision models are also presented in

Saaty (2008), created by Da Silva and Santos, Vanko et.al.; and two ANP outsourcing location selection models are created by Arisoy and Wu, and Sethia and Ballal.

Other existing researches on outsourcing, not listed in Table 1, are mostly one-dimensional models based on transaction cost theory (TCT), resource based theory (RBT)/knowledge based theory (KBT), power theory and a few others. The superiority of BSC over those one dimensional (monetary, property, or power) measurements has been discussed (Marr & Neely, 2003). Therefore, it seems logical to explore a BSC-based outsourcing decision model and study its strength and weakness relative to the other unidirectional models.

One of the key features of BSC is the interactions (or influences) of indicators amongst each other both within and between each perspective; and the interactions and influences of one perspective on the other. Kaplan and Norton (1996), Campbell et.al (2002) and Cobbold & Lawrie (2002b) have shown that the necessity and importance for including the linkage/interactions among indicators and perspectives while developing BSC metrics. However, most of the past implementations of BSC have fallen short in realizing the power of these interactions. Interaction with other indicators may increase or decrease the intensity of certain indicators. By not including the interactions, the power and accuracy of the BSC framework is significantly weakened. In short, the existing applications of BSC without including the interaction effects compromise BSC's potential. In our case study (chapter 4), we apply the Analytical Network Process to implement the BSC framework for outsourcing strategy selection. This approach was first proposed for an BSC firm performance system (Leung et al., 2006). ANP is designed to account for the interactions between indicators (criteria), clusters of criteria, actors, and alternatives. Lee and Kim (2000) proposed an ANP-Goal Programming (GP) framework for the IS project selection problem and they used a small hypothetical example given by Marc and Wilson (1991) to illustrate the necessity and advantage of combining ANP and GP. In their paper, ANP is utilized to reflect the interdependencies among criteria and alternatives (candidate projects). Cobbold and Lawrie (2002b) state that "management teams find the necessary selection of priority elements within their collective vision and strategic goals difficult" in practical experience with developing BSC. With the inherent capability to assist the elements prioritization, ANP is an ideal tool to handle such difficulty. There are two major problems of BSC implementation: (1) accounting for interdependency of different perspectives, and (2) the prioritization of elements (Leung et al., 2006). Clearly, being able to address both of these problems make ANP an ideal fit for a BSC based framework, either performance evaluation or decision making. In chapter 4, the significant interactions among criteria are conveniently included by using ANP.

A prior implementation of BSC-ANP framework, in which the indicator interactions are considered, can also be found in a performance measurement system (Thakkar, Deshmukh, Gupta, & Shankar, 2007). Thakkar, et.al (2007) use ANP to determine the weights of BSC perspectives for the purpose of designing a performance measurement system for an organic food company (KVIC) in India. The specificity of their framework requires the deployment of a set of indicators pertinent only to the performance of KVIC, quite a number of them have no influence on IT outsourcing decision.

Inherently, firm level IT outsourcing strategy selection is a multi-objectives and multi-criteria decision problem, where the outcome can have a serious impact that can be wide spread and long lasting. In general, a decision model that comprehensively examines the problem from various perspectives is more trustworthy.

Other than the AHP/ANP framework there are several other MCDMs that are proposed for outsourcing decisions. Among them, the major weakness in using GP is that the decision-maker must specify both goals and their relative importance (priority). In the formulation of a GP outsourcing model, it is very difficult to determine the level of attainment for each goal and the penalty weights for over-attainment or under-attainment. Furthermore, formulating a GP model with many criteria (17 in our case), especially with some being qualitative and others interacting with each other, can be quite challenging, not to mention solving it.

Using ANP/AHP alone without the aid of BSC, one may get a model with an incomplete set of decision criteria, possibly missing some important ones, as in Udo (2000), Yang & Huang (2000), and Yang et al. (2007) while other criteria being repeated or otherwise not very well organized. BSC provides us with a structured framework to ensure that all important criteria are examined and relevant ones are logically organized into our decision model. ANP, on the other hand, provides an easy way to represent BSC indicator interactions and to prioritize the BSC indicators. In other words, BSC and ANP truly enhance each other.

2.2.3 Balanced Scorecard – BSC

Since its introduction by Kaplan and Norton (1992), Balanced Scorecard has been widely adopted as a performance measurement framework (Rigby, 2001). Despite the claim of BSC being a strategic management tool, our literature review concurs with Cobbold and Lawrie (2002a), that it largely remains as a performance measurement tool, with the exceptions of Hafeez, et.al (2002) and Hong, et.al (2003). Since Hafeez et.al (2002) took the approach of evaluating firm capability to identify firm’s core capability, as a result, they generate guidelines for outsourcing non-core capabilities, much of the measures categorized by Kaplan and Norton as “Internal Business perspective” and “Learning and growth perspective” are not included as evaluating criteria. Hong, et.al (2003) proposes a set of BSC based multi-dimensional measurement for evaluating the ASPs, but they fell short of developing it into a complete framework to achieve its goal. Most notably, it does not quantify the measures for practical evaluation of ASPs. In their recent paper, Hafeez et.al (2007) takes the RBT/KBT approach to identify non-core assets for possible outsourcing. They look at the firm’s resources, capabilities, and competences to determine the key assets of a company. Then, based on the “uniqueness” and the “collectiveness” of those key assets, they determine, for a specific company, that they should not pursue aggressive outsourcing. One major dimension that is missing from their framework, as far as outsourcing is concerned, is the financial perspective. Since cost savings were cited in the literature by about 50% of the companies as the main driver for outsourcing, the omission of the financial perspective is a major detriment of their framework. Another omission of Hafeez et.al (2007) is the customer perspective, being able to maintain and/or improve customer satisfaction is a key determinant that affects a firm’s outsourcing strategy. Compared with RBT/KBT, the BSC approach is better suited.

2.3 EMPIRICAL STUDIES OF THE ECONOMIC IMPACT OF OUTSOURCING

2.3.1 Classic Data Analysis Methods

Based on their study of the outsourcing literature from 1990 to 2003, Jiang and Qureshi (2006) find that there are “three main gaps in the current literature: lack of objective metrics for outsourcing results evaluation, lack of research on the relationship between outsourcing implementation and firms’ value, and lack of research on the outsourcing contract itself.” They concluded that, “every business activity’s fundamental goal is to increase the firm’s value. However, so far few studies provide any evidence of the relationship between a firm’s outsourcing decision and its stock market value. It seems reasonable to borrow the event study methodology from finance discipline to simultaneously analyze the changes of outsourcing firms’ performance and their stock market value.”

Jones (2000) used UK government statistics to recognize that drug companies must be part of the global knowledge network to remain competitive. Jones’ study only examined outsourcing impact of a single functional division rather than the whole firm. Hays et al. (2000), based on event study, examine 3-day stock prices of the firms surrounding the outsourcing announcement – the event (announcement) day, the day before, and the day after. To be more precise, the Hays et al. (2000) paper studied impact of outsourcing announcements rather than the impact of outsourcing implementation on firms’ value. In the Barrar et al. (2002) study, outsourcing firm’s employee productivity rather than firm’s value was the major concern. Using government statistics, McCarthy & Anagnostou (2004) studied the impact of outsourcing on the transaction costs and boundaries of manufacturing firms. Their main emphasis was the impact of outsourcing on an entire industry instead of individual firms.

Since then, several financial data analysis papers have appeared in research journals. Most notably ones are Bardhan et. al (2006), Jiang et. al (2007) and Geishecker and Gorg (2008). Table 2 provides a list of the most influential financial data analysis research papers regarding outsourcing impact. Our research aims at addressing the first two gaps pointed out by Jiang and Qureshi (2006).

Table 2 Literature on Outsourcing Impact – Financial Data Analysis Research Papers

Author(s)	Title	Description
Jones (2000)	Innovation management as a post-modern phenomenon: the outsourcing of pharmaceutical R&D	Uses government statistics to recognize that drug companies must be part of the global knowledge network if they are to remain competitive. Managers in major drug companies have generally not invested directly in biotechnology, preferring instead to buy-in knowledge from smaller firms. R&D, which until recently has been a core activity within the pharmaceutical industry, is increasingly bought-in
Hays et al. (2000)	Information system outsourcing announcements: investigating the impact on the market value of contract-granting firms	Examined the impact of information systems outsourcing announcements on the market value of outsourcing firms. They utilized the event study method to examine the abnormal return of stock price on -1 day (the day before the announcement), 0 day (the announcement date) and +1 day (the day after the announcement), i.e., the event window is 3-day. Their results provided empirical evidence from the capital market that outsourcing announcements can immediately increase outsourcing firms' value
Barrar et al. (2002)	The efficiency of accounting service provision	Compare internal against external efficiency in the delivery of finance function activities. Findings: outsourcing presents a more efficient solution for the management of very small firm accounting than internal provision. It concludes that outsourcing provision is likely to offer worthwhile savings to small firms, allowing them to shed competitive weaknesses and operate at efficient or best practice levels
McCarthy & Anagnostou (2004)	The impact of outsourcing on the transaction costs and boundaries of manufacturing	examine the corresponding change (decline) in UK manufacturing as an economic activity, and consider how the economic benefits of outsourcing alter the contribution that an organization makes to a sector's gross domestic product
Jiang et al. (2006)	Outsourcing effects on firms' operational performance	This research aims to empirically investigate the effect of outsourcing on firm level performance metrics, providing evidence about outsourcing influences on a firm's cost-efficiency, productivity and profitability
Jiang et al. (2007)	Outsourcing impact on manufacturing firms' value: Evidence from Japan	This study views outsourcing effects from its future revenue-generation potential, using market value. The relation between firms' market valuation and outsourcing decisions is investigated using a **cross-sectional** valuation approach. Results based on Japanese manufacturing industries data from 1994 to 2002 indicate that core business-related outsourcing, offshore outsourcing, and shorter-term outsourcing have positive effects on outsourcing firms' market value. In contrast, non-core business-related outsourcing, domestic outsourcing, and longer-term outsourcing are not found to enhance firm value.
Bardhan, Whitaker, and Mithas (2006)	Information Technology, Production Process Outsourcing, and Manufacturing Plant Performance	A theoretical framework for the antecedents and performance outcomes of production outsourcing at the plant level. Validating the framework using **cross-sectional** survey data from U.S. manufacturing plants. Findings: plants with greater IT investments are more likely to outsource their production processes, and that IT investments and production outsourcing are associated with lower COGS and higher quality improvement. Provides an integrated model for studying the effects of IT and production outsourcing on plant performance.
Geishecker & Gorg (2008)	Winners and losers: a micro-level analysis of international outsourcing and wages	Investigates the link between international outsourcing and wages utilizing a large household panel and combining it with industry-level information on industries' outsourcing activities from input-output tables.

Jiang et al. (2006) was concerned with outsourcing effects on firms' operational performance, such as cost-efficiency, productivity and profitability. Bardhan, Whitaker, and Mithas (2006) examined the relations between IT investment and production process outsourcing and assessed the effects of IT investment and production process outsourcing on firm performance. Geishecker and Gorg (2008) identified the winners and losers of offshore outsourcing on wages at the micro-level.

Jiang et.al (2007) “views outsourcing effects from its future revenue-generation potential, using market value.” They investigated the relation between firms’ market valuation and outsourcing decisions using a cross-sectional valuation approach. Japanese manufacturing industries data from 1994 to 2002 was used in their model. Their results indicate that core business-related outsourcing, offshore outsourcing, and shorter-term outsourcing have positive effects on outsourcing firms’ market value, but non-core business-related outsourcing, domestic outsourcing, and longer-term outsourcing do not enhance firm value. The shortcomings of Jiang et.al (2007) include (1) data is limited to Japanese manufacturing industries; (2) limited to linear regression model.

2.3.2 Machine Learning

The author turns to the field of machine learning in search of a better performing descriptive model from the outsourcing data since machine learning is concerned with design and deployment of algorithms that automatically improve with experience (Mitchell, 1997). A major focus of machine learning research is to automatically produce (induce) models, such as rules, patterns, and equations from data. The specific machine learning algorithms that are applicable to our data (continuous dependent variable) are regression tree, neural network, and support vector machine.

2.3.2.1 Regression Trees

Classification and regression trees are nonparametric (i.e. the model structure is not pre-specified, but determined from data) and nonlinear, but can often yield simpler models. Tree methods are also well suited for our purpose, since we have neither prior knowledge nor a coherent set of theories or predictions regarding whether or which independent variables are related to the variable of interest, let alone how they are related. In the analyses of our outsourcing data, tree models have the potential to reveal simple relationships between just a few independent variables that other analytic techniques could have easily missed.

In section 5.3 of chapter 5 , machine learning models using the regression tree algorithm – M5 (Quinlan, 1992) based software – Cubist, was developed to predict the changes in Tobin's q. In the regression tree model, firms' current accounting data and the relative outsourcing contract value were the independent variables, they included: six accounting variables, previous year's changes in Tobin's q and the relative amount of the outsourcing contract. In building a regression tree, the data was analyzed and rules were developed that splitting the data into a number of different groups, producing a decision tree. A regression equation was then generated at each leaf node. In essence, a linear approximation to the highly non-linear relationship was produced for each outsourcing case.

2.3.2.2 Neural Network

The first artificial neuron was proposed in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pitts (McCulloch & Pitts, 1943). Their invention did not find its purpose until the advent of high-speed computing.

A neural network (NN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionistic approach to computation. Most of the time a NN is an adaptive system that changes its structure based on external stimuli and/or internal information that passes through the network.

NN consists of a network of simple processing elements (artificial neurons) which can exhibit complex global behavior, determined by the connections between the processing elements and element parameters. In the machine learning world, neural networks are non-linear statistical data modeling or decision making tools. They can be used to model complex relationships between independent variables and response variables. A fairly concise and simple description, application areas, advantages, history, as well as examples of real life applications of neural networks can be found at: http://palisade.com/neural tools/neural_networks.asp

In a typical NN model, there are at least three layers of nodes, or "neurons" that are connected together to form a network of nodes. Usually, a neural network comes with algorithms designed to alter the strength (weights) of the connections in the network to produce a desired signal flow from input layer through the hidden layer(s) to output layer. Figure 2 below depict a 2-hidden layers (8 and 3) neural network with a 5-neurons input layer and one neuron output layer. The output can be either categorical or numerical. The response variables in this research are numerical.

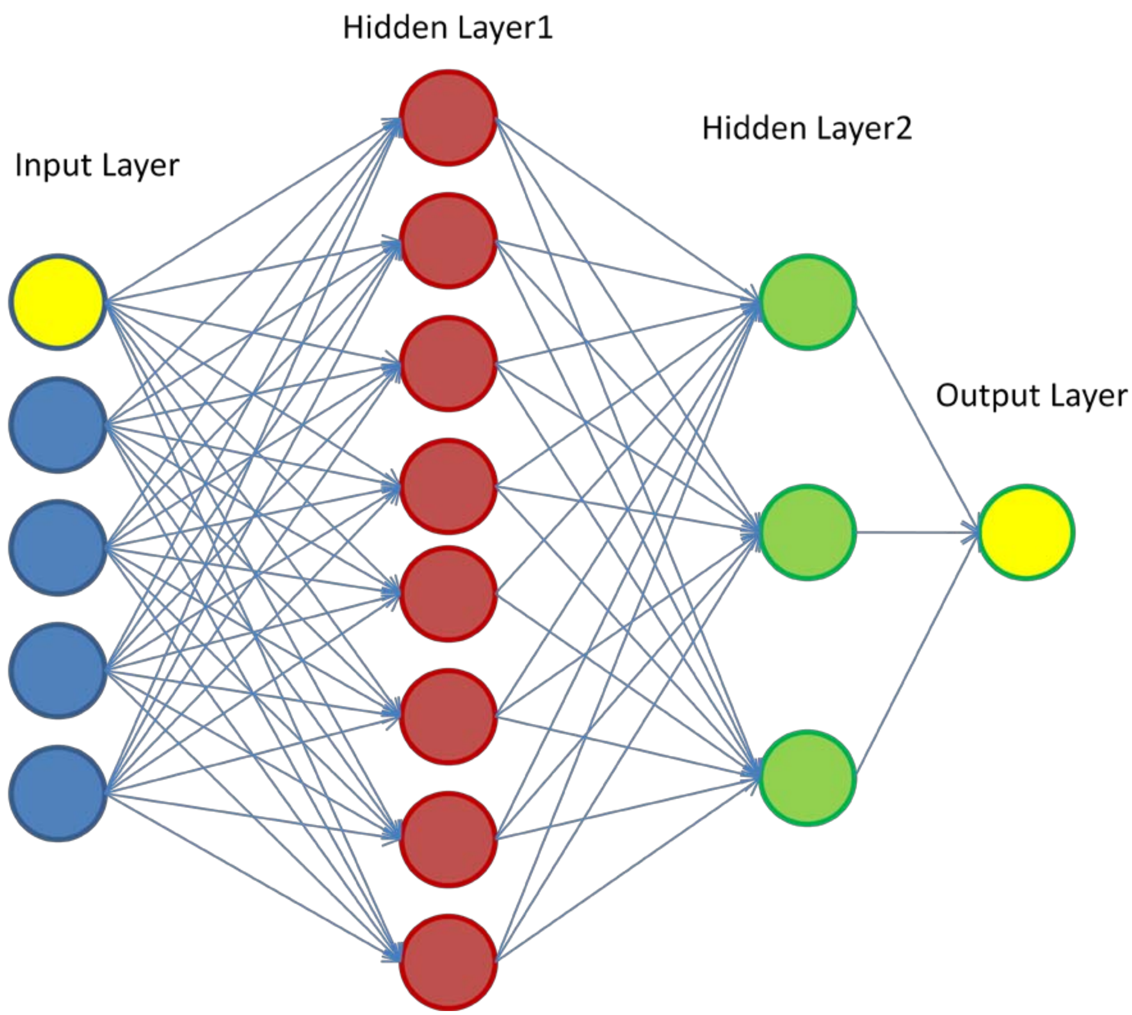

Figure 2 **A 2-Hidden Layers Neural Network**

3.0 CHAPTER 3 GOVERNMENT POLICY DECISION

This chapter aims at finding the best governing policy for offshore outsourcing of business activities. The Analytical Network Process, a multi-criteria decision making methodology, is used to create the evaluation framework. From the perspective of decision makers, stakeholders, and influence groups, four policy options are evaluated with respect to approximately 50 economic, political, technological, and other factors. The model provides both long term and short term views of the outsourcing issue concerned to all parties. The all-inclusive approach helps policy-makers decide on the best policy and has the potential to ease tension between proponents and opponents of offshore outsourcing.

3.1 INTRODUCTION TO OUTSOURCING POLICY DECISION

Manufacturing outsourcing has been an established business practice for decades. However, outsourcing of non-manufacturing activities, such as IT and other services did not commence until the landmark Kodak deal in 1989 (Applegate et al. 1990; Pearlson et al. 1990). Due to the distress caused by white-collar worker displacement, the escalation in offshore outsourcing of service has kindled fierce debate among economists, business consultants, academia, politicians, and the news media. The negative sentiment towards offshore outsourcing in U.S. has stipulated the action from local, state and federal government. By the end of 2006, law-makers from over 40 states had introduced a number of bills to restrict offshore outsourcing of government contracts. At the same time, supporters of free trade led by mainstream economists strongly criticized those actions as the return of protectionism and warned ardently about its consequences. The open conflict between the two sides has captured the attention of the general public and the legislative body of this nation. Local, state, and federal governments are facing increasing pressure to make crucial decisions with regard to offshore outsourcing. Outsourcing thus has become an urgent matter U.S. policymakers must contend with. Should they or shouldn't they intervene with the offshoring practice adopted by many U.S. businesses? The outcome of the decision will directly affect the wellbeing of U.S. citizens and many businesses and individuals overseas. This part of the research is motivated by the pressing need to seek out a satisfactory guiding principle for the issue.

3.2 POLICY DECISION FRAMEWORK

3.2.1 The Analytic Network Process – ANP

A multi-criteria decision making (MCDM) tool, Analytical Hierarchy Process (AHP) was developed to meet the need of handling criteria that are not measurable in an absolute sense. AHP allows subjective judgments as well as quantitative information to enter into the evaluation process simultaneously and provides decision-makers with better communication. In addition to providing a clear procedure, AHP's framework is straightforward and comprehensive, and adaptable to both group and individual decision making. When optimization is not pursued, resources are not restricted, and interdependencies do not exist, AHP is a suitable tool to use for MCDM.

The Analytic Network Process (ANP) is a generalization of the AHP (Saaty, 2001; 2005). Both AHP and ANP can help decision-makers learn, respect, and understand other members' viewpoints. Like AHP, ANP can improve communication and resolve conflicts, and help diffuse responsibility; this is particularly attractive when a good decision calls for actions that may not be well-liked, such as outsourcing. Both AHP and ANP are capable of evaluating a wide range of criteria, including tangible and intangible factors (criteria) that have impact on the outcome. However, AHP uses a unidirectional hierarchical relationship to model decision levels, while the ANP allows for complex interactions and influences among criteria, subcriteria, actors (people involved in or impacted by the decision) as well as alternatives. Figure 3 shows a typical ANP alternatives evaluation framework. In Figure 3, C_1 can be a cluster of one or multiple criteria, and there are three arcs connected to it. The one way arrow pointing to C_2 indicates criteria within C_2 have influence on criteria within C_1. The one way arrow from A_2 pointing to C_1 represents the influence of criteria within C_1 on the actors within A_2. The two-way arrow between C_1 and Alts indicates there are influences of criteria within C_1 on Alternatives within Alts and also impacts of the alternatives within Alts on the criteria within C_1.

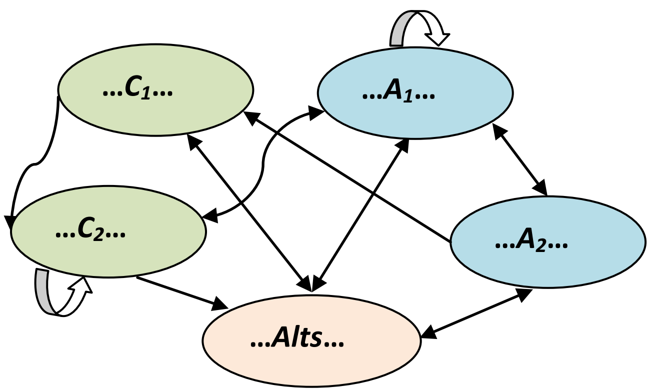

Figure 3 General ANP Alternatives Evaluation Framework

An ANP based model can also prioritize a wide spectrum of tangible and intangible decision criteria. ANP allows the decomposition of a complex problem into well organized clusters. It converts a problem into sub-networks of objectives, criteria, sub-criteria, actors, and alternatives (Saaty, 2001) and provides a sensible and logical way of synthesizing them into a unique final outcome. Although the widely used Analytic Hierarchy Process gives decision-maker a straightforward view of the decision model, the more complicated decision problems are best studied through the ANP (Saaty & Ozdemir, 2004). More specifically, the ANP brings decision objective, criteria, alternatives, and all the actors (such as decision makers, stakeholder, and influencers) into one unified framework and it permits interaction and feedback of elements (alternatives, criteria and actors) within groups (inner dependence) and between groups (outer dependence). Most complex real life decision problems have numerous inter-dependent elements (criteria). These can be easily captured and dealt with by utilizing the feedback and interaction in an ANP model. ANP has been applied to transportation project selection (Shang et al. 2004), policy decisions (Saaty, 2005; Tjader et al. 2009) supply chain management system analysis (Meade & Sarkis, 1998; Nakagawa & Sekitani, 2004). For more examples of ANP applications, see Saaty and Vargas (2006).

To derive the global priorities of the criteria using ANP, it is necessary to first pairwise compare criteria with respect to the node representing their category, and with respect to all other criteria with which they interact (or have influence on). Next, the principal right eigenvector of each comparison matrix is computed to obtain the local priority of every criterion (Saaty, 1980). In the last step, a super-matrix (Saaty, 1980) consisting of all the local-limiting matrices is formed for overall criteria prioritization and alternative ranking. The weighted supermatrix is taken to the limit for the final results.

The strategic alternatives are pairwise compared under each of the criteria. The example questions asked for pairwise comparisons of the alternatives are: "with respect to a specific criterion, is Alternative X better than Alternative Y and if the answer is yes, then how much better?" An inverse value is chosen if under the specified criterion, Alternative Y is better than Alternative X. Similar to criteria rankings, each set of comparison matrix is used to calculate the local rankings of the alternatives. The local rankings of the alternatives are included in the "super-matrix" for final calculation (or synthesis). The composite scores of the alternatives are the overall rankings of the alternatives. They are summarized as the final synthesized alternative rankings.

Outsourcing policy evaluation involves many factors, it is a typical multicriteria decision making problem. Since its outcome affects many people, the views of all affected constituents should be included in the decision making process. Among all the multi-attribute decision making techniques, we found ANP to be the most suitable evaluation framework for outsourcing decisions, since it can incorporate many stakeholders' opinions and allow for opposing views to interact with each other during the deliberation process.

3.2.2 Factors Affecting the Outsourcing Policy Decision

Through intensive literature search (e.g. Abraham & Taylor, 1996; Deavers, 1997; McCarthy & Anagnostou, 2004; Ngwenyama & Bryson, 1999; and Sharpe 1997), we have compiled a list of factors that are relevant to the outsourcing policy decision making. Based on the nature of these factors, we divide them into four categories: benefits, opportunities, costs, and risks. There are a number of benefits that U.S. corporations can realize when offshoring. They are: (1) reducing costs; (2) improving core competency focus; (3) increasing flexibility; (4) creating variable cost structures; (5) improving productivity; (6) gaining competitiveness; (7) accessing external talents; (8) sharing risk; (9) improving quality; (10) conserving capital; and (11) stimulating innovation. Other benefits are (1) increasing consumer buying power; (2) gaining political support from EU countries; (3) gaining political support from WTO member countries; (4) gaining political support from vendor countries; and (5) increasing wealth of overseas vendors.

In the long run, the practice of offshore outsourcing offers these opportunities: (1) facilitating global market development; (2) expanding utilities, manufacturing, transportation, and communication networks for goods and services in the vendor countries, and (3) globally.

Offshore outsourcing is not without its negative effects. Researchers and practitioners have identified the following 27 costs and risks factors: (1) vendor shirking; (2) opportunistic bargaining by vendor; (3) vendor inability brought by rapid turnover of skilled employees; (4) vendor violating intellectual property right; (5) vendor violating labor laws; (6) inadequate infrastructure in vendor countries; (7) difference in culture and business practices in vendor countries; (8) political turmoil, terrorism or war bringing instability to the vendor country; (9) costs due to vendor evaluation and selection; (10) monitoring costs; (11) switching costs; (12) loss of management control to core business competencies; (13) reduction in flexibility; (14) fall in employee morale; (15) potential management changes; (16) potential leaks of confidential information and loss of intellectual property rights; (17) downward pressure on domestic wages; (18) job losses, unemployment backlashes; (19) economic imbalance due to the destruction of certain industries; (20) trade deficit; (21) instability of society; (22) negative sentiment of the public; (23) security concerns; (24) legal ramifications of global outsourcing arrangements; (25). losing IT technology leadership; (26) dependency on foreign R&D and imported goods and services; (27) long-term labor market downward trends – H-1B visa brings qualified foreign technical workers to the U.S., which drives the wages of U.S. technical labor market lower.

In all, we have identified 46 factors. Although the size is manageable, it is somewhat unwieldy in the ANP model. Through discussion with other researchers and practitioners, redundant factors are eliminated and similar ones are combined, which yield 31 independent factors. These factors become the criteria for ANP decision model and are discussed below.

3.2.3 The ANP Criteria and Their Theoretical Foundation

The EquaTerra polls (Bednarz, 2005) on 589 Human Resource Executives show that corporate cost-cutting and process-improvement directives are main outsourcing drivers. Large and highly specialized outsourcing vendors often possess economies of scale, therefore they are able to help customers cut costs and improve operational efficiency. Abraham & Taylor (1996) found that taking advantage of lower wages is the main reason for outsourcing. Grady (2005) believes that the eminence of offshoring is due to the 8:1 ratio of U.S. professional salary to that in developing countries such as India. Ang & Straub (1998) and Sharpe (1997) found transaction costs play a role in outsourcing decision, but they are much smaller than the production costs advantage offered by vendors. Sharpe (1997) and Ngwenyama & Bryson (1999) indicate that by combining many customers, large outsourcing vendors do enjoy economies of scale and are likely to achieve a more efficient scale of production.

Quinn & Hilmer (1994) point out that by concentrating on firms' core competencies and strategically outsourcing other activities, firms could create unique value for their customers, and therefore, maintain their long term competitive advantage. Alternatively, Carlson (1989), Domberger (1998), and Thondavadi & Albert (2004) empirically prove that outsourcing can provide greater flexibility, especially in the purchase of rapidly developed new technologies, fashion goods, and the myriad of components of complex systems. Companies are allowed to incorporate the latest technology and respond to changing business environments more quickly and at a lower cost than vertically integrated organizations. Instead of devoting fixed investments to internal operations, a firm can choose to create a more variable cost structure through outsourcing (Corbett, 2003; 2004), Thondavadi & Albert (2004) consider being able to access talents and skills not available internally as an important gain of outsourcing. Then again, Deavers (1997) and Sharpe (1997) believe outsourcing is the solution for tapping into lucrative but risky projects without actually "taking on" those projects.

Business functions that don't produce unique competitive advantages are often the last to be funded and invested in, thus making continuous improvements in quality difficult to achieve. Corbett (2003) points out that there have been considerable improvements in quality resulting from outsourcing. Finally, Ellis (1994) and Quinn (2000) believed capital conservation and innovation are advantages of outsourcing. Readers interested in outsourcing are referred to "The Outsourcing Revolution" (Corbett, 2004), which takes in a critical aspect of outsourcing and explains essential management principles.

A closer examination of the 31 independent factors reveals that eight of these factors are strategically significant. The eight factors are grouped into three categories: Domestic Interest, Human Wellbeing, and Foreign Relations. They are used in the AHP ratings model to determine the relative weights of *Benefits*, *Opportunities*, *Costs*, and *Risks.* Details are given in section 3.2.3.1. The remaining 23 factors are categorized into four groups: *Benefits*, *Opportunities*, *Costs*, and *Risks*. The definition and literature base of these 23 criteria are summarized in Appendix I.

3.2.4 Creating the ANP Model

We utilize the ANP software Super Decisions (www.creativedecisions.net) to develop the proposed decision model. Based on the factor groupings, four separate multi-level networks are created — *Benefits*, *Opportunities*, *Costs*, and *Risks* — BOCR sub-networks. Each sub-network (subnet) consists of clusters of factors (i.e. criteria or sub-criteria) that are relevant to the sub-goal of the subnet. The BOCR subnets make up the essential part of our decision framework, as shown in Figure 4. The bottom part of Figure 4 shows a typical decision subnet. A decision subnet is an important part of ANP decision framework, which includes alternatives and many decision makers and stakeholders. In the following, we detail the structure of each BOCR subnet and the decision subnet.

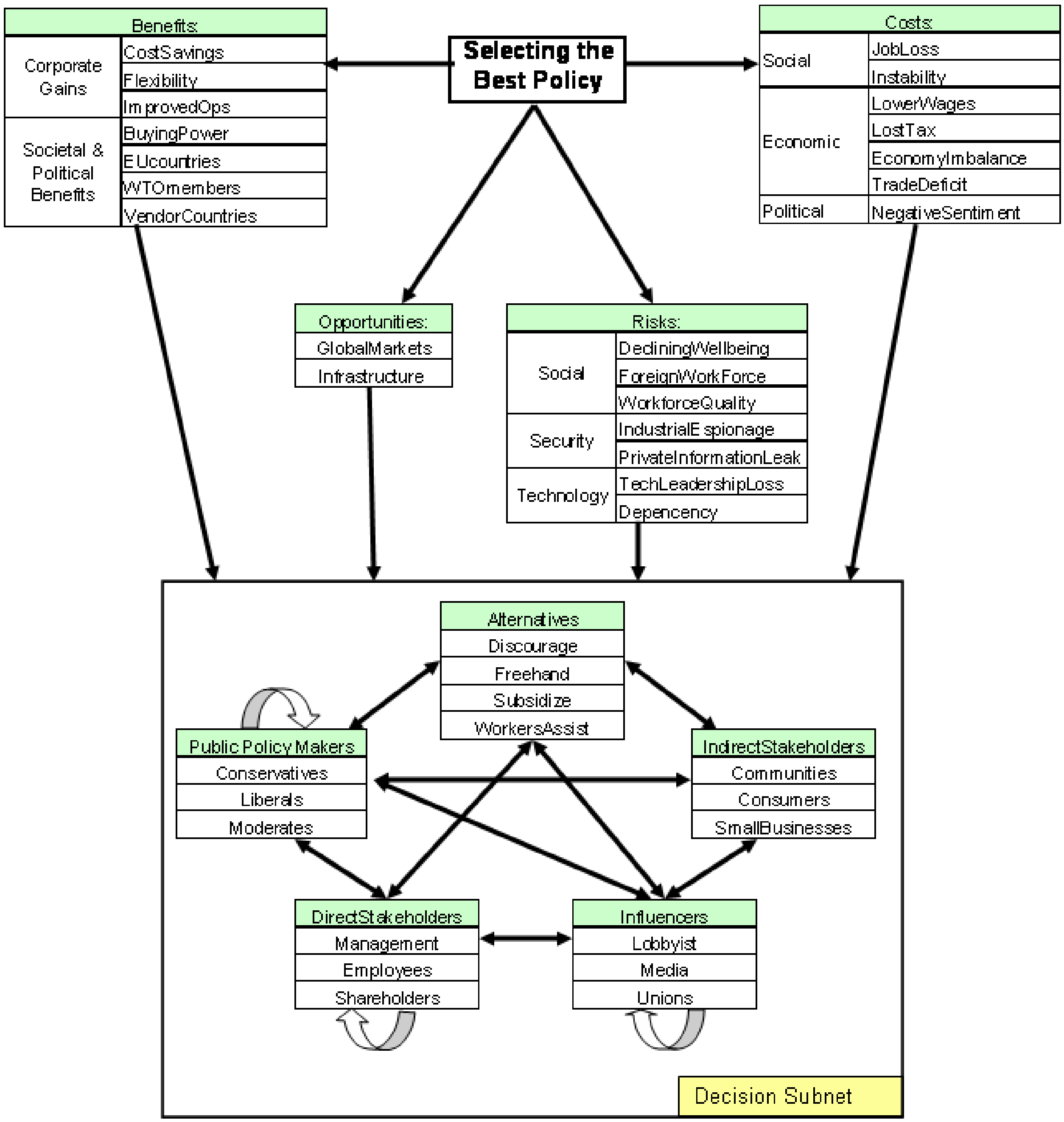

Figure 4 The ANP-Based Outsourcing Policy Evaluation Framework

3.2.4.1 Deriving the Weights for BOCR Using the AHP Ratings Model

On the upper half of Figure 4, we can find the four BOCR subnets. Figure 5 details the structure of the *Benefits* subnet. The relative importance (weights) of these subnets can be derived using an AHP ratings model.

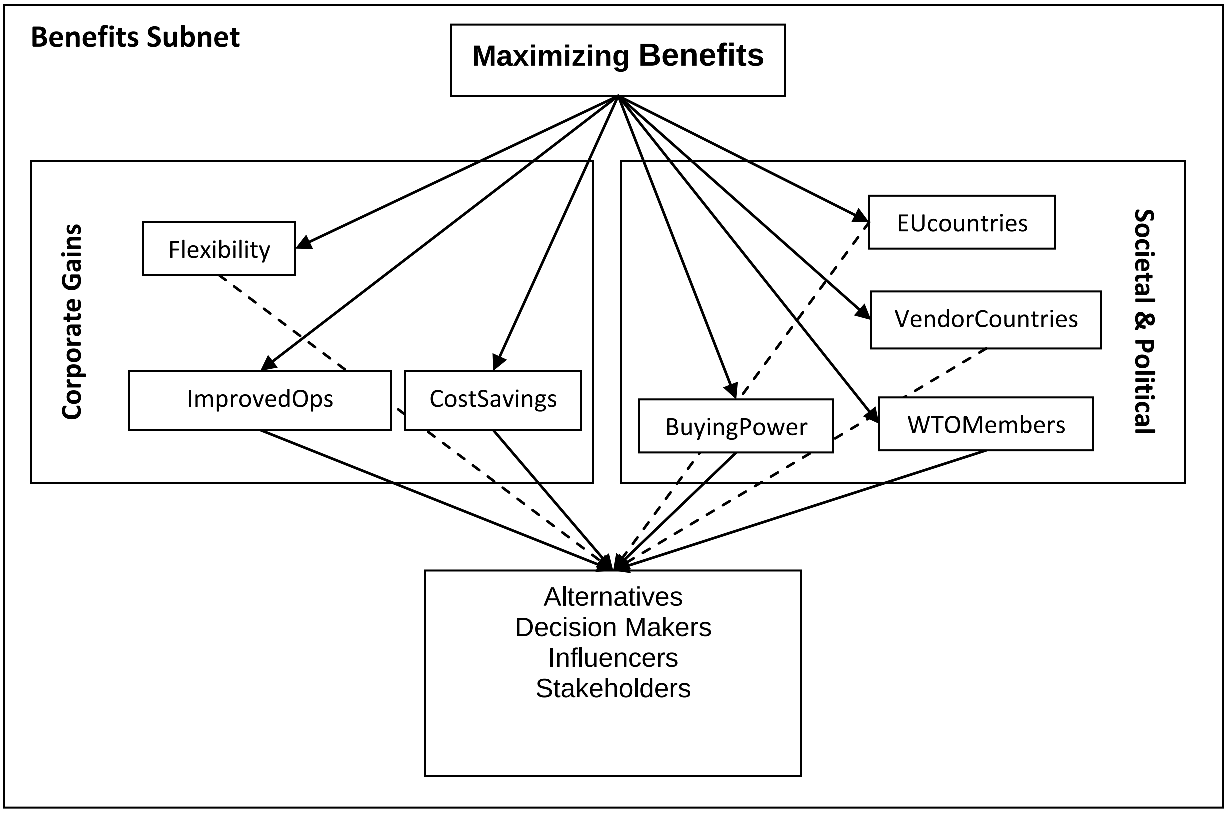

Figure 5 Benefits Subnet

Figure 6 summarizes the AHP model and shows the hierarchy structure. We've identified *domestic interest, human wellbeing, and foreign relations* as the three primary strategic concerns that are relevant to our problem. Each includes 2-3 strategic control criteria, which are used to determine the BOCR weights for our ANP model. Details are discussed below:

(A) Domestic Interests. For the domestic interest, we consider the following issues: (i) *US economy*. Outsourcing may improve the prosperity of the U.S. economy as measured by the Consumer Price Index, (CPI), Gross Domestic Product (GDP), Index of Leading Economic Indicators, and Personal Consumption Expenditures. (ii) *National security*. Overseas outsourcing of government, military, and hi-tech work makes U.S. national security vulnerable. Terrorists and rogue countries may gain access and penetrate the U.S. national defense system. (iii) *Social*

Stability. In order to maintain stability, our labor laws need to better address the displaced workers from offshore outsourcing.

(B) Human Wellbeing. In considering overall human wellbeing, the strategic concerns include: (i) *Advancing technology*. (ii) *Ending poverty*, (iii) *Ensuring global security*. Due to offshore outsourcing, terrorists may have better access to important targets to mount attacks.

(C) Foreign Relations. Friendly relationships with the governments of vendor countries can lead to more support to U.S. foreign policy initiatives. The sub-criteria considered are *diplomatic relations* and *trade relations*.

These strategic criteria are prioritized by first conducting pairwise comparisons and then calculating the eigenvector. The priorities derived for BOCR (b, o, c, and r) will be used to weigh the alternatives under each of the BOCR sub-networks in synthesizing the Additive Negative model (detailed in section 3.3.3).

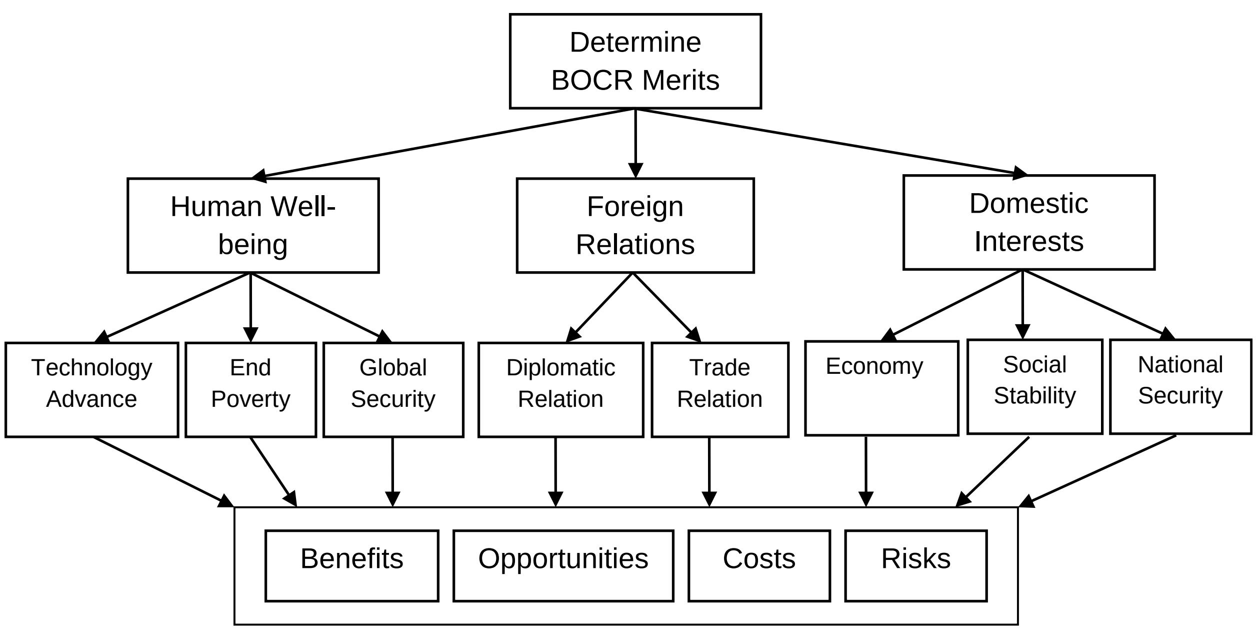

Figure 6 The AHP Ratings Model for Deriving the BOCR Weights

3.2.4.2 The BOCR Subnets and Decision Subnet

The Benefits Subnet

The Benefits subnet has a sub-goal of maximizing benefits. Under the sub-goal node, there are two clusters of control criteria: *Social* and *Global Political Support* Benefits, and *Corporate Gains* Benefits. The numerical priorities derived from *Benefits* subnet represent the intensity of positive contribution imparted by each alternative to the overall decision goal. Therefore, for a specific alternative, its priority is the greater the better.

The social and global political support benefits include the increased consumer buying power (*BuyingPower*), the increased political support coming from vendor countries (*VendorCountries*), the countries in the European Union (*EUcountries*), and the other member countries of the WTO (*WTOmembers*). The benefits to the U.S. corporations include procurement and other operational cost reductions (*CostSavings*), operational efficiency improvement (*ImprovedOperations*), and increased agility or flexibility and other gains (*Flexibility*). The operational efficiency improvements encompass productivity gain, improved focus, variable cost structure improvement, and access to skills. Besides *flexibility*, the "other corporate gains" include revenue growth, improved quality, capital conservation, and innovations (see Bean (2003) and Weidenbaum (2005)).

The Costs Subnet

The sub-goal of the *Costs* subnet is to minimize the total costs. The alternative priorities derived from the *Costs* subnet represent the level of negative impact each alternative has on the overall decision objective. Therefore, for a specific alternative's priority, it is the smaller the better. In other words, a smaller priority value in this subnet corresponds to less cost of an alternative. It has three control clusters: Economic Costs, Social Costs, and Political Costs. The economic costs to the U.S. include downward wage pressure to the domestic workforce (*LowerWages*), tax revenue loss (*LostTax*), increased trade deficit (*TradeDeficit*) and the economy imbalance (*EconomyImbalance*). Politically, negative sentiment (*NegativeSentiment*) from the public can be very costly for the elected officials and businesses. The social costs come from job losses (*JobLoss*) and an unstable society (*Instability*).

The Opportunities Subnet

The *Opportunities* subnet is a three-layered network with a sub-goal of seizing the best opportunity. The alternative that scores the highest in the opportunities subnet will contribute the largest positive score to the opportunities subnet. The bottom control criteria in this subnet are the global market development (*GlobalMarkets*), and the industrial infrastructure development (*Infrastructure*) in the vendor countries. Similar to *Benefits* subnet, the priority score is the higher the better.

The Risks Subnet

When it comes to risks, the objective is to minimize them by choosing the alternative with the smallest risk. The *Risks* subnet is headed by a sub-goal node connecting to three clusters of control criteria; *Social* risks, *Security* risks, and *Technological* risks.

The social risks are the declining wellbeing of our country (*DecliningWellbeing*), the declining quality of our domestic workforce (*WorkforceQuality*), and the shortage of skilled foreign workers (*ForeignWorkforce*). Security risks include possible private information leak (*PrivateInformationLeak*) and industrial espionage (*IndustrialEspionage*). Technically, the U.S. is at risk of losing its technology leadership position (*TechLeadership*) and increasing dependency (*Dependency*) upon foreign R&Ds and essential supplies in components, finished goods, and services.

The Decision Subnet

An ANP decision subnet typically consists of a cluster of alternatives and several clusters of actors. Our decision subsets for the outsourcing policy decision making has five clusters: alternatives, public policy makers, direct stakeholders, indirect stakeholders, and influencers. In the *Alternatives* cluster, there are four policy options: *Freehand, Subsidize, Discourage,* and *WorkersAssist.* In the Public Policy Makers' cluster there are *Conservatives, Liberals,* and *Moderates.* The influencers' cluster includes workers unions, business lobbyists, and the news media. The direct stakeholders' cluster has *Management, Shareholders*, and *Employees. Consumers*, *Communities*, and *Small businesses* belong to the indirect stakeholders cluster. A certain decision subnet may not have all those clusters because some of the actor groups do not play any part under a certain criterion. For instance when examining the benefit of gaining support from WTO member countries (*WTOmembers*), the *Shareholder*, *Management* and *Employees* of U.S. corporations and domestic *small businesses*, *communities* and *customers* are not concerned, therefore the two stakeholders clusters are not included in the decision subnet under the criterion *WTOmembers*.

3.3 EMPIRICAL STUDY AND COMPUTATIONAL RESULTS

3.3.1 Model Inputs

For numerical input of our decision model, we rely on three sources: (1) survey results of attendees at the 2004 Outsourcing World Summit as given by Corbett (2004); (2) survey results of government workers, business managers, small business owners, MBA, EMBA, senior business undergraduate students at the University of Pittsburgh (samples of the survey questionnaires can be found in appendix B); and (3) outsourcing literature.

Two different types of surveys were conducted. The first survey (survey 1) was designed for collecting data to determine the weights of the subcriteria in the ANP model. All the questions used in survey 1 can be seen in appendix B (A) (Questionnaire I). In survey 1, respondents were asked to rate each factor as un-important, somewhat important, important, very important or extremely important. The AHP 9-point scale was given to each of the answers. That is: unimportant = 1; somewhat important = 3; important = 5; very important = 7; and extremely important = 9. In the second survey (survey 2), we collect data as input for pairwise comparison within each decision subnet using questionnaire II. In order to capture all the interactions and influences within each decision subnet, at the same time limit the number of questions presented to each survey participant, several variations (versions) of questionnaire II are devised. Appendix B (B) shows a partial of the core of questionnaire II, which includes one of the eleven sets of questions utilized for pairwise comparison of all the alternatives with respect to a specific criterion – in this case, *CostSavings*. The core is included in every variation of questionnaire II. Appendix B (C) shows questions related to alternative impact on actors within

DirectorStakeholders group, the inner-dependency of actors within *DirectorStakeholders* group, and the influence on *Employees* from the actors within *Influencers* and *PolicyMakers* groups. A complete Questionnaire II is the combination of its different variations.

A total of 105 valid survey responses were collected, of which 65 were from Questionnaire I and 40 from Questionnaire II. We take a geometric mean of the first survey results to derive the group average responses for each question. The geometric mean is taken because when a group is involved, it is necessary to aggregate the preferences of individuals into a consensus rating. The basis for using the geometric rather than the arithmetic mean to combine judgments of different individuals has been justified mathematically by Aczel and Saaty (1983) and Saaty (2001). They proved that with the conditions of separability, associativity, cancellativity, consensus, and homogeneity needed to synthesize judgments of individuals, one could use the arithmetic or geometric means. However, when reciprocity is used, the geometric mean is the only way to combine judgments. For example, if four surveyed responses regard the benefits priority of “subsidize” over “freehand” as 3, 4, 6, and 5, respectively, then the aggregate preference of “subsidize” outsourcing alternative would be $(3, 4, 6, 5)^{1/4} = 4.36$. That is, individual judgments are replaced by the geometric mean for the group.

We further compared these group averages with sources from the existing literature and discovered some minor differences between them. For instance, in the literature, *CostSavings* is the highest rated *Benefits* factor and in most cases the driver of the outsourcing decision. However, our limited scope survey results show that *Costsavings* is ranked 2nd in the *Benefits* subnet. To offset our survey bias, we take a weighted average approach by giving the literature and Corbett’s survey 1/3 weight each, and 1/3 weight for our survey data. As a result, the *CostSavings* was moderately adjusted upward to make it more in line with the literature. By doing so we recognize the survey results given by Corbett (2004) and other outsourcing literature are more substantial. Since our survey participants are mostly lower level managers, students, and employees versus the decision making executives attending the Outsourcing World Summit, we consider it appropriate to assign no more than 1/3 weight to our survey data. Similarly, we take the geometric mean of survey #2’s responses as the pairwise comparison entries for each of the decision subnets.

By examining the weights (priorities) of sub-criteria, we determine which ones should have a decision subnet attached. The sub-criteria priorities for the *Benefits* subnet are displayed in the upper part of Table 3, where the sum is 0.5. The top four of the seven *Benefits* sub-criteria are selected to have decision subnets created under them. These four criteria represent 83% [(.125+.113+.092+.085)/0.5] of the total weights of all the *Benefits* sub-criteria, therefore, they are considered sufficient to represent all the benefits (Saaty, 2005). The next highest ranked sub-criterion *EUcountries* has a priority of 0.047, which is relatively low and is excluded, along with all the other lower ranked sub-criteria, from having a decision subnet attached.

Table 3 Priorities of Criteria/Sub-criteria at the BOCR Subnet Level

	Criterion Name	BOCR Subnet Level Criteria Priorities
Benefits	CostSavings	0.125
	BuyingPower	0.113
	WTOmembers	0.092
	ImprovedOps	0.085
	EUcountries	0.047
	VendorCountries	0.021
	Flexibility	0.017
Opportunities	GlobalMarkets	0.833
	Infrastructure	0.167
Costs	JobLoss	0.157
	LowerWages	0.152
	NegativeSentiment	0.064
	EconomyImbalance	0.045
	Instability	0.031
	TradeDeficit	0.029
	LostTax	0.021
Risks	IndustrialEspionage	0.153
	DecliningWellbeing	0.132
	PrivateInformationLeak	0.076
	WorkforceQuality	0.047
	TechLeadershiploss	0.044
	ForeignWorkforce	0.025
	Dependency	0.022

The *Opportunities* subnet has only two control criteria, *GlobalMarkets* and *Infruastructure*, without any sub-criterion. Since *GlobalMarkets* is far more important than *Infruastructure*, we create a decision subnet under it. Using the same approach as that in the *Benefits* subnet, we create decision subnets for three of the seven sub-criteria in the *Costs* subnet. They are: *JobLoss*, *LowerWages*, and *NegativeSentiments*. Likewise, under the *Risks* subnet, we create decision subnets for three of them: *IndustrialEspionage, DecliningWellbing*, and *PrivateInformationLeak*. Table 3 shows the weights of all sub-criteria under the *Benefits*, *Opportunities*, *Costs*, and *Risks* subnets.

By keeping all the sub-criteria in the model but not creating decision subnets under some of the less important ones, we get a simplified (parsimonious) model. This approach is first proposed and implemented by Saaty (2001) in the ANP National Missile Defense (NMD) system decision model. The invariance of the alternative rankings based on this approach is also proved by Shang et.al. (2004).

After completing the model structure, we make pairwise comparison of the alternatives by using data collected from survey of different groups represented in the decision subnets (see the bottom half of Figure 4). The respondents of our survey represent the influence group, the stakeholder group, and the policy decision making group. For instance, a corporate executive would identify himself as *Managements* in the direct stakeholder group. Besides the different degree of preference each groups have regarding the alternatives, policy decision-makers, influencers, and stakeholders are also impacted by the alternatives in various degrees. These are built into the model by the answers to questions such as: when considering *ImprovedOperations*, with respect to *FreeHand*, how much more is *Employee* affected than *Management*? Furthermore, the stakeholder groups will have influence and interaction with the decision-makers, influencers, and vice versa. All interactions, influences, and preferences are captured in the decision subnet and pairwise compared by using the input derived from the survey complemented by the data found in literature.

3.3.2 The Computation and Synthesis

The priority vectors derived from the pairwise comparisons within a decision subnet are summarized in a supermatrix. A supermatrix takes into consideration all influences, interactions, and preferences of the actors on the alternatives and on each other. It also captures the impacts of alternatives on actors. A decision subnet level supermatrix contains all local priority vectors. Table 4 shows the unweighted supermatrix of the decision subnet under one of the Benefits criteria: *CostSavings*. The sub-matrices on the main diagonal represent inner-dependencies of actors within each group (cluster). The sub-matrices off the main diagonal represent interdependencies of actors between groups (clusters). Under the three columns from the *DirectStakeholders* cluster in Table 4, there are five sub-matrices. The first four rows show the degree of impact each alternative has on each direct stakeholder: Employees, Management, and Shareholders. The rows 5-7 are on the main diagonal and they represent the influence of Employees, Management, and Shareholders on each other. For instance, Management's influence to Employees is 0.875 and Shareholders influence to Employees is 0.125. In other words, Management has 7-times more influence on Employees than Shareholders. Rows 8-10 represent the impact of the *IndirectStakeholders* on the *DirectStakeholders*, in this case non-exist, so the entries are all zeros. Rows 11-13 represent the impact of influence-group on *DirectStakeholders*. Example, Unions' influence on Employees is 0.88889 while the influence of Media on Employees is 0.11111. In other words, Unions have 7-times more influence on Employees than Media. Table 5 shows impact priorities (weights) of clusters within the decision subnet under the criterion *CostSavings*. By multiplying a cluster entry of Table 5 into the corresponding entries of Table 4, we get the weighted supermatrix as shown in Table 6.

Table 4 The Un-weighted Supermatrix – CostSavings

	Discourage	Freehand	Subsidize	Workers Assist	Employees	Management	Shareholders	Communities
Discourage	0	0	0	0	0.09219	0.0428	0.04104	0.09091
Freehand	0	0	0	0	0.21547	0.43104	0.48717	0.36364
Subsidize	0	0	0	0	0.23843	0.27736	0.18074	0.18182
WorkersAssist	0	0	0	0	0.45391	0.24879	0.29105	0.36364
Employees	0.77778	0.05263	0.2	0.76079	0	0.24998	0.2	0
Management	0.11111	0.47368	0.4	0.1576	0.875	0	0.8	0
Shareholders	0.11111	0.47368	0.4	0.08161	0.125	0.75002	0	0
Communities	0.46644	0.09091	0.53961	0.71429	0	0	0	0

Consumers	0.1005	0.72727	0.16342	0.14286	0	0	0	0
SmallBusinesses	0.43306	0.18182	0.29696	0.14286	0	0	0	0
Lobbyists	0.09999	0.9	0.75	0.16667	0	0.58155	0.4	0
Media	0	0	0	0	0.11111	0.10945	0.2	0.24998
Unions	0.90001	0.1	0.25	0.83333	0.88889	0.309	0.4	0.75002
Conservatives	0.10945	0.58155	0.33333	0.26307	0.16342	0.44332	0.77031	0
Liberals	0.58155	0.10945	0.33333	0.54722	0.53963	0.1692	0.06793	0
Moderates	0.309	0.309	0.33333	0.18971	0.29696	0.38748	0.16176	0

Table 4 Part 2

	Consumers	Small Businesses	Lobbyists	Media	Unions	Conservatives	Liberals	Moderates
Discourage	0.05398	0.04032	0.04032	0	0.09896	0.04297	0.07674	0.0446
Freehand	0.40159	0.41459	0.41459	0	0.35794	0.38496	0.40311	0.42084
Subsidize	0.14284	0.17359	0.17359	0	0.18515	0.19784	0.15586	0.19927
WorkersAssist	0.40159	0.37149	0.37149	0	0.35795	0.37423	0.36429	0.3353
Employees	0	0	0.05724	0.53961	0.875	0.12827	0.83333	0.33333
Management	0	0	0.34582	0.29696	0.125	0.27635	0.16667	0.33333
Shareholders	0	0	0.59693	0.16342	0	0.59538	0	0.33333
Communities	0	0	0	0.4	0.53961	0.08096	0.53961	0.25
Consumers	0	0	0	0.4	0.16342	0.18839	0.29696	0.25
SmallBusinesses	0	0	0	0.2	0.29696	0.73064	0.16342	0.5
Lobbyists	0	0	0	0.24998	0.16667	0.58155	0.05724	0.28571
Media	0.83333	0.66667	0.83333	0	0.83333	0.309	0.34582	0.57143
Unions	0.16667	0.33333	0.16667	0.75002	0	0.10945	0.59693	0.14286
Conservatives	0	0	0.29696	0	0.25991	0	0.66667	0.66667
Liberals	0	0	0.16342	0	0.41261	0.33333	0	0.33333
Moderates	0	0	0.53961	0	0.32748	0.66667	0.33333	0

Table 5 The Impact Priority of all the Clusters under CostSavings

Cluster Node Labels	Alternatives	Direct Stakeholders	Indirect Stakeholders	Influencers	Public Policy Makers
Alternatives	0.00000	0.47023	0.75000	0.28729	0.22598
DirectStakeholders	0.29017	0.17815	0.00000	0.14503	0.14364
IndirectStakeholders	0.12728	0.00000	0.00000	0.07597	0.07475
Influencers	0.06487	0.07982	0.25000	0.05663	0.13192
Public Policy Makers	0.51768	0.27179	0.00000	0.43508	0.42372

Table 6 The Weighted Supermatrix under CostSavings

	Discourage	Freehand	Subsidize	Workers Assist	Employees	Management	Shareholders	Communities
Discourage	0	0	0	0	0.04335	0.02013	0.0193	0.06818
Freehand	0	0	0	0	0.10132	0.20269	0.22908	0.27273
Subsidize	0	0	0	0	0.11212	0.13042	0.08499	0.13636
WorkersAssist	0	0	0	0	0.21344	0.11699	0.13686	0.27273
Employees	0.22569	0.01527	0.05803	0.22076	0	0.04453	0.03563	0

Management	0.03224	0.13745	0.11607	0.04573	0.15588	0	0.14252	0
Shareholders	0.03224	0.13745	0.11607	0.02368	0.02227	0.13362	0	0
Communities	0.05937	0.01157	0.06868	0.09092	0	0	0	0
Consumers	0.01279	0.09257	0.0208	0.01818	0	0	0	0
SmallBusinesses	0.05512	0.02314	0.0378	0.01818	0	0	0	0
Lobbyists	0.00649	0.05838	0.04865	0.01081	0	0.04642	0.03193	0
Media	0	0	0	0	0.00887	0.00874	0.01596	0.0625
Unions	0.05838	0.00649	0.01622	0.05406	0.07095	0.02466	0.03193	0.18751
Conservatives	0.05666	0.30106	0.17256	0.13619	0.04442	0.12049	0.20937	0
Liberals	0.30106	0.05666	0.17256	0.28328	0.14667	0.04599	0.01846	0
Moderates	0.15996	0.15997	0.17256	0.09821	0.08071	0.10531	0.04396	0
Table 6 Part 2								
	Consumers	Small Businesses	Lobbyists	Media	Unions	Conservatives	Liberals	Moderates
Discourage	0.04048	0.03024	0.01254	0	0.02843	0.00971	0.01734	0.01008
Freehand	0.30119	0.31095	0.1289	0	0.10283	0.08699	0.09109	0.0951
Subsidize	0.10713	0.1302	0.05397	0	0.05319	0.04471	0.03522	0.04503
WorkersAssist	0.30119	0.27862	0.1155	0	0.10284	0.08457	0.08232	0.07577
Employees	0	0	0.00898	0.28189	0.1269	0.01842	0.1197	0.04788
Management	0	0	0.05428	0.15513	0.01813	0.03969	0.02394	0.04788
Shareholders	0	0	0.09369	0.08537	0	0.08552	0	0.04788
Communities	0	0	0	0.10945	0.04099	0.00605	0.04033	0.01869
Consumers	0	0	0	0.10945	0.01242	0.01408	0.0222	0.01869
SmallBusinesses	0	0	0	0.05473	0.02256	0.05461	0.01222	0.03737
Lobbyists	0	0	0	0.05099	0.00944	0.07672	0.00755	0.03769
Media	0.20833	0.16667	0.05107	0	0.04719	0.04076	0.04562	0.07538
Unions	0.04167	0.08333	0.01021	0.15299	0	0.01444	0.07875	0.01885
Conservatives	0	0	0.13983	0	0.11308	0	0.28248	0.28248
Liberals	0	0	0.07695	0	0.17952	0.14124	0	0.14124
Moderates	0	0	0.25408	0	0.14248	0.28248	0.14124	0

The weighted supermatrix is column stochastic, meaning that its column sums to 1. By raising the column stochastic matrix to large powers, we obtain the limit matrix which contains the eigenvectors of the original matrix. In the Super Decision software, the power method is stopped when the difference between components of the priority vector obtained at the k^{th} power and at the $(k+1)^{th}$ power is less than some predetermined small value (Saaty, 2001). Table 7 depicts the limit supermatrix of the *CostSavings* benefits. It has the same form as the weighted supermatrix, but all columns are the same and each column sums to one. The priorities for the four alternatives are 0.0149, 0.0968, 0.0499, and 0.0896 respectively, which can be normalized to 0.060, 0.385, 0.199, and 0.357 correspondingly. This indicates that *FreeHand* (nor=0.385) is the most favored option when *CostSavings* benefits criterion is concerned. The supermatrices and weights for all other sub-criteria can be obtained similarly.

Table 7 The Limit Supermatrix under CostSavings

	Discourage	Freehand	Subsidize	Workers Assist	Employees	Management	Shareholders	Communities
Discourage	0.01495	0.01495	0.01495	0.01495	0.01495	0.01495	0.01495	0.01495
Freehand	0.09709	0.09709	0.09709	0.09709	0.09709	0.09709	0.09709	0.09709
Subsidize	0.04994	0.04994	0.04994	0.04994	0.04994	0.04994	0.04994	0.04994
WorkersAssist	0.08927	0.08927	0.08927	0.08927	0.08927	0.08927	0.08927	0.08927
Employees	0.06935	0.06935	0.06935	0.06935	0.06935	0.06935	0.06935	0.06935
Management	0.06487	0.06487	0.06487	0.06487	0.06487	0.06487	0.06487	0.06487
Shareholders	0.05648	0.05648	0.05648	0.05648	0.05648	0.05648	0.05648	0.05648
Communities	0.02665	0.02665	0.02665	0.02665	0.02665	0.02665	0.02665	0.02665
Consumers	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
SmallBusinesses	0.02335	0.02335	0.02335	0.02335	0.02335	0.02335	0.02335	0.02335
Lobbyists	0.03286	0.03286	0.03286	0.03286	0.03286	0.03286	0.03286	0.03286
Media	0.03605	0.03605	0.03605	0.03605	0.03605	0.03605	0.03605	0.03605
Unions	0.04197	0.04197	0.04197	0.04197	0.04197	0.04197	0.04197	0.04197
Conservatives	0.14707	0.14707	0.14707	0.14707	0.14707	0.14707	0.14707	0.14707
Liberals	0.10604	0.10604	0.10604	0.10604	0.10604	0.10604	0.10604	0.10604
Moderates	0.12107	0.12107	0.12107	0.12107	0.12107	0.12107	0.12107	0.12107

Table 7 (continued)

	Consumers	Small Businesses	Lobbyists	Media	Unions	Conservatives	Liberals	Moderates
Discourage	0.01495	0.01495	0.01495	0.01495	0.01495	0.01495	0.01495	0.01495
Freehand	0.09709	0.09709	0.09709	0.09709	0.09709	0.09709	0.09709	0.09709
Subsidize	0.04994	0.04994	0.04994	0.04994	0.04994	0.04994	0.04994	0.04994
WorkersAssist	0.08927	0.08927	0.08927	0.08927	0.08927	0.08927	0.08927	0.08927
Employees	0.06935	0.06935	0.06935	0.06935	0.06935	0.06935	0.06935	0.06935
Management	0.06487	0.06487	0.06487	0.06487	0.06487	0.06487	0.06487	0.06487
Shareholders	0.05648	0.05648	0.05648	0.05648	0.05648	0.05648	0.05648	0.05648
Communities	0.02665	0.02665	0.02665	0.02665	0.02665	0.02665	0.02665	0.02665
Consumers	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
SmallBusinesses	0.02335	0.02335	0.02335	0.02335	0.02335	0.02335	0.02335	0.02335
Lobbyists	0.03286	0.03286	0.03286	0.03286	0.03286	0.03286	0.03286	0.03286
Media	0.03605	0.03605	0.03605	0.03605	0.03605	0.03605	0.03605	0.03605
Unions	0.04197	0.04197	0.04197	0.04197	0.04197	0.04197	0.04197	0.04197
Conservatives	0.14707	0.14707	0.14707	0.14707	0.14707	0.14707	0.14707	0.14707
Liberals	0.10604	0.10604	0.10604	0.10604	0.10604	0.10604	0.10604	0.10604
Moderates	0.12107	0.12107	0.12107	0.12107	0.12107	0.12107	0.12107	0.12107

The un-weighted supermatrix for the *Benefits* subnet is shown in Table 8. Due to its hierarchical structure, there is no interdependence among clusters and no intra-dependence within each cluster. At this stage, the *Benefits* subnet has not been weighted yet, therefore the weighted supermatrix is the same as the un-weighted supermatrix. The limit supermatrix for the *Benefits* subnet is shown in Table 9. The overall synthesis under *Benefits* is obtained from the results of the four decision subnets. After deriving the limit supermatrices for all four decision subnets, we compute the ideal priority for each policy alternative under a specific criterion by using this formula: $\frac{\text{limit value}}{\text{highest limit value}}$. The Ideal values of *CostSavings* in Table 10 are derived from the raw values of Table 7. They are then copied to the 2nd column of Table 11. In particular, the ideal values of the *CostSavings* criterion are: *discourage* = 0.0149/0.968 = 0.1543; *FreeHand* = 0.0968/0.0968 = 1; *Subsidize* = 0.0499/0.0968 = 0.5152; and *WorkerAssit* = 0.0896/0.0968 = 0.9252. Similarly, columns 3, 4, and 5 are populated with idealized values under *ImprovedOperations*, *BuyingPower*, and *WTOmembers*.

Table 8 The Unweighted Supermatrix under Benefits

	Maximizing Benefits	SocialPolitical Benefits	USCorporate Cains	Cost Savings	Flexibility	Improved Ops	Buying Power	EU countries	Vendor Countries	WTO countries
Maximizing Benefits	0	0	0	0	0	0	0	0	0	0
SocialPoliticalBenefits	0.54546	0	0	0	0	0	0	0	0	0
USCorporateCains	0.45454	0	0	0	0	0	0	0	0	0
CostSavings	0	0	0.54891	0	0	0	0	0	0	0
Flexibility	0	0	0.07663	0	0	0	0	0	0	0
ImprovedOps	0	0	0.37445	0	0	0	0	0	0	0
BuyingPower	0	0.41408	0	0	0	0	0	0	0	0
EUcountries	0	0.17157	0	0	0	0	0	0	0	0
VendorCountries	0	0.07862	0	0	0	0	0	0	0	0
WTOcountries	0	0.33573	0	0	0	0	0	0	0	0

Table 9 The Limit Supermatrix under Benefits

	Maximizing Benefits	SocietalPolitical Benefits	USCorporate Cains	Cost Savings	Flexibility	Improved Ops	Buying Power	EU countries	Vendor Countries	WTO countries
Maximizing Benefits	0	0	0	0	0	0	0	0	0	0
SocietalPoliticalBenefits	0.27273	0	0	0	0	0	0	0	0	0
USCorporateCains	0.22727	0	0	0	0	0	0	0	0	0
CostSavings	0.12475	0	0.54891	0	0	0	0	0	0	0
Flexibility	0.01742	0	0.07663	0	0	0	0	0	0	0
ImprovedOps	0.0851	0	0.37445	0	0	0	0	0	0	0
BuyingPower	0.11293	0.41408	0	0	0	0	0	0	0	0
EUcountries	0.04679	0.17157	0	0	0	0	0	0	0	0
VendorCountries	0.02144	0.07862	0	0	0	0	0	0	0	0
WTOcountries	0.09156	0.33573	0	0	0	0	0	0	0	0

Table 10 The Priorities of Alternative Outsourcing Policies under CostSavings

	Raw	Normal	Ideal
Discourage	0.01495	0.05950	0.15398
Freehand	0.09709	0.38643	1.00000
Subsidize	0.04994	0.19877	0.51437
WorkersAssist	0.08927	0.35530	0.91946

The ideal priorities are multiplied by the criterion weight to obtain the weighted priority of the alternatives under each criterion. The criteria weights are derived earlier by pairwise comparison of the criteria, and then re-normalized after discarding the insignificant criteria. In the last column of Table 11, we show the sum of weighted alternatives under the *Benefits* subnet. Under each significant criterion, the weighted alternatives are calculated by multiplying the idealized decision subnet vectors by the re-normalized control criterion weight (the third row of Table 11). The sums of all of the weighted alternative priorities for the *Benefits* subnet are displayed in the last column of Table 11. The weighted priorities of the alternatives for the other subnets are derived similarly.

Table 11 Idealized Priorities of Alternatives under Four Sub-criteria in the Benefits Subnet

Benefits	CostSavings	ImprovedOps	BuyingPower	WTOmembers	SUM of Weighted Alternatives
Control Criterion wt.	0.125	0.085	0.113	0.092	
Normalized	*0.301*	*0.205*	*0.272*	*0.222*	
Alternatives	*Idealized*	*Idealized*	*Idealized*	*Idealized*	*SUM*
Discourage	0.1540	0.2569	0.1558	0.2619	0.1995
Freehand	1.0000	1.0000	1.0000	1.0000	1.0000
Subsidize	0.5144	0.4654	0.3958	0.4152	0.4501
WorkersAssist	0.9195	0.9674	0.9463	0.9141	0.9354

The second row of Table 12 shows the priorities (weights) of BOCR (b, o, c, and r) derived from the AHP ratings model. The idealized results for BOCR subnets are shown in the last four rows of Table 12. From Table 12 we notice that *FreeHand* scores the highest in the *Benefits* subnet, and at the same time, it also has the highest Costs and Risks, which will offset its overall ranking. *WorkersAssist*, on the other hand scores the highest in *Opportunities* and the second highest in *Benefits*, *Costs* and *Risks*. *Subsidize* scores the second lowest in all four subnets and *Discourage* scores the lowest in all four subnets. It appears that *WorkersAssist* and *FreeHand* are the top choices.

Table 12 The Alternative Priorities under Each BOCR Subnet

Alternatives	Benefits (B) b=0.3996	Opportunities (O) o=0.2299	Costs (C) c=0.2661	Risks (R) r=0.1044
	CC Sum	*CC Sum*	*CC Sum*	*CC Sum*
Discourage	0.1995	0.2680	0.2143	0.4165
Freehand	1.0000	0.9247	1.0000	1.0000
Subsidize	0.4501	0.4956	0.5938	0.5601
WorkersAssist	0.9354	1.0000	0.7951	0.8581

In the next section, we illustrate how the final rankings of the four policy options are derived using both Additive Negative formula and Multiplicative formula as proposed by Saaty (2005).

3.3.3 The Top Level Synthesis

The final synthesis of the model using both additive negative formula and multiplicative formula is shown in Table 13. The multiplicative model assumes that all control subnets (BOCR) are equally important. It uses the Multiplicative formula, $\frac{B \times O}{C \times R}$, for calculation. This assumption of equal weight in BOCR may not always be true. To allow the weight variation in BOCR for sensitivity analysis, the Additive Negative model is used. The Additive Negative formula is $bB + oO - cC - rR$, the value of b, o, c, and r are displayed in Table 12.

Table 13 Final Synthesized Results

Final Results, matches model: OutsourcingPolicy.mod			
Alternatives	**BO/CR** (Unweighted)	(Normalized)	**bB+oO-cC-rR** (Weighted)
Discourage	0.5990	0.1680	0.0408
Freehand	0.9247	0.2594	0.2417
Subsidize	0.6706	0.1881	0.0773
WorkersAssist	1.3710	0.3845	0.3025

The additive negative model explicitly takes into account the BOCR priorities. From the formula we see that *Costs* and *Risks* scores are subtracted from the overall score. This reflects that the more costly or the more risky an alternative is, the more its negative contribution towards the total score is. When using the additive negative model, we can easily change the priority of one of the BOCR subnet while holding the relative priorities distribution among the other subnets constant to conduct sensitivity analysis. The overall synthesized results given in Table 13 show that *WorkersAssist* dominates under both the additive negative and the multiplicative synthesis methods whereas *Freehand* comes second. This confirms our earlier speculation that *WorkersAssist* and *Freehand* are the top choices, with *WorkersAssist* being the best.

3.3.4 Model Sensitivity Analysis

Sensitivity analysis tests the what-if scenarios by changing the priority of one criterion, an entire cluster of criteria, or an entire subnet. Through such sensitivity analysis, policy-makers can discover how changes in judgments or priority about the importance of each criterion might affect the recommended decisions. For instance, what if *JobLoss* is much more important than all the other criteria in the *Costs* subnet? What if *Benefits* are much more important than *Costs*? Ideally a decision model's outcome should be fairly stable under small variations of the situations or environment (robustness), but under more significant changes in situation or environment, the model outcome should reflect them. For our model, we conducted both single independent variable and multiple independent variables analyses. The results are discussed in the following paragraphs.

For single variable sensitivity analysis, one takes m number of steps to vary the input variable from the minimum of 0.0001 to the maximum of 0.9999 (this range can be manually determined based upon researchers' or practitioners' knowledge about the variable under study). The integer m can vary from 2 to a relatively large number. The Superdecisions software default is $m = 6$. Our experiments show that $m = 20$ for single variable sensitivity analysis yields very smooth curves. When m gets too large, the perturbations become very small, therefore, their impact towards the priorities are negligible. As an example, in Figure 7 we use $m = 20$ and vary the *Benefits* priority from 0.0001 to 0.9999. The interval for each step is Δ = (0.9999-0.0001)/(m-1) = 0.9998/19 = 0.05262. Then the priority of *Benefits* changes as follows: 0.0001, 0.0001+Δ, 0.0001+ 2Δ, 0.0001+ 3Δ … 0.0001+19Δ. When varying the priority of *Benefits*, the relative priorities of other control criteria have to be maintained. For instance when the priority of *Benefits* equals 0.42107, the priorities of *Costs*, *Opportunities*, and *Risks* have to add up to 0.57893 while maintaining the relative proportion of their original priorities.

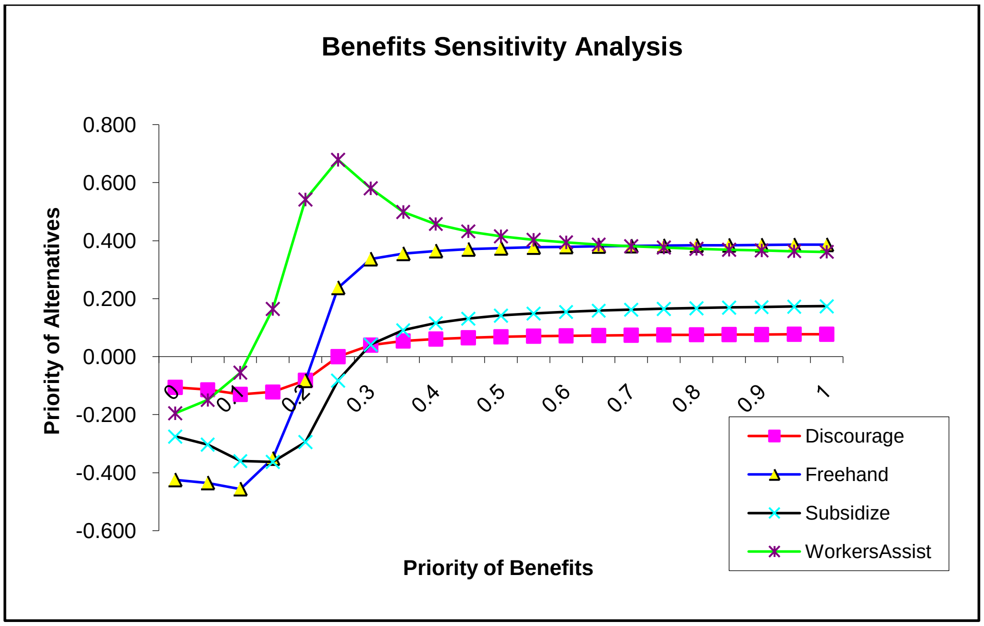

Figure 7 Sensitivity Analysis with the Priority of Benefits as the Independent Variable

Figure 7 shows the changes in alternative ranking when varying the weight of the *Benefits* subnet and holding the other subnets constant. We find that when the priority of *Benefits* is 0.7 or higher, *FreeHand* becomes the best choice. This is logical, since the four most important criteria in the *Benefits* subnet − cost savings, improved operations, increased consumer buying power, and better political support from WTO member countries are dominated by *FreeHand*. If these factors become more important for all the stakeholders and decision makers, then *FreeHand* becomes the best policy to pursue.

Figure 8 shows the changes in alternative rankings while changing the weights of *Costs* subnet. We find that if the priority of *Costs* is increased to 0.52 or above, *Discourage* would become the highest scored alternative. This is because *Discourage* has the lowest cost under the

Costs subnet, therefore when *Costs* become more important, *Discourage* becomes the best choice. As long as the priority of *Costs* is below 0.52, *WorkersAssist* dominates.

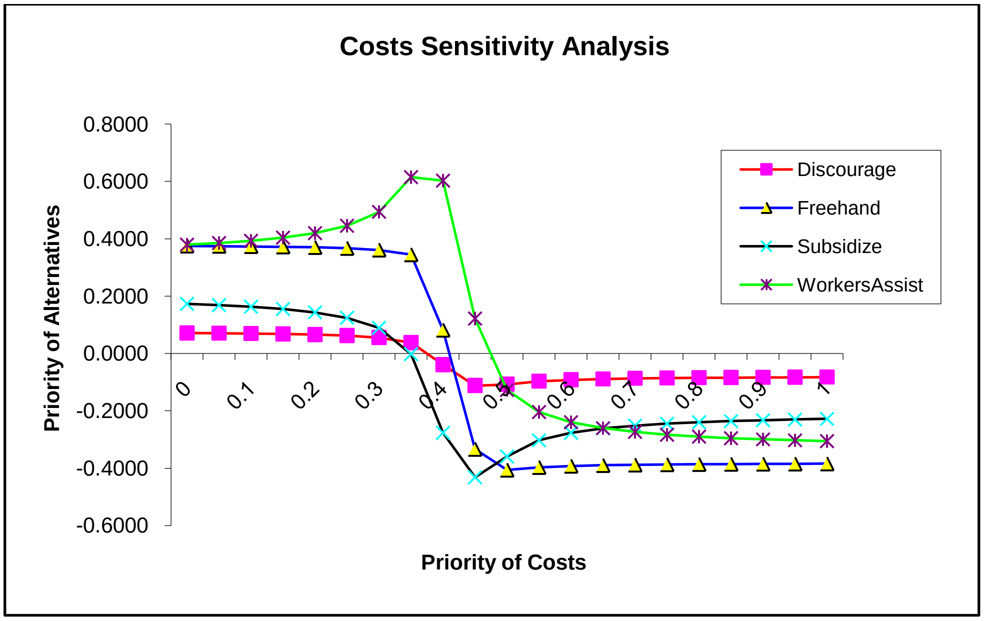

Figure 8 Sensitivity Analysis with the Priority of Costs as the Independent Variable

Figure 9 gives some interesting insights. We find that as far as the sub-criterion *JobLoss* is concerned, *WorkersAssist* policy is the top choice almost throughout the entire independent variable domain. Only when the priority of *JobLoss* goes above 0.96, does *Discourage* become the recommended choice. The most important inference we obtain from Figure 3c is the robustness of our model results. As we all know, job loss is the most visible and devastating side effect cited by opponents of offshore outsourcing. Proponents of offshore outsourcing try to downplay the job loss figures given by many reputable research groups. Our results show that while holding the proportion of other criteria constant, when the importance of *JobLoss* changes from extremely insignificant to its maximum importance, the best policy choice given by our model remains the same: *WorkersAssist*. This is a very powerful argument for the free trade supporters who are seeking some kind of government program to compensate the displaced workers due to offshore outsourcing.

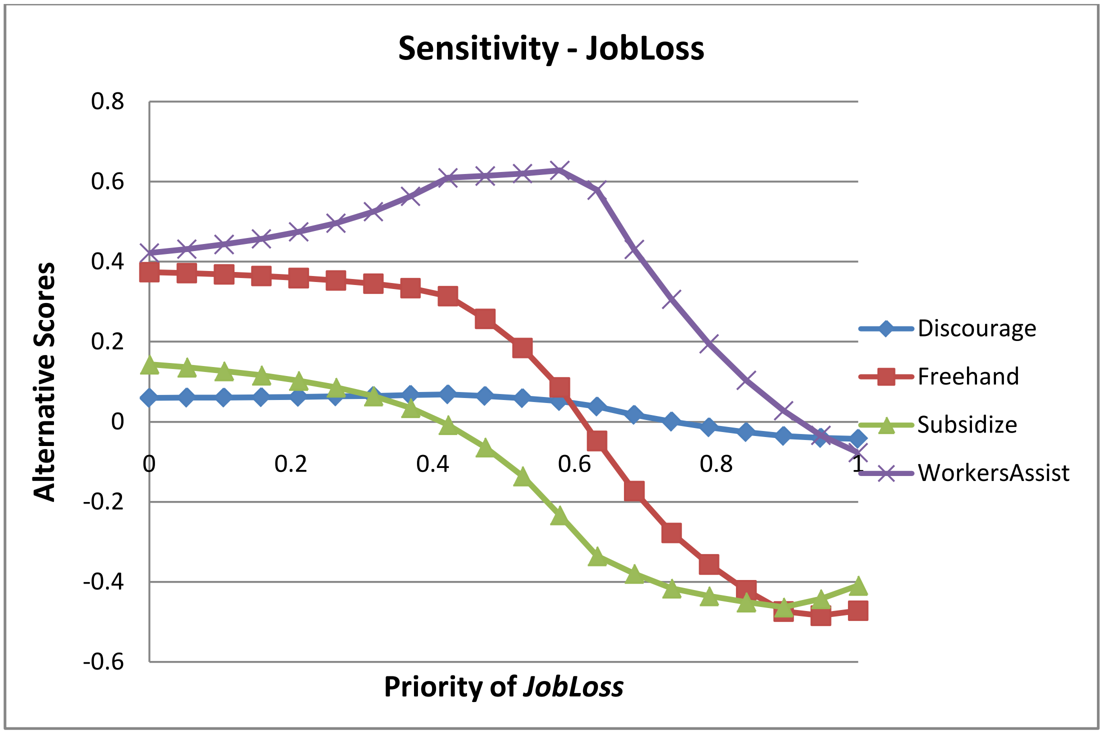

Figure 9 Sensitivity Analysis with the Priority of JobLoss as the Independent Variable

Figure 10 below shows the sensitivity analysis results of one of many possible multiple independent variables scenarios: the alternative priorities change while changing the weights of the BOCR subnets (b, o, c, and r). For example, along the vertical dotted line where b = 0.4095, c = 0.2898, o = 0.2394, and r = 0.0612; we have the following alternative priorities: *Discourage* = 0.075, *Freehand* = 0.361, *Subsidize* = 0.125, and *WorkersAssist* = 0.439. Looking at the entire graph, it is obvious that *WorkersAssist* dominates throughout most of the sensitivity analysis spectrum. There are only a few very small regions where *Discourage* becomes the top choice.

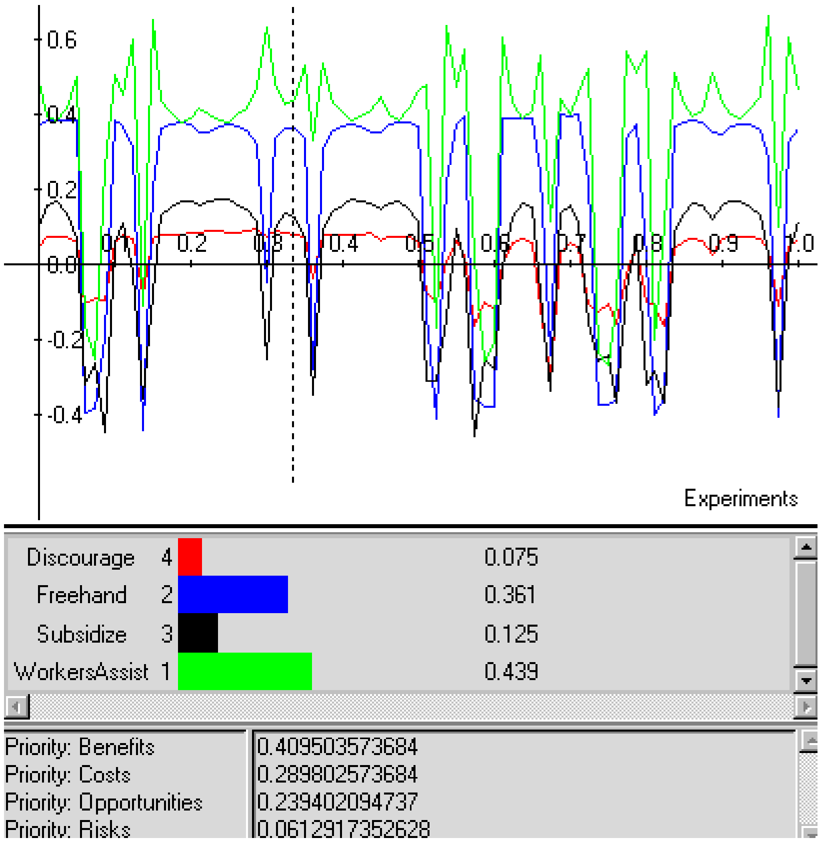

Figure 10 Multiple Independent Variables Sensitivity – Changing BOCR Weights

Figure 11 shows the effect of changing multiple sub-criteria priorities. In this analysis, we use seven top ranked control criteria from the *Benefits* and *Costs* subnets. The selection of those criteria as independent variables for sensitivity analysis is based on their relative importance as well as the likelihood of those criteria become true benefits or real costs. Once again, Figure 4b demonstrates the complete dominance of *WorkersAssist* over all the other alternatives throughout the analysis spectrum. Both of the multiple independent variable sensitivity analysis results confirm the robustness of our evaluation model and the reliability of model results.

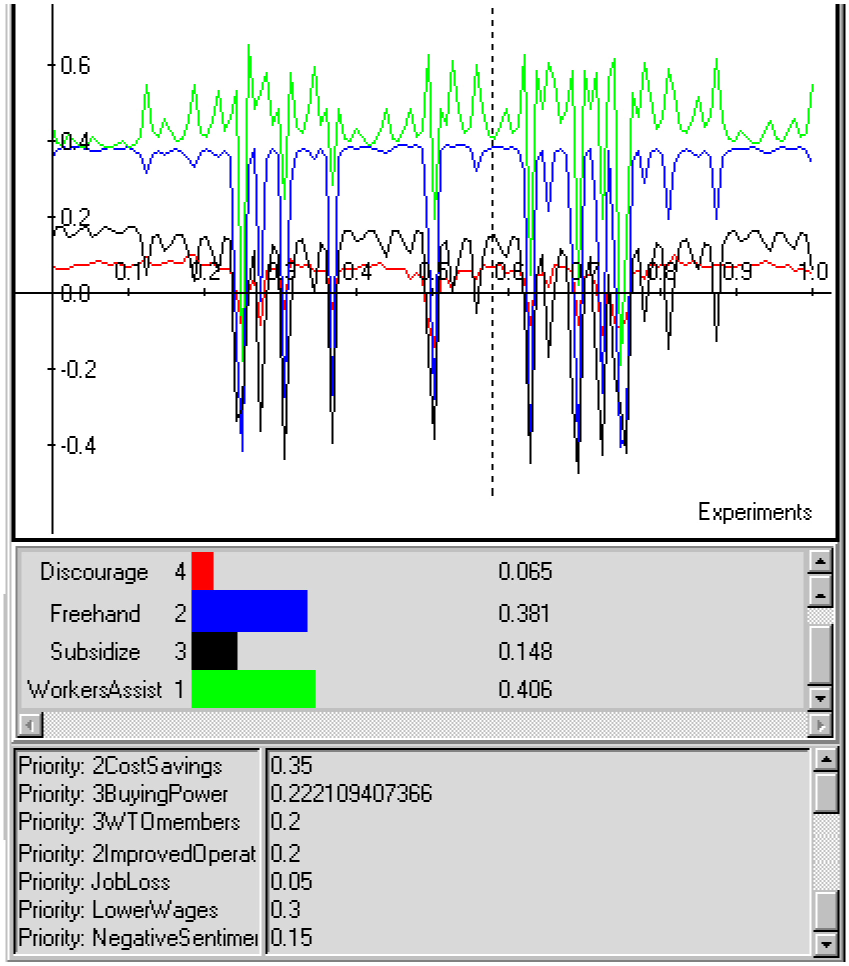

Figure 11 Multiple Independent Variables Sensitivity
–Changing Sub-criteria Weights in Benefits and Costs Subnets

3.3.5 Model Validation

Before drawing conclusions on the proposed ANP model, we demonstrate the validity of our model by comparing model output vectors with the real world survey data. This is a method recommended by Whitaker (Whitaker, 2007). Under the subtitle: "Capturing Outsourcing's Benefits", Michael Corbett (Corbett, 2004) reports the survey results of executives attending the 2004 Outsourcing World Summit (see Table 14). The survey reports the percentage of executives who consider each of the eight factors to be the primary reason (benefit) for outsourcing. To match our model, we group the eight factors into three distinct benefit subcriteria under *CorporateGains*. *They are*: *CostSavings*, *ImprovedOps*, and *Flexibility*. In

Table 14, we found that 17% of those surveyed cited “improved focus” as the primary reason for outsourcing, which constitutes a main part of the subcriterion *ImprovedOps*. We believe using factor frequency from the survey is a good representation of the importance of factors. Column 2 of Table 15 gives the priorities of the subcriteria *CorporateGains* benefits from our ANP model. Corresponding values derived from Corbett (2004), are displayed in column 3 of Table 15; no marked differences are observed.

Table 14 Corbett Survey Results and Groupings

<table>
<tr><td>Reduce costs</td><td>49%</td><td rowspan="2">CostSavings</td><td rowspan="2">52%</td></tr>
<tr><td>Conserve capital</td><td>3%</td></tr>
<tr><td>Improve focus</td><td>17%</td><td rowspan="4">ImprovedOps</td><td rowspan="4">41%</td></tr>
<tr><td>Variable cost structure</td><td>12%</td></tr>
<tr><td>Access to skills</td><td>9%</td></tr>
<tr><td>Improve quality</td><td>3%</td></tr>
<tr><td>Grow revenue</td><td>4%</td><td rowspan="2">Flexibility</td><td rowspan="2">7%</td></tr>
<tr><td>Innovation</td><td>3%</td></tr>
</table>

Table 15 Partial Validation

	ANP Vector	Corbett Survey
CostSavings	0.54891	52%
ImprovedOps	0.37445	41%
Flexibility	0.07663	7%

We have also compared costs, opportunities, and risks factors in the ANP model with our survey data, and found that most of the values are comparable with some exceptions. Overall, it gives us assurance about the validity of our approach in modeling this real world problem. The validation of the final model results will not be conducted here due to the lack of comprehensive data, but it will be considered, together with the validation of all the decision criteria, as a topic for future research.

3.4 POLICY RECOMMENDATIONS

In this chapter, we propose a comprehensive framework for evaluating the legislative options with regard to offshore outsourcing. Our framework enables lawmakers of every level in the U.S. — federal, state, and local, to take a stand on this controversial issue based on the results of a thorough and comprehensive analysis. Our results indicate that providing the displaced workers' assistance programs is the best approach for U.S. government to take. The sensitivity analysis also shows the robustness of our model results, when the most urgent criterion (job loss) is studied.

Providing useful analysis framework and viable solutions to an important and complex problem is our main contribution. The importance of the topic, the necessity for an all-inclusive analysis framework, and the urgency of deriving meaningful policy guidelines warrant our effort. The need of a resolution on this issue comes not only from the American public, but also from the business community, the media, researchers, and consulting groups. The general public may be reassured that the course of action taken by governments (local, state and federal) could be, first of all, for the greater good of the U.S. and benefits the global humanity.

When *WorkersAssist* policy is implemented by various levels of the U.S. government, firms will be provided with both the freedom of hands and the freedom of minds to pursue offshore outsourcing as they deem necessary based solely on the companies' strategic, operational and tactical needs. At the same time, corporate managements are also aware that the government's displaced workers programs are in place for them to draw on whenever necessary.

From a research perspective, the immediate next step would be to provide a comprehensive framework for any U.S. firm to make outsourcing decision: what should be outsourced and how to choose the right vendor. Naturally, in the globalized business environment, selecting a suitable vendor where all entities form an inter-connected network is a challenge. Another area of future research may be the exploration of the another policy option: adapt and innovate as given by Atkinson (2004a). The question we ask here is "how to handle an alternative that is by itself a complex entity?"

4.0 CHAPTER 4 FIRM LEVEL DECISIONS – A CASE STUDY

IT outsourcing is expected to achieve costs savings, operational efficiency, better customer satisfaction, and promote company growth. In this chapter, we propose a framework using Analytical Network Process to integrate the four perspectives of Balanced Scorecard into a cohesive decision model for selecting the best IT outsourcing strategy at the individual firm level. BSC offers insight into the potential impact of the IT outsourcing strategy on all dimensions of a firm, not just the financial aspect. In a systematic manner, ANP helps prioritize the BSC indicators while considering the interactions of them. Although the existence of the indicator interaction and the impact of the interaction on firm performance measurement was proposed by Kaplan and Norton (1992) and also corroborated by others such as Campbell, et. al (2002), it has been greatly neglected by prior researches and implementations of BSC. We will show numerical evidence of the impact of interaction on the indicators rankings (criteria priorities), and then provide explanation both intuitively and mathematically (theoretically, based on network flow theory). One of the reasons prior BSC implementations omit the indicator interaction is the difficulty that management teams face in prioritizing the elements when developing their BSC framework (Cobbold & Lawrie, 2002b). Prioritization of items is inherent in ANP. Therefore, the integration of BSC with ANP becomes advantageous and evident. A thorough "what-if" analysis is followed to help boosting the model's adaptability by different companies, therefore broadens the practicable region of the proposed decision framework. Based on the recommended outsourcing strategy, selective outsourcing, we then detail an AHP ratings model to assist firms prioritizing the specific IT functions for outsourcing.

Since Kodak's 1989 contract with IBM (Applegate et al. 1990), IT outsourcing has grown steadily to become a popular corporate strategy. The pressure of globalization, the rapid technology evolution, and the necessity for cost reduction compel companies to turn to outsourcing for their information technology needs. In the early 90s, the two main objectives for IT outsourcing were cost savings and technical efficiency. Today, the list of the objectives for IT outsourcing has grown longer, and so has the significance of the objectives increased considerably. In essence, outsourcing has become a strategic option for firms to improve their overall business performance.

Although the perceived benefits of outsourcing are numerous, failed projects are reported, by Gartner, as high as 50% (2004). To succeed in outsourcing, a firm needs to understand and prioritize its objectives, set specific and obtainable goals, select the right vendor(s), and negotiate an enforceable contract with vendor(s) (Domberger, 1998; Corbett, 2004). From a daily operations point of view, effective communications and monitoring are keys to successful vendor relationships management. Outsourcing allows firms to develop alliance while keeping pace with technology advancement, to expand their IT infrastructure, and to extend their operations reach. These broader objectives reflect the importance of outsourcing as a strategic option.

The main purpose of this study is to lay an integrative groundwork for evaluating IT outsourcing strategies based their impact on the performance of the firm as measured by the BSC indicators. We tackle this complex issue from a broad perspective, and ultimately help firms find the best strategy suitable to align their individual IT needs with firms' strategic goals. Furthermore, a specific case is used to illustrate the application of our proposed framework at both the strategic and the operational level.

4.1 BALANCED SCORECARD FOR FIRM OUTSOURCING DECISION

Many companies face difficult decisions as to whether to outsource or not. Given that IT outsourcing has strategic implication on enterprise-wide performance, its decision has to be made under the strategic management framework. It is therefore important to choose a sensible strategic level of justification and a rigorously constructed framework so that the recommended decision is reliable.

The one-dimensional financial performance measures are losing their relevance to management (Francis & Shipper, 1999), since the existing performance measurement systems are inadequate for guiding and evaluating organizations as they attempt to generate continued growth for future economic value creation. The Balanced Scorecard is believed to be able to address this problem (Kaplan & Norton, 1992). Since its original introduction, the popularity of BSC has been increasing steadily. As Marr and Neely (2003) report, BSC is used by more than 60% the Fortune 1000 companies.

BSC reflects a balance between short-/long-term objectives, financial/non-financial measures, lagging/leading indicators, and external/internal measures. It differs from a typical performance measurement system in its emphasis on linking and aligning multiple measures to strategic objectives.

BSC is a method for conceptualizing the strategic alignment between business goals and specific tactics. It views an organization from four perspectives: financial measures, customer satisfaction, internal operations, and company learning and growth (including employee satisfaction). It provides feedback to both the internal business processes and the external outcomes for continuous improvement in strategic performance. Since IT outsourcing is a business-related decision, not simply a technology need; and BSC can transform business unit's strategy into a linked set of measures that define both the long-term strategic objectives and the mechanisms for achieving those objectives, it is reasonable to use BSC to translate a firm's outsourcing vision into a set of performance indicators. Through the use of BSC, an organization can monitor its existing performances in finance, customer satisfaction, and operations efficiency; and motivate and educate employees, and enhance their ability to learn and improve. A BSC-based outsourcing decision model will provide management with a transparent tool to align outsourcing decisions with the company's mission and vision.

In the next subsection, we identify the outsourcing evaluation metrics under the framework of BSC. We examine the applicability of BSC in outsourcing decisions, and integrate the four perspectives of BSC with the IT outsourcing strategies in the hope that the technological decision of outsourcing is in consonance with, supports, and enhances the vision of the firm.

4.1.1 Customers' Perspective

From the customers' perspective, firms are to provide them with quality goods and services at a stable and reasonable price, whenever and wherever they need. In other words, to achieve customer satisfaction firms need to deliver maximum value to their customers. Therefore, the winning formula is to provide timely, convenient, and high quality products and services to customers, while ensuring the availability and price stability. Customer satisfaction is essential for customer retention and new customer acquisition, which translates to lower cost of sales (COS) and higher revenue.

Due to their technology specialization, IT vendors often can directly provide for or indirectly facilitate better quality of goods or services than the in-house team can. Superior IT vendors can also support a firm's efforts in improving its credibility and image towards it customers, and in gaining the trust of its customers. Furthermore, IT outsourcing could present the possibility for firms to increase business activity and gain market access and business opportunities. It is particularly meaningful during the periods when expansion opportunity cannot be financed and resources are not available internally.

Successful outsourcing has the potential to bring tremendous value to customers, employees, and shareholders. On the other hand, outsourcing often opens up a firm's customer database to its vendor, which increases the risk of the firm's customer information being compromised. Furthermore, if a company's IT vendor is inexperienced, it could cause customer un-satisfaction. Therefore, prudent vendor selection, careful contract negotiation, and vigilant monitoring of daily operations are critical in minimizing such risk.

4.1.2 Financial Perspective

The financial perspective looks at creating long-term shareholder value through cost reduction, value creation, and profit-seeking. Outsourcing allows firms to free up internal manpower and resources, and ease up the need for management oversight. As a consequence of the provider's economy of scale, IT outsourcing can often lead to cost reduction. Firms seeking cash infusion may indirectly increase capital by cutting down investments in fixed assets, and turning fixed costs into variable costs, which in turn will affect the cash flow of the company.

By taking advantage of external suppliers' lower costs, a firm can reduce its own "Fixed cost", "Variable cost" and "Human cost." Due to less capital expenditure, firms would free up funds, make capital available for other purposes, and achieve greater financial flexibility.

Another financial indicator is the industry leadership position of the firm. A better outsourcing strategy can increase a firm's competitive advantage, which in turn increases the market share of the company. Large market share normally implies better financial performance, which moves the company to a better financial position, and becomes the industry leader.

The financial indicator is the profitability of the firm. Even though cost savings usually lead to greater profitability, there is a potential risk of transition costs and project and vendor management costs, which can greatly offset the savings, resulting in profit decrease. It is clear that a firm's profitability is greatly affected by IT outsourcing decisions.

4.1.3 Internal Operations Perspective

To meet customers' expectations with timely and quality goods and services, organizations need to identify and concentrate on the core processes and activities that are directly linked with the revenues and profitability. A firm may consider outsourcing the non-core activities, in order to excel at core business processes, improve company focus, and increase operating efficiency. By minimizing routine maintenance and nonessential infrastructure in IT, a firm can apply its internal resources to meet changing business conditions, accelerate reengineering, and improve response time.

Experienced and competent vendors make client firms agile, responsive to market needs, and technologically smart. Client firms become more flexible, because they can obtain extra capacity and new technologies whenever they are in need. High flexibility enables a firm to react quickly to changing business environments and market situations. However, some companies are found to have lost the control over outsourced activities. Therefore, prudent vendor(s) selection, careful coordination, integration, and supervision are necessary.

The "quality of products or services" indicator is unique since it is considered important under both the customers' and the internal operations' perspective. Under the concern of internal operations, "quality" is often associated with certifications and professional licenses, which many companies pursue to ensure proper processes for efficient and effective production of goods and services.

Finally, partnering with outsourcing vendors helps a firm to obtain technologies, develop world-class capabilities, as well as share operational risks, consequently improving infrastructure and broadening operational reach.

4.1.4 Company Learning and Growth Perspective

Innovation, management expertise, employees' competency and development, and the organization's effectiveness are parts of the intangible assets that are critical for the success of a knowledge-based company, as well as an integral part of the company's learning and growth. For socially responsible employers, outsourcing frees up human resources and provides them with the opportunity to retrain their employees to learn new skills and technology. Learning cutting-edge technologies brings employees closer to formulating new concepts and generating novel ideas. However, many firms found outsourcing makes employees anxious and insecure, which may deplete a firm's skill-base, and reduce learning and growth potential. The pressure of creating greater immediate profit can also push the management to lower re-training budget, which contributes to additional IT workers being laid off and the dissatisfaction of those in need of retraining.

On the other hand, by tapping into provider's world-class IT capabilities, firms can reallocate more resources to focus on organizational effectiveness, management expertise, and technology research and development. Therefore, well planned resource allocation post outsourcing could make the company more capable in innovation and R&D, while inferior resource allocation will do the opposite. Thus, the choice of outsourcing and subsequent strategy may either enhance or weaken the technology research and development for new products and/or services. Finally, as an important indicator to company learning and growth, a company's other know-how is affected by different outsourcing strategies.

4.1.5 Strategic Alternatives

Three different IT outsourcing strategies (strategic alternatives) are identified for our analysis – *Insourcing*, *Outsourcing* and Selective Outsourcing (*SelectOut*). They are defined by Lacity and Willcocks (2000), and they represent the set of strategic options available for companies, when considering IT outsourcing. Below is a discussion of the three strategic alternatives.

- *Insourcing*. *Company retains the management and provision of more than 80% of the IT budget internally* (Lacity & Willcocks, 2000). It used to be the preferred option for large corporations, such as US Steel. Others have long followed the path of Kodak and outsourced majority of their IT department starting in the early 90s. Even today some world-class corporations such as the Shanghai Baosteel Group, China's largest and most highly modernized high-end steel plate producer and Anshan Iron & Steel Group, the second largest steel maker in China, continue relying on their own IT department (*Insourcing*) for their manufacturing related IT needs. (go to: http://english.hanban.edu.cn/english/BAT/155653.htm, and http://www.chinadaily.com.cn/english/doc/2005-08/16/content_469340.htm)
- *Outsourcing*. Lacity and Willcocks (1998) define it as *the decision to transfer IT assets, leases, staff, and management responsibility for delivery of IT services from an internal IT function to an external IT provider which represents more than 80% of the IT budget.* It is the type of IT outsourcing that has been put into practice by many in recent years. Since Kodak, both success and failure stories have been reported abundantly.
- Selective outsourcing (*SelectOut*). This strategy entails selectively outsourcing certain IT functions. According to Lacity and Willcocks (Lacity & Willcocks, 1998), selective outsourcing is "*to source selected IT function from external provider(s) while still*

providing between 20% and 80% of the IT budget internally." For companies which heavily emphasize the safety and security of their customer database, selective outsourcing is often the practice of choice. Cullen and Willcocks (2003) find selective outsourcing tends to have lower risk. For example, to ensure customer privacy, Giant Eagle Supermarket Chain, Highmark Health Insurance, and PNC Bank all have their customer database securely maintained in-house, but have IT vendors providing other services. In Giant Eagle's case, it has its own fully staffed IT department, but it outsourced its HR and payroll service to Oracle (formally PeopleSoft). Another situation where selective outsourcing is preferred is software companies that own certain proprietary or patented software.

In conjunction with any of the above three options, firms can periodically purchase external IT resources to supplement or enhance their existing IT capabilities. For example, many steel makers, large and small around the world, have purchased steel-making software packages and services from US Steel and other top U.S. companies.

Our decision model applies ANP (Saaty, 2005) to formulate BSC metrics into an integrated evaluation framework. We will show that the proposed model is both practical and robust, via an empirical case study. More importantly, we demonstrate the superiority of our framework as compared to traditional BSC implementations of not considering indicator interactions. Our model provides important insights and is easily adaptable to various companies when different conditions and specific needs are encountered.

4.2 THE BSC-ANP MODEL AND RESULTS

As discussed earlier, a key feature of BSC proposed by Kaplan and Norton (1996) is the interaction (or influences) of indicators with each other both within and between each perspective (see Figure 12 below). Most of the past implementations of BSC have failed to include these interactions. Interaction with other indicators may increase or decrease the intensity of the overall importance of the indicators. By not including the interactions, the power and accuracy of the evaluation system is significantly weakened. Therefore the existing applications of BSC without looking into interaction effects compromises BSC's potential. In the following, we apply ANP to implement the BSC framework for outsourcing strategy selection. ANP is designed to cope with both qualitative and quantitative indicators (criteria) and also to account for the interactions between criteria, clusters of criteria, actors, and alternatives. The pairwise comparison method in ANP also simplifies the prioritization of criteria. Therefore, it is the most suitable instrument for developing a BSC-based outsourcing strategy selection model.

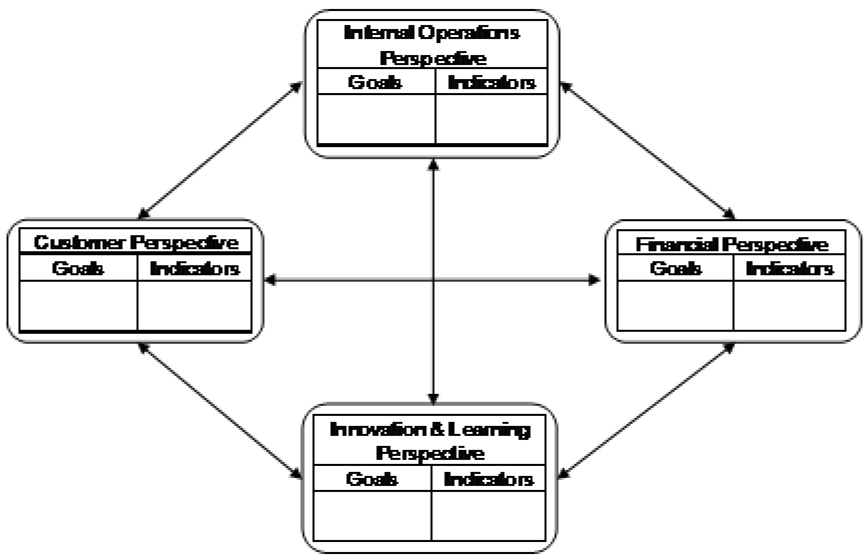

Figure 12 Basic BSC Framework

In our BSC-ANP model, the analysis network consists of nodes representing decision criteria and alternatives and arcs depicting relationships between criteria and alternatives. An arc is present between a pair of nodes only when there is significant interaction (with a two way arrow) or impact from one to the other (with a one way arrow) and vice versa. After all the necessary connections are made, criteria are parirwise compared according to Saaty (1980), both within and between clusters. For instance, when comparing the criteria within the internal operations cluster with respect to the *Profitability* criterion in the financial cluster, we capture the relative importance of internal operations criteria when *Profitability* is concerned. To demonstrate the proposed framework, we empirically address the IT needs of a Pittsburgh-based construction company. The studied firm is a commercial building contractor that generates approximately $50 million revenue annually. A recent system problem almost caused serious delay to the bid submission of an important project. This could have resulted in the loss of a sizeable contract. To ensure quality and on-time bidding document preparation and submission, management of the company was compelled to reconsider streamlining their IT functions, where IT outsourcing is one of the options. The situation warrants a comprehensive study and this research was motivated by the need to assist with their decision, The authors were provided with access to key personnel of the company, and were readily accepted for an across-the-board examination. Top executives of the firm, including the owner and CEO of the company, were interviewed to establish alternatives and criteria, connect elements in the network, and determine the numerical inputs of the base ANP model.

Besides the base case, the applicability of the proposed model is validated in the "what-if" analysis. We examine various cases in the sensitivity analyses. As we know different companies and different decision makers have different views, objectives, and goals based on the firm's vision, mission, and overall strategy. How can one model incorporate such diverse views, objectives, and goals? This question is answered by way of the ANP sensitivity (what-if) analysis.

The criteria used for evaluating the IT outsourcing strategic alternatives are the performance metrics in each of the four BSC perspectives. The overall goal of the proposed model is to derive a numerical score for each of the strategic alternatives. The thoroughness and comprehensiveness of the BSC framework plus its proven records in company performance measurement and strategy evaluation also adds reliability to our approach as an instrument for evaluating different IT outsourcing strategies. Firms faced with the IT outsourcing decision will be able to use our model and modify it with their specific judgments to derive the alternative scores reflecting their own situations.

4.2.1 Model Structure

Table 16 lists 17 performance indicators, used in our BSC-ANP model, along with a brief description of each. They are established based on their relevance in the context of outsourcing decision making.

Table 16 List of Relevant BSC Performance Measurement Indicators with Descriptions

BSC Perspectives	Description of Balanced Scorecard Indicators & Corresponding ANP Criteria		
	Indicator Name	Description	ANP Criteria
Customer	Availability of Product/Service	Product or service availability to customers	AvailabilityPS
	Customer Database	The firm's customer information database and how well it has been managed	Database
	Customer Satisfaction	Customer satisfaction survey results	Satisfaction
	Price Stability	Stability of product/service prices to customer	PriceS
Financial	Cash Flow	Improved cash flow due to capital infusion	CashFlow
	Cost Savings	Cost of sales reduction due to vendor's efficiency and economy of scale	CostSavings
	Industry Leadership	Measured by the increased revenue and market share	IndLeader
	Profitability	As measured by the firm's ROI and/or EVA	Profitability
Internal Operations	Agility	Firm's responsiveness to change – new or changing demand	Agility
	Certifications	Professional licenses, and quality or environmental certifications	Certifications
	Core Focus	Firm's success in focusing on its core business processes	CoreFocus
	Internal Control	Firm's ability to control all its business processes and departments	InternalControl
	Quality	The quality improvement of firm's products/services	Quality
Company Learning & Growth	Employee Competency	The competency of the firm's employees	EmpCompetency
	Employee Satisfaction	The satisfaction level of employees based on salary and/or promotions within	EmpSatisfaction
	Management Knowhow	Management expertise and other know-how to facilitate innovation and learning	MgtKnowHow
	Technology RD	Technology research and development effort and success	TechRD

Figure 13 below gives the overview of the proposed framework. The grouping (clustering) of the criteria is based on the four perspectives of BSC. The top portion of Figure 13 is a network of the 17 BSC performance indicators, alias the criteria for the firm's outsourcing decision. The construction of the network is based on close examination of each criterion. A one-way arrow is placed between node A and node B only when A influences B or vice versa. One-way arrows can also represent subordinate relationship between nodes. A two-way arrow is placed between node A and node B when changes in A affect B, and at the same time, changes in B affect A. In other words, two-way arrows as well as some one-way arrows are used to illustrate the interdependencies (interactions) of criteria within clusters and between clusters.

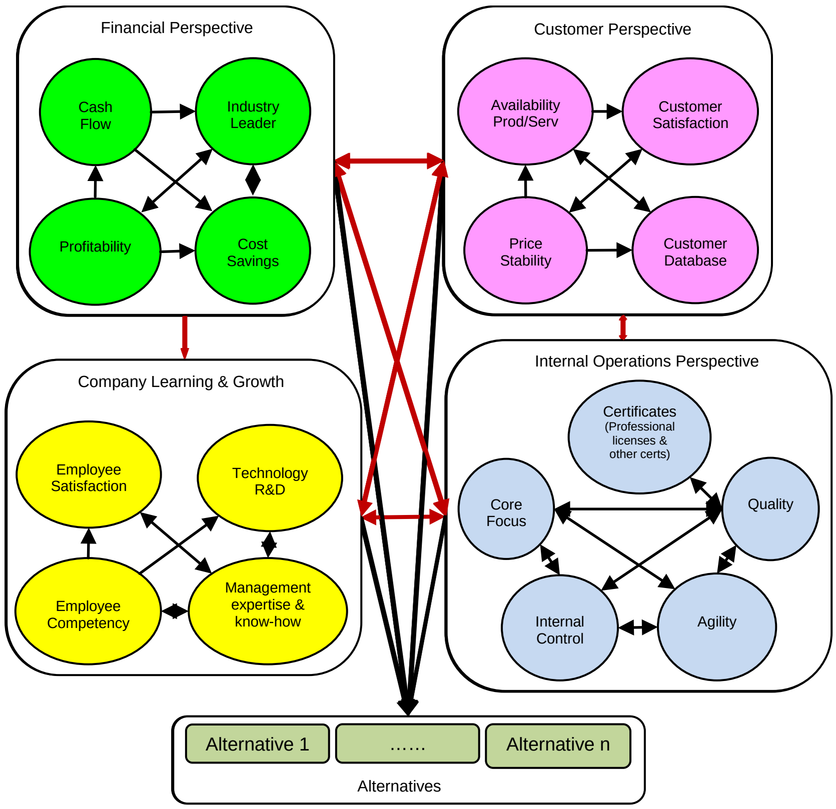

Figure 13 Firm Level Strategic Decision Framework

Figure 14 below shows the detailed network connections, of the 17 BSC performance indicators, (criteria) representing relationships and interactions amongst the indicators.

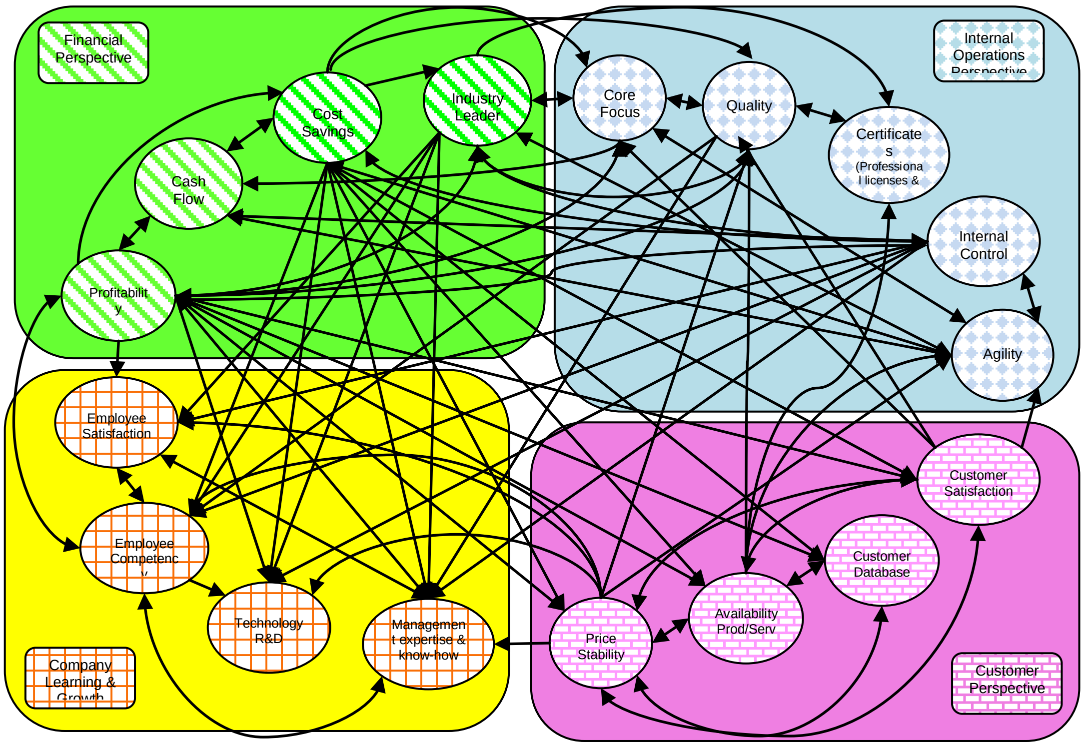

Figure 14 Detailed Network

Due to the existence of interactions among some of the performance indicators (criteria) both within and between perspectives (clusters), without using ANP, it would have been very difficult to determine their weights (importance or priorities) numerically. ANP helps us derive the global priorities of the criteria by first pariwise comparing them with regard to their BSC perspective and then to all other criteria which they interact with (or have influence on). Next, each normalized comparison matrix is taken to the limit to calculate the local priority of every criterion. In the last step, a supermatrix consisting of all the local-limiting matrices is formed for overall criteria prioritization and alternative ranking. The weighted supermatrix is taken to the limit for the final results. Table 17 shows the pairwise comparison results of the four criteria with respect to Financial Perspective and the derived local priorities of those criteria within the Financial Perspective cluster. In Figure 14, we find financial indicators such as *Profitability* and *Cost Savings* interact with indicators under the other three perspectives. To understand such interaction effects, Table 18 gives an example pairwise comparison of indicators under the *Customers Perspective* with respect to the financial indicator *Profitability*. The last row of Table

18 shows the local priorities of the *Customers Perspective* indicators when the financial indicator *Profitability* is concerned, these local priorities represent the importance ranking of the indicators with respect to *Profitability*. Table 19 shows the global priorities of all 17 criteria derived by taking the limit of weighted supermatrix of the ANP model. The 10 highest scored criteria are in boldface and are underlined.

Table 17 Pairwise Comparisons of Criteria within the Financial Perspective

Pairwise comparisons of the criteria within the *Financial* perspective cluster with respect to the *Financial* Node				
	CashFlow	CostSavings	IndLeader	Profitability
CashFlow	1	1/5	1/2	1/7
CostSavings	5	1	2	1/2
IndLeader	2	1/2	1	1/3
Profitability	7	2	3	1
Local Priorities	0.0671	0.2908	0.1473	0.4948

Table 18 Pairwise Comparisons of Criteria within the Customers Perspective

Pairwise comparisons of criteria within the *Customers* perspective cluster with respect to the financial criterion *Profitability*				
	AvailabilityPS	Database	PriceS	Satisfaction
AvailabilityPS	1	4	2	1/2
Database	1/4	1	1/2	1/5
PriceS	1/2	2	1	1/3
Satisfaction	2	5	3	1
Local Priorities	0.2879	0.0809	0.1539	0.4773

Table 19 Criteria in the BSC-ANP Model, Ranked by Priority.

Criteria Global Priorities		
	Criterion Name	Priority
Customers	AvailabilityPS	0.05695
	Database	0.03934
	PriceS	0.04269
	Satisfaction	0.11730
Financial	CashFlow	0.01178
	CostSavings	0.04054
	IndLeader	0.04076
	Profitability	0.05031

Criteria Priorities Sorted	
Criterion Name	Priority
Satisfaction	**0.11730**
AvailabilityPS	**0.05695**
Profitability	**0.05031**
MgtKnowHow	**0.04758**
Agility	**0.04340**
PriceS	**0.04269**
Quality	**0.04245**
CoreFocus	**0.04233**

Internal Operations	Agility	0.04340		**IndLeader**	**0.04076**
	Certifications	0.01765		**CostSavings**	**0.04054**
	CoreFocus	0.04233		Database	0.03934
	InternalControl	0.02854		TechRD	0.02970
	Quality	0.04245		InternalControl	0.02854
Company Learning & Growth	EmpCompetency	0.02228		EmpCompetency	0.02228
	EmpSatisfaction	0.01172		Certifications	0.01765
	MgtKnowHow	0.04758		CashFlow	0.01178
	TechRD	0.02970		EmpSatisfaction	0.01172

4.2.2 The Evaluation of Strategic Alternatives

The three strategic alternatives are pairwise compared under each of the 17 criteria. The example questions asked for pairwise comparisons of the alternatives are: "with respect to a specific criterion, is outsourcing better than insourcing and if the answer is yes, then how much better?" An inverse value is chosen if under the specified criterion, the *Insourcing* is a better alternative than *Outsourcing*. Similar to criteria rankings, each set of comparison matrix is used to calculate the local rankings of the alternatives. These local rankings of the alternatives are included in the supermatrix for final calculation (or synthesis). The composite scores of the alternatives are the overall rankings of the alternatives. They are summarized as the final synthesized alternative rankings given in Table 20. Pursuing selective outsourcing is the clear winning strategy for the case company.

Table 20 Priorities of Strategic Option

Overall Alternative Rankings - ANP			
Name	Ideals	Normals	Raw
Insourcing	0.6579	0.2650	0.0417
Outsourcing	0.8252	0.3323	0.0523
SelectOut	1	0.4027	0.0634

4.2.3 Sensitivity Analysis

To understand how criteria priorities may affect the final outcome of alternative rankings, we conducted the "what-if" analysis using the SuperDecisions software. We apply the model to different scenarios, and examine the situations in which a firm's motivation and concerns toward outsourcing vary. Scenario 1 a company considers *Agility* as its number one priority followed by *AvailabilityPS* (Product or service availability to customers). In scenario 2, managers of the company are very conscientious about customer satisfaction as well as the safety and security of their customer database, and believe that the company's success depends upon them. In the third scenario, firm's management strives for rapid response to changing customer demands and believes that a high level of internal control is necessary to achieve it. *Agility* (timely and cost-effective execution) and internal control are regarded as keys to firm success. The different objectives and focus dictate different views on the relative importance of these BSC indicators: *Satisfaction, AvailabilityPS, Quality, Agility, InternalControl,* and *Database*. We show below an approach managers can take to conduct analyses in various situations. By changing priority distribution of the indicators (criteria) in the "what-if" analysis, decision makers are able to derive a set of scores for various scenarios faced by this diverse group of firms.

We first conduct single variable sensitivity analysis by varying the priority of *Database*. And the results are shown in Table 21 below

Table 21 The Alternative Scores Change as Database Priority Changes

Database Priority	*Insourcing*	*Outsourcing*	*SelectOut*
0.0001	0.2573	0.3369	0.4058
0.0715	0.2631	0.3334	0.4035
0.1429	0.2689	0.3300	0.4011
0.2143	0.2747	0.3265	0.3988
0.2858	0.2805	0.3231	0.3964
0.3572	0.2863	0.3196	0.3941
0.4286	0.2921	0.3162	0.3917
0.5	0.2979	0.3127	0.3894
0.5714	0.3037	0.3093	0.3870
0.6428	0.3095	0.3058	0.3847
0.7142	0.3153	0.3024	0.3823
0.7857	0.3211	0.2989	0.3800

0.8571	0.3269	0.2955	0.3776
0.9285	0.3327	0.2920	0.3753
0.9999	0.3385	0.2886	0.3729

We next conduct a 4-step sensitivity analysis using 6 out of the 17 criteria: *Satisfaction*, *AvailabilityPS*, *Quality*, *Agility*, *Database*, and *InternalControl*. They are selected due to their importance, as stated by the companies we interviewed and furthermore, five of the six are the highest scored criteria (see Table 19). The last criterion, *InternalControl* is often viewed as a countering force against outsourcing and is much emphasized by one of the contacted managers. The SuperDecisions software conducts sensitivity analysis by changing the criteria weights one at a time while holding the relative weights of the other criteria constant. Figures 15, 16, and 17 shows the three sets of alternative rankings based on three different combinations of criteria weights for the three example companies A, B, and C.

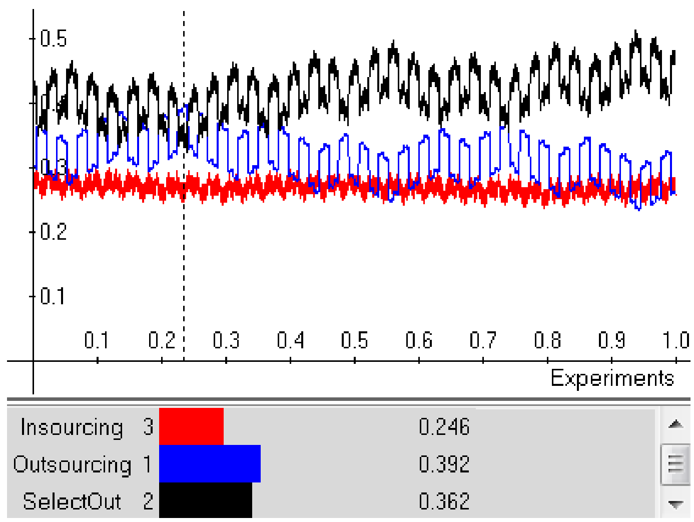

Figure 15 For Company A

Figure 15 shows the alternative rankings for scenario 1. The company views *Agility* as extremely important, followed by *AvailabilityPS*, while others are less important. The alternative scores are: *Insourcing* = 0.246, *Outsourcing* = 0.392 and *SelectOut* = 0.362 respectively. Therefore for company A, the BSC-ANP model recommends it to pursue *Outsourcing*, with *SelectOuts* as a close second.

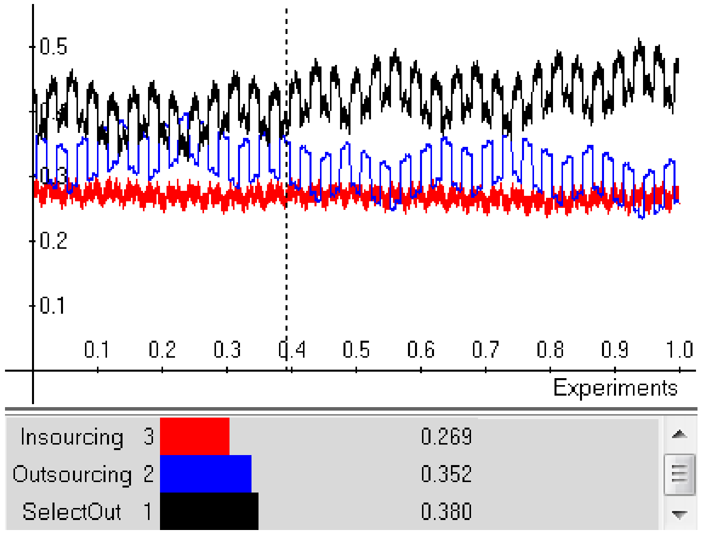

Figure 16 For Company B

For company B, Figure 16 demonstrates that given customer *Satisfaction* as the most important criteria followed by Database security, the difference amongst the alternative rankings are relatively small: *Insourcing* = 0.268, *Outsourcing* = 0.352 and *SelectOut* = 0.380 respectively. The best choice for company B is selective outsourcing, same as our base case company, but unlike the base case company, *Outsourcing* is ranked not too far behind it.

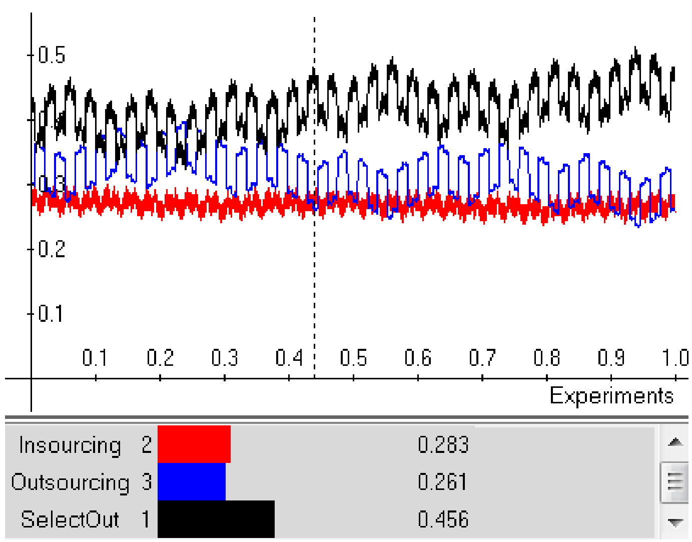

Figure 17 For Company C

Figure 17 shows the alternative rankings for company C, under a different set of criteria priorities distributions: *Insourcing* = 0.283, *Outsourcing* = 0.261 and *SelectOut* = 0.456 respectively. Interestingly, even though selective outsourcing is still ranked the highest, *Insourcing* is ranked the second highest above *Outsourcing*. It is clear that this is due to the weight of *InternalControl*.

4.2.4 The Significance of Criteria Interaction

In order to compare our BSC-ANP approach with a BSC model that does not include the interactions amongst decision criteria. We re-create the model by removing all the arcs that represent interactions. By doing so, the model is converted into a BSC-AHP model with all criteria organized into a two level hierarchy. The same procedure as the ANP model is used to derive the global priorities for the 17 criteria, the results are shown in Table 22. As we can see, there is a significant difference in the criteria rankings between the two models. For instance, the criterion *Profitability* is ranked 15th in the BSC-ANP model, but is ranked 2nd in the BSC-AHP model. The questions then become: (1) does this priority shift make sense intuitively? (2) Can we explain the shift mathematically or theoretically? (3) Is it justified to use a more complex interaction model rather than a simpler no-interaction model? The answers to all three questions are affirmative. By comparing the two Tables 19 and 22 side by side, we can see an increase in the priorities of customer perspective criteria and a decrease in priorities of financial perspective criteria. Undoubtedly, a financial indicator, such as *Profitability*, is important to a firm, but it is largely driven by the customer indicators such as *Satisfaction* and *AvailabilityPS*. In other words, intuitively, these results agree with our common sense.

Table 22 Criteria Rankings without Interaction

Criteria Priorities Sorted	
Criterion Name	Priority
Satisfaction	**0.071058**
Profitability	**0.043936**
PriceS	**0.037087**
CostSavings	**0.02582**
AvailabilityPS	**0.023823**

CoreFocus	**0.019811**
Quality	**0.016715**
MgtKnowHow	**0.016419**
Agility	**0.013287**
IndLeader	**0.01308**
Database	0.012968
TechRD	0.011648
InternalControl	0.01047
EmpCompetency	0.007547
CashFlow	0.005958
EmpSatisfaction	0.004787
Certifications	0.004087

4.2.5 The Recommended Strategy for Case Company

We have applied ANP methodology on a BSC model for the IT outsourcing strategy selection. With the criteria priorities derived from the numerical input of the base case company, our initial results show that *selective outsourcing* scores the highest amongst all three alternatives under consideration. *Outsourcing* came in second and *Insourcing* last. We experiment the six key criteria with different weights (5%-60%) for multiple replications. The overall sensitivity analysis results show that within the entire analysis spectrum, *Insourcing* is the lowest scored alternative for at least 65% of the analysis spectrum, whereas *SelectOut* ranks the highest in about 95% of the sensitivity analysis domain. The sensitivity analysis results demonstrate both the robustness and responsiveness of the proposed model, and they concur with the survey results conducted by Lacity and Willcocks (2000) in 2000. Furthermore, they also provide us with an explanation for the widespread acceptance and practice of selective IT outsourcing by companies large or small. Upon closer examination of the conditions under which *Outsourcing* ranked higher than *SelectOut* we find that *Database* security and *InternalControl* are both at their lowest priority, which is in agreement with common sense.

As illustrated in the "what-if" analysis, our evaluation framework can be adopted by vastly different companies considering IT outsourcing. The Balanced Scorecard approach to decision making ensures the breadth and depth of the decision process, and hence adds to the reliability of the recommended strategy.

Based on the recommendation made to our case company, i.e. to pursue selective IT outsourcing, we further prioritize the firm's assorted IT functions to determine the best ones for outsourcing.

4.3 THE AHP RATINGS MODEL FOR OPERATIONAL DECISION

To prioritize the IT functions for outsourcing, we employ an AHP ratings model (Figure 18 below), using the criteria provided by the company along with the outsourcing criteria suggested by Cullen and Willcocks (2003). When evaluating multiple IT functions for outsourcing, management has to assess tradeoffs of alternatives among various criteria. The evaluation structure and the process may grow cumbersome and impart difficulty in maintaining consistency. Furthermore, when alternatives are many, the number of pairwise comparisons of alternatives can become very large. In the current case of 8 alternatives, 28 pairwise comparisons are needed under each criterion, combining those with 14 criteria, we will have a total of 392 pairwise comparisons of alternatives. With an AHP ratings model, each alternative is evaluated as to how it performs on each criterion. It provides consistent evaluation of alternatives while dramatically shortens the number of judgments required and therefore, it is the perfect choice for our purpose. In the model, each IT function, under consideration for outsourcing, is evaluated on the same four sets of relevant criteria: *Benefits*, *Opportunities*, *Costs*, and *Risks* (BOCR). The ratings obtained from each set of criteria are then synthesized using the Additive Negative formula (Saaty, 2005). Next, we discuss the details of our AHP ratings model developed for the case company.

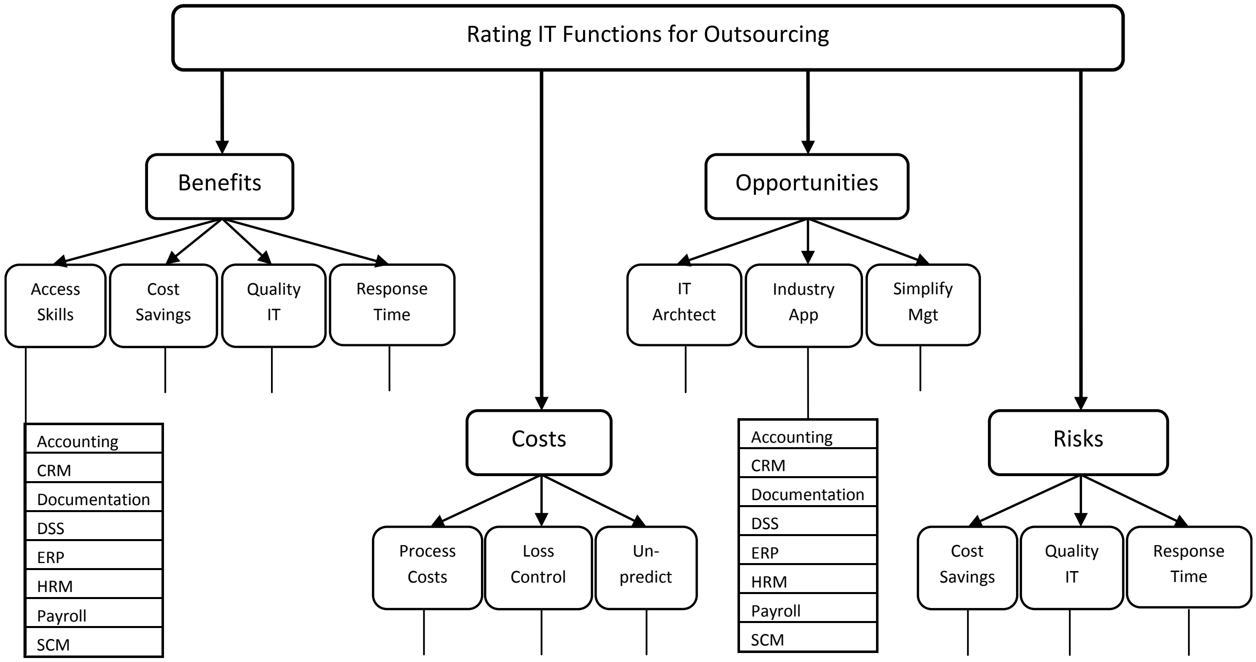

Figure 18 AHP Ratings Model for Selecting IT Function to Outsource

The evaluation criteria are grouped into BOCR clusters according to Saaty's (1980) original framework. In assigning a specific criterion to a category, a qualitative approach is used where both the appropriateness and the importance are considered. In general, a definite positive impact of outsourcing, which is to occur in the near future, is placed under the *Benefits* cluster, whereas a definite short-term negative impact is assigned to the *Costs* cluster. Long-term, uncertain factors are allocated to either *Opportunities* or *Risks*, depending on whether they bring a positive or negative impact on the firm. The clusters and a brief description of each criterion are given in the following subsections.

4.3.1 Benefits Criteria

The most cited benefit of IT outsourcing is still cost savings (*CostSavings*), which can be achieved through the introduction of competitive processes and taking advantage of vendors' economy of scale as well as their lower labor costs. When companies streamline IT services, they can improve the response time (*ResponseTime*) or shorten lead time. Often, IT outsourcing brings high quality and reliable IT services (*QualityIT*) plus better IT planning which results in improved operational efficiency and removes internal inflexible working practices. When special skills and leading edge technology are not available internally, companies gain access (*AccessSkill*) to those skills and technologies through outsourcing. Improving cost structure (*ImpCostStructure*) is another key benefit very important to our case company. By transforming fixed costs to variable costs, companies can reduce capital spending and bring cash flow relief (by selling assets or transferring staff).

4.3.2 Opportunities Criteria

For this ratings model, the long term positive impact of IT outsourcing considered are (1) compensation to the inadequate IT architecture of the in-house IT (*ITarchitectures*); (2) leverage industry specific application; and (3) simplify management (SimplifyMgt) agenda in order to achieve better core focus and improved customer focus.

4.3.3 Costs Criteria

Besides transaction costs, companies also incur monetary costs when conducting outsourcing projects and monitoring vendor performance, those are combined into one criterion: process costs (*ProcessCosts*). An outsourcing project is only worthwhile to consider when the cost savings is considerably greater than the process costs. Other than monetary cost, another cost resulting from IT outsourcing is loss of control over key IT functions (*LossControl*). Furthermore, some IT functions have high variability which makes the usage requirements impossible to anticipate (*Unpredictability*). For instance, due to the rapid change in numbers of temp workers, the payroll processing of our case company involves significant changes from month to month. It is almost impossible to estimate the work load for every month.

4.3.4 Risks Criteria

Three factors cause the most concern to the management of our case company. They are: (1) not meeting expectation or expectation cannot be anticipated (*FailExpectation*); (2) unreliable vendors (*UnreliableVendor*) – vendor instability, inadequate skills, and unreliability; and (3) the security risk of preparatory data (*SecurityConcerns*) and internal knowledge.

4.3.5 Outsourcing Candidates – IT Functions

The alternatives (candidates) in the AHP ratings model are the IT functions currently under consideration for outsourcing by the case company. They are identified as: Accounting, Customer Relationship Management (CRM), Documentations, Decision Support System (DSS), ERP (including job scheduling/project management, and inventory management), Human Resources Management (HRM), Payroll, and Supply Chain Management (SCM).

4.3.6 Outsourcing Candidates – Prioritization

Since this model is specifically designed for the case company, the numerical model input is based on the views of the case company staff members and upper management. The firm's CIO, with the help of the IT group, first derives the criteria weights through pairwise comparisons (Table 23 shows the sample questions and Table 24 is the corresponding comparison table); such results are then corroborated by the company's CEO. The BOCR-based AHP ratings model, along with all criteria weights, is shown in Figure 18, which gives a complete model construct.

Table 23 Sample Interview Questions

For Table 24, (green shaded cells) the respondents are asked the following question:						reverse
With respect to the goal of maximizing benefits, how much more important is *Costsavings* than *AccessSkills?*	1	3	5	7	9	
With respect to the goal of maximizing benefits, how much more important is *Costsavings* than *QualityIT?*	1	3	5	7	9	

With respect to the goal of maximizing benefits, how much more important is *Costsavings* than *ResponseTime?*	1	3	5	7	9	
With respect to the goal of maximizing benefits, how much more important is *AccessSkills* than *QualityIT?*	1	3	5	7	9	√

Table 24 Pairwise Comparisons Based on Interview Process

Pairwise Comparison of Benefits Criteria With Respect to the Goal of Maximizing Benefits of IT Outsourcing				
	AccessSkills	*CostSavings*	*QualityIT*	*ResponseTime*
AccessSkills	1	1/7	1/3	1/4
CostSavings	7	1	3	2
QualityIT	3	1/3	1	1/2
ResponseTime	4	1/2	2	1

Next, the company's personnel are further involved in rating the alternatives under each criterion using an absolute scale. For instance, the *CostSavings* criterion uses a 5-level scale: Very High, High, Medium, Low, and Very Low. When considering outsourcing the company's ERP system, the question asked would be: will outsourcing the firm's ERP system bring about very high, high, medium, low, or very low *CostSavings*? Table 25 shows the ratings of alternatives under *Benefits* criteria, *Costs* criteria, *Opportunities* criteria, and *Risks* criteria.

Table 25Alternative Ratings – Under B, O, C, and R

Name	Ideals	Normals	Raw
Accounting	0.5359	0.1048	0.1048
CRM	0.6471	0.1266	0.1266
Documentation	0.5166	0.1010	0.1010
DSS	0.6181	0.1209	0.1209
ERP	1	0.1956	0.1956
HRM	0.4474	0.0875	0.0875
Payroll	0.6586	0.1288	0.1288
SCM	0.6891	0.1348	0.1348
Under *Benefits*			

Name	Ideals	Normals	Raw
Accounting	0.6250	0.1139	0.1139
CRM	0.5237	0.0955	0.0955
Documentation	0.6966	0.1270	0.1270
DSS	1	0.1823	0.1823
ERP	0.9283	0.1693	0.1693
HRM	0.4257	0.0776	0.0776
Payroll	0.4553	0.0830	0.0830
SCM	0.8303	0.1514	0.1514
Under Opportunities			

Name	Ideals	Normals	Raw
Accounting	0.3370	0.0618	0.0618
CRM	0.8059	0.1479	0.1479

Name	Ideals	Normals	Raw
Accounting	0.5961	0.1052	0.1052
CRM	0.8818	0.1557	0.1557

Documentation	0.3498	0.0642	0.0642
DSS	0.5752	0.1056	0.1056
ERP	1	0.1835	0.1835
HRM	0.6459	0.1185	0.1185
Payroll	0.9948	0.1826	0.1826
SCM	0.7404	0.1359	0.1359
Under *Costs*			

Documentation	0.5271	0.0930	0.0930
DSS	0.6059	0.1070	0.1070
ERP	0.7931	0.1400	0.1400
HRM	0.3202	0.0565	0.0565
Payroll	1	0.1765	0.1765
SCM	0.9409	0.1661	0.1661
Under *Risks*			

The overall ratings of all the alternatives are summarized in Table 26 below. They are derived using the Additive Negative formula as proposed by Saaty (2001). It is clear that *Documentation* is the top one on the list with the highest score, whereas Payroll is on the bottom with the lowest score.

Table 26 Overall Alternative Ratings

Name	Ideals	Normals	Raw
Documentation	1	0.2149	2.1487
DSS	0.9085	0.1952	1.9521
Accounting	0.8542	0.1836	1.8354
ERP	0.5996	0.1289	1.2884
HRM	0.4717	0.1014	1.0136
SCM	0.4207	0.0904	0.9041
CRM	0.2443	0.0525	0.5249
Payroll	0.1544	0.0332	0.3318

Based on the ranking results shown in Table 26 above, it is recommended to first consider outsourcing its Documentation, Decision Support Systems, and possibly the Accounting functions, while keeping Payroll and Customer Relationship Management in-house.

4.4 FIRM LEVEL OUTSOURCING RESEARCH, NOW AND FUTURE

This chapter summarizes a two-step decision making process originated from real life problems faced by a small commercial building construction company. A BSC-ANP model enabled us to recommend the strategy of selective IT outsourcing to the case company. The second step generated a prioritized list of IT functions (Table 26) to assist the case company in choosing the appropriate set of functions to outsource based on their available resources. The recommendations to the case company to first consider outsourcing *Documentation* while keep the payroll processing in-house was well received by the CEO and other company personnel assisting this research project.

Integrating BSC and ANP into an outsourcing decision model is one of the main contributions of this chapter, because the unified framework is significantly more superior than either BSC or ANP alone. Applying this integrated framework to outsourcing strategy selection is not only a novel approach, but also an instrument that links the selected strategy to a performance measurement system. Specifically, the decision criteria used to select the best strategy can be used as indicators to measure firm performance post-implementation of the chosen strategy.

Our BSC-ANP framework is a robust and comprehensive model with a high degree of sophistication. Nevertheless, as demonstrated in the sensitivity analysis, it can be easily adapted by a wide range of firms. The effectiveness of the framework combined with the model adaptability marks the main contribution achieved in this chapter. Providing a direct linkage between the selected strategy and the firm performance measurement system adds a new dimension to the model usefulness. The simplicity and transparency of the AHP ratings model makes it a perfect approach for prioritizing issues faced by small to midsized firms, such as our case company.

For future firm level outsourcing research, vendor selection, followed by contract negotiation would be the most logical steps to proceed with. Based on the final ratings of the functions and the resources needed, one can also use Goal Programming to select a set of IT functions to outsource based on resource restrictions.

5.0 CHAPTER 5 ECONOMIC IMPACT OF OUTSOURCING

In this chapter, we study the economic impact of outsourcing on individual firms by examining the relative changes in the firms' Tobin's q both pre-outsourcing and post-outsourcing. The purpose of the study is to forecast the possible economic performance change (as measured by changes in Tobin's q) associated with outsourcing of firms' business activities. Both traditional data analysis and advanced data mining tools were applied to outsourcing data to construct an empirical model for future prediction of likely economic impact of outsourcing.

5.1 CHAPTER OUTLINE

Outsourcing of business activities has been gaining ground in the business world since the early 1990s. The overriding issue of job loss brought on by the immediate impact of outsourcing, particularly offshore outsourcing, struck at the core of the U.S. social and political system. As a result, multi-dimensional in depth studies, as well as one dimensional analyses of the merits and perils of outsourcing, have been abundant. Surprisingly, little has been done with regard to the economic impact of outsourcing on firms engaged in that activity. In this chapter, we look into the economic issue from two different angles: (1) in what way, if at all, does the outsourcing contract amount impact a firm's future performance economically, and (2) does outsourcing have significant impacts on a firm's economic performance change?

In chapter 2, we examined the existing literature to demonstrate what motivated us to conduct the research presented here. Section 5.2 outlines the proposed approach. Section 5.3 details the modeling processes, to show how the models are constructed and how they are evaluated based on their summary statistics. Section 5.4 conducts further cross-method model comparison based on two important criteria – (1) the predictive power, i.e. how well the model predicts the response variable(s); and (2) the explanatory power, i.e. the our ability to decipher the derived function to draw meaningful managerial insights. Section 5.4 concludes with a presentation of the top performing models selected from the best models for each method. Section 5.5 concentrates on model as well as variable interpretation, and concludes with inferences of the managerial implications from the results. Section 5.6 gives a summary of the chapter with conclusions, and points out limitations as well as possible follow-up research.

5.2 PROPOSED APPROACH

Outsourcing data analysis focusing on the Tobin's q is carried out in this chapter. The Tobin's q change from the year prior to outsourcing (year minus 1) to the announcement year (year 0) represents the company's pre-outsourcing condition. The Tobin's q change from the year of the outsourcing announcement (year 0) to the year after the announcement (year plus 1) represents the company's post-outsourcing condition. We will be looking into: (1) whether and how does the outsourcing contract amount (relative to company size) impact the changes in Tobin's q? (2) Does the post-outsourcing change in Tobin's q significantly differ from that of pre-outsourcing? To answer the first question, extensive empirical modeling is carried out. We first explore various methods to find the best linear regression model as the basis of comparison for the final model's predictive power (forecasting performance) and its explanatory power (managerial interpretation). By applying different machine learning methods, the ultimate goal is to find (derive) the best prediction equation(s) for our variable of interest. In the exploratory process, we examine models created by applying neural networks, regression trees and support vector regressions (is this still going to be included?) to our data. The second question is answered by performing hypothesis tests using statistics obtained from pre and post outsourcing models.

5.2.1 Data Collection, Preparation, and Preprocessing

The outsourcing announcement data (including both the U.S. and foreign companies) collected from the Factivae database by Gao (2006) are used with the owner's permission. In her initial sample, Gao (2006) included 1296 firms publicly announcing an outsourcing contract from January 1, 1990 through December 31, 2003.

Out of the 1296 outsourcing announcements, 566 reported the outsourcing amount. Eliminating the government deals and those of non-profits, 290 cases were left. Because we were using firms' annual accounting data, multiple outsourcing announcements within one calendar year are combined into one entry. Due to limitations in the availability of reported accounting data, only 164 cases were successfully matched with their corresponding COMPUSTAT accounting data to form our master data-file. From the master data-file, we computed the relative deal size (contract amount divided by the company's market value of equity) as well as four years of Tobin's q for each firm. The calculated variables included: Tobin's q at one year before the outsourcing announcement (*Qtm1*); at the year of the announcement (*Qt*); at one year after the announcement (*Qtp1*); at two years after the announcement (*Qtp2*); changes in Tobin's q from year *t*-1 to year t (*ChgdBFO*); changes in Tobin's q from year *t* to year *t*+1 (*ChgdPost1*); and finally changes in Tobin's q from year *t*+1 to year *t*+2 (*ChgdPost2*).

Much of our analysis variables selection and sample assembly are parallel to those of Jiang et al. (2006), but with these exceptions. (1) In their empirical study of outsourcing effects on firms' operational performance, Jiang et al. (2006), manually eliminated cases in which firms were affected by other events such as lawsuits, strikes, acquisitions, mergers, etc. that could obscure the impact of outsourcing from the analysis sample. We choose to leave those in our dataset, because we intend to employ more sophisticated data mining technique to isolate or filter out such cases. (2) Jiang et al. (2006) only considered outsourcing contracts of more than 10 million dollars, because they believe that a small outsourcing contract amount result in a significant impact on a firm. In other words, they only included large companies with large outsourcing contract amount. We choose to include smaller contracts and smaller companies, and compute the relative deal size (contract amount divided by the market equity of the firm) because it is reasonable to assume that the economic impact of outsourcing is a function of the relative size of the contract, not on its absolute size. (3) Jiang et al. (2006) selected a separate control sample consisting of non-outsourcing firms to compare with their outsourcing counter parts. We choose to use the same firms, to conduct pre and post outsourcing comparison.

When selecting the independent variables for the analysis, we closely followed Jiang et.al (2007) and Table 27 lists their variable descriptions. Jiang et.al (2007) assessed the effects of outsourcing by examining outsourcing companies' market value, which reflects firms' future revenue-generation potential. Firms' outsourcing decision at time *t* along with their accounting variables at time *t*, were analyzed to discover whether and how they affect firms' market value. Japanese manufacturing industries data from 1994 to 2002 were used for their study. They found that core business-related outsourcing, offshore outsourcing, and shorter-term outsourcing had positive effects on outsourcing firms' market value. On the other hand, non-core business-related outsourcing, domestic outsourcing, and longer-term outsourcing did not enhance firm value.

Table 27 Jiang et.al Variable Descriptions

MV_t	market value by the end of fiscal year t (dependent variable)
β_0	a constant term to allow for potential omitted variables.
BV_t	the closing book value at the end of fiscal year t (shareholders' equity).
E_t	the current earnings before exceptional and extraordinary items at the end of fiscal year t.
DIV_t	the declared dividend at the end of fiscal year t.
GW_t	the goodwill on acquisition at the end of fiscal year t.
CC_t	capital contributions which is measured as the negative of the sum of equity raised for cash and for acquisitions at the end of fiscal year t.
$RDAD_t$	represents current research/development and advertising expenditures at the end of fiscal year t.
OUT_t	the outsourcing contract's value in the fiscal year t.
CI	Capital Intensity = FA/BV
ε	a mean zero random variable to control for the effect of unobservable factors.

Jiang's (Jiang et al., 2007) cross-sectional evaluation model is an extended version of Ohlson's (Ohlson, 1995) model, in which market value is expressed as a linear function of earnings, book value and net dividends. After considering firm size and adjusting for capital intensity, Jiang's (2007) final equation is:

$$\frac{MV_t}{BV_t} = \beta_0 \frac{1}{BV_t} + \beta_1 + \beta_2 \frac{E_t}{BV_t} + \beta_3 \frac{DIV_t}{BV_t} + \beta_4 \frac{GW_t}{BV_t} + \beta_5 \frac{CC_t}{BV_t} + \beta_6 \frac{RDAD_t}{BV_t} + \beta_7 \frac{OUT_t}{BV_t} + \beta_8 CI_t + \varepsilon$$

Instead of linking firms' market value to the outsourcing decision, we propose to employ Tobin's q as the key indicator of firms' performance. Table 28 lists the variable descriptions and the variable assignment of our analysis dataset.

Table 28 Variable Descriptions

X_1 =	RDSGA_ME	Research & Development Expense plus selling, general & administrative expenses per company market value of equity (ME)
X_2 =	IBE_ME	Income Before Extraordinary Items per company ME
X_3 =	GW_ME	Goodwill per company ME
X_4 =	CI_DM	Capital Intensity, dummy variable
X_5 =	DIV	Dividends Per Share
X_6 =	nAcqst	Normalized Capital Contribution
X_7 =	CDM_ME	Contract Value per Company ME
X_8 =	ChgdBFO	Changes in Tobin's q from year t-1 to year t, (pre-outsourcing)
X_8'=	pctChgdBFO	Percent changes in Tobin's q from year t-1 to year t, (pre-outsourcing)
Y =	Qt	Tobin's q of the announcement year t
	Qtp1	Tobin's q of the announcement year t + 1
	Qtp2	Tobin's q of the announcement year t + 2
	ChdgPost1	Changes in Tobin's q from year t to year t + 1
	ChgdPost2	Changes in Tobin's q from year t + 1 to year t + 2
	pctChgdPost1	Percent changes in Tobin's q from year t to year t + 1
	pctChgdPost2	Percent changes in Tobin's q from year t + 1 to year t + 2

In this chapter, Tobin's q of the announcement year, one year after, two years after, as well as the relative changes in Tobin's q, both pre and post outsourcing, were investigated as response variables given the relative outsourcing deal size along with other relevant accounting variables in the year that the outsourcing contract announcement (year *t*) was made. When studying changes in Tobin's q from year *t*+1 (*ChgdPost1*) to year *t*+2 (*ChgdPost2*), it is possible to utilize more current accounting data as independent variables, for instance, year *t*+1 or year *t*+2, because we are dealing with historical data. We chose to use year *t* data to ensure the realistic usefulness of the model for future forecasting. When one is faced with an immediate outsourcing decision, accounting data will not be available for year *t*+1 nor *t*+2, but will be available for year *t* through own internal reports from the accounting department. As will be shown in the later sections, this choice of which accounting data to use does have an impact on the models.

5.2.2 Variable of Interest – Changes in Tobin's Q

Tobin's q is the ratio of the market value of a firm's assets (outstanding stock and debt) to the replacement cost of the firm's assets (Tobin, 1969). If a firm is worth more than what it would cost to rebuild it, then profits are being earned and the firm can remain in the industry. Using Tobin's q avoids the difficult of estimating rates of return or marginal costs. If Tobin's q is above 1, the firm is earning a rate of return higher than that justified by the cost of its assets. Therefore, the higher the Tobin's q the better the company's performance is.

Many different methods have been proposed for computing Tobin's q. Perfect and Wiles (1994) concluded that most approaches generate comparable results. Bharadwaj et al. (1999) make use of Chung and Pruitt's (1994) method to calculate q. Their method is simple because it only requires information available in the Compustat database, and because is highly correlated with q as calculated by Lindenberg and Ross (1981), a well-known theoretically correct model. In this chapter, we adopt the Bharadwaj et al. (1999) formula.

Following Bharadwaj et al. (1999) we calculate Tobin's q as:

$$\text{Tobin's q} = (MVE + PS + DEBT)/TA$$

where:

- MVE = (Closing price of share at the end of the financial year)*(Number of common shares outstanding);
- PS = Liquidating value of the firm's outstanding preferred stock;
- DEBT = Max(0, Current liabilities - Current assets) + (Book value of inventories) + (Long term debt), and
- TA = Book value of total assets.

For each outsourcing announcement case, besides calculating Tobin's q at one year before the outsourcing announcement (*Qtm1*); at the year of the announcement (*Qt*); at one year after the announcement (*Qtp1*); at two years after the announcement (*Qtp2*); changes in Tobin's q from year *t*-1 to year t (*ChgdBFO*); changes in Tobin's q from year *t* to year *t*+1 (*ChgdPost1*); and changes in Tobin's q from year *t*+1 to year *t*+2 (*ChgdPost2*), we also calculated the percent changes in Tobin's q both one (*pctChgdPost1*) and two years (*pctChgdPost2*) post outsourcing. The reason for this approach is given at subsection 5.3.1.1.

5.2.3 Methodologies

In the following section, linear regression, regression tree, as well as neural network are utilized to analyze our outsourcing data. A brief description of those methodologies and their origins were given in chapter 2.

LR shines with its modeling simplicity, straight forward variable interpretation, and proven performance evaluation measures. Its drawback is potentially inferior performance when the relationship between the response variable and the independent variables is nonlinear. By including interaction terms and other higher order terms of the original variables, model performance may improve, but strictly speaking, it is no longer a linear model as far as the original variables are concerned. On the other hand, the model is still linear in the new variables. A linear regression approach with interaction terms will be thoroughly investigated in this chapter.

More sophisticated data mining techniques do, in general, yield better models when nonlinear relationships exist. The modern machine learning community has provided us with ample efficient and effective new tools to model the data. When our response variables, Tobin's q and the changes of them, are numerical, the choices of those state-of-the-art machine learning tools include regression trees, neural networks, and support vector machines. Standard practice is to try them all to find the superior method for a particular data set.

In the next section, section 5.3, we start with linear regression using SPSS and STATGRAPHICS, follow it by regression trees using Cubist (Quinlan, 1992), then move on to Neural Networks using Clementine.

5.3 EMPIRICAL MODELING

5.3.1 Least Squares Regression

Linear regression is the most often used modeling tool for Finance and Accounting data analysis. The model simplicity and the ease of drawing managerial insights have made it the heavy favorite over all other more sophisticated models. To establish a benchmark for more advanced modeling, the author will systematically exhausts all popular linear models in this subsection. The best linear model along with its performance statistics will be used in model comparison in section 5.4.

5.3.1.1 First Order Full Model – Enter Method

First, we investigate whether there is a linear relationship between the variables of interest, Y (various forms and time frames of Tobin's q) and all the independent variables $X_1 \sim X_8$ which can be represented by the following equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \varepsilon$$

To assess the validity of the model, we test the following hypothesis:

H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = 0$

H_1: At least one $\beta_i \neq 0$

The coefficients were estimated using the "Least Squares" method implemented in a standard Statistical software package SPSS and STATGRAPHICS. Seven such models were built representing the seven response variables: *Qt*, *Qtp1*, *Qtp2*, *ChgdPost1*, *ChdgPost2*, *pctChgdPost1*, and *pctChgdPost2* (refer to Table 28 in section 5.2.1 for a description of each).

By entering all the independent variables (without X_8 for *Qt*, *Qtp1*, and *Qtp2*), we obtained the following fitted model:

$$Qt = 2.427 - 0.664X_1 - 0.646X_2 - 0.783X_3 - 0.189X_4 - 0.403X_5 - 0.174X_6 - 0.092X_7 \quad (1)$$

The ANOVA table (Table 29) provided the test statistics we utilized to assess the model validity. Since the F-Ratio = MSR/MSE = 3.503 was large, and the p-value = 0.002 was less than 0.01, we rejected the null hypothesis at the 99% confidence level, which indicated that the model was statistically significant. We therefore concluded that there was a statistically significant relationship between the variables at the 99% confidence level. In other words, the model was valid.

Table 29 Analysis of Variance – Qt LR Enter Method

ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	41.736	7	5.962	3.503	0.002
	Residual	265.547	156	1.702		
	Total	307.283	163			

Once it was determined that the model was valid, we needed to check the adjusted R-square to see how well the models fitted the data, and we also needed to check the required conditions for the error term. For future comparison and also serve as a reference point, we retained the statistics from the “Model Summary Table” in the SPSS output. The adjusted R-Squared was only 0.097 (see below), i.e., only 9.7% of the variations in *Qt* were explained by the model.

Model Summary:

Regression Coefficient R = 0.369

R-Square = 0.136

Adjusted R-Square = 0.097

Standard Error of Estimate = 1.3047

To assess the statistical significance of each individual variable, we examine the coefficients given in Table 30. The p-value of the t-test for each coefficient was examined to determine the whether the variable was a significant predictor of *Qt*. The P-value for the t-tests for X_4, X_6, and X_7 were greater than 0.1, therefore, they could be removed individually from the model. Because X_7 represented the relative outsourcing amount, CDM_ME, we concluded that there might not statistically significant linear relationship between relative outsourcing amount and the firm's Tobin's q at the year of the outsourcing announcement.

Table 30 Coefficients – Qt LR Enter Method

Coefficients						
Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
	(Constant)	2.427	.197		12.312	.000
X_1	RDSGA_me	-.664	.205	-.296	-3.248	.001
X_2	IBE_me	-.646	.239	-.287	-2.697	.008
X_3	GW_me	-.783	.245	-.268	-3.193	.002
X_4	CI-DM	-.189	.125	-.120	-1.506	.134
X_5	DIV	-.403	.146	-.221	-2.767	.006
X_6	nAcqst	-.174	1.147	-.011	-.151	.880
X_7	CDM_ME	-.092	.289	-.030	-.317	.751

Using the same procedure in SPSS, we obtain the following models for all of the response variables:

$$Qtp1 = 3.217 - 1.136X_1 - 1.197X_2 - 1.145X_3 - .567X_4 - .587X_5 - 3.076X_6 - .577X_7 \quad (2)$$

Because the p-value of the F-test is 0.106, the model is only marginally significant. The adjusted R-squared is 0.032, even if we did consider the model as valid; it would not be useful at all. On the other hand, of the seven independent variables entered, four of them, X_1, X_2, X_3, and X_5, are significant at the 10% level. This tells us that a sub-set of independent variables (attributes) may be used to construct a better model. For Tobin's q at two years after outsourcing, we get

$$Qtp2 = 2.797 - .768X_1 - .79X_2 - .823X_3 - .31X_4 - .48X_5 - 2.706X_6 - .435X_7 \quad (3)$$

The summary statistics showed that for Tobin's q in year t+2, the linear regression model's p-value of the F-test equals 0.082 and the adjusted R-square is 0.038. Of the independent variables entered, X_1, X_2, X_3, and X_5 are significant at the 10% level. All the statistics for this model are very similar to that of Qtp1, therefore, similar inferences as that of Qtp1 would be drawn from it.

Among the response variables, *ChgdPost1* was the primary focus, because it represented the economic impact immediately after the firm implemented outsourcing. In a relatively short period, it would not unreasonable to conjecture that relatively fewer outside influences on Tobin's q changes would have been introduced than would be two years after the outsourcing decision. In other words, we hypothesized that our regression equations for *ChgdPost1* was more reflective of the impact of outsourcing decision than is the regression equation for *ChgdPost2*. Note that the overall performance of the regression equation as a predictor of changes in q would not necessarily follow suit. It was easy to recognize that other accounting variables may contribute in a larger degree to the changes in q from year t+1 to year t+2 than they do to the changes in q from year t to t+1.

$$ChgdPost1 = .040 + .014X_1 - .051X_2 - .031X_3 - .016X_5 - .064X_6 - .21X_7 + .595X_8 \quad (4)$$

The p-value of the F-test is less than 0.0001, indicating that (4) is a statistically significant model. The adjusted R-squared is 0.213, therefore, 21.3 percent of the variation in *ChgdPost1* is explained by the model. But, of all the independent variables entered, only X_8 is significant at 99.999999999% confidence interval, making it the most dominant attribute. Intuitively, it is reasonable to believe that the previous period's change in Tobin's q (*ChgdBFO*) would be highly correlated with the following period's change in Tobin's q (*ChgdPost1*), making *ChgdBFO* a good predictor for *ChdgPost1*. The drawback of this high correlation between one independent variable and the response variable is the possibility of it overshadowing the contribution of other independent variables. As a remedy to this, we explore variable re-scaling next.

ChgdPost2 = .017 + .065X_1 – .025X_2 – .022X_3 + .01X_4 + .009X_5 – .203X_6 + .076X_7 + .384X_8 (5)

The p-value of the F-test is 0.002 and the adjusted R-squared is 0.108. Similar to the model for *ChgdPost1*, of the independent variables entered, only X_8 is significant at 99.999924% confidence level. All the statistics for this model are also very similar to that of *ChgdPost1*, therefore, we draw similar inferences.

Next, we re-scaled the variables by defining two new response variables as follows:

pctChgdPost1 = *ChgdPost1*/*Qt*

the percent change in Tobin's q from year t to year t+1

pctChgdPost2 = *ChgdPost2*/*Qtp1*

the percent change in Tobin's q from year t+1 to year t+2

Furthermore, for input, we also computed:

pctChgdBFO = *ChgdBFO*/*Qm1*

the percent change in Tobin’s q from year t-1 to year t.

The two new response variables represent the percentage changes of Tobin’s q from the outsourcing announcement year to the year after, and from one-year to two-years after the outsourcing announcement. By using *pctChgdBFO* and *pctChgdPost1* instead of *ChgdBFO* and *ChgdPost1*, we numerically lessen the relative contribution of the most dominating attribute in order to boost the relative contribution of the other independent variables. Through this approach, we hoped to be able to identify other important variables. Theoretically, this should result in models with more independent variables when stepwise regression methods were used.

SPSS linear regression output (using the Enter method) yielded the following equations:

pctChgdPost1 = .017 + .022X_1 – .042X_2 – .016X_3 + .013X_4 – .004X_5 – .225X_6 + .001X_7 + .077pctChgdBFO (6)

pctChgdPost2 = – .012 + .055X_1 – .023X_2 – .005X_3 – .011X_4 + .033X_5 – .362X_6 + .03X_7 – .046pctChgdBFO (7)

The model coefficients and related statistics were given in Table 31 and Table 32. Much as expected, other independent variables, namely IBE_me, nAcqst, and RDSGA_me, became statistically significant in the models (see Table 31 and Table 32 respectively). Unfortunately, the outsourcing contract amount (CDM_ME) was not significant in either (6) or (7). Therefore, we conclude: there is no statistically significant linear relationship between relative outsourcing contract amount and the changes in Tobin's q.

Table 31 Coefficients for *pctChgdPost1* – LR Enter Method

Coefficients						
		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
	(Constant)	.017	.018		.988	.325
X_1	RDSGA_me	.022	.018	.113	1.205	.230
X_2	IBE_me	-.042	.022	-.198	-1.881	.062
X_3	GW_me	-.016	.023	-.064	-.699	.486
X_4	CI-DM	.013	.011	.099	1.190	.236
X_5	DIV	-.004	.013	-.028	-.337	.737
X_6	nAcqst	-.225	.119	-.149	-1.884	.061
X_7	CDM_ME	.001	.027	.002	.021	.984
X_8	pctChgdBFO	.077	.066	.093	1.165	.246

Table 32 Coefficients for *pctChgdPost2* – LR Enter Method

Coefficients						
		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
	(Constant)	-.012	.029		-.402	.688
X_1	RDSGA_me	.055	.029	.180	1.863	.065
X_2	IBE_me	-.023	.036	-.069	-.634	.527
X_3	GW_me	-.005	.037	-.013	-.137	.891
X_4	CI-DM	-.011	.019	-.053	-.611	.542
X_5	DIV	.033	.021	.135	1.587	.115
X_6	nAcqst	-.362	.198	-.150	-1.828	.070
X_7	CDM_ME	.030	.045	.063	.679	.498
X_8	pctChgdBFO	-.046	.126	-.031	-.369	.713

Because all the "Enter" models included some variables with t-statistics less than 1, they contribute negatively to the adjusted R-squared of the model. By eliminating those variables, we should get models with improved adjusted R-squared values. Even though the pursuit of a better linear model without the influence of the outsourcing decision and relative contract amount depart from our path to find the true relationship between CDM_ME and the changes in Tobin's q, the result of it would serve as a good performance benchmark for other nonlinear models. Before employing different variable selection techniques to find the best linear model, we checked the correlation matrix among the dependent variables given in Table 33.

Table 33 Correlations Matrix of Model Coefficients

	IBE_me	GW_me	CI_DM	DIV	nAcqst	CDM_ME	ChgdBFO	pctChgdBFO
IBE_me	1	0.3278	-0.0362	-0.1107	0.0578	0.372	0.0448	0.0526
GW_me	0.3278	1	0.0877	0.0225	-0.0411	-0.1357	0.0823	-0.0548
CI_DM	-0.0362	0.0877	1	-0.1958	0.0165	0.0728	0.0522	0.0166
DIV	-0.1107	0.0225	-0.1958	1	0.0615	0.0901	0.0785	-0.1095
nAcqst	0.0578	-0.0411	0.0165	0.0615	1	0.1141	-0.0472	0.1693
CDM_ME	0.372	-0.1357	0.0728	0.0901	0.1141	1	-0.0357	0.1167
ChgdBFO	0.0448	0.0823	0.0522	0.0785	-0.0472	-0.0357	1	-0.7905
pctChgdBFO	0.0526	-0.0548	0.0166	-0.1095	0.1693	0.1167	-0.7905	1

There was no surprise that there is a high correlation between ChgdBFO and pctChgdBFO (-0.7905), the later is calculated from the former. Besides this pair, there is no other possible concern for multiple co-linearity.

5.3.1.2 First Order Stepwise – Forward and Backward Selection

Forward selection method computes the F-statistic for each independent variable and then the one with the largest F-statistic (or the smallest p-value) is selected to enter into the model. Backward selection will first enter all variables into the model and calculate the F-statistics. First, we choose the setting of F = 2.0 to enter and F = 1.5 to remove using forward selection. SPSS yielded the following statistically significant model (p-value =0):

ChgdPost1 = .034 + 0.609*ChgdBFO (8)

The adjusted R-square was .234.

In order to include more variables in the model, we experiment with lowering the threshold as well as trying different selection technique. When using F = 1.5 to enter and F = 1 to remove, both forward and backward selection yielded the same model.

ChgdPost1 = .030 – .058*IBE_me + .596*ChgdBFO (9)

As we'd expected, the model was significant with p-value = 0, adjusted R-square = 0.238, and standard error of estimate = 0.282. While ChgdBFO was significant with a p-value near zero, IBE_me was only marginal, with p-value = 0.161, significant at the 83.9% confidence level.

The stepwise regression equation for changes in Tobin's q two years after outsourcing is:

ChgdPost2 = 0.02 + .398*ChgdBFO + .069*RDSGA_me + .077CDM_ME (10)

The same technique was applied to *ChgdPost2*, it was as expected; the adjusted R-square was only 0.1313. In other words, the yielded model could only explain 13.13% of the variation in *ChgdPost2*, not a very good predictor. The surprising part of the results was one of the variables included in the model: relative outsourcing contract amount (CDM_ME). This could very well signify the delayed effect of outsourcing on firm performance. The other explanation was that due to our choice to use the SPSS' default setting for treating missing values: casewise exclusion. Like in most data mining software, it is possible to choose to replace missing with the mean, max, or min of the data column. At this time we chose casewise exclusion, because there was a more than likely chance that those 11 excluded cases were ones that did not get any performance boost from outsourcing, because missing accounting data from Compustats database meant the firm in question no longer existed (having being bought out or having gone bankrupt) or was having some other difficulty in financial reporting. In order to determine the cause, more extended exploration is necessary. In section 5.5, we consider this matter and gave preliminary results. We felt that more rigorous investigation into the firms with missing *ChgdPost2* is necessary for future research.

Table 34 shows that the p-value of the t-test for β_{CDM_ME} is 0.201, so we cannot reject the null hypothesis: $\beta_{CDM\_ME} = 0$ at the 10% significance level, but we can reject the null with 79.8% confidence. In other words, there might have been a weak positive linear relationship between CDM_ME and *ChgdPost2*. Because its t-statistic was greater than 1, the inclusion of CDM_ME had positive contribution to the model's adjusted R-squared.

Table 34 Coefficients for ChgdPost2 – LR Stepwise Method

Coefficients							
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	.020	.026		.775	.439
X_8	ChgdBFO	.398	.089	.338	4.467	.000
X_1	RDSGA_me	.069	.038	.143	1.814	.072
X_7	CDM_ME	.077	.060	.101	1.284	.201

Table 35 showed the steps in the forward selection stepwise regression model (backward selection yielded the same model in step 6). When CDE_ME was entered into the model at step 3, the adjusted R-square increased from 0.1275 to 0.1313, and the standard error of the estimate decreased from 0.2790 to 0.2784. The inclusion of CDM_ME resulted in an improvement of the model, even if it was only to a very small degree.

Table 35 Model Summary for *ChgdPost2*

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Step 1	.332	.110	.1042	.282730124
Step 2	.373	.139	.1275	.279028132
Step 3	.385	.148	.1313	.278426726

Following the same procedure as for the "Enter" models, we next regress using the re-scaled response variables *pctChgdPost1* and *pctChgdPost2*. For *pctChgdPost1*, the forward selection method yielded a different model from backward selection. The variables included in the models from both forward and backward selections were shown in Table 36.

Table 36 Coefficients for *pctChgdPost1* – Forward and Backward Selection

Coefficients (Forward selection)						
Model at Step 3		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
	(Constant)	0.03	0.01		3.045	0.003
X_2	IBE_me	-0.057	0.018	-0.27	-3.149	0.002
X_6	nAcqst	-0.244	0.117	-0.161	-2.088	0.038
X_3	GW_me	-0.027	0.021	-0.109	-1.275	0.204
Coefficients (Backward selection)						
Step 4	(Constant)	0.011	0.013		0.828	0.409
X_1	RDSGA_me	0.026	0.017	0.137	1.557	0.121
X_4	CI-DM	0.014	0.011	0.104	1.294	0.197
X_6	nAcqst	-0.222	0.117	-0.147	-1.895	0.06
X_2	IBE_me	-0.035	0.018	-0.167	-1.927	0.056
X_8’	pctChgdBFO	0.082	0.065	0.1	1.271	0.206

Both models were statistically significant (p-values equal to 0.004 and 0.006 respectively), but were not very useful due to the very small adjusted R-squared (0.066 and 0.072 respectively). The backward selection method yielded a model with more independent variables, higher adjusted R-square (see Table 37), and lower standard error of estimate than that of forward selection method. The two final models are:

pctChgdPost1 = $.03 – .57X_2 – .027X_3 – .244X_6$

pctChgdPost1 = $.011 + .026X_1 – .035X_2 + .014X_3 – 0.222X_6 + .082{*}X_8$’ (11)

where X_8’ = X_8/*Qtm1* = *pctChgdBFO* represents percentage change in Tobin’s q pre-outsourcing.

Table 37 Model Summary *pctChgdPost1* – Forward and Backward Selections

Model Summary (Forward Selection)				
	R	R Square	Adjusted R Square	Std. Error of the Estimate
Step 1	0.217	0.047	0.041	0.11413
Step 2	0.273	0.074	0.062	0.11286
Step 3	0.29	0.084	0.066	0.11264

Model Summary (Backward Selection)				
	R	R Square	Adjusted R Square	Std. Error of the Estimate
Step 1	0.324	0.105	0.057	0.11318
Step 2	0.324	0.105	0.063	0.11281
Step 3	0.323	0.104	0.069	0.11248
Step 4	0.319	0.102	0.072	0.11228

SPSS linear regression forward and backward selection for *pctChgdPost2* also yielded different models, similar to the results for *pctChgdPost1*. The variables included in the models from both forward and backward selections were shown in coefficients Table 38. Also parallel to *ChgdPost2*, the variable for outsourcing amount was included in the backward selection model.

Table 38 Coefficients for *pctChgdPost2* – LR Stepwise Method

Coefficients for pctChgdPost2 – Forward Selection						
Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
	(Constant)	-0.013	0.024		-0.534	0.594
X_1	RDSGA_me	0.071	0.025	0.234	2.883	0.005
X_6	nAcqst	-0.352	0.191	-0.146	-1.847	0.067
X_5	DIV	0.027	0.02	0.11	1.352	0.179
Backward Selection						
Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
	(Constant)	-0.021	0.025		-0.833	0.406
X_1	RDSGA_me	0.065	0.025	0.213	2.556	0.012
X_5	DIV	0.031	0.02	0.124	1.507	0.134
X_6	nAcqst	-0.339	0.191	-0.141	-1.779	0.077
X_7	CDM_ME	0.043	0.04	0.09	1.089	0.278

Both models were statistically significant, with p-values equal to 0.007 and 0.009 respectively. As with *pctChgdPost1*, they were not very useful because of the very small adjusted R-squared (0.06 and 0.07 respectively). The backward selection method yielded a model with more independent variables, higher adjusted R-squared (see Table 39), and lower standard error of estimate than that of forward selection method.

$$pctChgdPost2 = -.013 + .71X_1 + .027X_5 - .352X_6$$
$$pctChgdPost2 = -.021 + .065X_1 + .031X_5 - 0.339X_6 + .043X_7 \qquad (12)$$

Table 39 Model Summary *pctChgdPost2* – Forward and Backward Selections

Model Summary – Forward Selection				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.209	0.044	0.037	0.18425
2	0.26	0.068	0.055	0.18254
3	0.281	0.079	0.06	0.18204
Backward Selection				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.298	0.089	0.045	0.18355
2	0.297	0.089	0.051	0.18293
3	0.297	0.088	0.057	0.18234
4	0.293	0.086	0.061	0.18193

Also identical to the linear model for *ChgdPost2*, the outsourcing amount variable, CDM_ME was included. Regarding this, we offer the same explanation as we did previously with *ChgdPost2*. Also, further details of the explanation will be investigated in section 5.5.

Comparing regression equations (9) with (11) and (10) with (12), the LR models for *pctChgdPost1* (11) and *pctChgdPost2* (12) did include more variables than their respective counterparts *ChgdPost1* (9) and *ChgdPost2* (10). But, upon examining the model statistics and the model performance indicators, the respective adjusted R-squared values for both *pctChgdPost1* (Adj. R^2 = 0.072) and *pctChgdPost2* (Adj. R^2 = 0.061) were significantly worse than *ChgdPost1* (Adj. R^2 = 0.238) and *ChgdPost2* (Adj. R^2 = 0.1313). Therefore, from here on forward, no further modeling will be done for *pctChgdPost1* and *pctChgdPost2* in the remainder of this chapter.

5.3.1.3 Second Order Models – LR with Interaction Terms

After exhausting all the procedures (using SPSS) without finding an acceptable first order linear model for any of the seven response variables studied, we concluded that linear models do not make good predictors for the dependent variables. Following this, we experimented with second order models by exploring all the interaction terms. We computed all of the interaction terms from X_1-X_8, and presented them to another statistical software package, STATGRAPHICS. First, using the backward selection stepwise regression, we were able to eliminate 10 least significant variables based on the greedy algorithm used by this method. Then we apply the subset selection method within STATGRAPHICS to search for the best regression model. The initial 36 variables entered were:

X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8,
X_1*X_2, X_1*X_3, X_1*X_4, X_1*X_5, X_1*X_6, X_1*X_7, X_1*X_8,
X_2*X_3, X_2*X_4, X_2*X_5, X_2*X_6, X_2*X_7, X_2*X_8,
X_3*X_4, X_3*X_5, X_3*X_6, X_3*X_7, X_3*X_8,
X_4*X_5, X_4*X_6, X_4*X_7, X_4*X_8,
X_5*X_6, X_5*X_7, X_5*X_8,
X_6*X_7, X_6*X_8,
X_7*X_8.

5.3.1.3.1 Tobin's q Change 1-Year after Outsourcing

The dependent variable is *ChgdPost1*. For simpler representation within STATGRAPHICS, the following variable assignments were made, let:

$A = X_1$
$B = X_2$
$C = X_3$
$D = X_4$
$E = X_5$
$F = X_6$
$G = X_7$
$H = X_8$

In other words, the original independent variables become: A, B, C, D, E, F, G, H, with the following interaction terms:

AB, AC, AD, AE, AF, AG, AH,
BC, BD, BE, BF, BG, BH,
CD, CE, CF, CG, CH,
DE, DF, DG, DH,
EF, EG, EH,
FG, FH,
GH

We first check out the correlations amongst independent variables by examining correlations of regression coefficients. Table 40 contained the estimated correlations between the coefficients in a fitted model (with all 36 independent variables entered). It enabled us to detect the presence of any serious multicollinearity amongst the predictor variables. In the upper diagonal of Table 40, there were a total of 35! = 630 pairs of variables. Of those 630 pairs, 30 correlations (in red) were significant with the absolute values greater than 0.5, which was under 5% of the total pairings. Out of the 30 correlations with absolute values above 0.5, 6 were above 0.7 and only one just reached 0.90. Since both the number of and the severity of the correlations were low, we could safely assume that there were no serious multicollinearity problems.

Table 40 Correlation Matrix of the 36 Independent Variables

	A	B	C	D	E	F	G	H	AB	AC	AD	AE	AF	AG	AH	BC	BD	BE
A	1	0.33	0.05	0.07	0.42	0.25	0.18	0.04	-0.28	-0.11	0.38	-0.57	-0.37	-0.52	0.10	0.07	0.25	-0.16
B	0.33	1	-0.02	0.04	0.20	0.07	0.10	0.27	-0.58	0.02	0.14	-0.17	-0.10	-0.15	-0.27	-0.07	-0.18	-0.47
C	0.05	-0.02	1	0.43	0.12	-0.30	0.13	-0.08	0.16	-0.73	-0.38	0.23	0.30	-0.15	0.13	0.40	-0.27	0.19
D	0.07	0.04	0.43	1	0.26	-0.10	0.28	-0.04	0.06	-0.30	-0.55	0.21	0.14	-0.43	0.14	0.41	-0.35	0.09
E	0.42	0.20	0.12	0.26	1	0.19	0.29	-0.01	-0.13	0.01	0.04	-0.50	-0.06	-0.37	0.07	0.08	0.00	-0.47
F	0.25	0.07	-0.30	-0.10	0.19	1	0.12	0.14	-0.13	0.26	0.24	-0.19	-0.50	-0.11	-0.07	-0.13	0.16	-0.06
G	0.18	0.10	0.13	0.28	0.29	0.12	1	-0.07	-0.16	-0.06	-0.16	-0.04	0.02	-0.67	0.11	-0.07	-0.22	0.09
H	0.04	0.27	-0.08	-0.04	-0.01	0.14	-0.07	1	-0.32	0.18	0.13	-0.03	-0.26	0.06	-0.23	-0.27	0.05	-0.13
AB	-0.28	-0.58	0.16	0.06	-0.13	-0.13	-0.16	-0.32	1	-0.13	-0.27	0.24	0.23	0.12	0.14	0.07	-0.49	0.25
AC	-0.11	0.02	-0.73	-0.30	0.01	0.26	-0.06	0.18	-0.13	1	0.41	-0.20	-0.30	0.16	-0.27	-0.42	0.28	-0.19
AD	0.38	0.14	-0.38	-0.55	0.04	0.24	-0.16	0.13	-0.27	0.41	1	-0.57	-0.47	0.37	-0.43	-0.18	0.61	-0.24
AE	-0.57	-0.17	0.23	0.21	-0.50	-0.19	-0.04	-0.03	0.24	-0.20	-0.57	1	0.21	0.11	0.11	0.01	-0.35	0.51
AF	-0.37	-0.10	0.30	0.14	-0.06	-0.50	0.02	-0.26	0.23	-0.30	-0.47	0.21	1	-0.02	0.29	0.22	-0.35	0.03
AG	-0.52	-0.15	-0.15	-0.43	-0.37	-0.11	-0.67	0.06	0.12	0.16	0.37	0.11	-0.02	1	-0.43	-0.07	0.29	-0.02
AH	0.10	-0.27	0.13	0.14	0.07	-0.07	0.11	-0.23	0.14	-0.27	-0.43	0.11	0.29	-0.43	1	0.06	-0.07	0.17
BC	0.07	-0.07	0.40	0.41	0.08	-0.13	-0.07	-0.27	0.07	-0.42	-0.18	0.01	0.22	-0.07	0.06	1	-0.12	0.00
BD	0.25	-0.18	-0.27	-0.35	0.00	0.16	-0.22	0.05	-0.49	0.28	0.61	-0.35	-0.35	0.29	-0.07	-0.12	1	0.03
BE	-0.16	-0.47	0.19	0.09	-0.47	-0.06	0.09	-0.13	0.25	-0.19	-0.24	0.51	0.03	-0.02	0.17	0.00	0.03	1
BF	-0.22	-0.22	-0.51	-0.26	-0.04	-0.14	-0.08	-0.03	-0.15	0.74	0.22	-0.12	0.12	0.16	0.01	-0.40	0.45	-0.04

BG	-0.07	-0.75	-0.24	-0.17	-0.08	0.10	0.22	-0.17	0.05	0.19	0.24	-0.13	-0.13	0.02	0.13	-0.05	0.52	0.31
BH	0.09	0.11	-0.21	-0.16	0.01	0.22	0.05	0.54	-0.34	0.25	0.07	-0.08	-0.20	-0.13	0.14	-0.25	0.14	-0.06
CD	-0.12	-0.03	-0.41	-0.59	-0.15	0.06	-0.10	0.05	0.02	0.21	0.17	0.01	-0.11	0.17	-0.03	-0.57	0.08	0.05
CE	0.11	0.03	-0.66	-0.09	-0.10	0.28	-0.02	0.07	-0.17	0.39	0.21	-0.23	-0.21	-0.03	-0.01	-0.15	0.21	-0.15
CF	0.13	0.07	0.12	0.14	-0.05	-0.41	-0.03	-0.18	0.05	-0.31	0.05	-0.02	-0.20	0.03	-0.19	0.36	-0.10	-0.04
CG	0.02	0.00	-0.30	0.02	-0.03	0.06	-0.22	-0.19	-0.05	0.03	0.07	-0.13	0.03	0.06	-0.02	0.71	0.01	-0.15
CH	0.01	0.05	-0.08	0.02	0.07	0.05	0.08	-0.40	0.04	0.03	0.07	-0.05	0.05	-0.01	-0.14	0.37	-0.05	-0.04
DE	-0.11	0.03	-0.19	-0.63	-0.41	0.05	-0.15	0.12	0.01	0.13	0.32	-0.18	-0.03	0.27	-0.18	-0.14	0.03	-0.24
DF	-0.28	-0.13	-0.10	-0.23	-0.05	0.04	0.00	-0.21	0.10	0.13	-0.11	0.09	0.54	0.09	0.13	-0.08	-0.02	0.06
DG	-0.11	0.01	0.01	-0.19	-0.06	-0.02	-0.40	-0.20	0.14	-0.07	-0.21	0.22	0.14	0.22	0.17	-0.04	0.04	0.07
DH	-0.22	-0.37	0.03	-0.16	-0.21	-0.14	-0.12	-0.16	0.28	-0.02	0.18	0.02	0.05	0.35	-0.21	0.03	0.17	0.18
EF	-0.16	-0.04	0.32	0.13	-0.20	-0.90	-0.07	-0.09	0.09	-0.27	-0.14	0.16	0.34	0.12	-0.07	0.12	-0.11	0.09
EG	-0.05	0.00	-0.13	-0.22	-0.28	-0.01	-0.79	0.10	0.11	0.10	0.31	-0.13	-0.06	0.54	-0.28	0.13	0.14	-0.16
EH	0.00	-0.13	0.07	0.15	0.08	-0.13	0.05	-0.54	0.08	-0.12	-0.16	0.04	0.12	-0.07	0.14	0.09	0.06	0.18
FG	0.01	-0.07	-0.08	0.01	-0.03	-0.41	-0.15	-0.02	-0.05	0.14	0.02	0.00	-0.14	0.00	0.11	-0.08	0.15	0.01
FH	0.00	0.00	0.30	0.08	-0.01	-0.39	-0.06	-0.25	0.16	-0.32	-0.05	0.03	0.16	0.06	-0.11	0.19	-0.17	-0.03
GH	0.07	0.20	-0.01	0.00	0.10	0.10	0.16	-0.33	0.03	0.03	-0.06	-0.04	0.11	-0.15	-0.06	0.12	-0.20	-0.08

Table 40 – part II

	BF	BG	BH	CD	CE	CF	CG	CH	DE	DF	DG	DH	EF	EG	EH	FG	FH	GH
A	-0.22	-0.07	0.09	-0.12	0.11	0.13	0.02	0.01	-0.11	-0.28	-0.11	-0.22	-0.16	-0.05	0.00	0.01	0.00	0.07
B	-0.22	-0.75	0.11	-0.03	0.03	0.07	0.00	0.05	0.03	-0.13	0.01	-0.37	-0.04	0.00	-0.13	-0.07	0.00	0.20
C	-0.51	-0.24	-0.21	-0.41	-0.66	0.12	-0.30	-0.08	-0.19	-0.10	0.01	0.03	0.32	-0.13	0.07	-0.08	0.30	-0.01
D	-0.26	-0.17	-0.16	-0.59	-0.09	0.14	0.02	0.02	-0.63	-0.23	-0.19	-0.16	0.13	-0.22	0.15	0.01	0.08	0.00
E	-0.04	-0.08	0.01	-0.15	-0.10	-0.05	-0.03	0.07	-0.41	-0.05	-0.06	-0.21	-0.20	-0.28	0.08	-0.03	-0.01	0.10
F	-0.14	0.10	0.22	0.06	0.28	-0.41	0.06	0.05	0.05	0.04	-0.02	-0.14	-0.90	-0.01	-0.13	-0.41	-0.39	0.10
G	-0.08	0.22	0.05	-0.10	-0.02	-0.03	-0.22	0.08	-0.15	0.00	-0.40	-0.12	-0.07	-0.79	0.05	-0.15	-0.06	0.16
H	-0.03	-0.17	0.54	0.05	0.07	-0.18	-0.19	-0.40	0.12	-0.21	-0.20	-0.16	-0.09	0.10	-0.54	-0.02	-0.25	-0.33
AB	-0.15	0.05	-0.34	0.02	-0.17	0.05	-0.05	0.04	0.01	0.10	0.14	0.28	0.09	0.11	0.08	-0.05	0.16	0.03
AC	0.74	0.19	0.25	0.21	0.39	-0.31	0.03	0.03	0.13	0.13	-0.07	-0.02	-0.27	0.10	-0.12	0.14	-0.32	0.03
AD	0.22	0.24	0.07	0.17	0.21	0.05	0.07	0.07	0.32	-0.11	-0.21	0.18	-0.14	0.31	-0.16	0.02	-0.05	-0.06
AE	-0.12	-0.13	-0.08	0.01	-0.23	-0.02	-0.13	-0.05	-0.18	0.09	0.22	0.02	0.16	-0.13	0.04	0.00	0.03	-0.04
AF	0.12	-0.13	-0.20	-0.11	-0.21	-0.20	0.03	0.05	-0.03	0.54	0.14	0.05	0.34	-0.06	0.12	-0.14	0.16	0.11
AG	0.16	0.02	-0.13	0.17	-0.03	0.03	0.06	-0.01	0.27	0.09	0.22	0.35	0.12	0.54	-0.07	0.00	0.06	-0.15
AH	0.01	0.13	0.14	-0.03	-0.01	-0.19	-0.02	-0.14	-0.18	0.13	0.17	-0.21	-0.07	-0.28	0.14	0.11	-0.11	-0.06
BC	-0.40	-0.05	-0.25	-0.57	-0.15	0.36	0.71	0.37	-0.14	-0.08	-0.04	0.03	0.12	0.13	0.09	-0.08	0.19	0.12
BD	0.45	0.52	0.14	0.08	0.21	-0.10	0.01	-0.05	0.03	-0.02	0.04	0.17	-0.11	0.14	0.06	0.15	-0.17	-0.20
BE	-0.04	0.31	-0.06	0.05	-0.15	-0.04	-0.15	-0.04	-0.24	0.06	0.07	0.18	0.09	-0.16	0.18	0.01	-0.03	-0.08
BF	1	0.39	0.10	0.21	0.25	-0.25	-0.12	0.03	0.04	0.26	-0.02	0.10	0.05	0.00	0.04	0.40	-0.11	-0.11
BG	0.39	1	-0.01	0.12	0.16	-0.07	0.06	0.02	0.05	0.07	-0.34	0.34	-0.08	-0.18	0.07	0.09	-0.11	-0.23
BH	0.10	-0.01	1	0.09	0.19	-0.27	-0.09	-0.29	0.12	-0.06	0.12	-0.55	-0.21	-0.01	-0.31	-0.04	-0.29	0.26
CD	0.21	0.12	0.09	1	-0.17	-0.12	-0.09	0.13	0.27	0.05	0.07	0.11	-0.10	0.03	-0.10	0.08	-0.16	-0.05
CE	0.25	0.16	0.19	-0.17	1	-0.09	0.21	-0.18	0.02	0.06	-0.03	-0.14	-0.27	0.07	-0.01	0.00	-0.17	0.03
CF	-0.25	-0.07	-0.27	-0.12	-0.09	1	0.29	0.39	-0.03	-0.50	-0.15	0.02	0.51	0.04	0.07	0.30	0.57	-0.10
CG	-0.12	0.06	-0.09	-0.09	0.21	0.29	1	0.45	0.05	-0.03	-0.02	0.00	-0.09	0.26	0.00	-0.02	-0.02	0.14
CH	0.03	0.02	-0.29	0.13	-0.18	0.39	0.45	1	-0.02	0.05	-0.01	0.09	-0.06	-0.01	0.07	-0.08	-0.07	0.22
DE	0.04	0.05	0.12	0.27	0.02	-0.03	0.05	-0.02	1	0.03	-0.09	0.13	-0.06	0.25	-0.40	-0.04	0.01	0.01
DF	0.26	0.07	-0.06	0.05	0.06	-0.50	-0.03	0.05	0.03	1	0.21	0.08	-0.20	-0.04	0.12	-0.41	-0.09	0.11
DG	-0.02	-0.34	0.12	0.07	-0.03	-0.15	-0.02	-0.01	-0.09	0.21	1	-0.16	-0.04	0.07	0.21	-0.09	-0.09	0.44
DH	0.10	0.34	-0.55	0.11	-0.14	0.02	0.00	0.09	0.13	0.08	-0.16	1	0.11	0.12	-0.01	0.05	-0.07	-0.29
EF	0.05	-0.08	-0.21	-0.10	-0.27	0.51	-0.09	-0.06	-0.06	-0.20	-0.04	0.11	1	0.01	0.15	0.26	0.47	-0.14
EG	0.00	-0.18	-0.01	0.03	0.07	0.04	0.26	-0.01	0.25	-0.04	0.07	0.12	0.01	1	-0.14	0.02	0.03	-0.01
EH	0.04	0.07	-0.31	-0.10	-0.01	0.07	0.00	0.07	-0.40	0.12	0.21	-0.01	0.15	-0.14	1	0.03	0.16	0.09
FG	0.40	0.09	-0.04	0.08	0.00	0.30	-0.02	-0.08	-0.04	-0.41	-0.09	0.05	0.26	0.02	0.03	1	0.21	-0.15
FH	-0.11	-0.11	-0.29	-0.16	-0.17	0.57	-0.02	-0.07	0.01	-0.09	-0.09	-0.07	0.47	0.03	0.16	0.21	1	-0.14
GH	-0.11	-0.23	0.26	-0.05	0.03	-0.10	0.14	0.22	0.01	0.11	0.44	-0.29	-0.14	-0.01	0.09	-0.15	-0.14	1

In STATGRAPHICS, we conducted a stepwise regression with the backward selection method and set F-to-enter to 2.0 and F-to-remove to 1.2. All variables were entered at step 0, then the software computed F-statistics for each variable and started to remove the variables with the smallest F-statistics one at a time and continued in each subsequent step. The process stopped when all F-statistics are greater than 1.2. Table 41 presented the summary of all ten steps taken to find the final model.

Table 41 Backward Selection Summary of Steps

Step	# of Variables	Error d.f	R-square	Adj. R-square	MSE	Variable Removed	F-Remove
0	36	121	71.15%	62.57%	0.0392011	Enter	
1	35	122	71.15%	62.87%	0.0388872	GH	0.0228809
2	34	123	71.11%	63.12%	0.0386184	BG	0.150047
3	33	124	71.09%	63.40%	0.0383295	BF	0.0720741
4	32	125	71.07%	63.66%	0.0380544	DF	0.102901
5	31	126	70.90%	63.75%	0.0379677	DE	0.713028
6	30	127	70.78%	63.88%	0.0378285	CD	0.53447
7	29	128	70.62%	63.96%	0.0377453	G	0.718306
8	28	129	70.47%	64.06%	0.0376361	C	0.626936
9	27	130	70.21%	64.03%	0.0376731	D	1.12787
10	26	131	70.01%	64.05%	0.0376467	CE	0.908099

As the variables were removed one by one in each step, the adjusted R-squared was increasing and the MSE decreasing. When the last variable CE was removed, the adjusted R-squared increased by 0.02%, indicating that the inclusion of variable CE was actually having a negative impact on the model performance. Therefore, it was removed.

The equation below gave us the stepwise regression (with backward selection) results of fitting a multiple linear regression model to describe the relationship between *ChgdPost1* and the 36 independent variables. In the final step, 26 independent variables were left in the fitted model:

***ChgdPost1* = -0.103436 + 0.259198*A + 0.401314*B + 0.0785338*E + 1.73306*F + 0.757196*H - 0.0996732*AB + 0.614459*AC + 0.342181*AD - 0.312507*AE - 2.98974*AF +**

0.0972811*AG - 1.43083*AH - 0.24002*BC + 0.366442*BD - 0.479031*BE - 1.07453*BH - 4.90623*CF - 0.358519*CG - 1.09754*CH - 0.139946*DG - 0.273541*DH - 1.17458*EF + 0.206856*EG - 0.421202*EH - 5.78374*FG - 2.44545*FH (13)

In the ANOVA table (Table 42) given by STATGRAPHICS, the P-value of the model was less than 0.01, so we concluded that there was a statistically significant relationship between the variables at the 99% confidence level.

Table 42 ANOVA ChgdPost1 – LR Backward Selection with Interaction Terms

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	11.5105	26	0.442711	11.76	0.0000
Residual	4.93172	131	0.0376467		
Total (Corr.)	16.4422	157			

The R-Squared statistic (shown in the textbox below) indicated that the model as fitted explained 70.0057% of the variability in *ChgdPost1*, which demonstrated a significant improvement in performance as compared to the first order linear models. In other words, we could safely deduce that interactions existed amongst the independent variables. The adjusted R-square statistic was **64.0527%**, which would be used as the benchmark for comparing models with different numbers of independent variables. The standard error of the estimate showed the standard deviation of the residuals to be **0.194028**. It was used to construct prediction limits for new observations. The mean absolute error (MAE) of 0.116809 was the average value of the residuals.

R-square = 70.0057 percent
R-square (adjusted for d.f.) = 64.0527 percent
Standard Error of Est. = 0.194028
Mean absolute error = 0.116809

Table 43 listed the estimated coefficients of the 26 independent variables included in the model as well as their respective statistics. Among the 26 variables, 5 were interaction terms of the outsourcing amount with another variable: AG, CG, DG, EG, and FG. In our subsequent search for the best model, we would also pay close attention to whether or not these 5 terms were included in the models produced.

Table 43 *ChgdPost1* – Backward Selection LSR Model Coefficients

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	-0.103436	0.0369388	-2.80019	0.0059
A	0.259198	0.0852963	3.03879	0.0029
B	0.401314	0.127481	3.14804	0.0020
E	0.0785338	0.0435629	1.80277	0.0737
F	1.73306	0.856423	2.0236	0.0450
H	0.757196	0.13687	5.53223	0.0000
AB	-0.0996732	0.0578664	-1.72247	0.0873
AC	0.614459	0.283149	2.17009	0.0318
AD	0.342181	0.066373	5.15543	0.0000
AE	-0.312507	0.139279	-2.24374	0.0265
AF	-2.98974	1.56329	-1.91247	0.0580
AG	0.0972811	0.0720084	1.35097	0.1790
AH	-1.43083	0.246705	-5.79978	0.0000
BC	-0.24002	0.160546	-1.49502	0.1373
BD	0.366442	0.103801	3.53022	0.0006
BE	-0.479031	0.337472	-1.41947	0.1581
BH	-1.07453	0.320474	-3.35293	0.0010
CF	-4.90623	1.60651	-3.05397	0.0027
CG	-0.358519	0.240938	-1.48801	0.1392
CH	-1.09754	0.705925	-1.55476	0.1224
DG	-0.139946	0.0719152	-1.94599	0.0538
DH	-0.273541	0.0898428	-3.04467	0.0028
EF	-1.17458	0.865673	-1.35684	0.1772
EG	0.206856	0.101867	2.03064	0.0443
EH	-0.421202	0.176271	-2.38951	0.0183
FG	-5.78374	2.54344	-2.27398	0.0246
FH	-2.44545	1.74241	-1.40348	0.1628

To determining whether the model can be further simplified, we looked for the largest P-values from Table 43. The highest p-value was 0.179 and it belonged to the independent variable AG. Because it was greater than 0.10, AG was not statistically significant at the 90% or higher confidence level. We further identified four (4) more variables with large P-values from Table

43, they were: BE, CG, EF, and FH. After the removing the five interaction terms, AG, BE, CG, EF, and FH we were left with 21 input independent variables. Then we utilized the subset (model) selection option within STATGRAPHICS. The model selection procedure built all models based on the user specified minimum to maximum number of attributes (variables) to include in the models. In our case, we set the minimum number of variables to 0 and maximum number of variables to 21. Based on the formula for choose all possible subsets of size r out of a total of n, denoted by *nCr* = choose(*n*,*r*), the total number of models created, *N*, would be:

$$N = \sum_{r=0}^{n} nCr = \sum_{r=0}^{n} \frac{n!}{r! \times (n-r)!}$$

When n = 21 we have:

$$N = \sum_{r=0}^{21} \frac{21!}{r!\,(21-r)!} = \mathbf{2{,}097{,}152}$$

For r = 7, we have:

choose(21,7) = $\frac{21!}{7! \times (21-7)!}$ = 116280

(see table 44 for the calculations of r = 0, 1, 2, …21)

Table 44 Calculation of Choose(n,r)

n	r	n-r	n!	r!	(n-r)!	# of Models
21	0	21	5.10909E+19	1	5.10909E+19	1
21	1	20	5.10909E+19	1	2.4329E+18	21
21	2	19	5.10909E+19	2	1.21645E+17	210
21	3	18	5.10909E+19	6	6.40237E+15	1330
21	4	17	5.10909E+19	24	3.55687E+14	5985
21	5	16	5.10909E+19	120	2.09228E+13	20349
21	6	15	5.10909E+19	720	1.30767E+12	54264
21	7	14	5.10909E+19	5040	87178291200	116280
21	8	13	5.10909E+19	40320	6227020800	203490

21	9	12	5.10909E+19	362880	479001600	293930
21	10	11	5.10909E+19	3628800	39916800	352716
21	11	10	5.10909E+19	39916800	3628800	352716
21	12	9	5.10909E+19	479001600	362880	293930
21	13	8	5.10909E+19	6227020800	40320	203490
21	14	7	5.10909E+19	87178291200	5040	116280
21	15	6	5.10909E+19	1.30767E+12	720	54264
21	16	5	5.10909E+19	2.09228E+13	120	20349
21	17	4	5.10909E+19	3.55687E+14	24	5985
21	18	3	5.10909E+19	6.40237E+15	6	1330
21	19	2	5.10909E+19	1.21645E+17	2	210
21	20	1	5.10909E+19	2.4329E+18	1	21
21	21	0	5.10909E+19	5.10909E+19	1	1

Table 44 gave us the number of all possible models created under each different subset size. In theory, we should be able to set the minimum = 0 and the maximum = 21 and let STATGRAPHICS create 2,097,152 models in one run. In practice, we were restricted by the computer software and hardware limitations. To overcome these limitations, we took a piece-wise approach. First, we set the number of variables in the model at minimum of one and maximum of five. Consequently, STATGRAPHICS built 21 models with one variable, 210 models with two variables, 1330 models with three-variables, 5985 models with four-variables, and 20349 models with five-variables, a total of 27890 models were created.

During the first run, models were fitted containing all combinations of from 1 to 5 variables. The results of fitting these multiple regression models to describe the relationship between *ChgdPost1* and the predictor variables were given in the STATGRAPHICS output. To determine which model was the best, we consulted the table of the largest adjusted R-squared values (Table 45) produced. The statistics tabulated in Table 45 included the mean squared error (MSE), the adjusted and unadjusted R-Squared values, and Mallows' Cp statistic.

Table 45 *ChgdPost1* – the Best Models Using 1 to 5 Attributes

		Adjusted		*Included*
MSE	*R-Square*	*R-Square*	*Cp*	*Variables*

0.0429697	60.2767	58.97	22.8714	EKNOR
0.0440085	59.3164	57.9781	26.9538	EJKNR
0.0440112	59.3138	57.9754	26.9647	EKNRT
0.0440217	59.3042	57.9655	27.0056	EKNRU
0.0441729	59.1644	57.8211	27.6	EGKNR
0.0444467	58.6409	57.5596	27.8254	EKNR
0.0476587	55.6521	54.4926	40.5314	EKNO
0.0481539	55.1913	54.0198	42.4902	EFKN
0.0482184	55.1312	53.9582	42.7457	EJKN
0.0482558	55.0964	53.9225	42.8935	EGKN
0.0490001	54.1058	53.2118	45.1047	EKN
0.0525286	50.801	49.8425	59.1543	ENR
0.0525924	50.7412	49.7816	59.4084	FKN
0.052713	50.6283	49.6665	59.8884	EKR
0.0528188	50.5292	49.5655	60.3098	KNO
0.0555019	47.6786	47.0035	70.4282	ER
0.0568931	46.3671	45.6751	76.0035	KN
0.0588019	44.5677	43.8525	83.653	NR
0.0608775	42.611	41.8705	91.9713	FN
0.0616553	41.8778	41.1279	95.0883	GN
0.0669286	36.4997	36.0926	115.952	N
0.0784592	25.5597	25.0825	162.46	R
0.0802583	23.8528	23.3646	169.716	E
0.103126	2.15637	1.52917	261.952	B
0.104721	0.643483	0.00658204	268.383	F

Table 45 presented the models which yielded the largest adjusted R-Squared values when the minimum number of variables was set to one and the maximum number of variables was set to five. Up to 5 models in each subset of between 1 and 5 variables were shown. The best model contained 5 variables, H, AH, BH, CF, and DH, with the adjusted R-squared = 58.97%. A list of the variables included in each model was also given in Table 45 (under the heading “Included Variables”). Notice this list of variable names is different from the original input variables entered. This was due to the reassignment of variable names within STATGRAPHICS. In our models, the reassignments were specified in Table 46 below.

Table 46 Variable Name Reassignments

A=A	D=F	G=AC	J=AF	M=BD	P=CH	S=EG
B=B	E=H	H=AD	K=AH	N=BH	Q=DG	T=EH
C=E	F=AB	I=AE	L=BC	O=CF	R=DH	U=FG

We next investigated models with six (6) independent variables (subset size equals to 6). STATGRAPHICS yielded 54264 models. Of the 54264 models, we were interested in the ones with the largest adjusted R-squared values. Of all the models containing 6 independent variables, the top five (5) models with the highest adjusted R-Square values were shown in Table 47. In the last column of Table 47, the list of "Included Variables" in column 5 were substituted with the original input variables. The best model's adjusted R-squared equaled 59.74%, MSE = 0.04216, and it contained 6 variables: H, AH, BH, CF, CH, and DH. A quick glance at the last column of Table 47 also assured us of the frequent involvement of variable H = *ChgdBFO*, and its interaction terms, in all top performing models.

Table 47 Models with Largest Adjusted R-Square – Subset with 6 Variables

MSE	*R-Square*	*Adjusted R-Square*	*Cp*	*Included Variables*	*Input Variables*
0.0421625	61.2793	59.7407	20.609	EKNOPR	H, AH, BH, CF, CH, DH
0.0428546	60.6437	59.0799	23.3109	EKNORT	H, AH, BH, CF, DH, EH
0.0428895	60.6117	59.0466	23.4472	EKLNOR	H, AH, BC, BH, CF, DH
0.0429361	60.5688	59.002	23.6293	EIKNOR	H, AE, AH, BH, CF, DH
0.0429583	60.5484	58.9808	23.716	AEKNOR	A, H, AH, BH, CF, DH

We proceed with subset size equal to 7, 8, 9, 10, 11, 12, 13, 14, 15 16, 17, 18, 19, and 20 to obtain the best models under each subset. We summarized all subset models into four (4) tables – Tables 48, 49, 50, and 51.

Table 48 Subset Size 1~5

	MSE	*R-Squared*	*Adjusted R-Square*	*Included Input Variables*
1	0.0669286	36.4997	36.0926	BH
	0.0784592	25.5597	25.0825	DH

	0.0802583	23.8528	23.3646	H
	0.103126	2.15637	1.52917	B
	0.104721	0.643483	0.00658204	AB
2	0.0555019	47.6786	47.0035	H, DH
	0.0568931	46.3671	45.6751	AH, BH
	0.0588019	44.5677	43.8525	BH, DH
	0.0608775	42.611	41.8705	AB, BH
	0.0616553	41.8778	41.1279	AC, BH
3	0.0490001	54.1058	53.2118	H, AH, BH
	0.0525286	50.801	49.8425	H, BH, DH
	0.0525924	50.7412	49.7816	AB, AH, BH
	0.052713	50.6283	49.6665	H, AH, DH
	0.0528188	50.5292	49.5655	AH, BH, CF
4	0.0444467	58.6409	57.5596	H, AH, BH, DH
	0.0476587	55.6521	54.4926	H, AH, BH, CF
	0.0481539	55.1913	54.0198	H, AB, AH, BH
	0.0482184	55.1312	53.9582	H, AF, AH, BH
	0.0482558	55.0964	53.9225	H, AC, AH, BN
5	0.0429697	60.2767	58.97	H, AH, BH, CF, DH
	0.0440085	59.3164	57.9781	H, AF, AH, BH,DH
	0.0440112	59.3138	57.9754	H, AH, BH, DH, EH
	0.0440217	59.3042	57.9655	H, AH, BH, DH, FG
	0.0441729	59.1644	57.8211	H, AC, AH, BH,DH

Table 48 contained models with subset sizes of 1 to 5, Table 49 contained models with subsets of 6 to 10, Table 50 contained models with subset sizes of 11 to 15, and Table 51 contained models with subset sizes of 16 to 20.

Table 49 Subset Size 6-10

	MSE	*R-Squared*	*Adjusted R-Square*	*Included Input Variables*
6	0.0421625	61.2793	59.7407	H, AH, BH, CF, CH, DH
	0.0428546	60.6437	59.0799	H, AH, BH, CF, DH, EH
	0.0428895	60.6117	59.0466	H, AH, BC, BH, CF, DH
	0.0429361	60.5688	59.002	H, AE, AH, BH, CF, DH

	0.0429583	60.5484	58.9808	A, H, AH, BH, CF, DH
7	0.0420124	61.6727	59.8841	A, H, AH, BH, CF, CH, DH
	0.0420993	61.5934	59.8011	H, AH, BH, CF, CH, DH, EH
	0.0421439	61.5527	59.7584	H, AE, AH, BH, CF, CH, DH
	0.042144	61.5526	59.7584	H, AH, BD, BH, CF, CH, DH
	0.042149	61.548	59.7536	H, AF, AH, BH, CF, CH, DH
8	0.0412786	62.5931	60.5847	A, H, AB, AD, AH, BH, CF, DH
	0.0417067	62.2052	60.1759	A, B, H, AD, AH, BH, CF, DH
	0.0417356	62.179	60.1484	A, H, AH, BD, BH, CF, CH, DH
	0.041853	62.0726	60.0363	A, H, AB, AD, AH, BH, DH, EH
	0.041858	62.0681	60.0315	A, H, AH, BH, CF, CH, DH, EH
9	0.0398533	64.1271	61.9457	A, B, H, AD, AH, BD, BH, CF, DH
	0.0403631	63.6683	61.4589	A, H, AD, AH, BD, BH, CF, CH, DH
	0.0407579	63.3129	61.0819	A, B, H, AD, AF, AH, BD, BH, DH
	0.0410493	63.0506	60.8037	A, H, AB, AD, AH, BH, CF, DH, EH
	0.0411684	62.9434	60.6899	A, B, H, AD, AH, BD, BH, DH, EH
10	0.0393098	64.8555	62.4647	A, B, H, AD, AH, BD, BH, CF, CH, DH
	0.0394863	64.6976	62.2961	A, B, H, AD, AH, BD, BH, CF, DH, EH
	0.0398686	64.3559	61.9311	A, B, H, AD, AE, AH, BD, BH, CF, DH
	0.039904	64.3242	61.8973	A, B, H, AD, AH, BD, BH, CF, DG, DH
	0.0399222	64.3079	61.8799	A, B, H, AD, AH, BD, BH, CF, DH, FG

Table 50 Subset Size 11-15

	MSE	*R-Squared*	*Adjusted R-Square*	*Included Input Variables*
11	0.0389459	65.4176	62.8121	A, B, H, AD, AH, BD, BH, CF, CH, DH, EH
	0.0393342	65.0729	62.4414	A, B, H, AD, AE, AH, BD, BH, CF, CH, DH
	0.0394326	64.9855	62.3474	A, B, H, AD, AH, BD, BH, CF, DG, DH, EH
	0.0394467	64.973	62.3339	A, B, H, AB, AD, AH, BD, BH, CF, CH, DH
	0.0394619	64.9595	62.3194	A, B, H, AD, AH, BD, BH, CF, CH, DG, DH
12	0.0390161	65.5926	62.7451	A, B, H, AB, AD, AH, BD, BH, CF, CH, DH, EH
	0.0390189	65.5901	62.7424	A, B, H, AD, AH, BD, BH, CF, CH, DG, DH, EH
	0.0390391	65.5723	62.7231	A, B, E, H, AD, AH, BD, BH, CF, CH, DH, EH
	0.0390829	65.5337	62.6813	A, B, H, AD, AE, AH, BD, BH, CF, CH, DH, EH
	0.0391339	65.4887	62.6326	A, B, H, AD, AH, BD, BH, CF, CH, DH, EH, FG

13	0.038801	66.0183	62.9505	A, B, E, H, AD, AE, AH, BD, BH, CF, CH, DH, EH
	0.0389158	65.9178	62.8409	A, B, H, AB, AD, AH, BD, BH, CF, CH, DG, DH, EH
	0.0390311	65.8167	62.7308	A, B, H, AD, AH, BD, BH, CF, CH, DG, DH, EG, EH
	0.0390391	65.8097	62.7231	A, B, H, AB, AD, AF, AH, BD, BH, CF, CH, DH, EH
	0.0390657	65.7865	62.6977	A, B, H, AB, AD, AH, BD, BH, CF, CH, DH, EH, FG
14	0.0387692	66.2819	62.9808	A, B, E, H, AD, AE, AH, BD, BH, CF, CH, DG, DH, EH
	0.038774	66.2778	62.9763	A, B, H, AB, AD, AH, BD, BH, CF, CH, DG, DH, EG, EH
	0.0389215	66.1494	62.8354	A, B, H, AE, AD, AH, BD, BH, CF, CH, DG, DH, EG, EH
	0.03893	66.1421	62.8273	A, B, H, AB, AD, AE, AH, BD, BH, CF, CH, DG, DH, EH
	0.0389334	66.1391	62.8241	A, B, E, H, AD, AE, AH, BD, BH, CF, DG, DH, EG, EH
15	0.038458	66.7865	63.278	A, B, H, AB, AD, AE, AH, BD, BH, CF, CH, DG, DH, EG, EH
	0.0386422	66.6274	63.1021	A, B, E, H, AD, AE, AH, BD, BH, CF, CH, DG, DH, EG, EH
	0.0387333	66.5488	63.0152	A, B, E, H, AB, AD, AE, AH, BD, BH, CF, CH, DG, DH, EH
	0.038845	66.4523	62.9085	A, B, H, AC, AD, AE, AH, BD, BH, CF, CH, DG, DH, EG, EH
	0.038881	66.4212	62.8741	A, B, H, AB, AD, AE, AF, AH, BD, BH, CF, DG, DH, EG, EH

Table 51 Subset Size 16-20

	MSE	*R-Squared*	*Adjusted R-Square*	*Included Input Variables*
16	0.0383624	67.1023	63.3693	A, B, E, H, AB, AD, AE, AH, BD, BH, CF, CH, DG, DH, EG, EH
	0.0385464	66.9446	63.1936	A, B, H, AB, AD, AE, AF, AH, BD, BH, CF, CH, DG, DH, EG, EH
	0.038564	66.9295	63.1768	A, B, H, AB, AD, AE, AH, BD, BH, CF, CH, DG, DH, EG, EH, FG
	0.0386034	66.8957	63.1392	A, B, E, H, AC, AD, AE, AH, BD, BH, CF, CH, DG, DH, EG, EH
	0.0386849	66.8258	63.0613	A, B, H, AB, AD, AE, AH, BC, BD, BH, CF, CH, DG, DH, EG, EH
17	0.0384546	67.2571	63.2812	A, B, F, H, AB, AD, AE, AH, BD, BH, CF, CH, DG, DH, EG, EH, FG
	0.038475	67.2398	63.2618	A, B, E, H, AB, AD, AE, AH, BD, BH, CF, CH, DG, DH, EG, EH, FG
	0.038483	67.233	63.2542	A, B, E, H, AB, AD, AE, AF, AH, BD, BH, CF, CH, DG, DH, EG, EH
	0.0386009	67.1326	63.1416	A, B, E, H, AB, AD, AE, AH, BC, BD, BH, CF, CH, DG, DH, EG, EH
	0.0386186	67.1176	63.1247	A, B, E, F, H, AB, AD, AE, AH, BD, BH, CF, CH, DG, DH, EG, EH
18	0.038349	67.5803	63.3821	A, B, E, F, H, AB, AD, AE, AH, BD, BH, CF, CH, DG, DH, EG, EH, FG
	0.0386015	67.3669	63.141	A, B, E, F, H, AC, AD, AE, AH, BD, BH, CF, CH, DG, DH, EG, EH, FG
	0.0386104	67.3594	63.1325	A, B, E, H, AB, AC, AD, AE, AF, AH, BD, BH, CF, CH, DG, DH, EG, EH
	0.0386229	67.3487	63.1205	A, B, F, H, AB, AD, AE, AF, AH, BD, BH, CF, CH, DG, DH, EG, EH, FG
	0.0386416	67.333	63.1027	A, B, F, H, AB, AC, AD, AE, AH, BD, BH, CF, CH, DG, DH, EG, EH, FG
19	0.0384962	67.69	63.2415	A, B, E, F, H, AB, AC, AD, AE, AH, BD, BH, CF, CH, DG, DH, EG, EH, FG
	0.0385379	67.655	63.2018	A, B, F, H, AB, AC, AD, AE, AF, AH, BD, BH, CF, CH, DG, DH, EG, EH, FG
	0.0385425	67.6511	63.1973	A, B, E, F, H, AB, AD, AE, AF, AH, BD, BH, CF, CH, DG, DH, EG, EH, FG
	0.0386212	67.5851	63.1221	A, B, E, F, H, AB, AD, AE, AH, BC, BD, BH, CF, CH, DG, DH, EG, EH, FG

	0.0387098	67.5108	63.0376	A, B, E, F, H, AB, AC, AD, AE, AF, AH, BD, BH, CF, CH, DG, DH, EG, EH
20	0.0384006	68.0038	63.3329	A, B, E, F, H, AB, AC, AD, AE, AF, AH, BD, BH, CF, CH, DG, DH, EG, EH, FG
	0.0387586	67.7055	62.991	A, B, E, F, H, AB, AC, AD, AE, AH, BC, BD, BH, CF, CH, DG, DH, EG, EH, FG
	0.0388099	67.6627	62.942	A, B, F, H, AB, AC, AD, AE, AF, AH, BC, BD, BH, CF, CH, DG, DH, EG, EH, FG
	0.0388232	67.6517	62.9293	A, B, E, F, H, AB, AD, AE, AF, AH, BC, BD, BH, CF, CH, DG, DH, EG, EH, FG
	0.0388387	67.6387	62.9145	A, B, E, F, H, AB, AC, AD, AE, AF, AH, BC, BD, BH, CF, DG, DH, EG, EH, FG

As we mentioned earlier, variables DG, EG and FG represented the interaction terms between the relative outsourcing contract amount and three accounting variables. These three accounting variables were: capital intensity, dividends per share, and capital contribution. From Tables 48, 49, 50, and 51 we observed that DG, EG, and FG began to be included in the top-performing models when the variables in the model reached 10, with only one exception, where the subset size was 5.

Figure 19 illustrated the changes in adjusted R-squared when the subset size (number of variables in the model) changed. Initially, when the number of variables in the model was small, the adjusted R-squared experienced a rapid increase as the number of variables in the model increased. It leveled off when the number of variables in the model reached 10 or 11. In other words, after the number of variables in the model reached 11, each subsequent addition of a variable into the models only resulted in a very small increase in the models' adjusted R-squared. To balance off model complexity (represented by the number of variables in the model) and model performance (as measured by the adjusted R-square), we reason that a subset size of 10 or 11 would produce the best models.

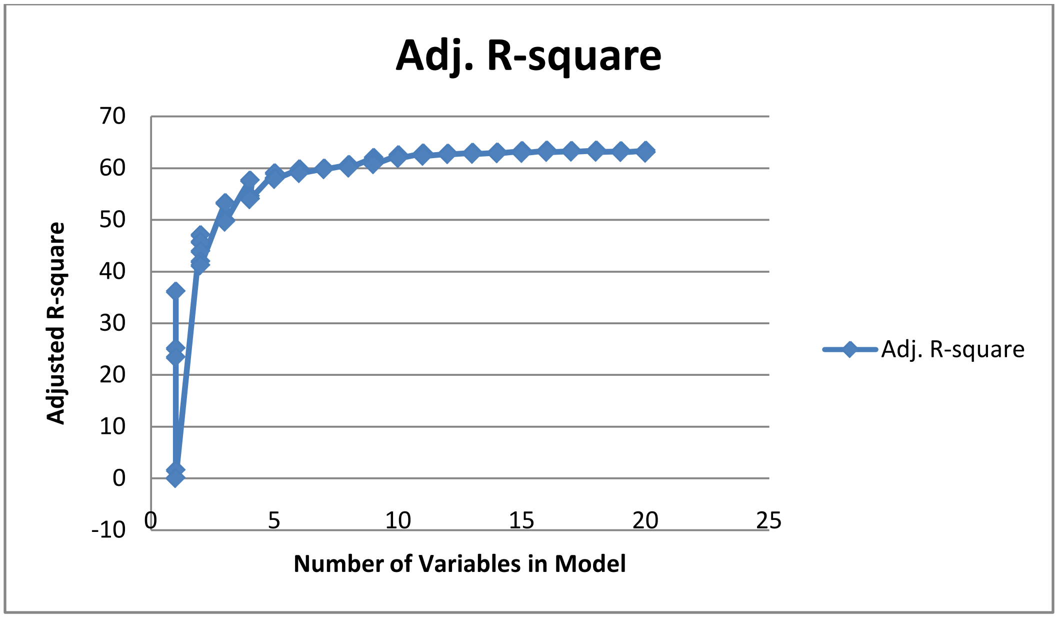

Figure 19 Subset Models' Adjusted R-square

Combining our observations from Tables 48~51 and from Figure 13, we infer that the interaction terms of the relative outsourcing amount with any other accounting variable did not make significant contributions to the most promising linear regression models that could be used to predict the changes in Tobin's q. Nevertheless, we were able to identify the best linear model that included the following variables: A, B, H, AD, AH, BD, BH, CF, CH, and DH. Its adjusted R-square was equal to 62.4647%. Compared to our benchmark model obtained using stepwise regression with backward selection (adjusted R-square = 64.05%), it was slightly worse. A 1.59% reduction on the model's adjusted R-square for a 16-variables reduction in the model's complexity was a worthy trade off. Therefore, with just 10 independent variables included, this model was preferred to the 26-variables backward selection model.

The details of the best model were captured in the ANOVA and coefficients tables (Table 52 and Table 53 below) as well as the following statistics:

R-square = 64.8555 percent
R-square (adjusted for d.f.) = 62.4647 percent
Standard Error of Est. = 0.198267
Mean absolute error = 0.128012

Finally, we present the best multiple linear regression (with interaction terms) model that described the relationship between *ChgdPost1* and 10 independent variables as follows.

ChgdPost1 **= -0.0380295 + 0.1713*A + 0.120934*B + 0.435716*H + 0.140806*AD - 0.912132*AH + 0.151688*BD - 1.48753*BH - 2.39209*CF - 0.787569*CH - 0.280781*DH (14)**

This model was significant because the model P-value was equal to zero (Table 52). Table 53 showed that all the independent variables in the model were significant, since all P-values were less than 0.05 except one (largest P-value = 0.0830). Besides, the adjusted R-square = 62.4647% indicated a very useful model as well.

Table 52 ANOVA – The Best LR with Interaction Model

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	10.6637	10	1.06637	27.13	0.0000
Residual	5.77854	147	0.0393098		
Total (Corr.)	16.4422	157			

Table 53 Coefficients – The Best LR with Interactions Model

	Parameter Estimate	*Standard Error*	*T Statistic*	*P-Value*
CONSTANT	-0.0380295	0.0217133	-1.75144	0.0820
A	0.1713	0.0473294	3.61931	0.0004
B	0.120934	0.0542693	2.22841	0.0274
H	0.435716	0.0940173	4.63442	0.0000
AD	0.140806	0.042313	3.32772	0.0011
AH	-0.912132	0.171236	-5.32677	0.0000
BD	0.151688	0.0467794	3.24263	0.0015
BH	-1.48753	0.252667	-5.88733	0.0000
CF	-2.39209	0.706205	-3.38724	0.0009
CH	-0.787569	0.451221	-1.74542	0.0830
DH	-0.280781	0.078142	-3.59322	0.0004

Comparing the adjusted R-squared of this interaction model (62.4647%) with that of the best first order model (23.8%), we see a noticeable improvement in the model's power to explain the variation in *ChgdPost1*. It is a strong indication that a non-linear relationship exists between the response variable *ChgdPost1* and the independent variables. Taking the natural log of the interaction terms is a fairly standard practice in Accounting and Finance. We decided not to pursue it because of the following reasons: (1) accounting variables were already scaled per firms' ME (market value of equity); (2) we used dividend per share instead of total dividend declared; (3) we intend to conduct further analysis using other nonlinear models in the following subsections.

5.3.1.3.2 Tobin's q Change 2-Years after Outsourcing

Because the subset selection method used for *ChgdPost1* did not yield a model superior to the one from the stepwise regression with backward selection, we chose stepwise regression to obtain the best linear model for changes in Tobin's q two years after the outsourcing announcement – *ChgdPost2*.

Within STATGRAPHICS, the dependent variable: *ChgdPost2* as well as the total of 36 independent variables, including the originals and all the second order interaction terms, were entered at step 0.

The original independent variables included:

A, B, C, D, E, F, G, H,

Interaction terms included:

AB, AC, AD, AE, AF, AG, AH,

BC, BD, BE, BF, BG, BH,

CD, CE, CF, CG, CH,

DE, DF, DG, DH,

EF, EG, EH,

FG, FH,

GH

By setting F-to-enter = 3.0 and F-to-remove =3.0, the resulting model details were captured in Table 54 (ANOVA), Table 55 (the table of coefficients), and the statistics in the text box below. Notice in the last modeling procedure, we choose a different F-to-enter and F-to-remove than before. The choice is not arbitrary, but based on a trial and error experiment to ensure that the largest P-value of the variable included is less than 0.05.

R-squared = 37.5149 percent
R-squared (adjusted for d.f.) = 32.6401 percent
Standard Error of Est. = 0.245172
Mean absolute error = 0.162777

Model Statistics for *ChgdPost2*

Table 54 ANOVA for *ChgdPost2* – Backward Selection Interaction Model

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	5.08845	11	0.462587	7.70	0.0000
Residual	8.47538	141	0.0601091		
Total (Corr.)	13.5638	152			

Table 55 Backward Selection Model Coefficients for *ChgdPost2*

	Parameter	*Standard*	*T*	
	Estimate	*Error*	*Statistic*	*P-Value*
CONSTANT	-0.0696815	0.0297687	-2.34076	0.0206
A	0.257245	0.0548843	4.68704	0.0000
B	0.432636	0.134169	3.22456	0.0016
H	0.61024	0.125406	4.86613	0.0000
AC	0.676701	0.177206	3.81873	0.0002
AD	0.235695	0.0505424	4.66331	0.0000
AH	-1.33479	0.219941	-6.06884	0.0000
BG	-0.266272	0.0842999	-3.15863	0.0019
CF	-1.89301	0.721644	-2.6232	0.0097
EG	0.356178	0.110799	3.21463	0.0016
EH	-0.501951	0.195903	-2.56224	0.0114
GH	1.26277	0.367721	3.43404	0.0008

Because the P-value in the ANOVA table is less than 0.05, there is a statistically significant relationship between the variables at the 95% confidence level.

The R-Squared statistic indicated that the model as fitted only explained 37.5149% of the variability in *ChgdPost2*, in other words, it is not a very useful model. The adjusted R-squared statistic was 32.6401%, compared to the 62.4647% adjusted R-square for *ChgdPost1*, so its prediction power was significantly weaker. The standard error of the estimate of 0.245172 and the mean absolute error (MAE) of 0.162777 were both comparable with the same statistics for ChgdPost1.

Table 55 showed that all the independent variables in the model were significant at the 95% or above confidence level, since all P-values were less than 0.05.

The regression equation:

***ChgdPost2* = -0.0696815 + 0.257245*A + 0.432636*B + 0.61024*H + 0.676701*AC + 0.235695*AD - 1.33479*AH - 0.266272*BG - 1.89301*CF + 0.356178*EG - 0.501951*EH + 1.26277*GH (15)**

We attribute the reason for the regression equation (15) for *ChgdPost2* being a much weaker predictor than that of *ChgdPost1*’s (14) to our choice of accounting variables used in the modeling process. For both *ChgdPost1* and *ChgdPost2*, we used the announcement year (year *t*) accounting variables of the subject firm. For *ChgdPost2*, the accounting variables of year t+1 might have yielded a model with stronger predictive power, but we chose to use data from year *t*. Our rationale for using year t accounting variables is as follows: when making a forecasting of changes in Tobin’s q while the decision of whether to outsource is under consideration, the year *t*+1 accounting data is not yet available. Therefore, by sacrificing prediction accuracy of LR model for *ChgdPost2*, we gain its practical applicability as a forecasting tool.

In the next subsection, we explore regression tree models using Cubist (Quinlan, 1992).

5.3.2 Regression Trees – Cubist

Quinlan (Quinlan, 1992) introduced a new algorithm, M5, to construct tree-based piece-wise linear models. Training cases are split into sub-sets based on the values of certain attributes, linear regression models are constructed for each sub-group (leaf nodes of the tree). The tree models preserve the simplicity and intuitiveness of the linear models and at the same time, improve the overall model fit since each sub-group model is built with like cases (along several attributes). We use the demo version of Cubist, a proprietary package written by Quinlan, to create tree models for our main response variables of interest: *ChgdPost1* and *ChgdPost2*. Because we had some missing values in both response variables, in the Cubist modeling, we experimented by first filling all missing response variables with the mean, and then deleting cases with missing response variables and re-run the same models. Afterwards, we further experimented with the second order models for both *ChgdPost1* and *ChgdPost2* by including all the interaction terms.

5.3.2.1 First Order Cubist Models

5.3.2.1.1 Replacing Missing with Mean

At first, all original independent variables were included, and all missing values for *ChgdPost1* and *ChgdPost2* were replaced with the respective means. Using all default settings: maximum rules = 100, Extrapolation allowed 100, and let Cubist decide the form of model.

The results for ChgdPost1 are shown below. The dataset was divided into three groups, two small groups of 6 cases each and a large group with 152 cases. Variables CDM_ME and ChgdBFO were used to create the split. It was very encouraging to see that the outsourcing contract amount was used to split data and also that the correlation coefficient of the model was greater than 0.8 (0.83). Below is the model output from Cubist:

```
Cubist [Release 2.06]
  Options:
    Allow use of instances with rules
```

```
  Target attribute `ChgdPost1'
Read 164 cases (19 attributes) from OutCubist090422.data
Model:
 Rule 1: [6 cases, mean -0.1097382, range -0.3058374 to 0.083883, est err 0.1591590]
  if
    CDM_ME <= 0.2092828
    ChgdBFO > 0.2672349
  then
    ChgdPost1 = -0.0445519
 Rule 2: [152 cases, mean 0.0192116, range -0.5518303 to 0.7299073, est err 0.1188372]
  if
    ChgdBFO <= 0.2672349
  then
    ChgdPost1 = 0.0160317 + 0.052 RDSGA_me
 Rule 3: [6 cases, mean 0.6133481, range -0.7584631 to 3.243655, est err 0.4738809]
  if
    CDM_ME > 0.2092828
    ChgdBFO > 0.2672349
  then
    ChgdPost1 = -0.692479 + 2.21 ChgdBFO + 0.738 IBE_me
Setting number of nearest neighbors to 8
Recommend using rules only
Evaluation on training data (164 cases):
  Average  |error|          0.1172192
  Relative |error|               0.79
  Correlation coefficient        0.83
    Attribute usage:
     Conds  Model
     100%     4%    ChgdBFO
              7%    CDM_ME
              93%    RDSGA_me
              4%    IBE_me
```

We proceeded by creating models for *ChgdPost2*. As with *ChgdPost1*, we first replaced the missing values for *ChgdPost2* with the series mean. After re-running Cubist for *ChgdPost2*, the output was displayed below:

Cubist [Release 2.06]

Options:

Allow use of instances with rules

Target attribute `ChgdPost2'

Read 164 cases (19 attributes) from OutCubist090422.data

Model:

Rule 1: [164 cases, mean 0.0534654, range -0.7678404 to 1.56089, est err 0.1822559]

ChgdPost2 = 0.0419073

Setting number of nearest neighbors to 7

Recommend using rules only

Evaluation on training data (164 cases):

Average |error| 0.1800468

Relative |error| 1.00

Correlation coefficient 0.00

Attribute usage:

Conds Model

In the above, Cubist did not choose to split the data set, and it returned a constant as the sole regression equation. In other words, none of the independent variables was used to build the model. As a result, the correlation coefficient was zero. This was not surprising since the first order linear model for *ChgdPost2* only had an adjusted R-squared of 10.8%.

5.3.2.1.2 Delete Cases with Missing Values

Next, we experimented with deleting all cases with missing response variables and re-build the previous two models. The datafile used, ChgdPost1Interact.data, includes all the interaction terms, but only the original first order terms were given to Cubists for modeling. Below was the output from Cubist for *ChgdPost1*

Cubist [Release 2.06]

Options:

Allow use of instances with rules

Target attribute `ChgdPost1'

Read 158 cases (38 attributes) from ChgdPost1CubistInteract.data

Model:

Rule 1: [147 cases, mean 0.0186328, range -0.5518303 to 0.7299073, est err 0.1223921]

```
    if
      H <= 0.2672349
    then
      ChgdPost1 = 0.0069395 + 0.052 A
  Rule 2: [11 cases, mean 0.2714026, range -0.7584631 to 3.243655, est err 0.3602929]
    if
      H > 0.2672349
    then
      ChgdPost1 = -0.6562091 + 1.94 H
Setting number of nearest neighbors to 8
Recommend using rules only
Evaluation on training data (158 cases):
    Average  |error|          0.1281798
    Relative |error|               0.84
    Correlation coefficient        0.78
      Attribute usage:
        Conds  Model
        100%     7%    H
                93%    A
```

In the above, the data was split into two subsets based on the value of H (ChgdBFO, representing pre-outsourcing changes in Tobin's q), and a linear model was created for each branch. When H <= 0.2672349, *ChgdPost1* was dependent upon A (RDSGA_ME) when H > 0.2672349 then H was the only variable included in the regression equation. The correlation coefficient equals 0.78, so that R-square = 0.78^2 = 0.6084, in other words, the model can explain 60.84% of the variance in *ChgdPost1*, an acceptably useful model.

When all missing response variable cases were deleted, employing the same set of independent variables, Cubist's output for *ChgdPost2*:

```
Cubist [Release 2.06]
    Options:
      Allow use of instances with rules
    Target attribute `ChgdPost2'
Read 153 cases (38 attributes) from ChgdPost2CubistInteract.data
```

```
Model:
  Rule 1: [138 cases, mean 0.0503790, range -0.7240624 to 0.6387258, est err 0.1558298]
    if
        H <= 0.1899439
    then
        ChgdPost2 = 0.0226901 + 0.087 A + 0.2 H
  Rule 2: [15 cases, mean 0.0818611, range -0.7678404 to 1.56089, est err 0.3952999]
    if
        H > 0.1899439
    then
        ChgdPost2 = -0.5296409 + 1.04 H
Setting number of nearest neighbors to 2
Recommend using rules only
Evaluation on training data (153 cases):
    Average  |error|         0.1661727
    Relative |error|             0.86
    Correlation coefficient        0.49
        Attribute usage:
          Conds  Model
          100%   100%    H
                  90%    A
```

In the above, the data were split into two subsets based on the value of H (*ChgdBFO*, representing pre-outsourcing changes in Tobin's q), and a linear model was created for each branch. When H <= 0.1899439, *ChgdPost2* depended upon A (RDSGA_ME) and H. When H > 0.1899439 then H was the only variable included in the regression equation. The correlation coefficients equals 0.49, so that R-square = 0.49^2 = 0.2401, in other words, the model can explain 24.01% of the variance in *ChgdPost2*, not a very useful model.

5.3.2.2 Second Order Cubist Models – with Interaction Terms

Similar to the previous processes under the linear regression modeling, next we proceed by feeding interaction term along with the original independent variables into Cubist. The following analyses were carried out by deleting cases with missing response variables. For *ChgdPost1*, the Cubist output with interaction terms yielded the following:

```
Cubist [Release 2.06]
  Options:
    Allow use of instances with rules
  Target attribute `ChgdPost1'
Read 158 cases (38 attributes) from ChgdPost1CubistInteract.data
Model:
 Rule 1: [147 cases, mean 0.0186328, range -0.5518303 to 0.7299073, est err 0.1201131]
  if
    H <= 0.2672349
  then
    ChgdPost1 = -0.0257996 + 0.112 A + 0.096 AD + 0.068 BD
 Rule 2: [11 cases, mean 0.2714026, range -0.7584631 to 3.243655, est err 0.3801794]
  if
    H > 0.2672349
  then
    ChgdPost1 = -0.3362399 + 1.16 H - 0.68 BH - 0.53 AH - 0.15 DH
Setting number of nearest neighbors to 9
Recommend using rules only
Evaluation on training data (158 cases):
  Average  |error|        0.1241544
  Relative |error|             0.81
  Correlation coefficient      0.81
    Attribute usage:
     Conds  Model
     100%     7%    H
              93%    A
              93%    AD
              93%    BD
               7%    AH
               7%    BH
               7%    DH
```

In the above, the data were split into two branches based on the value of H (*ChgdBFO*, representing pre-outsourcing changes in Tobin's q), and a linear model was created for each branch. When H <= 0.2672349, *ChgdPost1* was dependent upon A, AD, and BD, when H > 0.2672349 then H and H's interaction terms composed the entire subset of independent variables included in the regression equation. The correlation coefficient equals 0.81, so that R-squared = $0.81^2 = 0.6561$, in other words, the model can explain 65.61% of the variance in *ChgdPost1*, a simple but very good model.

Cubist output for *ChgdPost2* with interaction terms was as follows:

```
Cubist [Release 2.06]
    Options:
        Allow use of instances with rules
    Target attribute `ChgdPost2'
Read 153 cases (38 attributes) from ChgdPost2CubistInteract.data
Model:
 Rule 1: [153 cases, mean 0.0534654, range -0.7678404 to 1.56089, est err 0.1900135]
        ChgdPost2 = 0.0079273 + 0.086 A
Setting number of nearest neighbors to 8
Recommend using rules only
Evaluation on training data (153 cases):
    Average  |error|          0.1851100
    Relative |error|              0.96
    Correlation coefficient       0.16
        Attribute usage:
          Conds  Model
                 100%    A
```

In the above output, Cubist did not make any splits and the linear model built had only one independent variable – A (RDSGA_ME), and the correlation coefficient = 0.16 (translated to $R^2 = 0.0256$, 2.56%) was low. These results agreed with the first order linear model for *ChgdPost2* (adjusted R-squared =10.8%) and the first order Cubist model (correlation coefficient = 0).

Of the six models created by Cubist, Table 56 below recapitulates each model's three performance statistics: mean absolute error, relative absolute error, and model correlation coefficient. Because all six models were very simple, the model complexity would not be a factor in evaluating the merits of the models, therefore, the performance statistics would be the only valid criteria for determining the best model.

Table 56 Cubist Models Summary

		ChgdPost1	ChgdPost2
Missing Replaced by Mean	MAE	0.1172192	0.1800468
	RAE	0.79	1
	R	0.83	0
	Variable List	A, B, G, H	**None**
Missing Deleted	MAE	0.1281798	**0.1661727**
	RAE	0.84	**0.86**
	R	0.78	**0.49**
	Variable List	A, H	**A, H**
Second Order Model	MAE	**0.1241544**	0.18511
	RAE	**0.81**	0.96
	R	**0.81**	0.16
	Variable List	**A, H, AD, BD, AH, BH, DH**	A
MAE = Mean absolute error			
RAE = Relative absolute error			
R = Correlation coefficient			

With correlation coefficients equals to 0.83, 0.78, and 0.81 respectively, all three models for *ChgdPost1* were useful and they all had comparable MAE, RAE, and R. Even though the first order model with missing values replaced by the mean had the highest correlation coefficient, R = 0.83, the procedure of replacing missing values with the mean for this data has yet to be proven as a reasonably correct approach. Therefore, the final model with interaction terms will be chosen as the best Cubist model for *ChgdPost1*. It has a correlation coefficient R = 0.81 ($R^2 = 0.656$).

On the other hand, the three models for *ChgdPost2* were all poor predictors of the response variable. The best one of the three is the first order model with missing value cases deleted. It has the correlation coefficient R = 0.49 ($R^2 = 0.2401$).

One interesting observation: of the seven variables included in the best Cubist model for *ChgdPost1*, five of them were included in the best 7-variable LR model (second order model with interaction terms, see Table 49), derived in section 5.3.1.3.1. The sixth one, BD, was included in one of the top 5 best performing 7-variable LR models. The only exception was AD, which was not in any of the top 5 7-variable LR models, but was in the best 8-variable LR models. Furthermore, the variable list of the best Cubist model for *ChgdPost1* was almost an exact match to that of the best 8-variable LR model (Tables 49 and 56). The sole stranger was CF included in the LR model, but was not in the Cubist model.

5.3.3 Neural Network Models – Clementine

In this subsection, six Neural Network models were created using SPSS Clementine, a commercial data mining software package. Clementine implements six different training methods for its neural network modeling. In this chapter, we employed two of the six methods to train models for both *ChgdPost1* and *ChgdPost2*. The methods were: RBFN and Exhaustive prune. RBFN stands for radial basis function network which uses a technique similar to k-means clustering to partition the data based on values of the target field (SPSS Clementine). For more on RBFN, go to: http://en.wikipedia.org/wiki/Radial_basis_function_network.

The Exhaustive prune method uses the traditional logistic (sigmoid) transfer function and it starts with a large network and prunes the weakest units in the hidden and input layers as training proceeds. With Exhaustive Prune, network training parameters are chosen to ensure a very thorough search of the space of possible models to find the best one. This method is usually the slowest, but it often yields the best results (SPSS Clementine).

All model training was conducted with the “Prevent overtraining” option turned on. This option would randomly split the data into separate training and testing sets for purposes of model building. The network was trained on the training set, and accuracy was estimated based on the test set. We specified the proportion of the data to be used for training to be 80%, therefore, the remainder 20% of the data will be used for validation.

5.3.3.1 RBFN Models

When the RBFN training method was used for *ChgdPost1*, Clementine yielded the following model summary output:

Analysis
    Estimated accuracy: 94.22
    Input Layer: 9 neurons
    Hidden Layer 1: 20 neurons
    Output Layer: 1 neurons
Fields
    Target
        ChgdPost1
    Inputs
        CDM_ME
        CIDM
        ChgdBFO
        DIV
        GW_me
        IBE_me
        RDSGA_me
        nAcqst
Build Settings
    Use partitioned data: false
    Calculate variable importance: true
    Calculate raw propensity scores: false
    Calculate adjusted propensity scores: false
    Method: RBFN
    Stop on: Default
    Set random seed: false
    Prevent overtraining: true
    Sample %: 80.0
    Optimize: Speed
    Mode: Expert
    RBF clusters: 20
    Persistence: 30
    Compute Eta automatically: true
    Alpha: 0.9
    RBF overlapping: 1.0
Training Summary
    Algorithm: Neural net
    Model type: Approximation

The above model had an Input Layer with 9 neurons, one hidden layer with 20 neurons, and one output layer with 1 neuron. The model's estimated accuracy was 94.22. Clementine model output also gives a variable importance graph as shown in Figure 20. When the model predictions for *ChgdPost1* were compared with the actual values, the mean absolute error was 0.267 and the linear correlation between them was 0.331 (Table 57). Table 57 (the right side of) also listed the numerical values of the variables' importance.

A note on estimated model accuracy – within Clementine, the formula used for finding the accuracy of numeric fields is

$$(1.0 - |(\mathit{Actual} - \mathit{Predicted})| / (\mathit{Range\ of\ Output\ Field})) * 100.0$$

where *Actual* is the actual value of the output field, *Predicted* is the value predicted by the network, and *Range of Output Field* is the range of values for the output field (the highest value for the field minus the lowest value). This accuracy is calculated for each record, and the overall accuracy is the average of the values for all records in the training data (SPSS Clementine).

Typically, one focuses the modeling efforts on the variables that matter most and consider dropping or ignoring those that matter least. The variable importance chart in Clementine assists us to do this, by indicating the relative importance of each variable in estimating the model. These are relative values, meaning the sum of the values for all variables on the display chart is 1.0. Variable importance does not relate to model accuracy. It just relates to the importance of each variable in making a prediction, not whether or not the prediction is accurate (SPSS Clementine).

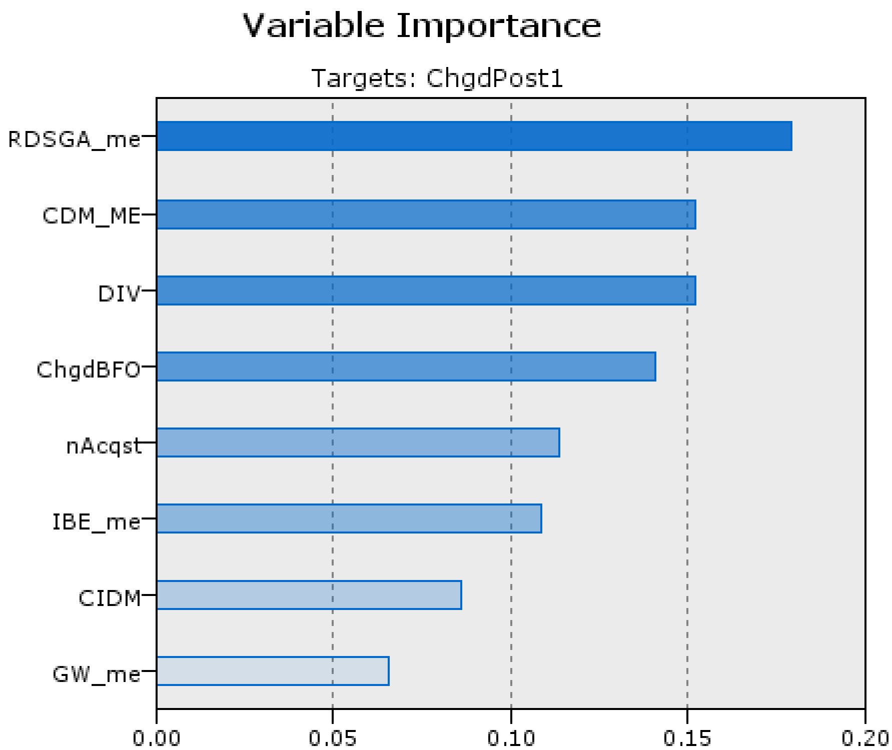

Figure 20 RBFN Variable Importance – *ChgdPost1*

Table 57 RBFN Model Statistics and Variable Importance – *ChgdPost1*

RBFN for *ChgdPost1* Analysis Results		**Nodes**	**Importance**
Compare Actual with Predicted		RDSGA_me	0.1794
Minimum Error	-0.636	CDM_ME	0.1524
Maximum Error	3.065	DIV	0.152
Mean Error	0.226	ChgdBFO	0.1411
Mean Absolute Error	0.267	nAcqst	0.114
Standard Deviation	0.306	IBE_me	0.1088
Linear Correlation	**0.331**	CIDM	0.0862
Occurrences	164	GW_me	0.0659

RDSGA_me was the most important variable in this model, followed by CDM_ME, and DIV. ChgdBFO came in 4th, which was a bit surprising.

Applying the RBFN training method for *ChgdPost2*, Clementine yielded the following model summary output:

Analysis
- Estimated accuracy: 93.253
- Input Layer: 9 neurons
- Hidden Layer 1: 20 neurons
- Output Layer: 1 neurons

Fields
- Target
  - ChgdPost2
- Inputs
  - CDM_ME
  - CIDM
  - ChgdBFO
  - DIV
  - GW_me
  - IBE_me
  - RDSGA_me
  - nAcqst

Build Settings
- Use partitioned data: false
- Calculate variable importance: true
- Method: RBFN
- Stop on: Default
- Set random seed: false
- Prevent overtraining: true
- Sample %: 80.0
- Optimize: Speed
- Mode: Expert
- RBF clusters: 20
- Persistence: 30
- Compute Eta automatically: true
- Alpha: 0.9
- RBF overlapping: 1.0

Training Summary
- Algorithm: Neural net
- Model type: Approximation

The model above included all the independent variables and provided the variable importance output in the right side of Table 58 as well as in Figure 21. The left side of Table 58 listed the statistics when comparing NN predictions with the actual response variable *ChgdPost2*. The network structure of the model consists of one 9-neuron input layer, a single 20-neuron hidden layer, and a one neuron output layer. The model estimated accuracy is 93.253%.

Table 58 RBFN Model Statistics and Variable Importance – *ChgdPost2*

RBFN for *ChgdPost2* Analysis Results		**Nodes**	**Importance**
Compare Actual with Predicted		RDSGA_me	0.1825
Minimum Error	-1.092	DIV	0.1626
Maximum Error	1.233	ChgdBFO	0.153
Mean Error	-0.092	CDM_ME	0.1313
Mean Absolute Error	**0.204**	nAcqst	0.1236
Standard Deviation	0.283	GW_me	0.105
Linear Correlation	**0.336**	IBE_me	0.0913
Occurrences	164	CIDM	0.0507

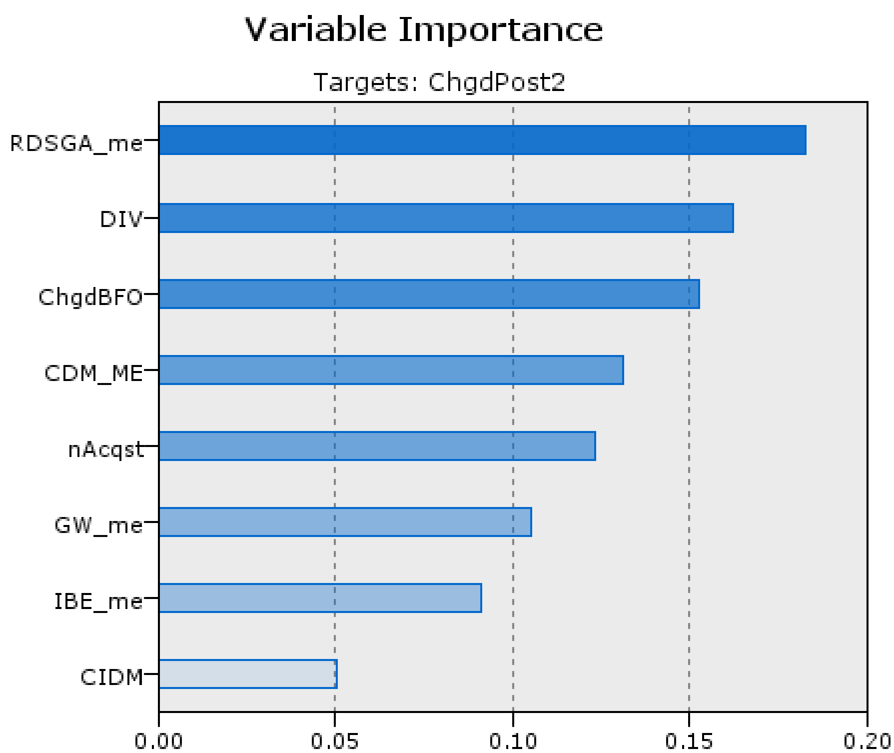

Figure 21 RBFN Variable Importance – *ChgdPost2*

One very important observation: the relative outsourcing amount variable, CDM_ME, was the 2nd most important variable in the RBFN-*ChgdPost1* model and the 4th in the RBFN-*ChgdPost2* model. This indicates that the radial basis function transferred CDM_ME into a significant predictor of both *ChgdPost1* and *ChgdPost2*. In other words, there is strong indication of a non-linear relationship between outsourcing and changes in firms' Tobin's q.

These two models also revealed evidence of the possible down side of using RBFN, as can be seen in the model performance statistics. In Table 57 and 58, the linear correlation between the models' predicted values and the actual response variables were low, 0.331 and 0.336 respectively. This distinctive position of being a significant but not very effective predictor after applying the RBF transfer function, naturally raises one's expectation in obtaining a better model using Support Vector Machine with a RBF kernel. Further investigation will be discussed in sections 5.3.4 and 5.3.5.

5.3.3.2 Exhaustive Prune Models

When the "Exhaustive prune" method was first applied, the NN model zoomed into ChgdBFO and disregarded all others. The model yielded had only one independent variable, with two hidden layers and the hidden layers had four and one neurons respectively. Below was the model summary for *ChgdPost1*.

Analysis
    Estimated accuracy: 96.811
    Input Layer: 1 neurons
    Hidden Layer 1: 4 neurons
    Hidden Layer 2: 1 neurons
    Output Layer: 1 neurons
Fields
    Target
        ChgdPost1
    Inputs
        ChgdBFO
Build Settings
    Use partitioned data: false
    Calculate variable importance: true
    Calculate raw propensity scores: false
    Calculate adjusted propensity scores: false
    Method: Exhaustive prune
    Stop on: Default
    Prevent overtraining: true
    Sample %: 80.0
    Optimize: Memory
    Mode: Simple
Training Summary
    Algorithm: Neural net

Even though the estimated accuracy of this model was high, 96.811%, from our point of view, it did not offer any useful information to us because none of the variables that we were interested in were included in the model. Interestingly, another identical run, by setting Optimize to Speed, and Mode to Expert, Clementine yielded the following more useful model:

- Analysis
  - Estimated accuracy: 96.302
  - Input Layer: 5 neurons
  - Hidden Layer 1: 8 neurons
  - Hidden Layer 2: 3 neurons
  - Output Layer: 1 neurons
- Fields
  - Target
    - ChgdPost1
  - Inputs
    - CIDM
    - ChgdBFO
    - RDSGA_me
    - nAcqst
- Build Settings
  - Use partitioned data: false
  - Calculate variable importance: true
  - Calculate raw propensity scores: false
  - Calculate adjusted propensity scores: false
  - Method: Exhaustive prune
  - Stop on: Default
  - Set random seed: false
  - Prevent overtraining: true
  - Sample %: 80.0
  - Optimize: Speed
  - Mode: Expert
- Training Summary
  - Algorithm: Neural net
  - Model type: Approximation

The above exhaustive prune model had an estimated accuracy of 96.302 and two hidden layers; hidden layer 1 had 8 neurons and hidden layer 2 had 3 neurons. The variables included in the model were: CIDM, *ChgdBFO*, RDSGA_me, and nAcqst. The variable importance was shown both in Table 59 (lower portion) and in Figure 22. The importance of *ChgdBFO* was more than twice the value of the next in-line. Clearly, it is the most dominating variable in this model.

Table 59 Exhaustive Prune Model Stats and Variable Importance – *ChgdPost1*

Comparing ChgdPost1 with Predicted	
Minimum Error	-0.854
Maximum Error	0.545
Mean Error	-0.096
Mean Absolute Error	**0.164**
Standard Deviation	0.201
Linear Correlation	**0.783**
Occurrences	164
Variable Importance	
Variable Name	Importance
ChgdBFO	0.5085
nAcqst	0.203
RDSGA_me	0.1981
CIDM	0.0904

As an analysis node was attached to the above exhaustive prune model for *ChgdPost1*, we obtained the comparison results of Neural Network predicted vs. actual in Table 59 (top portion) above. It was encouraging to see a high linear correlation, **0.783**, between the NN-predicted value and the actual *ChgdPost1* value. Furthermore, the mean absolute error is 0.164, lower than that of the RBFN model (= 0.204, shown in Table 58). Thus far, it is the top performing model.

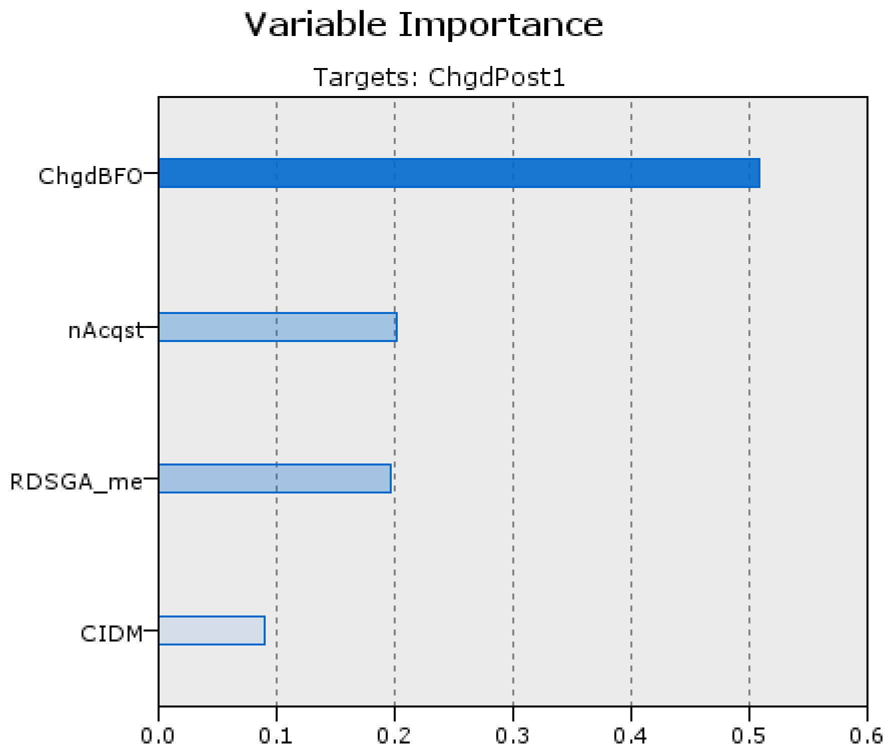

Figure 22 Exhaustive Prune Variable Importance – *ChgdPost1*

When using the "Exhaustive prune" method for *ChgdPost2*, Clementine yielded the following output, with two hidden layers of 16 and 3 neurons respectively. The exhaustive prune model summary for *ChgdPost2*:

```
Analysis
        Estimated accuracy: 93.767
        Input Layer: 7 neurons
        Hidden Layer 1: 16 neurons
        Hidden Layer 2: 3 neurons
        Output Layer: 1 neurons
Fields
        Target
                ChgdPost2
        Inputs
                CIDM
                ChgdBFO
                DIV
                GW_me
                IBE_me
```

RDSGA_me

Build Settings

Use partitioned data: false

Calculate variable importance: true

Calculate raw propensity scores: false

Calculate adjusted propensity scores: false

Method: Exhaustive prune

Stop on: Default

Set random seed: false

Prevent overtraining: true

Sample %: 80.0

Optimize: Speed

Mode: Expert

Training Summary

Algorithm: Neural net

Model type: Approximation

Elapsed time for model build: 0 hours, 1 mins, 3 secs

For a small dataset such as this, it took Clementine 1 minute and 3 seconds to train the exhaustive prune model. Figure 23 below shows the variable importance.

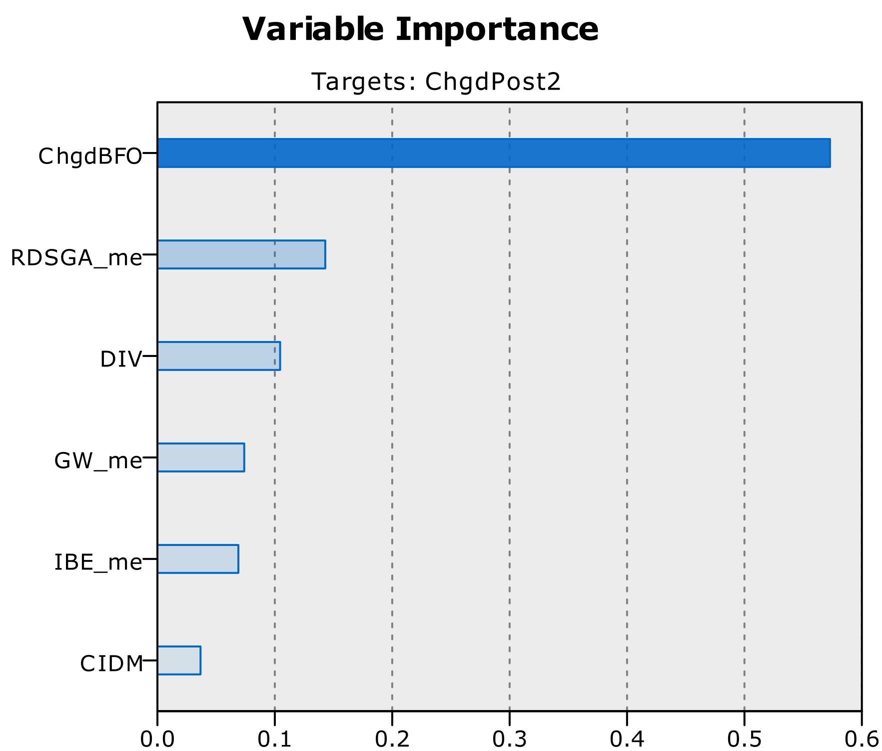

Figure 23 Exhaustive Prune Variable Importance - *ChgdPost2*

Table 60 below combines model analysis results with the variable importance provided by Clementine. ChdgBFO is the most important variable in this model. Similar to the exhaustive prune model for *ChgdPost1*, a high linear correlation, 0.575, and a low mean absolute error, 0.168, between the NN-predicted value and the actual *ChgdPost2* value is observed (left part of Table 60).

Table 60 Exhaustive Prune Model Stats and Variable Importance – *ChgdPost2*

Comparing ChgdPost2 with NN Predicted		Variable Importance	
Minimum Error	-0.87	**Nodes**	**Importance**
Maximum Error	1.244	ChgdBFO	0.5729
Mean Error	-0.009	RDSGA_me	0.143
Mean Absolute Error	**0.168**	DIV	0.1045
Standard Deviation	0.249	GW_me	0.074
Linear Correlation	**0.575**	IBE_me	0.0689
Occurrences	164	CIDM	0.0367

The following experiment involves applying the exhaustive prune training method to train models for two response variables, *ChgdPost1* and *ChgdPost2*, at the same time. This technique forces Clementine to build a model that will be applicable to both response variables. The inspiration for taking this unique approach came from the technique to enrich a smaller dataset via simulation. To simulate more data, one finds the probability distribution of the original data, and then randomly generates more data that follows the probability distribution of the original. In this experiment, we force the modeling software to work with the same set of independent variables coupled with two highly correlated response variables. The expectations are (1) decreased prediction accuracy; and (2) increased model generalization or applicability. The first expectation was met as exhibited in the model shown below, while the meeting of the second has yet to be produced. The summary report of the NN model with both response variables, *ChgdPost1* and *ChgdPost2*:

```
Analysis
        Estimated accuracy: 92.271
        Input Layer: 9 neurons
        Hidden Layer 1: 3 neurons
        Hidden Layer 2: 1 neurons
```

Output Layer: 2 neurons
Fields
Target
ChgdPost1
ChgdPost2
Inputs
CDM_ME
CIDM
ChgdBFO
DIV
GW_me
IBE_me
RDSGA_me
nAcqst
Build Settings
Use partitioned data: false
Calculate variable importance: true
Calculate raw propensity scores: false
Calculate adjusted propensity scores: false
Method: Exhaustive prune
Stop on: Default
Set random seed: false
Prevent overtraining: true
Sample %: 80.0
Optimize: Speed
Mode: Expert
Training Summary
Algorithm: Neural net
Model type: Approximation

Clementine used all eight independent variables in the model. There were two hidden layers. The first hidden layer had two neurons and the second hidden layer had one neuron. The model estimated accuracy was 92.271. The variable importance chart of the model is shown below.

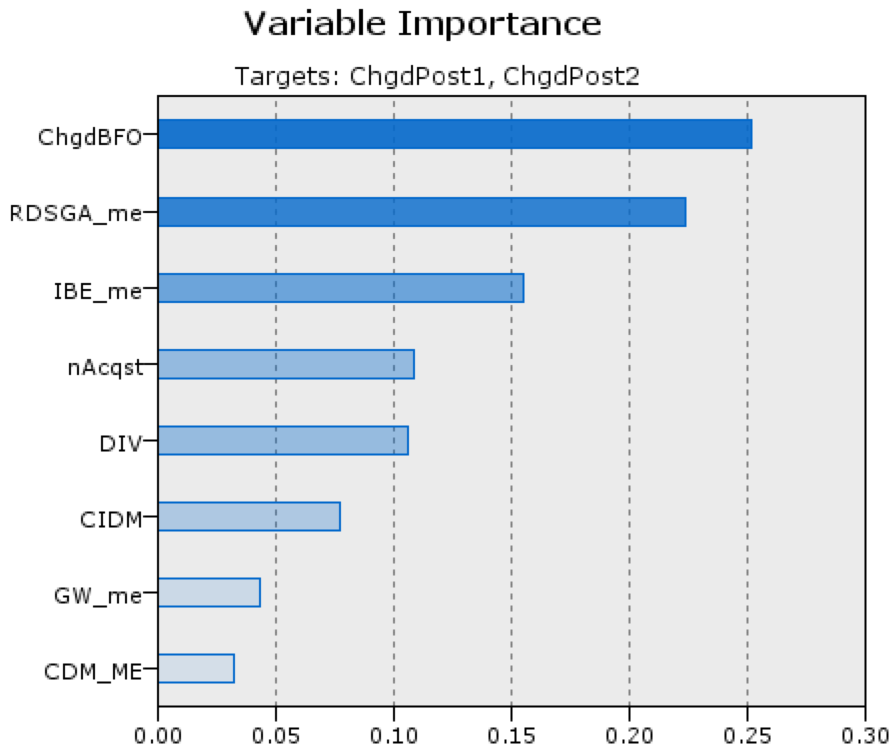

Figure 24 Exhaustive Prune Variable Importance 2 Dependent Variables

When an analysis node was attached to the model, we obtained the following comparison results of predicted vs. actual. Because the linear correlation for both *ChgdPost1* and *ChgdPost2* were low (0.256 and 0.435 respectively, in Table 61), it was not a very useful model.

Table 61 Exhaustive Prune Model Stats – *ChgdPost1* and *ChgdPost2* with Their Predicted

Comparing *ChgdPost1* with Predicted	
Minimum Error	-0.972
Maximum Error	3.027
Mean Error	-0.058
Mean Absolute Error	0.166
Standard Deviation	0.313
Linear Correlation	**0.256**
Occurrences	164
Comparing *ChgdPost2* with Predicted	
Minimum Error	-1.081
Maximum Error	1.296
Mean Error	0.009
Mean Absolute Error	0.179

Standard Deviation	0.27
Linear Correlation	**0.435**
Occurrences	164

This concluded the neural network modeling process.

5.3.3.3 Neural Network Model Summary

In this subsection, six neural network models were created for the two variables of interest utilizing two network training methods: RBFN and Exhaustive Prune. Usually, one assesses the models' merits by striving for a balance between performance and complexity. At the present time, due to the nature of the Neural Network, the model complexity was unknown to us, therefore the only available method of assessment was to examine the model performance.

Table 62 below displays a recapitulation of all model performance data as well as variables included in the models. The two expert setting exhaustive prune models came on top in every performance measurement category: mean absolute error, linear correlation, and estimated prediction accuracy. They also had a smaller number of independent variables included in the model. This could possibly be a merit as well as a peril. A smaller number of variables could signify a more compact model, which was a merit, provided the hidden layers were not too complex. If the hidden layers were very complex, then this merit did not exist. On the other hand, not being able to include the outsourcing variable into the model was a sure peril to our research goal. To sum it up: the best Neural Network models found here are still inadequate to achieve our objective.

Table 62 Neural Network Modeling Summary

		ChgdPost1	*ChgdPost2*
RBFN	MAE	0.267	0.204
	R	0.331	0.336
	Accuracy	94.22	93.253
	Variable List	A, B, C, D, E, F, G, H	A, B, C, D, E, F, G, H
Exhaustive Prune	MAE	**0.164**	**0.168**
	R	**0.783**	**0.575**
	Accuracy	**96.302**	**93.767**

	Variable List	A,D, F, H	A, B, C, D, E, H
Exhaustive Prune with Both Variables	MAE	0.166	0.179
	R	0.256	0.435
	Accuracy	92.271	
	Variable List	A, B, C, D, E, F, G, H	
MAE = Mean absolute error			
R = Linear correlation between actual and predicted			
Accuracy = estimated accuracy			

Based on our assessment of the NN models, it is the natural next step to pursue another modeling algorithm in order to reach our final goal. In the next subsection, support vector machine modeling is conducted.

5.4 THE BEST OF THE BEST – MODEL COMPARISONS

Within each modeling process, we have identified the best models for both response variables. In this section, we identify the best model for our response variables across all three modeling processes: Least Squares Regression (LSR), Regression Tree (RT), and NN. In the following, we first present the comparison criteria used and then assess the top models from each modeling process to select the best of the best.

5.4.1 Model Comparison Criteria

As mentioned earlier, there two key model comparison criteria for comparing models built using different machine learning tools. They are:

(a) the predictive power, i.e. how well it predicts the response variable(s); and

(b) the explanatory power, i.e. the ability to decipher the derived function to draw meaningful managerial insights.

For model prediction power, we examine the R or R^2 as well as the mean absolute error of prediction. For its explanatory power, we look at the symbolic representation of the model and try to identify how the original variable or the variation of it influences the response variable.

5.4.2 The Best Model

Of the numerous models created via Least Squares regression (LR), Regression Tree modeling, and NN modeling, we find the best one for *ChgdPost1* is the second order regression tree model created under Cubist. Unfortunately the outsourcing amount variable was not included in this model, although it was in other models. Here is the best model for changes in Tobin's q one year after outsourcing:

```
Rule 1: [147 cases, mean 0.0186328, range -0.5518303 to 0.7299073, est err 0.1201131]
  if
     H <= 0.2672349
  then
     ChgdPost1 = -0.0257996 + 0.112 A + 0.096 AD + 0.068 BD
 Rule 2: [11 cases, mean 0.2714026, range -0.7584631 to 3.243655, est err 0.3801794]
  if
     H > 0.2672349
  then
     ChgdPost1 = -0.3362399 + 1.16 H - 0.68BH - 0.53AH - 0.15 DH
                = -0.3362399 + (1.16 – 0.68B – 0.53A – 0.15D)
```

In this model, the cases were split into two groups of size 147 and 11. When the pre-outsourcing Tobin's q change, ChgdBFO, is less than or equal to 0.267249 (147 cases), one year after outsourcing Tobin's q change is positively correlated with RDSGA_me, the interaction term of CI_DM with RDSGA_me and with IBE_ME. Of the 11 cases included in the second group, while ChgdBFO is greater than 0.267249, one year after outsourcing Tobin's q change is negatively correlated with three interaction terms: ChgdBFO with IBE_ME, with RDSGA_me, and with CI_DM, but positively correlated with ChgdBFO.

From the three modeling process, we summarized the following statistics and variable lists for ChgdPost2, in order to identify the best model (Table 63 below). For the performance measures, R and MAE, NN and LSR are similar, but the 11-variables linear function yielded from LR is vastly simpler than the NN with 2 hidden layers (16, 3), thus, we prefer the LR model.

Table 63 Best from Each Method -ChgdPost2

Top Models for ChgdPost2				
Technique	R	R^2	MAE	Variables Included
NN	0.575	0.330625	0.168	A, B, C, D, E, H
RT	0.49	0.2401	0.166	A, H
LSR	**0.6125**	**0.375149**	**0.163**	**A, B, H, AC, AD, AH, BG, CF, EG, EH, GH**

The best model for two years after outsourcing is equation (15):

$$ChgdPost2 = -0.0696815 + 0.257245*A + 0.432636*B + 0.61024*H + 0.676701*AC + 0.235695*AD - 1.33479*AH - 0.266272*BG - 1.89301*CF + 0.356178*EG - 0.501951*EH + 1.26277*GH \quad (15)$$

5.5 VARIABLE INTERPRETATIONS – FROM THE BEST MODEL

When the firm's pre-outsourcing change in Tobin's q is less than and equal to 0.2672, change in Tobin's q one year post outsourcing is positively correlated with the followings:

- Research & development expenses plus selling, general & administrative expenses per company's ME
- The interaction term between "Research & Development Expenses plus selling, general & administrative expenses per company's ME" and "Capital Intensity"
- The interaction term between "Income Before Extraordinary Items per company ME" and "Capital Intensity"

When the firm's pre-outsourcing change in Tobin's q is greater than 0.2672, change in Tobin's q one year post outsourcing is positively correlated with "pre-outsourcing change in Tobin's q" and negatively correlated with the interaction term between "pre-outsourcing change in Tobin's q" and the following variables

- "Income Before Extraordinary Items per company ME"

- “Research & Development Expenses plus selling, general & administrative expenses per company’s ME”
- “Capital Intensity”

For change in Tobin’s q two years after outsourcing, the LSR function, equation (15), shows that seven terms have positive correlations with *ChgdPost2*, they are:

- “Research & Development Expenses plus selling, general & administrative expenses per company’s ME”
- “Income Before Extraordinary Items per company ME”
- “Pre-outsourcing change in Tobin’s q”
- The interaction term between “Research & Development Expenses plus selling, general & administrative expenses per company’s ME” and “Good Will per company ME”
- The interaction term between “Research & Development Expenses plus selling, general & administrative expenses per company’s ME” and “Capital Intensity”
- The interaction term between “Dividends Per Share” and “Contract value per company ME”
- The interaction term between “Outsourcing Contract value per company ME” and “Change in Tobin’s q pre-outsourcing”

There are 4 terms that have negative impact on *ChgdPost2*:

- The interaction term between “Research & Development Expenses plus selling, general & administrative expenses per company’s ME” and “Change in Tobin’s q pre-outsourcing”
- The interaction term between “Income Before Extraordinary Items per company ME” and “Contract value per company ME”
- The interaction term between “Goodwill per company ME” and “Capital Contribution”
- The interaction term between “Dividends Per Share” and “Contract value per company ME”

Here we offer a word of caution in that the results are preliminary without intensive validation by using separate test data. Furthermore, other method, such as support vector machine regression, has yet to be investigated.

5.6 THE IMPACT – MODELING SUMMARY

A non-linear relationship DOES appear to exist between the relative outsourcing contract value and the change in Tobin's q both one and two years post outsourcing. This non-linear relationship also appears to be more pronounced for two years after outsourcing, because it is detected by all three modeling processes. In the case of one year post outsourcing, some method/models are able to discover the relationship better than others. This phenomenon can be attributed to one of the followings:

(1) The delayed effect of outsourcing

(2) The deterioration of the prediction power of other variables

Nevertheless, further investigation is necessary to confirm, modify, or dispute the current findings through this research.

Both RBFN neural network models, for one year and two year post outsourcing change in Tobin's q, show that relative outsourcing contract size is an important predictor in the models (see Tables 57 and 58). This leads us to form the conjecture: RBF function transforms relative contract size into a "feature space" where the new variable has a first order linear relationship with changes in Tobin's q. To prove this conjecture will be a very interesting research subject.

There is variable interaction between the relative outsourcing contract size and the other accounting variables (examples: equation 13 with Table 43 and equation 15 with Table 55).

The relationship between the relative size of the outsourcing contract and Tobin's q is not the same for all firms (see Cubist model on page 121).

When the pre-outsourcing change in Tobin's q is less than or equal to 0.2672349 (majority of the cases, group 0), relative outsourcing contract size does not appear to have a linear relationship with post outsourcing changes in Tobin's q, nor it is used by the regression tree model to split data into groups (see rule #2). On the other hand, when the pre-outsourcing change in Tobin's q is greater than 0.2672349, relative outsourcing contract size is used by the regression tree model to split the data into two groups. The first group (group 1) includes large companies with the market equity of greater than 2.8 billion. Group 1 follows the regression tree model rule #1, which state that the post-outsourcing changes in Tobin's q is a small negative number: -0.0445519. The second group (group 2) follows the regression tree rule #3, which states that the post-outsourcing change in Tobn's q is positively correlated with *ChgdBFO* and *IBE_me*. Upon closer examination, we find that group1 consists of very large companies, the market equity is greater than 2.8 billion; and group 2 consists of smaller companies with market equity equals to 100MM$ or less. Further investigation is necessary to identify other factors that may have contributed to the findings described here.

6.0 CHAPTER 6 CONTRIBUTIONS, IMPLICATIONS AND CONCLUSION

In this research, we investigate the issue of outsourcing from three different perspectives: government policy makers, corporate management, and management scientists. The overall objective is to provide both macro and micro views of outsourcing. Within each designated perspective, finer and more specific goals are set to address the concerns of the major stakeholders regarding outsourcing. This chapter provides research contributions, managerial implications, limitations, future research directions, and concluding remarks.

6.1 CONTRIBUTIONS

In the course of studying different aspects of outsourcing, we discover evidences that are of interest to management researchers and, at the same time, we find practical implications useful for management practitioners. In the following subsections, we summarize our findings.

6.1.1 Implications for Research

The successful adaptation of sophisticated machine learning techniques to empirically analyze outsourcing data has not only provided a unique approach to how the outsourcing research is conducted, but also enabled us to discover some important indications. First of all, the relative outsourcing contract size appears to interact with firm's other accounting variables when it impacts the firm's post outsourcing change in Tobin's q, as exhibited in equation (15) from LSR. Evidences from other modeling processes further indicates the existence of a non-linear relationship between the relative outsourcing contract size and the post-outsourcing change in

Tobin’s q. These modeling processes are: the two RBFN NN models the paired exhaustive prune model (Table 62), and the Cubist model (Table 56). A related indication is exhibited by the results from applying RBF transfer to the outsourcing variable – transforming the relative outsourcing amount into a significant predictor for both one year and two years post outsourcing change in Tobin’s q. Secondly, the impact of the outsourcing on the post-outsourcing change in Tobin’s q is different for some firms than it is for others. This is exhibited by several Cubist (regression tree) models (see section 5.3.2).

Thus far, we have yet to find another study that utilizes data mining tools to model outsourcing data. Our methodologies as well as the findings in chapter 5 make this research a useful addition to the outsourcing literature.

In the MCDM methodology front, even though ours is not the first to propose the BSC-ANP approach, we are the first to put this union into the context of outsourcing strategy evaluation instead of the traditional performance measurement. A BSC-ANP valuation model is unique in that it is different from traditional ANP BOCR approach. At the same time, it is different from a traditional BSC implementation in which the main goal is to measure the firm’s performance. The BSC framework contributes a comprehensive set of evaluation criteria which are widely recognized by the research community, while the ANP enables all criteria to be included in the combined decision model in a coherent manner. In addition, a direct linkage is established between the selected strategy and the firm performance measurement system via a common set of BSC indicators.

6.1.2 Practical Contributions

From a policy perspective, the goal was to find the most suitable or least harmful policy option for law-makers in all levels of the government. A methodical approach is the key to achieving this goal. In this work, the author chooses the popular MCDM ANP to construct the decision model. Based on the model results (tested for its robustness as well as the effectiveness to detect extreme changes), “providing displaced workers’ assistance programs” is the recommended option. The comprehensive approach applied in this research assures everyone affected that the final decision is prudently made with due consideration given to every aspect of the issue. In other words, all concerns from every party at stake are factored in to identify the best policy.

For corporate management, much effort has been devoted to find the best strategic option for a firm and also providing it with a systematic way to prioritize a list of outsourcing candidates. In other words, the specific goals are: (1) finding and recommending the best practice with regard to a firm's outsourcing strategy and (2) providing assistance in the operational decision on which functions to outsource. In chapter 4, this was achieved by a two-step approach: a BSC-ANP strategy evaluation model to find the best strategy, followed by an AHP ratings model to prioritize the functional alternatives for outsourcing. The case company received the recommendation to pursue selective outsourcing by first considering the outsourcing of its Documentation function and then its DSS function. Even though the models are developed based on the case company's preference, they can be adjusted to suit other companies (shown in the sensitivity analysis).

To provide better guidance and tools for the management practitioners is the primary goal as well as major concern of the management science research community. In order to address that concern, we apply machine learning techniques to empirical outsourcing data to test our theory about the economic impact of outsourcing on firms. The preliminary results support our hypothesis and also provide us with managerial implications. More specifically, the outsourcing amount interacts with other accounting variables in their contribution to explain the changes in firm's future economic performance (Tobin's q). For example, equation (15) shows positive relationship between the interaction term of "Contract value per company ME" and these two accounting variables: (1) "dividend per share" and (2) "Change in Tobin's q pre-outsourcing." The full details are given in section 5.5.

6.2 LIMITATIONS

The main limitation of the economic impact analysis within this research is the small sample size of the data and also the non-inclusion of more recent data – outsourcing data from January 2004 to the present time are not included in the sample. Therefore the analysis results given in chapter 5 are preliminary, because a larger and more recent sample might bring out different patterns.

The models built in the case study in chapter 4 are structured without the company size limit, but the numerical inputs (reflecting specific judgments) of the models are solicited from a small company. Therefore, the models might need significant customization to suit the larger companies. In other words, the final results for the best strategy and the prioritized function list may not be directly applicable to larger companies.

New developments in outsourcing research have revealed limitation of our framework proposed in chapter 3. Since the completion of our study regarding outsourcing policy decisions, there have been proposals for more complex options for government to consider. In other words, an up to date model for policy decision could include alternatives that are not in the current model.

6.3 FUTURE RESEARCH

The empirical finding of a non-linear relationship between the relative outsourcing amount and post outsourcing change in Tobin's q is both unprecedented and significant. Along with the finding comes the question: (1) what is the exact relationship (we can either prove or disprove that it is a RBF transfer), and how do we approximate it with a mathematical equation? After deriving a mathematical expression of the relationship, (2) how do we validate it? After a positive validation, the question is: (3) can, or how, or what managerial inferences do we draw from the equation? Next, (4) what kind of managerial insight can we derive? Finally, what should be done to really enhance a firm's future performance (as measured by Tobin's q) based on our findings? As we can see, those are valid questions and they point towards new directions for future research. In order to answer them, further investigation is necessary.

6.4 CONCLUSIONS

Overall, what we have learned from this research provided both macro and micro views on the subject of outsourcing. At the macro level, government policy makers should proactively establish displaced workers' assistance programs. For each individual firm, the decision of whether to outsource, insource or selective outsource should be made with due consideration of all perspectives of the firm: customer, financial, internal operations, and company learning and growth. Furthermore, the relative contract size is related with the post outsourcing financial performance of the firm in a non-linear manner. The mathematical expression of this non-linear relationship can provide useful guidance to a firm contemplating outsourcing. For instance, the evidence shows that the interaction terms between the outsourcing variable and the firm's other accounting variables can have either positive of negative impact on the firm's future financial performance. Therefore, when a firm is considering outsourcing, it should also consider increasing the accounting variables that have positive influence on the financial impact of the outsourcing variable.

In this research, some existing questions at the policy, firm, and technology levels are answered, and at the same time, further questions are raised. Along with the answers to existing questions and the raising of the new, this chapter as well as this dissertation are coming to their closure, while a new chapter in a new book is waiting for tomorrow.

APPENDIX A

POLICY – CONTROL CRITERIA DESCRIPTIONS AND SOURCES

Control Criteria Descriptions and Sources			
Group	**Name**	**Description**	**Sources**
BENEFITS CRITERIA	**CostSavings**	Savings on the procurement and other operational costs to U.S. industries and government agencies	(Mann, 2003), (Mann, 2004a), (Anderson, 2005), (Bednarz, 2005), (Bean, 2003), (Weidenbaum, 2005)
	Improved Operations	The improvement of the operational efficiency of U.S. corporations who practice offshore outsourcing. These include improved business focus to maximize the effect of the company's core competence; productivity enhancement when goods and services are produced in countries with comparative advantage and then traded; variable cost structure changes; and access to skills outside the company.	(Kletzer, 2003), (Corbett, 2004), (Bednarz, 2005), (Thondavadi & Albert, 2004), (Harland, Knight, Lamming, & Walker, 2005), (Bean, 2003)
	Flexibility	The flexibility and other benefits to the U.S. businesses when practicing offshore outsourcing. These benefits include growing revenue, improving quality, conserving capital, and innovation.	(Corbett, 2004), (Thondavadi & Albert, 2004), (Harland et al., 2005), (Bean, 2003)
	BuyingPower	The increased buying power of the U.S. consumers. As a result of outsourcing, prices fall, Americans and Europeans have more money left after they buy what they need and can then spend it on new products and services.	(Kletzer, 2003),(Brown & Wilson, 2005)
	EUcountries	Political support of the European Union and other developed countries. There will be a general goodwill spillover towards the U.S. government's up-holding the free trade agreement.	
	WTOmembers	The political support and economical cooperation of other WTO member countries.	

	Vendor Countries	The economical prosperity of the vendor countries is a direct result from wage increase, employment increase, and better paying jobs. This can lead to vendor countries governments' political support to the U.S.	(Harland et al., 2005)
OPPORTUNITIES CRITERIA	**GlobalMarkets**	Global market development. Offshoring can create a presence enabling a company to sell more products and services into that market than it could otherwise. In the near future, the sourcing countries may become the marketplace of a company's goods or services.	(Corbett, 2004)
	Infrastructure	The development of utilities, manufacturing bases, transportation networks, and communication networks for goods and services in the vendor countries and in the entire world. It provides fertile grounds for future U.S. business opportunities.	(Mann, 2004b)
COSTS CRITERIA	**LowerWages**	Growing unemployment drives wages down. Most displaced U.S. workers will try to find new jobs. An excess supply of workers tends to push wages down even in industries in which outsourcing isn't happening. H-1B visa brings qualified foreign technical workers to the U.S., which drives the U.S. technical labor market lower. The general argument is that lower wages cause the middle class to shrink, and the shrinking middle class deteriorates the American way of life, hence the decline of our living standard.	(Samuelson, 2004), (Kletzer, 2003), (Bean, 2003), (Harland et al., 2005), (Feenstra & Hanson, 1998), (Colvin, 2005), (Dobbs, 2004)
	JobLoss	American job loss due to outsourcing. About 4.1 million service jobs will actually get offshored by 2008. America is the most service-intensive economy, with 76% of its jobs in services, whose offshore outsourcing will adversely affect the national employment.	(Mann, 2004b), (Kletzer, 1999; Mann, 2003; Mann, 2004a; Butcher & Hallock, 2005; Farber, 2005; Kletzer, 2005a; Lynch, 2005), (Kletzer, 2005b), (Kletzer, 2004), (Kletzer, 2003)
	Instability	Due to job loss, a society becomes instable.	(Dobbs, 2004)
	TaxLoss	Lost tax revenue from outsourcing and from tax incentive legislation	(Dobbs, 2004)
	Economy Imbalance	The fundamental imbalance in our economy	(Dobbs, 2004)
	TradeDeficit	Increased trade deficit is a direct result from "Free Trade"	(Mann & Pluck, 2006), (Dobbs, 2004), (Mann, 2004c)
	Negative Sentiment	The negative public opinion with regard to government's offshore outsourcing policy and the attitude of the corporate America.	(Mann, 2004b), (Dobbs, 2004)
S CRIT	**Declining Wellbeing**	There is long term decline of the nation's economical wellbeing.	(Samuelson, 2004)

	Private InformationLeak	Possible leak of private information. Critical, confidential, or private information may be at risk due to less stringent information safeguard requirements of sourcing countries. Companies have been cautioned to ensure that any data processed offshore complies with privacy legislation and ensures that all security requirements are being met.	(Zampetakis, 2005)
	Industrial Espionage	The increased possibility of industrial espionage enabled by the offshore outsourcing of IT systems. With IT outsourcing, client information residing on the vendor's network may be exploited by competitors. Particularly if the vendor's main hardware infrastructure is shared by multiple client organizations. Information security can also be an issue when vendors have substandard security practices.	(Chen & Perry, 2003)
	Foreign Workforce	India's business process outsourcing industry is also likely to face a workforce shortage of 262,000 employees by 2009. The long-term labor market trend Is a possible concern for outsourcers. Global labor market study finds the perspective on a shortage of China's talent. A recent article from Knowdedge@Wharton discusses concerns with regard to the growing worker shortage in China. According to the report, some suggests that China will lose its low-cost advantage in the next five to eight years. Others are saying China can only sustain the labor cost advantage for another three to five years	(Bean, 2003), (Ji, 2005), (Ribeiro, 2005), (Farrell & Grant, 2005), (Anonymous, 2006)
	USWorkForce	Along with the shrinking of the high-tech job market, the quality of the U.S. white collar workforce could decline in the long term	(Mann, 2004b)
	TechLeadership loss	Large amount of R&D works is being done overseas. There is great risk of the U.S. losing it technology leadership position. It is alarming that America's info-tech infrastructure is no longer world-class.	(Colvin, 2005)
	Dependency	Our dependency upon the foreign R&D and on imported foreign goods and services in every aspect of our life.	(Dobbs, 2004)
Strategic Criteria			
Domestic Interests	**US Economy**	Outsourcing may improve the prosperity of U.S. economy as measured by the Consumer Price Index, (CPI), Gross Domestic Product (GDP), Index of Leading Economic Indicators, and Personal Consumption Expenditures.	Add refs here
	National Security	Overseas outsourcing of government, military, hi-tech work makes U.S. national security vulnerable. Terrorists and rouge countries may gain access and penetrate U.S. national defense system.	

	Social Stability	In order to maintain stability, our labor laws need to better address the displaced workers from offshore outsourcing.	
Human Wellbeing	**Advancing Technology**	Better facilitating technology advancement	
	Ending Poverty	Promoting the economic well being of developing countries, and third world countries	
	Global Security		
Foreign Relations	**Diplomatic Relations**	Friendly relationship with the governments of vendor countries can lead to more support to U.S. diplomatic policy initiatives	
	Trade Relations	Friendly relationship with the governments of vendor countries can lead to more support to U.S. trade policy	

APPENDIX B

POLICY – PARTIAL QUESTIONNAIRES

(A) Questionnaire I (This questionnaire was used to derive the weights of strategic criteria, control criteria and sub-criteria.)

When evaluating the options for state/federal policy with regard to regulating offshore outsourcing, 31 factors are used. Please indicate the importance of each factors using: un-important, somewhat important, important, very important and extremely important.

In terms of benefits considerations:	Un-Impo	somewhat Impo	Impo	very impo	extreme impo
1. increased consumer buying power	ڤ	ڤ	ڤ	ڤ	ڤ
2. operational cost savings of US firms	ڤ	ڤ	ڤ	ڤ	ڤ
3. improved operations of US firms	ڤ	ڤ	ڤ	ڤ	ڤ
4. support from WTO countries	ڤ	ڤ	ڤ	ڤ	ڤ
5. support from vendor countries	ڤ	ڤ	ڤ	ڤ	ڤ
6. support from EU countries	ڤ	ڤ	ڤ	ڤ	ڤ
7. increased agility and flexibility of US firms	ڤ	ڤ	ڤ	ڤ	ڤ
In terms of costs considerations:					
8. the downward wages pressure	ڤ	ڤ	ڤ	ڤ	ڤ
9. the job loss in America	ڤ	ڤ	ڤ	ڤ	ڤ
10. negative public opinion	ڤ	ڤ	ڤ	ڤ	ڤ
11. instability	ڤ	ڤ	ڤ	ڤ	ڤ
12. lost taxes	ڤ	ڤ	ڤ	ڤ	ڤ
13. economic imbalance	ڤ	ڤ	ڤ	ڤ	ڤ
14. trade deficit	ڤ	ڤ	ڤ	ڤ	ڤ
In terms of opportunities considerations:					
15. Global market development	ڤ	ڤ	ڤ	ڤ	ڤ
16. Potential of infrastructure development	ڤ	ڤ	ڤ	ڤ	ڤ
In terms of risks considerations:	ڤ	ڤ	ڤ	ڤ	ڤ
17. Declining wellbeing of the US population	ڤ	ڤ	ڤ	ڤ	ڤ
18. Declining skills of domestic workforce	ڤ	ڤ	ڤ	ڤ	ڤ
19. Shortage of skilled foreign workforce	ڤ	ڤ	ڤ	ڤ	ڤ
20. Industry espionage	ڤ	ڤ	ڤ	ڤ	ڤ

21. Private information leak	ق	ق	ق	ق	ق
22. US loss of technology leadership	ق	ق	ق	ق	ق
23. US dependence on foreign countries	ق	ق	ق	ق	ق
In terms of overall human wellbeing:					
24. Advancing technology	ق	ق	ق	ق	ق
25. Ending poverty	ق	ق	ق	ق	ق
26. Ensuring global security	ق	ق	ق	ق	ق
In terms of foreign relations :					
27. Diplomatic relations	ق	ق	ق	ق	ق
28. Trade relations	ق	ق	ق	ق	ق
In terms of domestic interest:					
29. Economy	ق	ق	ق	ق	ق
30. Social stability	ق	ق	ق	ق	ق
31. National security	ق	ق	ق	ق	ق

(B) Questionnaire IIa (This is part of the core for survey 2, used to collect input for the decision subnets)

Which group do you identify with?

Public Policy Makers	**Conservatives**	**[ ]**
	Liberals	**[ ]**
	Moderates	**[ ]**
Direct Stakeholders	**Management**	**[ ]**
	Employees	**[ ]**
	Shareholders	**[ ]**
Indirect Stakeholders	**Communities**	**[ ]**
	Consumers	**[ ]**
	SmallBusiness	**[ ]**
Influencers	**Lobbyists**	**[ ]**
	Media	**[ ]**
	Unions	**[ ]**

Name: ______________________________

Occupation: ______________________________

Age group:	**8~24**	**5~35**	**6~55**	**5 & up**

(circle one)

Evaluating the following government policy options regarding offshore outsourcing

◊ *Freehand* – give it a freehand, and let the free market run its course and correct itself

◊ *Subsidize* – provide assistance to non-outsourcing domestic firms

◊ *WorkersAssist* – provide displaced workers assistance program to domestic workforce

◊ *Discourage* – government contract ban and other restrictive policies

1. For corporate cost savings,			(Circle one)			Reverse
a. How much better is Freehand than WorkersAssist?	1	3	5	7	9	[ ]
b. How much better is Freehand than Subsidize?	1	3	5	7	9	[ ]
c. How much better is Freehand than Discourage?	1	3	5	7	9	[ ]
d. How much better is WorkersAssist than Subsidize	1	3	5	7	9	[ ]
e. How much better is WorkersAssist than Discourage	1	3	5	7	9	[ ]
f. How much better is Subsidize than Discourage?	1	3	5	7	9	[ ]

(C) Questionnaire IIb (partial, varied)

1. For corporate cost savings, with respect to FreeHand		(Circle one) Reverse				
a. How much more is Employees affected than Management?	1	3	5	7	9	[ ]
b. How much more is Employees affected than Shareholders?	1	3	5	7	9	[ ]
c. How much more is Shareholders affected than Management?	1	3	5	7	9	[ ]
2. For corporate cost savings, with respect to Discourage						
a. How much more is Employees affected than Management?	1	3	5	7	9	[ ]
b. How much more is Employees affected than Shareholders?	1	3	5	7	9	[ ]
c. How much more is Shareholders affected than Management?	1	3	5	7	9	[ ]
3. For corporate cost savings, with respect to Subsidize						
a. How much more is Employees affected than Management?	1	3	5	7	9	[ ]
b. How much more is Employees affected than Shareholders?	1	3	5	7	9	[ ]
c. How much more is Shareholders affected than Management?	1	3	5	7	9	[ ]
4. For corporate cost savings, with respect to WorkersAssist						
a. How much more is Employees affected than Management?	1	3	5	7	9	[ ]
b. How much more is Employees affected than Shareholders?	1	3	5	7	9	[ ]
c. How much more is Shareholders affected than Management?	1	3	5	7	9	[ ]
5. For corporate cost savings, with respect to Employees						
a. How much more important is Management than Shareholders?	1	3	5	7	9	[ ]
b. How much more important is Union than Media?	1	3	5	7	9	[ ]
c. How much more important is Liberals than Moderates?	1	3	5	7	9	[ ]
d. How much more important is Liberals than Conservatives?	1	3	5	7	9	[ ]
e. How much more important is Conservatives than Moderates?	1	3	5	7	9	[ ]

REFERENCE

Abraham, K. G., & Taylor, S. K. (1996). Firm's use of outside contractors: theory and evidence. *Journal of Labor Economics*, 14, 394-424.

Aczel, J., & Saaty, T. L. (1983). Procedures for synthesizing rational judgments. *Journal of Mathematical Psychology*, 27(1), 93-102.

Alchian, A. A., & Demsetz, H. (1973). The property right paradigm. *Journal of Economic History*, 33, 16-27.

Anderson, S. (2005). Outsourcing saves money. *State Legislatures*.

Anderson, S., & Cavanagh, J. (2004). Outsourcing: A Policy Agenda. Silver City, NM & Washington DC: Foreign Policy in Focus.

Ang, S., & Straub, D. W. (1998). Production and transaction economies and IS outsourcing: a study of the U.S. banking industry. *MIS Quarterly*, 24(4), 535-552.

Anonymous (2004). Panel Debates Offshoring. McKinsey & Company, 1-14.

Anonymous (2006). Does a Growing Worker Shortage Threaten China's Low-cost Advantage? *Knowledge@Wharton*.

Applegate, L. M., Ibarra, H., & Ostrofsky, K. (1990). Digital Equipment Corp.: The Kodak outsourcing agreement (B). *Harvard Business Review*.

Atkinson, R. D. (2004a). Meeting the offshoring challenge. Washington DC: Progressive Policy Institute.

Atkinson, R. D. (2004b). Understanding the offshoring challenge. Washington DC: Progressive Policy Institute.

Baker, T., & Moore, A. T. (2005). Offshoring and public fear - assessing the real threat to jobs. Los Angeles: Reason Foundation.

Bardhan, I., Whitaker, J., & Mithas, S. (2006). Information Technology, Production Process Outsourcing, and Manufacturing Plant Performance. *Journal of Management Information Systems*, 23(2), 13-40.

Barrar, P., Wood, D., Jones, J., & Vedovato, M. (2002). The efficiency of accounting service provision. *Business Process Management Journal*, 8(3), 195-217.

Bean, L. (2003). The profits and perils of international outsourcing. *The International Journal of Management Science*.

Bednarz, A. (2005). Outsourcing HR applications growing up. *Network World*.

Berry, J. M. (2003). Greenspan Speaks Out Against Trade Restraints. *The Washington Post*, E. 01.

Bhagwati, J., Panagariya, A., & Srinivasan, T. N. (2004). The muddles over outsourcing. *Journal of Economic Perspectives*, 18(4), 93-114.

Bharadwaj, A. S., Bharadwaj, S. C., & Konsynski, B. R. (1999). Information technology effects on firm performance as measured by Tobin's q. *Management Science*, 45(7), 1008-1024.

Boser, B. E., Guyon, I. M., & Vapnik, V. N. (1992). A training algorithm for optimal margin classifiers. *the 5th Annual ACM Workshop on Computational Learning Theory*: ACM Press. 144-153.

Boykin, D. (2004). Offshore outsourcing stirs national debate. *Engineering Times*.

Brown, D., & Wilson, S. (2005). *The Black Book of Outsourcing: How to Manage the Changes, Challenges, and Opportunities*. Hoboken, New Jersey: John Wiley & Sons.

Butcher, K. F., & Hallock, K. F. (2005). Bringing together policymakers, researcher, and practitioners to discuss job loss. *Economic Perspective*: Federal Reserve Bank of Chicago.

Campbell, D., Datar, S., Kulp, S., & Narayanan, V. G. (2002). Using the Balanced Scorecard as a Control System for Monitoring and Revising Corporate Strategy. Working paper.

Carlson, B. (1989). Flexibility and theory of the organization. *International Journal of Industrial Organization*, 7, 189-203.

Chen, J.-R., Chou, T.-C., & Lin, Y.-C. (2007). Design and implementation of an ontology-based information technology outsourcing evaluation system using AHP. *Int. Journey;. Innovation and Learning*, 4(1).

Chen, Y.-C., & Perry, J. L. (2003). IT Outsourcing: a primer for public managers. IBM Endowment for The Business of Government.

Chung, K. H., & Pruitt, S. W. (1994). A Simple Approximation of Tobin's Q. *Financial Management*, 70-74.

Cobbold, I., & Lawrie, G. (2002a). Classification of Balanced Scorecards based on their intended use. *PMA Conference*. Boston, USA: 2GC Active Management.

Cobbold, I., & Lawrie, G. (2002b). The development of the Balanced Scorecard as a strategic management tool. *PMA Conference*. Boston USA.

Colvin, G. (2005). In the relentless, global, tech-driving, cost-cutting struggle for business... America isn't ready. *Fortune*.

Corbett, M. F. (2003). An inside look at outsourcing. *Fortune*.

Corbett, M. F. (2004). *The Outsourcing Revolution: why it makes sense and how to do it right*: Dearborn Trade Publishing.

Cristianini, N., & Shawe-Taylor, J. (2000). *An Introduction to Support Vector Machines and other Kernel-based learning method*. Cambridge, UK: Cambridge University Press.

Cullen, S., & Willcocks, L. (2003). *Intelligent IT Outsourcing - Eight Building Blocks to Success*: Elsevier.

Deavers, K. (1997). Outsourcing: a corporate competitiveness strategy, not a search for low wages. *Journal of Labor Research*, 4, 503-519.

Demsetz, H. (1967). Towards a theory of property rights. *The American Economic Review*, 57(2), 347-359.

Dobbs, L. (2004). *Exporting America*. New York: Time Warner Book Group.

Domberger, S. (Ed.) (1998). *The Contracting Organization: a strategic guide to outsourcing.* Oxford: Oxford University Press.

Drezner, D. W. (2004). The outsourcing bogeyman. *Foreign Affairs*, 83(3), 22-34.

Drucker, H., Burges, C. J. C., Kaufman, L., Smola, A., & Vapnik, V. (1997). Support Vector Regression Machines. *Advances in Neural Information Processing Systems 9, NIPS 1996*, 9, 155-161.

Ellis, J. E. (1994). McDonnell Douglas: Unfasten the Seat Belts. *Business Week*.

Farber, H. S. (2005). What do we know about job loss in the United States? evidence from the displaced worker survey, 1984-2004. *Industrial Relations Section*: Princeton University.

Farrell, D. (2003). Offshoring: is it a win-win game? Washington D.C.: McKinsey Global Institute.

Farrell, D., & Grant, A. (2005). Addressing China's Looming Talent Shortage. McKinsey & Company, Inc.

Feenstra, R. C., & Hanson, G. H. (1998). The impact of outsourcing and high-technology capital on wages: estimates for the United States, 1979-1990. *Working paper*.

Francis, J., & Shipper, K. (1999). Have financial statements lost their relevance? *Journal of Accounting Research*, 37, 319-352.

Gao, N. (2006). *The Short and Long-Run Financial Impact of Corporate Outsourcing Transactions*. PhD Dissertation, University of Pittsburgh, Pittsburgh.

Geishecker, I., & Gorg, H. (2008). Winners and losers: a micro-level analysis of international outsourcing and wages. *Canadian Journal of Economics*, 41(1), 243-270.

Grady, M. J. (2005). Outsourcing AEC Services. *Business and Management*.

Grossman, S. J., & Hart, O. D. (1986). The costs and benefits of ownership: A theory of vertical and lateral integration. *The Journal of Political Economy*, 94(4), 691-719.

Hafeez, K., Malak, N., & Zhang, Y. B. (2007). Outsourcing non-core assets and competences of a firm using analytic hierarchy process. *Computers & Operations Research*, 34(3592-3608).

Hafeez, K., Zhang, Y., & Malak, N. (2002). Determining key capabilities of firm using analytic hierarchy process. *International Journal of Production Economics*, 76, 39-51.

Harland, C., Knight, L., Lamming, R., & Walker, H. (2005). Outsourcing: assessing the risks and benefits for organisations, sectors and nations. *International Journal of Operations & Production Management*, 25(9), 831-850.

Hayes, D. C., Hunton, J. E., & Reck, J. L. (2000). Information systems outsourcing announcements: investigating the impact on the market value of contract-granting firms. *Journal of Information Systems*, 14(2), 109-125.

Holmstrom, B. (1979). Moral hazard and observability. *The Bell Journal of Economics*, 10(1), 74-91.

Hong, J.-y., Suh, E.-h., Yoo, K.-d., & Hong, D.-g. (2003). A model for evaluating the effectiveness of the ASP service using balanced scorecard. *Working paper*, 81-91.

Ip, G. (2004). Greenspan Warns Trade Standards Will Harm U.S. *Wall Street Journal*. Mar 12, 2004, A2.

Irwin, D. (2004). Outsourcing is Good for America. *New York Times*. January 28, 2004.

Ji, J. (2005). Why are there labor shortage in a country with the largest population? *The Duowei Times*. May 13, 2005, A10.

Jiang, B., Belohlav, J. A., & Young, S. T. (2007). Outsourcing impact on manufacturing firms' value: Evidence from Japan. *Journal of Operations Management*, 25, 885-900.

Jiang, B., Frazier, G. V., & Prater, E. L. (2006). Outsourcing effects on firms' operational performance. *International Journal of Operations & Production Management*, 26(12), 1280-1300.

Jiang, B., & Qureshi, A. (2006). Research on outsourcing results: current literature and future opportunities. *Management Decision*, 44(1), 44-55.

Jones, O. (2000). Innovation management as a post-modern phenomenon: the outsourcing of pharmaceutical R&D *British Journal of Management*, 11(4), 341-356.

Kaplan, R. S., & Norton, D. P. (1992). The Balanced Scorecard: Measures That Drive Performance. *Harvard Business Review*, 71-80.

Kaplan, R. S., & Norton, D. P. (1996). Using the balanced scorecard as a strategic management system. *Harvard Business Review*(Jan-Feb).

Kletzer, L. G. (1999). Trade and job loss in U. S. manufacturing, 1979-94. In R. C. Feenstra (Ed.), *The Impact of International Trade on Wages*. Chicago: University of Chicago Press.

Kletzer, L. G. (2003). Imports, exports, and American jobs: understanding the links and what they mean for U.S. workers. Center for National Policy.

Kletzer, L. G. (2004). Trade-related job loss and wage insurance: a synthetic review. *Review of International economics*, 12(5), 724-748.

Kletzer, L. G. (2005a). Globalization and job loss, from manufacturing to services. *Economic Perspectives*, 38-46.

Kletzer, L. G. (2005b). Tradable services: understanding the scope and impact of services offshoring. *Brookings Trade Forum 2005*.

Kletzer, L. G., & Litan, R. E. (2001). A prescription to relieve worker anxiety. *International Economics Policy Brief*: Institute for International Economics.

Lacity, M. C., & Willcocks, L. P. (1998). An empirical investigation of information sourcing practices: lessons from experience. *MIS Quarterly*, 22(3), 363-408.

Lacity, M. C., & Willcocks, L. P. (2000). Survey of IT outsourcing experiences in US and UK organizations (Industry trend and event). *Journal of Global Information Management*, 8(2), 5-34.

Lee, J. W., & Kim, S. H. (2000). Using analytic network process and goal programming for interdependent information system project selection. *Computers & Operations Research*, 27, 367-382.

Leung, L., Lam, K., & Cao, D. (2006). Implementing the balanced scorecard using the analytic hierarchy process & the analytic network process. *Journal of Operational Research Society*, 57, 682-691.

Lindenberg, E., & Ross, S. A. (1981). Tobin's q Ratio and Industrial Economics. *Journal of Business*, 54, 1-33.

Lokachari, P. S., & Mohanarangan, M. (2001). Outsourcing of Information Technology Services: A Decision-Making Framework.

Lynch, L. M. (2005). Job loss: bridging the research and policy discussion. *Economic Perspectives*: Federal Reserve Bank of Chicago.

Lyons, B. R. (1995). Specific investment, economies of scale, and the make-or-buy decision: A test of transaction cost theory. *Journal of Economic Behavior and Organization*, 26, 431-443.

Mankiw, G. N., Forbes, K. J., & Rosen, H. S. (2004). Testimony before the Joint Economic Committee, U.S. Congress: "The Economic Report of the President".

Mann, C. (2004a). Off-shore outsourcing and technology jobs: rationale and potential rote for the "human-capital" investment tax credit. Institute for International Economics.

Mann, C. L. (2003). Globalization of IT services and white collar jobs: the next wave of productivity growth. *International Economics Policy Briefs*(PB), 3-11.

Mann, C. L. (2004b). Globalization of services: why, how much, and what to do about it - some issues for the 'North' and the 'South'. Institute for International Economics, 1-9.

Mann, C. L. (2004c). The US current account, new economy services, and implications for sustainability. *Review of International Economics*.

Mann, C. L., & Pluck, K. (2006). Understanding the U.S. trade deficit: a disaggregated perspective.

Marc, J. S., & Wilson, R. L. (1991). Using the analytic hierarchy process and goal programming for information system project selection. *Information and Management*, 20, 333-342.

Marr, B., & Neely, A. (2003). Automating your scorecard: The balanced scorecard software report. Cranfield Management Research Institute.

McCarthy, I., & Anagnostou, A. (2004). The impact of outsourcing on the transaction costs and boundaries of manufacturing. *International Journal of Production Economics*, 88(1), 61-71.

McCulloch, W., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics*, 5, 115-133.

Meade, L., & Sarkis, J. (1998). Strategic analysis of logistics and supply chain management systems using the analytical network process. *Transportation Research E: The Logistics and Transportation Review*, 34(3), 201-215.

Mill, J. S. (1848). *Principles of Political Economy*. London: Longmans, Green and Co.

Mitchell, T. (1997). *Machine Learning*. New York: McGraw-Hill.

Nakagawa, T., & Sekitani, K. (2004). A use of analytic network process for supply chain management. *Asia Pacific Management Review*, 9(5), 969-998.

Ngwenyama, O. K., & Bryson, N. (1999). Making the information systems outsourcing decision: A transaction cost approach to analyzing outsourcing decision problems. *European Journal of Operational Research*, 115, 351-367.

Nickerson, J. A., & Zenger, T. R. (2004). A knowledge-based theory of the firm - The problem-solving perspective. *Organization Science*, 15(6), 617-632.

Ohlson, J. (1995). Earnings, book values, and dividends in equity evaluation. *Contemporary Accounting Research*, 11(2), 661-687.

Panagariya, A. (2004) Why the recent Samuelson article is NOT about offshore outsourcing, accessed, [available at http://www.Columbia.edu/~ap2231].

Pearlson, K., Ibarra, H., & Applegate, L. (1990). Digital equipment corporation: The Kodak outsourcing agreement (A). *Harvard Business Review*.

Perfect, S. B., & Wiles, K. W. (1994). Alternative Constructions of Tobin's q: An Empirical Comparison. *Journal of Empirical Finance*, 1, 313-341.

Quinlan, J. R. (1992). Learning with Continuous Classes. *AI'92*. Singapore: World Scientific. 343-348.

Quinn, J. B. (2000). Outsourcing Innovation: the new engine of growth. *Sloan Management Review*, 13-27.

Quinn, J. B., & Hilmer, P. G. (1994). Strategic Outsourcing. *Sloan Management Review/ Summer*, 43-55.

Rajan, R. G., & Zingales, L. (1998). Power in a theory of the firm. *The Quarterly Journal of Economics*, 387-432.

Ribeiro, J. (2005). Staff shortage in Indian BPO industry expected by 2009. *IDG News Services*.

Ricardo, D. (1817). *On the Principles of Political Economy and Taxation*. London: John Murray.

Rigby, D. K. (2001). Management tools and techniques: A survey. *California Management Review*, 43(2).

Saaty, T. L. (1980). *Analytic Hierarchy Process - Planning, Priority Setting, Resource Allocation*: McGraw-Hill, Inc.

Saaty, T. L. (2001). *The Analytic Network Process (2nd ed.)*. Pittsburgh: RWS Publications.

Saaty, T. L. (2005). *Theory and Applications of the Analytic Network Process: Decision Making with Benefits, Opportunities, Costs, and Risks*. Pittsburgh, PA: RWS Publications.

Saaty, T. L., & Ozdemir, M. (2004). *The Encyclicon: A Dictionary of Decisions with Dependence and Feedback Based on the Analytic Network Process*: RWS Publications.

Saaty, T. L., & Vargas, L. G. (2006). *Economic, Political, Social & Technological Applications of the Analytic Network Process (ANP): Benefits, Opportunities, Costs and Risks*: Kluwer Academic Publishers.

Saaty, T. L., & Cillo, B. (2008). *The Encyclicon (Volume 2.)*. Pittsburgh: RWS Publications.

Samuelson, P. A. (2004). Where Ricardo and Mill rebut and confirm arguments of mainstream economists supporting globalization. *Journal of Economic Perspectives*, 18(3), 135-146.

Schumpeter, J. A. (1950). *Capitalism, Socialism, and Democracy*. New York: Harper.

Shang, J. S., Tjader, Y., & Ding, Y. (2004). A unified framework for multicriteria evaluation of transportation projects. *IEEE Transactions on Engineering Management*, 51(3), 300-313.

Sharpe, M. (1997). Outsourcing, organizational competitiveness and work. *Journal of Labor Research*, XVIII, 535-549.

Thakkar, J., Deshmukh, S. G., Gupta, A. D., & Shankar, R. (2007). Development of a balanced scorecard -. *International Journal of Productivity and Performance Management*, 56(1), 25-59.

Thondavadi, N., & Albert, G. (2004). *Offshore outsourcing - path to new efficiencies in IT and business processes*: 1st Books Library.

Tjader, Y., Shang, J., & Vargas, L. (2009). Offshore Outsourcing Decision Making: A Policy-Maker's Perspective. *Working paper*.

Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of Money Credit and Banking*, 1(1), 15-29.

Udo, G. G. (2000). Using analytic hierarchy process to analyze the information technology outsourcing decision. *Industrial Management & Data Systems*, 100(9), 421-429.

Vapnik, V. N. (1998). *Statistical Learning Theory*: Wiley.

Walker, G., & Weber, D. (1984). A transaction cost approach to make-or-buy decisions. *Administrative Science Quarterly*, 29, 373-391.

Walker, G., & Weber, D. (1987). Supplier competition, uncertainty, and make-or-buy decisions. *Academy of Management Journal*, 30(3), 589-596.

Weidenbaum, M. (2005). Outsourcing: pros and cons. *Business Horizons*, 48, 311-315.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, 5, 171-180.

Whitaker, R. (2007). Validation examples of the Analytic Hierarchy Process and Analytic Network Process. *Math and Computer Modeling*, 46.

Yang, C., & Huang, J.-B. (2000). A decision model for IS outsourcing. *International Journal of Information Management*, 20, 225-239.

Yang, D.-H., Kim, S., Nam, C., & Min, J.-W. (2007). Developing a decision model for business process outsourcing. *Computers & Operations Research*, 34, 3769-3778.

Zampetakis, H. (2005). Outsourcing can be a risky business. The Australian Financial Review.