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Grabbing the Air Force by the Tail: Applying Strategic Cost Analytics to Understand and Manage Indirect Cost Behavior

Bradley C. Boehmke

GRABBING THE AIR FORCE BY THE TAIL:

APPLYING STRATEGIC COST ANALYTICS TO UNDERSTAND

AND MANAGE INDIRECT COST BEHAVIOR

DISSERTATION

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Abstract

Recent and projected reductions in defense spending are forcing the military services to develop systematic approaches to identify cost reduction opportunities and better manage financial resources. In response, the Air Force along with her sister services are developing strategic approaches to reduce front-line mission resources, commonly referred to as the *"Tooth"*. However, an underemphasized contributing source of costs are mission support activities, commonly referred to as the *"Tail"*.

With the *tail* historically representing a sizable portion of the annual Air Force budget, strategically managing cost behavior of these indirect activities has the opportunity to generate significant cost reductions. However, very little applied or academic research have focused on advancing the knowledge behind the economics of, or the analytic techniques applied to, these activities for cost management purposes.

To address this concern, this dissertation investigates *i*) how organizations use analytic methodologies and data sources to understand and manage cost behavior, *ii*) how to identify underlying cost curves of concern across tail activities, *iii*) how to distinguish historical relationships between the tooth and tail, *iv*) how to improve the performance assessment of tail activities for improved resource allocation, and *v*) how to provide a decision support tool for tooth-to-tail policy impact analysis.

The sacrifice, patience, love, and encouragement provided by my beloved wife and beautiful daughters made this possible. Although the doctoral journey has consumed my time, the experience of loving you three has been the greatest journey of my life thus far.

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Just as a dissertation expands the knowledge of a domain, the process equally expands the understanding of one's self. The experience of a doctoral journey teaches you that the archetype of a self-made PhD is only a myth as the limiting factors may be your own; however, transcending these limits can only be done with help of the people who surround us.

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Bradley C. Boehmke

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List of Symbols

Symbol	Definition
$CivPers^{dir}$	Direct civilian personnel costs
$CivPers^{ind}$	Indirect civilian personnel costs
$C(k)$	Calinski & Harabatz criterion
$Dist^{E}$	Euclidean distance
DMU_o	Decision-making unit singled out
ES	Total End-strength headcount
ES^{civ}	Civilian end-strength headcount
ES^{mil}	Military end-strength headcount
h_o	Efficiency rating for DMU_o
$MilPers^{dir}$	Direct military personnel costs
$MilPers^{ind}$	Indirect military personnel costs
$Pers^{dir}$	Total direct personnel costs
S_i^-	excess slack for input variable i
S_r^+	shortfall slack for output variable r
SS_B	Between cluster variance
SS_W	Within cluster variance
TAI	Total active inventory
"$Tooth$"	Total direct costs

List of Acronyms

Acronym	Definition
AF	Air Force
AFTOC	Air Force Total Ownership Cost
BCC	Banker, Charnes, and Cooper
BTCC	Bending the Cost Curve
CAIG	Cost Analysis Improvement Group
CCR	Charnes, Cooper, and Rhodes
COLS	Common Output Level of Service
DEA	Data Envelopment Analysis
DMU	Decision-making Unit
DoD	Department of Defense
DSS	Decision Support System
EEIC	Element of Expense and Investment Code
INFORMS	Institute for Operations Research and the Management Sciences
ISERC	Industrial and Systems Engineering Research Conference
MAJCOM	Major Command
MLM	Multi-level Modeling
O&S	Operations and Support
PRV	Plant Replacement Value
SBM	Slack-based Measure
SCA	Strategic Cost Analytics
SCM	Supply Chain Management

GRABBING THE AIR FORCE BY THE TAIL:

APPLYING STRATEGIC COST ANALYTICS TO UNDERSTAND

AND MANAGE INDIRECT COST BEHAVIOR

I. Introduction

The power of symbols and mathematics should not be underestimated.

Judea Pearl, 1996

Undeniably, the United States Department of Defense (DoD) finds itself in an economically challenging situation. With sequestration taking effect in 2013, as a result of the Budget Control Act of 2011 and the American Taxpayer Relief Act of 2012, the DoD estimates a total reduction in planned defense spending between fiscal years 2012 to 2021 to exceed $1 trillion [1]. In response to spending reductions, the Air Force (AF), along with her sister services, are developing systematic approaches to reduce front-line mission resources, commonly referred to as the *"Tooth"*. However, an underemphasized contributing source of costs are mission support activities such as force protection, installation support, facility sustainment, training, and other support functions, commonly referred to as the *"Tail"*[1].

With the *tail* historically representing over 40% of the annual DoD budget [2; 3] and nearly 60% of the AF budget [4], strategically managing cost behavior of these indirect activities has the opportunity to generate significant cost reductions. However, in order to strategically manage these costs one must first have a fundamental understanding of their underlying cost behavior and relationships. Herein lies the problem as very little applied or academic research have focused

[1]The term *"Tooth"* is commonly applied in the military departments to refer to activities and resources directly related to weapon systems; whereas *"Tail"* is commonly applied to all activities and resources that support the *Tooth* missions but cannot be related directly to an individual weapon system. This is synonymous to what industry commonly refers to as direct versus indirect.

on advancing the knowledge behind the economics of, or the analytic techniques applied to, these activities for cost management purposes.

1.1 Research Objective

The objective of this research is to aid decision-makers within large enterprises, such as the AF, in understanding how and where strategic cost analytics[2] can be applied to advance the understanding of the *tail* domain. With such a domain largely untapped we further focus this dissertation to investigate *i) how organizations use analytic methodologies and data sources to understand and manage cost behavior, ii) how to identify underlying cost curves of concern across tail activities, iii) how to distinguish historical relationships between the tooth and tail, iv) how to improve the performance assessment of tail activities in order to manage costs, and v) how to provide a decision support tool for tooth-to-tail policy impact analysis.*

1.2 Research Contributions

With regards to the targeted research objectives, this dissertation provides the following five contributions:

1. *Creates a framework for how strategic cost analytics are currently being applied across an organization's value chain.* A framework is proposed for categorizing quantitative methodologies and data across the enterprise for cost management purposes. Ultimately this research provides policy-makers with an understanding of how strategic analytics can be applied across the enterprise to guide cost management decisions in value chain activities. Results from this research were presented at the 2014 Industrial and Systems Engineering Research Conference (ISERC) in Nashville, Tennessee in June 2014.

2. *Develops a novel approach to identify underlying cost curve behavior across an enterprise.* An innovative growth curve clustering approach is applied to identify the pervasiveness of cost curves across differing support activities and locations. This research provides insights

[2]Strategic cost analytics is defined as the use of data along with the application of advanced analytic techniques to understand, manage, and align cost behavior to the organizations strategic intent.

to decision-makers to direct their focus, proposals and policy actions towards specific growth curve problems. This research resulted in a journal article accepted for publication in the forthcoming edition of the *Journal of Cost Analysis and Parametrics* [5].

3. *Establishes a methodology to analyze tooth-to-tail relationships across an enterprise.* Advancement in the understanding of tooth-to-tail relationships is made through the use of multilevel modeling. This research provides insight to senior AF decision-makers on how historical changes to force structure appear to relate to indirect costs across the enterprise. Early analysis led to a publication in the *Proceedings of the IIE Industrial and Systems Engineering Research Conference* (ISERC) [4] and was presented at ISERC in Nashville, Tennessee in June 2015. The full article presented in chapter IV is currently under review for publication in the *Journal of Production and Operations Management* and was presented at the 83rd Military Operations Research Symposium (MORS) in Washington, D.C. in June 2015.

4. *Improves performance assessments of tail activities to guide resource allocation decisions.* Improvement to the AF performance assessment process is provided by introducing a Data Envelopment Analysis (DEA) approach to measure efficiency in tail activities. This research guides decision-makers in understanding the relative robustness of specific tail services across the enterprise to inform resource allocation decisions. This research resulted in a journal article currently under review for publication in the *Military Operations Research* journal.

5. *Incorporates a decision support tool for tooth-to-tail impact analysis.* The tooth-to-tail discussion is moved from one that only considers the relationships between the two ends of the tooth-to-tail spear, to one that injects a decision support tool for assessing tooth-to-tail cost consequences. This research introduces Bayesian networks as an approach to model tooth-to-tail policy implications; providing decision-makers with the ability to reason in an

environment of uncertainty. This article will be submitted for publication to the *Journal of Cost Analysis and Parametrics*.

As a whole, these five contributions provide a robust foundation for the tooth-to-tail discussion and advances knowledge at multiple levels. First, it broadens the aperture by providing a robust understanding of the use of strategic cost analytics across the entire organization. It then compresses the viewpoint to advance tooth-to-tail knowledge and analytic capabilities for descriptive, predictive, and prescriptive means. Descriptive means being the understanding of historic trends and patterns of tail costs. Predictive means being the ability to predict future tail costs. Prescriptive means being the ability to make the optimal decision regarding tail resources. Individually, the advancements made within each of these three means provide improvements to aid senior leadership for specific policy considerations. Together, the advancements provide significant progress in the analytic rigor applied to, and the economic understanding of, the *tail* domain.

1.3 Overview and Organization

The remainder of this dissertation follows a scholarly article format. Chapters II-VI are self-contained research articles on strategic cost analytics that encapsulate the previously outlined research contributions in sequential order. Consequently, each chapter contains its own literature review, methodology, analysis, and conclusion sections with recommendations for future research relevant to that chapter. The synopsis of each chapter is as follows:

Chapter II gives an overview of strategic analytic practices across the enterprise value chain for cost management purposes. The intent of the chapter is to introduce the reader to *strategic cost analytics* and provide a comprehensive understanding of how the strategic use of data and advanced analytic techniques are being applied across the organizational value chain for the purpose of understanding and managing cost.

Chapter III provides a novel approach to identifying growth trends across an enterprise. The intent of this chapter is to address the concern that comes with focusing on a singular, aggregate cost curve across an organization which can obscure the true underlying growth curves which require attention. In response, a novel growth curve clustering approach is applied to identify underlying cost curve behavior in support activities across the AF enterprise. The results find that micro-level growth curves vary greatly from the aggregate cost curves. Furthermore, this research illustrates how this approach can help decision-makers to direct their focus, proposals, and policy actions towards specific growth curves needing to be addressed.

Chapter IV addresses the tooth-to-tail concept and advances this stream of research by establishing a methodology to analyze and understand the relationships between support costs and force structure. The intent of this chapter is to analyze indirect cost behavior and relationships across multiple levels of the enterprise by employing a multilevel modeling approach to capture the structural context of the Air Force enterprise. Furthermore, rather than focus solely on the tooth, empirical analysis is performed to assess how each of the front-line mission activities influence indirect costs across the enterprise. The results identify which tooth-to-tail relationships exist across the enterprise and how variable these relationships are.

Chapter V introduces a process to measure the efficiency of resource usage for support activities within an enterprise to guide resource allocation decisions. The intent of this chapter is to introduce DEA into the performance assessment process of support activities to benchmark performance, isolate best practices, and identify, along with quantify, potential cost savings. This research provides empirical analysis on Air Force installation support services to illustrate how DEA can guide decision-makers in understanding the relative robustness of these support services across the enterprise along with identifying best-practice peers and quantifying cost savings. The findings illustrate how DEA can guide AF decision-makers in resource allocation decisions.

Chapter VI provides a systematic approach to estimate and model tooth-to-tail policy implications. The intent of this chapter is to aid decision-makers when considering operational force structure policy considerations by modeling their impact on support costs in environments of uncertainty. A two-stage approach is applied using econometric modeling to identify tooth-to-tail relationships followed by a Bayesian network decision support tool to assess policy impacts. The results illustrate the applicability of Bayesian networks in modeling the dynamic nature of policy considerations.

Chapter VII provides concluding remarks and summarizes the research initiatives, products delivered to contribute to the knowledge building process, and recommendations for future research.

II. Understanding Strategic Cost Analytics Across the Supply Chain

With nothing but the power of your own mind, you operate on the symbols before you in such a way that you gradually lift yourself from a state of understanding less to one of understanding more.

Mortimer J. Adler, 1940

2.1 Introduction

In a time when organizations across all industries are facing economic challenges, Anderson's [6] introduction likely rings clearer now than when her article was first published:

> The headlines of the business press are replete with news of firms' cost management activities. Some are trimming the workforce or renegotiating wages and benefits. Others are re-engineering processes to use a more economical mix of inputs or to produce a more valued output. Still others are outsourcing work, forming strategic alliances, and partnering with customers and suppliers. What is unclear is whether this frenzy of cost management is guided by strategic intent and if it is, whether it is indicative of best practice in orchestrating organizational change. (p. 481)

Although efforts have been made [i.e. 7–11] there is, unfortunately, no single unifying theory or framework for how an organizations use data along with advanced analytic techniques to understand, manage, and align cost behavior to its strategic intent. Rather, as Anderson [6] points out, much of the advancements in regards to the strategic use of data and analytic techniques for cost management purposes have been occurring across multiple disciplines. This has led to fragmented lines of research rather than a comprehensive understanding of how data and advanced analytics are applied across the entire organization for strategic cost management purposes.

The focus of this paper is to create a framework that identifies and categorizes how organizations use data and advanced analytic techniques across its supply chain for the purpose of understanding and managing cost. To accomplish this, an assessment of historical literature will be performed with the purpose of addressing three objectives. First, we identify how advanced analytic techniques are being applied throughout the organization for the purpose of understanding and controlling costs. Second, we identify the types of data used as influencers of cost and value. Third, we discuss how advancements can be made in the strategic use of data and advanced analytic techniques for cost management purposes across the value chain.

The remainder of this paper is organized as follows. Section 2.2 provides the theoretical background for this research. Section 2.3 provides a framework for categorizing quantitative methodologies and data across the value chain. Section 2.4 provides results from our literature assessment. Section 2.5 will discuss how and where advancements can be made in future research and section 2.6 will conclude the paper.

2.2 Background

Porter posits that a firm's strategy defines its configuration of activities performed [12]. These discrete activities which a firm performs in designing, producing, marketing, delivering, and supporting its product and operations contributes to a firm's relative cost position and its ability to create a basis for differentiation [7]. As a systematic way of examining these activities a firm performs, Porter introduced the "value chain". A firm's value chain and the way it performs individual activities are a reflection of its history, its strategy, its approach to implementing its strategy, and the underlying economics of the activities themselves [7]. Shank [9] defines the value chain for any firm in any business as the linked set of value-creating activities all the way from basic raw material sources from component suppliers through the ultimate end-use product delivered into the final consumers' hands. Naturally, the value chain extends beyond the firm's boundaries and across the supply chain creating a strong relationship between value chain management and supply chain management (SCM)[3].

Mentzer, et al. define SCM *"...as the systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company*

[3]As a result, this research uses the terms value chain and supply chain interchangeably.

and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole" [13:p.18]. Their SCM model (Figure 2.1) is a schematic for this strategic coordination of activities a firm performs to create a product or service valuable to its buyers. The way a firm performs its SCM activities is also a reflection of its history, its strategy, its approach to implementing its strategy, and the underlying economics of the supply chain activities themselves. Mentzer, et al. [13] state that competitive advantage can be obtained through SCM by improving both efficiency through cost reduction and effectiveness through customer service in a strategic context. Harland, et al. [14] posit that organizations arrange and conduct themselves within a supply chain perspective based on economic environments in order to be competitive in the short and long time horizons. Multiple researchers have discussed how competitive advantages in the areas of cost leadership and differentiation can be obtained through SCM [see 15–21].

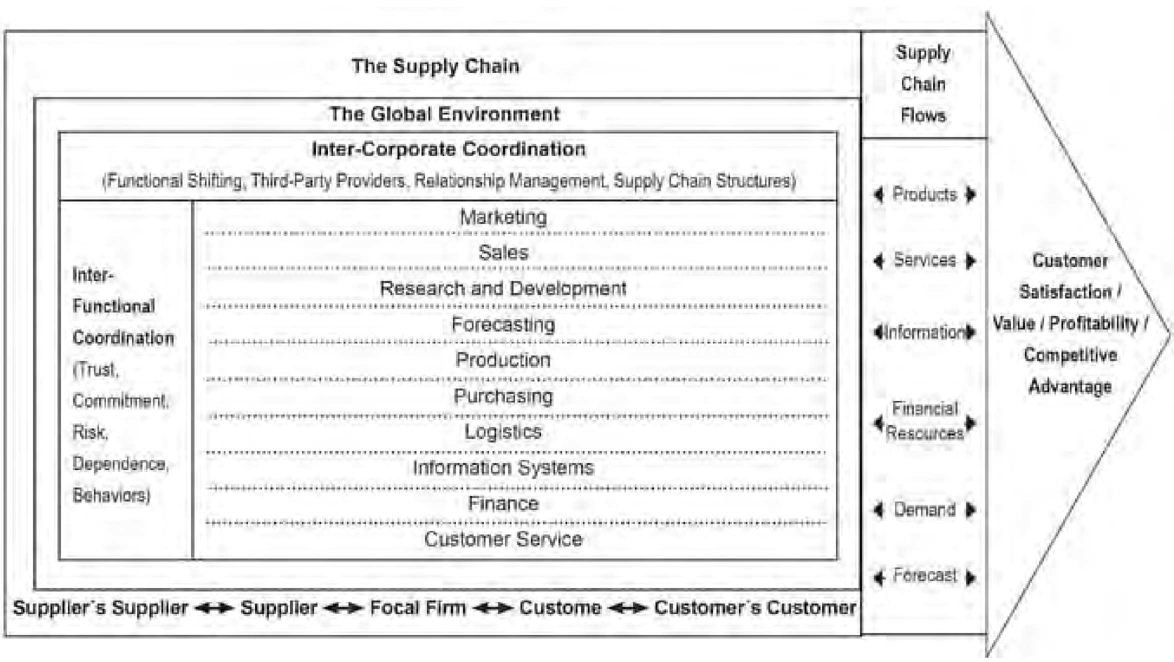


Figure 2.1: A Model of Supply Chain Management

If competitive advantage grows out of a firm's strategic ability to perform SCM activities both within and across organizational boundaries, then Porter [12] defines cost drivers as the 'why' behind why some firms are able to perform particular activities at lower cost or in ways that create superior value than others. Prior to the 1980s production volume was the primary cost driver used to model cost behavior; however, Porter [7] identified ten fundamental, strategic cost drivers and defined them as the structural causes of the cost of an activity and can be more or less under a firm's control. Porter [12] further postulates that this set of drivers determines both relative cost and differentiation of a firm.

This concept of fundamental strategic cost drivers was built on by Riley [8] and then further by Shank [9] and Shank and Govindarajan [10] by identifying two categories of strategic cost drivers based on Porter's [7] initial cost driver list:

1. Structural cost drivers which reflect five strategic choices by the firm regarding the underlying economic structure of costs that drive the firm's cost position on each product group: scale, scope, experience, production technologies for each stage of the value chain, and the complexity of the firm's product line [9].

2. Executional cost drivers that reflect the efficacy and efficiency of executing the strategy [20]. This captures the aim for continual improvement, quality management, optimum capacity utilization, plant layout efficiency and product design configuration [22].

Managing structural cost drivers includes the employment of tools for re-engineering organizational, product, and process design to build a cost structure that is coherent with strategy. Managing executional cost drivers includes the employment of tools for measuring cost performance of existing processes and making incremental improvements [6; 23].

Cooper and Kaplan [24] had a similar argument as Porter [7], Riley [8], Shank [9] and Shank and Govindarajan [10] in that volume output is not an adequate determinant of costs; however, Cooper and Kaplan [24] suggest that product line diversity and production process complexity characteristics drive costs. Cooper and Kaplan [24] primarily focused on the manufacturing industry and argued that, although support department costs had typically been treated as fixed, they actually varied and were being driven by product line diversity and operating activity complexity such as set-ups, inspections, materials handling, and scheduling [22]. Cooper and Kaplan [25] introduced the activity-based costing (ABC) concept and argued that almost all firm activities across the value chain including logistics, production, marketing and sales, distribution, service, technology, financial administration, information resources, and general administration exist to support the production and delivery of products and therefore should all be considered product costs. ABC was a concept that allowed these costs to be assigned to products or services by allocating support costs to them based on cost pools, activities, and resource consumption. Cooper [26–31], Cooper and Kaplan [32; 33], and Kaplan and Cooper [11] further developed and refined their framework into a fully developed ABC model and established a list of cost drivers across the value chain and supply chain. Literature focusing on the application of ABC is vast and has been applied across the entire value chain. These three cost driver taxonomies (displayed in Table 2.1) are the most complete strategic cost driver lists established in literature.

Table 2.1: Comparison of Cost Driver Taxonomies

Porter (1985)	**Riley (1987); Shank & Govindarajan (1992)**	**Cooper & Kaplan (1998)**
Scale	*Structural drivers*	*Manufacturing stage of value chain*
Learning and spillovers	Scale	Unit-level
Capactity utilization	Scope	Batch-level
Linkages between activities across the value chain (both within & across firm	Experience	Product-sustaining
Timing (first/late movers)	Production technology across the value chain	Facilities-sustaining
Policy choices (product design and mix, service levels, investments, delivery times, distribution channels, technology, materials quality)	Product line complexity	*Rest of firm value chain*
		Customer-sustaining
	Executional drivers	Product-line-sustaining
	Workforce commitment to continuous improvement	Brand-sustaining
Geographic locations		Channel-sustaining
Institutional factors (regulation, tariffs, unionization)	Quality management	Location-sustaining
	Capacity utilization	Corporate-sustaining
	Plant layout efficiency	
	Product design configuration	*Extended value/supply chain*
	Linkages with suppliers and customers (extended value/supply chain)	Vendor-sustaining

* adapted from Banker & Johnston, 2007, p.533

Understanding the theoretical importance of cost drivers is critical; however, just as important is the practical understanding of the types of data and analytic techniques used to understand, model, and manage costs. Rather than focus on the differences of the current cost driver taxonomies, our focus is to provide a comprehensive understanding of how the strategic use of data and analytic techniques are being applied across the value chain for the purpose of understanding and managing cost.

Independent lines of research have focused literature reviews on the specific cost driver taxonomies such as strategic cost management [6; 20; 21] and activity-based costing [34]. These reviews tend to focus on the theoretical expansion of the taxonomies across the organization rather than on the types of data and analytic techniques used to implement the taxonomies. Additionally, literature reviews have focused on cost management and analysis for specific SCM and value chain activities such as supplier selection [35; 36], inventory management [37; 38], new product estimating [39; 40] and cost of quality [41]. These reviews, although extremely beneficial, do not follow common categorizations of analytic techniques. As a result the practical understanding of how to integrate advanced analytic techniques to model and manage organizational costs is lacking. Furthermore, although these reviews discuss data used to model cost drivers, there have not been any reviews which categorize the types of data used to represent cost drivers in each supply chain activity. As a result, the practical understanding of how organizations currently use data, let alone understand how to take advantage of the growing volume, variety, and velocity of data is also lacking.

To maintain neutrality between the established cost driver taxonomies we formally define strategic cost analytics (SCA) as the use of data along with the application of advanced analytic techniques to understand, manage, and align cost behavior to the organizations strategic intent. This review will facilitate the process of understanding how SCA is being used across the organizational supply chain for cost management purposes.

2.3 Review Methodology and Descriptive Analysis

To analyze literature relevant to this review, the Air Force Institute of Technology's 360 Multiple Database Search tool which searches a comprehensive list of databases to include, but not limited to, EBSCOhost, Elsevier, IEEE, ProQuest, and RefWorks was used to search for papers containing key words such as “cost driver analysis”, “activity driver analysis”, “activity-based cost analysis”, “cost management”, “strategic cost”, “cost behavior”, “cost function”, and “supply chain cost” in combination with the key SCM processes identified in Mentzer, et al.’s [13] supply chain scheme (reference Figure 2.1). Papers identified were subjected to further analysis of their abstract and, in the case they appeared to be relevant, selected and their content examined to identify the advanced analytic modeling approach and cost driver data used. In addition, a snowball-approach was performed by identifying cited works in the identified articles which appeared relevant to this review. In addition, an inverse search was conducted to identify relevant works which cite the identified papers. The literature identified only includes peer reviewed journal articles and excludes peer reviewed conference proceedings, textbooks, dissertations, and non-scientific journal publishings.

To keep this review focused, papers were only included if they applied a quantitative analytic technique to model drivers and behaviors of costs based on internal or external data inputs. This excludes papers that only include price or a single cost value as their primary cost variable. Studies which were purely discussion papers or industry survey approaches were also not included simply to keep the review manageable. Ultimately, the concern is to understand how cost functions are being modeled and what data are being used as cost drivers. The functional field was not constrained; however, the search naturally resulted in a focus in the operations management and operations research (OM/OR), logistics and SCM, accounting, computer science and management fields. Since the concept of cost drivers and strategic use of cost data to obtain a competitive advantage was initially developed between 1985 and 1991, the time horizon was constrained to 1990-2012.

To categorize analytic methodologies, we adopt the Institute for Operations Research and the Management Sciences (INFORMS) methodology classifications as displayed in Table 2.2.

Descriptive methodologies focus on analyzing historic data for the purpose of identifying patterns or trends. Analytic techniques that fall into this category are most often associated with exploratory data analysis which identifies central tendencies, variations, and distributional shapes.

Table 2.2: Advanced Analytic Methodologies

Analytic Methodology	Description
Descriptive	Answers the question "What happened?". Can provide a representation of the knowledge discovered without necessarily modeling a specific outcome.
Predictive	Answers the question "What could happen?". Knowledge from historical data is extracted and used in such a form that we can apply the resulting model to new situations. The key factor here is to predict future trends and possibilities.
Prescriptive	Answers the question "What is the best action or outcome?". The key factor here is to provide new ways to improve or maximize certain types of performance.

Descriptive methodologies can also search for underlying structures within data when no a priori knowledge about patterns and relationships are assumed. This can include correlation analysis, exploratory factor analysis, principal component analysis, trend analyses, and cluster analysis.

Predictive methodologies use knowledge, usually extracted from historical data, to predict future, or otherwise unknown, events. Analytic techniques that fall into this category include a wide range of approaches to include parametric methods such as linear regression, multilevel modeling, activity-based costing, mathematical modeling; simulation methods such as discrete event simulation and agent-based modeling; classification methods such as logistic regression and decision trees; and artificial intelligence methods such as artificial neural networks and bayesian networks.

Prescriptive methodologies not only look into the future to predict likely outcomes but they also attempt to shape the future by optimizing the targeted business objective while balancing constraints. Analytic techniques that fall into this category include optimization techniques such as linear programming, goal programming, integer/mixed-integer programming, and search algorithms; artificial intelligence optimization techniques such as genetic algorithms and swarm algorithms; and multi-criteria decision models such as analytic hierarchy process, analytic network process, multi-attribute utility and value theories, and value analysis. The full categorization and coding of modeling techniques can be found in Appendix A.

To understand how data is leveraged in SCA we first need to understand and categorize the types of cost driver data we currently use. Our categorization provided in Table 2.3 attempts to organize and consolidate the current taxonomies previously discussed in Table 2.1 while describing their relationship in the value chain and providing illustrative data examples. This taxonomy allows us to categorize data in a similar lens across the entire value chain.

Table 2.3: Strategic Cost Analytics Data Coding Scheme

	Strategic Cost Driver	Description	Types of Data
Structural Cost Drivers	Scale	Represents the advantage of economies of scale; however, the relevant measure of scale differs among value chain activities and industry.	Quantity of suppliers, centralized vs. decentralized purchasing, investment size, facility location, economy of scale
	Scope	Assessing the options of verticle integration, performing distribution activities in-house vs. contracting out, incorporating reverse logisitcs vs. not, contractual relationships	Make vs. buy, vertical integration, postponement, supplier/vendor managed inventory
	Experience	Supplier determinations based on cost learning curves, industry age impact on supply chain decisions, innovation acceptance rate of customer base	Learning curve, organization/industry/sector age
	Technology	Impact that significant technology adoption (RFID, ERP, EDI, etc) has on supply chain cost, cost impact of early technology adoption vs. late adoption	RFID, ERP, technology advancement, supplier EDI capabilities
	Complexity	Impact of a wide product/service line on the supply chain, cost of serving a wide customer base vs. focusing on specific customers	Product/service variety, product/service attributes, multiple distribution channels
	External Risks	Represents risks outside of the firms operating control which may result in choices to reconfigure the value chain	Political stability, natural disasters, market risks
Executional Cost Drivers	R&D Specific	Represents data and measurements for R&D specific activities and processes	Development time, quantity of drawings and prototypes
	Quality Management	Represents the data and measurements regarding product and process quality to include prevention, appraisal, internal/external failure	Rejection rate, failure rate, inspection requirements, rework
	Product Sustaining & Capacity Utilization	Represents the data and measurements regarding the activities and processes used to convert resources into products	Labor, production rate, setup cost, volume, machine time, material cost
	Logistics Management	Represents data and measurements regarding the transportation, storage and warehousing activities of a firm	On-time delivery rates, freight costs, leadtime, warehouse capacity
	Forecasting	Represents data typically included in purely forecasting activities	Demand, leadtime, projected completion dates, safety stock
	Financial	Represents financial data that would be acquired through open market resources or open book accounting practices	Exchange rates, tariffs, interest rates, supplier liquidity & financial stability
	Marketing & Sales	Represents marketing and sales data for activities	Sales figures, marketing activities,
	Customer Sustaining	Represents data which measures the level, and management, of external relationships	Service level, vendor/supplier relationship costs, warranty & customer claims,
	Infrastructure Sustaining	Includes support activities which support the business' primary operations; commonly referred to as indirect or overhead related activities	Ordering activities, flexible billing, facility sustainment, manpower levels
	Corporate Social Responsibility	Factors relating to the continuing commitment by business to contribute to economic development while improving the quality of life of the workforce and their families as well as of the community and society at large	Carbon emissions, solid & chemical waste, brand sustainment such as reputation,

In total, 278 papers were identified and included in the analysis; however, to keep the length of the review within reasonable limits not all papers will be discussed. Figure 2.2 shows the growth rate of papers focusing on SCA and illustrates that the focus of intra-firm cost analytics has stagnated while the focus on inter-firm cost analytics is increasing.

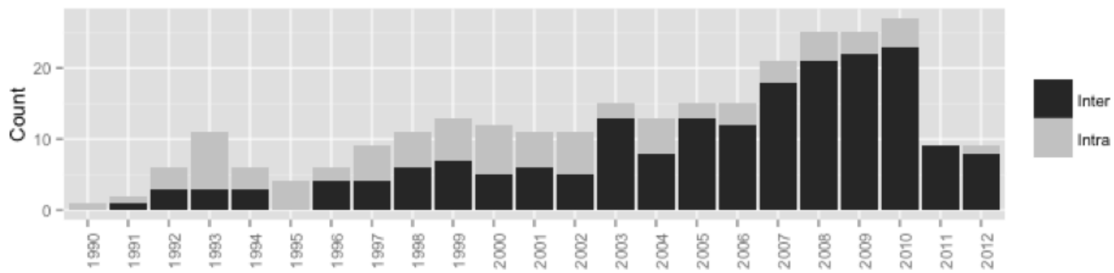


Figure 2.2: Strategic Cost Analytics Articles Published per Year

Papers were published in 88 different journals focusing on 10 fields and an 11th category labeled “Other” to capture journals not directly related to an individual field. Figure 2.3 illustrates how the OM/OR field produces more than 50% of the SCA literature and Figure 2.4 illustrates that nearly 50% of the literature is focused on the purchasing process followed by research and development (R&D), production, and then a category labeled “multiple” which usually focuses on the R&D and production processes or on the production process and indirect activities.

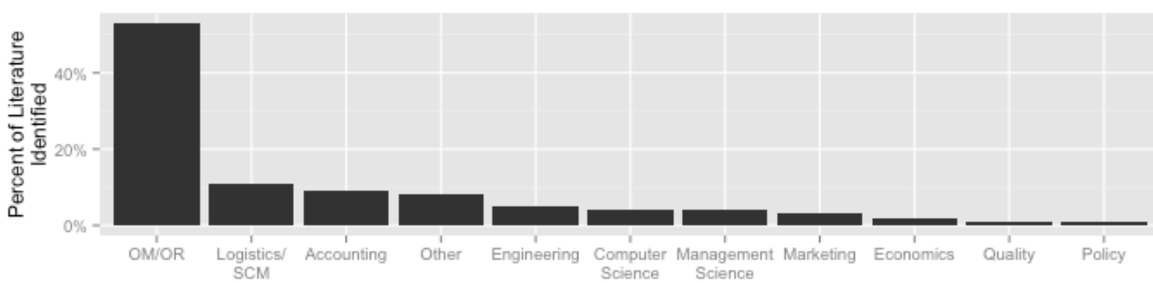


Figure 2.3: Strategic Cost Analytics Articles Published by Journal Field

Together, these results show the rate of growth and breadth of research that focuses on SCA and illustrates that understanding analytic techniques and data used for modeling cost behavior throughout the value chain comes from various fields. In addition, application of SCA to understand cost behavior may not be equally applied across the value chain due to the disproportionate amounts of research in certain SCM processes.

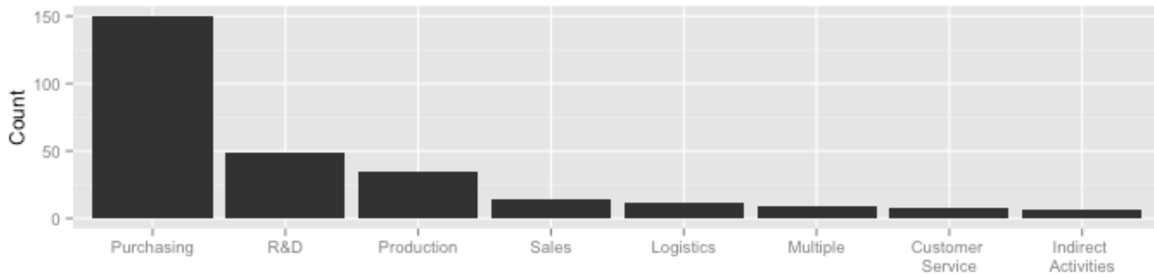


Figure 2.4: Strategic Cost Analytics Articles Published by Supply Chain Process

2.4 Analytic Approaches and Data Utilized Across the Supply Chain

Comprehending how advanced analytic techniques are applied across the supply chain to understand and manage costs, along with the types of data typically used, can provide us insight into how future research can advance SCA. The following sections use Mentzer, et al.'s [13] supply chain scheme previously identified in Figure 2.1 to identify and discuss the advanced analytic techniques employed and data used in each of the supply chain processes.

2.4.1 Purchasing Activities.

Previous comprehensive literature reviews focused on purchasing have revealed two primary decisions related to strategic sourcing: (1) supplier selection and (2) inventory management. Each of these purchasing domains have significant depth in research; which is likely a result of the fact that approximately 50-80% of the cost of a firm's products and services come from purchased materials and services [21; 42].

2.4.1.1 Supplier Selection.

The supplier selection problem primarily focuses on which supplier to select, how many suppliers to select, and how much to order from the supplier. Ho et al. [36], Aissaoui et al. [35], and Degraeve et al. [43] provide relevant reviews on the supplier selection problem. Fifty out of the 278 papers (18%) applied SCA to the supplier selection problem. A significant amount of excluded supplier selection papers included only price as a cost parameter, whereas the identified papers incorporated a cost function or cost parameters which interact with other types of data. As

Table 2.4 shows the majority of these papers used prescriptive analytic methodologies, which is appropriate since the targeted business objective is to select the optimal supplier(s).

Table 2.4: Analytic Methodologies Applied to Supplier Selection SCM Activity

Analytic Methodology	Paper Count	Percentage
Descriptive	0	0%
Predictive	13	26%
Prescriptive	32	64%
Combination	5	10%
Total	50	100%

Of the prescriptive methodologies, multi-criteria decision modeling (MCDM) is the most prevalent technique and is applied to score suppliers based on metrics such as cost, quality and performance for a final supplier choice decision. The primary MCDM technique used was analytic hierarchy process (AHP) which provides a decision making technique to score suppliers on their cost, quality, flexibility, and delivery performance measures by decomposing a complex problem into a multi-level hierarchical structure of objectives, criteria, sub-criteria and alternatives [44]. Other MCDM techniques used included data envelopment analysis and multi-attribute utility theory.

Following MCDM, optimization techniques were the next common prescriptive methodology for the supplier selection problem. These techniques include linear programming, integer programming, and mixed integer programming. These optimization models are primarily used to select the best supplier(s) by minimizing cost while constraining for items such as quality, delivery, production capacity and budget. In addition, a useful approach to ensure the reliability of a supply stream is to follow a multiple sourcing policy and these mathematical optimization techniques allow for consideration of internal policy constraints and externally imposed system constraints placed on the buying process in order to determine an optimal ordering and inventory policy simultaneously while selecting the best combination of suppliers [35]. Cost functions in these mathematical optimization models typically include perfect information or a priori knowledge on the relationships between the specified drivers and their behaviors are assumed to hold true.

Multiple papers combined these prescriptive techniques by combining AHP and linear programming [45], AHP and goal programming [46; 47], AHP and integer programming [48], AHP and mixed integer programming [49], and AHP and dynamic programming [50]. These integrated approaches first use the MCDM methodologies (primarily AHP) to develop and weight the evaluation criteria applied to the suppliers and then the mathematical optimization methodology incorporates these evaluation requirements as objective functions typically by minimizing a total cost function with constraints to meet quality, delivery and/or operational constraints.

Predictive analytics were used in 26% of the supplier selection papers identified. Parametric estimating and decision support systems were the two most common predictive analytic techniques used. In parametric estimating mathematical modeling (MM) and activity-based costing (ABC) were used to develop total cost functions; however, rather than objective functions and constraints to optimize the decision, predicted costs of suppliers based on differing values of key parameters included in the cost function are observed and analyzed allowing the decision-maker to understand the variation and patterns of the cost behavior dependent on the stochastic nature of certain parameters.

Decision support systems (DSS), defined as computer-based systems that help decision-makers confront ill-structured problems through direct interaction with data analysis and models [51], have been integrated into the supplier selection problem. These predictive models can take the form of a model-based reasoning DSS in which predictive models such as MM or ABC can be turned into a computer-based program with a user interface [52; 53], data-based reasoning DSS in which the computer interface links the user to internal or external supplier databases to provide supplier cost functions [54], and knowledge-based reasoning DSS in which the user is linked to expert opinion databases on supplier performance and risks to identify their influence on supplier costs [55; 56].

A couple papers combined multiple predictive techniques; one in which ABC was used along with fuzzy logic to create variability around some of the supplier metrics [57] and another [58] combined ABC with discriminant analysis (DA) in which ABC was used to model historical cost data for 51 identified activities across the value chain and DA was used to identify the activities which had statistically significant cost differences between low cost country suppliers and traditional procurement markets sourcing options.

Only one paper included a combination of predictive and prescriptive analytics. Hong et al. [59] use sales data such as recency and frequency of purchases along with dollar amount spent to group customers using cluster analysis. Customer attributes characterized by these sales data along with quality requirements by the clusters are then used to develop metrics required to pre-qualify potential suppliers. A mixed-integer program is then used to identify the supplier that maximizes revenue while satisfying the differing levels of customer attributes. Figure 2.5 illustrates the popularity of analytic techniques for the supplier selection process.

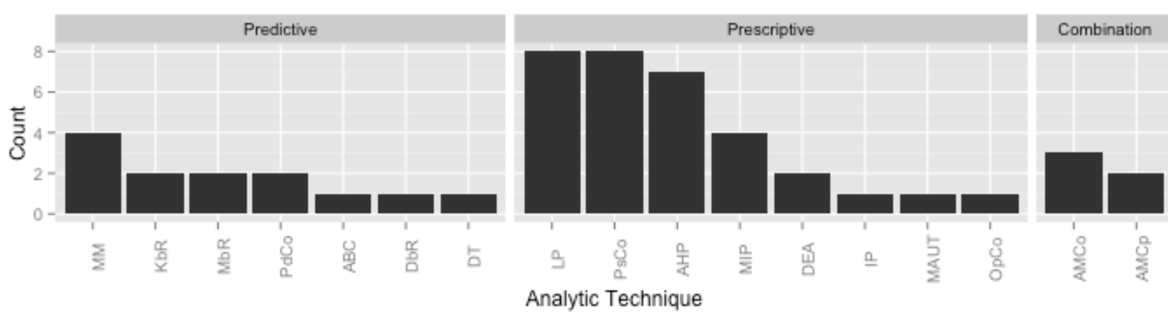


Figure 2.5: Analytic Techniques Applied to the Supplier Selection SCM Activity

Data used in the supplier selection problem often include both subjective and objective inputs on qualitative and quantitative data to rate, weight, and rank supplier attributes and performance. Many times, data inputs assume perfect information or a priori knowledge which is likely a result of the lack of publicly available historic data, and also the sensitivity of actual supplier performance and bid data, available to researchers.

Structural cost drivers incorporated into the supplier selection problem include scale data such as number of suppliers [50; 52; 59], capital investment [60], and geographic dispersion [61]; technology data such as subjective evaluation of the suppliers technological capabilities [62; 63] and technology cost impacts of the supplier for value chain activities such as designing and engineering [64]; product complexity data such as subjective evaluation of the suppliers ability to adjust product mix required by buyer and the number of product variations to be sourced [63; 65]; and external risk drivers such as subjective risk weightings of political stability and cultural barriers associated with geographic scale of operations [55; 56].

Executional drivers include data representing quality characteristics such as failure/rejection rates, inspection requirements, compliance standards [60; 66; 67]; product sustainment data such as the level of interoperability with the buyer's systems, product costs, production capacity [45; 49], production flexibility characteristics such as volume flexibility [46; 68], ability to adjust manufacturing processes, ability to fill emergency order processing , and cost of rework; logistics management data such as freight costs [47], on-time delivery rates [68], inventory holding costs, warehousing space [69] and delivery reliability; forecasting data such as as lead time and demand; financial data such as financial stability and budget constraints [63; 70] and cash-to-cash cycle times [46]; marketing and sales data such as purchasing discounts [71], customer sustainment data such as support service quality and costs [66], customer sustainment relationship costs [43], warranty costs and customer claim costs [64]; infrastructure data such as ordering costs; and corporate social responsibility data such as subject ratings of supplier reputation [63]; environmentally friendly material and control costs [50; 54]; and subjective ratings of supplier ethical standards [62].

Figure 2.6 illustrates the frequency that each cost driver category was represented in in the supplier selection literature. This shows that the data used is primarily focused on executional cost drivers, of which is heavily targeted towards product sustainment/capacity utilization (PS/CU), logistics management (LM), forecasting (For), and quality management (QM) data. For structural cost drivers, data that represents scale (Sca) was most common followed by data representing technology.

Figure 2.6: Cost Drivers Used in the Supplier Selection SCM Activity

Appendix B provides a cross tabulation of references with advanced analytic techniques and cost drivers used in the supplier selection literature. References are sorted in an hierarchical fashion: first by analytic methodology, then analytic classification, analytic technique and finally by year.

2.4.1.2 Inventory Management Activities.

The inventory management problem focuses on how much to order, in what periods to order, what products to order, and where or whom should manage the inventory. The inventory management problem is steep in history and Glock [38], Ben-Daya et al. [37], and Aissaoui et al. [35] provide relevant reviews on the inventory management problem. Ninety-four out of the 278 papers (34%) applied SCA to the inventory management problem. Prior to the 1990s inventory management was traditionally seen from an internal perspective in which inventory replenishment decisions were made taking into account only those cost parameters that could be directly influenced by the planning company [38]. This leads to a local optimum for a single firm; however, since the 1990s inventory management research has focused on reaching global optimums across the supply chain. This focus has become known as the joint economic lot sizing (JELS) problem and the vast majority of the identified inventory literature fall into this category.

The bulk (74%) of this literature uses prescriptive analytic methodologies while 21% use predictive analytics and 4% use a combination of predictive and prescriptive analytics[4].

Table 2.5: Analytic Methodologies Applied to the Inventory Management SCM Activity

Analytic Methodology	Paper Count	Percentage
Descriptive	0	0%
Predictive	20	21%
Prescriptive	70	74%
Combination	4	4%
Total	94	100%

The cost function in the inventory problem is most often represented as a total relevant cost for the supply chain system (TRC_s) and can be illustrated with Goyal's [72] model which is one of the first JELS models. In equation 2.1 TRC_s is a function of lot size (Q), holding cost per unit for the buyer (h_b), order cost per order for the buyer (A), demand rate for the buyer (D), holding cost per unit for the supplier (h_s), setup cost per setup for the supplier (S), number of transportation batches per lot.

$$TRC_s = \frac{Q}{2}h_b + A\frac{D}{Q} + \frac{(n-1)Q}{2}h_s + S\frac{D}{nQ} \tag{2.1}$$

As thoroughly explained in comprehensive reviews by Glock [38] and Ben-Daya et al. [37], this model, or variations of it, has been extended in multiple directions for purposes we'll explain shortly. The primary difference between the predictive and prescriptive models is prescriptive models solve for the optimal solution which is minimizing TRC_s whereas the predictive models were primarily used to illustrate the changes in TRC_s based on a range of values for certain parameters such as transportation costs, ordering costs, deterioration rates,and vendor-managed inventory (VMI) vs. buyer holding the inventory. Naturally, the prescriptive models are aimed to provide the decision-maker with the best course of action to take whereas the predictive models provide the decision-maker with an understanding of the range of possible outcomes; however,

[4]The lack of the percentage columns equating to 100% in Table 2.5 and future tables is purely due to rounding differences.

one common theme in the majority of the inventory management literature identified is these predictive and prescriptive models are mainly used with assumed a priori information or perfect knowledge of the data used for the parameters, parameter distributions and the relationships between the parameters. This assumption has been relaxed in some literature to try to incorporate the distribution-free demand approach [i.e. 73; 74]; however, virtually no empirical research has been performed in this area.

All prescriptive analytic methodologies applied fell into the optimization category with 45% using a search algorithm (SA) heuristic approach, 49% using mathematical optimization programming approaches such as LP, IP, MIP and NLP, only 3% (two papers) using genetic algorithms which are a form of artificial intelligence and the remaining 3% used a combination of techniques. Predictive analytic techniques almost solely focused on the parametric approach using mathematical modeling. One unique predictive approach used by Kang and Kim [75] combined simulation with mathematical modeling. Finally, several authors combined predictive and prescriptive methodologies such as fuzzy logic and search algorithms [76], mathematical modeling and genetic algorithms [77], DSS and non-linear programming [74], and fuzzy logic and genetic algorithms [78].

Figure 2.7 illustrates the popularity of analytic techniques for the inventory management process.

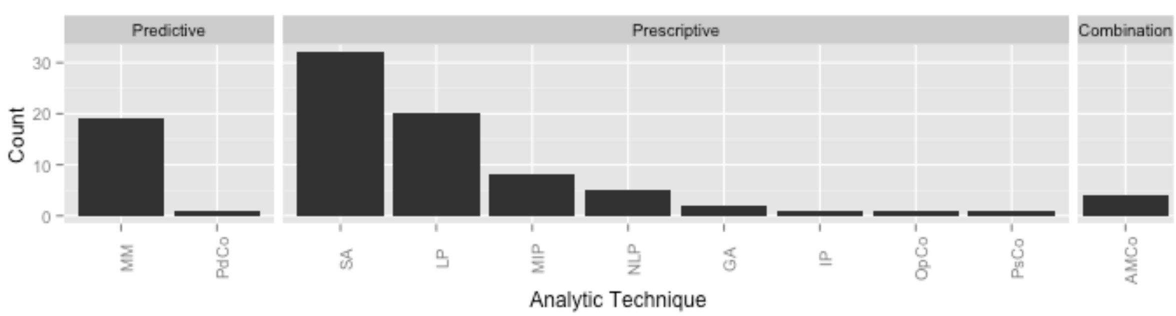


Figure 2.7: Analytic Techniques Applied to the Inventory Management SCM Activity

The fundamental data included in most all inventory management literature include product sustainment data such as production rate, logistics management data such as holding costs, forecasting data such as demand and lead-time, and infrastructure sustainment data such as ordering costs. We classify demand as forecasting data when it is not based on historical consumer consumption. Although demand would likely be based on consumer consumption, in our analysis we wanted to differentiate historical sales and consumption data from the generic demand parameter that is based on a predefined distribution. In addition to this fundamental data, as previously mentioned the TRC_s mathematical model has been extended for multiple purposes and incorporates the following types of data.

Structural cost drivers incorporated into the inventory management models have primarily focused on scale with a focus on the number of vendors [i.e. 79–81], the number of buyers [i.e. 82–84], or both multiple vendors and buyers [i.e. 85–87]. Other scale cost driver data included capital investment costs for items such as leadtime crashing [i.e. 73; 88], order cost reduction [89; 90], technology [91; 92] and quality improvement [93]. Scope cost drivers analyzed include modeling multiple stages of the supply chain over and above the normal two-stage vendor-buyer relationship [i.e. 94–96] and assessing the cost impacts when reverse logistics and remanufacturing processes are incorporated into a value chain [97]. Three papers incorporated learning curve data to assess how experience, or interruption of learning, in the production operation effects TRC_s [98–100]. Papers which incorporated a complexity cost driver do so by incorporating a variable that indicates multiple products.

Executional cost drivers other than the fundamental data previously discussed include quality variables such as defective item rate, screening/inspection rate, cost of rework, and warranty costs [i.e. 101; 102] along with deterioration rates [i.e. 103; 104]. Additional product sustainment data captured in Sawik [105; 106] included a variable indicating the presence of parallel production lines and their differing production rates. Supplementary logistics management variables include transportation data such as cost of transportation/shipment, shipment sizes and weight, shipments per batch, transportation capacity, transportation distance, and freight rates [i.e. 85; 107–110] and warehouse data such as warehouse capacity, transfer costs from warehouse to display [i.e. 111; 112]. Financial data incorporated includes annual interest rates for the buyer and vendor [113] and inflation [114]. Customer sustainment variables included data on vendor-buyer relationship management costs [81] and level of vendor-buyer cooperation [115] represented through shared and non-shared data such as demand, deterioration, etc in the TRC_s. Figure 2.8 illustrates the cost driver categories most often represented by data in the inventory management literature along with the cost driver categories that have received little or no attention. Appendix C provides a cross tabulation of references with analytic approaches and cost drivers used in the inventory management literature.

Figure 2.8: Cost Drivers Used in the Inventory Management SCM Activity

2.4.2 Research and Development Activities.

Multiple studies have stated that 70-80% of a products total cost is committed in the research, design and development (R&D) phase [ref. 116–118]. Due to the increased changes in the manufacturing industries and the need to adjust product designs and manufacturing systems to meet changing market needs, scientific methods and frameworks are required to capture existing data and using the existing data to generate estimates that are timely, relevant and meaningful [c.f. 119; 120]. As a result, research has focused on identifying the influence that new product drivers such as speed to market, quality, product attributes, and product processes have on costs. Forty-six out of the 278 papers (17%) applied SCA in the R&D phase and Table 2.6 illustrates the proportions of methodologies used.

Table 2.6: Analytic Methodologies Applied to the Research and Development SCM Activity

Analytic Methodology	Paper Count	Percentage
Descriptive	0	0%
Predictive	43	93%
Prescriptive	2	4%
Combination	1	2%
Total	46	100%

For predictive analytics, parametric techniques were the most prevalent in R&D cost analytics with ABC the primary approached used. Activity-based costing has been used to model new product costs as a result of the activities required to design, produce and deliver the product [i.e. 121–123]; to predict product costs based on production and processing activities driven by product features [124–126]. Time series analysis has also been integrated with ABC analysis to analyze the tradeoff of investment and profitability of new advanced manufacturing systems [127] and design for manufacturing capabilities [128; 129].

Artificial neural networks (ANN), the second most common predictive technique, have proven to be an effective way to use historical data of a product's attributes, production processes and tolerance levels to predict partial or total life cycle costs of a new product [i.e. 117; 130; 131].

Mathematical modeling has been used for economic value added (EVA) and net present value (NPV) analysis [132; 133] to predict the economic value of a new product or project. Mathematical modeling has also been used to predict cost savings due to product design, parts commonality, and modularity options [134] along with predicting new product costs dependent on product features [135].

Combining and comparing predictive techniques has also become common in R&D SCA literature. When combining, regression is often used to identify and extract cost drivers and parameter values and then this information is integrated into mathematical models [136–138], ABC models [139], and DSS models [140]. In addition, several studies have compared the predictability of ANNs to parametric methods for the R&D phase and often obtain improved results by using ANNs [i.e. 141–144].

Other predictive techniques include regression techniques to predict future costs for the new products based on historical data [145–147], target costing through top-down generative modeling to decompose elementary activity level costs to determine areas of cost reductions to meet new product target costs [148; 149], and DSS for interactive modeling of new product costs [150; 151].

The two prescriptive analytics papers used linear programming to optimize new product attribute mix based on quality function deployment metrics along with budget restrictions [152] and to optimize the direct performance and intangible benefits from investing in a green manufacturing system [153]. Finally, three additional papers combined analytic methodologies such as AND/OR decision trees with multiple integer programming to identify the lowest cost among alternative product manufacturing processes for a new product [154]; combining ABC and dynamic programming to predict and optimize new product development processes [155]; and combining cluster analysis with a case-based reasoning DSS to determine similarities of a new product to already produced products and then use the process costs for these analogous items to determine the proposed cost of producing the new product [156]. Figure 2.9 illustrates the popularity of analytic techniques for the R&D process.

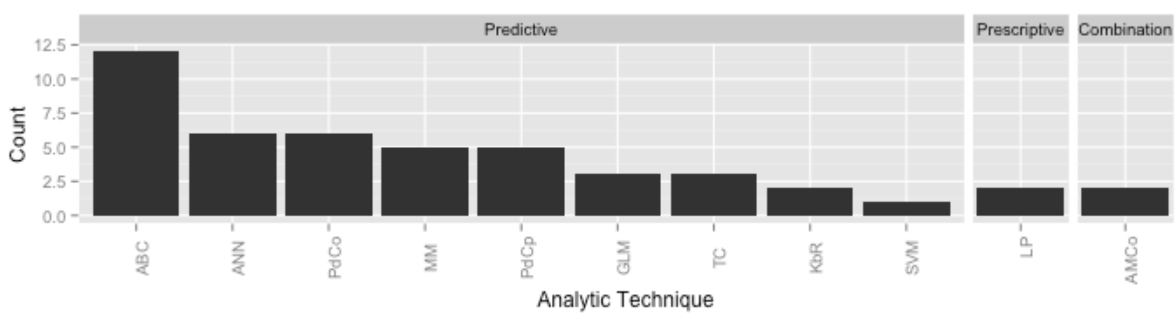


Figure 2.9: Analytic Techniques Applied to the Research and Development SCM Activity

Structural cost drivers incorporated into the R&D phase include scale data such as number of vendors per part [128] and capital investment into a product/project [132; 133] or for manufacturing technology improvements [i.e. 127; 129; 153]. Data for the level of technology in a product has been incorporated by using subjective inputs on the percent of parts considered as advanced technology [146]. Additionally, complexity has been measured by using subjective inputs on a Likert scale for product complexity [138], the quantity of different products and the level of modularity of the products [134], and the number of parts in a product [121].

Executional cost driver data incorporated into the R&D phase include design and development data such as costs to generate CAM drawings and to produce a prototype, labor hours, number of parts in a new product assembly and a measurement of concurrent design activities [122; 138; 139]; quality data such as number of inspections required per part, quality rankings for product attributes derived from customer requirements, and general quality measures for the new product [i.e. 127; 134]; product sustainment data in the form of product attributes [i.e. 137; 149; 157] and production processes and volume [i.e. 121; 124; 144; 158]; logistics management costs such as delivery costs and inventory holding and retrieval costs [i.e. 122; 158; 159]; financial data such as depreciation, income & capital gains tax rates, discount rates, interest payments on debt, payment plan conditions [i.e. 132; 160; 161]; marketing & sales data such as time to peak sales, product margin, sales growth rate, product/project revenues and historical bids provided by marketing department [i.e. 133; 136; 144]; customer sustainment data such as customer requirements [152]; infrastructure support data such as supervision overhead, overall indirect costs, number of orders and number of patents [i.e. 128; 144; 161]; and corporate social responsibility data such as carbon emissions and pollution fines [153; 162].

Figure 2.10 illustrates the frequency of use for each cost driver represented in the R&D literature. Product sustainment/capacity utilization has been the primary cost driver focused on in the R&D literature. With far less emphasis, the structural cost driver scale was the second most often represented followed by the executional cost drivers of logistics, marketing & sales, infrastructure sustainment, financial, R&D and quality management. Appendix D provides a cross tabulation of references with analytic approaches and cost drivers used in the R&D literature.

2.4.3 Production Activities.

Thirty-five out of the 278 papers (13%) applied SCA in the production phase. This research typically focuses on understanding how quality control, production planning, postponement

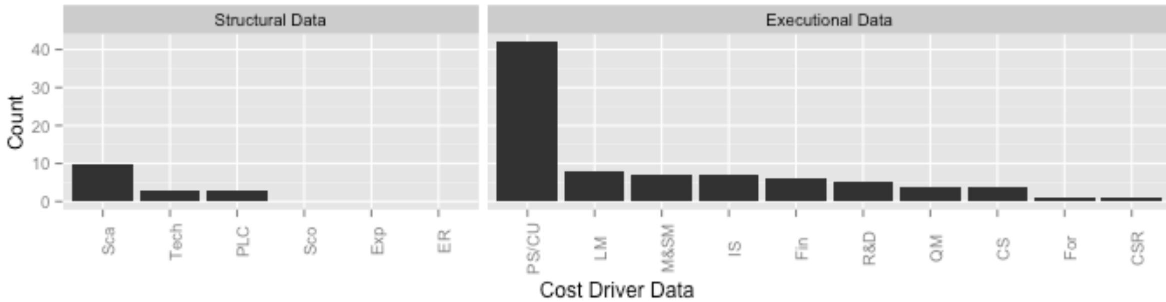


Figure 2.10: Cost Drivers Used in the Research and Development SCM Activity

strategies, capacity expansion, production learning, and normal operating activities influence cost. Table 2.7 shows that predictive analytics is the most prevalent methodology in the production activity.

Table 2.7: Analytic Methodologies Applied to the Production SCM Activity

Analytic Methodology	Paper Count	Percentage
Descriptive	1	3%
Predictive	24	69%
Prescriptive	6	17%
Combination	4	11%
Total	35	100%

For predictive analytic methodologies, parametric analytics were the most prevalent with the focus primarily on using mathematical modeling. Mathematical modeling was most often used to develop cost of quality equations which included modeling the total lost function with Taguchi's quality loss function [i.e. 163; 164] and developing multiple process cost functions to incorporate quality control activities [165].

Similar mathematical modeling was used to model cost functions of production processes [166–168], estimate cost of machined parts [169], and predict cost impacts of postponement strategies [170; 171]. Activity-based costing was also used to model production process costs with the intention of allocating overhead expenditures to the production process costs [i.e. 172; 173].

Very little research has been performed specific to the production process which first extracts parameter values from historical data and then applies the parameter values to predict future costs. Exceptions include Evans et al. [174] who used a simultaneous system of regression equations approach to regress hospital operating costs on patient type (medicaid vs. non-medicaid) and throughput. This is akin to a manufacturing firm regressing production operation costs on product type and volume. Similar research has been performed for the purpose of identifying overhead cost drivers or multiple supply chain processes (i.e. production costs and overhead costs) and will be discussed in later sections. Additionally, system dynamic modeling has been used to model and predict cost of quality based on historical conformance, prevention, and appraisal activities [175; 176].

Descriptive analytics have rarely been applied in the production activity; however, Balakrishnan et al. [177] analyzed the proportional relationship between capacity utilization and total firm costs, which identifies if costs behave symmetrically for production activity increases and decreases. To understand the proportionality of cost behavior, a log-log regression is used. Although this is a form of regression, since the primary purpose of this form of analysis is to understand the symmetry of the cost distribution, we identify it as a descriptive analytic methodology.

A similar approach was used by Ittner [178] in which basic descriptive statistics, trend analysis, and proportionality analysis of the change in quality costs in relation to the change in sales was analyzed. Ittner's longitudinal analysis showed that investing in quality conformance activities had rather immediate impact on sales.

Prescriptive analytic methodologies included all mathematical optimization techniques in the form of search algorithms, LP and MIP. These techniques were applied, based on a priori and perfect information, to optimize production planning [179–181], postponement [182; 183], and capacity expansion decision problems [159] based on total cost considerations. In addition, two papers [184; 185] compared the performance of ABC predictive models to prescriptive optimization models for production process planning to assess how close ABC's approximations fall in relation to the mathematical optimization models. Figure 2.11 illustrates the popularity of analytic techniques for the production process.

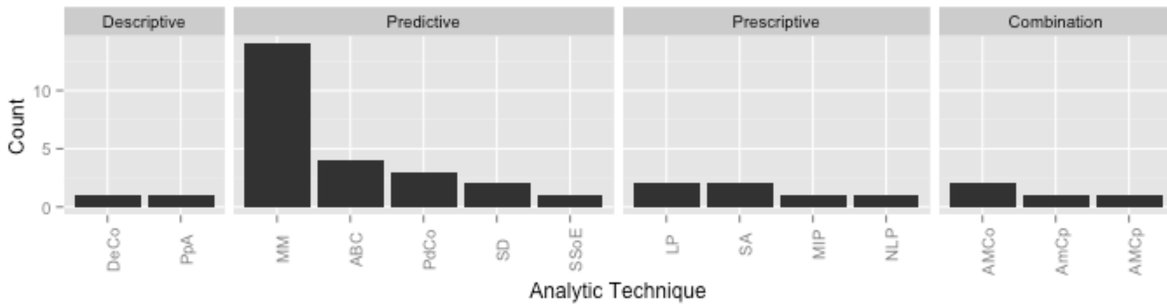


Figure 2.11: Analytic Techniques Applied to the Production SCM Activity

Structural cost drivers analyzed in the production phase include scale data such as capital investment for changes in the production design or capacity expansion[i.e. 170; 184] and multi-site locations [181]. Similarly, Tsai and Lai [159] analyzed the cost comparison of outsourcing versus capacity expansion which would be considered a scope cost driver decision variable. Jaber et al. [100] analyzed the experience structural cost driver by incorporating data on learning through improved production capacity utilization, reduction in set-up times and improved quality. Finally, the structural cost driver "complexity" was measured by incorporating multi-product data and the capacity, unit customization cost, change in production rates and inventory cost, and change in demand for modularization and postponement options.

Executional cost driver data incorporated into the production phase include R&D data such as number of engineering drawings for product changes over its lifetime [180]; quality data such as failure rate, cost of rework, conformance metrics, tolerance, inspection costs, salvage value and subjective customer dissatisfaction costs [i.e. 163; 186; 187]; product sustainment data was in almost all literature and included data such as labor hours and cost, material costs, setup cost, processing times, machine hours, machine maintenance costs, assembly rates, work in progress and capacity; logistics management data such as warehouse space and cost, holding cost, transportation time and cost [i.e. 166; 188]; forecasting data included demand and priority of demand [i.e. 173; 182]; financial data in the form of pre-developed general admin rates supplied by accounting department [167]; marketing and selling data such as annual product sales and revenue, demand based on customer contracts, selling price and product profit margin [i.e. 178]; customer sustainment data such as customer dissatisfaction cost, expected customer utility and airline passenger service costs [176; 186; 189]; infrastructure sustainment data such as facility square footage, age, usage and repair costs, utility costs, insurance costs, firing/hiring and training costs, office equipment and supply costs [i.e. 166; 181]; and corporate social responsibility data included carbon emission quantity and cost [190].

Figure 2.12 illustrates the frequency of use for each cost driver represented in the production literature. Executional cost drivers have received the most attention with product sustainment/capacity utilization receiving the most focus. With far less emphasis, structural cost drivers have primarily been represented by product complexity and scale data. Appendix E provides a cross tabulation of references with analytic approaches and cost drivers used in the production literature.

Figure 2.12: Cost Drivers Used in the Production SCM Activity

2.4.4 Logistics Activities.

Definitions of logistics costs vary considerably. Heskett et al. [191] identified four components of logistics: transportation, warehousing, inventory management and administration. This classification has been widely used with the primary differences in what specific activities, or additional activities, make up these components [192]. Inventory management is primarily researched from a purchasing perspective and was previously discussed. Administration and infrastructure activities which support logistics activities are often considered indirect or overhead activities and will be discussed in following sections. In addition, the facility location problem, which often seeks to minimize total costs, has been extensively reviewed recently by Melo et al. [193] in which a similar discussion was provided on analytic modeling techniques and the data incorporated in that stream of literature. Additionally, the vehicle routing problem often includes a total cost function, however, due to its extensive stream of research which has recently been reviewed by Eksioglu et al. [194] this topic will not be included in our discussion. Therefore, our primary focus in this section will be on the use of SCA to develop cost models for logistics activities such as transportation and warehousing of goods.

Twelve of the 278 papers (4%) applied SCA to logistics SCM processes. These papers focused on developing cost models for transportation costs [195; 196], multimodal transportation options [197–199], total cost-to-serve for a 3PL service provider [200], reverse logistics [201; 202] or a combination of multiple logistics functions [192; 203–205]. Table 2.8 shows that predictive analytics has been the primary methodology used.

Table 2.8: Analytic Methodologies Applied to the Logistics SCM Activity

Analytic Methodology	Paper Count	Percentage
Descriptive	0	0%
Predictive	8	67%
Prescriptive	4	33%
Combination	0	0%
Total	12	100%

Activity-based costing was the most prevalent predictive analytic technique used for logistics cost modeling, in which logistics costs are allocated to products based on the logistics activity perceived to be the cost driver rather than using data mining techniques to identify cost drivers. Regression has been used by Varila et al. [203] to compare the predictive capabilities of simple regression to multiple linear regression. The purpose was to show that various logistics activity costs cannot be traced to a single cost driver as is commonly done with ABC. Engblom et al. [192] used generalized linear mixed regression models to estimate six logistics cost categories as a percentage of turnover: transport, warehousing, inventory carrying, logistics administration, transport packaging, and indirect costs of logistics. Mathematical modeling was used by Beuthe et al. [198] to model a total cost function; monte carlo analysis was integrated to assess the cost variation of different modes of transportation, which have different cost per distance metrics, to identify lowest cost options. Kengpol et al. [199] created a DSS model for multimodal transportation options in which the different modes of transportation had a linear cost function but the intermodal transfers were captured with a step cost function allowing the overall multimodal routes to have a non-linear cost function.

For prescriptive analytics, three papers used linear programming to minimize total reverse logistics operating costs subject to constraints that take into account internal and external factors [201; 202] and to identify the optimal cost minimizing solution for a global third party logistics (3PL) scenario [200]. Bertazzi et al. [195] used mixed integer programming to minimize transportation costs when shipping products from one origin to several destinations given a set of possible shipping frequencies. Figure 2.13 illustrates the frequency of analytic techniques in the logistics SCM activity.

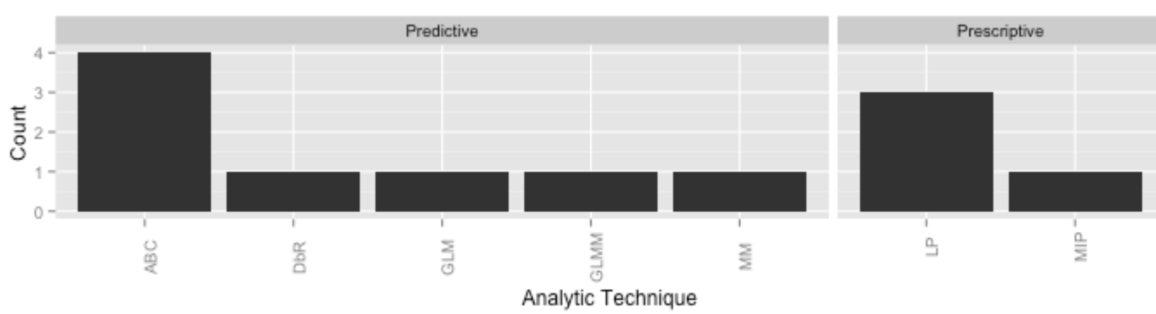


Figure 2.13: Analytic Techniques Applied to the Logistics SCM Activity

Structural cost drivers used for logistics cost analytics include measurements of scale with data such as customer size based on revenues and employees [192; 205], level of geographic scale based on cost of customs clearance for delivering to customers [204] and measuring percent of sales and production outside domestic markets [192]; complexity was measured with data such as number or variety of products [i.e. 201; 202], variety of products required at each destination [195], and subjective inputs on product type (i.e. easy, moderate, difficult) [203]; and finally external risks were measured by incorporating expert opinion on cultural, political, regulatory, and environmental risks for different delivery regions [197; 199].

Executional cost drivers included product sustainment data such as operational cost and time for the reverse logistics studies [201; 202], product weight, volume and value [195; 203]; logistics management data was considered fundamental for all studies and included transportation modes, distance, and time, intermodal transfer costs, transportation capacity, fuel consumption, unit traveling cost, number of vehicles, number of deliveries, reusable containers returned, risk of damaged freight during delivery, inventory carrying costs and wages for logistics personnel; financial data such as depreciation costs of vehicles; marketing and sales data such as type of customer, whether it is the customer's first order or not, and advertising costs per customer; and infrastructure sustainment data such as insurance costs, leasing costs, time to process payroll; staff training costs, facility taxes, insurance and utilities. Figure 2.14 illustrates the frequency of use for each cost driver represented in the production literature and Appendix F provides a cross tabulation of the analytic approaches and data used in the logistics cost analytics literature.

Figure 2.14: Cost Drivers Used in the Logistics SCM Activity

2.4.5 *Customer-Oriented Activities.*

Customer-oriented cost analytics focuses on understanding how cost or profitability is related to the customer. The objective is that a customer-driven approach enables a company to focus on individual customers, customer segments and customer behavior in order to minimize the cost (cost-to-serve) or maximize the profit (customer profitability analysis) by serving the customer. The three types of analysis that fall in this area include cost-to-serve (CTS), customer profitability analysis (CPA), and customer lifetime value (CLV) [see 206; 207:for recent reviews]. This type of analysis is most often used in the following SCM processes: marketing, sales, and customer service. Twenty-two of the 278 papers (8%) applied SCA to model customer-oriented segments of the supply chain and Table 2.9 identifies the popularity of analytic methodologies applied.

Table 2.9: Analytic Methodologies Applied to the Customer-oriented SCM Activities

Analytic Methodology	Paper Count	Percentage
Descriptive	2	9%
Predictive	16	73%
Prescriptive	1	5%
Combination	3	14%
Total	22	100%

Predictive analytic methodologies has focused primarily on ABC parametric techniques followed closely by MM parametric techniques. Papers using ABC [208–212] typically allocate costs of pre-identified cost pools (i.e. production costs, delivery costs, marketing and customer support costs) to cost drivers which can be linked to customers (i.e. quantity and weight of delivered goods/services, quantity of bills issued, number of sales visits, number of orders, etc). The costs to serve a customer can then be developed by analyzing cost driver consumption by, or in support of, the customer If customer revenues are included in the analysis customer profitability can be analyzed by subtracting CTS from customer revenue.

Mathematical models of CLV and CPA [213–216] typically analyze costs at a more aggregated level by focusing on the estimation of three key drivers to include (1) propensity of the customer to make a future purchase, (2) predicted product contribution margin from future purchases and (3) the direct marketing resources allocated to the customer in future periods [c.f. 68; 207]. For examples of these models reference Mulhern [214]. The primary difference as described by Mulhern is customer lifetime models are appropriate when customers have ongoing relationships with organizations and future purchase and cost streams can be accurately forecasted at the individual level. In marketing situations where lifetime analysis is not relevant, or when accurate projections of lifetime purchases cannot be made, a historical profitability analysis can be performed. Therefore, the CPA model is very similar to the CLV model except that it represents an adjustment factor to eliminate the time value of money (e.g., annual inflation rate).

Other predictive analytic techniques used include a decision tree [217] and decision tree-like approach [218], which the author calls a customer migration model. The decision tree approach segregates future purchases by customers by the likelihood of purchase [218] or segregates customers by account attributes (net worth, size of loans, usage) which best predict contribution margin [217]. Combining predictive techniques included using ABC to allocate costs to serve the customers and GLM to regress CTS and CPA metrics of customers against customer attributes (i.e. number of delivery locations, type of shipping units, number of different purchased items) to identify customer attribute cost drivers [219]. In addition, Kumar et al. [220] used MM to develop CLV for customers, GLM to regress gross margin and purchase frequency on customer attributes, and finally logistic regression to classify customers into low, medium or high CLV segments.

Descriptive analytics were used by Dwyer [221] by using time series analysis on customers to generate probabilities of purchases in subsequent periods along with expected value of sale; Dwyer then used NPV to generate the customer's CLV. Structural equation modeling was used by van Triest [222] to test the relationships between customer size, product margin, exchange efficiency, support and customer profitability margin.

Only one prescriptive analytic technique was identified [223] in which non-linear modeling and a genetic algorithm was used to find the number and location of facility sites to maximize customer service while minimizing the CTS. Three papers used a combination of descriptive and predictive analytic techniques.

Combinations of analytic methodologies include McManus [224] who used an ABC-like approach to develop CTS metrics for customers and then used basic exploratory data analysis by comparing costs of customers by geographic location. Cugini et al. [225] used ABC to allocate costs to customers but also used cluster analysis to segment customers based on their ranking of service components and Kone and Karwan [226] used cluster analysis to segment customers and then regressed the costs of these customers against the attributes associated with them (product use rate, distance from plant, etc).

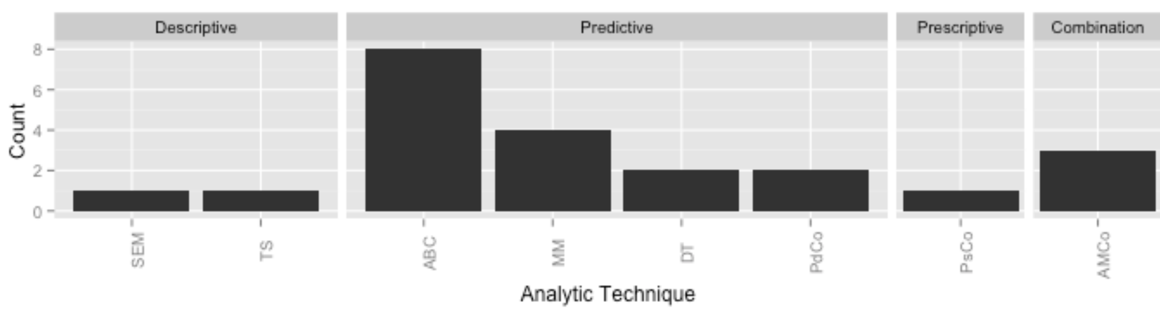


Figure 2.15: Analytic Techniques Applied to the Customer-oriented SCM Activities

Structural cost driver data used to support customer-oriented cost analytics include measurements of scale through customer size via revenues [i.e. 208; 222], geographic dispersion of customer facilities [223; 226], and population size by geographic location [224] and one paper introduced a complexity measure by including the number of delivery locations for a customer [219].

Executional cost drivers include a heavy reliance on marketing and customer sustainment data such as customer ratings of service components or product attributes, marketing costs and promotion activities by customer, order history, product margins, time and cost of technical and maintenance support provided to the customer, acquisition cost of a new customer, and yearly retention rate. In the few studies which were not business-to-business (B2B) and were business-to-consumer (B2C) additional data included customer attributes such as age, net worth, marital status and number of children [209; 217; 218; 225]. Other executional cost drivers included R&D data such as product development costs; product or operations sustainment data such as machine costs, hotel operations costs and activities; logistics management data such as distribution costs, warehousing costs, quantity and weight of delivered items, holding costs; financial data such as discount and interest rates; and infrastructure sustainment activities such as general admin costs, billing costs, quantity of bills per customer, call center costs and quantity of calls. Figure 2.16 illustrates the frequency that each cost driver is represented in the customer-oriented literature and Appendix G provides a cross tabulation of the analytic approaches and data used in the customer-oriented literature.

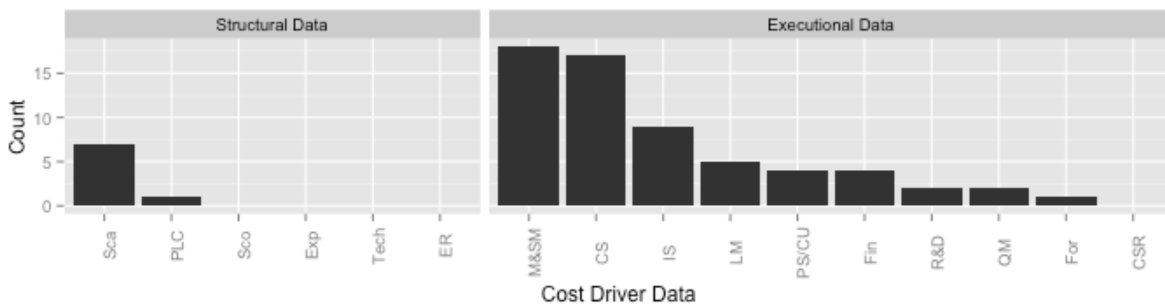


Figure 2.16: Cost Drivers Used in the Customer-oriented SCM Activities

2.4.6 Support Activities.

Remaining value chain activities include activities meant to support inter and intra supply chain activities. This includes the remaining activities identified in Mentzer, et al. [13]: finance and information systems but also includes activities such as human resources, legal support, "c-suite" management, and facility management. These type of activities are often referred to as indirect or overhead activities; however, we will refer to them as support activities. Seven out of the 278 papers (3%) applied SCA to model support activity costs and Table 2.10 illustrates the analytic methodologies applied. Strategic cost analytics in this area have been scarce and typically focuses on understanding what influences support activity costs.

Table 2.10: Analytic Methodologies Applied to the Support SCM Activities

Analytic Methodology	Paper Count	Percentage
Descriptive	4	57%
Predictive	3	43%
Prescriptive	0	0%
Combination	0	0%
Total	7	100%

Support activity costs are often assigned to products or services through ABC when performing R&D and production SCA; however, there has been a line of research that has focused on understanding the behavior of support costs with descriptive analytics and trying to identify statistically significant cost drivers in order to predict support cost behavior using predictive analytics.

Descriptive analytics on support costs include correlation and partial correlation analysis to assess relations between support costs and variables representing production volume, complexity and efficiency [227]. In addition, proportionality tests in the form of cost stickiness, or variations of, have been used to model the change in support activity costs compared to the change in throughput [228; 229] and the change in selling, general and administration (SG&A) costs compared to the change in sales revenue [230].

Predictive analytics on support activity costs include a log-log regression model used by Banker et al. [231] to regress manufacturing overhead costs on strategic cost driver data (shop floor area per part, number of personnel involved in purchasing and production, and number of engineering change orders). System of equations were used by Datar et al. [232] and MacArthur and Stranahan [233] in which endogenous regression models were used to identify cost drivers while capturing interactions between variables.

Structural cost driver data used to model support activity costs include controlling for the scale of facility size by incorporating facility square footage [228; 229; 233] and total number of customers for a product [227]; and including product complexity by including data on the number

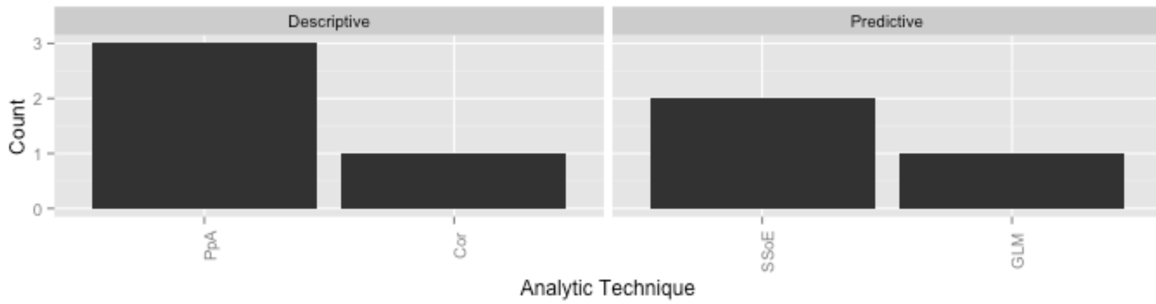


Figure 2.17: Analytic Techniques Applied to the Support SCM Activities

of services offered [233] and including the number of vendors per product and parts per product [227].

Executional cost driver data included quality management data such as amount of personnel and time spent on quality processes [231; 232]; product sustainment data such as product attributes, production labor costs, material costs, replacement cost of machines, capacity and throughput was considered in all studies except for Anderson [230]; logistics management data such as ending inventory dollar value [227]; marketing and sales data such as number of customers and number of orders shipped per month [227] and total operational revenue [230]; and infrastructure sustainment data included in all studies was the dependent variable of interest which was the overhead or supporting activity costs. Figure 2.18 illustrates the frequency that each cost driver is represented in the support activity cost literature and Appendix H illustrates the analytic approaches and data used in the support activity cost literature.

Figure 2.18: Cost Drivers Used in the Support SCM Activities

2.4.7 *Multiple Activities.*

Although most papers approach SCA from a specific SCM perspective, 11 out of the 278 papers (4%) could not be allocated to a single SCM process focus and, rather, applied SCA to model costs across multiple SCM processes. Table 2.11 illustrates the analytic methodologies applied to these remaining papers.

Table 2.11: Analytic Methodologies Applied to Multiple SCM Activities

Analytic Methodology	Paper Count	Percentage
Descriptive	3	27%
Predictive	5	45%
Prescriptive	2	18%
Combination	1	9%
Total	11	100%

The majority of these papers were of a diagnostic intent in which descriptive and predictive analytic methodologies were used to understand and identify cost drivers of both operational activities and non-operational activities based on historic data. This included path analysis used by Ittner and MacDuffie [234] to measure the impact of cost drivers on both direct and indirect labor; cost stickiness analysis performed by Balakrishnan and Gruca [235] to assess the level of cost symmetry, or asymmetry, for both operational departments and support departments based on the cost driver customer throughput; and trend analysis used by Heptonstall et al. [236] to analyze ”levelised cost” of disaggregated offshore wind power costs and assessed their sensitivity to historical costs/prices of potential cost drivers. In addition, Banker and Johnston [237] used a system of equations approach in which 10 multiple regression formulas for cost categories (fuel, maintenance labor, maintenance materials & overhead, general overhead, etc) were used to captured the total airline industry costs. In a similar fashion Balakrishnan et al. [238] regressed 18 disaggregated cost pools representing direct, ancillary, and support services using multiple linear regression. Finally, Ittner et al. [239] used PCA to align operating variables to three factors representing unit, product and batch level sustainment factors then regressed six production cost pools and eight support cost pools against the factor scores to identify significant cost drivers.

Non-diagnostic research that analyzed multiple SCM activity costs simultaneously included integrating ABC and EVA methods [240] to allocate costs and capital investments to activities which produce and support products; the intent was to show where money should be invested to balance product costs and shareholder value. In addition, prescriptive analytics included linear programming [241] and nonlinear programming [242] with the intention of optimizing total supply chain costs.

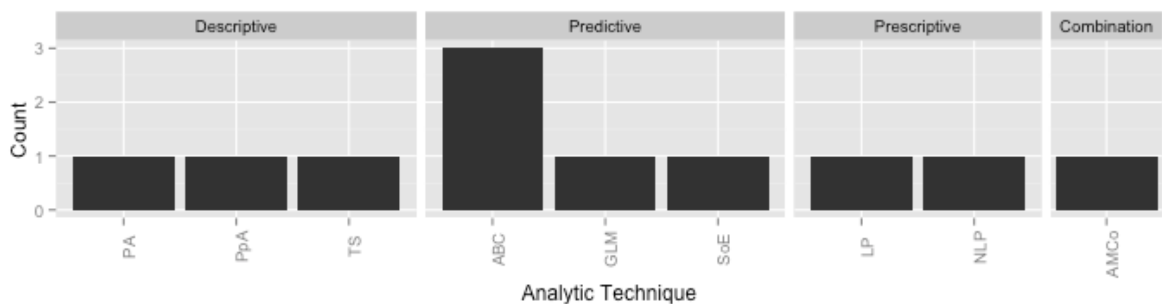


Figure 2.19: Analytic Techniques Applied to Multiple SCM Activities

Structural cost drivers include scale data such as number of suppliers, geographic dispersion of supply chain measured by total distance a product travels, network scale measured by airline hub density and stage lengths, plant scale and the amount of capital investment. Technology was measured by incorporating data on the perceived level of automation used across the business [234]; and complexity was measured via number of products, subjective assessment of model mix and parts complexity, and patient-case mix in a healthcare setting [238].

Executional drivers included R&D data such as development costs; quality data included cost of quality; product sustainment data such as material costs, processing and assembly costs, level of multi-skilling [234], operational costs for fueling, flying and maintaining aircraft [237], capacity utilization, and production volume; logistics management data included inventory holding costs and transportation costs; forecasting data included demand and lead-time forecasts; marketing and sales data included consumer consumption along with location and population of consumer location [242], promotion & sales labor, and service revenues; customer sustainment data such as customer contacts and labor to provide passenger services; infrastructure sustainment data such as ordering costs, overhead labor; and corporate social responsibility data such as cost to develop employees and environmental data such as environmental degradation cost due to depletion of natural resources. Figure 2.20 illustrates the frequency of data usage to represent the respective cost drivers in these remaining pieces of literature. Appendix I provides a cross tabulation of the analytic approaches and data used in literature that focused on multiple supply chain processes.

Figure 2.20: Cost drivers used in multiple SCM activities

2.5 Discussion

A firm must recognize the alternative forms of value creation and cost impact influenced by its internal and external supply chain activities. This starts with understanding how we currently apply advanced analytic techniques for SCA across the supply chain along with an awareness of the types of data used to extract information and knowledge on cost behavior. Figure 2.21 illustrates the use of analytic methodologies applied across the supply chain. As previously stated, SCA is being applied disproportionately across the supply chain with the front-end of the supply chain (purchasing and R&D) receiving the bulk of the attention. Purchasing, made up of supplier selection and inventory management, receives the majority focus of SCA with 53% of all identified literature; followed by R&D, production and then customer oriented analytics.

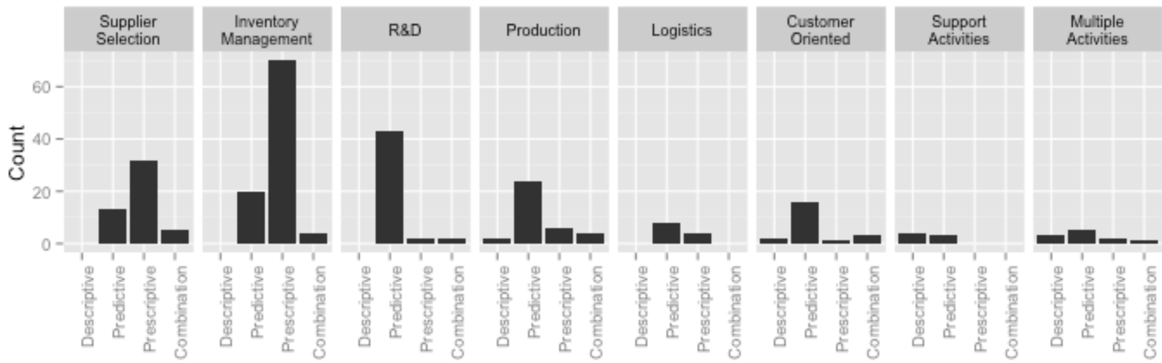


Figure 2.21: Analytic Methodologies Applied Across the Supply Chain

Overall, predictive analytics represent the most often used methodology with 48% of the SCA literature, prescriptive analytics are used in 42%, combining multiple methodologies are used in 6%, and descriptive analytics are used in only 4%. Furthermore, Figure 2.22 illustrates the top 5 analytic techniques applied in each supply chain activity.

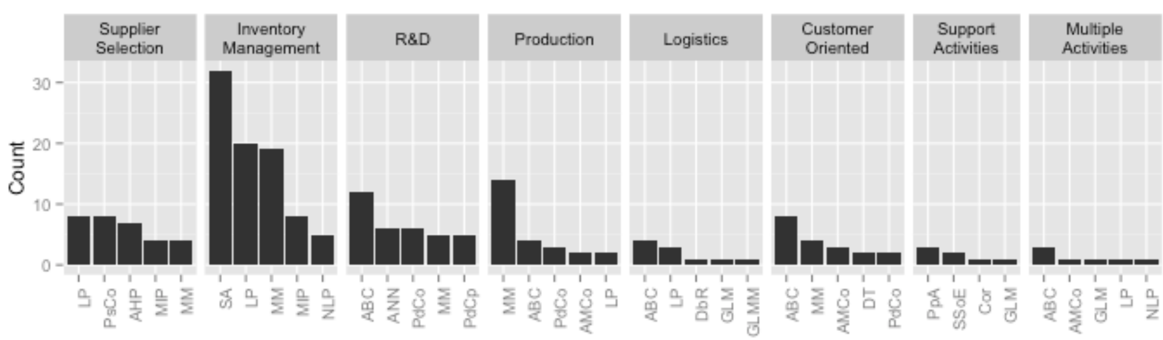


Figure 2.22: Top 5 Analytic Techniques per Supply Chain Activity

As observed, very little descriptive analytics have been performed throughout the supply chain. Much of the research in supply chain processes such as purchasing, R&D, production and logistics assume perfect knowledge or *a priori* information on the data used rather than using historical data; therefore, there has been little need for descriptive analytics. However, much of the current hype around the advancements of analytic techniques and data collection is the ability to filter large amounts of historical data to understand what has happened and what can be predicted to happen in the future [243]. As a result, descriptive analytics should play a larger role in future SCA research across all supply chain processes.

Predictive analytic techniques have been used across all supply chain processes and have been the dominant approach in R&D, production, logistics, and customer oriented SCA. One common characteristic on the use of predictive analytics across the supply chain is that ABC tends to be the preferred method; however, as already mentioned the assumptions that ABC places on the symmetry of cost behavior may have limitations. Although ABC has similar features to linear regression, very few studies have actually applied linear regression techniques to determine statistically significant cost drivers based on historical data. Linear regression is considered a fundamental predictive analytic technique, yet very little research has applied it to understand cost behavior across the supply chain. In addition, several forms of regression have not been used such as multilevel modeling, which could be applicable to modeling cost across the hierarchical structure of an organization (i.e. product level, batch level, department level); logistic regression, which could be applicable in modeling the propensity of a customer's purchasing activity or the likelihood of a risk experienced in a supply chain process which could influence cost behavior; and other non-linear regression models. One interesting note is the level of acceptance in using ANN as a predictive analytic technique in the R&D supply chain process for new product costing. Seven papers used ANN as their predictive modeling technique and five other R&D papers compared the predictive abilities of ANN to regression techniques and found increased prediction accuracies; however, ANNs were used in no other supply chain process for SCA. This also highlights another difference in SCA approaches between supply chain processes. The R&D process has published several pieces of research which compares the predictive capabilities of multiple techniques, while other supply chain processes has performed very little comparison. Producing more research that compares multiple methods will allow organizations to gain insights into which predictive techniques may perform better than others in each supply chain process.

Additional predictive techniques which have received very little attention but may prove beneficial to understanding cost behavior in the supply chain include simulation techniques such as discrete event simulation for understanding transportation costs; support vector regression or least-squares support vector machine to classify customers or products into categories and then regressing costs on classification characteristics; decision trees to analyze vendor selection or capital investment options; and decision support systems which provide interactive means for decision makers to analyze the cost trade-off space in a problem.

Prescriptive techniques have received the most focus in vendor selection and inventory management. In addition, they are heavily used in the vehicle routing and facility location problems which we did not review in this paper. Prescriptive techniques have focused on mathematical optimization techniques with the primary focus on proving inventory theorems that assume known, continuous demand with perfect information. Waller and Fawcett [243] state this line of research is less relevant and the focus needs to shift to analyzing the quality of the optimal solutions, the ability to implement it, and understanding how the system behaves when it is not optimal. Only three papers (Production: [184; 185]; Purchasing: [43]) compared the predictive accuracy of ABC and linear models to optimization models. More research is needed to compare predictive and prescriptive models so that organizations can understand the cost impact they experience when non-perfect information is known. This type of analysis may provide evidence that sub-optimal predictive modeling does not have a sizable cost impact or it may provide evidence that significant costs are experienced by lack of perfect information and, therefore, investment in improved data collection via big data is justified. In addition, additional research on incorporating prescriptive techniques such as data envelopment analysis into other supply chain activities may assist decision-makers in optimizing performance across the entire value chain.

Figure 2.23 illustrates the count of structural versus executional cost driver variables represented in the SCA literature across the supply chain activities. Executional cost drivers receive the primary attention in SCA literature across all supply chain activities; receiving more than twice as much attention as structural cost driver data. Furthermore, the front end of the supply chain, primarily inventory management, has incorporated significantly more cost driver variables than other supply chain activities; this is principally a result of the maturity and depth of inventory management research.

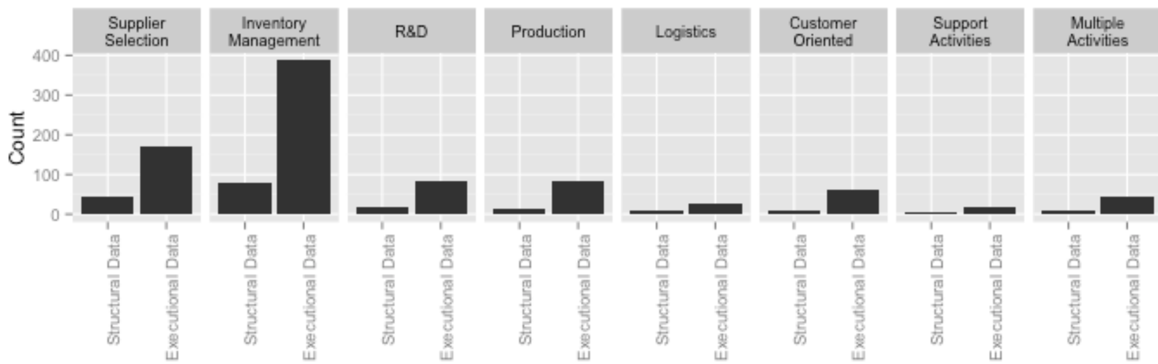


Figure 2.23: Use of Structural vs. Executional Cost Driver Variables Across the Supply Chain

Figure 2.24 identifies the top 5 cost drivers represented by data across the supply chain activities. Scale represents the only structural cost driver consistently in the top five across all supply chain activities and product line complexity is represented in the production, logistics, and support supply chain activities. Scale was most often represented by number of suppliers/buyers, capital investment, geographical distance, and customer size via revenue and product complexity was typically captured by incorporating the number of products for a product line in vendor selection and inventory management problems and the option of modularity; both of which typically incorporates different production rates, material costs, holding costs, and delivery costs for the different products or modularity options. All other top five cost drivers are represented by executional cost drivers with product sustainment (i.e. production rates, capacity utilization, labor, product attributes), logistics management (i.e. inventory holding costs, warehouse & transportation capacity, on-time delivery rates), and infrastructure sustainment (ordering costs, support costs, overhead labor, facility sustainment variables) being represented in the majority of supply chain activities.

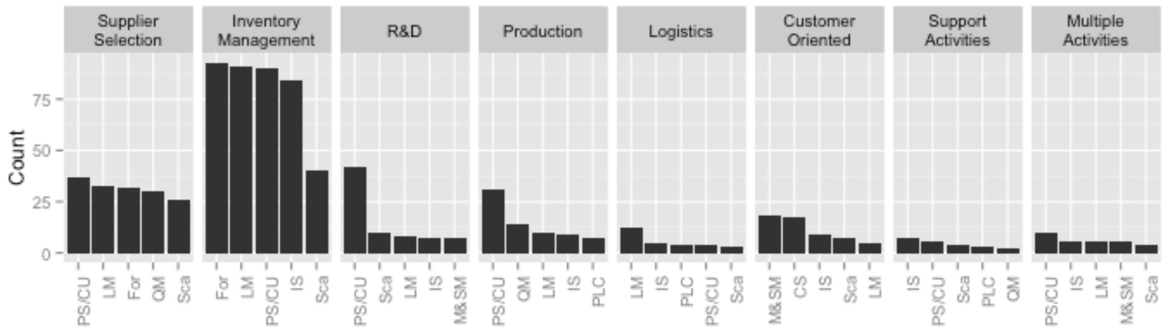


Figure 2.24: Top 5 Cost Drivers Represented Across the Supply Chain Activities

The primary dimension of data that structural cost drivers would benefit from is variety. Since structural cost drivers tend to be long term decisions, they often do not require quick-turn analyses or real-time analytics which usually benefits from increased velocity of data. Rather, incorporating more variety of structural measures can allow an organization to understand how long-term decisions influence costs and, possibly more important, how to use data to measure these decision variables. Scale has been measured the most in the purchasing process but can also be measured in multitude of ways across the supply chain such as incorporating the scale of geographic sales when analyzing the cost-profit tradeoff for a new product, regional scale by capturing the number of regional clusters serviced when analyzing delivery costs, and employee scale by measuring if the employees are unionized and, if so, how many union workers there are and its impact on operating costs. Scope cost drivers can be measured through understanding the differences of the primary organization's resources in a value activity (i.e. holding inventory, order processing, assembly, delivering goods) and the level of resources a provider requires to do the same activity. This could be measured by incorporating the level of manpower, capacity and utilization, quality metrics, processing speed, etc. required by other organizations which could be provided by data sharing between organizations or third party providers of general operating data for businesses.

Although most of the research was manufacturing based, very little research incorporated data to measure learning or experience. To capture how cost of activities can decline over time, experience could be incorporated and measured with historical data on labor hours for activities, utilization of assets, total process time for activities, level of continuous investment required for an activity, etc. This would require more research which includes longitudinal data rather than simply cross-sectional data. Technology continues to impact an organization's capabilities at a rapid rate; however, very few studies have incorporated this measure to understand how it drives costs. To understand how technology impacts costs, SCA can incorporate measurements of the number of EDI transactions in the purchasing function, the age of the technology in the production process, the level of technology in new products by measuring the lines of codes, or the level of technology interchanges between the organization and its customers to understand if technology impacts customer costs and profits. Complexity has been analyzed primarily by measuring the complexity of the product or service offering; however, little research in this line has incorporated historical data. Complexity could be analyzed by comparing historical operating costs based on the variations or models of a product over time, analyzing historical purchasing costs relative to the number of suppliers required by different products or service offerings, analyzing transportation costs relative to the number of different types of customers served, or analyzing the cost to serve different customer demographics to identify if simply serving one customer type is more profitable than serving multiple customers.

Finally, very little research has incorporated measurements of external risks and how they can drive costs. As supply chains become more global they also become more risky than domestic supply chains due to increased susceptibility to disruptions, bankruptcies, breakdowns, macroeconomic and political changes [244]. Additionally, Revilla and Sáenz [245] show that supply chain risk sources differ across countries and regions. To further an organization's understanding of how risk impacts its cost structure, data such as delays and disruptions due to weather, intra and inter-organizational systems breakdowns, intellectual property breaches, political and cultural risk ratings, and financial market metrics could be incorporated into the analytic models to identify how they have historically impacted costs in the purchasing, operations and product sustainment, logistics and customer oriented supply chain processes.

The organizational use of executional data can benefit from growth in all three dimensions of data. The volume and variety dimensions of data should be expanded on in the R&D, marketing and sales, customer sustainment, infrastructure and social corporate responsibility domain. Marketing and sales data along with customer sustainment data could likely see the greatest benefit from volume and variety. Other than the customer oriented research, most research used a forecasted demand rate based on perfect knowledge of the distribution. By collecting more data around customer attributes and sentiments, purchasing history including bundling preferences, and browsing history, organizations can better understand the types of customers they serve, the cost to serve the different customer types and, most importantly, how to direct the purchasing, R&D, production, and logistics supply chain processes to best serve each client type at the most granular level. R&D data was rarely incorporated into supply chain SCA. By incorporating R&D data such as labor hours for new product development, engineering change orders over a product lifetime, time to new product launch, and new product adoption rates into cost models, an organization can begin to trace both the suppliers' impact on R&D costs and also R&D activities on a product's total lifecycle cost. Finally, incorporating more volume and variety of infrastructure sustainment data could allow organizations to get a better understanding of their support costs. This could include more granular details on the activities being conducted by personnel often considered overhead (i.e. management, finance, administrative). This could help organizations to more accurately trace support costs to the activities they are serving.

In addition, production, quality and logistics data have been measured in a large variety of ways across the supply chain; however, incorporating velocity data measurements could allow organizations to further improve its cost behavior such as using data on real-time quality measurements to minimize rework costs, constant inventory levels and real-time tracking of re-stock to minimize inventory costs, instantaneous capacity utilization and production rates to improve daily scheduling and reduce labor costs, and real-time material costs data so that optimal pricing decisions can be made in shorter increments. In addition, velocity on marketing, sales, and customer sustainment data could also provide instantaneous information on customer activities and desires which could help organizations to real-time target market and price discriminate to customers to minimize costs and maximize profits.

2.6 Conclusion

This review shows that the groundwork for understanding how an organization can implement analytic techniques and data sources to understand its cost behavior across the supply chain has been established; however, its vastness has resulted in a non-centralized stream of research. This paper brings together this wide-range of research and categorizes them by supply chain domain, analytic methodology, and data categorization in order to unify this research under the SCA construct. This establishes a much needed framework that standardizes the use of analytics and data across the value chain for cost management purposes. In addition, this paper proposes where organizations and future research can focus to improve SCA across the supply chain.

Although this research establishes the necessary framework to organize this stream of research, much more empirical research is required to create a more robust understanding of how organizational costs behave and why. Future research must seek to balance the level of knowledge of SCA across the supply chain activities. Furthermore, deficiencies in the use of analytic techniques and data must be addressed before a well-framed theory can be established on how best to use SCA across the supply chain to align an organization's cost management activities with its strategic intent.

III. Bending the Cost Curve: Moving the Focus from Macro-level to Micro-level Cost Trends with Cluster Analysis

Which curve?

CBO Director Douglas Elmendorf, 2009

3.1 Introduction

Bending curves has become the ambiguous jargon employed in recent years to emphasize the notion of changing unwanted trends. From housing development [246], climate change [247], health care [248–250] to Air Force acquisition initiatives [251], this term has become the popular metaphor for verbally illustrating a forced change in trajectory, most notoriously, *cost* trajectories. *Bending the Cost Curve* (BTCC) has become a ubiquitous newspaper heading for the health care industry and has experienced a direct focus in health care literature [252–256] with an emphasis of reducing the cost burden, and more specifically, the cost growth in the United States.

In a similar fashion the United States Department of Defense (DoD) finds itself in an economically challenging situation. In an effort to control long-term budget growth, sequestration took effect in 2013, as a result of the Budget Control Act of 2011 and the American Taxpayer Relief Act of 2012. Consequently, the DoD estimates a total forced reduction in the planned defense budget between fiscal years 2012 to 2021 to exceed $1 trillion [1]. In response to the budget reductions, the Air Force (AF) has launched its own BTCC initiative [251] in an effort to reduce its proverbial cost growth.

A principal concern with these initiatives and research articles to date is the lack of expounding on actual historic cost curves. In the health care research, the cost growth curves discussed are primarily limited to aggregate industry-wide health care costs. Within the AF, although significant research has been performed on weapon system cost growth [e.i. 257–263], a well-defined cost curve(s) has yet to be explicitly attached to the BTCC initiative. Without a clear understanding to which cost curves exist and in which form, any BTCC initiative will remain focused only on aggregated cost trajectories which implies only a single cost curve exists; however, this single cost curve may or may not be an accurate representation of underlying cost curves at the micro-level (*operational level*). Although an emphasis on aggregate level cost behavior is certainly important, decision-makers benefit from having a thorough understanding of the underlying cost curves which, when combined make up the aggregate cost curve, thus providing enhanced insight for developing policy actions.

Rather than presume that a single cost curve is present, this research illustrates an exploratory approach that can be used to identify underlying AF cost curves and to understand the existence of homogeneous cost curve trajectories among cost activities and locations. For brevity this paper focuses on select sustainment cost curves across AF bases but has the potential for wider application across the AF and DoD enterprises. The remainder of this paper is organized as follows. Section 2 provides background to the problem at hand. Section 3 describes the analytic methodology and the data used. Section 4 discusses the empirical analysis performed and its results and section 5 offers concluding remarks.

3.2 Background

Department of Defense cost growth, and more specifically, weapon-system cost growth has been a subject of interest for many years (examples: [257–263]); however, a common theme in nearly all cost growth studies is their focus on *acquisition* cost growth. Although significant cost savings could theoretically be achieved through management improvement of the acquisition process, acquisition reform has yet to achieve the changes in cost growth in which they target [259; 264–266]. Furthermore, acquisition cost savings, if achieved, could potentially be a product of considerable out-years rather than achievable current-year cost reductions required by current budget constraints and sequestration actions. As a result, this leaves senior leaders grasping for actionable cost saving initiatives and policies on operations and sustainment (O&S) activities which can be influenced immediately and, hopefully, achieve prompt cost savings to align with current budget reductions.

Sustainment expenditures in the AF offer a significant pool of costs in which to try to extract savings. Since 1996 total sustainment expenditures at U.S.-based active duty AF installations have remained over $50 billion annually. In fact, these costs peaked at $72.5 billion in 2005 and have since declined to $65.2 billion in 2014 representing a 13% cost growth over and above inflation since 1996. Furthermore, as Boehmke et al. [4] identified, and illustrated in Figure 3.1, over 50% of installation-level O&S costs are a result of the support or *"Tail"* activities that aid weapon systems or provide supporting roles at installations.

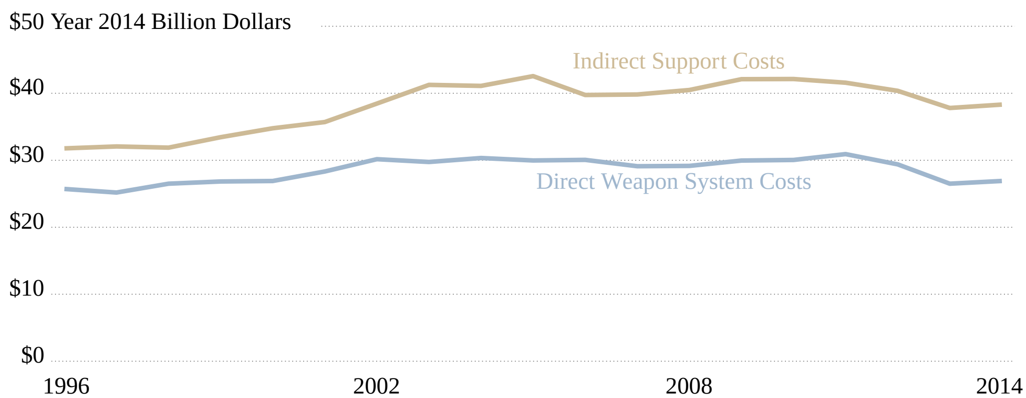


Figure 3.1: Total Direct & Indirect Sustainment Costs at U.S.-based Active Duty AF Installations

In an attempt to bend the O&S cost curve downward, the AF is working to reduce its *direct* costs by trimming the war-fighting workforce; changing the mix of inputs of weapon system type, quantity and usage; and re-engineering processes by closing bases and consolidating activities [1; 267]. However, efforts to bend the *support* cost curve primarily focus on an aggregated *Tooth-to-Tail* ratio relationship which conceals underlying support cost behavior [2; 4; 268–271]. This is illustrated in Figure 3.1 in which aggregated support costs appear to rise and fall in coordination with direct costs; however, Boehmke et al. [4] illustrated that this behavior does not always apply at the installation level suggesting that the aggregate support cost curve does not always represent the operational level support cost curves.

To aid policy decisions this research will focus on identifying AF support activity cost curves so that decision-makers can focus their attention on cost elements and locations that have cost curve trajectories that still require being *bent*.

3.3 Methodology

3.3.1 Analytic Approach.

A reasonable concern with an initiative such as BTCC is that it gives the perception that a single cost curve trajectory exists. Furthermore, conventional growth modeling approaches give a single average growth estimate for a sample of individual growth trajectories [272]. Rather than presume that a single cost curve is present, we apply an exploratory approach to identify the existing cost curves for the support activity cost elements and to understand the existence of homogeneous cost curve trajectories within cost activities and across bases. By applying a non-parametric k-means partitional clustering algorithm specifically designed for longitudinal data, unobserved clusters or groupings of sub-population trajectories within each cost category can be identified. The particular benefits of applying a k-means algorithm for an exploratory analysis of longitudinal data is that is does not require any normality or parametric assumptions within clusters which is of benefit when no prior information is available. Also, it does not require any assumption regarding the shape of the trajectory allowing for linear and non-linear cost curves to be identified [273].

K-means is an established partitioning method [274; 275] that applies a hill-climbing algorithm to maximize the separation between clustered observations. Consider a sample of n subjects. For each subject, the outcome cost variable Y at t different times is measured. The value of Y for subject i at time j is noted as y_{ij}. For subject i, the sequence of cost observations noted as $y_{i1}, y_{i2}, \ldots, y_{it}$ is called its cost trajectory. The aim of clustering is to divide the sample of subjects into k sub-groups in which each sub-group has its own unique cost curve and the individual trajectories of all subjects within that sub-group resemble the overall cost curve more than they resemble another sub-groups cost curve.

To maximize the separation between grouped cost trajectories, multiple distance measures can be used; however, our research utilizes the Euclidean distance as illustrated in Equation (3.1).

$$Dist^E(y_i, y_m) = \sqrt{\sum_{j=1}^{t}(y_{ij} - y_{mj})^2} \tag{3.1}$$

Since k-means is a hill-climbing algorithm, we run the algorithm for k = 2, 3, 4, 5 and 6 clusters and, for each k cluster, we perform 20 iterations each time varying the initial seed to minimize the chance of converging to a local maximum. To assess the optimal number of clusters, the primary criterion used is the Calinski and Harabatz criterion $C(k)$ [276–278], also referred to as the variance ratio criterion, illustrated in Equation (3.2)

$$C(k) = \frac{SS_B}{SS_W} \times \frac{(N-k)}{(k-1)} \tag{3.2}$$

where SS_B is the overall between-cluster variance, SS_W is the overall within-cluster variance, k is the number of clusters, and N is the total number of cost trajectories. The between-cluster variance is defined by Equation (3.3) where n_p represents the number of trajectories in cluster p, $\bar{y}$ represents the mean cost trajectories for all observations, $\bar{y_p}$ represents the mean cost trajectories for cluster p, and $\| \bar{y_p} - \bar{y} \|$ is the L^2 norm (Euclidean distance) between the two vectors.

$$SS_B = \sum_{p=1}^{k} n_p \| \bar{y_p} - \bar{y} \|^2 \tag{3.3}$$

Furthermore, let the within-cluster covariance be represented by Equation (3.4) where y_{pj} represents the cost trajectory of subject j within cluster p and $\| y_{pj} - \bar{y_p} \|$ is the L^2 norm between the two vectors.

$$SS_W = \sum_{p=1}^{k}\sum_{j=1}^{n_p} \| y_{pj} - \bar{y_p} \|^2 \tag{3.4}$$

Well defined clusters have a large between-cluster variance (SS_B) and a small within-cluster variance (SS_W); therefore, the Calinski and Harabatz criterion maximizes $C(k)$ with respect to k. There is no desirable cut-off value for the $C(k)$ criterion; rather, the higher the value, the *"better"* is the solution. If, on the line-plot of $C(k)$ values, there appears that one solution results in a definite peak or the values that follow result in a quick decreasing elbow then the highest valued cluster is desirable. If, on the contrary, the line is horizontally smooth, then there is no reason to prefer one solution to others.

Although the $C(k)$ criterion can be used to assist in finding clusters, it does not always provide the correct optimal number of clusters [278]. To add benchmark robustness to our criterion, we also assess and compare the criterions introduced by Ray and Turi [279] and Davies and Bouldin [280]. Finally, since this is an exploratory analysis, visual observation of the cluster options are also performed.

3.3.2 Data.

All data were extracted from the Air Force Total Ownership Cost (AFTOC) online analytical processing database for fiscal years 1996-2014. Only active duty U.S. Air Force bases which have both direct and indirect functions were of focus, resulting in a sample set of 58 bases. Support costs were pulled for Element of Expense & Investment Codes (EEICs) and categorized by their descriptions as discussed shortly. To minimize the influence of war-time contingency funding, Emergency and Special Program (ESP) codes for Overseas Contingency Operations (OCO) funding were filtered to remove all costs associated with OCO operations. All costs have been adjusted for inflation[5] and represent fiscal year 2014 base-year dollars. Facility data which include plant replacement value (PRV), square footage and building counts were extracted from the Real Property Assets and Automated Civil Engineer System - Real Property databases provided by the AF Civil Engineering office (HAF/A7C).

Support costs across the AF represent a wide range of activities. For purposes of this research the authors focus on three cost categories described as follows (EEIC identification for these cost categories can be found in Appendix J). These three categories combined have consistently represented approximately 75% of all support costs since 1996.

[5] 2014 Office of the Secretary of Defense (OSD) inflation indices were used to adjust costs for inflation.

Manpower: Captures pay, benefits, and allowances for military and civilian personnel providing support services.

Facility: Captures the cost of sustainment activities such as civil engineering, maintenance, repair, minor renovation, and utilities.

Discretionary: Captures the cost of supplies (office, chaplain, welfare & morale, etc supplies), traveling costs (air fare, lodging, per diem) for support personnel, local transportation of people (vehicle rental and bus services), professional advancement (continuing ed, membership & credential fees), printing (advertisements), and technology & software (IT training, database hosting, off-the-shelf software, software licenses).

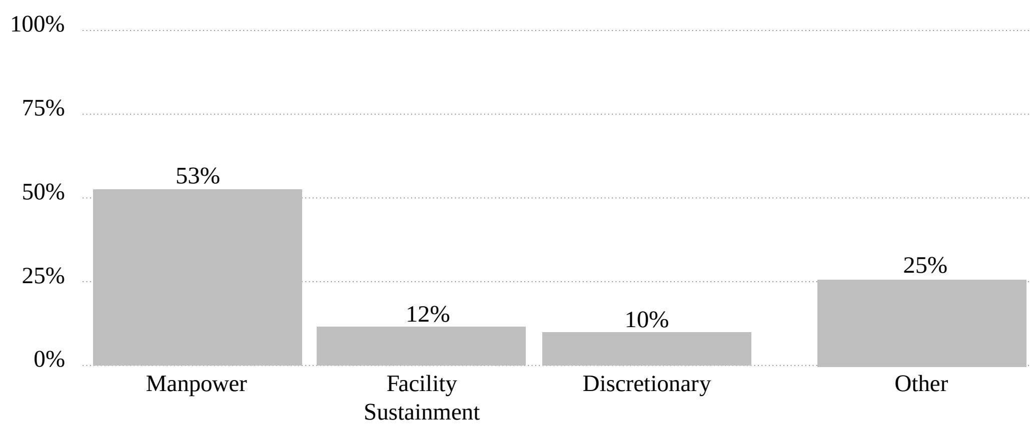


Figure 3.2: Percent of Total O&S Support Costs at U.S.-based Active Duty AF Installations in 2014

All three categories have experienced growth since 1996 but with different forms of trajectory. Manpower costs, although largest in magnitude, have seen the least amount of growth percentage-wise since 1996; experiencing a 14% growth over and above inflation from \$17.6 billion in 1996 to \$20.1 billion. Discretionary costs peaked in 2005 and have since decreased each year; however, discretionary costs in 2014 (\$3.8 billion) were still 31% greater than they were in 1996

($2.9 billion). Finally, facility sustainment costs have experienced the greatest growth since 1996 (74.3%) nearly doubling from $2.5 billion in 1996 to $4.4 billion in 2014.

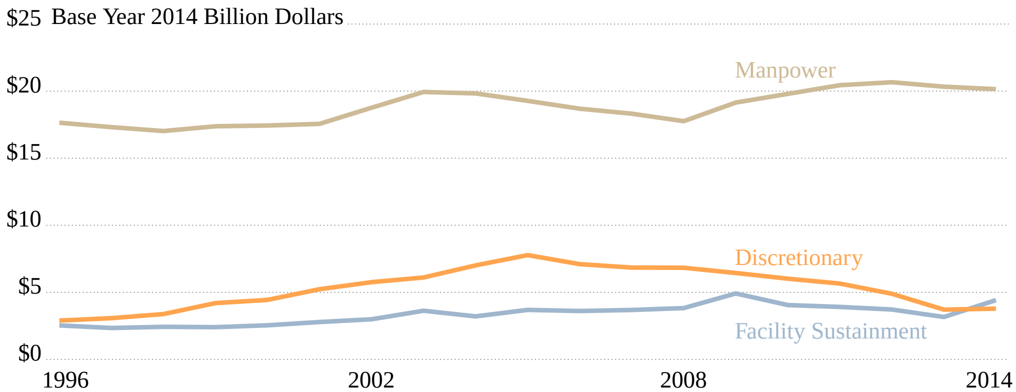


Figure 3.3: Aggregate Support Cost Categories at U.S.-based Active Duty AF Installations

3.3.3 Metrics Assessed.

Understanding that aggregate costs are changing provides only partial insight since it only acknowledges the cost output. On the direct side of operations, the AF focuses on how operational costs behave relative to flying hours or the number of aircraft, which provides a sense of economic efficiency. However, relational metrics have rarely been enforced for support activities. The concern should not only be whether support costs are increasing but, also, are support costs per unit increasing. In addition, applying this relational view allows for competitive benchmarking in which to compare across the AF enterprise. Competitive benchmarking is the measurement of performance against that of the best-in-class to determine how performance levels can be achieved [281]. Nearly all Fortune 500 firms engage in some sort of benchmarking [282]; therefore, it's only practical that the AF internally compares support cost categories which capture over $25 billion annually.

In addition to total output costs, the following metrics[6] will be analyzed and their growth curves identified for the 58 AF installations assessed:

Indirect Headcount per Direct Headcount: Captures the number of support personnel required to aid each front-line mission person[7] at a base. An increasing growth trend signals that for every operational person at a base, the number of support personnel is increasing. This signals that more support personnel are required to provide the same level of support at a base or the base is providing more support services for each operational person.

Indirect Manpower Cost per Indirect Manpower Headcount: Captures the average cost of each support person at a base. An increasing growth trend signals that it is becoming more expensive to provide the same level of support labor.

Facility Sustainment Cost per Plant Replacement Value: Captures the cost curve of operating, maintaining and repairing a facility relative to its PRV. PRV metrics are an industry standard and accepted DoD metric to perform macro level analysis [283]. An increasing growth trend of this metric signals that the cost to maintain the facilities is outpacing the value of the facilities. In contrast, a decreasing cost curve would suggest that increases in economic efficiencies to operate and maintain facilities are being achieved.

Facility Sustainment Cost per Square Foot: Captures the cost curve of operating, maintaining and repairing each square foot at a base. An increasing growth trend signals that it is becoming more expensive to maintain the existing infrastructure at a particular base.

Utility Cost per Plant Replacement Value: Captures the cost curve of energy requirements per plant replacement dollar. An increasing growth trend signals that it is becoming more expensive to provide energy requirements for each dollar of a buildings value, whereas a decreasing cost curve suggests energy efficiencies are being achieved.

[6]Note that these metrics are not currently employed by the AF but, rather, represent proposed metrics. The objective of this research is not to develop or identify preferred metrics but, instead, illustrate an approach to identify underlying growth curves once an organization has identified their metrics of interest.

[7]Front-line mission personnel are military and civilian personnel providing services directly tied to a weapon system.

Utility Cost per Square Foot: Captures the cost curve of energy requirements per square foot at a base. An increasing growth trend signals that it is becoming more expensive to provide energy requirements per square foot at a particular base.

Discretionary Cost per Person: Captures the cost curve of providing all discretionary resources per support person at a base. An increasing growth trend signals that more funds are being expended to provide supporting resources to support personnel.

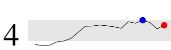
Table 3.1 provides the descriptive statistics for the seven selected metrics across all 58 installations and 19 years. There are a total of 1,097 observations as a result of one installation only having available data from 2001-2014; all other installations have longitudinal data available for all 19 years.

Table 3.1: Descriptive Statistics Across 58 Active Duty U.S.-base AF Installations (1996-2014)

Metric	Mean	Median	CV	Q_1	Q_4
Indirect Headcount per Direct Headcount	2.31	0.98	1.89	0.71	2.16
Cost per Indirect Manpower Headcount	$75,375	$74,890	0.19	$68,106	$82,416
Facility Sustainment Cost per PRV	$0.03	$0.24	1.25	$0.02	$0.04
Facility Sustainment Cost per Square Foot	$7.53	$5.45	2.35	$3.71	$8.11
Utility Cost per PRV	$0.010	$0.009	0.68	$0.007	$0.012
Utility Cost per Square Foot	$2.32	$1.86	0.72	$1.45	$2.67
Discretionary Cost per Support Person	$19,279	$10,349	1.65	$7,437	$19,110

3.4 Analysis

3.4.1 Total Support Cost Curve.

At the aggregate level total costs for the selected support categories (manpower, facility sustainment, and discretionary costs) have increased 28% over and above inflation since 1996. Total cost growth in these areas was at its steepest from 1996-2003 with total cost peaking in 2011 at a total cost value of $29.9 billion and remains at $28.3 billion in 2014 .[8] By scaling

[8]This inline chart is known as a sparkline. This research includes sparklines as a means to illustrate the overall trend of the item being discussed without the requirement of producing a full sized figure. Although the research will often identify the variable values for 1996 and 2014, along with the overall growth, by incorporating sparklines the reader will have a better understanding of the overall trend. All sparklines in this research represent a particular

the annual costs for each base we can easily compare the total support cost trajectories of all 58 bases in Figure 3.4. This allows us to interpret the y-axis in Figure 3.4 as the number of standard deviations the total support costs are from the historical mean for a particular base. The single cost curve represented by the smoothed conditional mean[9] of the base-level trajectories suggest that aggregated total cost trajectory grew from 1996-2004 and have since been rhythmically increasing and decreasing. This cost curve suggests that, on average, the total support cost curve per base has grown 26% from \$388.5 million in 1996 to \$488.4 million in 2014.

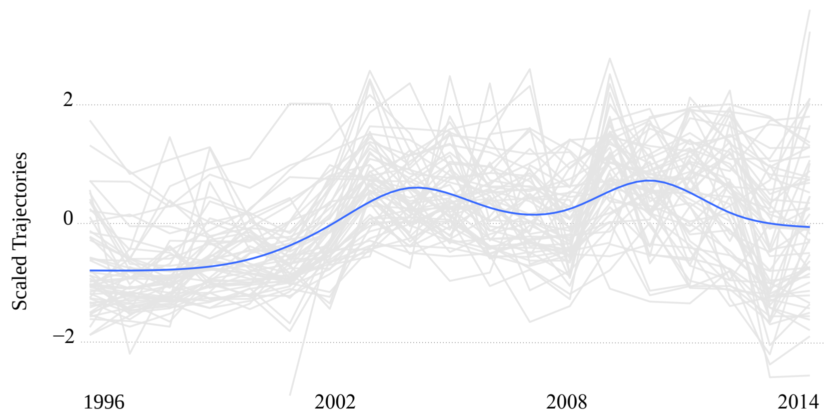


Figure 3.4: Historical Base-level Trajectories of Total Support Costs *(scaled)*

By applying the k-means algorithm, an optimal solution of partitioning into two homogenous clusters was found. This solution optimized all three validity criterions[10] and suggests that both clusters have followed a similar trajectory from 1996-2009; however, after 2009 total support costs for bases in cluster *A* have remained relatively unchanged whereas total support costs for bases in cluster *B* have decreased drastically. In fact, bases in cluster *A* have experienced an average cost growth of 48% since 1996 while bases in cluster *B* have expereinced a 3% decrease. This

trend occurring between 1996-2014. The red dot on the sparkline represents the value for 2014 and a blue dot, when included, represents the maximum value in the trend.

[9]Locally weighted polynomial regression (LOESS) was used to estimate the mean standard score (y-axis value) across all bases conditioned on the fiscal year. Reference Cleveland et al. [284] for more details on the LOESS function.

[10]For each metric throughout this research all three validity criterions ($C(k)$, Ray & Turi, and Davies & Bouldin) converged on the optimal solution.

suggests that approximately 45% of the AF bases have been *"bending"* their total support cost curve downwards for the past several years; however, over 50% of the bases continue to have an increasing cost curve.

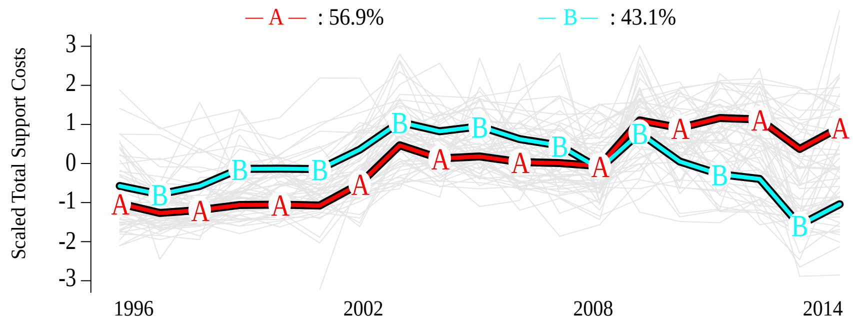
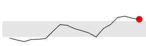
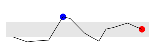


Figure 3.5: Optimal Clustered for Base-level Total Support Cost Curves *(scaled)*

3.4.2 Manpower Curves.

3.4.2.1 Total Manpower Cost Curves.

Total support personnel costs have grown from $17 billion in 1996 to $20.1 billion in 2014  representing an 18% cost growth over and above inflation. This has largely been driven by increasing civilian costs in recent years  as military personnel costs have decreased 50% from its peak in 2003 . At the disaggregated base level, total support manpower costs have followed a fairly rhythmic pattern as illustrated in Figure 3.6. The consistent increase in support manpower costs across all bases in 2003 followed by a decrease in 2008 is likely the fact that bases benefit from wartime supplemental by preserving more O&S funding for home-base purposes but then as the wartime funding decreases, as it did leading to 2008, the AF is forced to leverage O&S funding to support on-going efforts overseas leading to decreased funding for home-base purposes. The increase in expenditures after 2008 was likely a result of the increased civilian hiring efforts which came at the heels of the 2008 economic crisis. Regardless, the single cost curve for base-level personnel costs suggest that bases have, on average, experienced a 16% increase since 1996.

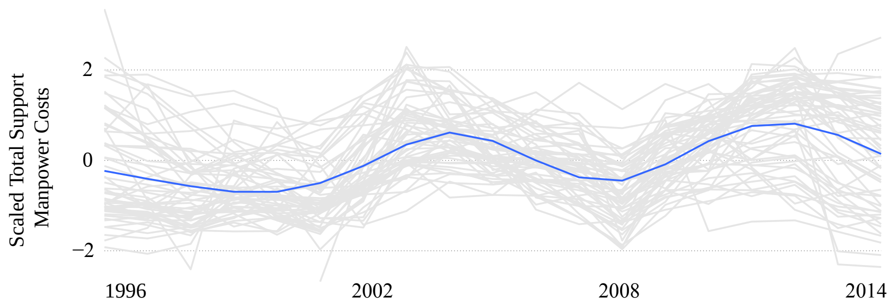


Figure 3.6: Historical Base-level Trajectories of Total Support Personnel Costs *(scaled)*

The k-means algorithm resulted in two optimal cost curve trajectories both of which follow a similar curve between 1996-2008; however, after 2008 over 60% of the bases (*cluster A*) have experienced a significant increase in total support manpower costs while less than 40% of the bases (*cluster B*) have experienced a decrease. This suggests that the significant spike in total manpower support costs was largely driven by approximately two-thirds of the AF bases. In fact, the mean total support personnel cost for bases in cluster *A* grew 30% from $327.1 million in 1996 to $426.8 million in 2014; whereas the mean total support personnel cost for bases in cluster *B* decreased 15% from $253.8 million in 1996 to $216.2 million in 2014.

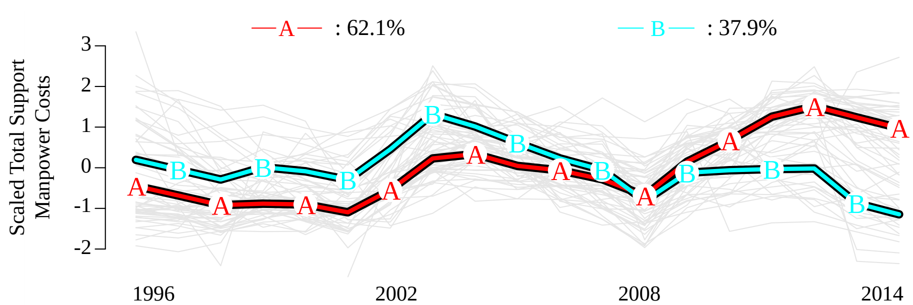
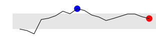
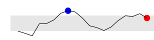


Figure 3.7: Optimal Clusters for Total Support Personnel Cost Curves *(scaled)*

3.4.2.2 *Indirect-to-Direct Headcount Curves.*

At the aggregate, the number of direct personnel peaked in 2005 at 178,900 and have since declined to 162,860 in 2014 which is equivalent to 1999-2000 levels  . Support personnel peaked at 267,504 in 2003, slightly earlier than direct personnel. In 2014 support personnel headcount was at 255,304, equivalent to 2001 levels . The fairly similar trends at the aggregate level result in a correlation of 0.84 and suggests that, on average, 1.5 indirect persons are required to support each front-line mission person with very little variation suggesting a flat-lined trajectory exists . However, as the data is disaggregated to the base level, greater variation in trajectories appear. In fact, when the trajectories are scaled at the individual base-level, as in Figure 3.8, the overall trend appears to decrease during the first eight years and then increase during the latter eight years. This suggests that a majority of bases had a decreasing ratio of support-to-direct headcount leading up to 2004 and since then this ratio has been increasing. However, the shallow curvature appears to support the flat-lined trajectory observed at the aggregate level.

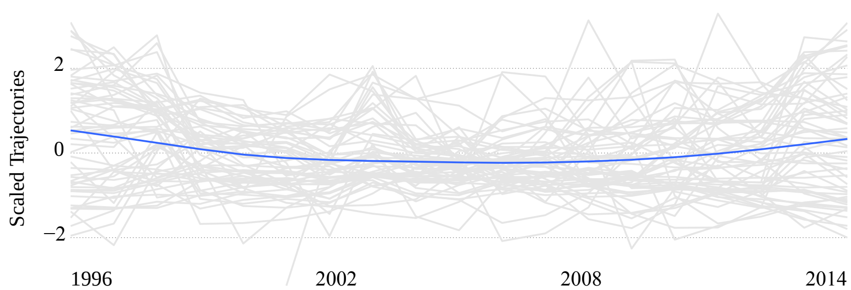


Figure 3.8: Historical Base-level Trajectories of Indirect-to-Direct Headcount *(scaled)*

Applying the k-means algorithm resulted in an optimal solution of partitioning into two homogenous clusters which validated all three criterions. The trajectories of these two clusters as displayed in Figure 3.9 suggests that, rather than a shallow or near flatlined curve existing, two diverging curves exist; one in which the ratio of indirect-to-direct headcount is increasing over the years and another in which the ratio is decreasing. This implies that half of the observed AF bases have a consistently increasing growth curve in their indirect-to-direct personnel ratio while the other half is experiencing a consistent decreasing curve. In fact, in 1996 the bases in cluster *A* required a mean of 1.66 indirect persons to support each front-line mission person which has increased to a mean of 3.8 in 2014. Whereas cluster *B* required a mean of 4.36 indirect persons to support each front-line mission person which has decreased to a mean of 1.82 in 2014.

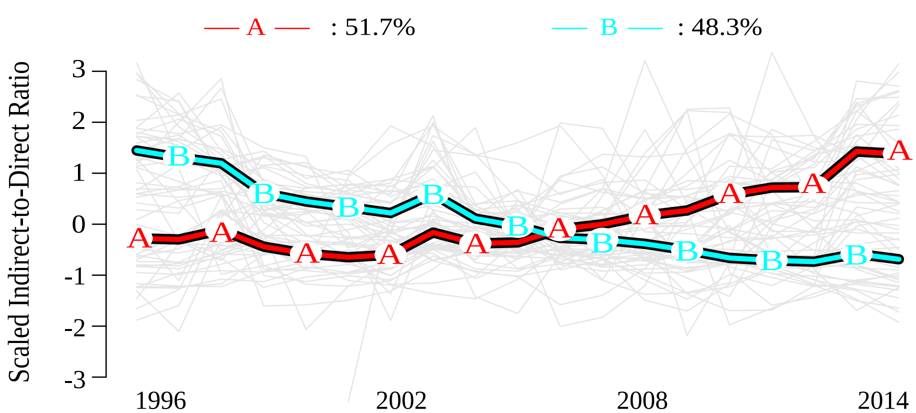
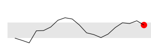


Figure 3.9: Optimal Clusters for Indirect Headcount per Direct Headcount Curves *(scaled)*

3.4.2.3 Per Support Person Cost Curves.

As previously stated, the aggregate number of support personnel at the observed bases has grown from 233,065 in 1996 to 255,304 in 2014  representing a 9% growth over the 19 years. Total support personnel costs, however, have grown from \$17 billion in 1996 to \$20.1 billion in 2014  representing an 18% cost growth over and above inflation. This has resulted in an aggregated annual cost-per-support person that has been steadily increasing from its lowest value of \$67,369 per person in 2001 to \$78,808 per person in 2014  suggesting that across the AF, all else constant, the cost to provide support labor has grown 17% above inflation since 2001.

The smoothed conditional mean of the annual cost-per-support-person trajectories at the disaggregated base-level, as displayed in Figure 3.10, displays a single cost curve fairly similar to the aggregated annual cost-per-support-person curve. Taken at face value, this single curve suggests that, on average, the annual cost per support person at a base has steadily increased since 2000; however, the k-means algorithm identifies two optimal trajectory trends.

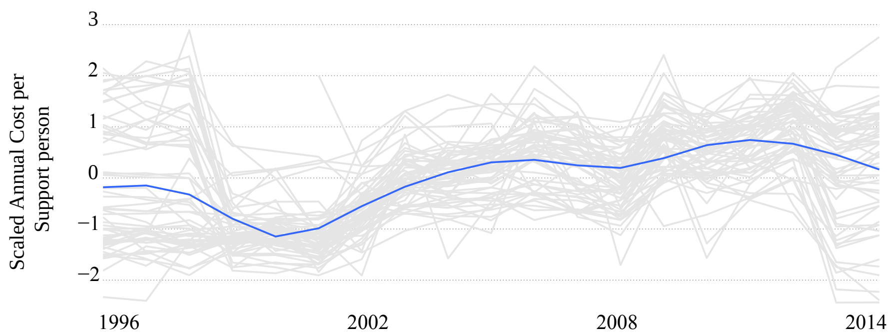


Figure 3.10: Historical Base-level Trajectories of Annual Cost per Support Person *(scaled)*

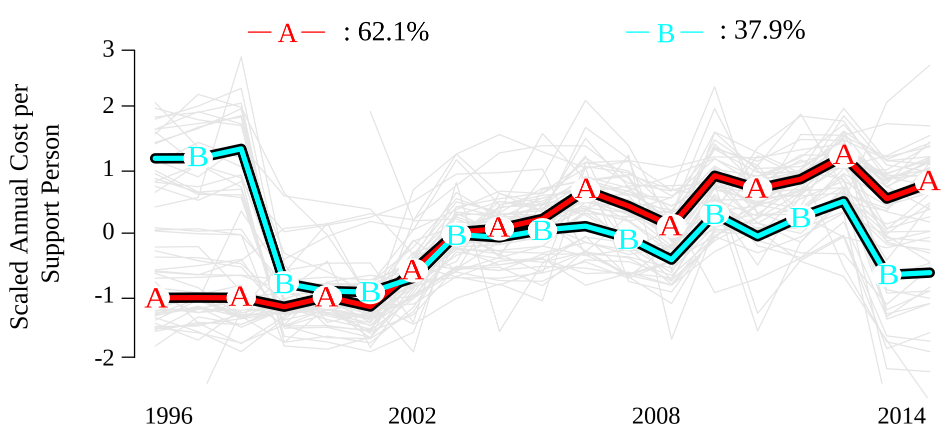


Figure 3.11: Optimal Clusters for Annual per Support Person Cost Curves *(scaled)*

Cluster *A* contains just over 60% of the bases and suggests that these bases have experienced a steady increase in the annual cost-per-support-person since 2001. In fact, cost per support person for bases in cluster *A* have grown 15% from a mean value of $73,924 in 1996 to a mean value of $84,881 in 2014. The remaining 40% of bases (*cluster B*), however, experienced a significant decrease in cost per support person from 1996 to 2001 and has since grown at a much slower rate than cluster *A*. In fact, bases in cluster *B* decreased from a mean value of $73,442 per support person in 1996 to $65,025 in 2001 and was $64,046 in 2014 representing a total 13% reduction since 1996. This suggests that bases in cluster *A* have an increasing cost curve to provide a particular level of support required in which bases in cluster *B* have not experienced.

3.4.3 Facility Sustainment Curves.

3.4.3.1 Total Facility Sustainment Cost Curves.

Total facility sustainment costs have historically represented 73% of total facility costs. At the aggregate, these costs have grown 88% from $1.8 billion in 1996 to $3.4 billion in 2014 . At the disaggregate, the smoothed conditional mean base-level facility sustainment cost trend closely resembles the aggregate trend. This single cost curve suggests that the average base facility sustainment cost grew from $31.9 million in 1996 to $59.2 million in 2014.

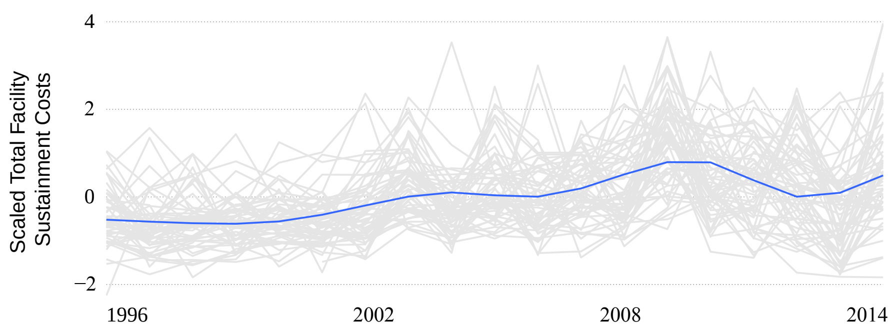


Figure 3.12: Historical Base-level Trajectories of Facility Sustainment Costs *(scaled)*

However, the k-means algorithm identifies two optimal cost curves as identified in Figure 3.13. Cluster *A*, which represents a majority of the bases, experienced a greater increase in facility sustainment costs through 2009; however, since then cluster *A* bases have experienced significant decreases in their cost curve. 2014 mean facility sustainment costs of $46 million represent a marginal 36% growth over 1996 mean costs of $33.9 million. In comparison, cluster *B* bases experienced a much slower growth curve leading up to 2008; however, since 2008 these bases have experienced significant increases. In 2014, cluster *B* bases had a mean facility sustainment cost of \$80.6 million representing a 182% increase over the 1996 mean value of \$28.6 million. This implies that in recent years, although the majority of bases have experienced a decreasing cost curve, 38% of bases are still experiencing an increasing cost curve of significant magnitude.

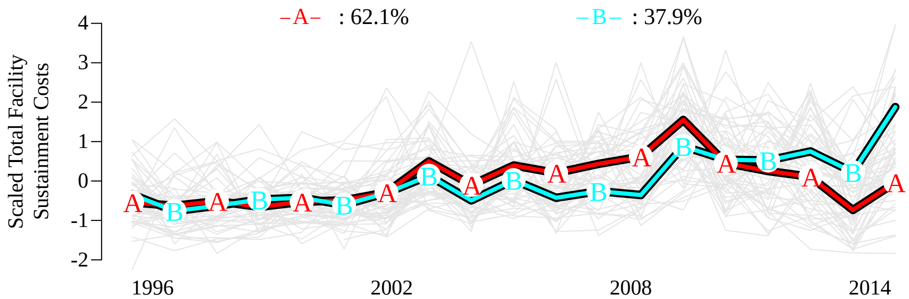
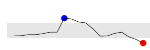


Figure 3.13: Optimal Clusters for Facility Sustainment Cost Curves *(scaled)*

3.4.3.2 Facility Sustainment Costs per PRV & ft^2 Curves.

Commonly excepted metrics to gauge the *efficiency* of facilities are to assess sustainment costs relative to PRV and square footage. Across the AF, total PRV grew from \$76.8 billion in 1996 to a high of \$113.7 billion in 2010 and has since remained relatively stable at approximately \$100 billion . Total square footage is currently at its lowest levels in the past 19 years. In 1996 total square footage was 384.3 million ft^2 which grew to a maximum of 459.8 million ft^2 in 2003 and has since declined to 353.3 million ft^2 in 2014 [11]

At the aggregate, facility sustainment cost per PRV and facility sustainment cost per ft^2 were at their highest levels in 2014 versus the previous 19 years. The single cost curve for each disaggregated metric illustrated in Figure 3.14 aligns to the aggregate trends. The mean base-level facility sustainment cost per \$1 of PRV was 0.029¢ in 1996 and grew to 0.041¢ in 2014. Similarly, the mean base-level facility sustainment cost per $1 ft^2$ was \$5.30 in 1996 and has since grown to \$10.63 in 2014.

[11] The sharp increase in square footage observed in 2001 was from an installation that was transferred into the Air Force's control in 2000. This particular base only had observed data for all metrics for the years 2001-2014 as mentioned in §3.3.

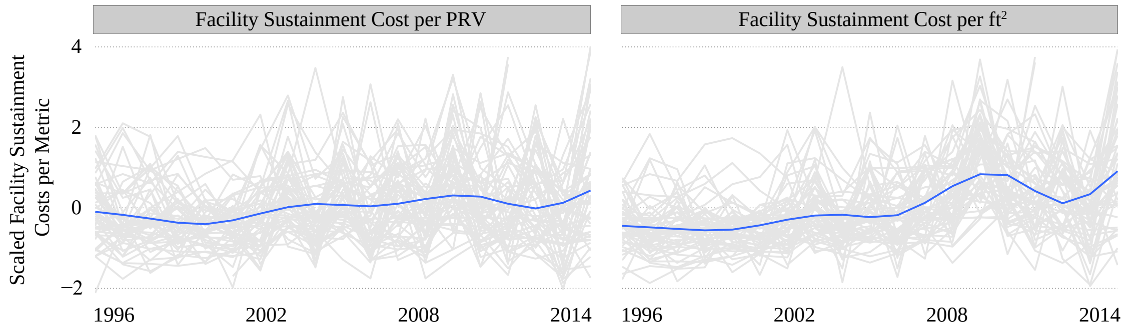


Figure 3.14: Historical Base-level Trajectories of Facility Sustainment Cost Metrics *(scaled)*

However, the k-means algorithm identifies some deviations in the cost curves as illustrated in Figure 3.15. First, three optimal cost curves were identified for the cost per PRV metric. The majority of bases follow cost curve *A* which suggests that sustainment costs per PRV reached a maximum in 2009 but have since been declining. In fact, in 1996 the per $1 PRV sustainment cost was 0.024¢ which grew consistently to 0.045¢ in 2009 and have since decreased to 0.031¢ in 2014. Approximately 30% of the bases follow cost curve *B* which has consistently grown from 1996 through 2014. The 2014 per $1 PRV sustainment cost was 0.066¢ for cost curve *B* bases which represents a growth of 144% over the 1996 cost of 0.027¢. Finally, bases following cost curve *C* have experienced a consistent decrease in their sustainment cost per PRV since 1996. In fact, these bases decreased steadily from 0.039¢ in 1996 to 0.023¢ in 2013 representing a 42% decrease; however, this cluster experienced a fair increase in 2014 to 0.037¢ which still represents a 15% decrease since 1996.

In comparison, two optimal cost curves were identified for the sustainment cost per ft^2 metric. Bases following cost curve *A* steadily increased from $5.51 per ft^2 in 1996 to $13.46 in 2009; however, since then these bases have, on average, decreased to $9.35. Bases following cost curve *B*, however, had a shallower cost curve from $4.97 in 1996 to $7.27 in 2009; however, these bases have experienced significant growth in 2014 spiking to $13.04 per ft^2. These findings suggest that not all bases are achieving the same level of efficiencies in their facility maintenance and sustainment operations relative to both PRV and ft^2.

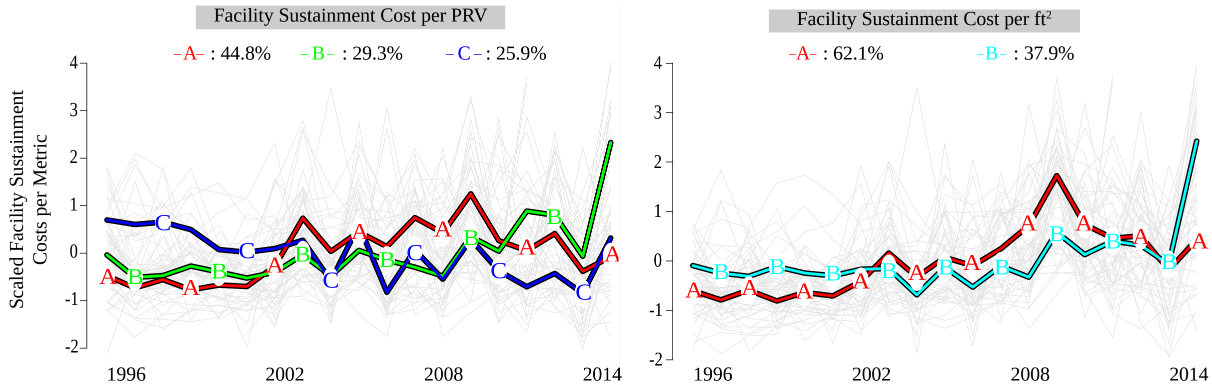
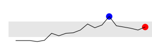
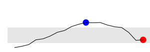


Figure 3.15: Optimal Clusters for Facility Sustainment Cost Metric Curves *(scaled)*

3.4.4 Remaining Metrics.

Similar analyses were performed for the remaining utility and discretionary cost metrics but due to brevity we limit the illustrations and discussion provided. However, it should be pointed out, and as the charts in the section that follows illustrate, diverging trends in these metrics were also discovered. The single utility cost curve has experienced an 81% cost growth from 1996-2009 with a slight reduction in recent years ; however, the k-means algorithm identifies that most of this growth was contributed to by 38% of AF bases which have experienced, on average, 123% cost growth while the remaining bases have experienced nominal growth or decreasing utility cost. Furthermore, we find that 24% and 40% of bases are becoming more efficient when assessing utility costs per PRV and square foot respectively, the remaining majority of bases are experiencing less efficiency in their utility usage.

The single discretionary cost curve has experienced a 45% cost growth from 1996-2014; however, this single cost curve also suggests that discretionary costs across bases has been bending downwards in recent years ; however, the k-means algorithm identifies approximately 70% of bases have, on average, decreased their total discretionary spending by 35% since 1996. Furthermore, we find that the remaining 30% of bases have experienced an increase of 137% in discretionary spending since 1996. The discretionary cost per support person metric also followed similar trends in which 65% of the observed bases are experiencing a significantly decreasing cost curve (-44%) with discretionary cost per support person at their lowest in over 19 years while the remaining 35% of bases have grown by 100%. Furthermore, we find that not only are the directions of the cost curves diverging, but the bases that are experiencing an increasing cost curve have, on average, four times the amount of discretionary costs per support person than bases experiencing a decreasing cost curve.

3.4.5 Analysis Summary.

Consolidation of the cost curves for the support activities assessed, as illustrated in Table 3.2, provides an enterprise view of the underlying cost curves, percent of bases associated with the cost curve, and the percent growth experienced on average. Extracting the cost curve profiles provides senior leaders with a better understanding of the pervasiveness of cost curve trends in order to direct their decision-making. For example, aggregate utility costs have grown by 81%; however, 38% of bases have experienced a growth of 123% while the remaining 62% have experienced a significantly lower, or even negative, growth curve. So rather than implement policy actions or initiatives that impact all bases, leadership may be better served by first focusing on the 38% of bases which align with the high growth cost curve.

Table 3.2: Air Force Enterprise Support Cost Curves

	Increasing Cost Curves			Decreasing Cost Curves		
Metric	Percent of Bases	Cost Curve	Percent Growth	Percent of Bases	Cost Curve	Percent Growth
Total Support Costs	57%		48%	43%		-3%
Total Manpower Costs	62%		30%	38%		-15%
Indirect-to-Direct Headcount Ratio	52%		129%	48%		-58%
Per Support Person Costs	62%		15%	38%		-13%
Total Facility Sustainment Costs	38%		182%			
	62%		36%			
Facility Sustainment Cost per PRV	29%		144%	26%		-42%
	45%		29%			
Facility Sustainment Cost per SqFt	62%		70%			
	38%		162%			
Total Utility Costs	38%		123%	31%		-26%
	31%		11%			
Utility Cost per PRV	60%		75%	40%		-71%
Utility Cost per SqFt	76%		105%	24%		-16%
Total Discretionary Costs	28%		137%	72%		-35%
Discretionary Cost per Support Person	36%		100%	64%		-44%

Similarly, by extracting the cluster, and therefore cost curve, association for each base as illustrated in Table 3.3 senior leaders can begin to identify isolated and systemic growth trends. This table can provide insights on these growth trends across activities within bases, across bases within Major Commands (MAJCOM), and across all bases within the AF enterprise. Examples of insights extracted include the following.

Assessing growth trends across activities within bases we find that bases 15 and 26 are experiencing high growth cost curves across nearly all assessed support activities whereas bases 6, 11, 14, 25, and 50 are experiencing decreasing cost curves across the majority of the assessed support activities. This may indicate that underlying structural changes at these bases may be occurring (i.e. force structure or infrastructure changes) resulting in impacts to the assessed support activities.

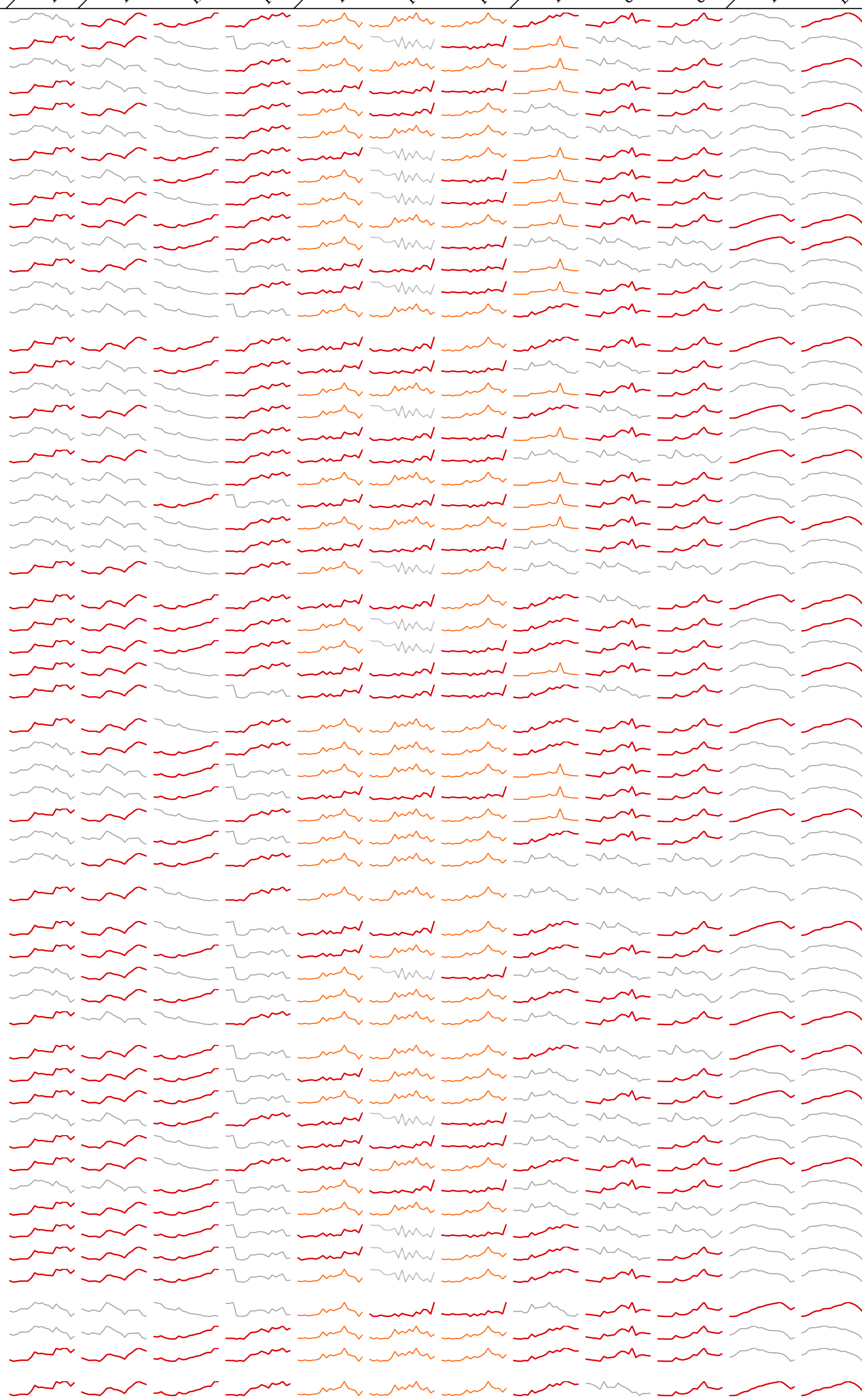
Assessing growth trends across bases within MAJCOMs we find that all but two bases in MAJCOM *G* are experiencing a high growth curve in total support manpower costs. Nearly all these bases are also increasing their indirect-to-direct headcount ratio but are experiencing a decreasing growth curve in the per support person cost. This may suggest to leadership that initiatives to better understand and control the mechanisms that are driving this increasing ratio may help in *"bending"* the total support manpower cost curve in MAJCOM *G*.

In comparison, MAJCOM *C* bases are all experiencing a high growth curve in total support manpower costs as well; however, some of these bases are experiencing an increasing indirect-to-direct ratio and also an increase in the per support person cost. This may suggest to leadership that initiatives to better understand and control the mechanisms that are driving both the increased ratio and increased compensation may be necessary to *"bend"* the total support manpower cost curve in MAJCOM *C*.

Assessing growth trends across all bases within the AF enterprise highlights systemic cost growth in two of the support activities assessed. Both total facility sustainment cost and facility sustainment cost per ft^2 are experiencing either moderate or high growth trends across the entire

Table 3.3: Base-level Support Cost Curves

MAJCOM	Base	Total Support Costs	Total Support Manpower Cost	Indirect-to-Direct Headcount Ratio	Per Support Person Cost	Total Facility Sustainment Cost	Facility Sustainment Cost per PRV	Facility Sustainment Cost per SqFt	Total Utility Costs	Utility Cost per PRV	Utility Cost per SqFt	Total Discretionary Cost	Discretionary Cost per Support Person
MAJCOM A	Base 1*												
	Base 2												
	Base 3												
	Base 4												
	Base 5												
	Base 6												
	Base 7												
	Base 8												
	Base 9												
	Base 10												
	Base 11												
	Base 12												
	Base 13												
	Base 14												
MAJCOM B	Base 15*												
	Base 16												
	Base 17												
	Base 18												
	Base 19												
	Base 20												
	Base 21												
	Base 22												
	Base 23												
	Base 24												
	Base 25												
MAJCOM C	Base 26*												
	Base 27												
	Base 28												
	Base 29												
	Base 30												
MAJCOM D	Base 31*												
	Base 32												
	Base 33												
	Base 34												
	Base 35												
	Base 36												
	Base 37												
MAJCOM E	Base 38												
MAJCOM F	Base 39*												
	Base 40												
	Base 41												
	Base 42												
	Base 43												
MAJCOM G	Base 44*												
	Base 45												
	Base 46												
	Base 47												
	Base 48												
	Base 49												
	Base 50												
	Base 51												
	Base 52												
	Base 53												
	Base 54												
MAJCOM H	Base 55*												
	Base 56												
	Base 57												
MAJCOM I	Base 58												



*Asterisk after Base number represents a headquarters base

High growth curve
Moderate growth curve
Contraction curve

enterprise. This may suggest to leadership that enterprise-wide initiatives and policies to control facility sustainment costs may be required to *"bend"* those curves.

3.5 Conclusion

With today's economic constraints, *"bending"* cost curves is likely to be a continued concept of focus; however, solely focusing on aggregate cost trajectories will likely obscure the true underlying growth curves which require attention. In a letter to Senator Max Baucus, Congressional Budget Office Director Douglas Elmendorf raised his concern of focusing on ambiguous curves [285]:

> *"...Which curve? Several cost trends are of interest to policymakers, and even though they are related, proposals might not have the same effects on each one."*

This research addresses these concerns by illustrating how focus can be moved from the aggregate cost curve to the underlying cost curves of concern.

The empirical findings in this paper provide a thorough understanding of the underlying cost curves for the AF support activities assessed. This provides AF decision-makers with enhanced insight for developing policy actions for the cost curves, among these activities, requiring attention. But more importantly, this research makes two distinct contributions that all organizations can benefit from. First, it underscores the fact that micro-level growth curves can greatly vary from the aggregate cost curves. Second, it demonstrates a novel approach to identifying growth trends across an enterprise without relying solely on aggregate level growth curves or on a single average growth curve as conventional growth modeling approaches provide. By understanding these underlying growth trends and their pervasiveness across differing activities and locations, decision-makers can direct their focus, proposals and policy actions towards specific growth curves needing to be *"bent"*.

It is important to note that certain organizational and analytical limitations exist in this research. First, although AFTOC business rules categorize costs consistently across the MAJCOMs, individual bases do have some discretion in how they classify certain expenses.

Furthermore, we acknowledge that our findings are subject to the reliability of AFTOC data mapping. As a result, discrepancies in how costs are accounted for may exist. Second, the metrics assessed in this research may or may not be the preferred measures to gauge economic efficiency; rather, the focus of this research was to illustrate an approach to identify underlying growth curves once an organization has identified their metrics of interest. Third, it is important to stress that, although the applied algorithm incorporates measures to minimize convergence to local maximums and includes multiple criterions to identify the preferred number of clusters, it is not possible to test the fit between the groupings found and a theoretical model, nor is it a guarantee that the appropriate number of clusters was found. Fourth, this research does not identify underlying causal factors that influence costs. Follow on research is being conducted to explore and identify force structure and mission attributes that influence the cost curves so that decision-makers better understand what measures must be taken to *"bend"* the support cost curves.

IV. The Influence of Front-line Activities on Enterprise-wide Indirect Costs: A Multilevel Modeling Approach

Assorted views of the same underlying data are often helpful. Multiple portrayals may reveal multiple stories, or demonstrate that inferences are coherent, or that findings survive various looks at the evidence in a kind of internal replication.

Edward Tufte, 2006

4.1 Introduction

Concern has turned into reality as overall defense contraction has taken affect. As a result of the Budget Control Act of 2011 and the American Taxpayer Relief Act of 2012, the Department of Defense (DoD) estimates a total reduction in planned defense spending between fiscal years 2012 to 2021 to exceed $1 trillion [1]. Consequently the Air Force (AF), along with her sister services, will need a systematic methodology to plan and implement force and budget reductions in sound logical ways that align with its overall strategy. With indirect (also referred to as support[12]) mission activities historically representing over 40% of the annual DoD budget [2; 3], and nearly 60% of the AF budget [4], strategically managing cost behavior of these indirect activities has the opportunity to generate significant savings.

Understanding cost behavior is fundamental to cost modeling and management. Cooper and Kaplan [33] stated that in order to understand cost behavior one has to focus on how the underlying resource levels change in response to activity changes; however, research on indirect costs in the DoD and AF has centered around an aggregate *"tooth-to-tail"* ratio with the assumption that total direct costs (*the "tooth"*) and total indirect costs (*the "tail"*) are, or should be, related in a proportional manner. Taken alone this fails to provide senior leaders with a robust understanding of how indirect costs change in response to changes in the various operational variables that decision-

[12]For purposes of this research the term support and indirect will be used interchangeably.

makers can control and which ultimately influence the *"tooth"*. Furthermore, Boehmke et al. [4] show that focusing only on an aggregate-level relationship leads to biased presumptions based on a single level of analysis rather than a comprehensive understanding based on evidence from multiple levels in an organization.

The purpose of this research is to create a robust understanding of how indirect costs change in response to changes in AF operational variables and to illustrate the cost behavior and relationships at the multiple levels of the AF enterprise so that decision-makers understand where policy decisions are and are not applicable. The remainder of this paper is organized as follows. Section 2 provides the background and theory for the problem at hand. Section 3 describes the conjectures analyzed. Section 4 outlines the methodology. Section 5 discusses the empirical analysis performed and its results and section 6 offers some concluding comments.

4.2 Background

Within the DoD and the AF, research has been scarcely conducted to better understand the economics of indirect activities. The policy emphasis has been on managing the DoD's, and AF's,*"tooth-to-tail"*; hence, as front-line mission (*direct*) budgets change, indirect budgets change in a proportional manner. Research focusing on the *"tooth-to-tail"* measure [2; 268–271] has primarily concentrated on whether the historic ratio is appropriate rather than gaining an understanding of economic behavior and relationships of indirect costs. Furthermore, ordinary least squares (OLS) multiple regression has been used to regress indirect costs on total direct costs [3], implying that the output of direct costs is the appropriate causal link to explain variance in the output of indirect costs.

Academic research on indirect costs, external to the DoD and AF, have focused heavily on the activity-based costing stream of research founded by Cooper and Kaplan [33]; however, similar to the *"tooth-to-tail"* approach, activity-based costing is a cost allocation method rather than a statistical process to identify underlying relationships between activities and processes. Additional academic research has focused on assessing relations between indirect costs and production volume, complexity and efficiency using correlation and partial correlation analysis [227]. A stream of research has assessed asymmetric behavior, referred to as *"cost stickiness"*, of selling, general and administration (SG&A) overhead costs using multiple regression [177; 228; 229; 235; 286–288]. Banker et al. [289] regressed indirect costs on manufacturing production variables using multiple regression. Datar et al. [232] and MacArthur and Stranahan [233] applied a system of equations approach to model indirect cost interactions with endogenous production regression models in the manufacturing and health settings. Ittner and MacDuffie [234] and Anderson [290] applied path analysis to measure the impact of manufacturing cost drivers on both direct and indirect costs. Although this research stream has advanced the knowledge of the modeling and behavior of indirect costs, four principal concerns still exist which this research aims to address.

First, DoD and AF indirect costs have been analyzed as a single cost pool, which groups multiple discrete categories (i.e. personnel costs, infrastructure sustainment, utilities, discretionary costs) into a single category. Furthermore, much of the academic research assesses indirect costs as a single pooled category. Pooling multiple cost categories can dull the underlying economic variance patterns of discrete categories, which can lead to reduced predictor variable signals. In addition, a key element of strategic and accurate cost analysis is the ability to analyze and understand the economics of discrete cost categories within and across the enterprise [6; 7; 9; 11]. Although an emphasis on overall support cost behavior is certainly important, decision-makers should also have a thorough understanding of the underlying discrete economic behavior so they have more insight for developing policy actions.

Second, DoD and AF research on enterprise-wide support costs have primarily been analyzed only at the DoD and AF aggregate level. Furthermore, academic research focusing on cost stickiness [177; 235; 286–288] has also focused heavily on aggregated data. Although this may provide a macro-economic view of indirect cost behavior, aggregate-level relationships provide very limited insight behind the economic behavior of lower level indirect costs. The effects of data aggregation have long been demonstrated to result in information loss and aggregation bias commonly referred to as the ecological fallacy [291–296]. Furthermore, Boehmke et al. [4] identified that, specific to the AF enterprise, aggregation conceals significant differences in the underlying economic behaviors of indirect costs at the installation level. In addition, much of the remaining academic research [227; 232; 233; 289] have focused on analyzing individual plant or hospital level costs. With the exception of Boehmke et al. [4], which this research builds on, the authors are aware of no additional research that models economic behavior across the multiple levels of an organization to provide a multilevel enterprise view of indirect costs.

Third, a common assumption made in the majority of these analytic techniques is the data structure represents a single level of analysis which fails to consider the hierarchical structure of organizations. Although segmenting can be applied in correlation and path analysis and categorical variables can be applied within multiple regression, these techniques fail to capture the unique variance structure of nested data found in the multilevel context of organizations and enterprises. Failing to capture this multilevel structure often results in violating assumptions of single level analysis techniques [297; 298].

Fourth, specific to the DoD and the AF, research on indirect costs has focused on relating indirect costs to total direct costs (front-line mission costs also referred to as the *"tooth"*). This makes the assumption that the direct cost output is the appropriate causal relationship to link with indirect costs rather than understanding which front-line activities and resources may be influencing indirect costs. To the authors' knowledge research has yet to be performed to assess how the various front-line activities and resources (referred to as force structure variables) relate to support costs across the AF enterprise.

This composition advances this stream of research in the following manner: First, this research will focus on a single discrete indirect cost category, indirect personnel costs, which represents the single largest indirect cost category within the AF. Second, this analysis will extend the research by Boehmke et al. [4] in analyzing support cost behavior and relationships at the multiple levels of the AF enterprise rather than focusing only on aggregated relationships. Third, this research utilizes multilevel modeling (also referred to as hierarchical linear models, nested models, mixed models, or random-effects models) to capture the structural context of the enterprise data which has yet to be applied to model enterprise-wide indirect costs with the exception of

Boehmke et al. [4]. Fourth, rather than focus solely on the *"tooth"*, this research assesses how each of the force structure variables influence indirect personnel costs across the AF enterprise. This will provide senior AF decision makers with knowledge of how indirect personnel cost adjustments are influenced by changes in force structure.

4.3 Conjectures

The underlying implication of managing indirect costs by a *"tooth-to-tail"* measure suggests that the output of direct costs is the appropriate causal link to explain variance in the output of indirect costs. This introduces the first presumption:

> *Conjecture 1: total direct costs, or the "tooth", is the front-line mission force structure variable that provides the strongest link to indirect personnel costs.*

This research will assess if the *"tooth"* is in fact the most appropriate force structure variable to link indirect personnel cost adjustments to changes in the operations on the direct side of the AF business.

Although it is important to understand relationships, it is equally important to understand how these relationships behave at the different levels of an organization. When implementing policy and making strategic decisions at different organizational levels, leaders and managers may rely too heavily on the assumption that a single relationship exists across the organization rather than understanding how relationships differ across the multiple levels of an organization. This introduces the second presumption:

> *Conjecture 2: relationships between front-line mission force structure variables and indirect personnel costs are consistent across the multiple levels of the enterprise.*

The ultimate goal in assessing conjecture 2 is to reveal the various relationships and economic behaviors of indirect personnel costs provided by the multilevel context of an enterprise.

4.4 Approach

4.4.1 Methodology Justification.

The rationale for multilevel modeling (MLM) can be founded on three justifications: *1*) theoretical, *2*) statistical, and *3*) empirical evidence.

The theoretical justification for MLM is founded on the contextual structure of the phenomena under investigation. Social and organizational observations are often influenced by processes and attributes from multiple levels of the environment they exist in. For instance, a child's education can be influenced by the classroom, school, and school district; an individual's economic status can be influenced by his or her level of education and career field; and an organization's cost structure can be influenced by its geographical locations, industry sector, and the phase of growth it is in. Similarly, indirect support costs within the AF may be influenced by attributes and processes determined by a higher organizational level such as the type of mission it is supporting, the demographic population it is supporting[13], or whether it is a headquarters or operational base. These characteristics, which can be influenced at the installation, Major Command[14] (MAJCOM) and AF level, can drive differing relationships between force structure and indirect costs. This can be captured by recognizing that individual support cost observations can be captured within a base and, furthermore, within a MAJCOM and each level can have a specific influence on the relationships within that observation. By ignoring this multilevel structure of the data, incorrect understanding or interpretation of relationships at the different levels may result.

Statistical justification for MLM results from two major flaws when the multilevel structure is not considered. First, all the un-modeled contextual information ends up pooled into the single individual error term of the model [299]. This is problematic because observations belonging to the same groups within the various levels will presumably have correlated errors, which violates one of the basic assumptions of multiple regression [300]. These within-group correlations will in turn bias the standard errors estimate for the model parameters, which can lead to biased *p*-values. Second, by ignoring the multilevel context, the model assumes that the regression coefficients

[13]Certain bases have higher concentrations of retiree populations that may require more support personnel.
[14]A Major Command is synonymous to a department or strategic business unit in the private sector.

apply equally to all groups [300]; *"thus propagating the notion that processes work out in the same way in different contexts"* [299:p.98].

Evidential justification for MLM for this specific research can be provided through simple graphical representation. Figure 4.1 illustrates the relationship between indirect personnel costs and the *"Tooth"* within selected MAJCOMs and bases across the AF. This illustrates that some variance in the relationship exists at the MAJCOM level and significant variance in relationship exist at the base level suggesting that a single slope coefficient across all bases will not suffice.

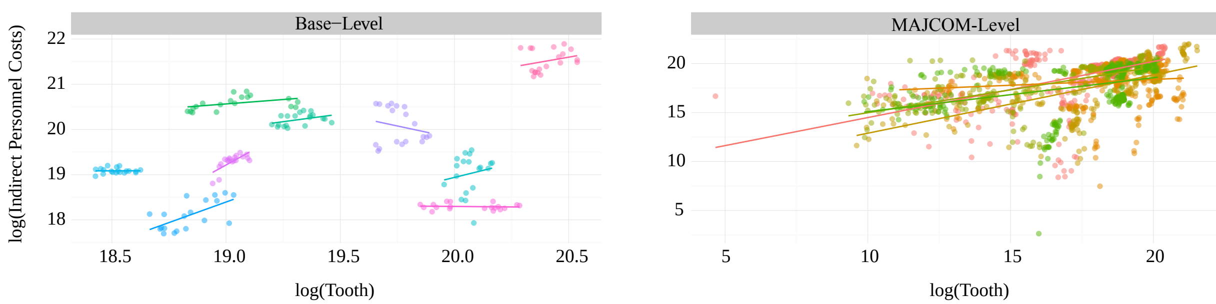


Figure 4.1: Evidence of Varying Relationships Between Indirect Support Costs and the *"Tooth"*

Furthermore, Figure 4.2 illustrates residual errors that are produced when applying multiple regression to regress indirect support costs against the *"Tooth"* [15] This single level model performs presumably well with all parameters being significant and an $adj\ R^2 = 0.96$. More over, the variance appears homoscedastic and the residuals do not appear to grossly violate the approximately normal assumption when assumed to be independent. If taken at face value, the slope coefficient suggests that for every 1% adjustment in the *"Tooth"* there is a 0.08% adjustment in total indirect personnel costs across all bases; however, Figure 4.2 clearly shows that when residuals are diagnosed at the base-level residual correlation exists. This further supports the assumption that a single slope coefficient will not accurately represent the relationship experienced at individual bases.

[15] This particular model is represented as $log\,(y_i) = \beta_0 + \beta_1 log\,(x_i) + \beta_2 I_i + \epsilon_i$ in which y_i represents indirect support costs, x_i represents total direct costs (aka *"Tooth"*), and I_i controls for the installation.

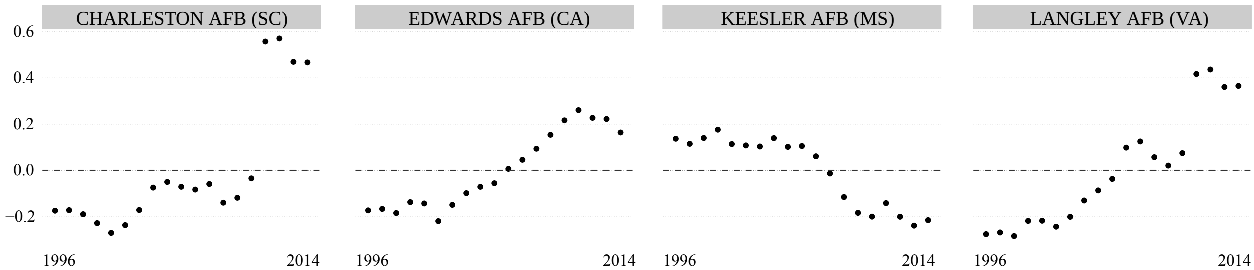


Figure 4.2: Illustration of Correlated Residual Patterns within Base-level Groups

Given these justifications, we now apply a methodical MLM approach to provide a comprehensive understanding of indirect cost behavior and the influence each level has across the AF enterprise. This approach sequentially applies a series of MLM models to assess the relationship between force structure variables and indirect personnel costs.

4.4.2 Methodology Process.

The dependent variable of concern in this research is indirect personnel costs. More specifically, we separate indirect civilian personnel costs ($CivPers^{ind}$) and indirect military personnel costs ($MilPers^{ind}$) to assess if relationships differ based on the type of employment. We run the series of models listed in Table 4.1 for each force structure variable to determine if each of these indirect personnel cost categories are influenced by changes in force structure variables. The variables of interest in this research are outlined in Table 4.2.

For purposes of this study, a log-log transformation is applied to reduce the chance of systematic heteroscedasticity biases which may influence the magnitude of the correlation coefficients. In addition, group mean centering is applied to the force structure predictor variables. Group mean centering allows for direct comparisons of variance components and minimizes correlation between random effects [301]. Furthermore, since the primary objective of our research is on understanding the relationship (*slope*) between force structure predictor variables and indirect personnel costs, and if this relationship varies across the organizational levels (level 1: base, level 2: MAJCOM), using group mean centering will provide unbiased estimates of these slopes and yield a more accurate estimate of the slope variance [302; 303]. Finally, the log-log transformation with group mean centered predictors provides for interoperable results. For example, Equation 4.1 models the relationship between $CivPers^{ind}$ and flying hours. The γ_{10} coefficient measures the percent change in support costs at base j for every one percent deviation from the mean flying hours (FH_{ij}).

$$log\left(CivPers_{ij}^{ind}\right) = \gamma_{00} + \gamma_{10} log\left(FH_{ij}\right) + U_{0j} + \epsilon_i \tag{4.1}$$

4.4.3 Data.

All data were extracted from the AFTOC database for the fiscal years 1996-2014 across 57 active duty U.S.-based Air Force bases. $CivPers^{ind}$ and $MilPers^{ind}$ were extracted from the AFTOC *Indirect* online analytical processing (OLAP) cube and categorized by element of expense and investment code (EEIC) 1* (*civilian personnel compensation*) and 201* (*military personnel compensation*). The force structure predictor variables were extracted from the AFTOC *CAPE14* OLAP cube. Cost predictor variables represent all costs associated with Cost Analysis Improvement Group (CAIG) elements 1.0-4.0, which represent normal operational activities related to weapon systems at a base. Only bases in which all 19 years of data were available were included in the analysis. All dollar values were adjusted for inflation and represent base year 2014 values.

In 1996 indirect personnel costs across the entire AF totaled \$25.1 billion and have since increased to \$28.7 billion in 2014. This category alone accounts for approximately 60% of all personnel costs in the AF, 33% of all indirect costs, and 20% of total annual AF costs (*direct + indirect*). Within our dataset (which restricts our research to 57 U.S. active duty bases), indirect personnel costs were \$17.2 billion in 1996 and have grown to \$20.2 billion in 2014. This means our research sample focuses on approximately 70% of the total AF population costs for this category. Within our dataset, indirect personnel costs account for 64% of all personnel costs across the 57 selected bases, 47% of all indirect costs, and 35% of total annual AF costs.

Table 4.1: Multilevel Model Building Process

Model	System of Equations	Multilevel Model Equation	Components	Description
Null	L1: $Y_{ij} = \beta_{0j} + \epsilon_{ij}$ L2: $\beta_{0j} = \gamma_{00} + u_{0j}$	$Y_{ij} = \gamma_{00} + u_{0j} + \epsilon_{ij}$	L1 fixed intercept (γ_{00}) L2 random intercept (u_{0j})	Output used to calculate ICC; provides information on how much variation in indirect personnel costs (Y_{ij}) exists between AF bases (j index represents base j).
(1)	L1: $Y_{ij} = \beta_{0j} + \beta_{1j}X + \epsilon_{ij}$ L2: $\beta_{0j} = \gamma_{00} + u_{0j}$ $\beta_{1j} = \gamma_{10}$	$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + u_{0j} + \epsilon_{i}$	L1 fixed intercept (γ_{00}) L2 random intercept (u_{0j}) L1 fixed slope (γ_{10})	Assesses the fixed relationship between base-level indirect personnel costs (Y_{ij}) and force structure variables (X_{ij}) across AF installations.
(2)	L1: $Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \epsilon_{ij}$ L2: $\beta_{0j} = \gamma_{00} + u_{0j}$ $\beta_{1j} = \gamma_{10} + u_{1j}$	$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + u_{0j} + u_{ij}X_{ij} + \epsilon_{i}$	L1 fixed intercept (γ_{00}) L2 random intercept (u_{0j}) L1 fixed slope (γ_{10}) L2 random slope (u_{ij})	Assesses the variability of the relationship between base-level indirect personnel costs and force structure variables across AF installations.
(3)	L1: $Y_{ijk} = \beta_{0jk} + \beta_{1jk}X_{ijk} +$ ϵ_{ijk} L2: $\beta_{0jk} = \gamma_{00k} + u_{0jk}$ $\beta_{1jk} = \gamma_{10k} + u_{1jk}$ L3: $\gamma_{00k} = \delta_{000} + v_{00k}$ $\gamma_{10k} = \delta_{100} + v_{10k}$	$Y_{ijk} = \delta_{000} + v_{00k} + u_{0jk} +$ $(\delta_{100} + v_{10k} + u_{1jk})X_{ijk} + \epsilon_{ijk}$	L1 fixed intercept (δ_{000}) L2 random intercept (u_{0jk}) L3 random intercept (v_{00k}) L1 fixed slope (δ_{100}) L2 random slope (u_{1jk}) L3 random slope (v_{10k})	Assesses the influence of the MAJCOM on the base-level intercept and the variability of the relationship between base-level indirect personnel costs and force structure variables.
(4)	L1: $Y_{ijk} = \beta_{0jk} + \beta_{1jk}X_{ijk} +$ $\beta_{2jk}T_{ijk} + \epsilon_{ijk}$ L2: $\beta_{0jk} = \gamma_{00k} + u_{0jk}$ $\beta_{1jk} = \gamma_{10k} + u_{1jk}$ $\beta_{2jk} = \gamma_{20k} + u_{2jk}$ L3: $\gamma_{00k} = \delta_{000} + v_{00k}$ $\gamma_{10k} = \delta_{100} + v_{10k}$ $\gamma_{20k} = \delta_{200} + v_{20k}$	$Y_{ijk} = \delta_{000} + v_{00k} + u_{0jk} +$ $(\delta_{100} + v_{10k} + u_{1jk})X_{ijk} +$ $(\delta_{200} + v_{20k} + u_{2jk})T_{ijk} + \epsilon_{ijk}$	L1 fixed intercept (δ_{000}) L2 random intercept (u_{0jk}) L3 random intercept (v_{00k}) L1 fixed slope (δ_{100}) L2 random slope (u_{1jk}) L3 random slope (v_{10k}) L1 fixed growth rate (δ_{200}) L2 random growth rate (u_{2jk}) L3 random growth rate (v_{20k})	Incorporates the potential influence of a growth rate (T_{ij}) at the MAJCOM & base level and corrects for residual autocorrelation due to longitudinal structure of the data.

Note: L1 represent the fixed and random components modeled at level 1 (*individual observation level*)
L2 represent the fixed and random components modeled at level 2 (*installation level*)
L3 represent the fixed and random components modeled at level 3 (*MAJCOM level*)

Table 4.2: Organizational Variables Analyzed

Variable Type	Variable of Interest	Abreviation	Description
Dependent Variables			
	Civilian Personnel Costs	$CivPers^{ind}$	All civilian employees providing supporting roles located at AF installations
	Military Personnel Costs	$MilPers^{ind}$	All military employees providing supporting roles located at AF installations
....	....	.....	....
Predictor Variables			
	Tooth	*"Tooth"*	All direct operations and sustainment expenditures related to personnel, consumables, goods and services, and investments associated with the peacetime operations of weapon systems and programs.
	Total Active Inventory	TAI	Total number of major weapon systems (i.e. aircraft, intercontinental ballistic missiles, etc) in inventory
	Flying Hours	FH	Number of hours that weapon systems are flown
	End Strength	ES	Total headcount of direct personnel
	Civilian End Strength	ES^{civ}	Total headcount of direct civilian personnel
	Military End Strength	ES^{mil}	Total headcount of direct military personnel
	Direct Personnel Costs	$Pers^{dir}$	Total cost of direct personnel
	Direct Civilian Personnel Costs	$CivPers^{dir}$	Total cost of direct civilian personnel
	Direct Military Personnel Costs	$MilPers^{dir}$	Total cost of direct military personnel

4.5 Empirical Analysis

4.5.1 Null Model.

The null model measures the level of indirect personnel cost variance across all observations (which we define with σ^2) and among the bases (τ^2), which can be used to calculate intraclass correlation (ICC) by applying Equation 4.2.

$$\rho = \tau^2 \div (\tau^2 + \sigma^2) \tag{4.2}$$

This allows us to interpret the level of correlation of indirect personnel cost variance within bases. Furthermore, the null model provides the baseline Akaike information criterion (AIC) and Bayesian information criterion (BIC) values which are measures of model quality relative to other models. When comparing models, lower AIC and BIC values generally represent the preferred models given the model choices; however, the normal procedure of residual diagnostics is still required to assess model quality.

Table 4.3 displays the results of the null models for both military and civilian indirect personnel costs. The γ_{00} for each model, which are in natural log form, is the average value of the dependent variable across all observations. The high levels of variances accounted for between the bases (τ^2) compared to across all observations (σ^2) indicates that the correlation (ρ) of military and civilian indirect personnel costs within the same base is 91% and 94% respectively. This high level of correlation further supports the need to treat observations within bases as nested rather than simply treat all observations independently.

Table 4.3: Intercept Coefficients and Model Fit for the Null Models

Indirect Cost Category	Intercept (γ_{00})	τ^2	σ^2	ρ	AIC	BIC
$CivPers^{ind}$	17.9	0.88	0.05	0.94	206	221
$MilPers^{ind}$	18.9	0.58	0.02	0.96	-611	-596

4.5.2 Model 1.

Model 1 allows for random intercepts and fits a fixed slope coefficient between the dependent variables and each force structure predictor variable. Model 1 is very similar to a multiple regression approach with a single fixed slope and categorical variables to adjust for differences in base-level intercepts. Table 4.4 displays the relationships between the indirect cost categories and each force structure variable[16]. Three important insights can be gleaned from these results. First, the elasticity in the indirect cost categories is low for the majority of the force structure variables suggesting that as force structure is adjusted, very small adjustments in both $CivPers^{ind}$ and $MilPers^{ind}$ are experienced. Second, by applying Bates' [301] multilevel pseudo R^2 approach, we can calculate the amount of variance accounted for by each level in the model. By applying Equation 4.3, the R_1^2 values in Table 4.4 identify the variability of $CivPers^{ind}$ and $MilPers^{ind}$ explained by its linear relationship to each force structure variable.

$$R_1^2 = \frac{\sigma^2(\text{Null Model}) - \sigma^2(\text{Model 1})}{\sigma^2(\text{Null Model})} \tag{4.3}$$

For the majority of the model 1 excursions, the low R_1^2 values in addition to only marginal changes in AIC and BIC values from the respective null models implies that incorporating a fixed slope relationship with each force structure variable provides minimal improvement in model performance. However, each indirect cost category did have model excursions that illustrate significant model performance leading to our third insight: for each indirect cost category, the *"Tooth"* does not provide the strongest fixed slope effect link. For $MilPers^{ind}$, the strongest fixed slope effect link is with FH followed by $CivPers^{dir}$. The fixed linear relationship with these force structure variables, although very inelastic[17], captures 21-30% of the variance in $MilPers^{ind}$ over and above the null model. For $CivPers^{ind}$, the strongest fixed slope effect link is with FH followed by $CivPers^{dir}$. The fixed linear relationship with these force structure variables suggests that a

[16]For brevity the intercept and additional model output such as degrees of freedom and t-values are not displayed. The primary concern in this research is to understand the relationship between indirect personnel costs and force structure variables so the results will focus on these parameters; however, in the event of abnormalities or anomalies in non-displayed parameters specific discussion will be made to address these concerns.

[17]The γ_{10} value of 0.05 suggests that for every 1% change in FH, a 0.05% adjustment in $MilPers^{ind}$ occurs. Although not fixed, this suggests that the relationship is far from proportional.

negative relationships exists with FH[18] and a positive relationship exists with $CivPers^{dir}$. These two fixed slope relationships account for 12-22% of the variance in $CivPers^{ind}$ over and above the null model.

4.5.3 Model 2.

Model 2 applies a random coefficient model in which the relationship between the force structure variables and the indirect cost categories are allowed to vary from one base to another. This model assesses the variability of the slope relationships across the bases and will indicate the sufficiency of Model 1's fixed slope relationship. Model 2 results are displayed in Table 4.5. All model 2 excursions were compared to their respective model 1 excursions to assess if including random slopes improved the models. An analysis of variance (ANOVA) test and Bates' [301] modified ANOVA test, which uses a mixture of χ_1^2 and χ_2^2 random variables with equal weights to produce a more accurate *p*-value as displayed in Equation 4.4, confirms that the addition of random slopes significantly improves all models at $p\text{-}value < 0.001$. This is also confirmed with the model fit parameters in Table 4.5 that show an increased R_1^2 and decreased AIC and BIC values for all models.

$$p\text{-}value = 0.5 \times P(\chi_1^2 > LR) + 0.5 \times P(\chi_2^2 > LR) \tag{4.4}$$

Model 2 results also show a change in the significance of several force structure predictor variable fixed effect coefficients (γ_{10}). This suggests that when the slope is allowed to vary across bases, their is no consistent relationship across the enterprise that is significantly different than zero[19]. This variability in the slope coefficient across AF bases can be assessed by the τ_2^2 parameter in Table 4.5. This also allows us to compare the variability in slopes (τ_2^2) against the variability in intercepts (τ_1^2) and individual observations (σ^2). This provides some useful insights. First, the largest source of variability for all model excursions is in the intercepts followed by the slope with the residuals representing the smallest source of variance. Second, the variability in force

[18]The γ_{10} value of -0.04 suggests that for every 1% change in FH, a -0.04% adjustment in $CivPers^{ind}$ occurs.

[19]The change in γ_{10} coefficient significance suggests that the fixed slope relationships and standard errors in Model 1 were likely biased from a possible Simpson's Paradox in which relationships that appear in different groups of data disappears or reverses when these groups are combined for an overall relationship.

structure relationships is noticeable. For example, the variability in the $CivPers^{ind} \Leftrightarrow CivPers^{dir}$ relationship is 0.213 whereas the variability in the $CivPers^{ind} \Leftrightarrow ES^{civ}$ relationship is 0.487. This suggests that a more consistent relationship exists between $CivPers^{ind}$ and $CivPers^{dir}$ across the enterprise, which is confirmed when the confidence interval is assessed. This insight is important to policy makers as it illustrates which relationships are more consistent and pervasive across an enterprise versus relationships that are more variable across operational sites.

Notably, Model 2 results suggest that a few common significant relationships exist across the AF enterprise. First, the force structure variables most strongly linked to $CivPers^{ind}$ include ES^{civ} and $CivPers^{dir}$. The relationships between $CivPers^{ind}$ and these two force structure variables maximize model performance and suggest a statistically significant coefficient. The similarity between these two predictor variables is self evident with the primary difference only being the growth rate in direct civilian personnel cost growth over and above inflation.

The γ_{10} for these model excursions suggest a higher elasticity than what was suggested in the fixed slope effect models. The $CivPers^{ind} \Leftrightarrow ES^{civ}$ γ_{10} coefficient of 0.25 suggests that a 1% change from the average ES^{civ} at a base typically results in a 0.25% change in $CivPers^{ind}$. Similarly, a 1% change from the average $CivPers^{dir}$ at a base typically results in a 0.20% change in $CivPers^{ind}$. However, as previously mentioned, the variability in the $CivPers^{ind} \Leftrightarrow CivPers^{dir}$ slope across AF bases is less than the variability in the $CivPers^{ind} \Leftrightarrow ES^{civ}$ slopes.

Similarly, the force structure variables most strongly linked to $MilPers^{ind}$ is $Pers^{dir}$ and $MilPers^{dir}$. These force structure relationships maximized model 2 performance with the highest R_1^2 value and lowest AIC and BIC values along with statistically significant coefficients. The γ_{10} coefficient of 0.17 suggests that a 1% change from the average $Pers^{dir}$ at a base typically results in a 0.17% change in $MilPers^{ind}$. Similarly, a 1% change from the average $MilPers^{dir}$ at a base typically results in a 0.18% change in $MilPers^{ind}$. This suggests that a greater elasticity exists than a fixed slope suggests. Furthermore, the τ_2^2 value of 0.158 for the $MilPers^{ind} \Leftrightarrow MilPers^{dir}$ slope compared to the τ_2^2 value of 0.240 for the $MilPers^{ind} \Leftrightarrow Pers^{dir}$ slope suggests that less variability in the $MilPers^{ind} \Leftrightarrow MilPers^{dir}$ relationship exists across the AF enterprise.

Table 4.4: Slope Parameters and Model Fit for Model 1

	*CivPers^ind^*							*MilPers^ind^*						
	Fixed Effect		Random Effect					Fixed Effect		Random Effect				
Predictor	γ_{10}	*se*	τ_1^2	σ^2	R_1^2	*AIC*	*BIC*	γ_{10}	*se*	τ_1^2	σ^2	R_1^2	*AIC*	*BIC*
"Tooth"	0.13***	0.020	0.881	0.050	4%	166	186	0.04**	0.014	0.576	0.024	1%	-619	-599
TAI	-0.04	0.021	0.904	0.041	22%	-39	-19	-0.01	0.013	0.552	0.017	29%	-887	-867
FH	-0.04*	0.019	0.903	0.041	22%	-34	-14	0.05***	0.012	0.550	0.017	30%	-893	-874
ES	0.08***	0.024	0.881	0.051	1%	197	217	0.02	0.017	0.576	0.024	0%	-610	-590
ES^{civ}	0.12***	0.017	0.881	0.050	4%	162	182	0.03*	0.012	0.576	0.024	0%	-614	-594
ES^{mil}	0.07**	0.022	0.881	0.051	1%	198	218	0.02	0.015	0.576	0.024	0%	-612	-592
$Pers^{dir}$	0.07***	0.019	0.881	0.051	2%	192	212	0.00	0.013	0.576	0.024	0%	-609	-589
$CivPers^{dir}$	0.09***	0.010	0.882	0.046	12%	80	99	0.02**	0.006	0.584	0.019	21%	-837	-817
$MilPers^{dir}$	0.07***	0.020	0.881	0.051	1%	197	217	0.03*	0.013	0.576	0.024	0%	-613	-593

[1] *p-value: < 0.001***, < 0.01**, <0.05**

Table 4.5: Slope Parameters and Model Fit for Model 2

	*CivPers^ind^*								*MilPers^ind^*							
	Fixed Effect		Random Effect						Fixed Effect		Random Effect					
Predictor	γ_{10}	*se*	τ_2^2	τ_1^2	σ^2	R_1^2	*AIC*	*BIC*	γ_{10}	*se*	τ_2^2	τ_1^2	σ^2	R_1^2	*AIC*	*BIC*
"Tooth"	0.13	0.071	0.200	0.882	0.039	24%	14	44	0.05	0.065	0.197	0.577	0.015	38%	-970	-940
TAI	-0.14	0.123	0.678	0.905	0.029	45%	-226	-196	-0.01	0.067	0.190	0.552	0.012	48%	-1058	-1029
FH	-0.16	0.105	0.534	0.904	0.029	45%	-202	-172	0.04	0.047	0.098	0.552	0.013	45%	-1004	-975
ES	0.09	0.078	0.243	0.882	0.039	25%	14	43	0.11	0.060	0.169	0.577	0.014	42%	-1046	-1016
ES^{civ}	0.25*	0.097	0.487	0.883	0.023	56%	-444	-414	0.02	0.048	0.109	0.577	0.012	49%	-1146	-1116
ES^{mil}	0.01	0.081	0.282	0.882	0.039	25%	18	48	0.08	0.054	0.129	0.577	0.015	38%	-985	-955
$Pers^{dir}$	0.42***	0.121	0.740	0.882	0.030	42%	-195	-165	0.17*	0.070	0.240	0.577	0.013	45%	-1070	-1041
$CivPers^{dir}$	0.20**	0.064	0.213	0.883	0.026	51%	-339	-309	0.02	0.035	0.061	0.584	0.012	51%	-1163	-1133
$MilPers^{dir}$	0.27**	0.097	0.445	0.882	0.035	32%	-51	-21	0.18**	0.058	0.158	0.577	0.014	41%	-1029	-1000

[1] *p-value: < 0.001***, < 0.01**, <0.05**

Ultimately, these results suggest that as the AF makes adjustments to its direct civilian and military workforce, the corresponding indirect workforce experiences a consistent adjustment of lesser magnitude but in the same direction; however, when other force structure variables, including the *"Tooth"*, are adjusted no consistent impact to the indirect workforce across the AF enterprise is experienced. [20]

4.5.4 Model 3.

Model 3 assesses if the MAJCOM that a base is assigned to influences the relationships; the objective is two fold: *a*) to assess the variability in the slopes across bases and across MAJCOMs; *b*) to assess the variability in the slopes across bases *nested within* MAJCOMs. Only the force structure variables that had a significant relationship in model 2 are assessed.

Table 4.6 provides the results for model 3a in which variability in the slopes across bases *and* across MAJCOMs are assessed. Although only marginal improvements in model fit were achieved an ANOVA test with the modified *p*-value indicates that allowing for MAJCOM random effects on each force structure's slope significantly improves all models[21]. Table 4.6 introduces a new parameter, τ_2^3, which indicates the variability in the slope across the MAJCOMs. By comparing τ_2^3 to τ_2^2, we can compare the variability in the slopes across MAJCOMs to the variability in the slopes across bases.

The results indicate that the relationships between $MilPers^{ind}$ and the relevant force structure variables vary more across MAJCOMs than across the bases; whereas, the relationships between $CivPers^{ind}$ and the relevant force structure variables vary more across bases than across MAJCOMs. In fact, the variability in the $CivPers^{ind}$ relationships across MAJCOMs appear to be negligible relative to the variability across bases.

Table 4.7 provides the results for model 3b in which variability in the slopes across bases *nested within* MAJCOMs are assessed. These results suggest that variability in the relationships across bases nested *within* MAJCOMs exist. In fact, for both $CivPers^{ind}$ and $MilPers^{ind}$

[20]Interaction effects were evaluated to assess if simultaneous influence of multiple force structure variables on $CivPers^{ind}$ and $MilPers^{ind}$ exist. No statistically significant interaction coefficients were identified.
[21]The ANOVA *p*-value results were $p < 0.01$ for $MilPers^{ind} \Leftrightarrow MilPers^{dir}$ and $p < 0.001$ for all other models.

relationships, the 95% confidence interval for the random slope coefficients is greater than zero implying that the relationship between $CivPers^{ind}$ and $MilPers^{ind}$ and each relevant force structure variable differs across bases within MAJCOMs. As a result, no standard relationship can be implied across all bases within a MAJCOM.

4.5.5 Model 4.

The final model assesses the influence of time and examines if potential autocorrelation exists. We find that the empirical autocorrelation for the within-group residuals for our model 3 excursions ranges from 0.60-0.70 suggesting that autocorrelation may be biasing our results. As a result, model 4 incorporates an autoregressive error structure to correct for the high within-group residual autocorrelation and includes a time variable to assess if a growth rate effect is occurring in the dependent variables. Table 4.8 displays the final results and illustrates some important insights.

First, although we can't directly compare the residual values to the orginal null models to produce R_2^2 values comparable to the previous models, comparing the residual values to updated null models with autoregressive error structures suggests that the $CivPers^{ind}$ models can account for approximately 80-85% of the variability in $CivPers^{ind}$ while the $MilPers^{ind}$ models can account for approximately 85-90% of the variability in $MilPers^{ind}$. Furthermore, an ANOVA test with the modified p-value indicates that accounting for the autoregressive error structure significantly improves all models which is also confirmed by the significant reductions in the AIC and BIC values from previous models. Furthermore, diagnostics confirm that residual homoscadisticity and normality assumptions are satisfied.

Second, a growth rate effect appears to be influencing the $CivPers^{ind}$ models but not the $MilPers^{ind}$ models. This can be confirmed by the significant δ_{200} coefficients in Panel A of Table 4.8. These coefficient values suggest that for every year, a 0.01% growth rate in $CivPers^{ind}$ occurs. The near zero variability values at the MAJCOM level (τ_3^3) suggest that very little variability in this growth rate exists between MAJCOMs. Furthermore, the near near zero variability values at the Base level (τ_3^2) suggest that very little variability in this growth rate exists between AF bases.

Table 4.6: Slope Parameters and Model Fit for Model 3a

	CivPers^{ind}									*MilPers*^{ind}								
	Fixed Effect		Random Effect							Fixed Effect		Random Effect						
Predictor	δ_{100}	*se*	τ_2^3	τ_2^2	τ_1^2	σ^2	R_1^2	*AIC*	*BIC*	δ_{100}	*se*	τ_2^3	τ_2^2	τ_1^2	σ^2	R_1^2	*AIC*	*BIC*
"Tooth"	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
TAI	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
FH	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ES	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ES^{civ}	0.25*	0.100	0.005	0.484	0.585	0.023	56%	-450	-405	-	-	-	-	-	-	-	-	-
ES^{mil}	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Pers^{dir}	0.43***	0.129	0.013	0.738	0.588	0.030	42%	-201	-156	0.35*	0.173	0.223	0.117	0.564	0.013	45%	-1078	-1033
CivPers^{dir}	0.20**	0.065	0.001	0.212	0.584	0.026	51%	-345	-300	-	-	-	-	-	-	-	-	-
MilPers^{dir}	0.27**	0.099	0.002	0.446	0.587	0.035	32%	-57	-12	0.30*	0.128	0.108	0.095	0.566	0.014	41%	-1032	-987

[1] *p-value: < 0.001***, < 0.01**, <0.05**

Table 4.7: Slope Parameters and Model Fit for Model 3b

	CivPers^{ind}								*MilPers*^{ind}							
	Fixed Effect		Random Effect						Fixed Effect		Random Effect					
Predictor	δ_{100}	*se*	τ_2^2	τ_1^2	σ^2	R_1^2	*AIC*	*BIC*	δ_{100}	*se*	τ_2^2	τ_1^2	σ^2	R_1^2	*AIC*	*BIC*
"Tooth"	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
TAI	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
FH	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ES	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ES^{civ}	0.25*	0.097	0.487	0.586	0.023	56%	-453	-418	-	-	-	-	-	-	-	-
ES^{mil}	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Pers^{dir}	0.42***	0.121	0.742	0.588	0.030	42%	-205	-170	0.17*	0.070	0.239	0.577	0.013	45%	-1068	-1034
CivPers^{dir}	0.20**	0.064	0.213	0.588	0.026	51%	-349	-314	-	-	-	-	-	-	-	-
MilPers^{dir}	0.27**	0.098	0.451	0.589	0.035	32%	-61	-26	0.18**	0.058	0.158	0.577	0.014	41%	-1027	-993

[1] *p-value: < 0.001***, < 0.01**, <0.05**

Together, this suggests that the 0.01% growth rate in $CivPers^{ind}$ appears to be a common rate occurring across all bases and all MAJCOMs. In comparison, the insignificant δ_{200} coefficients in Panel B indicate that no common growth rate in $MilPers^{ind}$ appears to be occurring across the AF enterprise.

Third, the autocorrelation and growth rate effect appears to bias the slope coefficients (δ_{100}) with the force structure variables. By comparing the δ_{100} values from model 3a with model 4, a sizable reduction in the coefficients appear for both $CivPers^{ind}$ and $MilPers^{ind}$models. For example, in model 3b, the fixed $CivPers^{ind} \Leftrightarrow ES^{civ}$ slope effect is 0.25. When model 3 is refitted with the growth rate effect, the fixed slope effect is reduced to 0.19. Furthermore, once the autoregressive error structure is accounted for, this fixed slope effect is further reduced to 0.08 as displayed in Table 4.8. This suggests that both $CivPers^{ind}$ and $MilPers^{ind}$ are more inelastic to changes in the force structure variables than model 3 indicated. In addition, once the autocorrelation and growth rate effect are incorporated, model 4 finds that the relationship between $CivPers^{ind}$ and $CivPers^{dir}$ is not statistically significant as previously indicated.

Finally, the autocorrelation and growth rate effect also appears to influence the variance estimate of the force structure slope across the MAJCOMs. Model 3a suggested that the relationships between $MilPers^{ind}$ and the relevant force structure variables vary more across MAJCOMs than across the bases and the relationships between $CivPers^{ind}$ and the relevant force structure variables vary more across bases than across MAJCOMs. However, after correcting for autocorrelation and growth rates in model 4, the variability in the statistically significant force structure relationships across the MAJCOMs (τ_2^3) are all less than the variability in the relationships across the AF bases (τ_2^2) as illustrated in Table 4.8.

4.5.6 Discussion.

So what can be concluded about AF indirect personnel costs and their relationship to force structure variables? *Conjecture 1* presumed that total direct costs, or the *"Tooth"*, is the front-line mission force structure variable that provides the strongest link to indirect personnel costs. Our analysis consistently finds this to be false; however, we find that relationships do exist

Table 4.8: Slope Parameters and Model Fit for Model 4

	Panel A: $CivPers^{ind}$										
	Force Structure Fixed Effect		Growth Rate Fixed Effect		Force Structure Random Effects		Growth Rate Random Effects				
Predictor	δ_{100}	$se\ (\delta_{100})$	δ_{200}	$se\ (\delta_{200})$	τ_2^3	τ_2^2	τ_3^3	τ_3^2	σ^2	*AIC*	*BIC*
"Tooth"	-	-	-	-	-	-	-	-	-	-	-
TAI	-	-	-	-	-	-	-	-	-	-	-
FH	-	-	-	-	-	-	-	-	-	-	-
ES	-	-	-	-	-	-	-	-	-	-	-
ES^{civ}	0.08*	0.038	0.01**	0.003	0.003	0.023	0.000	0.000	0.116	-1471	-1386
ES^{mil}	-	-	-	-	-	-	-	-	-	-	-
$Pers^{dir}$	0.20**	0.068	0.01**	0.003	0.018	0.060	0.000	0.000	0.135	-1471	-1386
$CivPers^{dir}$	0.09	0.060	0.01**	0.004	0.025	0.023	0.000	0.000	0.155	-1415	-1331
$MilPers^{dir}$	0.12*	0.048	0.01**	0.004	0.006	0.035	0.000	0.000	0.097	-1483	-1398

	Panel B: $MilPers^{ind}$										
	Force Structure Fixed Effect		Growth Rate Fixed Effect		Force Structure Random Effects		Growth Rate Random Effects				
Predictor	δ_{100}	$se\ (\delta_{100})$	δ_{200}	$se\ (\delta_{200})$	τ_2^3	τ_2^2	τ_3^3	τ_3^2	σ^2	*AIC*	*BIC*
"Tooth"	-	-	-	-	-	-	-	-	-	-	-
TAI	-	-	-	-	-	-	-	-	-	-	-
FH	-	-	-	-	-	-	-	-	-	-	-
ES	-	-	-	-	-	-	-	-	-	-	-
ES^{civ}	-	-	-	-	-	-	-	-	-	-	-
ES^{mil}	-	-	-	-	-	-	-	-	-	-	-
$Pers^{dir}$	0.14**	0.034	0.00	0.004	0.013	0.023	0.000	0.000	0.027	-2121	-2036
$CivPers^{dir}$	-	-	-	-	-	-	-	-	-	-	-
$MilPers^{dir}$	0.15**	0.036	0.00	0.004	0.012	0.036	0.000	0.000	0.031	-2147	-2062

[1] *p-value: < 0.001***, < 0.01**, <0.05**

between indirect personnel costs and other force structure variables as identified in Table 4.9. Furthermore, we find that these relationships are all directionally consistent. Primarily, $CivPers^{ind}$ and $MilPers^{ind}$ appear to have a relationship with $Pers^{dir}$ and $MilPers^{dir}$. This suggests that when the AF adjusts total personnel costs and/or military personnel costs on the direct operational side of the AF business, both civilian and military *indirect* personnel costs also experience adjustments. In addition, $CivPers^{ind}$ appears to have a relationship with ES^{civ} suggesting as the civilian headcount on the *direct* side is adjusted, *indirect* civilian personnel costs also experience an adjustment.

We find that these relationships have very low elasticities suggesting that adjustments in these direct personnel force structure variables do not lead to proportional adjustments in indirect personnel costs as a *"tooth-to-tail"* metric would imply. Rather, when a 1% adjustment in these

Table 4.9: Relationships Identified Between Indirect Cost Categories and Force Structure Variables

	Force Structure Predictor Variables								
Indirect Category	*"Tooth"*	TAI	FH	ES	ES^{civ}	ES^{mil}	$Pers^{dir}$	$CivPers^{dir}$	$MilPers^{dir}$
$CivPers^{ind}$					•		•		•
$MilPers^{ind}$							•		•

• Relationship exists

direct personnel force structure variables is made, indirect personnel costs typically experience a 0.08-0.20% adjustment. We also find that indirect civilian personnel costs are also being influenced by a growth rate whereas indirect military personnel costs are not.

Conjecture 2 presumed that relationships between front-line mission force structure variables and indirect personnel costs are consistent across the multiple levels of the enterprise. Our analysis also finds this to be false. A crucial finding in our results is the fact that when fixed relationships are assumed, a relationship appears to exist between indirect personnel costs and force structure variables. However, when relationships are allowed to vary across the multiple levels of the enterprise, many of these relationships are found to be baseless and lacking sufficient evidence. For the force structure variables found to have a statistically significant relationship with $CivPers^{ind}$ and $MilPers^{ind}$, we find that allowing the slopes to vary both between bases and between MAJCOMs significantly improves the models; however, we also find that the relationships vary more between bases than they do between MAJCOMs. As a result, senior leaders should not assume that a common relationship between indirect personnel costs and force structure variables exists across the entire AF enterprise, let alone across all the bases within a MAJCOM. Rather, it should be understood that a pervasive relationship does exist across the enterprise but there is sufficient variability in this relationship across MAJCOMs and even more so across bases.

The one common relationship we did find was a growth rate in indirect civilian personnel costs. Our results indicate that a constant growth rate of 0.01% per year is occurring with very little variability in this growth rate across bases and MAJCOMs. Although this rate does not appear sizable, a 0.01% growth rate for our sample equates to $52 million per year. If AF leadership deems this cost growth a viable concern, then an enterprise-wide approach to control this cost is suggested.

4.6 Conclusion

Edward Tufte [304] stated *"assorted views of the same underlying data are often helpful. Multiple portrayals may reveal multiple stories, or demonstrate that inferences are coherent, or that findings survive various looks at the evidence in a kind of internal replication."* By applying a multilevel modeling process, we have been able to provide an assorted enterprise view of indirect support costs. Furthermore, we identified that differing assumptions in relationship behavior between indirect costs and force structure variables will lead to multiple, and sometimes contradictory, stories. Only by strategically applying a multilevel modeling approach do we identify evidential relationships that exist across an organizational enterprise.

It is important to note that certain organizational and analytical limitations exist in this research. First, the AF requirement to work within the strictures of the Congressional budget may be a limiting factor in how cost and force structure adjustments can be made. Second, although AFTOC business rules categorize costs consistently across the MAJCOMs, individual bases do have some discretion in how they classify certain expenses. As a result, discrepancies in how cost accounting may exist. Third, although this research identifies relationships between force structure variables and indirect personnel costs, this should not be interpreted as a causal relationship; rather, underlying management or political drivers may be the true causal factors with force structure variables only acting as proxy variable.

V. Effectiveness Myopia: Improving the Air Force's "Visual Acuity" of Performance for Installation Support Activities through the Evaluative Prism of Data Envelopment Analysis

Employees lose respect for a company that fails to provide decent facilities for their comfort.

ScotTissue Towels, 1936

5.1 Introduction

Situated somewhere between an utopian dream and a dystopian nightmare, the vintage SoctTissue advertisement displayed in Figure 5.1 has meaningful undertones for those leading the Department of Defense (DoD) and, principally of concern to the authors, the Air Force (AF). While the risk of employee radicalization (i.e., becoming "Bolsheviks") is admittedly remote, the advertisement highlights that failure to adequately address the basic banalities of existence can contribute significantly to a disgruntled workforce. Herzberg noted the discontinuity between the things which demotivate employees and those which potentially motivate them, and famously referred to the demotivating elements as "hygiene factors" [305]. In an organizational sense, one may infer indifferent or miserly decisions on the part of leadership can form a common source of worker dissatisfaction across organizations. Deflecting some of the responsibility away from leadership, within the DoD and AF it is often suggested that the oppressive budget level is the common source for degradation in Installation Support activities such as facility sustainment [306]. In recent years, the AF has taken action to evaluate Installation Support performance; however, a significant gap remains in its current performance evaluation process.

Currently, the evaluation process places an emphasis on monitoring *effectiveness* rather than measuring *efficiency*. This is illustrated in the existing reporting mechanism in which Key Performance Indicators[22] (KPIs) are used to measure service levels achieved. When KPIs are the

[22] Organizations commonly rely on Key Performance Indicators to measure how well certain processes or entities are performing. KPIs are often singularly focused (i.e. *cost per plant replacement value, percent work orders performed, percent preventative maintenance performed*) and do not allow for a multifaceted performance evaluation.

Figure 5.1: *"Employees lose respect for a company that fails to provide decent facilities for their comfort."* - Vintage ScotTissue Towels advertisement, 1936.

primary focus, challenges surface in measuring the aggregate performance of Installation Support at a base and across the enterprise. This leads to stop-light dashboards which report how many measures are *"met"*, *"partially met"*, or *"not met"*; a visual depiction which may point to obvious performance problems but provides little in way of a comprehensive understanding of performance. To address this, firms often attempt to objectively weight the KPIs to assign a measure of utility so that aggregation can be performed; ample room for controversy emerges here as decision-makers often vary on their perception of utility [307].

Furthermore, by only monitoring *effectiveness*, the AF fails to consider the *efficiency* of bases to change input resources into performance outputs. This lack of focus on identifying *efficiencies* has been identified as a management deficiency by the Government Accountability Office [308]. Only by understanding *efficiencies* in resource usage across bases can the AF begin to benchmark performance, isolate best practices, and identify potential cost savings.

To address these concerns this analysis demonstrates how the AF can apply Data Envelopment Analysis (DEA) to measure and compare the relative efficiency of transforming resource inputs to performance outputs for Installation Support activities with an illustrative example focused on facility sustainment. This approach abandons the focus of comparing or aggregating single KPI measures and provides an overall measure of how well AF bases are utilizing the multiple resource inputs to obtain certain performance levels for the various facility sustainment metrics of interest to senior leadership. Furthermore, rather than assess how effective each individual AF base is in performing a process, DEA provides a benchmarking process by systematically comparing the performance of bases against one another. This helps to identify bases which are more efficient in their processes relative to other bases and may provide direction in subsequent analyses to establish best practices. Lastly, DEA can identify the levels of excess, or slack, in resource inputs and shortfalls in performance outputs which provides an initial assessment of potential cost savings. Contextualizing this conception in metaphor may help clarify the intent [309].

The result of light refracting through a prism depends upon the lens. Sharing some space with postmodern thought, there really is not a "right" lens. Rather, a specific type of lens can help improve the visual acuity of a given individual in a particular context. So it is with the "conceptual lenses" one could use to assess performance for facility sustainment activities. Currently, the AF is using effectiveness as the dominant lens through which it measures performance (Figure 5.2, version A). While there is certainly value in assessing effectiveness, such a myopic focus can lead to the phenomenon of performance-at-any-cost. Such an opulent pursuit tends to generate calls for greater restraint in spending. When budgets constrict, it is not uncommon for an organization to rotate the prism, and refract the light of performance through the lens of efficiency (Figure 5.2, version B). Again, there is value and insight to be gained from such an analytic focus. However, just as a singular focus on effectiveness generates "blind spots," so too do omissions and distortions emerge as one looks myopically at efficiency. Specifically, mission degradation could result from an overzealous cost consciousness. Fortunately, just as there are a variety of lenses, one is not constrained to the either/or of effectiveness vs. efficiency. One is able to rotate the prism a third time. Similar to how a dispersive prism breaks light into spectral colors; the envelopment lens provided through DEA (Figure 5.2, version C) allows one to assess performance in a more integrated and "colorful" way. Following Box [310], this does not make the lens "right;" merely useful.

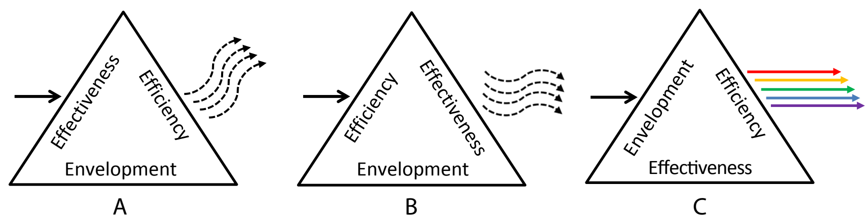


Figure 5.2: Evaluative Prism

The remainder of this paper proceeds as follows. First, additional background discussion is provided on the problem statement. We then introduce the methodology and data used in the analysis followed by an assessment of the results from the empirical analysis. We end with discussion on how this approach could be leveraged across the AF enterprise along with concluding remarks.

5.2 Background

5.2.1 Current Process.

In 2009, the Vice Chief of Staff of the Air Force tasked the development of the Air Force Common Output Level Standards (AF COLS) program. The intent was to provide more consistency in the way Installation Support services are delivered across the AF enterprise and to provide a standardized and streamlined process in reporting performance [311]. Furthermore, with ever increasing pressures on the DoD budget as a result of the Budget Control Act of 2011 and the American Taxpayer Relief Act of 2012, the need for the AF to become even more efficient and standardized in Installation Support services has intensified [1; 267; 308]; and the AF COLS program serves as "an instrument to assist the AF in streamlining operations in a fair and consistent manner" [311].

Currently, the AF COLS program addresses 40 Installation Support functions ranging from *Chaplain Corps, Child and Youth Programs*, and *Morale, Welfare and Recreation services* to *Security Forces, Food Services*, and *Utilities*. These support functions represent $14.8 billion in fiscal year (FY) 2014 expenditures and fall under the responsibility of 10 different Air Staff organizations. Logistics, Installations & Mission Support (AF/A4/7) is responsible for the largest percent (50%) of Installation Support functions which accounted for $8.1 billion (55%) of the FY14 expenditures. The single largest Installation Support function, which this study focuses on, is the *Facilities Sustainment* function which accounted for $3.3 billion in FY14.

For each Installation Support function, domain experts within the Air Staff organizations developed metrics to measure installation AF COLS performance and identified target performance levels based on acceptable risk standards. The target performance levels for each metric are categorized to represent the level of risk associated with them (i.e. achieving a 90% and above is green, 80-90% is yellow, and < 80% is red). These metrics were then vetted and approved by the AF COLS Executive Steering Group and by the Headquarters AF governance structure [311]. For the Facilities Sustainment function, the Facility Management Division (AF/A4CF) developed metrics to define and standardize the value used to confirm if bases are meeting the performance requirements for Facility Sustainment.

Currently, the AF COLS metrics data are officially reported using the AF COLS Reporting Tool. First, base-level functional representatives input data into the AF COLS Reporting Tool. Next, direct commanders at the base-level functional level review and approve the data followed by the host wing commander. The base level data are then reviewed by functional representatives at the MAJCOM level who then submit to Headquarters AF (HAF) for final review and approval. At the HAF level, these metrics are summarized into dashboard reports which provide the number (and percent) of bases that *"Meet"*, *"Partially Meet"*, or *"Does Not Meet"* the target performance levels, along with drill-down reports that identifies which bases are failing to fully *"Meet"* their target performance level. [311]

5.2.2 Effectiveness vs. Efficiency.

The primary purpose of this process is to provide information that HAF can use to inform future Installation Support resourcing decisions; however, a major drawback is the focus on metrics that describe the facility sustainment *effectiveness* of bases. By effectiveness we refer to the objective of meeting a particular performance level without concerning the amount of inputs required to achieve that performance level. For instance, one of the facility sustainment metrics is the *percent of preventative maintenance completed during the last six months*. If two bases had the exact same facility infrastructure and both bases sufficiently *"Met"* the desired target performance level, decision-makers lack the insight that it may have taken base *X* 30% more resources than base *Y* to achieve that performance level. As a result, decision-makers lack the ability to assess potential excess resource inputs at base *X*; a fundamental requirement of identifying potential cost savings. The only resourcing decision that can be made by monitoring effectiveness is to allocate more resources to underperforming bases, regardless of whether they are operating inefficiently with current resources.

Measuring *efficiency*, on the other hand, evaluates the bases ability to transform resource inputs to performance level outputs. In order to measure efficiency, HAF may take the following approaches. First, measuring total maintenance cost as a percent of *Replacement Asset Value* (RAV) has been recognized as a maintenance and reliability best practice in industry [312]. This economic efficiency metric allows for comparison of expenditures across locations with varying size, value and complexity. Within the DoD, plant replacement value (PRV) has become the standardized valuation to represent RAV across installations [283]. Therefore, HAF can measure total costs per PRV to gauge cost efficiency; however, this metric has the singular focus on cost without insight into whether target performance levels are being achieved.

A second approach, in an attempt to ensure performance is measured, may loosely be perceived as measuring productivity by taking the ratio of performance outputs to resource inputs. This may take the form of each performance level divided by total facility sustainment costs. This approach has two concerns: *i)* it assumes constant returns to scale suggesting that for every dollar of additional input leads to an equivalent increase in performance level, regardless of the size or complexity of the facility infrastructure at a base and *ii)* it creates partial evaluations, as calculating the ratio of a single performance metric to facility sustainment costs does not adequately reflect the entirety of the facility sustainment objectives[23].

A third approach, in an attempt to address the problem of partial evaluations, HAF may choose to weight the utility of each performance metric in an attempt to aggregate the performance levels achieved at a base. This often becomes controversial due to a lack of consistent preferences among decision-makers. In addition, many times aggregation is not possible if inputs and outputs are represented in different units[24]. Lastly, even if inputs and outputs can be aggregated, this process tends to conceal the potential cost savings of the different input resources. For instance, to perform facility sustainment activities multiple input resources are required such as labor, supplies, contracted services, equipment, and the like. If aggregated, any potential resource inefficiencies identified can only be identified at the aggregate level. As a result, decision-makers will not be able to delineate which type of resource inputs have excess. This may lead to decision-makers reducing the budget for contract service resources when in fact it is labor resources which are being used inefficiently.

The fourth, and our proposed, approach, is to measure efficiency by accounting for all resource inputs, performance outputs and exogenous factors simultaneously. Furthermore, since no established production function exists to measure the efficiency of Installation Support services, the AF must rely on relative measures of efficiency in which resource inputs and performance outputs are compared across the bases without *a priori* information. In essence, an internal benchmarking process is required to identify which bases are optimizing facility sustainment performance relative to the resource inputs being provided. It is this purpose that DEA is well suited to provide efficiency and benchmarking capabilities for AF Installation Support services.

[23]For example, assessing the ratio of percent of Preventative Maintenance completed ÷ facility sustainment costs disregards the importance placed on other facility sustainment performance metrics of interest such as Unscheduled Emergency Maintenance, Scheduled High Priority Maintenance, etc.

[24]For example, inputs and outputs can be in the form of dollars, labor hours, square footage, percent, etc.

5.3 Methodology

Data Envelopment Analysis is a mathematical programming technique originally proposed by Charnes et al. [313] to measure the efficiency of similar entities, also referred to as decision-making units (DMUs). The efficiency of a given DMU can be defined as the ratio of the weighted sum of all outputs to the weighted sum of all inputs [c.f. 314; 315]. Therefore, DEA is a method for identifying which DMUs in a comparable set are most efficient in transforming inputs to outputs, and using them as a benchmark for comparison to inefficient units [315].

Since its introduction, DEA has become recognized as a powerfully informative methodology for modeling operational processes for performance evaluations [316; 317]. Applications of DEA to measure efficiency include, but has not been limited to, areas such as schools [318; 319], hospitals [320; 321], airlines [322–325], recruiting [326–328], inventory management [329], and maintenance units [330]. Cook and Seiford [331] provide a useful review of DEA's theoretical developments and applications over the past 30 years.

Multiple DEA methods exist; however, all DEA models share the idea of estimating the empirical production *"technology"* frontier using a minimal extrapolation approach with differences only existing in the assumptions being made [307]. The three approaches applied in this analysis represent the fundamental models commonly applied and their explanations follow.

5.3.1 Charnes, Cooper, & Rhodes (CCR) Model.

The original input-oriented DEA ratio form illustrated in equation 5.1 is known as the Charnes, Cooper, Rhodes (CCR) *fractional* model. In regards to our business problem, y_{rj}, x_{ij} are the respective facility sustainment performance outputs and resource inputs of the jth DMU (synonymous to an Air Force installation), u_r and v_i are the variable weights to be determined and ϵ is a small positive number.

$$\text{Maximize:} \quad h_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{5.1}$$

$$\begin{aligned}
\text{Subject to:} \quad & \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1; \quad j = 1, 2, \ldots, n \\
& \frac{u_r}{\sum_{i=1}^{m} v_i x_{io}} > \epsilon; \quad r = 1, \ldots, s \\
& \frac{v_i}{\sum_{i=1}^{m} v_i x_{io}} > \epsilon; \quad i = 1, \ldots, m
\end{aligned}$$

Each DMU is singled out for evaluation and placed in the functional form (designated as DMU_o) while all DMUs are used in the constraint set to include DMU_o. The resulting h_o obtained from the ratio represents the efficiency rating of DMU_o such that $0 \leq h_o \leq 1$. A DMU that obtains an $h_o = 1$ is considered a fully efficient entity such that its transformation of inputs to outputs cannot be dominated by other DMUs; whereas $h_o < 1$ means inefficiencies exist.

The fractional model can be replaced with the equivalent linear programming model illustrated in equation 5.2, which is known as the *multiplier* problem,

$$\text{Maximize:} \quad h_o = \sum_{r=1}^{s} u_r y_{ro} \tag{5.2}$$

$$\begin{aligned}
\text{Subject to:} \quad & \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \\
& \sum_{i=1}^{m} v_i x_{io} = 1 \\
& u_r, v_i \geq \epsilon
\end{aligned}$$

while the corresponding dual program illustrated in equation 5.3 is known as the *envelopment* problem. The slack variables (s_i^- and s_r^+) represent input excesses and output shortfalls respectively. Therefore, DMU_o optimality is obtained with $\theta_o = 1$ and $s_i^-, s_r^+ = 0$ rendering DMU_o CCR-efficient and serving as the benchmark to other, less efficient DMUs. Furthermore, the CCR formulation states that inefficient DMUs should be able to sustain the same output while reducing each input by its respective s_i^- value and, conversely, for a given set of inputs could increase each output by its respective s_r^+ value.

$$\text{Minimize:} \quad \theta - \epsilon\Big[\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\Big] \tag{5.3}$$

$$\begin{aligned}
\text{Subject to:} \quad & \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta_o x_{io}; \quad && i = 1, \ldots, m \\
& \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}; \quad && r = 1, \ldots, s \\
& \lambda_j, s_i^-, s_r^+ \geq 0; && \forall j, i, r \\
& \theta_o \ \text{ unrestricted in sign}
\end{aligned}$$

5.3.2 Banker, Charnes, & Cooper (BCC) Model.

Another version of DEA is the Banker, Charnes, & Cooper (BCC) model [332]. Whereas the CCR model evaluates based on constant returns to scale, the BCC model allows variable returns-to-scale. The difference between CCR and BCC can be illustrated in equation 5.4 which is the BCC *multiplier* comparable to the CCR *multiplier* in equation 5.2. The only difference is the addition of u_o which represents the return to scale possibilities; where $u_o < 1$ implies increasing returns to scale, $u_o = 1$ implies constant returns to scale, and $u_o > 1$ implies decreasing returns to scale. As with CCR, DMU_o is considered BCC-efficient if $\theta_o = 1$ and $s_i^-, s_r^+ = 0$ in the dual to equation 5.4.

$$\text{Maximize:} \quad b_o = \sum_{r=1}^{s} u_r y_{ro} - u_o \tag{5.4}$$

$$\text{Subject to:} \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_o \leq 0$$
$$\sum_{i=1}^{m} v_i x_{io} = 1$$
$$u_r, v_i \geq \epsilon$$

5.3.3 Slack-based Measure (SBM) Model.

One of the drawbacks of the CCR and BCC models is that a DMU can have an efficiency score of 1 and still be inefficient in the sense that some inputs could be reduced or some outputs could be expanded without affecting the need for other inputs or the production of other outputs [307]. To address this issue, an additive model has been developed to measure DMU efficiency based on relative slack values [333]. However, although they can identify efficient and inefficient DMUs, the additive model does not provide a scalar measure of efficiency. As a result, a slack-based measure (SBM) model has been proposed to measure efficiency in a scalar form with relative slack values included in the objective function [334]. The *fractional* model form is provided in equation 5.5.

$$\text{Minimize:} \quad \theta = \frac{1 - (\frac{1}{m}) \sum_{i=1}^{m} \frac{s_i^-}{x_{io}}}{1 + (\frac{1}{s}) \sum_{r=1}^{s} \frac{s_r^-}{y_{ro}}} \tag{5.5}$$

$$\text{Subject to:} \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io}; \qquad i = 1, \ldots, m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_i^+ = y_{ro}; \qquad r = 1, \ldots, s$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda_j, s_i^-, s_r^+ \geq 0; \qquad \forall j, i, r$$

Additional linear programming DEA models exist; however, their technology set sizes fall between the ranges of CCR's constant returns to scale and BCC's variable return to scale. Therefore, modeling efficiencies with CCR and BCC will capture the two ends of the spectrum; providing both the most discriminate and conservative efficiency ratings [307]. Furthermore, the SBM model will project the DMU to the furthest point on the efficient frontier in the sense that the objective function is to be minimized by finding the maximal slacks [334]. As a result, modeling slacks with SBM and BCC will capture the two ends of the spectrum on resource slacks.

5.3.4 Resource Inputs & Outputs.

At the time of this research performance outputs for AF COLS metrics are only available for fiscal years 2013-2014; however, during the initial introduction of the COLS metrics changes have occurred to align KPIs to AF leadership's focus. As a result, our analysis focuses on 2014 data. Under direction of senior AF leadership within AF/A4/7, the data that most accurately reflect performance were used which include the end of year reported AF COLS metrics along with the full year expenditures related to facility sustainment activities. Currently 67 bases are reporting facility sustainment performance metrics. Of these, 13 bases were removed as they were overseas bases which are likely influenced by dissimilar operating environments. Furthermore, several bases have not reported performance data consistently; as a result our final dataset included 35 bases which have consistently reported across all performance metrics analyzed.

The resource inputs analyzed are described in Table 5.1 and represent over 98% of facility sustainment expenditures in recent years. A principal concern in only measuring costs as resource inputs is that it does not capture differences in resource requirements due to infrastructure differences (i.e. building count, square footage, or complexity). Naturally, a base with larger or more complex infrastructure will require more resource inputs to achieve the same level of effectiveness as a base with smaller or less complex infrastructure. To account for these infrastructure differences across AF installations we considered two options. First, infrastructure data such as building count, square footage, and\or PRV could be included as separate resource inputs. Including these variables as resource inputs would be acceptable when using them as a surrogate for capital investment to aid in producing the outputs (i.e. sales, revenue, etc.) [335]. However, since our outputs are measuring the performance of maintenance activities that are induced by infrastructure size and complexity we address this by a second option; by normalizing resource input costs by PRV.

Table 5.1: Facility Sustainment Resource Input

Resource Inputs*	Description	Units
Labor costs	Cost of civilian and military personnel performing facility sustainment activities.	$
Contract services costs	Facility sustainment resources (i.e. personnel, repairs, supplies) that have been contracted to external entities.	$
Maintenance & repair costs	Cost of major repairs or replacement of facility components to keep facility inventory in good working order.	$
Supply costs	Cost of supplies and materials for direct consumption (i.e. bench stock consumables, common supplies & materiel, and office supplies).	$

*Resource inputs represent cost of input per $1 PRV

Plant replacement value captures the number, size, type, and complexity of facilities at an AF installation. Normalizing resource inputs by PRV allows for comparison of expenditures across locations with varying size, value and complexity. As a result, normalizing allows us to interpret the inputs as the resource dollars provided per dollar of PRV. All costs were obtained from the AF Total Ownership Cost (AFTOC) database and PRV values were provided by AF/A4/7.

The performance outputs analyzed are described in Table 5.2 and were obtained from the AF COLS portal. Additional performance metrics tracked by the AF but excluded from our analysis include the following. *Execution of Distributed Funding* tracks the execution of funding received and *Enhancements* tracks the percent of funding spent on "nice to have" work such as replacing carpet, lighting upgrades, etc. These two metrics were excluded from our analysis for the following reasons: *i*) the objective of measuring execution of funding received is to align with the congressional budgetary requirements rather than to measure facility sustainment performance and *ii*) very little variation exists in the reported data for these measures as the vast majority of bases fully execute their budgets received and performed zero enhancement projects.

As a result, this analysis focuses on the performance measures that reflect the normal recurring facility sustainment activities at AF installations which addresses four fundamental facility sustainment maintenance activities: *i*) Emergency activities, *ii*) High Priority activities, *iii*) Low Priority activities, and *iv*) Preventative activities. Furthermore, the identified risk ratings associated with each metric are provided. The *"Green"* risk ratings illustrate what the AF considers acceptable levels of risk for facility sustainment performance while *"Yellow"* and *"Red"* are considered indicators of unacceptable performance and risk.

Table 5.2: 2014 Facility Sustainment Performance Outputs

Performance Output	Description	Units
Unscheduled Maintenance	Percent of emergency work orders responded to within 24 hours. A work order is considered an emergency if there is an interruption of utilities, immediate danger to human life, or there is a possibility of damage to the facility's infrastructure.	%
Risk/KPI ratings:	*Green* (= 100%), *Yellow* (98 – 99%), *Red* (< 98%)	
Scheduled High/Medium Maintenance	Percent of work tasks that are completed in the agreed upon time committed to the customer over the last six months. This sub-category is often associated with follow-up work to an emergency (work priority 1) that was responded to and downgraded.	%
Risk/KPI ratings:	*Green* (≥ 75%), *Yellow* (60 – 74%), *Red* (< 60%)	
Scheduled Low Maintenance	Percent of work tasks that are completed in the agreed upon time committed to the customer over the last six months. Represents low priority and low risk maintenance.	%
Risk/KPI ratings:	*Green* (≥ 60%), *Yellow* (45 – 59%), *Red* (< 45%)	
Preventative Maintenance	Percent of preventative maintenance completed during the last six months.	%
Risk/KPI ratings:	*Green* (≥ 95%), *Yellow* (85 – 94%), *Red* (< 85%)	

5.4 Empirical Analysis

We begin by looking at FY14 efficiency levels. Table 5.3 provides the efficiencies and input resources slacks across the 35 bases assessed. As illustrated, the larger technology frontier of the CCR model leads to the largest efficiency discrimination while the smallest technology frontier of the BCC model provides the most conservative efficiency ratings. An installation that is considered efficient has $\theta_o = 0$ and $S_i^- = 0$. To estimate slacks in resource inputs we use the BCC model to provide the most conservative slack estimates. Furthermore, the slack outputs provided by the BCC model are originally provided as excess *cost per PRV* in which we use to back into the total excess cost value by multiplying the slack value for a resource at base j by the respective facility PRV ($S_{ij}^- \times PRV_j$).

The results show that across the AF enterprise, installations were operating at an efficiency level of 0.64-0.76 on average. If constant returns to scale are assumed as in θ_o^{CCR} then 9 (26%) of the AF installations are operating efficiently; however, if variable returns to scale are assumed as in θ_o^{BCC} then 18 (51%) of the bases are operating efficiently in 2014. The inefficiencies identified amount to \$131.3 million in excess resource expenditures which represents 10% of the total funds allocated for the represented installations. The largest source of resource excess was in maintenance and repair costs ($S_{M\&R}^-$) followed by labor (S_{Labor}^-)and supply costs (S_{Supply}^-) respectively. This finding can be interpreted as follows: resource inputs for the inefficient installations should be able to be reduced by their respective slack values and still achieve the same level of performance. Hence, at the aggregate, the AF-enterprise should have been able to achieve the same level of facility sustainment performance for \$131.3 million less in resource inputs.

To gain a more robust perspective we can further assess enterprise-wide slacks to provide decision-makers with additional insight. First, considering our initial analysis assessed for the most conservative levels of input resource slacks we can extract the slacks for the CCR and SBM models as well to identify the full range of potential input resource slacks. This will provide decision-makers with a target range of the potential *magnitude* of cost savings that may be achieved by future benchmarking initiatives.

We assess the full range of resource slacks provided by all three models across the enterprise which is summarized in Table 5.4. The SBM model consistently identifies the largest amount of input slacks while the CCR and BCC models provide more conservative slack amounts. The

Table 5.3: FY14 Facility Sustainment Efficiencies & Slacks

Base	Efficiency θ_o^{CCR}	Efficiency θ_o^{SBM}	Efficiency θ_o^{BCC}	Resource Input Slacks S^-_{Labor}	Resource Input Slacks S^-_{CS}	Resource Input Slacks $S^-_{M\&R}$	Resource Input Slacks S^-_{Supply}
Arnold	1.00	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Beale	1.00	1.00	1.00	$0.00	$0.00	$0.00	$0.00
F.E. Warren	1.00	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Goodfellow	1.00	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Keesler	1.00	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Kirtland	1.00	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Laughlin	1.00	1.00	1.00	$0.00	$0.00	$0.00	$0.00
MacDill	1.00	1.00	1.00	$0.00	$0.00	$0.00	$0.00
USAF Academy	1.00	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Hill	0.99	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Buckley	0.90	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Los Angeles	0.86	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Travis	0.84	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Hanscom	0.79	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Mountain Home	0.65	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Wright-Patterson	0.64	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Maxwell	0.45	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Nellis	0.38	1.00	1.00	$0.00	$0.00	$0.00	$0.00
Eielson	0.92	0.32	0.94	$0.00	$0.00	$21,005,001	$3,092,074
Robins	0.52	0.47	0.85	$12,740,796	$0.00	$9,323,973	$0.00
Dyess	0.67	0.34	0.78	$0.00	$0.00	$20,225,526	$1,128,361
Davis Monthan	0.37	0.40	0.78	$5,168,320	$0.00	$0.00	$0.00
Whiteman	0.51	0.33	0.59	$0.00	$0.00	$14,318,035	$188,819
Offutt	0.32	0.32	0.51	$1,550,687	$0.00	$0.00	$0.00
Vandenberg	0.39	0.33	0.50	$0.00	$0.00	$702,599	$0.00
Fairchild	0.41	0.36	0.49	$0.00	$0.00	$3,472,104	$0.00
Cannon	0.41	0.41	0.48	$0.00	$0.00	$1,285,123	$346,744
Patrick	0.39	0.27	0.46	$2,146,394	$0.00	$7,901,067	$0.00
McConnell	0.37	0.28	0.43	$0.00	$0.00	$4,042,499	$826,235
Barksdale	0.33	0.30	0.43	$0.00	$0.00	$0.00	$1,019,559
Luke	0.39	0.19	0.39	$347,110	$0.00	$5,103,087	$0.00
Malmstrom	0.26	0.26	0.34	$1,432,438	$0.00	$0.00	$0.00
Minot	0.24	0.22	0.32	$1,032,007	$0.00	$0.00	$0.00
Peterson	0.16	0.13	0.24	$392,179	$0.00	$0.00	$0.00
Little Rock	0.11	0.07	0.16	$0.00	$0.00	$12,552,316	$0.00
Mean Efficiency:	0.64	0.66	0.76				
Total Excess Resource Inputs:				$24,809,931	$0.00	$99,931,332	$6,601,793

findings suggest that the AF could have achieved the same level of enterprise-wide efficiencies with 10-42% less resources in FY14. Furthermore, the largest source of input resource slack is in M&R costs followed by labor, supplies, and lastly contracted services.

Table 5.4: Input Resource Slacks Across All Air Force Installations

Resource	SBM	CCR	BCC
S^-_{Labor}	\$118.58 (47%)	\$18.34 (7%)	\$24.81 (10%)
S^-_{CS}	\$30.77 (19%)	\$9.36 (6%)	\$0.00 (0%)
$S^-_{M\&R}$	\$375.02 (45%)	\$112.45 (13%)	\$99.93 (12%)
S^-_{Supply}	\$40.11 (47%)	\$11.89 (14%)	\$6.60 (8%)
Total	\$564.47 (42%)	\$152.03 (11%)	\$131.34 (10%)
minus M&R	\$189.46 (14%)	\$39.59 (3%)	\$31.41 (2%)

*All cost values represented in millions.

*Percents listed represent percent of total enterprise-wide costs for that respective resource.

Of concern is the sizable slack values identified in M&R resources. For instance, our results in Table 5.3 indicated that Eielson AFB could have obtained the same level of performance with \$21 million less in maintenance and repair costs (M&R). This slack in M&R resources represents 66% of the total M&R costs incurred in FY14 (\$31.8 million) suggesting that an efficient level of M&R resources at Eielson would be \$10.8 million. By assessing historical M&R costs at Eielson since 1996, we found that the average M&R costs were \$12.9 million and between 2011-2013 were \$10.2 million. This suggests that the efficient level of M&R resources suggested for Eielson AFB by the BCC model align with historical M&R costs and the excessive FY14 costs may have been due to abnormal activity such as a construction project funded with M&R resources or an abnormal maintenance action; however, this abnormal activity did not result in efficient performance outputs.

As a result, we note that legitimate explanations may exist for the sizable slacks identified in M&R resources; however, this analysis at least illustrates how abnormalities in resource expenditures can be identified. Regardless, if AF leadership only focused on the labor, contracted services, and supply resources, benchmarking could still potentially identify 2-14% in total resource excess while still achieving current performance levels.

Although understanding enterprise-wide slacks is important, myopic focus on input resource slacks produces distortions akin to those produced through alternatively narrow foci (e.g. effectiveness, etc.). Assessing enterprise-wide slacks will not only identify excess resources consumed by inefficient installations meeting target performance levels but it will also identify excess resources as a result of inefficient installations not meeting target performance levels. If two installations have the same infrastructure levels and are funded at the same level and one installation achieves 90% on all its performance metrics while the other installation achieves only 50% across all the performance metrics then DEA will consider the ill-performing base to have consumed excess resources to achieve its level of performance.

In reality, the objective here for AF leadership is to identify cost savings while accepting certain levels of risk in facility sustainment. Principally, the AF is concerned with excess resources being consumed by installations that are meeting and/or exceeding the highest standard represented as achieving a *"Green"* risk rating. Furthermore, in times of tight fiscal constraints, the AF may also be willing to accept *"Yellow"* risk ratings and seek to identify excess resources by installations achieving a minimum *"Yellow"* rating to be allocated elsewhere. As a result, we can identify the total slack resources being consumed by only those bases achieving these minimum risk ratings which provides decision-makers with target cost savings in bases considered *effective* based on a given AF risk tolerance.

Table 5.5 summarizes the excess resources being consumed by AF installations achieving minimally acceptable risk standards. We find that bases achieving a *"Green"* risk rating, but were considered operating inefficiently, consumed an excess of up to $62.9 million resources, which represents 5% of the total facility sustainment budget. This suggests that by benchmarking, the AF could achieve up to 5% in total cost savings by focusing on bases achieving the *"Green"* risk rating but not necessarily operating efficiently. If AF leadership only focused on the labor, contracted services, and supply resources, benchmarking could still potentially identify 7% in total non-M&R resource excess. Furthermore, we find that bases achieving a *"Yellow"* and above risk rating but were considered operating inefficiently consumed an excess of $41.8-221.7 million in resources (or \$8.3-90.5 million non-M&R resources). This suggests that if the AF was willing to accept this level of risk and by benchmarking, the AF could identify 3-17% in resource excess (or 2-18% non-M&R resource excess) by focusing on bases achieving this minimally acceptable risk rating but not necessarily operating efficiently.

Table 5.5: FY14 Input Resource Slacks for Bases Considered *"Effective"*

	Installations achieving a "Yellow" above risk rating			Installations achieving a "Green" risk rating		
Resource	SBM	CCR	BCC	SBM	CCR	BCC
S^-_{Labor}	\$52.59 (21%)	\$3.65 (1%)	\$5.00 (2%)	\$18.83 (8%)	\$0.48 (<1%)	\$1.03 (<1%)
S^-_{CS}	\$18.44 (11%)	\$4.42 (3%)	\$0.00 (0%)	\$7.65 (5%)	\$4.42 (3%)	\$0.00 (0%)
$S^-_{M\&R}$	\$131.21 (16%)	\$42.10 (5%)	\$33.45 (4%)	\$26.38 (3%)	\$8.54 (1%)	\$4.04 (<1%)
S^-_{Supply}	\$19.45 (23%)	\$3.43 (4%)	\$3.32 (4%)	\$10.04 (12%)	\$1.98 (2%)	\$1.85 (2%)
Total	\$221.68 (17%)	\$53.60 (4%)	\$41.78 (3%)	\$62.90 (5%)	\$15.42 (1%)	\$6.92 (1%)
minus M&R	\$90.47 (18%)	\$11.50 (2%)	\$8.32 (2%)	\$36.52 (7%)	\$6.88 (1%)	\$2.88 (1%)

*All cost values represented in millions.
*Percents listed represent percent of total enterprise-wide costs for that respective resource category.

Shifting the analytic lens to an equally valid concern, AF leadership benefits from understanding what levels of performance output *should have been* achieved given the level of resources provided. By *"should have been achieved"* we mean, if installations would have performed along the efficient frontier with their given resources then what level of performance would have been achieved in FY14? This provides decision-makers with potential performance targets based on the efficient frontier if FY14 budgets are expected in the future.

First, we assess the enterprise-wide performance output slacks (S^+_r). Table 5.6 summarizes the results and displays the adjusted performance outputs for each performance metric had all AF installations operated efficiently in FY14 with the resources provided. Note that the efficient performance levels for the CCR model are greater than 100%. This is a result of the assumption that constant returns to scale are present; an assumption of questionable validity. An example of interpreting the results follows. Had all AF installations operated efficiently in FY14 the expected enterprise-wide average performance level for preventative maintenance (S^+_{PM}) would be in the range of 94-98%, which represents 5-10 percentage points (pp) increase from the actual performance levels obtained. However, since constant returns to scale are highly suspect, the range of 94-96% provided by the BCC and SBM models is more probable.

Table 5.6: Enterprise-wide Efficient Performance Outputs

Performance	SBM	CCR	BCC	Efficient Performance Range
S^+_{EM}	99% (+4pp)	114% (+19pp)	99% (+4pp)	99-100% (+4-5pp)
S^+_{HP}	92% (+5pp)	105% (+18pp)	91% (+5pp)	91-100% (+5-13pp)
S^+_{LP}	83% (+3pp)	85% (+5pp)	84% (+4pp)	83-85% (+3-5pp)
S^+_{PM}	96% (+7pp)	98% (+10pp)	94% (+5pp)	94-98% (+5-10pp)

*pp values listed represent the percentage point(s) increase gained if the installations would have operated efficiently.

This enterprise-wide perspective assumes that all bases operating inefficiently could increase their performance outputs regardless of whether target performance levels are being achieved or not. As with the objective of identifying excess resources at installations that are satisfactorily meeting performance targets, the initial objective for decision-makers is to identify performance shortfalls for those installations not meeting the acceptable risk levels. In essence, leadership would prefer to first increase performance at the bases not currently achieving the minimally acceptable levels of risk before focusing on improving performance at bases that are meeting the acceptable risk levels. By focusing on these under-performing bases, leadership can foresee what performance levels should be expected of them prior to allocating additional resources to increase performance.

Table 5.7 illustrates the efficient performance levels for the AF installations currently achieving less than a *"Green"* risk rating. These results suggest that for all bases currently achieving a *"Yellow"* risk rating, if these bases operated efficiently they should, on average, be able to increase their performance levels to a *"Green"* risk level for emergency, high priority and low priority maintenance actions with their currently levels of funding. However, operating efficiently would likely increase the preventative maintenance performance levels to 90-95% which is right at the *"Green"* - *"Yellow"* performance threshold[25]. This suggests to leadership that if a *"Green"*

[25]Current standards for preventative maintenance include: Green (≥ 95%), Yellow (85 – 94%), Red (< 85%).

risk rating is desired in preventative maintenance then additional resources may be required along with improving operating efficiency.

Table 5.7: Adjusted Performance Outputs for Bases Considered *"Ineffective"*

Performance	SBM	CCR	BCC	Efficient Performance Range
Installations achieving a "Yellow" risk rating:				
S^+_{EM}	99% (+6pp)	108% (+16pp)	99% (+6pp)	99-100% (+6-7pp)
S^+_{HP}	88% (+8pp)	96% (+17pp)	87% (+7pp)	87-96% (+8-17pp)
S^+_{LP}	78% (+5pp)	79% (+6pp)	79% (+6pp)	78-79% (+5-6pp)
S^+_{PM}	91% (+9pp)	95% (+12pp)	90% (+7pp)	90-95% (+7-12pp)
Installations achieving a "Red" or "Yellow" risk rating:				
S^+_{EM}	98% (+9pp)	102% (+12pp)	98% (+9pp)	98-100% (+9-12pp)
S^+_{HP}	85% (+10pp)	89% (+14pp)	84% (+9pp)	84-89% (+9-14pp)
S^+_{LP}	80% (+7pp)	81% (+9pp)	81% (+8pp)	80-81% (+7-9pp)
S^+_{PM}	86% (+7pp)	92% (+14pp)	85% (+6pp)	85-92% (+6-14pp)

*pp values listed represent the percentage point(s) increase gained if the installations would have operated efficiently.

Similar results apply to all installations achieving a *"Red'* or *"Yellow"* risk rating. Improving efficiency at these installations should allow these bases to achieve, on average, a *"Green"* risk level for emergency, high priority and low priority maintenance actions with their current levels of funding; however, one should not expect preventative maintenance performance to increase to greater than 92% which achieves a *"Yellow"* risk rating. As a result, more funds would likely be required to increase the average preventative maintenance performance level of these bases to a *"Green"* risk rating.

Lastly, we can illustrate how additional DEA analysis can provide decision-makers with further insight for initial benchmarking at the installation level. Table 5.8 illustrates the additional information that can be extracted from DEA analysis that informs decision-makers on excess resources being expended at McConnell AFB. McConnell AFB obtained *"Green"* risk ratings for all performance metrics in 2014; therefore, it is considered *effective*. However, our analysis found that McConnell AFB is potentially operating at only 0.43 efficiency[26] suggesting that

[26]For purposes of this section we are using results from the BCC model since the variable returns to scale assumption appears to be appropriate and the slack estimates are more conservative.

McConnell could likely continue achieving "Green" risk ratings with less resources. The best performing bases which McConnell is compared to in the DEA analysis (also referred to as peers) are Travis AFB and the USAF Academy; both of which operate on the efficient frontier and thus have efficiencies of 1.00. The weights listed indicate the influence each peer has on the subject base's rating. These peers would represent the bases in which the subject base would preferably perform a benchmarking process with to identify improvements in efficiencies. The input slacks represent the cost savings that may be achievable by benchmarking against the peers with the goal of maintaining its current performance. These slacks represent excess *cost per PRV* at the subject base. Converting these values back into whole dollar amounts suggests that cost savings of $4,042,499 in M&R resources and $826,235 in supply resources for a total of $4,868,734 could potentially be identified at McConnell AFB by benchmarking with the identified peers.

Table 5.8: Installation Level Results: McConnell AFB

	Subject Base	Benchmark Bases	
	McConnell AFB	Travis AFB	USAF Academy
Efficiency:	0.43	1.00	1.00
Weights:		0.64	0.36
Inputs*:			
x_{Labor}	0.0050	0.0031	0.0004
x_{CS}	0.0025	0.0008	0.0016
$x_{M\&R}$	0.0313	0.0055	0.0125
x_{Supply}	0.0043	0.0010	0.0001
Outputs:			
y_{EM}	● 100%	● 100%	● 100%
y_{HP}	● 100%	● 100%	● 100%
y_{LP}	● 91%	● 87%	● 100%
y_{PM}	● 95%	● 97%	● 100%
Slacks:			
$S^-_{M\&R}$	0.0055		
S^-_{Supply}	0.0011		

*Inputs are presented as cost per plant replacement value

Similar analysis can be performed for installations that are not achieving acceptable performance levels and risk ratings. Table 5.9 illustrates the additional insight which can inform decision-makers on potential performance improvements for a subject base currently not meeting target performance levels. Fairchild AFB is currently operating at 0.49 efficiency and achieving a *"Red"* risk rating for emergency maintenance activities, *"Green"* for high priority and low priority maintenance activities, and *"Yellow"* for preventative maintenance. The efficient frontier peers (and their respective weights) for Fairchild AFB are Beale AFB (0.45), Travis AFB (0.38), and Arnold AFB (0.17). Note that although the peers are operating efficiently, they are not necessarily achieving *"Green"* risk ratings across all performance categories. These bases are still considered efficient as no other bases are producing higher performance outputs with the same relative resource input mix. As a result, Fairchild AFB can still benefit by performing a benchmarking process with these bases as they likely can aid Fairchild AFB in identifying efficiencies in resource usage. In fact, the efficient frontier identified suggests that Fairchild AFB can increase emergency maintenance, low priority maintenance, and preventative maintenance performance by four, eight, and seven percentage points respectively without any increase in resources. This would change preventative maintenance performance from a *"Yellow"* to *"Green"* risk rating and increase emergency maintenance performance to near the *"Yellow"* risk rating threshold[27]. However, for Fairchild AFB to cross the *"Green"*, or even *"Yellow"*, risk rating threshold for emergency maintenance performance, additional resources may be required; which would now be more feasible with the resource slack identified at bases such as McConnell AFB.

5.5 Conclusion

Metaphorically we have shown how the evaluative prism of DEA improves the visual acuity of performance for AF facility sustainment activities. By correcting for the myopia induced from using lenses narrowly focused on either effectiveness or efficiency, insights derived through an application of DEA provide decision-makers with more actionable information and an enhanced trade space. Recent and projected reductions in defense spending make the timing of our analytic contribution all the more meaningful and relevant. A brief review of key results from this study explicates this perspective.

[27]Current standards for emergency maintenance include: Green (= 100%), Yellow (98 – 99%), Red (< 98%).

Table 5.9: Installation Level Results: Fairchild AFB

	Subject Base	Benchmark Bases		
	Fairchild AFB	Beale AFB	Travis AFB	Arnold AFB
Efficiency:	0.49	1.00	1.00	1.00
Weights:		0.45	0.38	0.17
Inputs*:				
x_{Labor}	0.0050	0.0028	0.0031	0.0000
x_{CS}	0.0013	0.0004	0.0008	0.0009
$x_{M\&R}$	0.0133	0.0015	0.0055	0.0058
x_{Supply}	0.0016	0.0008	0.0010	< 0.0001
Outputs:				
y_{EM}	93%	94%	100%	100%
y_{HP}	78%	83%	100%	60%
y_{LP}	62%	89%	87%	48%
y_{PM}	93%	90%	97%	92%
Slacks:				
S^+_{EM}	+4pp			
S^+_{LP}	+8pp			
S^+_{PM}	+7pp			

*Inputs are presented as cost per plant replacement value

Within DEA there are various models available to mathematically program and measure efficiencies across similar entities or DMUs. Modeling efficiencies with CCR and BCC provides one with the boundary conditions necessary to contextualize results generated from additional modeling approaches. Furthermore, the SBM model objective function seeks to find maximal slacks and, therefore, can provide the upper boundary of resource excess. Collectively these models enable one to develop a range of values from which leadership can determine the appropriate degree of aggressiveness or risk-aversion for a given elemental efficiency or efficacy within context at a given point-of-time. In regards to the AF-enterprise a range of mean efficiency values between 64-76% was determined for FY14 facility sustainment activities. In terms of input resource slack, the AF exhibited a range of 10-42% in total, and a range of 2-14% when M&R are excluded. In addition to the specific findings summarized here, this study illustrated how DEA can be used in conjunction with qualitative assessments (e.g., “Green/Yellow/Red”). Such a finding is *in-and-of-itself* important given the AF’s penchant for color coding performance. These preliminary results are promising and suggestive that further application is warranted. As data from subsequent years become available, future studies should enable one to replicate the approaches used here, and determine the degree of consistency and performance sedimentation in results. Sketching the contours of this DEA application simultaneously expands the assessment of performance beyond the simple effectiveness/efficiency duality while it creates new and perhaps even more constraining delimitations.

Piet Hein, as cited by Karl Weick, noted *"man is the animal that draws lines which he himself then stumbles over"* [336]. Just as reduced budgets form a constraint from which the need and value of a DEA application for AF facility sustainment activities emerges, so too do limitations emerge from employing DEA. One benefits from a thorough understanding of these limitations, as they shape and constrain the application potential of the approach. Inherent in DEA is the assumption that there is no noise in the data. As a result, exogenous influence from inaccurate performance metric reporting or accounting practices may render some results as imprecise or invalid. Furthermore, abnormal cost deviations from single year analysis is an issue for which the approach inadequately accounts. As previously stated, to assess the validity of the single year efficiency ratings and slacks, we recommend multi-year analyses be performed to identify installations with consistent trends as more data become available. Lastly, although input and output units are highly flexible in DEA, misspecification of these variables can alter results. Consequently, AF/A4/7 may desire an alternative parameter to normalize resource inputs. Collectively, these metaphors, findings, and limitations are of consequence as decision-makers and employees socially construct their organizational realities [337]. This leads us back to the work environment and the potential radicalization of the workforce.

Contrary to the admonishment contained in the ScotTissue Towels advertisement, there is little risk of employees radicalizing to the point of becoming Bolsheviks. In fact, one might wonder what proportion of the workforce today even knows what a Bolshevik is. But as Herzberg explained failing to adequately address hygiene factors can contribute to a demotivated workforce. This is particularly relevant here as the facility sustainment activities occur at the very nexus between AF mission execution and the majority of its workforce. In other words, it is the AF execution of Installation Support activities, and not the AF flying mission, which the workforce most directly experiences. Inefficiencies or failures in these activities can ripple throughout the organization. Consistent with Herzberg, the AF flying mission holds great motivational potential, but it is essential to address the demotivational consequences of inadequate Installation Support first. DEA provides decision-makers with the insights needed to move beyond the simple and reductionist tradeoffs available from a myopic focus on either effectiveness or efficiency, and provides a rigorous basis for benchmark comparisons. Only through this envelopment lens can AF leadership begin to view performance holistically.

VI. Tooth-to-Tail Impact Analysis: Combining Econometric Modeling and Bayesian Networks to Assess Support Cost Consequences Due to Changes in Force Structure

Bad reasoning as well as good reasoning is possible; and this fact is the practical side of logic.

Charles S. Peirce, 1877

6.1 Introduction

The United States Department of Defense (DoD) currently finds itself facing policy decisions due to budgetary constraints. With sequestration taking effect in 2013, as a result of the Budget Control Act of 2011 and the American Taxpayer Relief Act of 2012, the DoD estimates a total reduction in planned defense spending between fiscal years 2012 to 2021 to exceed $1 trillion [1]. In response to spending reductions, the Air Force (AF), along with her sister services, are developing systematic approaches to reduce front-line mission resources, commonly referred to as the *"tooth"*. A particular example, which is currently the subject of intense debate, is the AF's proposal to divest its fleet of 273 A-10 aircraft to save a supposed $4 billion over five years.

Consideration of such policy decisions often raises the question of how will these changes to the tooth impact mission support resources commonly referred to as the *"tail"*[28]. Although not relatedly directly to a weapon system, tail costs represent resources which provide support to the front-line missions and can surely be impacted by policy changes to the tooth. From a strategic perspective, understanding this *tooth-to-tail* cost consequence provides for better management of resources; however, remarkably, to date there have been few systematic attempts to estimate and model these policy implications on the tail.

This research seeks to inform this debate by providing a systematic approach to perform tooth-to-tail policy impact analysis. We first apply multivariate linear regression to identify relationships

[28]The term *"tooth"* is commonly applied in the military departments to refer to activities and resources directly related to weapon systems; whereas *"tail"* is commonly applied to all activities and resources that support the *tooth* missions but cannot be related directly to an individual weapon system. This is synonymous to what industry commonly refers to as direct versus indirect.

between the tooth and tail. We then introduce a novel decision support system with Bayesian networks (BNs) to model the tooth-to-tail cost consequences while capturing the uncertainty that often comes with such policy considerations. We illustrate our approach using the A-10 scenario.

The remainder of this paper proceeds as follows. Section 6.2 provides additional background discussion on the tooth-to-tail concept along with expounding on the contributions made by this research. Section 6.3 outlines the support cost categories of concern in this study. Section 6.4 identifies tooth-to-tail relationships with econometric modeling. Section 6.5 introduces the probabilistic properties of BNs and then applies this modeling tool to perform tooth-to-tail impact analysis. Section 6.6 provides further discussion along with suggestions for future work and section 6.7 provides concluding remarks.

6.2 Tooth-to-Tail Literature

6.2.1 Background.

Within the DoD and the AF, research has been scarcely conducted to better understand the consequences that policy decisions regarding front-line mission activities have on the support activities and resources. Since the 1990s, the policy emphasis has remained on managing the tail via an aggregate tooth-to-tail ratio; hence, as front-line mission budgets changed, support activity budgets changed, at the aggregate, in relative accordance. Although this tooth-to-tail concept has been around for nearly 20 years, only a handful of studies have addressed the topic [cf. 2; 268–271]. Furthermore, the argument, to date, has primarily centered on the rudimentary ratio approach, and whether the magnitude of the tooth-to-tail ratio is appropriate, rather than gaining an understanding of the cause and effect relationships underlying the tooth-to-tail link. When assessing policy considerations such as the A-10 debate, simply applying the tooth-to-tail ratio to assess cost consequences to support costs provides three concerns.

First, the tooth-to-tail ratio assumes that total direct costs is the correct force structure variable to link to tail costs. This makes the assumption that the direct cost output is the appropriate causal relationship to link with indirect costs rather than understanding which front-line activities and resources drive indirect costs. Recent research by Boehmke et al. [338] has demonstrated this to be false and found that the number, and costs, of front-line mission personnel to be the primary cost driver for the support costs under investigation. This link between support costs and the operational forces at a base is supported by previous empirical evidence [cf. 339; 340]. From a theoretical perspective, this relationship is fairly intuitive as the majority of indirect costs at operational bases are the by-product of providing installation support (i.e. facilities, equipment, and personnel) services to the operational force population at an installation. In other words: to feed, house, protect, provide medical support to, and otherwise support the operational force population in the performance of their day-to-day tasks [339].

Second, the tooth-to-tail ratio assumes that tail costs change in a proportional manner with regard to changes in the tooth without considering the fixed versus variable nature of support costs. Even if the tooth-to-tail ratio were adjusted to link support costs to the operational force population at a base, this approach would be similar to simply dividing the total support costs at an installation by the total number of operational personnel. This proportional approach results in overestimating the variable component of support costs and disregarding the fixed component. In fact, direct analysis of AF manpower planning documents have identified that fixed and variable components exist empirically for installation support activities [339]. This consideration requires the use of econometric modeling to identify the variable components of tail costs and their relationship to the operational force population. Recent research [4; 338; 339] has begun to illustrate the success of applying regression approaches to identify underlying relationships between the tooth and tail.

Third, the tooth-to-tail ratio does not provide decision-makers with an adequate decision support tool to assess tooth-to-tail impact analysis. Although econometric modeling approaches identify underlying relationships, naïvely applying results from these models to estimate cost consequences to the tail disregards the level of uncertainty in such policy considerations and only allows for unidirectional analysis. Within a large enterprise such as the AF decisions are, often, not made sequentially or by a single party. Rather, many decisions are being made at the same time by multiple decision-makers that can impact the planning and programming of resources for, and in support of, weapon systems. Consequently, significant uncertainty exists that econometric models alone cannot capture. Furthermore, the tooth-to-tail ratio does not provide adequate levels of reasoning. During the AF programming and budgeting process, decisions can be made regarding the tooth and tail independently. Relying on a modeling approach that only assesses tooth-to-tail consequences in one direction fails to meet the needs of AF decision-makers.

6.2.2 Contributions.

This research provides the following three contributions to this relatively immature, yet growing, stream of literature:

First, in section 6.4, we provide further empirical evidence that supports the applicability of regression approaches to identifying relationships between the tooth and tail. More specifically, we further illustrate that a strong relationship holds between support costs at an installation and the operational force population.

Second, in section 6.5, we move the discussion from one that only considers the relationship between the two ends of the tooth-to-tail spear, to one that seeks to inject a decision support tool for assessing tooth-to-tail cost consequences. To accomplish this task, we apply a BN approach to capture the uncertainty in the decision environment. Bayesian networks are becoming an increasingly popular tool for modeling uncertainty [341] and also provide for multiple forms of reasoning, which allows us to update our knowledge in light of new evidence within the decision environment. This research illustrates that BNs are well suited to model the tooth-to-tail policy implications.

Third, consequently to introducing BNs into the tooth-to-tail discussion, we also introduce BNs into the greater cost analysis domain. This contribution has the potential to expand the cost modeling capabilities across a wide variety of cost analysis practices; providing a means for expansion within this body of knowledge. Section 6.6 discusses this potential expansion in greater detail to, hopefully, drive future research.

6.3 Defining the Tail

As Boehmke et al. [4] pointed out, the term *"tail"* has, historically, been used ambiguously. As a result, its important that we provide some context around the cost categories focused on within this research. Tail costs represent mission support costs which *cannot* be attributed directly to a weapon system. Across the greater AF, these costs can often capture a wide variety of activities which may include general research and development (R&D) initiatives, training, infrastructure sustainment & recapitalization, medical support[29], installation support, and numerous other categories.

For purposes of this research, we narrow the aperture of the tail to the following cost categories[30]:

- **Indirect Mission Operations:** Includes support activities more directly related to mission operations such as air traffic control, vehicle fleet management and maintenance, and flight line security.

- **Supply Operations:** Includes general shipping, transportation, and supply processing of goods such as fuel, clothing, food services, and vehicles.

- **Medical Operations:** Includes routine medical, preventative health, dental, and veterinarian services.

- **Base Services:** Includes law enforcement and personnel support services (i.e. in/out-processing, customer pay, travel vouchers, base passes, and Identification Cards).

- **Administration:** Includes the command functions at an installation and the supporting staff functions serving the command (i.e. financial management, public affairs, legal, etc.)

- **Morale, Welfare, and Recreation:** Includes chaplain services, community centers, recreation services, family care, and dining services.

- **Military Personnel:** Includes all military personnel providing support services[31].

[29] While DoD medical support is provided under the Defense Health Program (DHP), the AF bears most of the direct cost burden while DHP costs are more representative of administrative costs [339]. As a result, the AF cost burden for medical support are captured in AF cost databases.

[30] These cost categories represent functional categories provided in the indirect online analytic processing data cube within the Air Force Total Ownership Cost (AFTOC) database.

[31] The cost of military personnel is captured in a separate accounting code. As a result, although military personnel will provide supporting roles in each of the previously itemized categories, the cost of these services cannot be directly

These categories generally reflect the the costs associated with resources and services provided to operational force personnel to support the performance of their day-to-day tasks. These costs are often referred to as base operating support (BOS); however, we also include costs associated with activities that are conventionally outside the BOS umbrella such as indirect mission operations. These seven cost categories are likely to represent support resources that may be most directly impacted by changes to the operational force structure at an installation.

We excluded cost categories such as facility sustainment, military construction, utilities, and engineering support as these categories generally reflect resources and services provided to support the facility infrastructure at an installation. These services are, generally, not impacted unless infrastructure is removed from an installation (i.e. demolition), which is generally not the case when general force structure reduction activities take place[32]. Furthermore, we exclude support costs that are categorized as headquarters and *"Other"* as these categories generally represent costs associated with tenant units (i.e. U.S. Central Command Headquarters, National Oceanographic and Atmospheric Administration's Aircraft Operations Center, etc.) and temporary units on loan from Air Force staff level that may not be permanently stationed at the base.

Ultimately, for purposes of this research, we seek to provide decision-makers a decision support tool that allows them to assess policy impacts on the support costs most directly, and most likely, impacted by changes to operational forces. We justify the selection of the seven identified cost categories based on this purpose; however, we acknowledge that these costs likely do not represent an exhaustive list of the support categories facing potential tooth-to-tail cost consequences.

attributed to the categories and can only be accounted for separately. In contrast, civilian personnel costs associated with the previously listed categories are captured within those cost categories.

[32]These resources are generally planned and programmed for in the AF budgeting process by using mathematical formulae built around the Plant Replacement Value (PRV) of a base. As a result, unless the PRV changes by way of facility removal, expansion, or remodel, the planning factors will remain relatively unchanged when developing their budgetary needs. For more, see the review provided by R.C. Cole [342]

6.4 Assessing Tooth-to-Tail Relationships with Regression Analysis

We now move the discussion to identifying the fixed and variable relationships between the tooth and tail. The purpose of this step is to identify the variable relationship between force structure and support costs, which we can then incorporate into the decision support tool.

6.4.1 Methodology.

To assess these relationships we apply a series of regression models that specify support costs as the dependent variables, force structure variables as the predictor variables, and various control variables.

For the dependent variables we separate total support costs into two categories. The purpose for this is two fold. First, many system changes and revisions to the AF accounting structure for support costs have been made over the years. As a result, analyzing the seven support cost categories individually will not provide an accurate assessment of trends and patterns; however, assessing them across all the categories will provide an accurate analysis of the aggregate relationships[33]. As a result, we separate support costs into *i*) personnel costs and *ii*) discretionary costs. This provides the second purpose: to provide decision-makers additional fidelity when deciding on resource management. This allows decision-makers to assess tooth-to-tail impacts to the largest indirect cost category - *personnel* [338]. As a result, decision-makers will have a better idea of the amount of support personnel that will be impacted by the force structure changes. The second dependent variable category will capture the other costs associated with providing these support services (i.e. supplies, equipment, travel, etc.) which we call *discretionary*.

On the other side of the equation, we assess multiple independent variables. For slope predictor variables we assess the three primary activities and resources that make up the tooth: *i*) the number of operational force personnel, *ii)* the number of weapon system assets at a base (number of aircraft, intercontinental ballistic missiles, etc.), and *iii*) flying hours which represent the usage of the weapon system assets. We also assess the applicability of using control variables to account for differences in individual installations and fiscal years.

[33] As an example, several subcategories which fall under the purview of *Base Services* and *Supply Operations* have been re-aligned to the *Indirect Mission Operations* over multiple years.

In the course of our analysis we assessed multiple forms of linear specifications to assess the adequacy of logarithmic transformations to account for heteroskedasticity. Furthermore, we assessed for potential concerns with correlated residuals which may result from a nested data structure that can occur and drive the need for a random effects model [4; 338].

6.4.2 Data.

The data set used for this analysis originates from the Air Force Total Ownership Cost (AFTOC) database. The support costs were extracted from the *Indirect* data cube within AFTOC in which further selection of the functional categories previously outlined in section 6.3 were made. To further separate these into *personnel* and *discretionary* costs we used Element of Expense and Investment Codes (EEICs) which allows us to isolate civilian and military personnel costs, leaving the remaining costs as discretionary. The force structure variables were extracted from the *CAPE14 Weapon System* data cube within AFTOC.

Within our analysis we sought to provide an adequate example to illustrate the A-10 dilemma. Furthermore, our focus is on the tooth-to-tail impact at normal operational bases. By normal, we mean a base that primarily serves an operational role. As a result, we focused on AF installations that adequately represent this role which excluded bases which have a significant role relating to Major Command headquarters, tenant headquarters (i.e. U.S. Central Command), and Air logistics centers. This resulted in a dataset that captured 36 U.S.-based Active Duty AF installations for fiscal years (FY) 1996-2014 resulting in 679 observations[34]. Further filtering was performed to exclude costs and resources associated with overseas contingency operations (OCO) funds, transportation working capital funding[35], and any additional funding not associated with AF appropriations. All costs were adjusted to account for inflation and represent 2014 base-year dollars[36].

[34]Note that one base only had available data from 2001-2014; however, all other bases had data available for all 19 years assessed.

[35]The removal of these sources of funding reduces the influence of war-time contingency funding and focuses on the base budget impacts of permanently stationed personnel and activities at AF installations [5; 339].

[36]2014 Office of the Secretary of Defense (OSD) inflation indices were used to adjust costs for inflation.

6.4.3 Results.

By iteratively testing a range of regression models, with each iteration assessing a combination of specified predictor and control variables, we were able to isolate the models that indicated the best performance of cost drivers for each support cost category (*personnel* support costs and *discretionary* support costs). We assessed the overall fit of the model as measured by the F-statistic and adjusted R^2 as an initial indication of model performance. We then performed residual diagnostics to assess the adequacy of the model and verification of meeting linear regression assumptions.

We identified that heteroskedasticity was a valid concern and, furthermore, we found that a log-linear regression form provided the greatest control over this lack of constant variance. In addition, we found that incorporating control variables for the base and year of observation improved model fit and residual diagnostics. As a result, our basic econometric form is illustrated in equation 6.1 where y represents the support cost category under investigation, x the force structure variable being assessed, γ the control variable for base i, and τ the control variable for fiscal year i.

$$log(y_i) = \beta_0 + \beta_1 x_i + \beta_2 \gamma_i + \beta_3 \tau_i + \epsilon_i \tag{6.1}$$

Our regression analysis revealed that the number of operational force personnel at a base provided the strongest model performance for both personnel and discretionary support cost categories. This predictor variable not only provided the strongest model performance for each support cost category but it was also the only predictor variable that was statistically significant (p-value < 0.05) for both support cost categories. Moreover, investigation of the residuals suggest this predictor variable was the only one that consistently satisfied the linear regression assumptions.

We found that total weapon system assets at a base was not statistically significant in predicting personnel support costs but was statistically significant (p-value $= 0.0069$) in predicting discretionary support costs. In contrast, we found that total flying hours at a base was statistically significant (p-value $= 0.029$) in predicting personnel support costs but not statistically significant in predicting discretionary support costs. Furthermore, in the scenarios in which these two predictor variables were statistically significant, residual diagnostics indicated signs of non-normality and, in addition, residual correlation nested by base and year. These residual concerns suggest the potential of biased standard errors for the coefficients terms which may lead to an overly optimistic p-value statistic. These results are consistent with previous research by Boehmke et al. [338].

The optimal regression models are displayed in Table 6.1. For brevity, we only display the coefficient parameters and statistics for the intercept (β_0) and predictor variable (β_1), which for both models corresponds to the influence that number of operational force personnel has on support costs. Furthermore, residual diagnostics are provided in Appendix K.

Table 6.1: Regression Analysis Results

Panel A: Results for Personnel Support Cost Model

Term	Estimate	Std Error	Lower 95%	Upper 95%	p-value
β_0	18.705	0.025	18.655	18.754	$p < 0.0001$
β_1	5.346e-5	7.959e-6	3.783e-5	6.910e-5	$p < 0.0001$

Fit Summary: adj. $R^2 = 0.94$; RMSE = 0.087; F Ratio = 477.82 (< 0.0001)

Panel B: Results for Discretionary Support Cost Model

Term	Estimate	Std Error	Lower 95%	Upper 95%	p-value
β_0	18.046	0.0659	17.916	18.176	$p < 0.0001$
β_1	4.255e-5	2.100e-5	1.493e-6	8.361e-5	$p = 0.0423$

Fit Summary: adj. $R^2 = 0.85$; RMSE = 0.229; F Ratio = 84.63 (< 0.0001)

To provide interpretation of these results we will go into further detail with the personnel support cost model (Table 6.1 Panel A). This model had an adjusted R^2 of 0.94 and both parameters of interest are statistically significant at the $p < 0.0001$ level. The β_0 term represents the y-intercept of our model. With regards to our problem this can be interpreted as the approximate level of fixed costs at an installation. The average fixed costs across our sample set is \$132,885,711 ($e^{18.705} \approx 132885711$). In other words, on average, the minimum cost of personnel required to run bare minimum levels of support services at a base is approximately \$132.9M. However, we should be cautious in extrapolating outside the boundaries of our data, as no bases in our sample experienced operational force personnel levels equal to zero, although a few scenarios in which bases had minimal operational levels did provide a fair level of assurance in this fixed cost interpretation[37].

The β_1 term represents the variable component of support costs. In our log-linear model form this can be interpreted as the percent change in personnel support costs for any 1-unit change in the number of operational force personnel. For example, if a particular installation has a current personnel support cost level of $223,380,846, a reduction of 500 operational personnel results in a reduction of approximately $5,971,193.

The high adjusted R^2 value is worth a short discussion as this can often cause concern. First, the most common reason for exaggerated R^2 values is from overfitting; however, our minimalistic model provides for sufficient degrees of freedom to guard against overfitting. Second, to guard against the possibility of an over-trained model in which the model begins to "memorize" training data rather than "learning" to generalize a trend, we performed two sets of validations in which the same models were trained on a random subsample of our dataset (50% and 70%) and then validated on the remaining test set. In both instances similar model performance was achieved between the training and test sets and, furthermore, the parameter results aligned with the full model results. A third concern can come from biased coefficient standard errors. This is common when residuals are correlated; often a result from a nested data structure. To assess this concern we validated that residuals were not correlated when nested by base or year. Furthermore, we tested a multilevel model in which random effects allowed the slope to vary by base; however, the results validated that there are no concerns of a nested data structure. Approaching the high R^2 concern from a more theoretical perspective, the most likely reason is the fact that the AF develops much of its installation support manpower requirements based on manpower standards and mathematical formulae which calculate manpower needs based, in part, on installation population[38] [339]. As a

[37] i.e. Due to the 2005 Base Realignment and Closure process Grand Forks AFB lost its primary operational mission. As a result, the level of force structure reduced drastically from 2005-2012 to near zero levels.

[38] For more information the reader can reference Air Force Instruction 38-201, *Management of Manpower Requirements and Authorizations*, Washington, D.C., September 26, 2011.

result, our model likely represents an adequate surrogate for the underlying formulae used by the AF.

6.4.4 Applying the Results.

The results of this analysis can be applied by decision-makers to assess the tooth-to-tail cost consequences for the A-10 situation. For example, we will assess the potential cost savings as a result of eliminating A-10 operational force personnel from three different installations. Furthermore we can assess multiple levels of proposed personnel reductions (10%, 25%, 50%, 75%, 100%) at each of these bases. The results are provided in Table 6.2 and represent actual level of activities at three AF bases. In 2014 the number of A-10 operational forces at these three bases represented 42%, 8%, and 25% of the total operation force population respectively.

Table 6.2: Force Reduction Assessment for A-10 Scenario

			Personnel Support Costs			Discretionary Support Costs		
Installation	A-10 Policy Options	Reduction of A-10 Personnel	2014 Costs	Fixed Cost Component	Variable Cost Reduction	2014 Costs	Fixed Cost Component	Variable Cost Reduction
Base 1								
	10%	213	$ 223,380,846	$ 189,051,155	$ 2,537,757	$ 102,809,484	$ 85,175,211	$ 929,656
	25%	531			$ 6,344,393			$ 2,324,140
	50%	1063			$ 12,688,786			$ 4,648,280
	75%	1594			$ 19,033,179			$ 6,972,420
	100%	2125			$ 25,377,572			$ 9,296,560
Base 2	10%	45	$ 393,292,817	$ 230,750,062	$ 941,975	$ 165,726,535	$ 150,612,519	$ 315,937
	25%	112			$ 2,354,937			$ 789,842
	50%	224			$ 4,709,873			$ 1,579,684
	75%	336			$ 7,064,810			$ 2,369,526
	100%	448			$ 9,419,747			$ 3,159,368
Base 3	10%	95	$ 157,980,095	$ 130,679,328	$ 801,519	$ 81,286,023	$ 68,745,442	$ 328,256
	25%	237			$ 2,003,797			$ 820,639
	50%	475			$ 4,007,595			$ 1,641,278
	75%	712			$ 6,011,392			$ 2,461,918
	100%	949			$ 8,015,189			$ 3,282,557

For explanatory purposes we walk through the data for Base 1. In FY 2014 this base housed 2,125 A-10 operational personnel[39]. The total personnel support cost for FY 2014 was \$223M and the results from our econometric model suggest that \$189M represent the approximate fixed costs for this support category at this installation. Removal of A-10 personnel in the range of 10-100% at this base is predicted to result in support personnel cost reductions ranging from \$2.5-25.4M respectively and discretionary support cost reductions ranging from \$0.9-9.3M respectively.

[39]Total operational personnel captures enlisted member, officers, and civilians.

However, this simplistic approach to assessing tooth-to-tail policy implications assumes a level of certainty within the decision-making environment.

First, it assumes a static reduction in A-10 personnel across all three bases. Significant policy decisions are often driven by organizational and political influences. As a result, set levels of reductions across bases are generally not assumed in the early phases of policy assessment. An adequate decision tool should allow for assessment of this level of uncertainty around how many A-10 personnel will be reduced from each base.

Second, it assumes no changes in the other weapon system operational personnel that are stationed at a base. During the early phases of policy assessments, changes in other programs are often uncertain so the net change in operational personnel at a base is indefinite. For example, at Base 1, the historical fluctuation in *non* A-10 operational personnel has ranged from a 5% reduction to a 16% increase. An adequate decision tool should allow for assessment of this level of uncertainty around the net operational personnel population of each base.

Third, it does not illustrate the level of uncertainty around the predicted cost reduction. Although confidence levels of the variable cost reduction could be provided for each example, this often becomes burdensome when many scenarios are being assessed due to the copious amounts of numbers being digested by decision-makers. An adequate decision tool should allow for an appropriate visual assessment of this level of uncertainty around the predicted support cost reductions.

To provide decision-makers with a tooth-to-tail decision support tool that addresses these concerns we now introduce Bayesian networks into the decision-making environment.

6.5 Bayesian Networks

Bayesian networks are a well established method for reasoning under uncertainty by combining *i*) a graphical structure to represent causal relationships and *ii*) probability calculus to quantify these relationships and update beliefs given new information. Their application has crossed a wide range of domains (see Korb and Nicholson [343] for a recent survey); however, they have remained relatively elusive in the field of cost analysis and resource management. In this section we will first outline the properties of BNs followed by an illustration of their application in modeling tooth-to-tail impact analyses.

6.5.1 Bayesian Network Properties.

Bayesian networks are a class of graphical models that allow a concise representation of the probabilistic dependencies between a given set of random variables $T = \{\tau_1, \tau_2, \ldots, \tau_n\}$ as a directed acyclic graph (DAG) $G = (\Theta, A)$ where each node $\theta_i \in \Theta$ corresponds to a random variable τ_i [344]. Furthermore, for T to be a BN with respect to G it must satisfy the local Markov property such that each variable is conditionally independent of its non-descendants ($\tau_{nde(i)}$) given its parent variables ($\tau_{pa(i)}$) expressed as $\tau_i \perp\!\!\!\perp \tau_{nde(i)} \mid \tau_{pa(i)}$ [345]. This is more generally referred to in BN literature as d-separation[40] whereas two distinct variables τ_A and τ_B are d-separated if for all paths between τ_A and τ_B there is an intermediate variable τ_C. If τ_A and τ_B are not d-separated then they are d-connected.

Given all variables in T are conditionally independent, the probability of T can be calculated from the conditional probabilities such that:

$$P(T) = \prod_{i=1}^{n} P(\tau_i | \tau_1, \ldots, \tau_{i-1}) \tag{6.2}$$

Therefore, if BN_T is a Bayesian network over T, a unique joint probability distribution $P(T)$ can be specified by the product of all conditional probabilities specified in BN_T such that:

$$P(T) = \prod_{i=1}^{n} P(\tau_i | pa(\tau_i)) \tag{6.3}$$

where $pa(\tau_i)$ are the parent nodes of τ_i in BN_T.

Furthermore, as new knowledge presents itself, posterior probabilities can be computed by inserting evidence via instantiation. This is often referred to as belief updating or probabilistic inference [343]. If variable τ_i has l states with $P(\tau_i) = (\tau_i^1, \ldots, \tau_i^l)$ and evidence is available that τ_i is in $n < l$ states we can annotate this as evidence $\mathbf{e}$. Additionally, evidence may become available

[40] Originally termed by Pearl [346] as a graphical criterion, d-separation refers to direction-dependent separation.

for multiple nodes such that $\mathbf{e} = \mathbf{e}_1, \ldots, \mathbf{e}_m$. Consequently, posterior probability for T can be computed with equation 6.4

$$P(T, \mathbf{e}) = \prod_{\tau \in T}^{n} P(\tau_i | pa(\tau_i)) \cdot \prod_{i=1}^{m} \mathbf{e_i} \tag{6.4}$$

and the posterior probability for variable $\tau_i \in T$ is illustrated in equation 6.5

$$P(\tau_i \mid \mathbf{e}) = \frac{\sum_{T \backslash \{\tau_i\}} P(T, \mathbf{e})}{P(\mathbf{e})} \tag{6.5}$$

where $P(T \backslash \{\tau_i\})$ is the prior likelihood. As a result, values of any combination of nodes in BN_T can be set and this newly inserted evidence propagates through the network, producing a new probability distribution over all the variables in the network[41] [348].

To illustrate, Figure 6.1 represents a theoretical naïve BN where δ represents a common cost driver for the installation support activity costs (IS_i) at bases $1, 2, \ldots, n$ and the arrows (commonly referred to as arcs) represent the direction of influence. Using previously defined parameters we can say this represents BN_T where $T = \{\delta, IS_1, IS_2, \ldots, IS_n\}$ and relationships between the variables, as portrayed by the arcs between variable nodes, satisfy the conditional independence requirement.

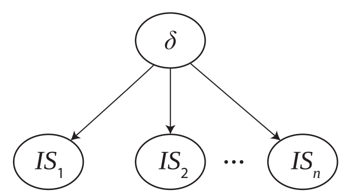


Figure 6.1: Theoretical Naïve Bayesian network

As a result, we can express the conditional probabilities for the cost of IS_1 by calculating $P(IS_1|\delta)$ for every possible state of the parental variable δ. Furthermore, as certain knowledge, or evidence ($\mathbf{e}$), of the observed cost driver are obtained, posterior probabilities of installation support costs are obtained by calculating $P(IS_i \mid \mathbf{e}) = \sum_{T \backslash \{IS_i\}} P(T, \mathbf{e}) \div P(\mathbf{e})$.

[41] There are a number of of efficient exact and approximate inference algorithms for performing this probabilistic updating. For more detail on these algorithms see Korb and Nicholson [343], Pearl [346], or Nielsen and Jensen [347]

6.5.2 *Tooth-to-Tail Impact Analysis with Bayesian Networks.*

With the semantics of BNs established, we can now illustrate their applicability as a decision support tool for tooth-to-tail impact analysis.

Framework for Tooth-to-Tail Bayesian Network. We continue with the previously used A-10 example introduced in section 6.4.4. The graphical structure of the the BN for our decision environment is illustrated in Figure 6.2. The root node of this model is the decision node under investigation. In our example this represents the potential levels of A-10 personnel reductions under consideration. This decision will cause a direct impact on the total number of AF-wide A-10 personnel reductions which, in turn, influences the number of A-10 reductions at each of the three bases being assessed. The number of A-10 personnel reductions at each base will influence the number of total operational force personnel at each base; however, changes in *non* A-10 personnel will also influence the total operational force personnel node. Lastly, the net effect of total operational force personnel will cause an impact to both personnel and discretionary support costs.

Inputs for the Bayesian Network. The following provides more details on each node:

- **Decision:** As in our earlier example, the decision being considered is the reduction of AF-wide A-10 personnel. We consider five levels of reduction: 10%, 25%, 50%, 75%, and 100%.
- **A-10 Reduction:** Represents the direct impact of the decision chosen. Assuming a total A-10 workforce of 6,539 a decision to reduce personnel by 10%, 25%, 50%, 75%, and 100% will result in AF-wide reductions of 654, 1635, 3270, 4904, and 6539 respectively.
- **Base *i*: A-10 Reduction:** Represents the potential impact that AF-wide A-10 reductions have on the level of A-10 personnel at each of the three assessed bases. For simplicity we assume the level of reduction at each base will be approximately relative to the historical ratio of AF-wide A-10 personnel assigned at each of the bases (i.e. Base 1 has historically housed 42% of the A-10 fleet. As a result, we assume any reductions will be made in a

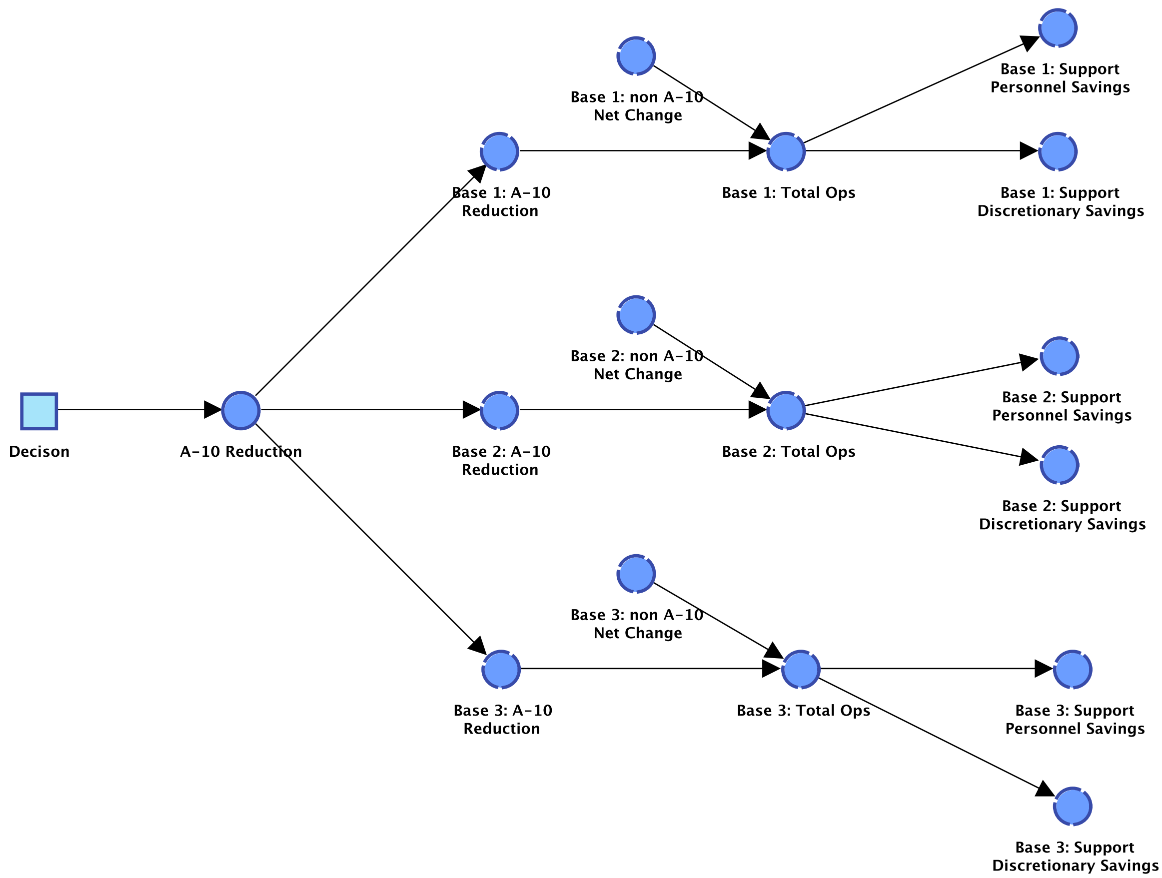


Figure 6.2: Framework for Tooth-to-Tail Bayesian Network

manner that maintains this relative ratio.). However, to capture uncertainty around this ratio we apply a Monte Carlo simulation to generate a range and distribution which allows the level of reductions at each base to very from their historical ratios.

- **Base *i*: Non A-10 Net Reduction:** Represents the potential *reduction* in *non* A-10 personnel at each of the three assessed bases. To capture uncertainty in this parameter we assess the historical percent changes made to *non* A-10 operational personnel at each base. We use the Monte Carlo simulation, to generate a range and distribution of these changes.

- **Base *i*: Total Ops:** Represents the net total operational force personnel assigned at each base. Using the Monte Carlo simulation results for the previous two nodes, this node sums the net effects of total A-10 personnel remaining at Base *i* and the total *non* A-10 operational personnel.

- **Base *i*: Support Personnel Savings:** As a result of the *Total Ops* node, we leverage the regression analysis results from section 6.4.3 to predict the reduction in personnel support costs at each base as compared to 2014 actual costs. Furthermore, using the point estimate and standard error of the β_1 coefficient in Figure 6.1: Panel A, we allow the slope to vary in our Monte Carlo simulation to account for the uncertainty around the relationship. These nodes are represented in fiscal year 2014 million dollars.

- **Base *i*: Support Discretionary Savings:** As a result of the *Total Ops* node, we leverage the regression analysis results from section 6.4.3 to predict the reduction in discretionary support costs at each base as compared to 2014 actual costs. Furthermore, using the point estimate and standard error of the β_1 coefficient in Figure 6.1: Panel B, we allow the slope to vary in our Monte Carlo simulation to account for the uncertainty around the relationship. These nodes are represented in fiscal year 2014 million dollars.

We applied a Monte Carlo simulation that sampled 1000 iterations for each of the decision levels resulting in dataset totaling 5000 observations. The parameters and distributions applied to each node for the Monte Carlo simulation are further documented in Appendix L.

With our BN framework established and dataset generated we can now use the BN to illustrate the conditional probabilities across our decision environment. Figure 6.3 displays the conditional probabilities for each node prior to any decision being made or evidence instantiated. The CPTs for the continuous variables have been discretized into five ranges using *k*-means clustering. The discretized ranges are displayed on the right side of the node and the probability for each range is on the left side of the node. For example, taking a closer look at the node *Base 3: Support Personnel Savings* in Figure 6.4, we see that prior to any of the possible decisions being made, the mean potential savings achieved is \$3.1M with the greatest likelihood of savings ranging from \$0-2.9M (34% probability) followed by \$3-6.9M (23% probability). Although generally informative,

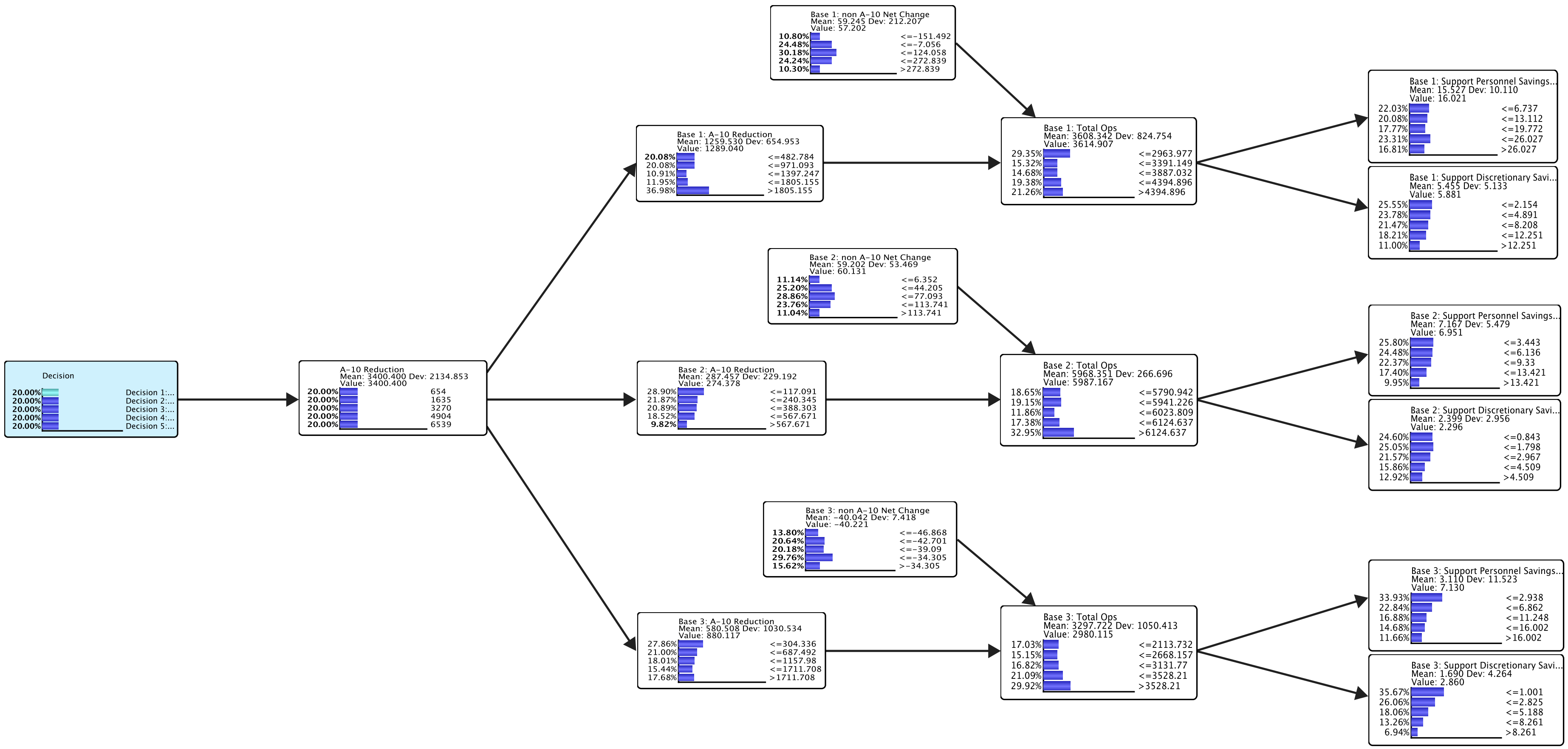


Figure 6.3: Bayesian Network for A-10 Example

the principal advantage of BNs is in their ability to revise probabilities in light of new information. We will now illustrate how decision-makers can use BNs to update their knowledge on possible tooth-to-tail impacts.

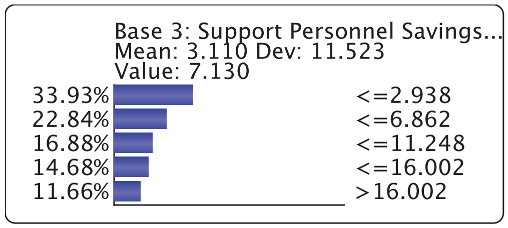


Figure 6.4: Conditional Probability Table for *Base 3: Support Personnel Savings* Node

Predictive Reasoning. Also referred to as deductive or causal reasoning, predictive reasoning allows for decision-makers to instantiate evidence on the decision under investigation and assess the posterior probabilities of potential support cost savings. This allows us to predict the posterior probability distribution of the installation support cost reductions in light of the policy decision options and the uncertainty surrounding the changes in operational personnel at each base; providing informative insights to decision-makers regarding tooth-to-tail consequences from the policy decision made.

We can illustrate by instantiating the decision to reduce AF-wide A-10 personnel by 50%. Figure 6.5 displays the updated CPTs for each node. The arrows within the CPT bars illustrate the direction and magnitude of changes to the nodes influenced by this decision. For instance, this reduction suggests Base 1 will most likely experience a reduction of 1,371 A-10 personnel with a high probability of the losses falling in the range of 971-1,805 personnel. This high probability is a result of this base, historically, being a primary base for A-10 aircraft and personnel so any substantial decrease in A-10 resources will likely have an impact on this base. Note that the *non A-10 Net Change* nodes are unaffected by the decision illustrated by no change in their CPTs. However, the uncertainty around the potential changes in *non* A-10 personnel continue to influence the posterior probabilities of the *Base 2: Total Ops* nodes. As a result of the proposed policy decision, and no other information known, the total operational force population at Base 1 will likely fall in the range of 3,391-3,887 ($mean = 3,523$). This decision causes a *potential* reduction in both personnel and discretionary costs of $17.98M and $6.6M respectively as illustrated by the mean values noted in the *Base 1: Support Personnel Savings* and *Base 1: Support Discretionary Savings* nodes. Moreover, the CPTs illustrate to the decision-maker the level of certainty around the potential cost savings at each base. For instance, there is a greater level of certainty (as demonstrated by the higher probability) in the potential cost savings of support personnel at Base 1 than at Base 3.

We can continue this example by illustrating the ability to update our beliefs in light of new evidence. Suppose decision-makers propose the following reductions in A-10 personnel: Base 1→ 1000, Base 2→ 475, Base 3→ 1000. We can update the BN by fixing the values within these nodes, providing the decision-maker with updated CPTs for the nodes influenced by these changes. Figure 6.6 illustrates the changes in the CPTs across the BN. This proposed scenario reduces the amount of potential cost savings in both support cost categories for Base 1 as the proposed reduction of 1,000 personnel was less than the likely reduction of 1,371 prior to base-level decisions being made. In contrast, the posterior probabilities for both support cost categories at Base 2 experienced a significant shift as the proposed reduction of 475 was significantly higher than the prior probability of potential base-level reductions. Lastly, Base 3 experienced very little change in the posterior probabilities for both support cost categories. This is due to the prior probability of base-level A-10 personnel cuts closely aligning with the proposed reductions.

Lastly, let us now assume that updated evidence has surfaced that a *non* A-10 weapon system may be re-locating some of its aircraft to Base 1. As a result, a potential 150-250 additional personnel may be relocated[42] to Base 1. By further updating the *Base 1: non A-10 Net Change* node, the BN will provide updated posterior probabilities for Base 1 support cost categories. This is illustrated in Figure 6.7 which shows the greatest probability in support personnel and discretionary cost savings at Base 1 has shifted to $0-6.74M and $0-2.2M respectively.

[42]Or, as can be common, some of the personnel filling the A-10 positions being cut may be re-assigned to these new positions being created.

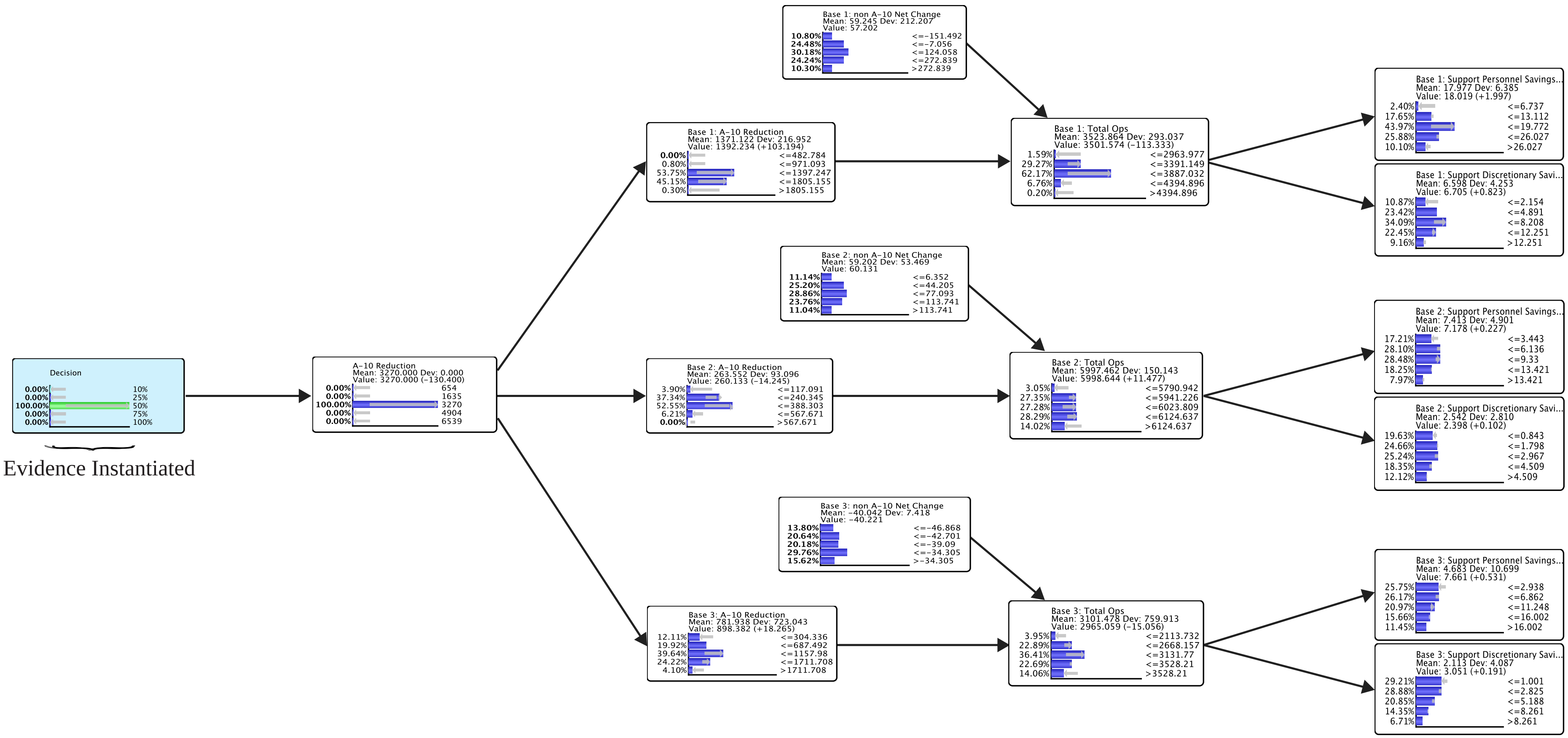


Figure 6.5: Posterior Probabilities for a 50% Reduction in AF-wide A-10 Personnel with Undetermined Cuts at Each Base

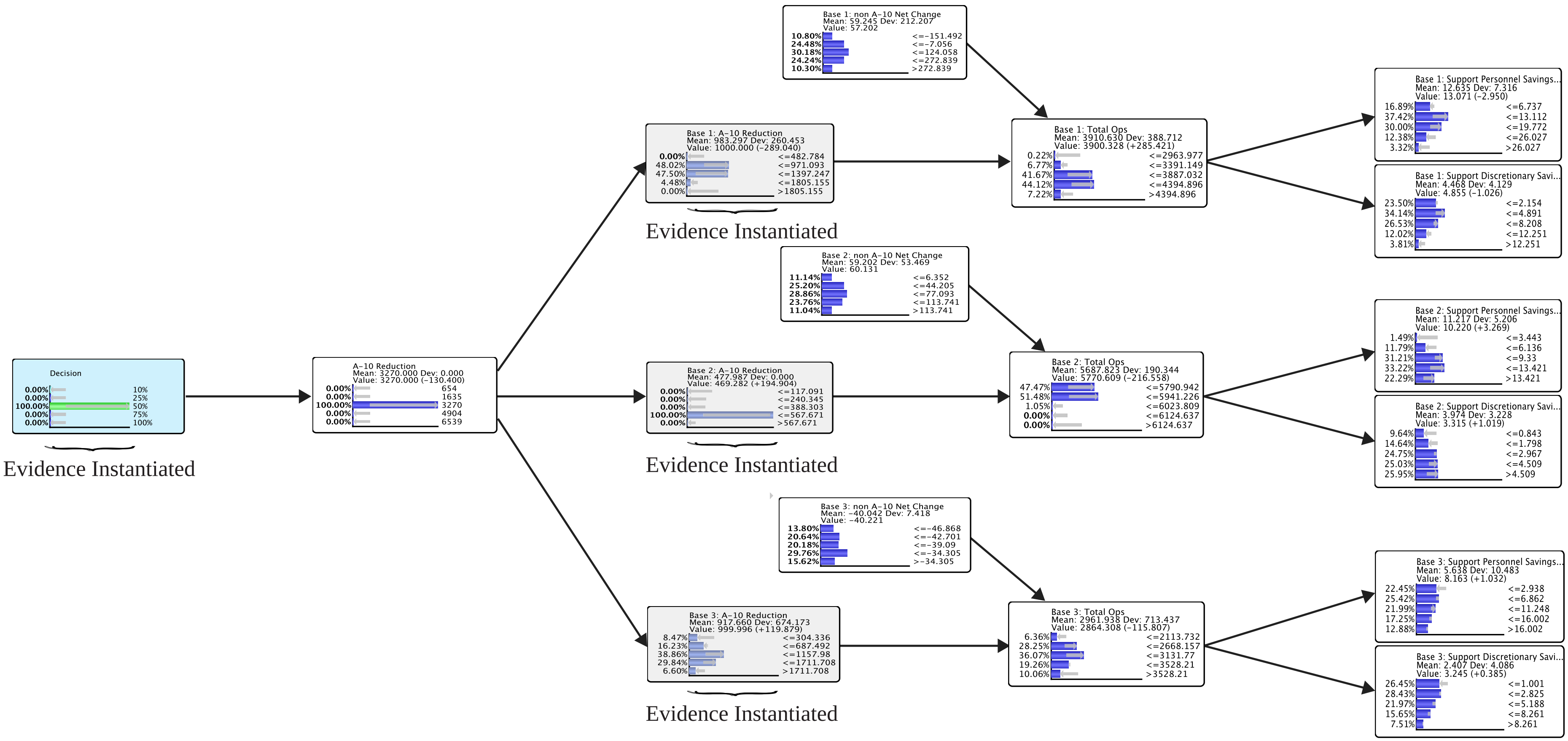


Figure 6.6: Updated Posterior Probabilities for a 50% Reduction in AF-wide A-10 Personnel with Proposed Cuts at Each Base

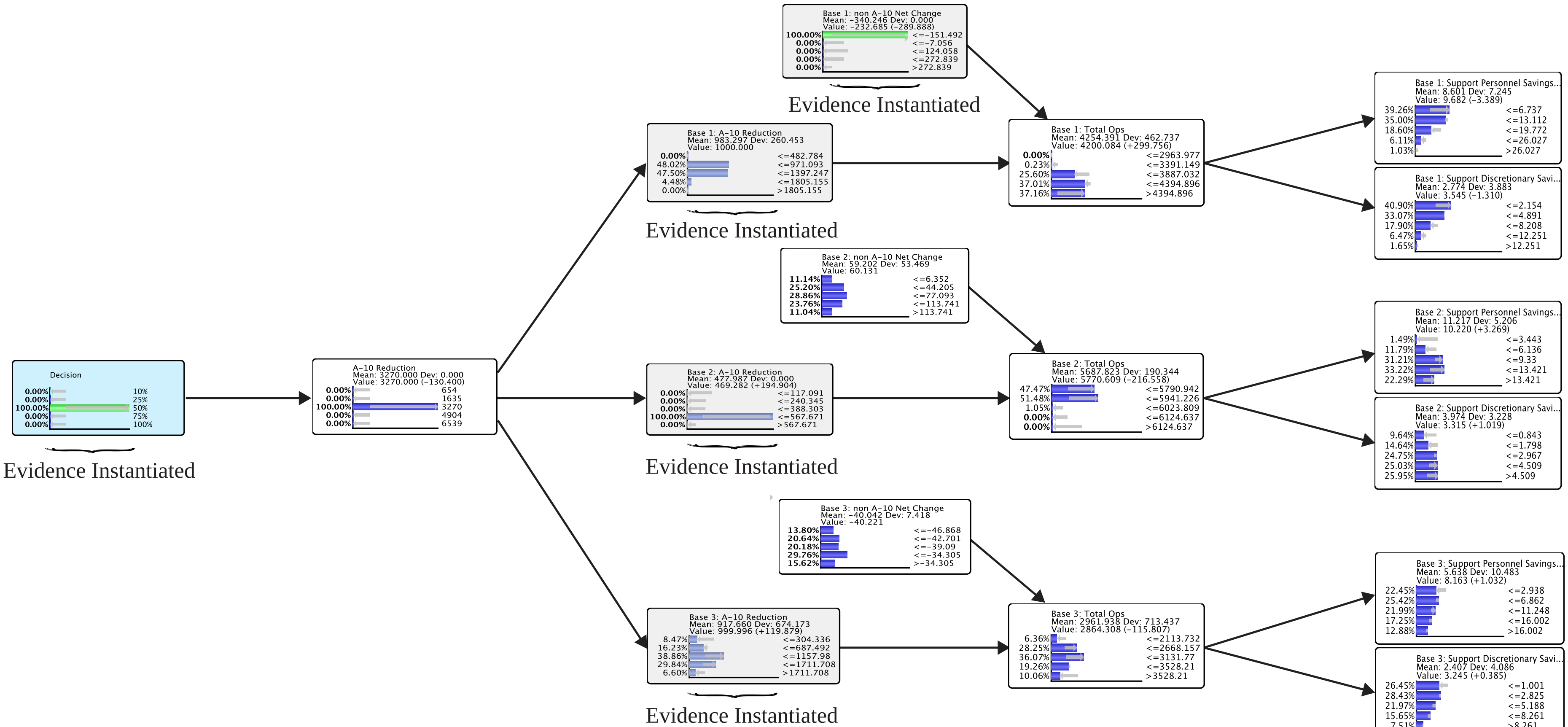


Figure 6.7: Updated Posterior Probabilities for a 50% Reduction in AF-wide A-10 Personnel with Proposed Cuts at Each Base and Updated Evidence on *Non* A-10 Personnel Changes

Diagnostic Reasoning. Another use of BNs is the ability to assess the influence that changes in support costs may have on the ability to support operational personnel. In other words, the ability to perform *tail-to-tooth* impact analysis. Whereas predictive reasoning follows the causal flow of the BN, diagnostic reasoning allows for performing inference against the causal flow.

For instance, say decision-makers have not made a decision regarding A-10 personnel reductions; however, budget constraints have been imposed on support costs independent of the tooth force structure[43]. This can be demonstrated using the following example.

Let us assume that a due to fiscal constraints the AF has imposed a 5% budget reduction for all support activities; however, no decision has been made yet on A-10 personnel reductions. As a result, we can instantiate this evidence within the support cost category nodes for each base as illustrated in Figure 6.8. The updated CPTs for the *Base i: Total Ops* nodes indicate the probability of the levels of operational force personnel that the new levels of support costs would support. In other words, a 5% reduction in support costs would likely impact the level of support provided unless the total operational force population adjusted to the most probable levels indicated in the *Base i: Total Ops* nodes. Furthermore, this impact to support costs propagates all the way back through the BN to the *Decision* node. In this instance, the *Decision* node posterior probabilities have adjusted with the most probable level of A-10 reductions being 50%. This indicates that, without any additional information, a 50% reduction in A-10 personnel best aligns the operational workforce population at these three bases to the level of support costs that can be provided.

Now let us assume that, due to political bargaining, rather than the entire A-10 fleet being removed from the AF (or even a 50% reduction) only a 25% reduction is made; however, no decision has been made on how particular installations will be impacted. Figure 6.9 illustrates the updated posterior probabilities to the base-level nodes. The results suggest that the most likely levels of A-10 reductions to be made at each base as a result of the decision, and that align with

[43]This is a realistic scenario as, historically, tail activities have been budgeted for independent of tooth activities. Furthermore, in the AF budgeting process, cuts and/or trades are often made to fiscal resources across the MAJCOMs and functions prior to front-line mission resource levels being determined. A classic example was with budget cuts due to sequestration. The Air Force made across-the-board budget cuts; as a result support activities at a particular base received cuts independent of changes made to operational force personnel at that base

the new level of support costs available, are 726, 183, and 389 for bases 1, 2, and 3 respectively. This provides decision-makers with key insights that can help drive decisions for balanced tooth-to-tail resource alignment. We can further illustrate this capability by assuming that, due to fiscal constraints, the AF has directed a hiring freeze for all programs. As a result we can instantiate the *non* A-10 reduction nodes to zero to reflect that no changes should take place[44]. Figure 6.10 illustrates the updated posterior probabilities to the non-instantiated nodes.

Most important in this scenario are the changes to the *Base i: A-10 Reduction* nodes. Any changes to these nodes reflect changes to the most probable A-10 personnel reductions at each base that aligns with the new constraints. Although substantial changes are not evident to the CPTs for these nodes, changes to the most likely value as reflected by the mean are experienced for bases 2 and 3. Base 2 experiences a relatively minor change as this new information suggests the most likely A-10 personnel reduction aligning with the decision environment constraints changed from 182 to 193. However, Base 3 experiences a more significant change in that the most likely A-10 personnel reduction changed from 389 to 263; suggesting that Base 3 has the ability to support a smaller reduction than previously believed. The reason for this is because Base 3 has consistently been growing year-to-year. By constraining this growth, the uncertainty of the magnitude of *non* A-10 operational personnel growth is reduced leading some slack in which additional A-10 personnel can fill.

6.6 Discussion and Future Work

Although not exhaustive, the examples provided illustrate the dynamic nature of BNs and their applicability as a tooth-to-tail decision support tool. However, to become a comprehensive application for enterprise-level use more empirical analysis is required. This is discussed in the subsection that follows. We then move the discussion to one that addresses the larger impacts that BNs can have on the cost analysis domain.

[44] It should be noted that Base 3 has, historically, experienced a consistent increase in *non* A-10 operational workforce every year. As a result, and even with the Monte Carlo simulation incorporating variable components to this consistent increase, the range of *non* A-10 work force reductions is remains negative implying an increase. Consequently, we instantiate the smallest increase possible for this installation.

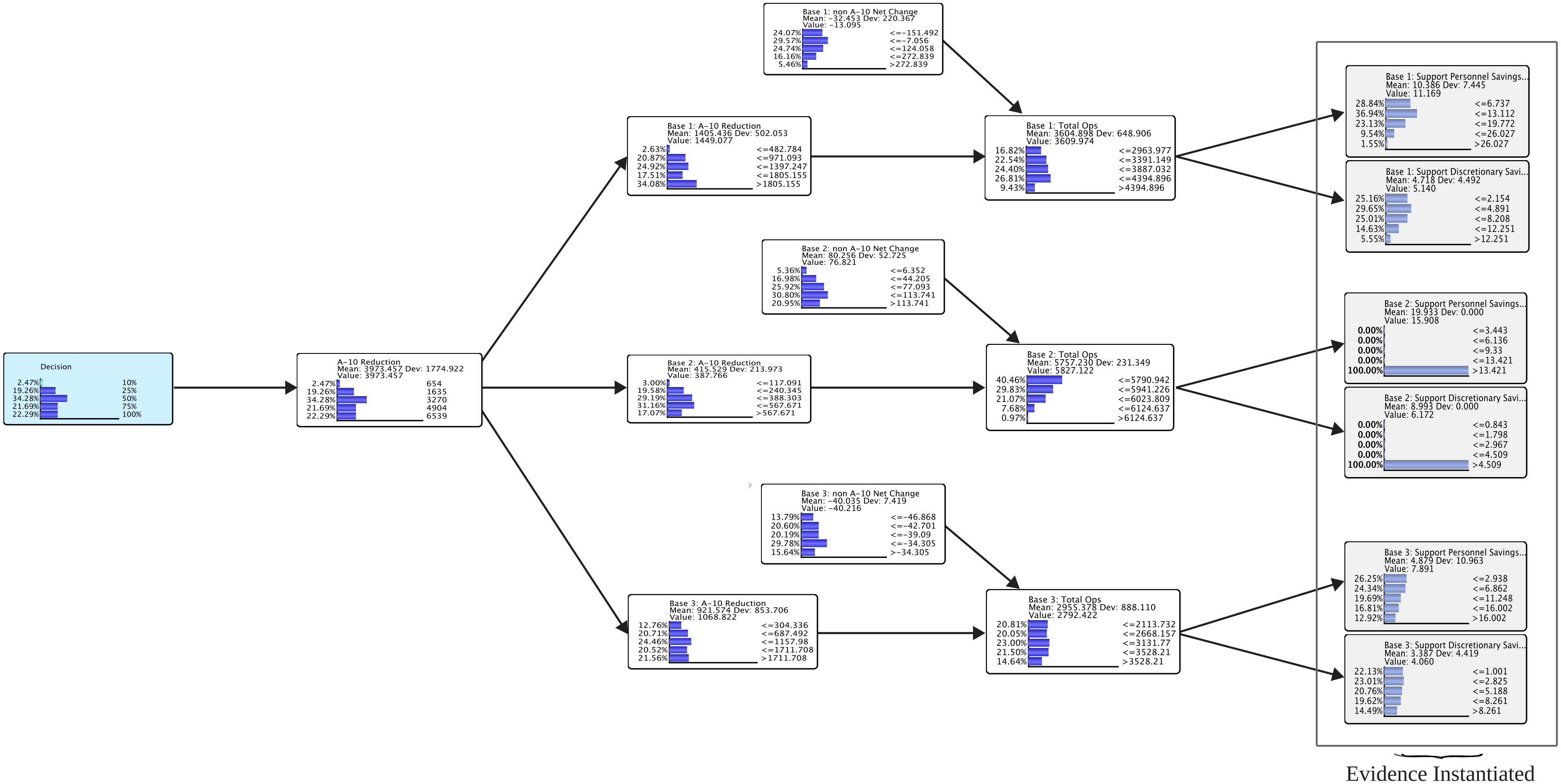


Figure 6.8: Posterior Probabilities for a 5% Reduction in AF-wide Support Costs at Each Base

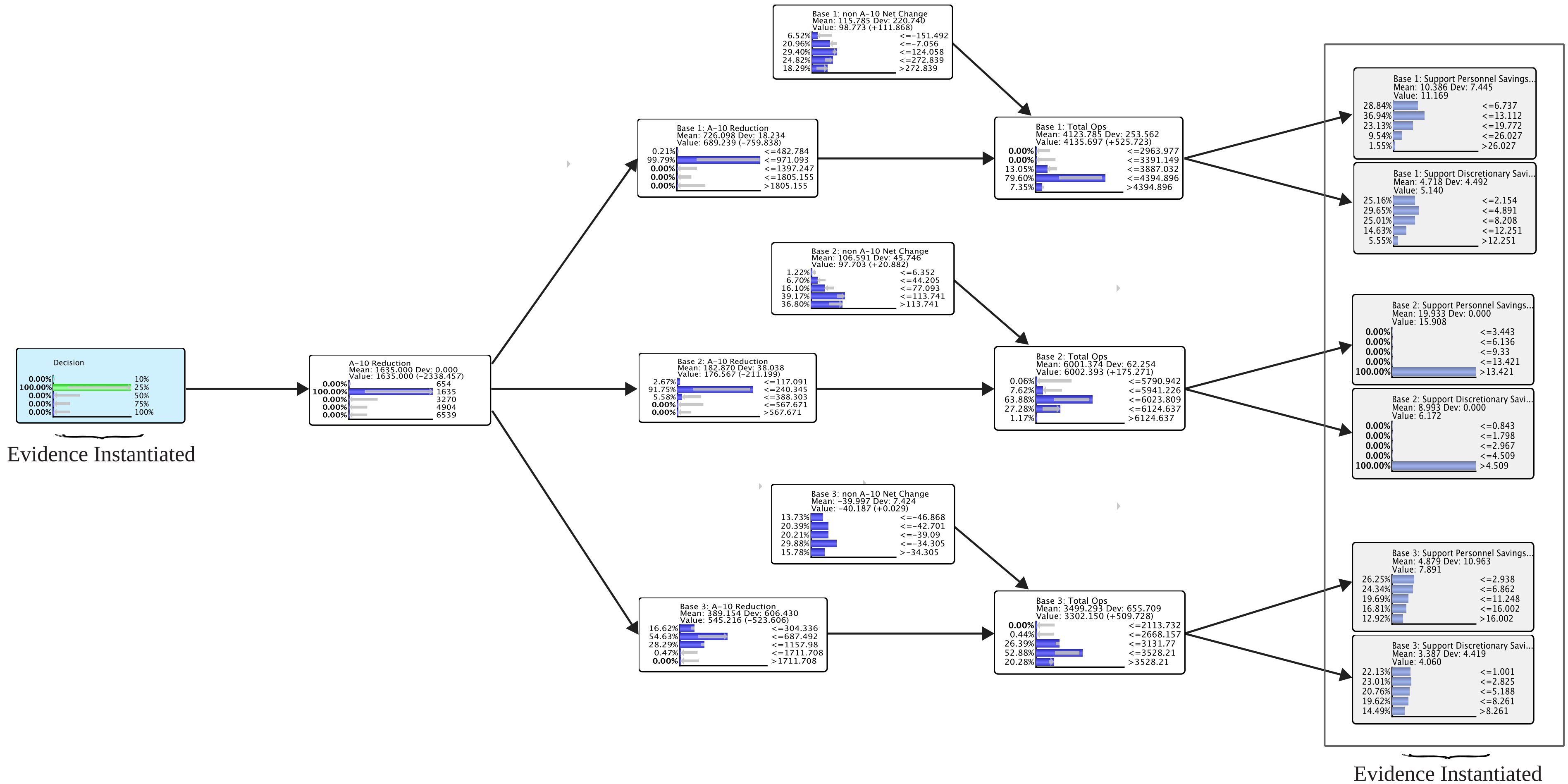


Figure 6.9: Updated Posterior Probabilities for a 5% Reduction in AF-wide Support Costs at Each Base and a 25% Reduction in AF-wide A-10 Personnel Proposed but with Undetermined Cuts at Each Base

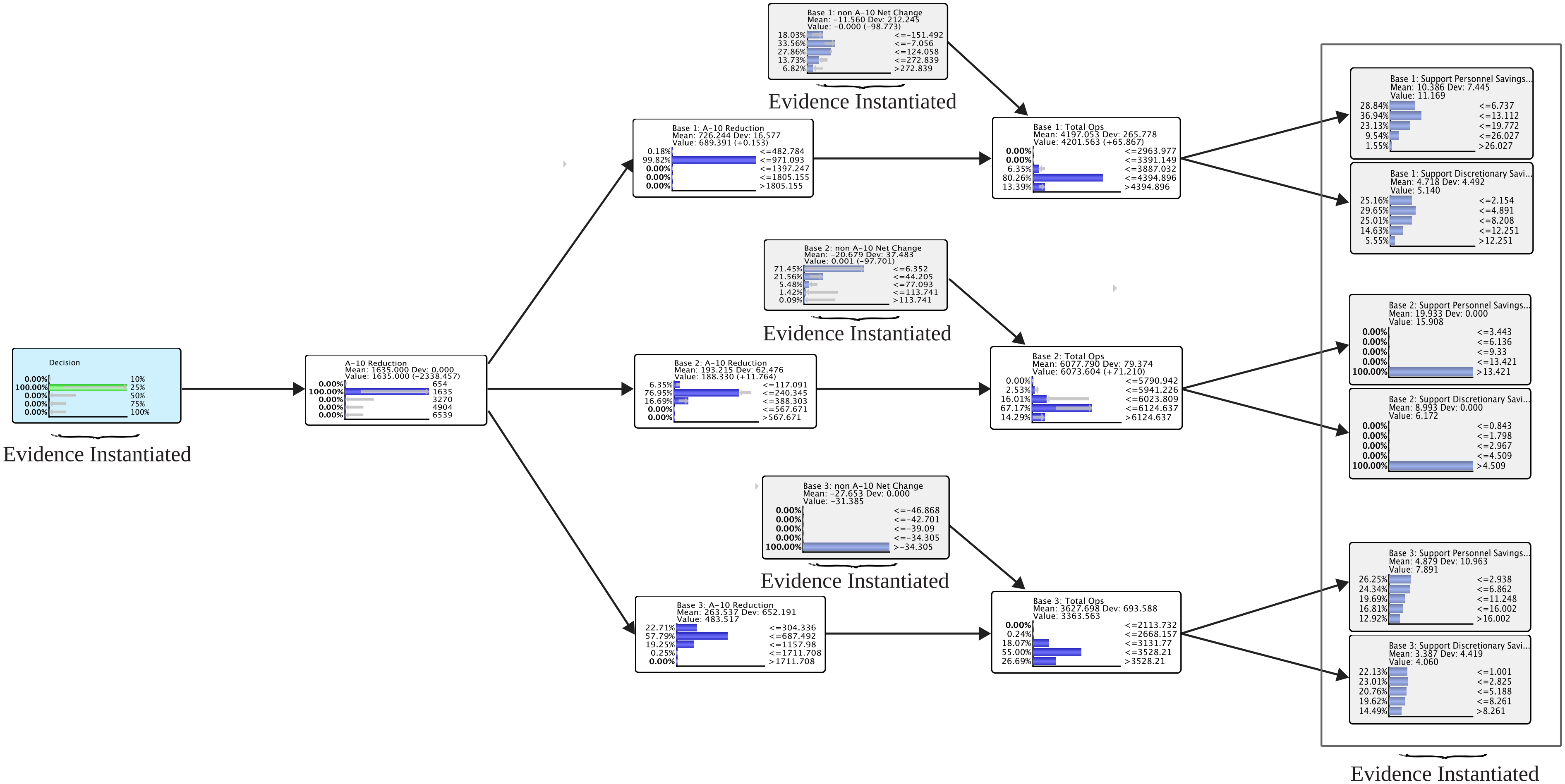


Figure 6.10: Updated Posterior Probabilities for a 5% Reduction in AF-wide Support Costs at Each Base, a 25% Reduction in AF-wide A-10 Personnel Proposed but with Undetermined Cuts at Each Base, and a Hiring Freeze on All *Non* A-10 Operational Workforce

6.6.1 *Advancing the Tooth-to-Tail Decision Support Capabilities.*

This initial research focuses only on a small subset of bases that would be impacted by the force structure considerations. To provide a comprehensive understanding of how changes to the tooth impact enterprise-wide support costs, a larger mapping of impacted bases would be required. Furthermore, with the exception of the allocation of force reductions, our research assumes independence between base-level effects. Assessing an enterprise-level mapping of base-level impacts will likely result in identification of between-base dependencies. For instance, reducing force structure will likely reduce the need to train, supply, and manage lifecycle resources for the eliminated force structure. As many of these supporting roles are performed at various bases apart from the operational base, a chain of effects could result in that reductions in operational force structure at one base could cause cascading reductions in other bases. To adequately capture these causal links a larger mapping of between-base interdependencies would need to be modeled.

In the same vein, our research assumes independence between the A-10 weapon system and the *non* A-10 weapon systems at a particular base. However, in many instances, dependencies may exist between the weapon system under investigation and the *other* weapon systems at a base. For example command and control systems, which provide surveillance, air control, and data link management to aircraft, are considered a separate weapon system in the AF weapon system construct. As a result, a particular installation that provides a significant electronic, reconnaissance, and surveillance aircraft mission will likely also have a large command and control mission. This would result in dependencies between the various weapon systems at a base that would require mapping.

Lastly, due to data restrictions, this research aggregated the support costs under investigation into two principal categories. However, to provide decision-makers more fidelity in resource management for support activities, disaggregation of these costs would be optimal. Rather than simply understanding the potential impacts to support personnel, AF decision-makers desire the ability to understand which personnel (i.e. security forces, logisticians, healthcare providers, etc.) and discretionary resources (i.e. supplies, travel funding, etc.) are most likely to be impacted.

Since data validity concerns exist, functional experts and knowledge elicitation would be required to provide subjective inputs for cause-and-effect relationships at this level. Bayesian networks provide a way to incorporate this information and the uncertainty pertaining to subjective inputs as recent research has focused on the process of eliciting expert knowledge and incorporating this information into BNs [i.e. 343; 347; 349–352]. Future research could provide this greater level of granularity for tooth-to-tail impact analysis.

6.6.2 Bayesian Networks for Improved Cost Analysis Capabilities.

Bayesian networks have been successfully employed in a wide range of applications, across engineering, computing, education, various sciences, and within the military. Remarkably, BNs have eluded much of the cost analysis domain; however, their unique properties provide inspiration for new cost analysis capabilities. Far from all-encompassing, the following discusses potential applications of BNs in the cost analysis domain.

Cost-Risk Analysis. Cost estimating and risk analysis often go hand-in-hand; consequently, improving the analytic capability in risk assessments can drive accuracy in cost estimates. Traditional risk assessments often rely on the standard impact-based risk measure[45] or risk registers/heat maps. These approaches lack insight into the levels of uncertainty surrounding the risk drivers and potential impact, do not account for dependencies between risks, and typically do not provide for an adequate cause-and-effect link between costs and risks. Applying BNs to this area has the potential to improve this cost-risk modeling link. First, a BN approach allows analysts to model the cause-and-effect relationships from risk drivers to the potential impact. This can improve the root cause analysis of risk assessments and allows decision-makers to visually comprehend risk relationships. Furthermore, uncertainty surrounding the drivers and their influence on the impact can be captured. Second, BNs allow for dependencies between risks to be modeled, which can significantly influence probability of risk occurrences. Third, a greater granularity of relationships between risks and cost elements can be captured leading to a more

[45] The traditional impact-based measure is represented as $risk = probability \times impact$.

robust cost-risk analysis. Lastly, as new information surfaces regarding the risk environment, the reasoning capabilities of BNs can provide updated probabilities in light of this evidence.

Business Case Analysis. Business case analyses are decision support and planning tools that project the likely financial and performance outcomes of an action. The purpose of BCA are to address the question: "What happens if we take this or that course of action?" A BCA answers this question in terms of business costs, benefits, and risks. The difficulties in performing BCAs often rests in the lack of sufficient data to quantify benefits and risks. As a result, expert opinion is commonly relied on to quantify these values. Furthermore, the BCA process can also become stove-piped in that costs, benefits, and risks are modeled separately only to be combined at the end to produce the final results. This ignores many of the dependencies that can exist between costs, benefits, and risks. Applying BNs to this area allows analysts to incorporate subjective inputs from expert knowledge to quantify benefits and risks along with the levels of uncertainties around these quantified values. Furthermore, the modeling environment allows for complex dependencies between the BCA terms to be captured providing a more robust understanding of the various courses of action.

Product/Project Costing. The difficulty in accurately forecasting the cost of products or projects often lies in the uncertainties surrounding cost drivers such as technology, productivity levels, economic conditions, prices, inflation, and other internal and external factors. As products and projects progress, often the level of certainty pertaining to these cost drivers change. Applying BNs provides the ability to model the uncertainties and conditional dependencies between cost drivers and to update these uncertainties as the product and project progresses through its lifecycle. Furthermore, the ability to perform complex what-if analyses provides project managers understanding of potential funding exposure.

Earned Value Management. To aid project management, earned value management (EVA) provides a means for forecasting schedule and cost estimates at completion. By way of key performance and forecasting parameters, EVM can help project managers understand the current status and potential schedule and cost overruns. Bayesian networks can offer a modeling approach to assess the relationships between these key parameters and provide an understanding of the uncertainty in the estimates of both cost and schedule at the completion of the project. Furthermore, EVM provides an approach to track project performance through the lifecycle of the project and BNs would allow for progressive changes in the project environment to be updated in the model. Lastly, EVM often relies on both existing data and qualitative knowledge provided by experts and BNs provide an appropriate means to integrate and reason with these forms of information.

Productivity Assessment. Constrained fiscal environments are requiring organizations to find more effective ways to utilize resources. Effective operations are critically dependent on the accurate analysis of production outcomes and resource utilization. Applying BNs for productivity assessment could provide for improved operational efficiency by first identifying the key drivers affecting operational efficiency and providing decision-makers with a graphical illustration of their causal relationships. Second, conditional dependencies and uncertainties of the key drivers can be modeled to gauge the influence each driver has on the level of productivity. Third, by performing sensitivity analysis through what-if analyses, the key drivers which negatively impact productivity the most can be identified for process improvement initiatives. Lastly, through process improvement these variables should become more efficient leading to increased productivity; BNs provide decision support tool that can "learn" this new evidence and update the posterior probabilities to reflect the new operational environment.

These proposed applications represent areas ripe for improved modeling to capture uncertainty within the decision environment and BNs could provide significant advancement in the knowledge building process for these cost analysis topics. However, we suspect that these suggestions only represent a small subset of potential applications for BNs in the cost analysis domain. Consequently, a call for research with regards to cost analysis Bayesian networks could reap significant benefits to our community.

6.6.3 Limitations of Bayesian Networks.

Although BNs offer substantial capabilities as previously addressed, it is important that we also comment on their inherent limitations and liabilities. The first is the computational difficulty of exploring a previously unknown network as to calculate the probability of any branch of the network, all branches must be calculated. In line with this limitation is the challenge of modeling continuous variables and the fact that exact computation of posterior marginal probabilities is not always possible. As a result, through discretization of continuous variables or through simulation, posterior marginal probabilities are approximated. The second is the quality of the prior beliefs used for the nodes. A BN is only as useful as the prior knowledge is reliable. The choice of statistical distributions to describe the variables will have a notable effect on the results. If relying on expert knowledge, overly optimistic or pessimistic prior belief inputs can result in invalid results. In addition, to elicit expert input for medium to large BNs with substantial nodes can become time intensive.

6.7 Conclusion

Current constraints in the fiscal environment are forcing the AF, and its sister services, to assess operational force reduction considerations. With significant force reduction comes the concern of how to model and assess the potential impact that these changes may have on support resources. Previous research has remained heavily focused on a ratio approach for linking the tooth and tail ends of the AF cost spear and, although recent research has augmented this literature stream by providing more statistical rigor behind tooth-to-tail relationships, an adequate decision support tool has yet to be explored to aid decision-makers. This research directly addresses this concern by introducing a systematic approach to perform tooth-to-tail policy impact analysis.

We first apply an econometric approach to assess the relationship between the tooth and tail resulting in further evidence that supports the notion that the strongest link is between the operational personnel at a base and the support costs which service this workforce. Furthermore, these results support the conjecture that a fixed and variable component exists for support costs. We then illustrate how the sole use of this modeling approach disregards important aspects of the decision-making environment.

To address this concern we combine a Bayesian network approach with our econometric modeling results to assess the probabilities, and uncertainties, between tooth policy decisions and tail cost consequences. Through multiple scenarios we illustrate how a Bayesian network can provide decision-makers with *i*) a visual illustration of cause-and-effect impacts, *ii*) the ability to model uncertainty in the decision environment, and *iii*) the ability to perform predictive and diagnostic reasoning in light of new information available to decision-makers. Through our overarching example we demonstrate the applicability of using Bayesian networks as a tooth-to-tail decision support system.

The framework proposed in this article can help us move the tooth-to-tail discussion to a more analytically sophisticated level. However, the presented example is not intended to be exhaustive and we discuss how future research is required in order to advance the application of the model to a comprehensive enterprise level. Furthermore, we discuss how Bayesian networks can have a greater impact to the cost analysis body of knowledge which has the potential to drive a new generation of cost analysis tools.

VII. Conclusion

A story has no beginning or end: arbitrarily one chooses that moment of experience from which to look back or from which to look ahead.

Graham Greene, 1951

Recent and projected reductions in defense spending are forcing the military services to develop systematic approaches to identify cost reduction opportunities and better manage financial resources. Although a significant contributing source of costs are attributable to support activities, very little analytical rigor has, historically, been applied to this area known as the *tail*. This dissertation addresses this weak link in the tooth-to-tail chain by first providing a robust understanding of *strategic cost analytics* followed by four additional contributions, each advancing the tail domain by injecting analytical rigor and extracting economic understanding.

Chapter II gave an introduction to *strategic cost analytics* and provided the reader with a comprehensive understanding of the strategic use of advanced analytics and data across the enterprise for cost management purposes. It illustrates the unbalanced nature of current SCA research in which minimal focus has been placed on support activities, or the tail end, of the supply chain. Furthermore, it provides a framework to organize and stratify this broad literature base and identifies areas for future research which may lead to a more balanced and robust use of SCA across an organization's value chain.

Chapter III turned the reader's focus to the descriptive analysis of the tail; addressing a current concept of policy focus known as *bending the cost curve*. This chapter discussed the concerns in which BTCC research has remained focused on an aggregate-level growth curve. It then demonstrates a novel approach to identifying growth trends across an enterprise without relying solely on aggregate level growth curves or on a single average growth curve as conventional growth modeling approaches provide. The findings illustrate the fact that micro-level growth curves can greatly vary from the aggregate cost curves. Moreover, the research underscores how understanding these underlying growth trends and their pervasiveness across the enterprise allows decision-makers to better direct their focus, proposals, and policy actions.

Chapter IV assessed the predictive means of tooth-to-tail relationships. This chapter discussed how large enterprises can result in nested data structures and, as a result, can lead to biased results when assessing tooth-to-tail relationships with ordinary least squares. In response, this research applied a multilevel modeling approach to analyze tooth-to-tail relationships across the AF enterprise. This research focused on indirect civilian and military personnel costs and found that total direct cost, which has historically been used to link and manage indirect costs, is not the strongest tooth-to-tail connection for these cost categories. Rather, the findings suggest that operational force personnel (headcount and costs) are the best indicators of indirect personnel cost variance. Furthermore, we found that variability in this relationship occurs across bases and MAJCOMs supporting the need for a multilevel modeling approach.

Chapter V discussed the need and ability to introduce prescriptive analysis into the performance assessment process of Installation Support activities. This chapter highlights the gaps in the current assessment process for this subset of tail activities and illustrates how the process fails to inform senior decision-makers on resourcing decisions. Consequently, this research proposes a process that incorporates Data Envelopment Analysis to provide an internal benchmarking process to measure performance efficiency. Providing an example with facility sustainment costs, the findings suggest the mean operational efficiency of these activities in 2014 range between 64-76%. Moreover, this research illustrated how DEA can be used to identify the most inefficient bases with regards to facility sustainment activities along with the source of inefficiency - excess resource inputs versus lack of performance output; providing decision-makers the ability to balance their resource allocation.

Chapter VI made the final contribution by proposing a decision support tool for tooth-to-tail impact analysis. This chapter stresses the lack of a systematic approach to estimate and model tooth-to-tail policy implications. Furthermore, it discusses the difficulties caused by uncertainty in the decision-making environment and how solely relying on econometric modeling fails to provide a dynamic decision support tool. As a result, this research introduced a novel decision support system with Bayesian networks to model the tooth-to-tail cost consequences while capturing the uncertainty that often comes with policy considerations. The applicability of this approach is provided through an example of A-10 fleet reductions to illustrate how BNs allow decision-makers to reason, and update their beliefs in light of new evidence, in the dynamic environment that accompanies enterprise-wide policy considerations.

The five contributions provided by this dissertation advance the knowledge of, and establish a robust foundation for, the tooth-to-tail discussion. Each research initiative not only establishes new knowledge regarding strategic cost analytics and the tail domain but also contributed to the knowledge building process by delivering products. The products delivered for each contribution include the following:

1. *Creates a framework for how strategic cost analytics are currently being applied across an organization's value chain.*
   (a) **Presentation:** Boehmke, B.C. & Johnson, A.W. (2014). "Understanding Strategic Cost Analytics Across the Supply Chain." Institute of Industrial Engineering Annual Conference, Montreal, Canada.
   (b) **Publication:** Boehmke, B.C., Johnson, A.W., Weir, J.D., White, E.D. & Gallagher, M.A. (2015). "Understanding Strategic Cost Analytics Across the Supply Chain." *Proceedings of the INFORMS: Cincinnati-Dayton 2014 Fall Technical Symposium (Proposed Submission).*
2. *Develops a novel approach to identify underlying cost curve behavior across an enterprise.*
   (a) **Presentation:** Boehmke, B.C. (2015). "Identifying Underlying Cost Trends." Air Force Institute of Technology: Enterprise Logistics Executive Capstone Course, WPAFB, OH.
   (b) **Publication:** Boehmke, B.C., Johnson, A.W., Weir, J.D., White, E.D. & Gallagher, M.A. (2015). "Bending the cost curve: Moving the focus from macro-level to micro-

level cost trends with cluster analysis." *Journal of Cost Analysis and Parametrics, (Forthcoming).*

3. *Establishes a methodology to analyze tooth-to-tail relationships across an enterprise.*

   (a) **Presentation:** Boehmke, B.C. (2015). "A Multilevel Understanding of Tooth-to-Tail." Institute of Industrial Engineering Annual Conference, Nashville, Tennessee.

   (b) **Presentation:** Boehmke, B.C. (2015). "The Influence of Front-line Activities on Indirect Costs: A Multilevel Modeling Approach." 83^{rd} Military Operations Research Symposium, Washington D.C.

   (c) **Publication:** Boehmke, B.C., Johnson, A.W., Weir, J.D., White, E.D. & Gallagher, M.A. (2015). "A multilevel understanding of Tooth-to-Tail." *Proceedings of the IIE Industrial and Systems Engineering Research Conference.*

   (d) **Publication:** Boehmke, B.C., Johnson, A.W., Weir, J.D., White, E.D. & Gallagher, M.A. (2015). "The influence of front-line activities on indirect costs: A multilevel modeling approach." *Under Review - Production and Operations Management.*

4. *Improves performance assessments of tail activities to guide resource allocation decisions.*

   (a) **Presentation:** Boehmke, B.C. (2015). "Managing Performance and Resources for Air Force Installation Support Activities: A DEA Approach." INFORMS: Cincinnati-Dayton 2014 Fall Technical Symposium (*Forthcoming*).

   (b) **Publication:** Boehmke, B.C., Jackson, R.A., Johnson, A.W., Weir, J.D., White, E.D. & Gallagher, M.A. (2015). "Effectiveness myopia: Improving the Air Force's "visual acuity" of performance for installation support activities through the evaluative prism of data envelopment analysis." *Under Review - Military Operations Research.*

5. *Incorporates a decision support tool for tooth-to-tail impact analysis.*

   (a) **Presentation:** Boehmke, B.C. (2016). "Tooth-to-Tail Impact Analysis: Combining Econometric Modeling and Bayesian Networks to Assess Support Cost Consequences

Due to Changes in Force Structure." Western Decision Sciences Institute Annual Conference, Las Vegas, Nevada (*Proposed Submission*).

(b) **Publication:** Boehmke, B.C., Johnson, A.W., Weir, J.D., White, E.D. & Gallagher, M.A. (2015). "Tooth-to-Tail Impact Analysis: Combining Econometric Modeling and Bayesian Networks to Assess Support Cost Consequences Due to Changes in Force Structure." *Under Review - Journal of Cost Analysis and Parametrics*

This research was designed to address, in a limited fashion, specific gaps in the understanding of, and the analytical rigor applied to, the tail domain. As such, this study can be interpreted as an initial step in implementing strategic cost analytics for understanding and managing tail costs. The results of each contribution are in-and-of-themselves important. However, as a whole, establishing this foundation should be viewed as the initial building blocks to continue injecting strategic cost analytics into the tail domain.

Within each chapter, detailed suggestions for future work are provided to extend the benefits of the research. As such, the following provides a consolidated summary of the main points of these recommendations. Chapter II identifies the need to balance the level of knowledge of SCA across the supply chain activities. As such, recommendations for how descriptive, predictive, and prescriptive analytic applications can be improved across the supply chain are provided. Furthermore, improvements in how cost driver data are used across the enterprise are given.

Chapter III provides a means to identify underlying cost curves that require the decision-makers' focus. Future research could seek to integrate this means into a decision support tool that allows for automated identification of support activities and AF installations which align to cost curves identified as concerning. Chapter IV identified the strongest tooth-to-tail linkages for indirect civilian and military personnel costs. Future research can expand these insights to identify the strongest tooth-to-tail linkages for the remaining support cost categories not assessed. This would provide a comprehensive understanding of which force structure variables drive which support cost categories.

Chapter V introduces DEA into the performance assessment process and illustrates its applicability using cross-sectional data for a single installation support activity. Future studies should seek to inject a longitudinal DEA assessment to provide a greater degree of consistency and performance sedimentation in results. Furthermore, with 41 installation support activities, future research could assess a means to assess and aggregate performance across all 41 categories to provide an overall health assessment of installation support activities as a whole.

Chapter VI proposed a decision support system for assessing support cost consequences as a result of force structure changes. The applicability of the proposed approach is illustrated with an isolated weapon system under investigation and a small subset of AF installations. However, to become a comprehensive application for enterprise-level use future research must extend the scope of the tool to include a larger set of installations and weapon systems to be modeled along with the independencies that arise between them. Furthermore, the use of Bayesian networks in the cost analysis domain appears promising and this chapter outlines how five research areas could receive immediate benefits from its application.

Moving from the parts to the whole, this research represents only a few brushstrokes on the blank canvas that is the tail domain. Discrete activities across an enterprise contribute differently to an organization's cost position. Furthermore, each activity is driven by its own economics and relationships. Consequently, understanding the underlying economic behavior and relationships of these activities requires a broad set of analytic tools. Through the lens of strategic cost analytics, this research begins the process of expanding the set of rigorous analytic tools used to establish the economic understanding of an enterprise's tail activities. However, there is need for further advancements in the use of data and advanced analytic techniques to understand and manage the cost behavior of the tail activities. Only through continued expansion of strategic cost analytics through theoretical and empirical research will the AF be able to grab its tail and align it with its strategic intent.

Appendix A: Analytic Methodology Coding Structure

Code	Analytic Methodology	Analytic Methodology Code	Parent Classification	Parent Classification Code	Technique	Code2
Cor	Descriptive	De	Dependence	Dp	Correlation analysis	Cor
SEM	Descriptive	De	Factor Analysis	FA	Structural Equation Modeling	SEM
PA	Descriptive	De	Factor Analysis	FA	Path Analysis	PA
PCA	Descriptive	De	Factor Analysis	FA	Principal Component Analysis	PCA
TS	Descriptive	De	Trend Analysis	TA	Time Series	TS
PpA	Descriptive	De	Trend Analysis	TA	Proportional Analysis	PpA
CA	Descriptive	De	Classification	Cf	Cluster analysis	CA
DeCo	Descriptive	De	Descriptive combination	DeCo	Descriptive combination	DeCo
TC	Predictive	Pd	Generative Modeling	GM	Target Costing	TC
BU	Predictive	Pd	Generative Modeling	GM	Build-up	BU
ABM	Predictive	Pd	Simulation	Si	Agent-based modeling	ABM
DES	Predictive	Pd	Simulation	Si	Discrete event simulation	DES
SD	Predictive	Pd	Simulation	Si	System Dynamics	SD
LR	Predictive	Pd	Classification	Cf	Logistic regression	LR
DT	Predictive	Pd	Classification	Cf	Decision Tree	DT
DA	Predictive	Pd	Classification	Cf	Discriminant Analysis	DA
SVM	Predictive	Pd	Classification	Cf	Support Vector Machines	SVM
MM	Predictive	Pd	Parametric	Pm	Mathematical modelling	MM
ABC	Predictive	Pd	Parametric	Pm	Activity-based Costing	ABC
GLM	Predictive	Pd	Parametric	Pm	Linear regression	GLM
MmA	Predictive	Pd	Parametric	Pm	Multimodal analysis	MmA
GLMM	Predictive	Pd	Parametric	Pm	Generalized Linear Mixed Models	GLMM
HLR	Predictive	Pd	Parametric	Pm	Hierarchical Linear Regression	HLR
	Predictive	Pd	Parametric	Pm	Comparison	Comparison
FL	Predictive	Pd	Artificial Intelligence	AI	Fuzzy Logic	FL
ANN	Predictive	Pd	Artificial Intelligence	AI	Artificial Neural Networks	ANN
SoE	Predictive	Pd	Parametric	Pm	System of Equations	SoE
SSoE	Predictive	Pd	Parametric	Pm	Simultaneous System of Equations	SSoE
DbR	Predictive	Pd	Decision Support System	DSS	Data-based Reasoning	DbR
CbR	Predictive	Pd	Decision Support System	DSS	Case-based Reasoning	CbR
MbR	Predictive	Pd	Decision Support System	DSS	Model-based Reasoning	MbR
KbR	Predictive	Pd	Decision Support System	DSS	Knowledge-based Reasoning	KbR
PdCo	Predictive	Pd	Combination	Co	Combination	Predictive Parent Combo
LP	Prescriptive	Ps	Optimization	Op	Linear Programming	LP
IP	Prescriptive	Ps	Optimization	Op	Integer Programming	IP
NLP	Prescriptive	Ps	Optimization	Op	Nonlinear Programming	NLP
MIP	Prescriptive	Ps	Optimization	Op	Mixed Integer Programming	MIP
GP	Prescriptive	Ps	Optimization	Op	Goal Programming	GP
NO	Prescriptive	Ps	Optimization	Op	Network Optimization	NO
DP	Prescriptive	Ps	Optimization	Op	Dynamic Programming	DP
SA	Prescriptive	Ps	Optimization	Op	Search Algorithm	SA
MH	Prescriptive	Ps	Optimization	Op	Metaheuristics	MH
SwA	Prescriptive	Ps	Artificial Intelligence	AI	Swarm algorithms	SwA
GA	Prescriptive	Ps	Artificial Intelligence	AI	Genetic algorithms	GA
AHP	Prescriptive	Ps	Multi Criteria Decision Modeling	MCDM	Analytic Hierarchy Process	AHP
ANP	Prescriptive	Ps	Multi Criteria Decision Modeling	MCDM	Analytic Network Process	ANP
DEA	Prescriptive	Ps	Multi Criteria Decision Modeling	MCDM	Data Envelopment Analysis	DEA
MAUT	Prescriptive	Ps	Multi Criteria Decision Modeling	MCDM	Multi-attribute Utility Theory	MAUT
MAVT	Prescriptive	Ps	Multi Criteria Decision Modeling	MCDM	Multi-attribute Value Theory	MAVT
VA	Prescriptive	Ps	Multi Criteria Decision Modeling	MCDM	Value Analysis	VA
WPM	Prescriptive	Ps	Multi Criteria Decision Modeling	MCDM	Weighted Product Model	WPM
WSM	Prescriptive	Ps	Multi Criteria Decision Modeling	MCDM	Weighted Sum Model	WSM
PsCo	Prescriptive	Ps	Combination	Co	Combination	Prescriptive Parent Combo
AMCo	Combination	AMCo	Combination	AMCo	Combination	Analytic Methodology Combo
OpCo	Prescriptive	Ps	Optimization	Op	Combination	Optimization Combo
MCDMCo	Prescriptive	Ps	Multi Criteria Decision Modeling	MCDM	Combination	MCDM Combo
AMCp	Analytic Methodology Comparison	AMCp	Analytic Methodology Comparison	AMCp	Comparison	AMCp
PdCp	Predictive	Pd	Comparison	PdCp	Comparison	PdCp

Appendix B: Supplier Selection: Strategic Cost Analytics Cross Tabulation

	Analytic Approach			Structural Data						Executional Data									
Reference	Analytic Methodology	Analytic Classification	Analytic Technique	Scale	Scope	Experience	Technology	Product Line Complexity	External Risks	R&D Specific	Quality Management	Product Sustainment / Capacity Utilization	Logistics Management	Forecasting	Financial	Marketing & Sales Management	Customer Sustaining	Infrastructure Sustaining	Corporate Social Responsibility
Berger & Zeng (2006)	Pd	Cf	DT	X					X			X		X	X				
Dogan & Sahin (2003)	Pd	Co	PdCo								X	X	X					X	
Weber et al. (2010)	Pd	Co	PdCo								X		X					X	
Humphreys et al. (2003)	Pd	DSS	DbR				X					X							X
Micheli (2008)	Pd	DSS	KbR						X			X			X				
Micheli (2009)	Pd	DSS	KbR						X			X			X				
Akinc (1993)	Pd	DSS	MbR	X							X	X							
Sadrian & Yoon (1994)	Pd	DSS	MbR	X				X				X		X					
Roodhooft & Konings (1997)	Pd	Pm	ABC								X	X	X	X					
Ganeshan et al. (1999)	Pd	Pm	MM	X									X	X					
Piplani & Viswanathan (2003)	Pd	Pm	MM		X								X	X				X	
Laaksonen et al. (2009)	Pd	Pm	MM	X								X		X				X	
Vanteddu et al. (2011)	Pd	Pm	MM	X								X		X					
Ghodsypour & O'Brien (1998)	Ps	Co	PsCo								X	X	X	X			X		
Hammami et al. (2003)	Ps	Co	PsCo								X	X		X					
Wang et al. (2004)	Ps	Co	PsCo	X								X	X	X	X				
Wadhwa & Ravindran (2007)	Ps	Co	PsCo	X							X	X		X					
Kull & Talluri (2008)	Ps	Co	PsCo	X							X	X	X	X					
Demirtas & Ustun (2009)	Ps	Co	PsCo	X							X	X	X	X	X				
Kokangul & Susuz (2009)	Ps	Co	PsCo	X			X				X	X	X	X					
Mafakheri et al. (2011)	Ps	Co	PsCo	X							X	X	X						X
Nydick & Hill (1992)	Ps	MCDM	AHP								X	X	X				X		
Barbarosoglu & Yazgac (1997)	Ps	MCDM	AHP																
Tam & Tummala (2001)	Ps	MCDM	AHP	X			X				X	X	X				X		X
Bhutta & Huq (2002)	Ps	MCDM	AHP				X				X	X					X		
Chan (2003)	Ps	MCDM	AHP								X	X							
Liu & Hai (2005)	Ps	MCDM	AHP								X	X	X						
Lee (2009)	Ps	MCDM	AHP				X	X			X	X	X		X				X
Garfamy (2006)	Ps	MCDM	DEA				X				X	X					X		
Ramanathan (2007)	Ps	MCDM	DEA				X				X	X					X		
Min (1994)	Ps	MCDM	MAUT				X		X		X		X		X				X
Weber & Current (1993)	Ps	Op	IP	X							X	X	X	X					
Benton (1991)	Ps	Op	LP	X				X					X	X				X	
Hong & Hayya (1992)	Ps	Op	LP	X									X	X					
Rosenblatt et al. (1998)	Ps	Op	LP	X								X	X	X			X	X	
Degraeve & Roodhooft (1999a)	Ps	Op	LP	X							X	X	X	X					
Degraeve & Roodhooft (1999b)	Ps	Op	LP	X							X	X	X	X					
Degraeve & Roodhooft (1999c)	Ps	Op	LP	X							X	X	X	X					
Degraeve et al. (2005)	Ps	Op	LP	X			X				X	X	X	X				X	
Shaw et al. (2012)	Ps	Op	LP	X							X		X	X					X
Ghodsypour & O'Brien (2001)	Ps	Op	MIP	X							X	X	X	X	X				
Bonsor & Wu (2001)	Ps	Op	MIP										X	X	X				
Crama et al. (2004)	Ps	Op	MIP	X				X						X					
Kheljani et al. (2009)	Ps	Op	MIP										X	X				X	
Basnet & Leung (2005)	Ps	Op	OpCo	X				X					X	X					
Kumar et al. (2004)	AMCo	AMCo	AMCo								X	X	X		X				
Hong et al. (2005)	AMCo	AMCo	AMCo	X							X			X		X			
Tsai & Hung (2009)	AMCo	AMCo	AMCo								X	X	X	X				X	X
Degraeve et al. (2000a)	AMCp	AMCp	AMCp									X	X	X		X	X	X	
Degraeve et al. (2000b)	AMCp	AMCp	AMCp									X	X	X		X	X	X	

Appendix C: Inventory Management: Strategic Cost Analytics Cross Tabulation

	Analytic Approach			Structural Data						Executional Data									
Reference	Analytic Methodology	Analytic Classification	Analytic Technique	Scale	Scope	Experience	Technology	Product Line Complexity	External Risks	R&D Specific	Quality Management	Product Sustainment / Capacity Utilization	Logistics Management	Forecasting	Financial	Marketing & Sales Management	Customer Sustaining	Infrastructure Sustaining	Corporate Social Responsibility
Kang & Kim (2010)	Pd	Co	PdCo									X	X	X				X	
Tyworth & Zeng (1998)	Pd	Pm	MM									X	X					X	
Goyal & Nebebe (2000)	Pd	Pm	MM									X	X	X					
Woo et al. (2001)	Pd	Pm	MM	X								X	X	X				X	
Swenseth & Godfrey (2002)	Pd	Pm	MM									X	X	X				X	
Khouja (2003)	Pd	Pm	MM	X	X							X	X	X				X	
Kim & Ha (2003)	Pd	Pm	MM									X	X	X				X	
Huang (2004)	Pd	Pm	MM								X	X	X	X				X	
Abad & Aggarwal (2005)	Pd	Pm	MM									X	X	X		X		X	
Lo et al. (2007)	Pd	Pm	MM								X	X	X	X	X			X	
Gümüş et al. (2008)	Pd	Pm	MM									X	X	X				X	
Hoque (2008)	Pd	Pm	MM	X								X	X	X					
Kelle et al. (2009)	Pd	Pm	MM								X	X	X	X				X	
Leung (2009)	Pd	Pm	MM	X	X							X	X	X				X	
Bookbinder et al. (2010)	Pd	Pm	MM		X							X	X	X				X	
Ha (2010)	Pd	Pm	MM								X	X	X	X				X	
Leung & Nam (2010)	Pd	Pm	MM	X	X							X	X	X				X	
Lin et al. (2010)	Pd	Pm	MM								X	X	X	X			X	X	
Pasandideh et al. (2010)	Pd	Pm	MM		X							X	X	X				X	
Razmi et al. (2010)	Pd	Pm	MM									X	X	X				X	
Farahani & Elahipanah (2008)	Ps	AI	GA	X				X				X	X	X				X	
Srinivas & Rao (2010)	Ps	AI	GA	X	X							X	X	X				X	
Wadhwa & Ravindran (2007)	Ps	Co	PsCo	X							X	X		X					
Hoque & Goyal (2000)	Ps	Op	IP									X	X	X					
Affisco et al. (1993)	Ps	Op	LP				X					X	X	X				X	
Banerjee & Banerjee (1994)	Ps	Op	LP	X			X					X	X	X					
Hill (1997)	Ps	Op	LP									X	X	X				X	
Bylka (1999)	Ps	Op	LP	X								X	X	X				X	
Hill (1999)	Ps	Op	LP									X	X	X				X	
Affisco et al. (2002)	Ps	Op	LP								X	X	X	X				X	
Braglia & Zavanell (2003)	Ps	Op	LP		X							X	X	X				X	
Chen & Chen (2005)	Ps	Op	LP					X				X	X	X				X	
Banerjee et al. (2007)	Ps	Op	LP	X	X							X	X	X					
Cárdenas-Barrón (2007)	Ps	Op	LP	X	X							X	X	X				X	
Chen & Chen (2007)	Ps	Op	LP	X	X						X	X	X	X				X	
Chung & Wee (2007)	Ps	Op	LP		X							X	X	X				X	
Ertogral et al. (2007)	Ps	Op	LP									X	X	X				X	
Ben-Daya & Noman (2008)	Ps	Op	LP								X	X		X				X	
Chung et al. (2008)	Ps	Op	LP		X						X	X	X	X				X	
Chung (2008)	Ps	Op	LP								X	X	X	X				X	
Battini et al (2010a)	Ps	Op	LP									X	X	X				X	
Battini et al (2010b)	Ps	Op	LP	X								X	X	X	X			X	
Chen & Chang (2010)	Ps	Op	LP	X				X			X	X	X	X				X	
Chen & Sarker (2010)	Ps	Op	LP	X								X	X	X				X	
Abdul-Jalbar et al. (2007)	Ps	Op	MIP	X	X								X	X					
Zanoni & Zavanella (2007)	Ps	Op	MIP					X			X	X	X	X				X	
Abdul-Jalbar et al. (2008)	Ps	Op	MIP	X									X	X					
Chang et al. (2008)	Ps	Op	MIP	X								X	X	X				X	
El Saadany & Jaber (2008)	Ps	Op	MIP								X	X	X	X					
Sarker & Diponegoro (2009)	Ps	Op	MIP	X	X							X	X	X				X	
Sawik (2009a)	Ps	Op	MIP					X				X	X	X				X	
Sawik (2009b)	Ps	Op	MIP					X				X	X	X				X	
Comeaux & Sarker (2005)	Ps	Op	NLP	X							X	X	X	X				X	
Chang et al. (2006)	Ps	Op	NLP	X			X					X	X	X				X	
Darwish (2009)	Ps	Op	NLP								X	X	X	X				X	
Darwish & Odah (2010)	Ps	Op	NLP	X									X	X				X	
Chen & Cheng (2010)	Ps	Op	NLP	X							X	X	X	X					
Taleizadeh et al. (2011)	Ps	Op	OpCo	X				X				X	X	X				X	
Nanda & Nam (1992)	Ps	Op	SA			X						X	X	X				X	
Yang & Wee (2002)	Ps	Op	SA	X							X	X	X	X				X	
Rau et al. (2003)	Ps	Op	SA		X						X	X	X	X				X	
Toptal et al. (2003)	Ps	Op	SA									X	X	X				X	
Ben-Daya & Hariga (2004)	Ps	Op	SA									X	X	X				X	
Ouyang et al. (2004a)	Ps	Op	SA	X								X	X	X				X	
Ouyang et al. (2004b)	Ps	Op	SA	X								X	X	X				X	
Wee & Yang (2004)	Ps	Op	SA	X								X	X	X				X	
Kim et al. (2005)	Ps	Op	SA		X							X	X	X				X	
Hoque & Goyal (2006)	Ps	Op	SA									X	X	X				X	
Huang & Yao (2006)	Ps	Op	SA	X	X						X	X	X	X				X	
Kim et al. (2006)	Ps	Op	SA	X	X			X				X	X	X				X	
Law & Wee (2006)	Ps	Op	SA								X	X		X				X	
Nie et al. (2006)	Ps	Op	SA									X	X	X				X	
Chan & Kingsman (2007)	Ps	Op	SA	X								X	X	X				X	
Hsiao (2008a)	Ps	Op	SA									X	X	X				X	
Hsiao (2008b)	Ps	Op	SA									X	X	X				X	
Jaber & Goyal (2008)	Ps	Op	SA	X	X							X	X	X				X	
Jong & Wee (2008)	Ps	Op	SA								X	X	X	X				X	
Kim et al. (2008)	Ps	Op	SA			X						X	X	X				X	
Kim & Hong (2008)	Ps	Op	SA	X				X					X	X				X	
Jha & Shanker (2009a)	Ps	Op	SA									X	X	X				X	
Jha & Shanker (2009b)	Ps	Op	SA								X	X	X	X				X	
Lin (2009)	Ps	Op	SA	X								X	X	X				X	
Sajadieh & Jokar (2009a)	Ps	Op	SA									X	X	X				X	
Sajadieh et al. (2009)	Ps	Op	SA									X	X	X				X	
Sajadieh & Jokar (2009b)	Ps	Op	SA									X	X	X				X	
Sajadieh et al. (2010a)	Ps	Op	SA									X	X	X				X	
Taleizadeh et al. (2010)	Ps	Op	SA					X				X	X	X				X	
Sajadieh et al. (2010b)	Ps	Op	SA									X	X	X				X	
Glock (2011)	Ps	Op	SA	X	X							X	X	X			X	X	
Taleizadeh et al. (2012)	Ps	Op	SA	X				X				X	X	X				X	
Ouyang et al. (2006)	AMCo	AMCo	AMCo								X	X	X	X				X	
Pourakbar et al. (2007)	AMCo	AMCo	AMCo	X	X							X	X	X				X	
Hsu & Lee (2009)	AMCo	AMCo	AMCo	X								X	X	X				X	
Panda et al. (2010)	AMCo	AMCo	AMCo	X								X	X	X				X	

Appendix D: Reseach and Development: Strategic Cost Analytics Cross Tabulation

	Analytic Approach			Structural Data						Executional Data									
Reference	Analytic Methodology	Analytic Classification	Analytic Technique	Scale	Scope	Experience	Technology	Product Line Complexity	External Risks	R&D Specific	Quality Management	Product Sustainment / Capacity Utilization	Logistics Management	Forecasting	Financial	Marketing & Sales Management	Customer Sustaining	Infrastructure Sustaining	Corporate Social Responsibility
Shtub & Zimerman (1993)	Pd	AI	ANN	X						X		X							
Zhang & Fuh (1998)	Pd	AI	ANN									X							
Shtub & Versano (1999)	Pd	AI	ANN									X							
Lin & Chang (2002)	Pd	AI	ANN									X							
Seo et al. (2002a)	Pd	AI	ANN									X							
Caputo & Pelagagge (2008)	Pd	AI	ANN									X				X		X	
Ibusuki & Kaminski (2007)	Pd	GM	TC									X							
Filomena et al. (2009)	Pd	GM	TC									X							
Kee (2010)	Pd	GM	TC	X								X			X				
Deng & Yeh (2010)	Pd	Cf	SVM									X							
Mileham et al. (1993)	Pd	Co	PdCo									X							
Bayus (1997)	Pd	Co	PdCo	X								X			X	X			
Shehab & Abdalla (2001)	Pd	Co	PdCo									X							
Hicks et al. (2002)	Pd	Co	PdCo									X							
Qian & Beh-Arieh (2008)	Pd	Co	PdCo							X		X	X					X	
Johnson & Kirchain (2009)	Pd	Co	PdCo					X		X		X							
Chou et al. (2010)	Pd	Pm	PdCp									X			X	X		X	
H'Mida et al. (2006)	Pd	DSS	KbR									X	X						
Wasim et al. (2013)	Pd	DSS	KbR									X							
Zhang et al. (1996)	Pd	Pm	PdCp									X							
Duverlie & Castelain (1999)	Pd	Pm	PdCp									X							
Seo et al. (2002b)	Pd	Pm	PdCp									X							
Cavalieri et al. (2004)	Pd	Pm	PdCp									X							
Ulrich et al. (1993)	Pd	Pm	ABC	X							X	X	X				X	X	
Ong (1993)	Pd	Pm	ABC									X							
Ong & Lim (1993)	Pd	Pm	ABC					X				X	X					X	
Ong (1995)	Pd	Pm	ABC									X	X					X	
Park & Kim (1995)	Pd	Pm	ABC	X			X				X	X	X						
Ou-yang & Lin (1997)	Pd	Pm	ABC									X							
Tseng & Jiang (2000)	Pd	Pm	ABC									X							
Ben-Arieh & Qian (2003)	Pd	Pm	ABC							X		X	X					X	
Park & Simpson (2005)	Pd	Pm	ABC	X								X							
Thyssen et al. (2006)	Pd	Pm	ABC									X					X		
Chen & Wang (2007)	Pd	Pm	ABC																
Lin et al. (2012)	Pd	Pm	ABC									X							
Greer & Moses (1992)	Pd	Pm	GLM				X					X							
Roy et al. (2005)	Pd	Pm	GLM				X					X					X		
Quintana & Ciurana (2011)	Pd	Pm	GLM									X							
Kim & Chhajed (2000)	Pd	Pm	MM					X			X					X			
Hartman (2000)	Pd	Pm	MM	X											X	X			
Shrieves & Wachowicz (2001)	Pd	Pm	MM	X											X	X			
Jung (2002)	Pd	Pm	MM									X							
Kee & Matherly (2006)	Pd	Pm	MM	X						X		X		X	X	X			
Wei & Egbelu (2000)	AMCo	AMCo	AMCo									X							
Ray et al. (2010)	AMCo	AMCo	AMCo									X							
Bode & Fung (1998)	Ps	Op	LP								X						X		
Tsai et al. (2011)	Ps	Op	LP	X								X	X						X

Appendix E: Production: Strategic Cost Analytics Cross Tabulation

	Analytic Approach			Structural Data						Executional Data									
Reference	Analytic Methodology	Analytic Classification	Analytic Technique	Scale	Scope	Experience	Technology	Product Line Complexity	External Risks	R&D Specific	Quality Management	Product Sustainment / Capacity Utilization	Logistics Management	Forecasting	Financial	Marketing & Sales Management	Customer Sustaining	Infrastructure Sustaining	Corporate Social Responsibility
Balakrishnan et al. (2004)	De	TA	PpA									X							
Kendall et al. (1998)	Pd	Co	PdCo									X							
Spedding & Sun (1999)	Pd	Co	PdCo								X	X							
Marsh et al. (2010)	Pd	Co	PdCo									X							
Natchmann & Needy (2003)	Pd	Cp	PdCp									X	X			X	X	X	
Zhuang & Burns (1992)	Pd	Pm	ABC									X							
Koltai et al. (2000)	Pd	Pm	ABC									X		X				X	
Tsai & Kuo (2004)	Pd	Pm	ABC								X	X					X	X	
Tang et al. (2012)	Pd	Pm	ABC								X	X							
Son (1991)	Pd	Pm	MM								X	X	X					X	
Albright & Roth (1992)	Pd	Pm	MM								X								
Kim & Liao (1994)	Pd	Pm	MM								X								
Seog et al. (1996)	Pd	Pm	MM								X	X	X				X		
Aderoba (1997)	Pd	Pm	MM									X			X			X	
Sandoval-Chávez & Beruvides (1998)	Pd	Pm	MM								X	X	X			X			
Ben-Arieh (2000)	Pd	Pm	MM									X							
Chiadamrong (2003)	Pd	Pm	MM																
Yeh & Yang (2003)	Pd	Pm	MM	X				X				X	X	X					
Xiong & Wang (2004)	Pd	Pm	MM								X	X	X					X	
Özbayrak et al. (2004)	Pd	Pm	MM									X	X			X			
Su et al. (2005)	Pd	Pm	MM									X	X					X	
Naidu (2008)	Pd	Pm	MM								X	X							
Jaber et al. (2010)	Pd	Pm	MM			X					X	X	X	X					
Evans et al. (2001)	Pd	Pm	SSoE					X				X							
Burgess (1996)	Pd	Si	SD								X								
Kiani et al. (2009)	Pd	Si	SD								X	X					X		
Tsai & Lai (2007)	Ps	Op	LP		X					X		X				X		X	
Tsai et al. (2012)	Ps	Op	LP									X				X			X
Mirzapour Al-e-hashem et al. (2011)	Ps	Op	MIP	X				X				X	X	X				X	
Graman (2010)	Ps	Op	NLP					X				X	X	X					
Kiritsis et al. (1999)	Ps	Op	SA									X							
Fu et al. (2012)	Ps	Op	SA					X				X				X			
Ittner (1996)	AMCo	AMCo	AMCo								X	X				X			
Kee & Schmidt (2000)	AMCo	AMCo	AMCo					X		X		X		X		X			
LaScola et al. (1998)	AMCp	AMCp	AMCp	X								X							
Schneeweiss (1998)	AMCp	AMCp	AmCp	X				X				X		X				X	

Appendix F: Logistics: Strategic Cost Analytics Cross Tabulation

	Analytic Approach			Structural Data						Executional Data									
Reference	Analytic Methodology	Analytic Classification	Analytic Technique	Scale	Scope	Experience	Technology	Product Line Complexity	External Risks	R&D Specific	Quality Management	Product Sustainment / Capacity Utilization	Logistics Management	Forecasting	Financial	Marketing & Sales Management	Customer Sustaining	Infrastructure Sustaining	Corporate Social Responsibility
Kengpol et al. (2012)	Pd	DSS	DbR						X				X						
Banamyong & Beresford (2001)	Pd	Pm	ABC						X				X						
Thomas & Roth (2002)	Pd	Pm	ABC										X					X	
Baykasoğlu & Kaplanoğlu (2008)	Pd	Pm	ABC	X									X			X		X	
Everaert et al. (2008)	Pd	Pm	ABC	X									X			X			
Varila et al. (2007)	Pd	Pm	GLM					X				X	X						
Engblom et al. (2012)	Pd	Pm	GLMM	X									X					X	
Beuthe et al. (2001)	Pd	Pm	MM										X		X			X	
Hu et al. (2002)	Ps	Op	LP					X				X	X						
Pati et al. (2004)	Ps	Op	LP					X				X	X						
Ross et al. (2007)	Ps	Op	LP										X		X			X	
Bertazzi et al. (1997)	Ps	Op	MIP					X				X	X						

Appendix G: Customer-oriented Activities: Strategic Cost Analytics Cross Tabulation

	Analytic Approach			Structural Data						Executional Data									
Reference	Analytic Methodology	Analytic Classification	Analytic Technique	Scale	Scope	Experience	Technology	Product Line Complexity	External Risks	R&D Specific	Quality Management	Product Sustainment / Capacity Utilization	Logistics Management	Forecasting	Financial	Marketing & Sales Management	Customer Sustaining	Infrastructure Sustaining	Corporate Social Responsibility
van Triest (2005)	De	FA	SEM	X												X	X		
Dwyer (1997)	De	TA	TS													X			
Berger et al. (2003)	Pd	Cf	DT													X			
Haenlein et al. (2007)	Pd	Cf	DT													X	X		
Niraj et al. (2001)	Pd	Co	PdCo	X				X								X	X		
Kumar et al. (2006)	Pd	Co	PdCo												X	X	X		
Yoshikawa et al. (1994)	Pd	Pm	ABC								X	X	X				X	X	
Foster et al. (1996)	Pd	Pm	ABC	X									X			X	X	X	
Ortman & Buehlmann (1999)	Pd	Pm	ABC																
Noone & Griffin (1999)	Pd	Pm	ABC													X	X	X	
Freeman et al. (2000)	Pd	Pm	ABC													X	X	X	
McNair et al. (2001)	Pd	Pm	ABC							X	X	X	X			X	X	X	
van Raaij et al. (2003)	Pd	Pm	ABC							X		X				X	X	X	
Guerreiro et al. (2008)	Pd	Pm	ABC	X									X			X	X	X	
Berger & Nasr (1998)	Pd	Pm	MM												X	X	X		
Mulhern (1999)	Pd	Pm	MM												X	X			
Gupta et al. (2006)	Pd	Pm	MM													X	X		
Kumar et al. (2008)	Pd	Pm	MM												X	X	X		
Shen & Daskin (2005)	Ps	Co	PsCo	X									X	X					
Cugini et al. (2007)	AMCo	AMCo	AMCo									X				X	X	X	
McManus (2007)	AMCo	AMCo	AMCo	X												X	X	X	
Kone & Karwan (2011)	AMCo	AMCo	AMCo	X													X		

Appendix H: Support Activities: Strategic Cost Analytics Cross Tabulation

	Analytic Approach			Structural Data						Executional Data									
Reference	Analytic Methodology	Analytic Classification	Analytic Technique	Scale	Scope	Experience	Technology	Product Line Complexity	External Risks	R&D Specific	Quality Management	Product Sustainment / Capacity Utilization	Logistics Management	Forecasting	Financial	Marketing & Sales Management	Customer Sustaining	Infrastructure Sustaining	Corporate Social Responsibility
Foster & Gupta (1990)	De	Dp	Cor	X				X			X	X	X			X		X	
Noreen & Soderstrom (1994)	De	TA	PpA	X								X						X	
Noreen & Soderstrom (1997)	De	TA	PpA	X								X						X	
Anderson et al. (2007)	De	TA	PpA													X		X	
Banker et al. (1995)	Pd	Pm	GLM								X	X						X	
Datar et al. (1993)	Pd	Pm	SSoE					X				X						X	
MacArthur & Stranahan (1998)	Pd	Pm	SSoE	X				X				X						X	

Appendix I: Multiple Activities: Strategic Cost Analytics Cross Tabulation

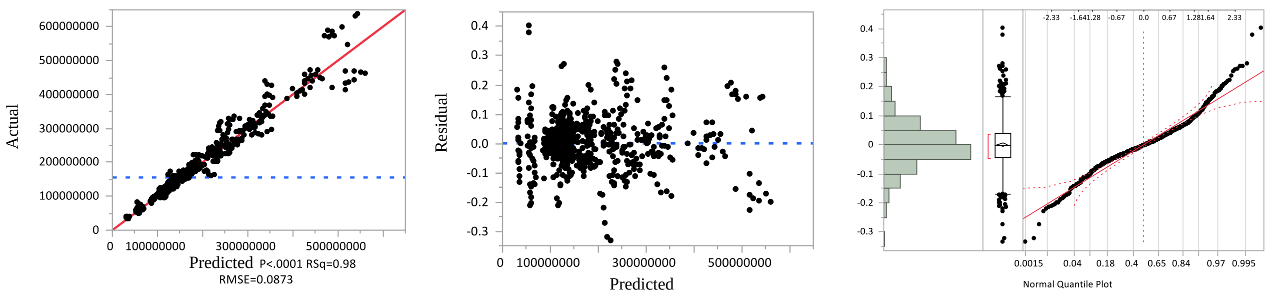
	Analytic Approach			Structural Data						Executional Data									
Reference	Analytic Methodology	Analytic Classification	Analytic Technique	Scale	Scope	Experience	Technology	Product Line Complexity	External Risks	R&D Specific	Quality Management	Product Sustainment / Capacity Utilization	Logistics Management	Forecasting	Financial	Marketing & Sales Management	Customer Sustaining	Infrastructure Sustaining	Corporate Social Responsibility
Ittner & MacDuffie (1995)	De	FA	PA	X			X	X				X						X	
Balakrishnan & Gruca (2008)	De	TA	PpA													X			
Heptonstall et al. (2012)	De	TA	TS							X		X			X				
Yoskikawa et al. (1994)	Pd	Pm	ABC								X	X	X				X	X	
Roztocki & Needy (1999)	Pd	Pm	ABC							X		X	X				X	X	X
McNair et al. (2001)	Pd	Pm	ABC							X	X	X	X			X	X	X	
Balakrishnan et al. (1996)	Pd	Pm	GLM					X				X				X			
Banker & Johnston (1993)	Pd	Pm	SoE	X								X	X			X	X	X	
Kumar et al. (2006)	Ps	Op	LP	X							X	X	X	X				X	X
Nicholson et al. (2011)	Ps	Op	NLP	X				X				X	X			X			
Ittner et al. (1997)	AMCo	AMCo	AMCo					X				X				X			

Appendix J: Element of Expense & Investment Codes

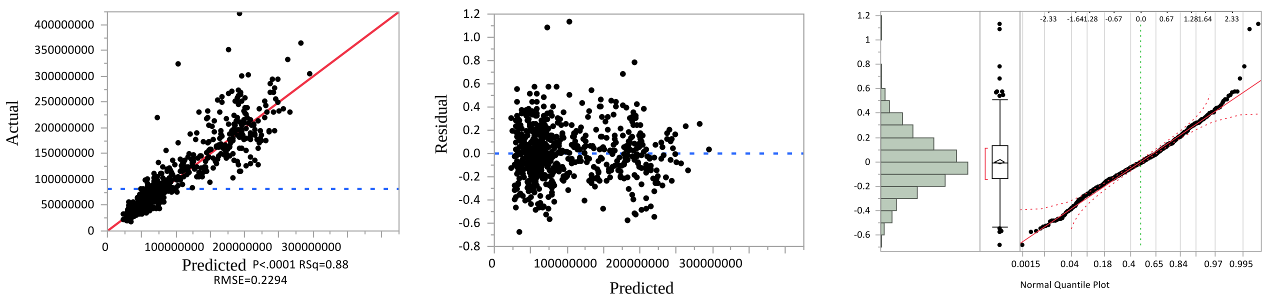
Category	EEIC	Description
Manpower	1*	All Civilian compensation EEICs starting with 1*.
	201*	All Military compensation EEICs starting with 201*.
Facility Sustainment	52* & 56*	All facility maintenance, repair and minor construction EEICs starting with 52* and 56*
	480*, 513*, 600* & 642*	All utility EEICs
	570*	Contracted facility operations & maintenance costs
	532* & 533*	Facility/civil engineering & architecture costs
	531*	Facility custodial service costs
Discretionary Spending	618* & 619*	Non-DWCF clothing & supply purchases
	409*	TDY expenses for mission support travel
	431*, 432*, 433*, 434* & 435*	Base bus service, limousine service, passenger vehicle rental (commercial & GSA)
	501*, 502*, 503* & 504*	Printing, binding, coping, publications, & paid advertisements
	558*, 559*& 592*	Continuing education, professional memberships, credential fees, certification fees, short-term clerical support, and morale & welfare services (award & trophy engravings, conferences, counter-drug program, etc)
	439*, 567*, 568*, 637*, 701*, 702*	IT purchases services (application & database hosting), leased computer equipment, AF-owned IT equipment (purchase, repair, maintenance), off-the-shelf software & licenses, and government development & maintenance of software

Appendix K: Residual Diagnostics for Regression Analysis

Panel A: Residual Diagnostics for the Personnel Support Cost Model



Panel B: Residual Diagnostics for the Discretionary Support Cost Model



Appendix L: Node Parameters for Monte Carlo Simulation

Node Variable	Parameters	Distribution Assumed	Description
Decision	10%, 25%, 50%, 75%, 100%	NA	Ranked variable assuming reductions of 10%, 25%, 50%, 75%, and 100%
A-10 Reduction	654, 1635, 3270, 4904, 6539	NA	Total AF appropriated A-10 personnel × Decision node value
Base 1: A-10 Reduction	$\mu = 0.42; \sigma = 0.05$	$X \sim \mathcal{N}(\mu, \sigma^2)$	*A-10 Reduction* × X; reduction value constrained to total A-10 personnel allocated to the installation in 2014
Base 2: A-10 Reduction	$\mu = 0.08; \sigma = 0.025$	$X \sim \mathcal{N}(\mu, \sigma^2)$	*A-10 Reduction* × X; reduction value constrained to total A-10 personnel allocated to the installation in 2014
Base 3: A-10 Reduction	$\mu = 0.28; \sigma = 0.15$	$X \sim \mathcal{N}(\mu, \sigma^2)$	*A-10 Reduction* × X; reduction value constrained to total A-10 personnel allocated to the installation in 2014
Base 1: Non A-10 Reduction	$\mu = 0.02; \sigma = 0.06$	$X \sim \mathcal{N}(\mu, \sigma^2)$	Reduction value constrained to total non A-10 personnel allocated to the installation in 2014
Base 2: Non A-10 Reduction	$\mu = 0.01; \sigma = 0.0075$	$X \sim \mathcal{N}(\mu, \sigma^2)$	Reduction value constrained to total non A-10 personnel allocated to the installation in 2014
Base 3: Non A-10 Reduction	$\mu = -0.014; \sigma = 0.002$	$X \sim \mathcal{N}(\mu, \sigma^2)$	Reduction value constrained to total non A-10 personnel allocated to the installation in 2014
Base i: Total Ops	NA	NA	Summation of A-10 and *non* A-10 personnel remaining at base i after reductions are made
Base i: Support Pers. Reduction	$\mu = 5.346e\text{-}5; \sigma = 7.959e\text{-}6$	$\beta_1 \sim \mathcal{N}(\mu, \sigma^2)$	Each base's cost reduction ≡ Change in Total Ops personnel from 2014 × β_1 × 2014 total support personnel costs; constrained to the fixed support personnel cost parameter for Base i.
Base i: Support Disc. Reduction	$\mu = 4.255e\text{-}5; \sigma = 2.100e\text{-}5$	$\beta_1 \sim \mathcal{N}(\mu, \sigma^2)$	Each base's cost reduction ≡ Change in Total Ops personnel from 2014 × β_1 × 2014 total support discretionary costs; constrained to the fixed support discretionary cost parameter for Base i.

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14. ABSTRACT

Recent and projected reductions in defense spending are forcing the military services to develop systematic approaches to identify cost reduction opportunities and better manage financial resources. In response, the Air Force along with her sister services are developing strategic approaches to reduce front-line mission resources, commonly referred to as the *"Tooth"*. However, an underemphasized contributing source of costs are mission support activities, commonly referred to as the *"Tail"*.
With the *tail* historically representing a sizable portion of the annual Air Force budget, strategically managing cost behavior of these indirect activities has the opportunity to generate significant cost reductions. However, very little applied or academic research have focused on advancing the knowledge behind the economics of, or the analytic techniques applied to, these activities for cost management purposes.
To address this concern, this dissertation investigates *i*) how organizations use analytic methodologies and data sources to understand and manage cost behavior, *ii*) how to identify underlying cost curves of concern across tail activities, *iii*) how to distinguish historical relationships between the tooth and tail, *iv*) how to improve the performance assessment of tail activities for improved resource allocation, and *v*) how to provide a decision support tool for tooth-to-tail policy impact analysis.

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Support Costs, Tooth-to-Tail, Strategic Cost Analytics, Cluster Analysis, Multilevel Modeling, Data Envelopment Analysis, Bayesian Networks

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