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**A COMPARATIVE ANALYSIS OF THE COST ESTIMATING ERROR RISK
ASSOCIATED WITH FLYAWAY COSTS VERSUS INDIVIDUAL
COMPONENTS OF AIRCRAFT**

THESIS

Jonathan D. Ritschel, Captain, USAF

AFIT/GCA/ENV/03-08

**DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY**

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

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AFIT/GCA/ENV/03-08

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OF AIRCRAFT

THESIS

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In Partial Fulfillment of the Requirements for the
Degree of Master of Science in Acquisition Management

Jonathan D. Ritschel, BBA

Captain, USAF

March 2003

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Jonathan D. Ritschel

Table of Contents

	Page
Acknowledgements.....	iv
List of Figures.....	vii
List of Tables	x
Abstract.....	xii
I. Introduction	1
Background.....	1
Problem Statement.....	4
Research Objectives	5
Methodology.....	6
Scope and Limitations	7
Thesis Overview	8
II. Literature Review.....	9
Chapter Overview.....	9
Work Breakdown Structure.....	9
WBS Terminology Clarification	13
Cost Estimating Relationships.....	13
Aircraft Estimation Techniques.....	18
Parametric Estimation	19
Grass Roots Estimation	22
Previous Research	24
Large, Campbell, and Cates: 1976	24
Hess and Romanoff: 1987.....	26
Rester, Rogers, and Hess: 1991	28
Younossi, Kennedy, and Graser: 2001.....	29
Summary.....	30
III. Methodology.....	31
Chapter Overview.....	31
Methodology Overview.....	31
Data.....	31
Data Limitations	33
Variables.....	33
Regression	34

	Page
Monte Carlo Simulation	37
Bootstrap.....	38
Application of The Bootstrap, Monte Carlo, and Crystal Ball	39
Drawing Conclusions.....	40
Summary.....	40
IV. Findings and Discussion.....	42
Chapter Overview.....	42
Multiple Regression Models for the Fighter Category.....	42
Data	42
Preliminary Modeling Problem.....	43
Basic Airframe Model.....	45
Other Air Vehicle Model	54
Flyaway Cost Model	62
Bootstrap Comparison for Flyaway Versus Basic Airframe.....	68
Bootstrap Comparison for Flyaway Versus Other Air Vehicle.....	70
Multiple Regression Models for the Inter-theatre Airlift Category.....	72
Data	72
Basic Airframe Model.....	72
Other Air Vehicle Model	80
Flyaway Cost Model	86
Bootstrap Comparison for Flyaway Versus Basic Airframe.....	91
Bootstrap Comparison for Flyaway Versus Other Air Vehicle.....	94
Summary.....	95
V. Conclusions.....	97
Importance of Findings.....	97
Limitations.....	97
Discussion of Results	98
Practical versus Statistical Significance	100
Future Research.....	100
Appendix A. Basic Airframe Regression Model at Quantity 100	102
Appendix B: Bootstrap Data for Fighter Category	105
Appendix C: Bootstrap Data for Inter-theatre Airlift Category.....	110
Bibliography	115
Vita.....	119

List of Figures

Figure	Page
Figure 1. AFCAA Personnel Changes (Deputy, 1999:53)	2
Figure 2. CER Development Process (Department of Defense (c), 1995:III-10).....	17
Figure 3. Composite Material Usage (Resetar, Rogers, and Hess, 1991:3).....	29
Figure 4. Monte Carlo Simulation of a Physical System (Nelson, 1997).....	37
Figure 5. Constructing Bootstrap Samples (Stine, 2002:Chapter 1:10).....	39
Figure 6. Continuous Data Histogram for Basic Airframe	45
Figure 7. Assumption Violation Plots for Basic Airframe	46
Figure 8. Cook's D Influence for Basic Airframe	48
Figure 9. Normality Histogram for Basic Airframe.....	50
Figure 10. Autocorrelation Function for Basic Airframe	51
Figure 11. Residual by Predicted Plot for Basic Airframe	52
Figure 12. Plot of Residuals for Basic Airframe.....	54
Figure 13. Continuous Data Histogram for Other Air Vehicle.....	54
Figure 14. Cook's D Influence for Other Air Vehicle.....	56
Figure 15. Revised Cook's D Influence for Other Air Vehicle.....	58
Figure 16. Normality Histogram for Other Air Vehicle	58
Figure 17. Autocorrelation Function for Other Air Vehicle	60
Figure 18. Residual by Predicted Plot for Other Air Vehicle	61
Figure 19. Plot of Residuals for Other Air Vehicle	62

	Page
Figure 20. Continuous Data Histogram for Flyaway Cost	62
Figure 21. Cook's D Influence for Flyaway Cost	63
Figure 22. Normality Histogram for Flyaway Cost.....	65
Figure 23. Autocorrelation Function for Flyaway Cost.....	66
Figure 24. Residual by Predicted Plot for Flyaway Cost.....	67
Figure 25. Plot of Residuals for Flyaway Cost.....	68
Figure 26. Frequency Chart of Flyaway Bootstrap Data	69
Figure 27. Frequency Chart of Basic Airframe Bootstrap Data	69
Figure 28. Differenced Flyaway vs. Basic Airframe Data.....	70
Figure 29. Frequency Chart of Other Air Vehicle Bootstrap Data	71
Figure 30. Differenced Flyaway vs. Other Air Vehicle.....	71
Figure 31. Continuous Data Histogram for Basic Airframe	73
Figure 32. Cook's D Influence for Basic Airframe	74
Figure 33. Revised Cook's D Influence for Basic Airframe	75
Figure 34. Normality Histogram for Basic Airframe.....	77
Figure 35. Autocorrelation Function for Basic Airframe	78
Figure 36. Residual by Predicted for Basic Airframe.....	79
Figure 37. Plot of Residuals for Basic Airframe.....	80
Figure 38. Continuous Data Histogram for Other Air Vehicle.....	80
Figure 39. Cook's D Influence for Other Air Vehicle.....	81
Figure 40. Normality Histogram for Other Air Vehicle	83
Figure 41. Autocorrelation Function for Other Air Vehicle	84

	Page
Figure 42. Residual by Predicted Plot for Other Air Vehicle	85
Figure 43. Plot of Residuals for Other Air Vehicle	86
Figure 44. Continuous Data Histogram for Flyaway Cost	86
Figure 45. Cook's D Influence for Flyaway Cost	87
Figure 46. Normality Histogram for Flyaway Cost.....	88
Figure 47. Autocorrelation Function for Flyaway Cost.....	89
Figure 48. Residual by Predicted Plot for Flyaway Cost.....	90
Figure 49. Plot of Residuals for Flyaway Cost.....	91
Figure 50. Frequency Chart of Flyaway Bootstrap Data	92
Figure 51. Frequency Chart of Basic Airframe Bootstrap Data	93
Figure 52. Differenced Flyaway vs. Basic Airframe Data.....	93
Figure 53. Frequency Chart of Other Air Vehicle Bootstrap Data	94
Figure 54. Differenced Flyaway vs. Other Air Vehicle Data	95
Figure 55. Distributions from Macro vs. Micro Comparisons	96

List of Tables

Table	Page
Table 1. DoD Annual Budget Authority (Cohen, 2000:Appendix B)	3
Table 2. Air Force Aircraft Inventory (Cohen, 2000:Appendix D).....	4
Table 3. Work Breakdown Structure Levels (Department of Defense (b), 1998:A.3)	11
Table 4. Methodology Applicability by Phase (Long, 2000:7)	20
Table 5. PCEI Pilot Program Site Results (Long, 2000:8)	21
Table 6. Independent Variables Considered for CER Development	34
Table 7. Portion of F-16 Independent Variables Data	43
Table 8. ANOVA Table for Basic Airframe.....	47
Table 9. Parameter Estimates for Basic Airframe	48
Table 10. Summary of Fit for Basic Airframe.....	49
Table 11. ANOVA Table for Other Air Vehicle	55
Table 12. Summary of Fit and Parameter Estimates for Other Air Vehicle	57
Table 13. Quartiles for Other Air Vehicle	59
Table 14. ANOVA Table for Flyaway Cost	63
Table 15. Summary of Fit and Parameter Estimates for Flyaway Cost.....	64
Table 16. Quartiles for Flyaway Cost.....	65
Table 17. ANOVA Table for Basic Airframe.....	73
Table 18. Summary of Fit and Parameter Estimates for Basic Airframe	76
Table 19. Quartiles for Basic Airframe.....	77
Table 20. ANOVA Table for Other Air Vehicle	81

	Page
Table 21. Summary of Fit and Parameter Estimates for Other Air Vehicle	82
Table 22. Quartiles for Other Air Vehicle	83
Table 23. ANOVA Table for Flyaway Cost	87
Table 24. Summary of Fit and Parameter Estimates for Flyaway Cost.....	88
Table 25. Quartiles for Flyaway Cost.....	89
Table 26. Practical Significance of WBS Estimation Levels	100

Abstract

A shrinking workforce, unstable budgets, and rapidly changing objectives under stricter time constraints characterize today's cost analysis and acquisition environment. In concert with this environment, cost analyst positions have rapidly decreased as demonstrated by Aeronautical Systems Centers 54% decline in total authorized slots from 1992 to 2001. The question is how to deal with this 'more with less' mentality.

The purpose of this research is to investigate and measure the risks associated with taking a macro versus micro approach to aircraft cost estimation. By analyzing the fidelity of a cost estimate developed at the flyaway cost level versus a cost estimate developed at the individual components level, this research provides guidelines for appropriate allocation of cost analyst resources. This objective is accomplished by looking at the cost estimation error risk of recurring costs at level one of the Work Breakdown Structure (WBS) and at level two of the WBS.

Results show that there is a statistically significant difference between estimating at the differing WBS levels. However, from a practical standpoint, the difference in dollar terms is too small to be considered significant. As a result, program manager should allocate resources based on other constraints such as time allotted to complete the estimate or required level of visibility into the estimate.

A COMPARATIVE ANALYSIS OF THE COST ESTIMATING ERROR RISK
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OF AIRCRAFT

I. Introduction

Background

A shrinking workforce, unstable budgets, and rapidly changing objectives under stricter time constraints characterize today's cost analysis and acquisition environment. The end result of this environment is that today's cost community is being asked to do more with less (Cho, Jerrel, and Landley, 2000:1-1). This is driving the need for cost analysts to increase their productivity or identify and concentrate on those areas of analysis that encompass the majority of estimation error risk in order to meet the demand.

The Department of Defense (DoD) civilian workforce has been downsized by 420,000 employees over the past decade, a ten percent decrease, with an additional 70,000 job cuts projected by the end of fiscal year 2005 (Garamone (a), 2000:10). While this trend in civilian downsizing is consistent across the cost analysis career field, military cost analyst slots are also declining. This phenomenon is taking place across all Air Force installations, including those at the highest level (see Figure 1) as addressed by the Air Force Cost Analysis Agency (AFCAA):

During 1998-1999, AFCAA saw a continual decrease in personnel numbers, especially on the military side. The shrinking numbers are a familiar occurrence across the entire Air Force as the cost analysis field has become absorbed into the overall financial management field (Deputy, 1999:53).

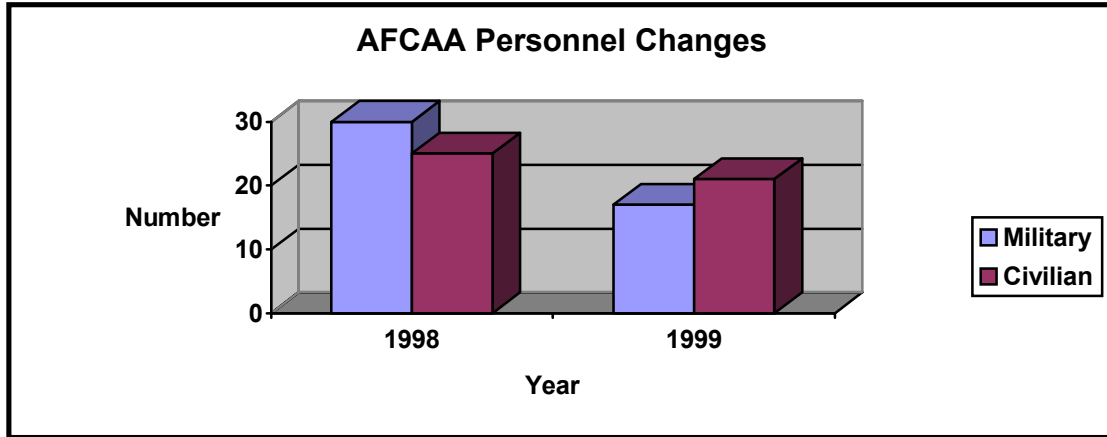


Figure 1. AFCAA Personnel Changes (Deputy, 1999:53)

These reductions in manpower have impacted operations level organizations such as the Aeronautical Systems Center (ASC) cost analyst resources located at Wright-Patterson AFB, OH. Since 1992, ASC's total authorized cost analyst slots have declined by 54%, from 136 authorizations to only 63 in 2001 (Ruffner, 2002). This includes a 69% loss of military slots and a 44% drop in civilian authorizations (Ruffner, 2002).

While the workforce has seen steady declines over the past decade, and will continue to see them into the future, defense funding has also shown instability. Both the overall DoD and Air Force budgets, including procurement funding, experienced sharp declines during the early 1990's (see Table 1).

Table 1. DoD Annual Budget Authority (Cohen, 2000:Appendix B)

Base Year (BY) 01\$M	FY 91	FY 92	FY 93	FY 94	FY 95	FY 96	FY 97	FY 98	FY 99	FY 00	FY 01
DoD Proc. Budget	84	72	59	48	47	45	45	47	52	55	60
DoD Total Budget	346	345	318	293	292	284	282	277	292	288	291
Air Force Proc. Budget	29	27	24	19	17	18	15	16	19	19	21
Air Force Total Budget	112	101	94	87	84	83	80	82	85	85	86

The result of these funding decreases has been a slowdown in new aircraft acquisitions starts, driving current aircraft to remain in service longer than initially planned. Thus, the current aircraft fleet is rapidly aging, with the average age of Air Force aircraft at 22 years (Garamone (b), 2000). This problem has caught the attention of the Chief of Staff of the Air Force, “In 15 years it (average age of Air Force aircraft in years) will be nearly 30, even if we execute every modernization program we currently have on the fiscally constrained books” (Garamone (b), 2000). This aging aircraft problem has resulted in calls for an increase in the number of modernization programs and funding in future defense budgets (Druyan, 2001:iv). Future Presidential budgets are acting on these modernization requests by increasing projected funding. Therefore, a trend towards larger defense budgets, including procurement, appears likely to materialize over the next several years (Department of Defense (d), 2001: table 6.1).

Although the workforce has been shrinking and the funding unstable, there have been no significant declines in existing acquisition programs or inventories of aircraft these programs support (see Table 2).

Table 2. Air Force Aircraft Inventory (Cohen, 2000:Appendix D)

Active & Reserve A/C	FY94	FY95	FY96	FY97	FY98	FY99	FY00	FY01
Inter-theater Airlift	808	802	799	775	756	756	733	722
Bombers	151	140	125	126	138	143	152	154
Fighters	1605	1512	1440	1440	1440	1455	1485	1455
Total Inventory	2564	2454	2364	2341	2334	2354	2370	2331

The workload and product demand from the typical system program office (SPO) has remained relatively stable despite these declines in manpower and funding.

The objectives of acquisition programs, however, are quickly changing. The “world is entering the ‘era of globalization’” (Garamone (c), 2001:2) and the threat to the United States is rapidly changing from nations engaged in a Cold War to rogue terrorist factions. This changing paradigm was clearly brought into focus after the terrorist attacks in New York City and Washington D.C., and the ensuing military operations in Afghanistan. The result of these events is that the Air Force is quickly moving to take advantage of new technology and develop new programs that will be able to “respond with the lethality and precision to pop-up targets in seconds or minutes, not hours, not days” (Grier, 2002:3). Although manpower levels have not increased, aggressive goals are being implemented to field weapon systems at a much more rapid rate:

The threat environment is now unstable and constantly changing. Therefore, we need to be more flexible and responsive in meeting the needs of our warfighters by fielding new systems in much less time. Our goal is to reduce the cycle time of new programs by 25 percent (Cohen Reports, 2000: 75).

Problem Statement

The current aircraft acquisition environment presents several challenges to the cost analysis community. First, cost analysts must operate within the reality of a smaller

workforce, while still accomplishing their mission of providing the best possible cost analysis and estimating for their program. Second, cycle time reduction goals require cost analysts to complete estimates in a compressed timeframe. Finally, in this unpredictable environment, cost analysts do not have the luxury of knowing in advance future estimation requirements. Thus, the ability to accomplish data collection in support of developing low-level, grass-root estimates will be greatly reduced.

Despite these changes in time, manpower, and predictability, it is extremely important that weapon systems perform at optimal operating capabilities. Achieving this objective necessitates the highest quality level of work from cost and acquisition personnel be maintained, “With budgets shrinking and requirement steadily growing, DoD has logically focused on initiatives to increase efficiency” (Ciccotello, Green, and Hornyak, 1997:28). Determining methods to meet these challenges is imperative for cost analysts in today’s environment. In order to keep the quality of work high, with less personnel, increasing programs, and dynamic technology, analysts will be required to increase not only productivity, but also efficiency. To achieve increased productivity and efficiency under these conditions, cost analysts must recognize where in a new weapon system the greatest estimation error risk resides. These high-risk areas must then be where efforts are concentrated when developing an aircraft cost estimate.

Research Objectives

The purpose of this research is to investigate and measure the risks associated with taking a macro versus micro approach to aircraft cost estimation. By analyzing the fidelity of a cost estimate developed at the flyaway cost level versus a cost estimate

developed at the individual components level, this research will provide guidelines for appropriate allocation of cost analyst resources in today's constrained environment.

Flyaway costs for aircraft are defined as follows:

It relates to production cost and includes the prime mission equipment (basic structure, propulsion, electronics), systems engineering, program management, and allowances for engineering changes and warranties. Flyaway costs include (all) recurring ... production costs (contractor and Government furnished equipment) that are incurred in the manufacture of a usable end-item (AFSC Cost Estimating Handbook, 1986:217).

In particular, two categories of aircraft will be considered: fighters and inter-theater airlift. Inter-theater airlift are those aircraft used for supply and transportation.

The following questions regarding each of these categories will be addressed:

1. Which aircraft components have the most cost estimation error risk, and what is that risk?
2. What is the cost estimation error risk associated with estimating at the flyaway cost level?
3. Is there a statistically significant difference in estimating at the component level versus the flyaway level?
4. Given a constrained resource environment, where should a cost analyst focus their attention when developing an aircraft cost estimate?

Methodology

These research objectives will be accomplished by analyzing historical data at both the aircraft component cost and flyaway cost level. Aircraft under review will be separated into two categories to analyze: fighters and inter-theater airlift. Cost data for these categories of aircraft will be acquired from the Cost Estimating System Volume 2,

Aircraft Cost Handbook, Book 1: Aircraft, Nov 87, which was prepared for the AFCAA by Delta Research Corporation.

Individual component costs for each category of aircraft will be subdivided into two parts, basic airframe costs and other air vehicle costs. Basic airframe costs will include engineering, tooling, manufacturing, quality control and other airframe costs. Other airframe costs are comprised of purchased equipment, material overhead, subcontractor costs, other costs not shown elsewhere, and/or General and Administrative (G&A) and fees associated with outside production and services. Other air vehicle costs will include system test and evaluation, program management, and other (for example avionics subsystems). Cost estimating relationships (CERs) at the individual aircraft components level and flyaway cost level will then be developed using linear regression techniques.

A statistical analysis of these CERs will be accomplished to determine the standard error associated with each CER through the use of Monte Carlo simulation techniques. The component level and flyaway level error risk will be compared for statistically significant differences. These results will provide guidelines for areas of emphasis when developing an aircraft cost estimate when time and resources to conduct a grass-roots estimate are constrained.

Scope and Limitations

The scope of this study is limited to the allocation of cost analyst resources for aircraft programs. Specifically, this study is tailored for applicability to program offices located at ASC. The methodology used for this research may be applicable to other

human resource functional categories or to other categories of weapon systems.

However, any such extrapolation of this methodology will first require a full investigation of the risks involved in any such application.

Thesis Overview

Chapter two addresses the fundamental concepts and techniques of aircraft cost estimation and the previous research conducted in this area. Chapter three explains the methodology behind this research. Chapter four applies the methodology of chapter three to analyze the data. Chapter five clarifies the results and conclusions that can be derived from chapter four's analysis. Future research is also outlined in this chapter.

II. Literature Review

Chapter Overview

This chapter focuses on the fundamental components and techniques used to develop an aircraft cost estimate. First, a discussion of the basic building block for any cost estimate, the Work Breakdown Structure (WBS), is examined. Next, the role of CERs in aircraft estimation is explored to understand why and how they are used. Then, an explanation of aircraft cost estimation techniques, specifically the parametric and grass roots methods, are covered. Finally, an overview of past research that has been accomplished on comparisons of macro and micro aircraft estimation techniques is investigated.

Work Breakdown Structure

Due to its versatility, the WBS is a useful tool for both program managers and cost analysts in defining the scope of a project. The WBS is formally defined as:

A deliverable-oriented grouping of project elements that organizes and defines the total scope of the project: work not in the WBS is outside the scope of the project. As with the scope statement, the WBS is often used to develop or confirm a common understanding of project scope. Each descending level represents an increasingly detailed description of project elements (PMI Standards Committee, 1996:54).

The overarching objective of the WBS is to integrate a project into a singularly unique and cohesive effort (Flemming and Koppelman, 2000:49).

The WBS is a basic building block of all Major Defense Acquisition Programs (MDAPs). As such, DoD Regulation 5000.2-R mandates that, “A program work breakdown structure (WBS) shall be established that provides a framework for program

and technical planning, cost estimating, resource allocation, performance measurement, and status reporting” (Department of Defense (a), 1996: Part 4). In addition to developing a WBS, every program office is required to tailor their WBS using the guidelines set forth in Military Handbook-881 (Department of Defense (a), 1996: Part 4).

The benefits associated with using a WBS include:

- Separates a defense materiel item into its component parts, making the relationships of the parts clear and the relationships of the tasks to be completed—to each other and to the end product—clear.
- Significantly affects planning and the assignment of management and technical responsibilities.
- Assists in tracking the status of engineering efforts, resource allocations, cost estimates, expenditures, and cost and technical performance.
- Helps ensure that contractors are not unnecessarily constrained in meeting item requirements (Department of Defense (b), 1998:9).

The WBS can be broken down into as many levels as required. However, a breakout of the top three levels satisfies all regulatory requirements (Department of Defense (b), 1998:11). This research will focus its comparisons between level one and level two of the WBS to facilitate the macro versus micro properties. Level two is selected as the micro level because of data availability and the fact that, “Level two of any WBS is the most critical, because at level two the project manager will indicate the approach planned to manage the project” (Fleming and Koppelman, 2000:54).

Level one of the WBS is the entire defense material item, represented in this research by a complete aircraft system. Level two of the WBS is the major elements that

comprise the aircraft system. Level two includes equipment specific elements and common elements found in all major weapons systems. These common elements include systems engineering and program management, training, data, system test and evaluation, etc. The guidelines for the WBS structure of an aircraft system come from Military Handbook Standard 881 (MIL-HDBK-881), as shown in Table 3.

Table 3. Work Breakdown Structure Levels (Department of Defense (b), 1998:A.3)

Level 1	Level 2	Level 3
Aircraft System	Air Vehicle (AV)	Airframe Propulsion AV Applications Software AV System Software Communications/Identification Navigation/Guidance Central Computer Fire Control Data Display and Controls Survivability Reconnaissance Automatic Flight Control Central Integrated Checkout Antisubmarine Warfare Armament Weapons Delivery Auxiliary Equipment
	Sys Engineering/Program Management	
	System Test and Evaluation	
		Development Test and Evaluation Operational Test and Evaluation Mock-ups Test and Evaluation Support Test Facilities
	Training	

Level 1	Level 2	Level 3
		Equipment Services, Facilities
	Data	
		Technical Publications Engineering Data Management Data Support Data Data Depository
	Peculiar Support Equipment	
		Test and Measurement Equipment Support and Handling Equipment
	Common Support Equipment	
		Test and Measurement Equipment Support and Handling Equipment
	Operational/Site Activation	
		System Assembly, Installation and Checkout on Site Contractor Technical Support Site Construction Site/Ship/Vehicle Conversion
	Industrial Facilities	
		Construction/Conversion/Expan. Equipment Acquisition or Modernization Maintenance (Industrial Facilities) Initial Spares and Repair Parts

WBS Terminology Clarification

While the suggested WBS structure is being followed for data collection and analysis purposes, there are some terminology differences between MIL-HDBK-881 and the subsequent language used to describe the data collected. Specifically, at WBS level one, the term Flyaway Cost is substituted for Aircraft System. This change is made because program office costs and costs not directly related to the contractor are not being considered. At WBS level two, the term Basic Airframe is substituted for Air Vehicle. Also, the common elements of System Engineering/Program Management, System Test and Evaluation, Data, and Training are reclassified into a single category called Other Air Vehicle. The form of the available data for collection drives these changes.

Cost Estimating Relationships

The CER is one of the fundamental techniques used to estimate aircraft cost. A CER is formally defined as a “technique used to estimate a particular cost or price by using an established relationship with an independent variable” (Office of the Deputy Director of Defense Procurement for Cost, Pricing, and Finance, 2000:1). The dependent variable is the item of interest that the CER will estimate, (i.e. airframe cost). The independent variables are comprised of a multitude of explanatory variables. The CER is a mathematical relationship that predicts the dependent variable as a function of the independent variables. This relationship is typically developed using a historical dataset of variables and applying a statistical technique, usually regression, to find the parameter estimates of the independent variables (Younassi, Kennedy, and Graser, 2001:83).

The selection of independent variables is extremely important. To ensure an accurate and meaningful CER is developed, the independent variables must be identified as cost drivers for the dependent variable. “Cost drivers are those characteristics of a product or item that have a major effect on the product or item cost” (Long, 2000:2). Typically, performance parameters are the most useful and accurate independent variables (AFSC Cost Estimating Handbook, 1986:6.1), however physical and technical variables are common in CERs. Identification of cost drivers to include in the CER depends on the type of CER being developed. Depending on the life cycle phase of the program, CERs can be categorized into three types: Research and Development, Production, or Operating and Support (AFSC Cost Estimating Handbook, 1986:6.3.1). This research will focus on aircraft production CERs. Past research has identified conventional cost drivers for aircraft CERs to include empty weight, speed, useful load, wing area, power, landing speed, and production quantity (Office of the Deputy Director of Defense Procurement for Cost, Pricing, and Finance, 2000:3).

Historical data is typically used to populate the statistical models that generate the parameter estimates for the independent variables. “Collecting data is usually the most difficult and time-consuming element of CER development” (Office of the Deputy Director of Defense Procurement for Cost, Pricing, and Finance, 2000:2). The advantage of using historical data is that it has an objective and proven level of cost performance (Institute for Defense Analysis, 2000:1). However, special care must be taken to ensure that the data collected is free of errors or other influential factors that may skew a CER under development. Another limitation of using historical data in CER development is that it focuses on the past, while the purpose is to predict the future (Institute for Defense

Analysis, 2000:1). Fortunately, functional relationships for items such as aircraft structure have remained relatively stable for the past several decades (Institute for Defense Analysis, 2000:1).

The most common statistical technique used to develop aircraft CERs is the multiple least squares regression method. To ensure the resultant CER from the regression model is valid, several assumptions and tests must be conducted. First, the assumptions of independence, normality, and constant variance must be satisfied (Devore, 2000:547). A Lag 1 correlation test, such as the Durbin-Watson test, can analyze the assumption of independence (Neter, Kutner, Nachtsheim, and Wasserman, 1996:504). At an $\alpha = 0.05$ level, the Durbin-Watson test must return a p-value of greater than 0.05 to demonstrate independence. If a lower p-value is realized, the data is not useful and the CER should be considered invalid. The Shapiro-Wilk test is an objective measure to determine if the assumption of normality is met (Neter, Kutner, Nachtsheim, and Wasserman, 1996:111). Conducted at an $\alpha = 0.05$ level, the assumption is validated if the test returns a p-value greater than 0.05. Similarly, the assumption of constant variance can be confirmed using the Breusch-Pagan test if the p-value is greater than the $\alpha = 0.05$ threshold (Neter, Kutner, Nachtsheim, and Wasserman, 1996:115). While the assumption of independence is non-negotiable in achieving a valid regression model, the assumptions of normality and constant variance can be violated if it can be shown that the violation is a “reasonable violation” (Osborne and Waters, 2002:1). Determining if a violation of an assumption is “reasonable” is the responsibility of the modeler based on the known facts of the individual case. After the assumptions have been met, it is imperative that the regression model be tested for validity. This is accomplished by

populating the CER with a randomly selected portion of the raw data. This randomly selected portion of raw data is set aside prior to building the regression model. The validity of the model can then be determined through analysis of the Mean Square Error (MSE) resulting from this data and the model. The complete CER development process is shown in Figure 2.

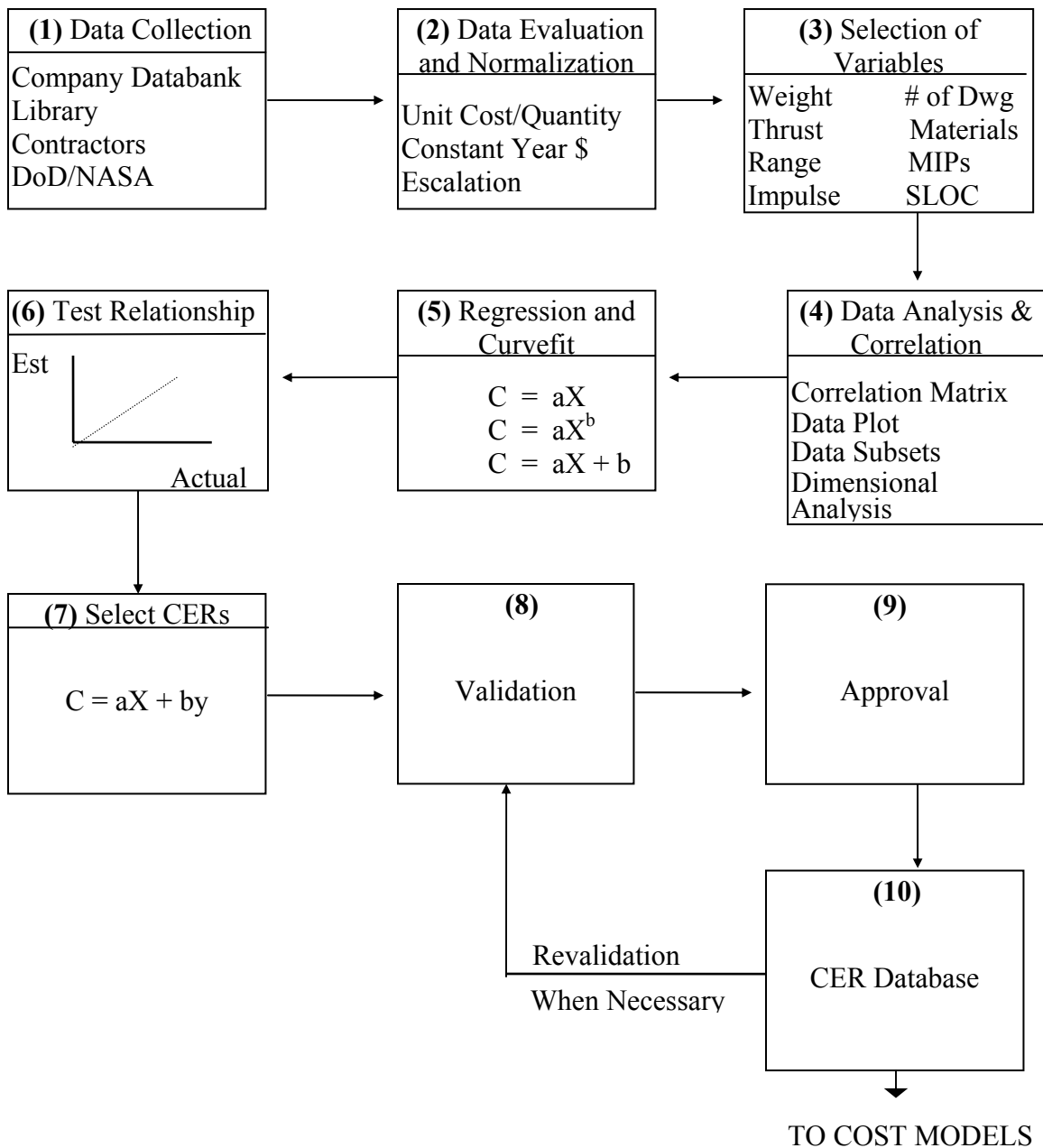


Figure 2. CER Development Process (Department of Defense (c), 1995:III-10)

CERs are prevalent in many different cost estimation techniques. They are the cornerstones of the parametric estimation technique developed by the RAND Corporation in the 1950's to predict the cost of aircraft (Nhysoft Inc, 2002). As such, they are now

the primary component underlying most commonly used parametric software estimating suites (Air Force Material Command, 2001). The versatility of CERs can be shown by their cross utilization among other estimation techniques. The grass roots technique uses CERs to develop detailed labor and material estimates which are then summed as components of the total estimate (AFSC Cost Estimating Handbook, 1986:9.4.1). Because CERs are versatile and widespread, they can be found in virtually every cost analyst's toolbox.

There are several characteristics that make CERs desirable across these cost estimation techniques. First, they are able to “provide quick estimates without a great deal of detailed information” (Long, 2000:2). This is important, as a CER can be used early in a program's life, before any actual data is available, to forecast and plan for future budgets. Second, because CERs are based on historical data, they incorporate the impacts of system growth, schedule changes, and engineering changes (AFSC Cost Estimating Handbook, 1986:3.4.1). These changes are a fact of virtually every DoD program. Because these items are part of the historical data, the CER is able to give a more realistic picture of the future. Most importantly, CERs have proven to be good predictors, which is the goal of any cost estimation technique.

Aircraft Estimation Techniques

A variety of estimation techniques are available to the cost analyst for developing aircraft cost estimates. The two ends of the estimation technique spectrum are parametric estimation and grass roots estimation. The parametric estimation technique can be

considered a macro approach to cost estimation, while the grass roots approach is consistent with a micro approach to cost estimation.

Parametric Estimation

In today's acquisition environment of doing more with less, parametric estimating has become a common tool for the cost analyst. Parametric estimation can be defined as:

A technique employing one or more CERs and associated mathematical relationships and logic. The technique is used to measure and/or estimate the cost associated with the development, manufacture, or modification of a specified end item. The measurement is based on the technical, physical, or other end item characteristics (Department of Defense (c), 1995:16).

The CERs developed to populate the parametric cost model are typically derived through non-experimental regression techniques (Robbins and Daneman, 1999:24).

The parametric cost model represents the macro approach to estimation for several reasons. First, the focus is on high-level cost drivers and high-level data from which trends can be extracted (Nhysoft Inc, 2002). Second, the parametric method is often used early in the acquisition cycle when program and technical definition is limited (AFSC Cost Estimating Handbook, 1986:3.4.1). At this point in the life cycle, the details to develop a comprehensive estimate are scarce, so the parametric estimate is a more useful estimation tool. Finally, capturing total program costs can be accomplished with a single parametric model (AFSC Cost Estimating Handbook, 1986:3.4.1). This one-size fit all approach can be characterized as a macro technique.

The stochastic nature of cost estimates is changing the goal of cost estimates to that of cost realism. This paradigm shift from desiring an exact estimate to one in which the foundation of the cost estimate is more important lends credibility to more widespread use of parametric cost models (Department of Defense (c), 1995:17). This is

because parametric estimates are built on the foundation of CERs that are typically derived through regression techniques that attempt to minimize the sum of square errors. The presence of an error factor in the estimate, while minimized, is recognized as a fundamental component of parametric estimates. Therefore, the shift in emphasis to cost realism facilitates the expansion of parametric techniques from its origins as a technique primarily used in the early stages of an acquisition program, to one used throughout the life cycle phases (see Table 4).

Table 4. Methodology Applicability by Phase (Long, 2000:7)

Life Cycle Phases	Parametric	Bottom Up
Conceptual	X	
Development	X	X
Production	X	X
O&S	X	

Parametric estimation has become the preferred method for many organizations within the DoD, including the Defense Contract Audit Agency (DCAA). “The DCAA policy is clear – parametric cost estimating is a preferred approach based on proven statistical concepts and techniques” (Long, 2000:8). These policy decisions are a result of the multitude of benefits derived from using parametric techniques. These benefits include the ability to complete a parametric cost estimate in less time than a traditional grass-roots estimate. Additionally, parametric techniques are more user friendly due to the inherent flexibility of the cost model (Department of Defense (c), Intro). Estimate changes can be made simply by changing parameters. This flexibility in the parametric model is most useful for sensitivity analysis, which is common in aircraft SPOs due to typical programmatic changes such as quantity changes, scope changes, and budget cuts. Additionally, parametric estimates have proven to be very accurate, even for complex

systems (Nhysoft Inc, 2002). These benefits of parametric cost models are most clearly seen by examining the results of a pilot study conducted on contractor proposals submitted to the government by 13 Reinvention Laboratory sites in 1995 (Long, 2000:8). This study was a result of the Parametric Cost Estimating Initiative (PCEI) to examine the viability of expanding the use of parametric models. As shown in Table 5, the parametric models proved to be better than or equal to their traditional counterparts at aircraft cost estimation when tested with various contractors.

Table 5. PCEI Pilot Program Site Results (Long, 2000:8)

Site	Faster	Cheaper	Accuracy
Raytheon (E-Systems)	25%	33%	More Accurate
Northrup Grumman ESSD	33%	33%	Equal or Better
Lockheed Martin Astronautics	25%	25%	More Accurate
Boeing SSD	40%	35%	More Accurate

Due to the benefits of accuracy, time efficiencies, and cost savings, many commercial firms have adopted parametric cost models (Department of Defense (c), Background). DoD benefits from this commercial parametric methodology adoption primarily in the form of lower proposal costs and easier auditability of proposals.

Another form of parametric estimation is the factor or ratio. These parametric techniques are often applied to the common elements found at WBS level two, such as training, data or program management. For example, the data cost for a new aircraft may be estimated as a factor of 5% of Prime Mission Product (PMP) based on analogous programs. The primary benefit to using a factor is that a large part of an estimate can be

captured with limited historical data (Long, 2000:4). Ratios are used in a similar manner as factors, and usually relate items such as recurring to non-recurring costs.

There are some limitations to parametric estimation that must be considered. As a result of the cost typically being captured at a high level, limited visibility into specific areas is not provided. This becomes an issue when subtle changes in design or manufacturing techniques occur in low level areas and is not reflected in the estimate (Long, 2000:5). In addition, the individual components of an estimate may not be separable, causing problems when additional analysis on individual elements is needed.

Grass Roots Estimation

The grass roots technique for cost estimation is synonymous with the phrases “detailed,” “bottom-up,” and “engineering build-up” (AFSC Cost Estimating Handbook, 1986:3.4.3). As implied, the underlying crux of a grass roots estimate is to start at the lowest level of the WBS, estimate the components, and sum their parts. For this reason, the grass roots estimation technique is categorized as a micro approach to cost estimation.

Grass roots techniques are traditionally applied during the production phase of a weapons system for several reasons (AFSC Cost Estimating Handbook, 1986:3.4.3). First, in order to develop a high fidelity estimate, the preparatory process requires a highly detailed examination of the system and program (AFSC Cost Estimating Handbook, 1986:3.4.3). This process can exhaust a program’s valuable resources. Second, actual data from the program is helpful to develop the estimate. This data is not available until the production phase. Additionally, it is important that the configuration of the system is stable and the test results are available, as the estimate is based on past historical data about the actual system (AFSC Cost Estimating Handbook, 1986:3.4.3).

Elements such as configuration of the system and test results can dramatically change the course of a program, and stabilization of these elements does not occur until the production phase. While the grass roots technique is typically used during production, it is important to note that it can also be used to predict future system costs during other phases of the life cycle with the help of CERs. These CERs are used to develop detailed labor and material estimates that are then summed to arrive at the cost estimate (AFSC Cost Estimating Handbook, 1986:9.4.1).

The application of the grass roots technique normally requires detailed historical data. Often, the system is broken down and estimated at the various labor categories, materials, and subcontract components (AFSC Cost Estimating Handbook, 1986:9.4.1). The summation of these elements comprises the cost estimate. There are several benefits to this approach. First, because there is an extensive detailed breakout of an individual WBS element, it is easier to scrutinize and analyze deviations from the estimate. Additionally, unlike the parametric technique, there is little need for engineering support when developing a grass roots estimate (AFSC Cost Estimating Handbook, 1986:3.4.3). This is due in large part to the availability of actual system data.

It is important to recognize limitations that exist with the grass roots technique. More time is required to derive a grass roots estimate than any other cost estimating technique (AFSC Cost Estimating Handbook, 1986:3.4.3). Also, actual data is needed which may or may not be available. Even if data is available, it is often costly to purchase it from the contractor. A final limitation addresses the risk inherent in an underlying assumption of a grass roots estimate; that future costs can be predicted from historical costs, which may not necessarily be true (AFSC Cost Estimating Handbook,

1986:3.4.3). Thus, the grass roots risk is fundamentally different from a parametric estimate, which relies on causal relationships to achieve an estimate. Despite these limitations, the grass roots technique is widely used and accepted in cost estimation.

Previous Research

This research is the first of its kind to explore a statistical comparison of micro versus macro cost estimating techniques. A critical component for this comparative analysis is the development of CERs for level one and level two WBS elements. The RAND Corporation is a leading organization in analyzing and hypothesizing aircraft CERs (Seibel, 2002). RAND studies on estimating aircraft airframe costs date back to the 1960s. Several components of these studies are relevant to this research effort. For example, while analyzing airframe components for a study, CERs were developed at the lowest level and compared to the aggregate level. In addition, RAND has examined the benefits and detriments to segregating CERs by aircraft categories. RAND has also completed extensive research in identifying those explanatory variables that are of most significance when developing regression models for aircraft airframes. This research will examine elements of these studies, to include the segregation of aircraft by categories, identifying explanatory variables to derive CERs, and analyzing the validity of micro versus macro cost estimation techniques.

Large, Campbell, and Cates: 1976

Parametric Equations for Estimating Aircraft Airframe Costs provided an update to earlier research conducted by Levenson and Barro (1966) of the RAND Corporation. Large, Campbell, and Cates' (1976) goal was to derive equations through multiple

regression techniques for estimating acquisition costs of aircraft airframes to use in long term planning. The scope of the study encompassed 25 aircraft, both development and procurement phases, with first flight occurring between 1953 and 1970.

A multitude of aspects relating to aircraft airframe cost estimates was explored in this study. First, prior research in this area had essentially found only two main cost drivers: airframe unit weight and max speed. The research implemented a three-pronged criterion to find other cost driver variables. For inclusion in the model, a variable needed to provide consistently accurate estimates, be logically related to cost, and be easily determined prior to actual design and development. There were no new variables found that met this criterion. A second major contribution of this study involved the exploration into developing separate CERs for different categories of aircraft. They concluded that while it was intuitively appealing to make such distinctions, the sample size of aircraft available was too small to be representative, with the exception of fighters. Thus, unless the new aircraft being developed was considered very homogeneous to the segregated sample, it was better to have a larger group of diverse aircraft as the data sample.

Another new aspect investigated by this study was the difference in estimating from equations developed for total cost versus the individual elements of an aircraft airframe (i.e. manufacturing, tooling, etc). Minimal difference was discovered in the errors associated with the two approaches. Additionally, it was found that segregation based on aircraft type for the total cost equations was actually better, even with a small sample size, than developing composite equations with all aircraft categories represented. Despite these findings, Large, Campbell and Cates concluded:

The total-cost equation has a serious deficiency. The equation is based on the composite rates above and cannot be adjusted to any other set of rates. One could assume (erroneously) that material costs, engineering labor, tooling labor, etc., increase at the same annual rate and in that manner adjust for inflation. But the basic problem is that the composite rates ... may not approximate those expected to be in effect for any specific program (Large, Campbell, and Cates, 1976:42).

Summarizing their results, this study developed estimating equations that were similar to previous work in this field, as the primary explanatory variables remain weight and speed. Neither the total cost, nor individual element equations, produced estimates that were consistently within 20% of actual costs. Therefore, the study recommended further research be conducted to examine non-deterministic factors such as contractor experience, economic conditions, schedule, etc as possible explanatory variables for this inconsistency in estimation.

Hess and Romanoff: 1987

Aircraft Airframe Cost Estimating Relationships was the third RAND study examining this and provided an update to the 1976 study compiled by Large, Campbell, and Cates. Hess and Romanoff's (1987) primary objective of the study was to update CERs for aircraft airframes through multiple least squares regression techniques. This update was driven by the addition of new aircraft platforms such as the F-15, F-16, F-18, and A-10, bringing the total number of aircraft analyzed to 34. CERs were developed for the individual components of the airframe (i.e. manufacturing, tooling, etc.) and at the total airframe level. Comparisons of the fidelity of the equations at the varying levels found virtual equivalence in accuracy.

Three sub-objectives of the study were also considered. First, the effect of dividing the 34 aircraft into subcategories of homogeneous data sets to determine whether

better CERs resulted was examined. The categories used by RAND included fighters, bombers/transport, and attack aircraft. The results of these CERs were then compared to the CERs developed at the aggregate aircraft level. Hess and Romanoff were only able to develop acceptable estimating relationships for the fighter aircraft category. The inability to develop CERs for the other two categories was attributed to three items: “a lack of variation in performance variables, the heterogeneity of the samples, and the distribution of aircraft with respect to size” (Hess and Romanoff, 1987:57). Comparisons of these CERs to the composite aircraft CERs led to mixed results. Their research concluded that the overall sample estimating relationships should be the primary equations, with the fighter relationships serving as a complement to the full set.

Second, as a recommendation of the Large, Campbell, and Cates study to examine the effects of program structure and airframe construction characteristics as independent variables in the regression model, Hess and Romanoff divided the independent variables under consideration for the regression models into four categories: size, performance, construction, and program. Due to concerns about collinearity, they limited each CER to only one variable from each category for a total of four potential independent variables. While many of the variables in the construction and program categories were found significant during the regression analysis, none were included in any of the final equations; Hess and Romanoff determined that the addition of the variables did not give any substantial improvement to the quality of the equations.

Finally, an attempt to add a technology index to help account for the ever-increasing complexity of aircraft was explored. The technology index was explored only within the fighter category. The equations of the technology index were compared with

alternate equations that did not include a technology index. Based on standard error comparisons, it was determined that the inclusion of a technology index had little benefit for the fighter airframe CERs.

In summary, Hess and Romanoff updated the cost estimating relationships for aircraft airframes. During this update, no new explanatory variables were found. In addition, attempts to find equations for homogeneous categories of aircraft were largely unsuccessful, as were attempts to include a technology index to account for increasing aircraft complexities.

Rester, Rogers, and Hess: 1991

Advanced Airframe Structural Materials: A Primer and Cost Estimating Methodology expanded the variables previously considered in estimating airframe costs to examine the effects of advanced materials. Specifically, advanced composite materials and new metal alloys were examined. Rester, Rogers, and Hess (1991) used a unique approach to their study, as a survey of industry was used as the basis for their analysis instead of the traditional statistical approach.

The expansion to include advanced materials as a consideration in airframe costs was driven by the growing percentage of these materials being used in new aircraft (see Figure 3).

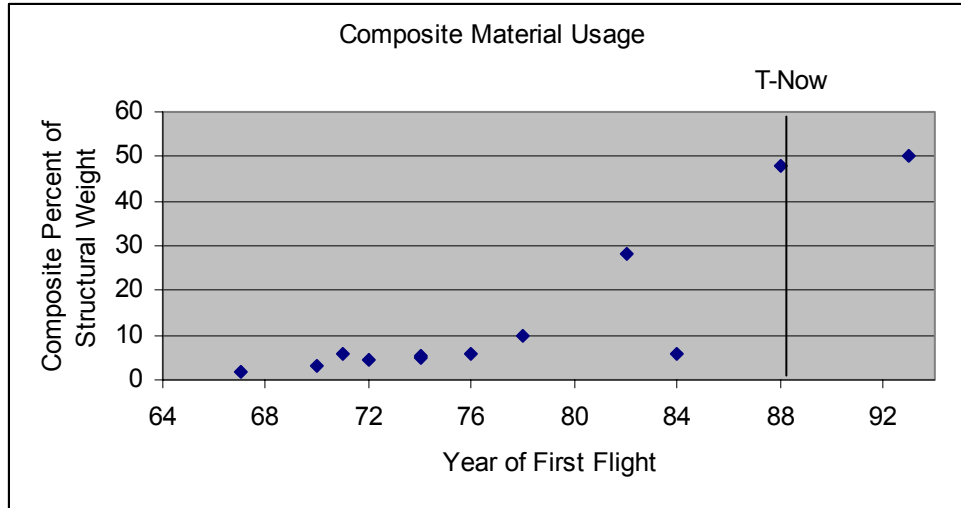


Figure 3. Composite Material Usage (Resetar, Rogers, and Hess, 1991:3)

In contrast to previous studies, only the lowest levels were examined for the effects of advanced materials. Rester, Rogers, and Hess found that for both the recurring and non-recurring airframe elements, the cost of aircraft with these new materials will increase. A factor was then developed to account for the effect of advanced materials on airframe cost. To arrive at total airframe costs, they combined this factor with the traditional CERs for airframe cost estimation.

Younossi, Kennedy, and Graser: 2001

Military Airframe Costs: The Effects of Advanced Materials and Manufacturing Processes is the most recent research the RAND Corporation has completed on military airframe costs. It expands upon the 1987 Hess and Romanoff study and the 1991 Rester, Rogers, and Hess studies. “This study both updates and extends these earlier studies, focusing on the effects of material mix, manufacturing technique, and part geometric complexity on cost” (Younossi, Kennedy, and Graser, 2001:xiii). Unlike the Rester, Rogers, and Hess study, which relied upon industry surveys as a primary source of data,

this study used actual data obtained from the Multi-Aircraft Cost Data and Retrieval (MACDAR) database to perform statistical regression analysis. A final CER recommended for estimating fighter/attack airframe costs was derived through the compilation of four regression equations. These equations factored in the effects of advanced materials and manufacturing processes. In addition, they allow for more flexibility than the earlier studies, as lot size and cumulative quantity were included as independent variables in the model. In summary, Younossi, Kennedy, and Graser presented a CER for aircraft airframe that incorporated the increasing manufacturing and material complexities of next generation aircraft.

Summary

This chapter has focused on gaining an understanding of the concepts behind the basic building blocks of aircraft cost estimation. These include an explanation of the WBS for aircraft and the role of cost estimating relationships. Next, the two ends of the spectrum for cost estimation, the parametric and grass roots techniques, were addressed. Finally, prior research conducted in this area was examined. Therefore, this research will expand upon the prior research by taking a statistical approach to the risks and validity associated with a macro versus micro approach to aircraft cost estimation.

III. Methodology

Chapter Overview

This chapter provides a detailed synopsis of the methodology applied to this research. First, an overview of the data sources, the data segregation rationale, and its limitations are explored. Second, an explanation of the independent and dependent variables of the regression models is examined. Finally, a summary of the application of statistical processes in this research, including multiple regression, Monte Carlo simulation, and the Bootstrap technique are explained.

Methodology Overview

The analysis begins by segregating the aircraft cost data into the aircraft category subsets of fighter and inter-theater airlift, and by their macro and micro components of Flyaway cost, Basic Airframe, and Other Air Vehicle. Next, multiple regression equations are developed for each of these categories, six in total. A Monte Carlo simulation is then applied to these regression equations. Specifically, the Bootstrap technique is used to estimate the standard error of the equations. The resulting distribution from the differences of the standard error of the micro (Basic Airframe and Other Air Vehicle) versus macro (Flyaway Cost) equations is analyzed to answer the original research questions.

Data

Total cost and component cost data for aircraft are required for this micro versus macro analysis. Two primary sources were used to gather data. The main source of data

is the Cost Estimating System Volume 2, Aircraft Cost Handbook, Book 1: Aircraft, Nov 87, which was prepared for the AFCAA by Delta Research Corporation. This data source provided information on the F-15, F-16, F-18, B-1, C-5, C-130, and C-141. The Delta Research Corporation generated the data for their study through interaction with the SPOs, Contractor Cost Data Reports (CCDRs), and their associated contractors. In addition to the data gathered through the Delta Research Corporation study, data was collected directly from the SPOs for aircraft under consideration that were not included in the study. This applies to the data from the C-17.

The primary benefit of using the data from the Delta Research Corporation is that it is normalized to constant year 1987 dollars. The C-17 data was manually adjusted through the use of the Office of the Secretary of Defense (OSD) inflation indices to normalize to constant year 1987 dollars. This normalization provides a homogeneous database for the purpose of analysis.

Although both recurring and non-recurring cost data are available, only the recurring data will be used for this analysis. Recurring costs are costs that are incurred on an ongoing basis, such as final assembly, while non-recurring costs are made up of one-time expenses such as initial tooling and production planning. Because these two categories are influenced by different sets of predictors, they are typically estimated separately by cost analysts (Seibel, 2002). Not separating them for this analysis would add unnecessary variance to the results, hampering a comparison of the macro and micro techniques (Seibel, 2002).

To facilitate the analysis, the data is segregated into two distinct categories, based on aircraft type, to achieve homogeneity in the data sample. The two categories are

fighters and inter-theater airlift. The fighter category is comprised of the F-15, F-16, F-18, and B-1. The inter-theater airlift category consists of the C-17, C-5, C-130, and C-141. In addition to segregation by category, the data will also be subdivided by WBS level. This WBS breakdown, as described in Chapter two, will consist of Flyaway cost which is analogous to level one of the WBS. The two analogous components for WBS level two are the Basic Airframe costs and the Other Air Vehicle costs.

Data Limitations

There are two limitations with this data. The major limitation is that the majority of the data is from pre 1987. This is due to the limited availability of the Delta Research Corporation Database. Since there is not much data available from newer systems such as the F-22 or Joint Strike Fighter, this is not a debilitating limitation. However, future research would benefit from obtaining additional data points from more recent history. The other limitation results from the WBS level breakdown. Once again, due to the available data, a comparison between level one and level two of the WBS is analyzed. Practitioners may object that cost estimation does not normally occur at level one. Thus, future research may want to look at a different database that can be broken down for a level two versus level three comparison.

Variables

The development of high fidelity CERs is crucial to making an accurate micro versus macro cost comparison. The variables, especially the independent variables selected, play a critical role in this CER development process. The dependent variable is cost; as the goal of this research is to determine whether there is a difference in the

resulting cost estimates based on the approach taken. As detailed in Chapter two, previous research has demonstrated that performance parameters are the most useful and accurate independent variables used for aircraft CERs (AFSC Cost Estimating Handbook, 1986:6.1). Additionally, the RAND Corporation has published several studies that indicate that weight and speed are the most important variables for aircraft CERs (Hess and Romanoff, 1987:v). Therefore, performance parameters, physical characteristics, and technical variables will all be considered as independent variables in developing the aircraft CERs to ensure a robust model. The independent variables that are investigated for inclusion in the model are found below (see Table 6):

Table 6. Independent Variables Considered for CER Development

Dimensions (Ft)	Weight (Pounds)	Engines	Performance	Fuel	Quantity
Wing Span	Airframe Unit Weight	Number of Engines	Takeoff Weight	Max Fuel Internal	Lot Number
Wing Area (Sq Ft)	Empty Weight	Max Static Thrust Sea Level	Takeoff Run S.L. (Ft)	Max Fuel External	Cumulative Quantity
Length	Max Gross Takeoff Weight		Max Speed S.L. (Kts)		
Height	Max Landing Weight		Max Altitude (Kts)		
Tread					
Wheelbase					

Regression

A multiple regression methodology will be utilized to develop the aircraft CERs.

In total, six regression equations will be developed in the form of:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \quad (1)$$

where Y is the dependent variable (cost), β is the regression coefficient, X is the independent variables, and ε is the error term. The six regression equations consist of a Flyaway Cost, Basic Airframe, and Other Air Vehicle equation for each of the two categories: fighters and inter-theatre airlift.

Independent variables will be included in the model based on several diagnostic tests. First, any multi-collinearity problems between two independent variables will be examined. A multivariate plot of the independent variables serves as a descriptive measure to determine if multi-collinearity exists (Makridakis, Wheelwright, and Hyndman, 1998:246). Additionally, an r-value above 0.4 is considered a significant indicator of multi-collinearity and thus serves as the diagnostic test. Once multi-collinearity issues have been resolved in the model, the independent variable's t-statistic and associated p-values will be examined. The p-value associated with the t-statistic gives the probability of attaining the t-statistic under a true null hypothesis, which in this case is that the regression coefficient is zero (Makridakis, Wheelwright, and Hyndman, 1998:217). Thus, a small p-value indicates there is little probability that the t-statistic could be its current value with a true null hypothesis. An independent variable will therefore be considered significant if its p-value is less than 0.10 (Makridakis, Wheelwright, and Hyndman, 1998:217). The Variance Inflation Factor (VIF) is the final diagnostic that will be applied to the independent variables. A high VIF score indicates the existence of multi-collinearity. The rule of thumb is to accept a VIF score under ten (www.uky.edu/ComputingCenter/SSTARS/MulticollinearityinLogisticRegression.htm).

The overall model will be tested for predictive capability with an F-Test and its associated p-value. The F-Statistic is the ratio of the mean square for regression and the mean square for error (Makridakis, Wheelwright, and Hyndman, 1998:252). Under a true null hypothesis, which states all regression coefficients are zero, both the mean square for regression and the mean square for error estimate the variance of the error component. Thus, a large F-statistic indicates that the model is explaining the majority of the variance (Makridakis, Wheelwright, and Hyndman, 1998:252). The p-value associated with this F-statistic will be deemed significant if it is less than 0.10. A second diagnostic measure used to determine whether the overall model is acceptable is the R^2 value. R^2 gives the proportion of variance in the dependent variable that can be explained by the independent variables. In addition to R^2 , the adjusted R^2 value is also examined. Unlike R^2 , which increases with each additional independent variable added, adjusted R^2 penalizes the regression model for each additional independent variable (Devore, 2000:566). Thus, the adjusted R^2 value is a more robust indicator of the models validity.

Once the independent variables and the final model have been selected, the three underlying assumptions of independence, normality, and constant variance are tested. Given that the resulting regression model satisfies the assumptions, F-test, t-tests, R^2 diagnostic, and adjusted R^2 diagnostic, it will be deemed acceptable. The resultant six CER equations will then be ready for progression into the next phase, Monte Carlo simulation.

Monte Carlo Simulation

After the development of the regression equations is complete, the use of a Monte Carlo method is applied. The term Monte Carlo is very generic, as it can be applied to a multitude of differing methods (Woller, 1996:1). “In a Monte Carlo method, the quantity to be calculated is interpreted in a stochastic model and subsequently estimated by random sampling” (Niederreiter, 1992:3). Therefore, for an experiment to be considered a Monte Carlo experiment, it simply involves the use of random numbers to examine a problem. This technique can be applied to a variety of problems. Figure 4 depicts the general application of the Monte Carlo technique.

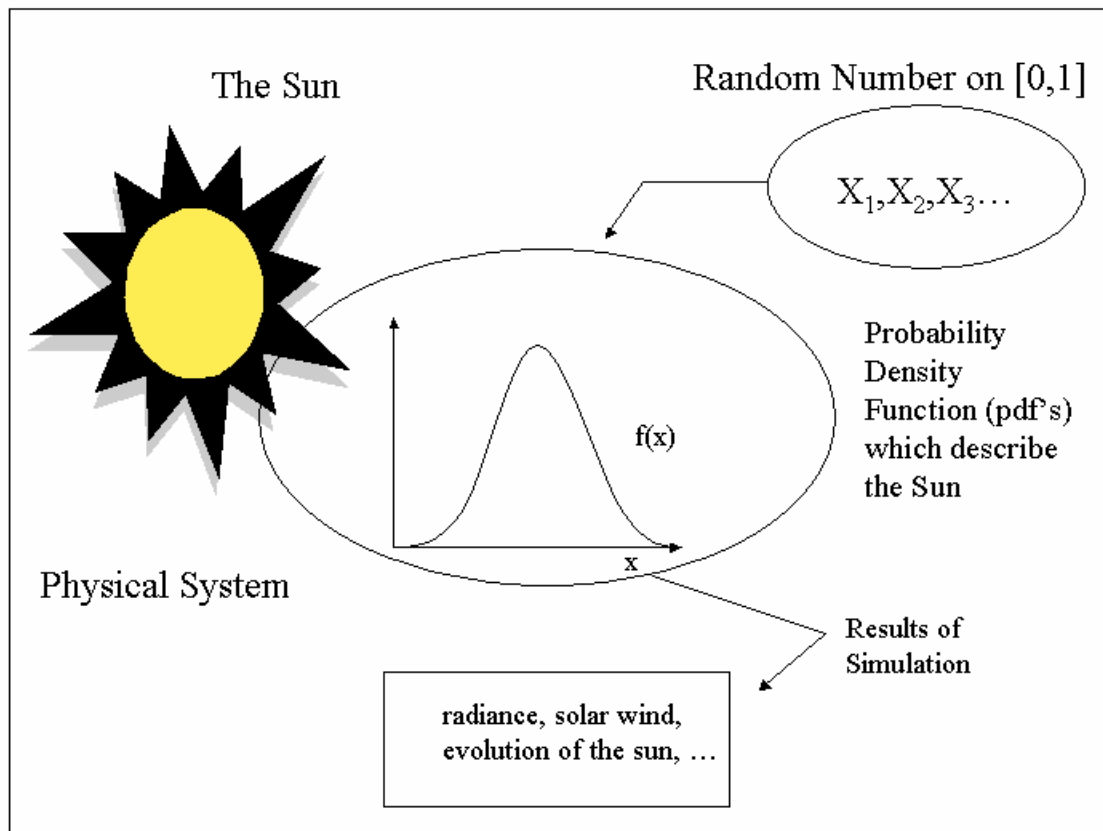


Figure 4. Monte Carlo Simulation of a Physical System (Nelson, 1997)

The Monte Carlo Simulation will generate multiple outcomes for the regression equations for Basic Airframe, Other Air Vehicle, and Flyaway costs. Commercially available software, Crystal Ball, is implemented to accomplish this simulation. The use of Crystal Ball necessitates defining a Forecast cell and Assumption cells. The Forecast cell represents the outcome of interest, in this case the individual regression equation. The Assumption cell represents the changing independent variable. The error terms from the regression equations must be modeled as random variables with a probability distribution. These errors will follow a Normal $(0, \sigma^2)$ distribution, and will constitute the Assumption cell in Crystal Ball. “To perform simulation in a spreadsheet, we must first place a random number generator (RNG) formula in each cell that represents a random, or uncertain, independent variable. Each RNG provides a sample observation from an appropriate distribution that represents the range and frequency of possible values for the variable” (Ragsdale, 2001:567).

Bootstrap

The Bootstrap technique and “resampling” are intrinsically tied together. The underlying construct behind Bootstrap resampling is that the original sample is considered the best estimate of the population (Stine, 2002:Chapter 1:9). The resampling occurs as one “samples the sample” (Stine, 2002:Chapter 1:9). Thus, the essence of the Bootstrap technique is:

That in many complex situations, where bootstrap statistics are awkward to compute, they may be approximated by Monte Carlo ‘resampling.’ That is, same-size resamples may be drawn repeatedly from the original sample, the value of a statistic computed for each individual resample, and the bootstrap statistic approximated by taking an average of an appropriate function of these numbers (Hall, 1992:1).

The following example illustrates how a simple bootstrap sample is constructed. It is of importance to note that the sampling occurs with replacement.

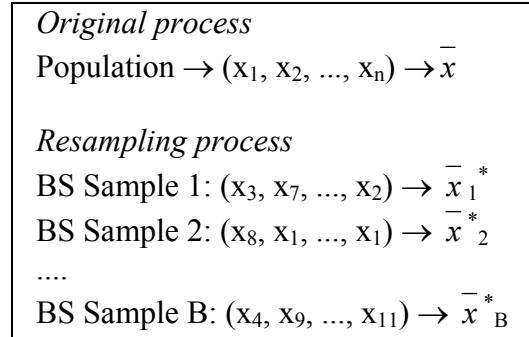


Figure 5. Constructing Bootstrap Samples (Stine, 2002:Chapter 1:10)

The Bootstrap technique is widely used with regression equations. Previous research on estimating the standard error of multiple regression equations found “model-based resampling will give adequate results for standard error calculations” (Davison and Hinkley, 1997:276). The specific regression resampling approach required for this research is the Fixed X, residual resampling (Stine, 2002:Chapter 3:11). This approach, as proposed by Stine, is a two-step process. First, a regression model must be fit and the residuals computed. Second, the bootstrap data is generated by

$$Y^* = (\text{Fit}) + (\text{BS sample of OLS residuals}) \quad (2)$$

where Y^* is the dependent variable, and Fit is the Fixed X portion of the regression equation. It is important to note that under this method, the “residual resampling keeps the same X’s in every bootstrap sample” (Stine, 2002:Chapter 3:23).

Application of The Bootstrap, Monte Carlo, and Crystal Ball

The idea of a Bootstrap is to estimate a characteristic (χ^*) of a population distribution, such as the standard deviation or mean, “by resampling from a distribution

determined by the original sample χ ” (Hall, 1992:7). Monte Carlo techniques and Crystal Ball can be used in combination to apply this bootstrap technique.

The statistic of interest for the macro versus micro comparison in this research is the standard error of the regression equation. Using the Bootstrap function in Crystal Ball, the regression equation as the Forecast cell, and the residual Normal (0, σ^2) distribution as the Assumption cell, the standard error can be calculated for each equation. “As a rule of thumb, about 200 samples are needed for finding a standard error” (Stine, 2002: Chapter 1:16).

Drawing Conclusions

The distribution resulting from the pairing of the data points from the bootstrap results will be examined. An analysis of this distribution, to include the mean and a 95% confidence interval around the mean, will be utilized to determine if the mean is significantly different from zero. If it is not different from zero, it can be concluded that the error of the two equations are statistically equivalent. If the means are statistically different, it can be concluded that there are different risks from taking a macro versus micro approach to cost estimation. Analysis of these risks at the various WBS levels enables decisions about appropriate allocation of resources to be made. Specifically, it will be possible to determine whether more resources should be allocated to the Basic Airframe or to the Other Air Vehicle category.

Summary

This chapter has focused on the underlying methodology necessary to conduct a micro versus macro cost estimation comparison. The origins of the data, segregation of

the data, and its limitations were explored. The techniques used to analyze the data, including multiple regression, Monte Carlo Simulation, and the Bootstrap technique were explained. Chapter four will take this theoretical methodology and apply it to the real world data in order to perform the analysis.

IV. Findings and Discussion

Chapter Overview

This chapter encompasses the analysis of data as outlined in the methodology chapter. Multiple regression models are developed for the macro and micro portions of the Fighter and Inter-theatre Airlift categories. The Bootstrap technique is then applied to the residuals that result from the regression models. Taking the difference of the paired data gives a distribution that can be analyzed to draw conclusions. The chapter begins with an analysis of the Fighter category data, followed by an analysis of the Inter-theatre Airlift category data.

Multiple Regression Models for the Fighter Category

Data

The data for the Fighter category comes from the Delta Research Corporations report, as detailed in the previous chapter. The four aircraft under consideration are the F-15, F-16, F-18, and B-1. These aircraft were chosen for three reasons. First, they are all operational aircraft that are currently utilized by their respective service. Second, multiple production data points are available for analysis. Multiple data points enhance the probability of generating a robust model, which is imperative for conducting the regression analysis. It is important to note that this condition eliminated next generation aircraft such as the F-22 or Joint Strike Fighter, which do not have production data. Third, the characteristics of these aircraft provide a natural grouping that allows for a

homogeneous database to analyze. The final database consisting of the four aircraft has 47 data points.

Preliminary Modeling Problem

Initial development of the regression models included consideration of all the independent variables listed in Table 6 (see Page 37). As shown below (see Table 7) with a portion of the F-16 data, there is duplicity in many of the independent variables. For example, although the average lot cost decreases as subsequent lot buys occur, the wing area remains constant at 300 square feet. While the learning curve effect is captured with variables such as cumulative quantity and lot size, a bias is introduced into the regression by the duplicate independent variables.

Table 7. Portion of F-16 Independent Variables Data

A/C	Lot #	Lot Qty.	Avg. Lot Cost	Wing Span	Wing Area (Sq Ft)	Length	Height	Tread	Wheel-base
F-16	1	8	23.66	32.8	300	49.4	16.4	7.8	13.1
F-16	2	55	7.84	32.8	300	49.4	16.4	7.8	13.1
F-16	3	105	9.02	32.8	300	49.4	16.4	7.8	13.1
F-16	4	145	7.13	32.8	300	49.4	16.4	7.8	13.1
F-16	5	75	6.74	32.8	300	49.4	16.4	7.8	13.1
F-16	6	348	7.44	32.8	300	49.4	16.4	7.8	13.1
F-16	7	175	5.28	32.8	300	49.4	16.4	7.8	13.1
F-16	8	180	5.23	32.8	300	49.4	16.4	7.8	13.1
F-16	9	160	5.11	32.8	300	49.4	16.4	7.8	13.1
F-16	10	120	6.68	32.8	300	49.4	16.4	7.8	13.1
F-16	11	144	5.85	32.8	300	49.4	16.4	7.8	13.1
F-16	12	150	6.26	32.8	300	49.4	16.4	7.8	13.1

There are two potential solutions to this problem. First, changes in the performance parameters and physical characteristics occur as the aircraft changes (i.e. from an F-15 to an F-16) and as the aircraft model changes. For instance, when the F-15

was updated to the C model, the maximum internal fuel characteristic changed. Thus, one way to model the regression is to make a qualitative independent variable that represents an aircraft that has the same performance parameters and physical characteristics. The learning curve portion of the regression model would still be captured through independent quantity variables. A major benefit to this approach is that all 47 data points would remain in the model. The major detriment to this approach is that the independent variables may not be meaningful to the practitioner. However, it is important to note that the objective is not to have a practitioner use the regression equations, but rather to achieve the best estimate of the standard error of the regression equation for comparative purposes.

The second option would be to only use one data point from each aircraft at a specific quantity, such as 100. This option would alleviate the bias found in the independent variables. However, this approach would result in a regression model with only four data points. Therefore, the number of independent variables would be limited to two, due to the degrees of freedom in the regression model. The primary benefit of this approach is that the regression equation would be useful to a practitioner. However, there are some significant problems with this approach. Preliminary models using this technique found that the B-1 was a highly influential data point. Leaving this data point in the model may invalidate the results of the regression, including the p-values associated with the independent variables, the assumptions, and the regression coefficients (Makridakis, Wheelwright, and McGee, 1983: 213).

To achieve the objectives of a comparison of the micro and macro approaches to cost estimation, the validity of the errors resulting from the regression models must be of

the highest quality. Therefore, the first solution of using qualitative variables is the preferred solution to this problem. This method provides a mathematical model that best estimates the errors. For comparative purposes only, the second method's model for the Basic Airframe is developed and attached as Appendix A.

Basic Airframe Model

The variable of interest in this model is the cost of fighter aircraft. The first step in any regression model is to ensure the response is continuous. A histogram of the dependent variable can be utilized for this purpose (see Figure 6). Although there are small gaps in the data, it still appears to be relatively continuous. In addition, the data does not appear to be gathering in bins. Thus, these characteristics lead to the conclusion that the data is continuous.

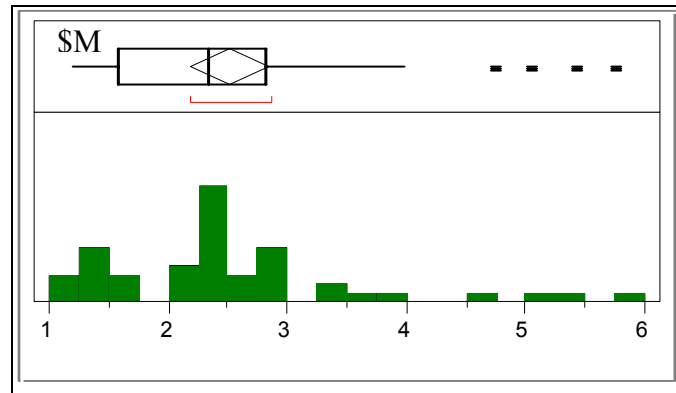


Figure 6. Continuous Data Histogram for Basic Airframe

Once the data is deemed continuous, preliminary regression analysis is conducted. The independent variables used are Category (due to the reasons explained above) and quantity variables including Lot #, Lot Size, and Cumulative Quantity. Running the initial regression model revealed significant independent variables but violated the assumptions of constant variance and normality. Looking at the residual by predicted

plot, the constant variance violation is apparent (see Figure 7). There is a clear megaphone pattern in this plot. Such a trend is an indication that constant variance is violated (Neter, Kutner, Nachtsheim, and Wasserman, 1996:102). The normality violation is shown with a plot of the studentized residuals. The bell-shaped line is the fitted normal distribution. In addition, the Shapiro-Wilk p-value associated with the residuals is $<.0001$ leading to a rejection of the null hypothesis (Neter, Kutner, Nachtsheim, and Wasserman, 1996:111). Clearly, the data is not normally distributed.

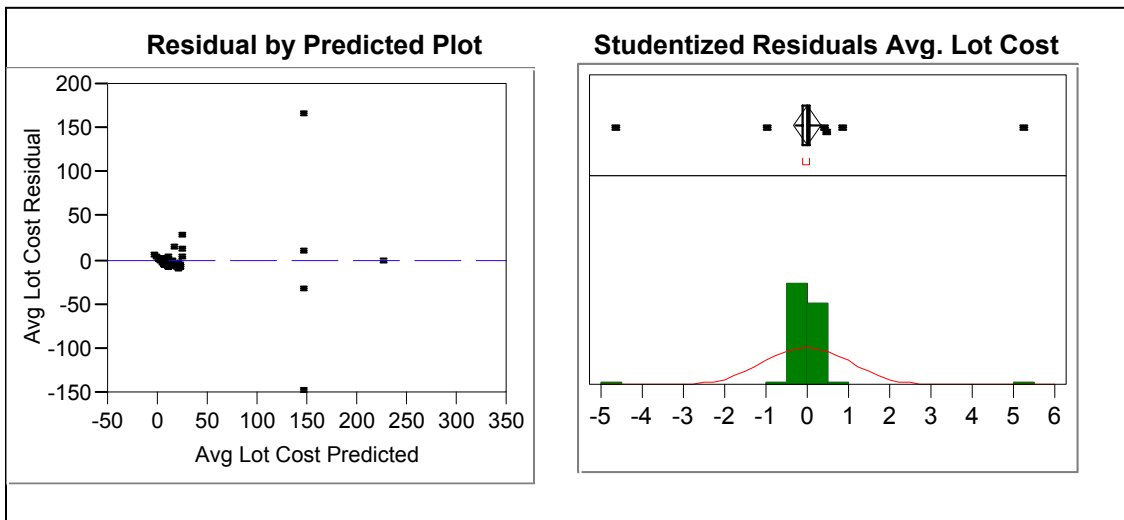


Figure 7. Assumption Violation Plots for Basic Airframe

The solution to these assumption violations is to take the natural log of the dependent (Y) variable (Neter, Kutner, Nachtsheim, and Wasserman, 1996:129). This approach is consistent with the methodology applied by the RAND studies discussed in Chapter 2. For consistency in comparison, all the regression models in the Fighter category will use the natural log of Y as the dependent variable.

The full model is now run again with $\ln(Y)$ as the response. All data points are included in the initial model. Through several iterations of searching for the best model

based on p-values, VIF scores, outliers, influential data points, and R^2 values, a final model is derived. The Analysis of Variance (ANOVA) table is shown in Figure 8. The F-Ratio is 50.95 and its associated p-value is $<.0001$. The p-value gives the probability of attaining an F statistic as large as 50.95, given the slope of the regression coefficients is zero. The p-value is less than the $\alpha = 0.10$ threshold, so it can be concluded that at least one of the parameters in the model has predictive capability.

Table 8. ANOVA Table for Basic Airframe

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	7	48.297758	6.89968	50.9514
Error	38	5.145845	0.13542	Prob > F
C. Total	45	53.443603		$<.0001$

Influential data points can skew regression model output. Cook's Distance Influence Test (Cook's D) can be used to determine if influential data points are present in a regression model (Neter, Kutner, Nachtsheim, and Wasserman, 1996:380). This test operates by removing each data point from the data set, one at a time, and producing a number associated with that points' influence. If the resultant number is between 0 and 0.25 then the point has little apparent influence on the fitted values. If the number is between 0.25 and 0.50 it is considered a mild influential data point. However, if the number is greater than 0.50 then that point has a major influence on the fit (Neter, Kutner, Nachtsheim, and Wasserman, 1996:381). A visual plot of Cook's D values (see Figure 8) indicates that there are no influential data points in this regression model, as the highest Cook's D value is 0.229.

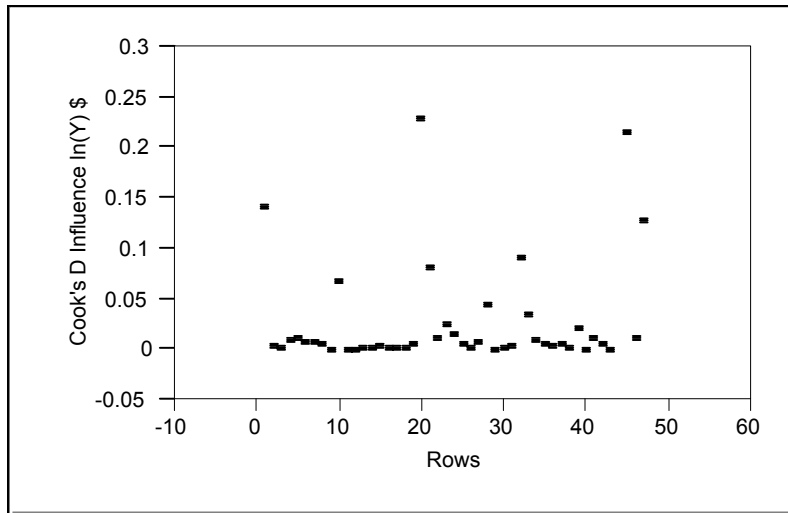


Figure 8. Cook's D Influence for Basic Airframe

Since there are no influential data points in the regression model, it is appropriate to look at the individual parameter estimate values to ensure they are significant (Neter, Kutner, Nachtsheim, and Wasserman, 1996:232). An $\alpha = 0.10$ threshold level is utilized. Analyzing the independent variables in Table 9, all p-values are significantly below the threshold level. Therefore, it can be concluded that all parameters in the model are significant.

Table 9. Parameter Estimates for Basic Airframe

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	3.3941178	0.136297	24.90	<.0001
Category[1]	-0.709052	0.153275	-4.63	<.0001
Category[2]	-0.534294	0.139719	-3.82	0.0005
Category[3]	-1.451749	0.130112	-11.16	<.0001
Category[4]	-0.891017	0.321027	-2.78	0.0085
Category[5]	-0.25603	0.137962	-1.86	0.0713
Category[6]	2.0370961	0.339241	6.00	<.0001
Cum Qty	-0.000796	0.000243	-3.28	0.0022

Another important diagnostic to determine the appropriateness of the goodness of fit of the model is the R^2 value and the adjusted R^2 value. R^2 gives the portion of Y that

is explained by the X's. One drawback to R^2 is that its value can be artificially inflated by adding additional X variables. To counter this effect, adjusted R^2 is often used in its place. Adjusted R^2 penalizes the model for each additional X variable added (Neter, Kutner, Nachtsheim, and Wasserman, 1996:230). Table 10 gives the Summary of Fit results for the Basic Airframe model. The R^2 value of 0.90 is extremely high, as is the adjusted R^2 value of 0.886. These results mean that 90% of the variability in the model can be explained by the independent variables. This is an extremely high result and supports the conclusion that this is a good model.

Table 10. Summary of Fit for Basic Airframe

RSquare	0.903714
RSquare Adj	0.885978
Root Mean Square Error	0.36799
Mean of Response	2.517431
Observations (or Sum Wgts)	46

Before concluding that the model is valid, the three underlying assumptions of normality, independence, and constant variance must be satisfied. Two diagnostics are utilized to check for normality. First, a histogram of the studentized residuals is plotted to analyze the normality assumption with a normal curve imposed over the histogram (Neter, Kutner, Nachtsheim, and Wasserman, 1996:111). Although there is a spike in the data, it appears that the data is normally distributed (see Figure 9). Further analysis of the spike indicates that the data points gathered there do not have any characteristics that suggest there is a split distribution of the data. This conclusion comes from an analysis of the raw data. The data points in the spike come from across all the aircraft categories.

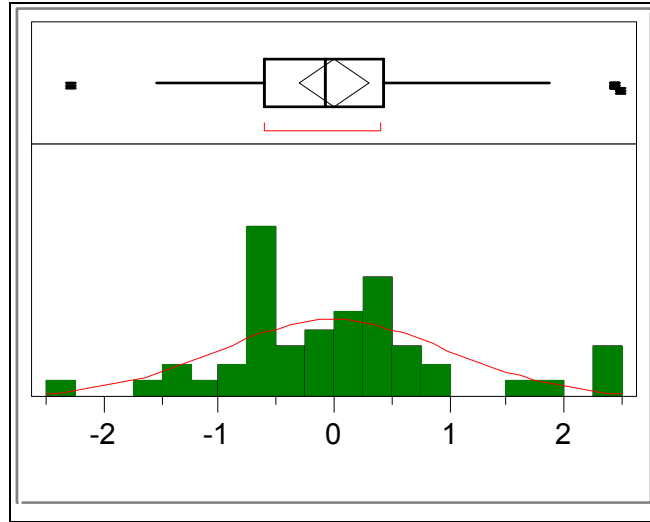


Figure 9. Normality Histogram for Basic Airframe

The Shapiro-Wilk test can be used as a quantitative diagnostic to evaluate the Goodness of Fit of the Normal Distribution. The null hypothesis of this test is that the data is normally distributed. The Shapiro-Wilk test produced a p-value of 0.0345, which is less than the α -level threshold of 0.05. Although this value is less than the threshold, it is not a significant violation. Therefore, this violation is deemed a reasonable violation and the normality assumption is satisfied.

The most important assumption that must be satisfied is the assumption of independence. Typically, the Durbin-Watson test can be used to determine if the model exhibits independence. The Durbin-Watson test examines the Lag 1 correlation of the residuals (Neter, Kutner, Nachtsheim, and Wasserman, 1996:504). However, the aircraft data in this model exhibits time series characteristics, as the data points come from production lot buys over time. Therefore, it is more appropriate to look at the full Autocorrelation Function rather than strictly at the Lag 1 autocorrelation of the Durbin Watson Test. Figure 10 shows the Autocorrelation Function for the Basic Airframe.

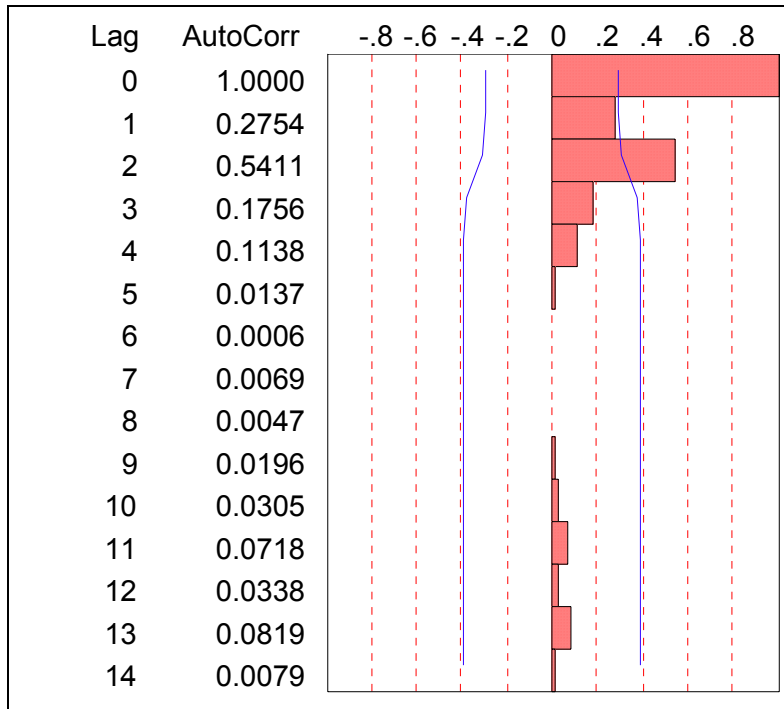


Figure 10. Autocorrelation Function for Basic Airframe

The two solid vertical lines in Figure 10 designate the critical value lines. These values are calculated as $2/\sqrt{n}$. To exhibit independence, several characteristics are desired. First, the function should dampen quickly. Second, there should not be any remaining pattern in the residuals. Third, the majority of the spikes should be within the critical value line limits (Makridakis, Wheelwright, and McGee, 1983:388). Clearly, this criterion is met with this model and thus the assumption of independence is satisfied.

The third assumption that must be considered is constant variance. Constant variance can be determined by two methods. A visual plot of the residual by predicted gives a descriptive measure for constant variance (see Figure 11). Constant variance is characterized by the absence of a pattern (Neter, Kutner, Nachtsheim, and Wasserman, 1996:102).

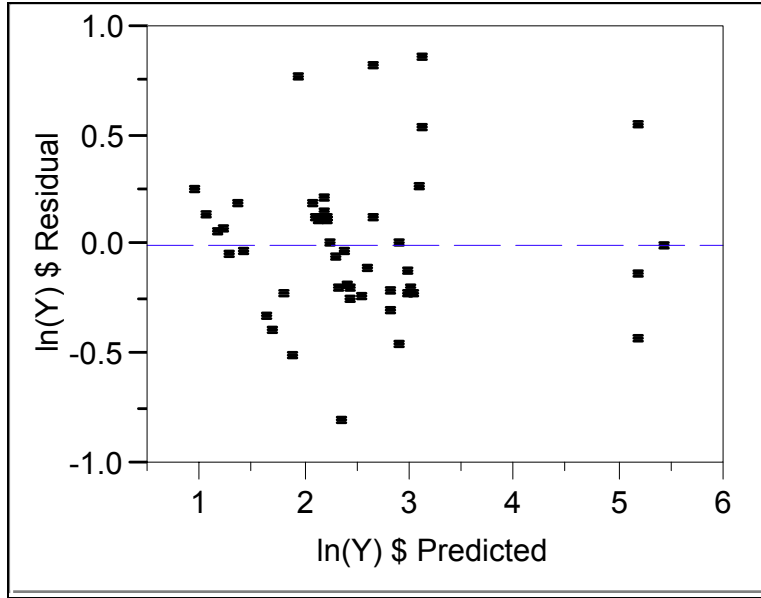


Figure 11. Residual by Predicted Plot for Basic Airframe

The Breusch-Pagan test is a quantitative test for constant variance. This test is used to calculate a test statistic that is approximately Chi-Square distributed, for large n , with degrees of freedom equal to the degrees of freedom of the model. The test statistic is defined as (Neter, Kutner, Nachtsheim, and Wasserman, 1996:115):

$$\chi^2 = \frac{SSR^*}{df + 1} \div \left(\frac{SSE}{n} \right)^2 \quad (3)$$

The test statistic for the Basic Airframe model is 3.905, calculated as follows:

$$\frac{\frac{.3908}{8}}{\left(\frac{5.145}{46} \right)^2} = 3.905$$

The p-value associated with this χ^2 value and seven degrees of freedom is 0.79. Thus the null hypothesis is not rejected and the assumption of constant variance is satisfied.

Checking for outliers is the final step before declaring the model valid. An outlier is found by looking at the minimum and maximum quantiles when the studentized residuals are fit with a normal distribution. Values outside the minimum bound of less than -3 or the maximum bound of greater than 3 indicates the presence of an outlier (Neter, Kutner, Nachtsheim, and Wasserman, 1996:103). The maximum value for this model is 2.47 and the minimum value is -2.29. Therefore, it can be concluded that there are no outliers in the model.

The Basic Airframe regression model is complete and validated by the various diagnostics discussed above. Thus, the resulting equation from this model is:

$$Y = 3.394 - 0.709 * Cat(1) - 0.534 * Cat(2) - 1.452 * Cat(3) - 0.891 * Cat(4) - 0.256 * Cat(5) + 2.037 * Cat(6) - 0.001 * CumQty + \epsilon \quad (4)$$

In order to perform the macro versus micro comparison we need the residual term for the model. The underlying distribution of the residuals is shown in Figure 12. The residuals have a Normal Distribution with $\mu = 0$ and $\sigma = 0.334$. The Kolmogorov-Smirnov Test returns a p-value of >0.15 , validating the normal distribution fit (Neter, Kutner, Nachtsheim, and Wasserman, 1996:111). This distribution is critical as an input to the Bootstrap technique that will be used to perform the micro versus macro comparison.

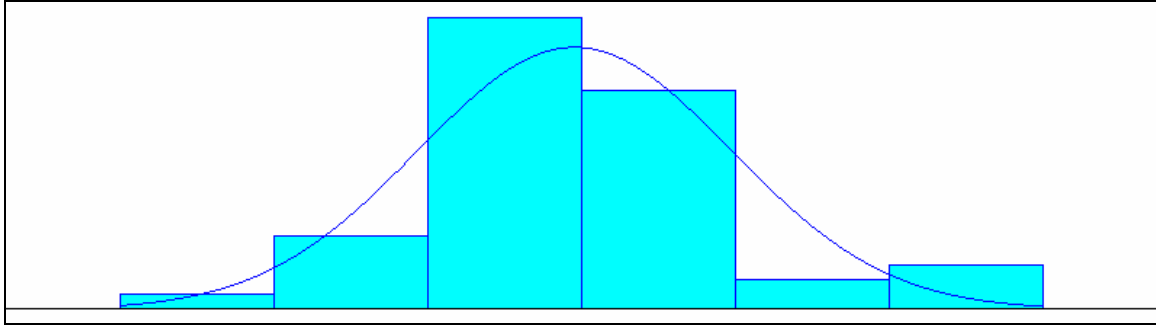


Figure 12. Plot of Residuals for Basic Airframe

Other Air Vehicle Model

The second WBS level two regression model developed was the Other Air Vehicle model. To begin the analysis, the dependent variable is examined to ensure it is continuous. As shown in Figure 13, there does not appear to be any major gaps nor does the data appear to be gathering in large bins. Therefore, it is appropriate to conclude that the data is continuous.

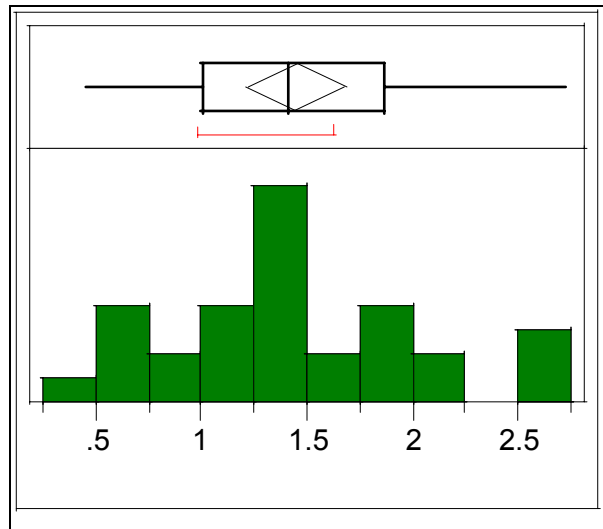


Figure 13. Continuous Data Histogram for Other Air Vehicle

As explained during the development of the Basic Airframe model, the independent variable used for analysis will be the natural log of Y. This is a direct result

of the violations of constant variance and normality in the model. The next step is to examine the ANOVA table to ensure the Other Air Vehicle model has predictive capability. As shown in Table 11, the p-value is $<.0001$ indicating that at least one of the model parameters has predictive capability. One other item of interest from the ANOVA table is the degrees of freedom. The degrees of freedom for the model are only 30, despite having 47 initial data points. This is due to the exclusion of an independent variable (Category 2) and some influential data points. The reasons behind these exclusions will be expanded upon further.

Table 11. ANOVA Table for Other Air Vehicle

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	5	7.556954	1.51139	9.6408
Error	25	3.919273	0.15677	Prob > F
C. Total	30	11.476227		$<.0001$

Cook's D test is run to check for influential data points in the model. As shown in Figure 14 below, all the data points fall below the 0.25 thresholds. However, looking at the graph, it appears that the majority of the data points are gathered in a very tight range with a couple lingering at the top right. Therefore, additional analysis on these data points and the effect they may have on the model is warranted.

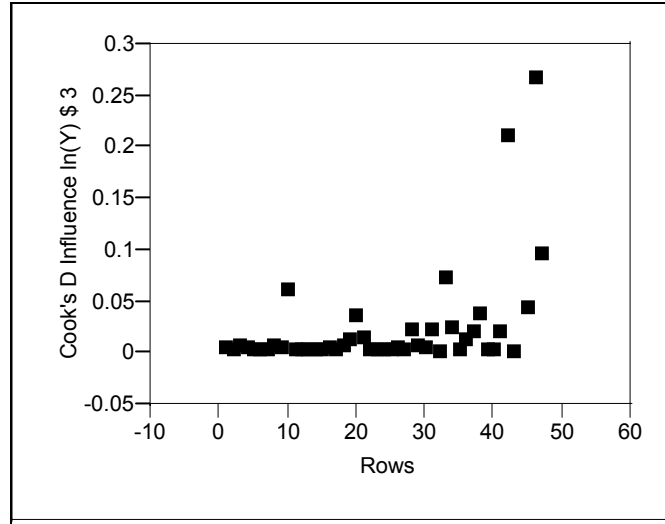


Figure 14. Cook's D Influence for Other Air Vehicle

A comparison of the R^2 values and the p-values associated with the parameter estimates of the independent variables found that three of the data points were indeed influencing the model. This was determined by re-running the model without the suspected influential data points. Removal of these data points resulted in a 0.22 improvement in the adjusted R^2 value. In addition, all of the independent variables, with the lone exception of Category 2, are now significant. The Summary of Fit and Parameter Estimates found in Table 12 below shows the results with the removal of the three influential data points and the Category 2 data.

Table 12. Summary of Fit and Parameter Estimates for Other Air Vehicle

Rsquare	0.658488
RSquare Adj	0.590185
Root Mean Square Error	0.395943
Mean of Response	1.443977
Observations (or Sum Wgts)	31

Summary of Fit

Term	Estimate	Std Error	t Ratio	Prob> t 	VIF
Intercept	2.1343389	0.161211	13.24	<.0001	.
Category[1]	-0.315531	0.164369	-1.92	0.0664	1.4120392
Category[3]	-0.395569	0.134653	-2.94	0.0070	1.0894043
Category[4]	0.5669808	0.345178	1.64	0.1130	3.7755367
Category[5]	-0.376998	0.157462	-2.39	0.0245	1.5713612
Cum Qty	-0.001152	0.000277	-4.16	0.0003	3.4467635

Parameter Estimates

The independent variables are deemed significant if the associated p-value is less than the $\alpha = 0.10$ level. Clearly, Category 4 does not meet this criterion. However, because the p-value of 0.113 is close to the threshold and it is desirable to have as many data points as possible in the model, the variable is kept in the model. Also of note in Table 12 are the VIF scores. The highest VIF score is 3.78, which is well below the target goal of less than ten. The potential problem of multi-collinearity is thus averted in this model.

Examining a plot of Cook's D test results with the remaining 30 data points yields the results found in Figure 15 below. The spread of the data points is now more uniform. In addition, all the values are below 0.15. Clearly, from an influential data point view, this is now a better model.

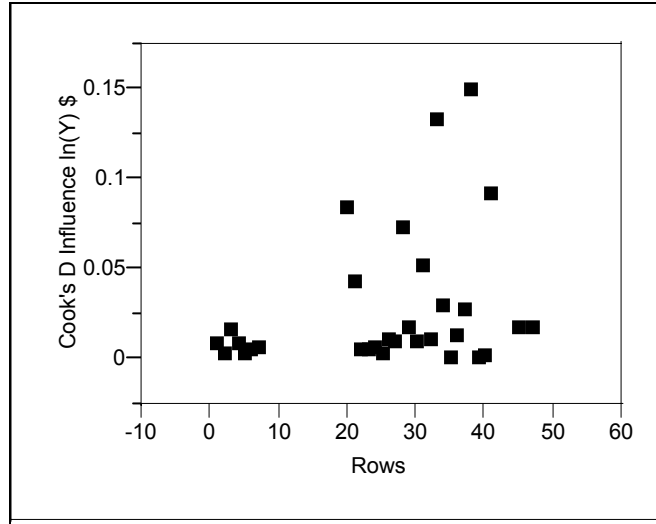


Figure 15. Revised Cook's D Influence for Other Air Vehicle

Before deeming the model valid, the three assumptions of normality, independence, and constant variance must be satisfied. The plot of the studentized residuals (see Figure 16) appears to have the expected bell shape associated with a normal curve. The Shapiro-Wilk test confirms this suspicion, returning a p-value of 0.16. This is well above the $\alpha = 0.05$ threshold. Thus, the assumption of normality is satisfied.

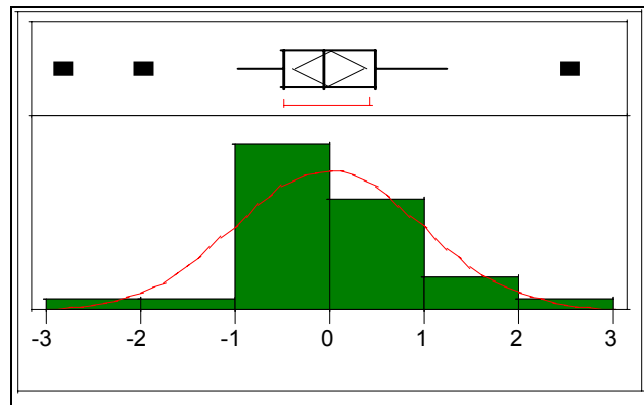


Figure 16. Normality Histogram for Other Air Vehicle

One final check that is accomplished with a histogram of the studentized residuals is to determine if outliers are present. As shown in Figure 16, it appears that all the data

points are within three standard deviations. The quartiles table confirms this visual assumption as the maximum and minimum values fall within negative three and three (see Table 13). Clearly, there are no outliers in this model.

Table 13. Quartiles for Other Air Vehicle

100.0%	maximum	2.521
99.5%		2.521
97.5%		2.521
90.0%		1.200
75.0%	quartile	0.480
50.0%	median	-0.049
25.0%	quartile	-0.486
10.0%		-0.889
2.5%		-2.822
0.5%		-2.822
0.0%	minimum	-2.822

The assumption of independence is confirmed by examining the Autocorrelation Plot (see Figure 17). Every lag in the autocorrelation plot is below the threshold level. This lack of pattern in the residuals is a clear indicator that independence is not a problem.

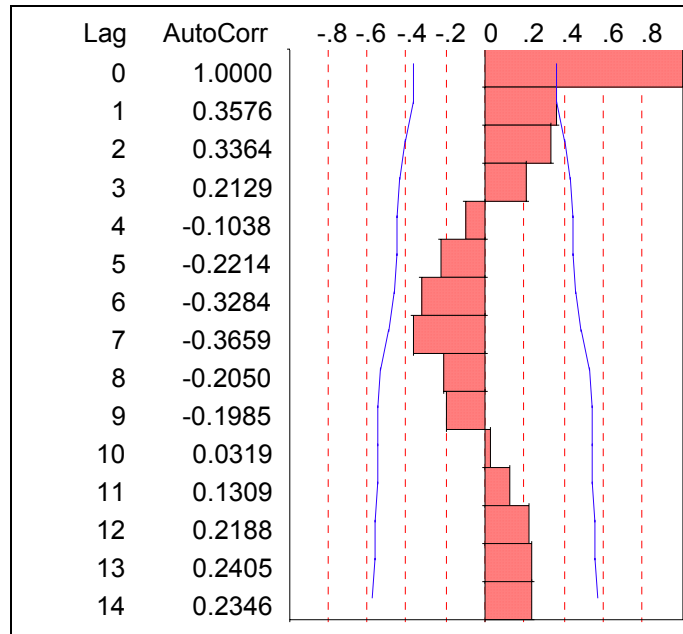


Figure 17. Autocorrelation Function for Other Air Vehicle

The final assumption is constant variance. Figure 18 gives a plot of the residuals versus predicted. While there is not an overwhelming pattern, there does appear to be a potential megaphone effect. To test this visual observation, the Breusch-Pagan test is applied.

$$\frac{\frac{.515}{6}}{\left(\frac{3.919}{31}\right)^2} = 5.371$$

The p-value returned from this test is 0.37, refuting the visual observation. Therefore, the assumption of constant variance is satisfied.

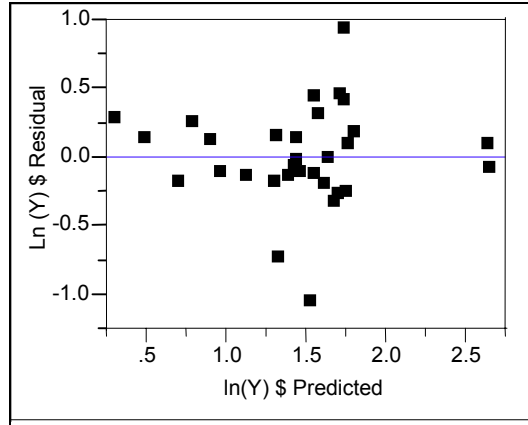


Figure 18. Residual by Predicted Plot for Other Air Vehicle

The Other Air Vehicle regression model is complete and validated by the various diagnostics discussed above. Thus, the resulting equation from this model is:

$$Y = 2.134 - 0.316 * Cat(1) - 0.396 * Cat(3) + 0.567 * Cat(4) - 0.377 * Cat(5) - 0.011 * CumQty + \epsilon \quad (5)$$

The residual term is the item of interest to perform the macro versus micro comparison. The underlying distribution of the residuals is shown in Figure 19. The residuals have a Normal Distribution with $\mu = 0$ and $\sigma = 0.356$. The Kolmogorov-Smirnov Test returns a p-value of >0.15 , validating the normal distribution fit. This distribution is critical as an input to the Bootstrap technique that will be used to perform the macro versus micro comparison.

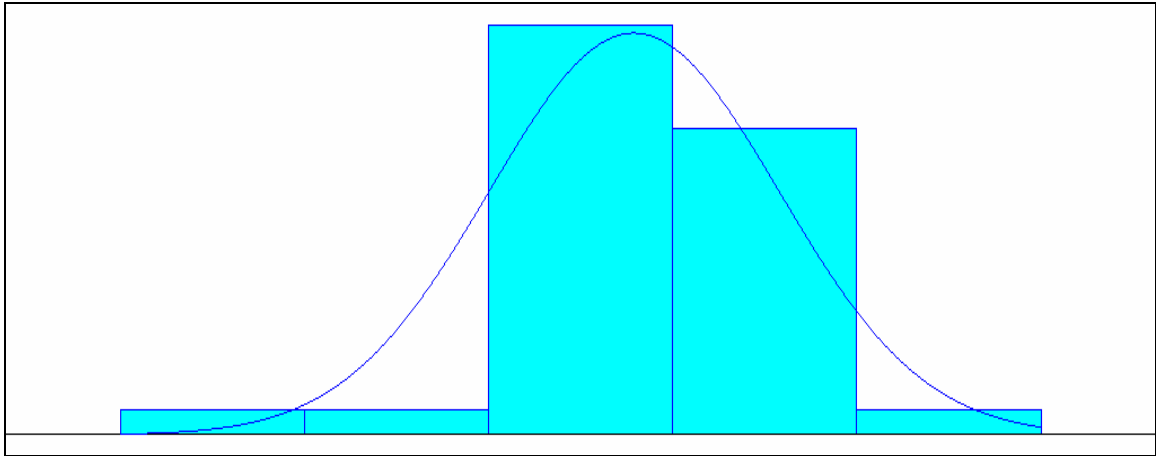


Figure 19. Plot of Residuals for Other Air Vehicle

Flyaway Cost Model

The Flyaway Cost model represents the macro portion of the analysis. The dependent variable is first analyzed to ensure it is continuous. While there are some small gaps in the data, it appears to be continuous (see Figure 20).

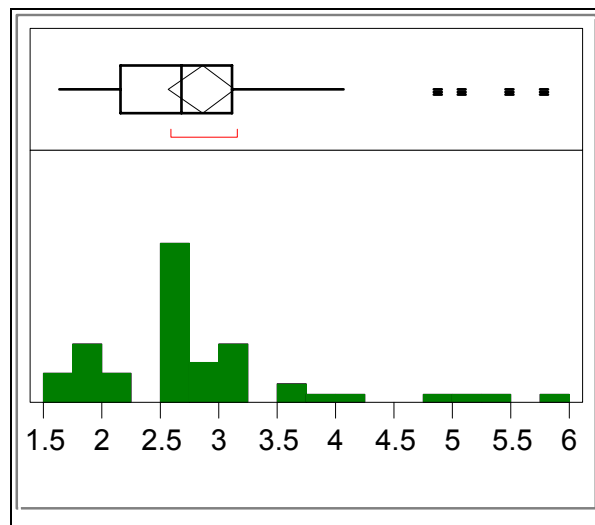


Figure 20. Continuous Data Histogram for Flyaway Cost

Determining whether the overall model has predictive capability is accomplished by examining the ANOVA table (see table 14). The p-value is $<.0001$, indicating that at least one of the parameters has predictive capability.

Table 14. ANOVA Table for Flyaway Cost

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	7	37.202530	5.31465	44.7988
Error	38	4.508085	0.11863	Prob > F
C. Total	45	41.710615		<.0001

A plot of Cook's D is used as a diagnostic for influential data points (see Figure 21). All the data points are below the 0.25 threshold. In addition, the spread of the data points is relatively uniform. An examination of the effects of removing the top right data point did not dramatically affect the model. Therefore, it is concluded that there are no influential data points in the model.

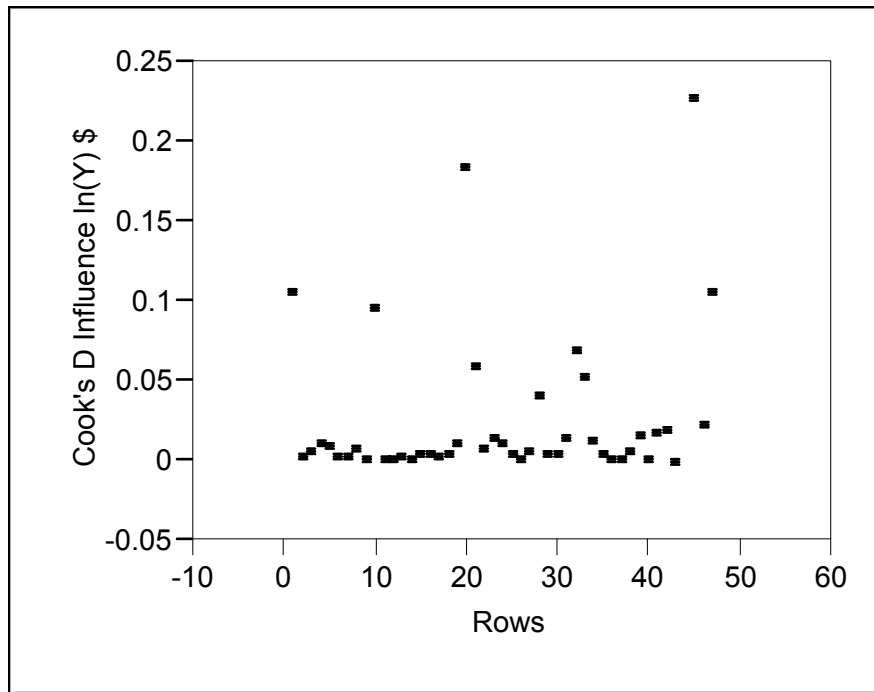


Figure 21. Cook's D Influence for Flyaway Cost

The Summary of Fit table (see Table 15) returns an R^2 of 0.89 and an adjusted R^2 of 0.87, indicating that this model does an excellent job of explaining the variability.

Additionally, the Parameter Estimates are all significantly below the $\alpha = 0.10$ threshold. Multi-collinearity in the independent variables is ruled out by the low VIF scores. Thus, all independent variables are included in the final model.

Table 15. Summary of Fit and Parameter Estimates for Flyaway Cost

RSquare	0.89192
RSquare Adj	0.87201
Root Mean Square Error	0.344433
Mean of Response	2.859426
Observations (or Sum Wgts)	46

Summary of Fit

Term	Estimate	Std Error	t Ratio	Prob> t 	VIF
Intercept	3.7395676	0.127571	29.31	<.0001	.
Category[1]	-0.697189	0.143462	-4.86	<.0001	1.6745295
Category[2]	-0.431093	0.130774	-3.30	0.0021	1.9085175
Category[3]	-1.221545	0.121782	-10.03	<.0001	1.402332
Category[4]	-0.548961	0.300476	-1.83	0.0756	4.5662778
Category[5]	-0.36779	0.12913	-2.85	0.0071	1.7722244
Category[6]	1.7433997	0.317524	5.49	<.0001	3.3255161
Cum Qty	-0.000895	0.000227	-3.94	0.0003	3.8783792

Parameter Estimates

The three assumptions of normality, independence, and constant variance must be satisfied before accepting the model as complete. Figure 22 shows a histogram of the studentized residuals. The bell shape of the data gives a visual check for normality. The more robust quantitative measure, the Shapiro-Wilk test, returns a p-value of 0.07. Thus, the assumption of normality is validated.

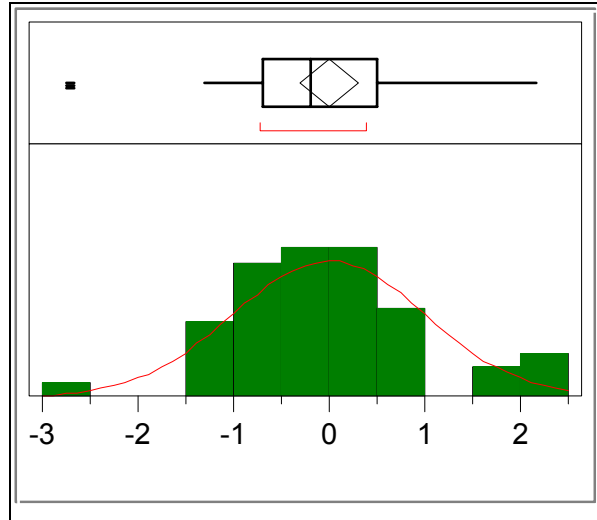


Figure 22. Normality Histogram for Flyaway Cost

The studentized residuals can also be used to check for outliers. Visually, Figure 22 does not show any data points beyond three standard deviations. Table 16 verifies this visual observation, as the farthest point is at -2.71. Therefore, it is concluded that this model does not contain any outliers.

Table 16. Quartiles for Flyaway Cost

100.0%	maximum	2.175
99.5%		2.175
97.5%		2.175
90.0%		1.905
75.0%	quartile	0.499
50.0%	median	-0.198
25.0%	quartile	-0.686
10.0%		-1.113
2.5%		-2.469
0.5%		-2.713
0.0%	minimum	-2.713

The Autocorrelation Plot confirms the assumption of independence (see Figure 23). There is one spike that exceeds the critical bounds at Lag 2. It is expected that five

percent of the values may be outside the critical bounds due to noise in the data.

Therefore, this spike is not a concern and the assumption of independence is satisfied.

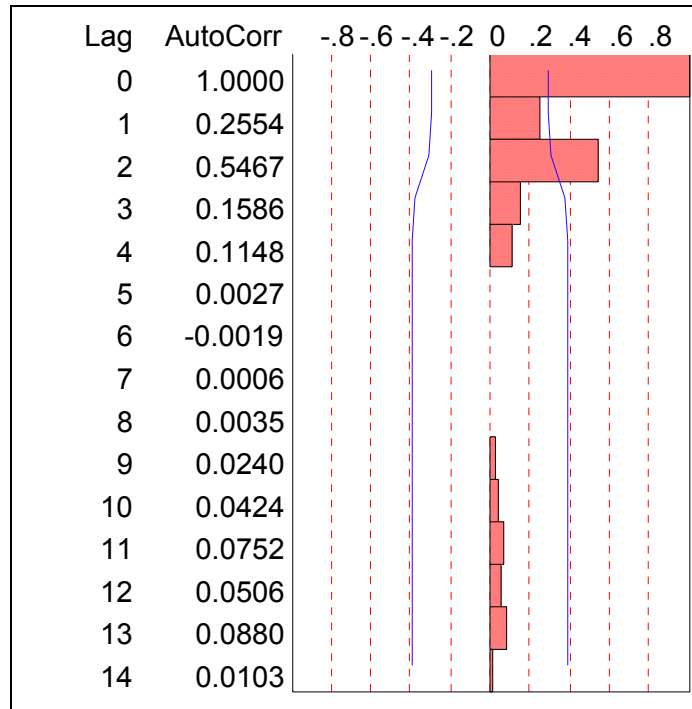


Figure 23. Autocorrelation Function for Flyaway Cost

The last assumption to explore is constant variance. Figure 24 shows a plot of the residuals against predicted. Visually, there does not appear to be an overriding pattern, however there does appear to be a slight megaphone effect. Using the Breusch-Pagan as the quantitative diagnostic, the following value is calculated:

$$\frac{\frac{.2116}{8}}{\left(\frac{4.508}{46}\right)^2} = 2.754$$

The p-value associated with the χ^2 statistic of 2.754 is 0.907. Constant variance is thereby satisfied.

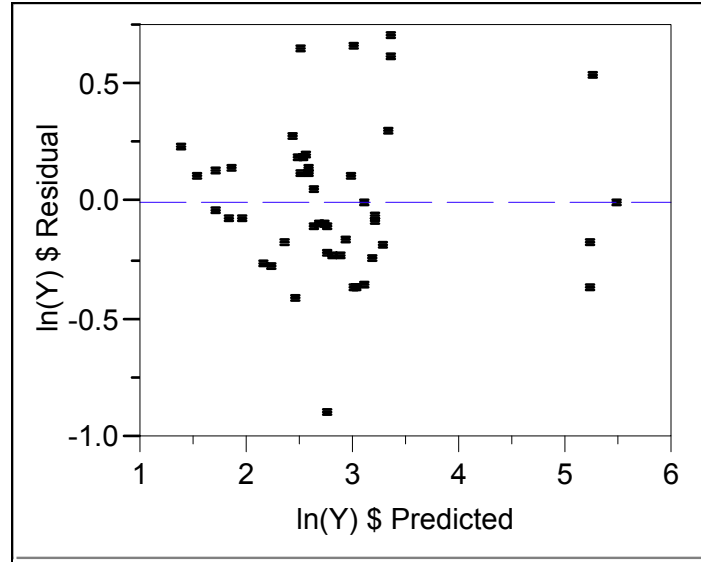


Figure 24. Residual by Predicted Plot for Flyaway Cost

The Flyaway Cost regression model is validated by the diagnostics above. The resulting equation is:

$$Y = 3.740 - 0.697 * Cat(1) - 0.431 * Cat(2) - 1.22 * Cat(3) - 0.549 * Cat(4) - 0.368 * Cat(5) + 1.743 * Cat(6) - 0.001 * CumQty + \varepsilon \quad (6)$$

The error term is the item of interest to perform the macro versus micro comparison. The underlying distribution of the residuals is shown in Figure 25. The residuals have a Normal Distribution with $\mu = 0$ and $\sigma = 0.313$. The Kolmogorov-Smirnov Test returns a p-value of >0.15 , validating the normal distribution fit. This distribution is critical as an input to the Bootstrap technique that will be used to perform the macro versus micro comparison.

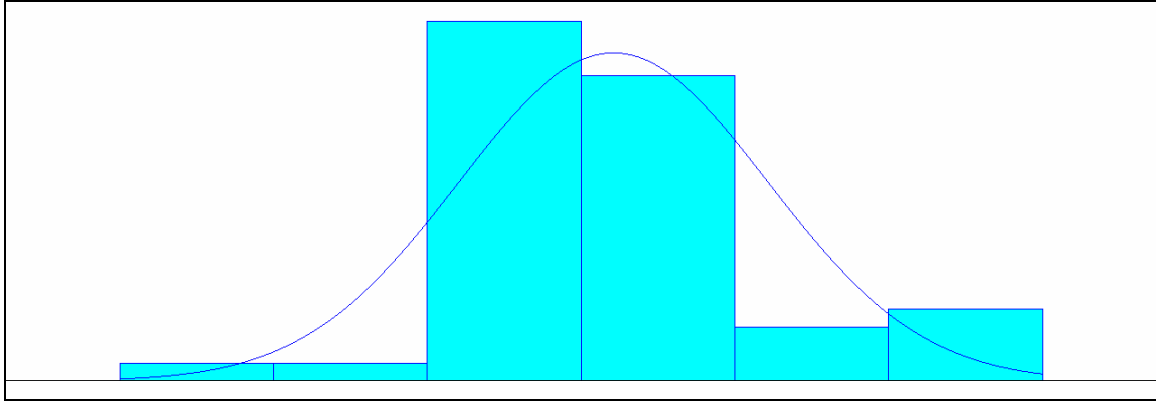


Figure 25. Plot of Residuals for Flyaway Cost

Bootstrap Comparison for Flyaway Versus Basic Airframe

Generation of the regression equations leads to the next step in the analysis: Fixed X, residual resampling. Starting with the Flyaway regression equation, Crystal Ball performs the bootstrap technique. This is accomplished by defining the assumption cell as a Normal (0, 0.313) distribution. This distribution represents the residuals as determined from the regression equation. 200 bootstrap samples are generated, with 1000 iterations occurring within each sample. The frequency histogram for the standard deviation from these trials is shown in Figure 26. As anticipated, the majority of the trials are found near the 0.32 value, with a relatively tight range from 0.30 to 0.33.

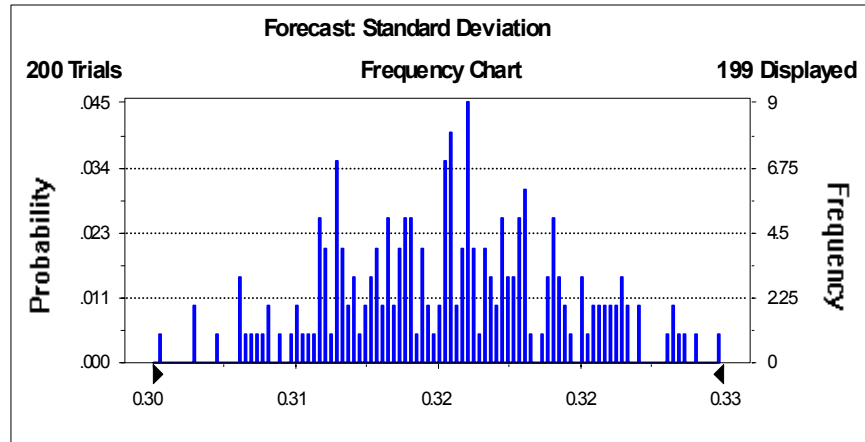


Figure 26. Frequency Chart of Flyaway Bootstrap Data

Next, the bootstrap technique is replicated for the Basic Airframe category. The only change is that the residuals are modeled as a Normal (0, 0.334) distribution, as determined from the regression equation. The resulting bootstrap standard deviation frequency chart is shown in Figure 27. One item of interest from this chart is that the spread of data is wider than the Flyaway Cost range by 0.01. This may give a preliminary indication that there is a difference in the two error components.

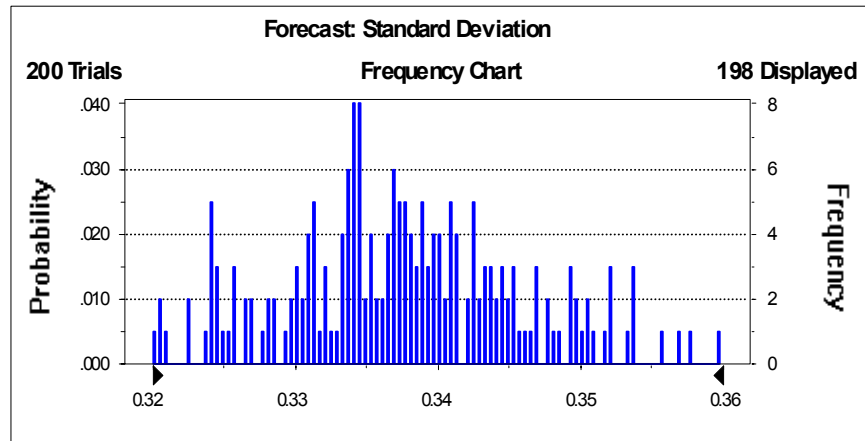


Figure 27. Frequency Chart of Basic Airframe Bootstrap Data

The standard error of the resulting 200 bootstrap samples from the Flyaway and Basic Airframe categories are then differenced. Appendix B shows the 200 trials and the

raw differenced data. The differenced data distribution allows for a comparison of the macro versus micro techniques. A histogram of this distribution is shown in Figure 28.

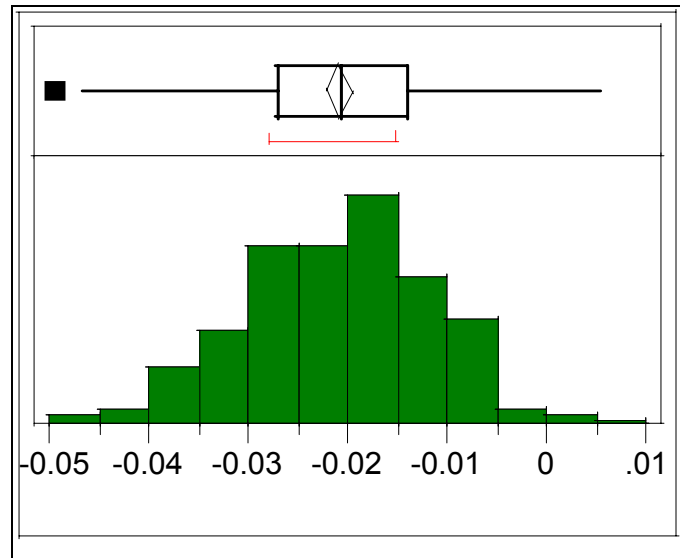


Figure 28. Differenced Flyaway vs. Basic Airframe Data

The mean of the distribution is -0.0208 . The 95% confidence interval is -0.0195 to -0.0222 . This interval does not contain zero. Therefore, it can be concluded that statistically there is a difference in the error risk between estimating at the Flyaway level versus the Basic Airframe level.

Bootstrap Comparison for Flyaway Versus Other Air Vehicle

The bootstrap technique is applied in an identical manner for the Other Air Vehicle data as it was for the Flyaway and Basic Airframe components. The only difference is the residuals are modeled as a Normal $(0, 0.356)$ distribution, as determined from the regression equation. The frequency chart of the standard deviation from the bootstrap data is shown in Figure 29. The range of values for the Other Air Vehicle component is wider by 0.01 than the range from the Flyaway component. While the

explicit values of this range are different from the Basic Airframe, it is of interest that the spread of the range is identical. Again, this may be an indication that there is a difference in the error components.

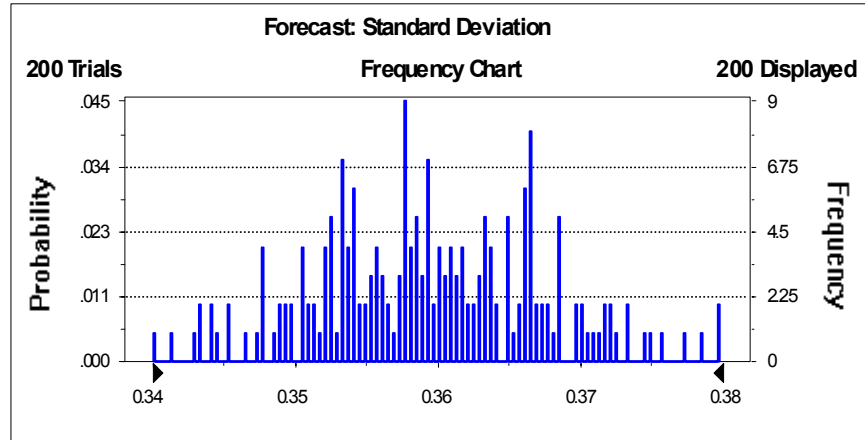


Figure 29. Frequency Chart of Other Air Vehicle Bootstrap Data

The resulting 200 standard deviation samples from the Flyaway data and Other Air Vehicle were differenced. See Appendix B for the raw data and differenced data. A histogram of the differenced data is shown in Figure 30.

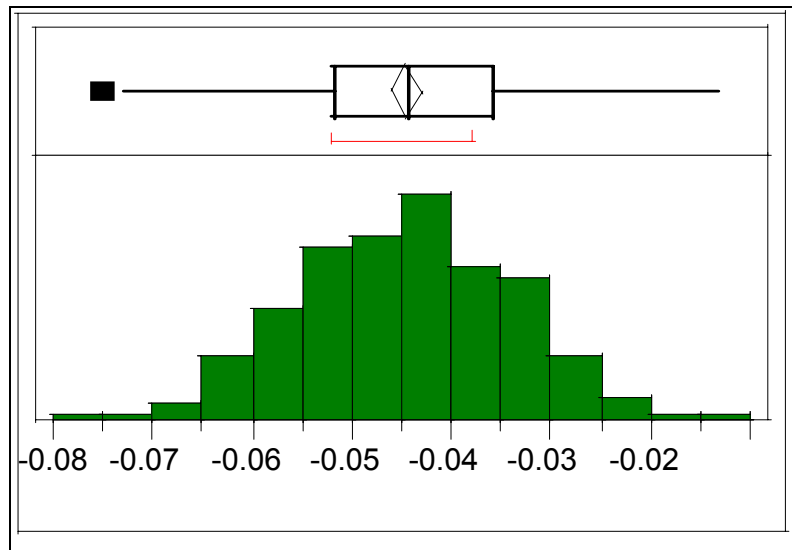


Figure 30. Differenced Flyaway vs. Other Air Vehicle

The mean of the distribution is -0.0445 . The 95% confidence interval is -0.0429 to -0.046 . This interval does not contain zero. Therefore, it can be concluded that statistically there is a difference in the error risk between estimating at the Flyaway level versus the Other Air Vehicle level.

Multiple Regression Models for the Inter-theatre Airlift Category

Data

The data for the Inter-theatre Airlift category comes from two sources, the Delta Research Corporation report and the SPOs, as detailed in the previous chapter. The four aircraft under consideration are the C-130, C-141, C-5, and C-17. These aircraft were chosen for several reasons. First, they are all operational aircraft that are currently utilized by their service. Second, there are multiple data points available from which to conduct the analysis. Third, the characteristics of these aircraft provide a natural grouping that allows for a homogeneous database to analyze.

Development of the regression model for the Basic Airframe, Other Air Vehicle, and Flyaway cost all had one common result. The parameter estimates for the C-141 data were found to be insignificant in all of the models. As the C-141 had the least amount of data points, this is not a major limitation and the C-141 data was discarded. Therefore, all three regression models developed below use only C-130, C-5, and C-17 data.

Basic Airframe Model

First, the dependent variable is analyzed to ensure it is continuous. Figure 31 shows that there are no major gaps or spikes in the data. This leads to the conclusion that the data is continuous.

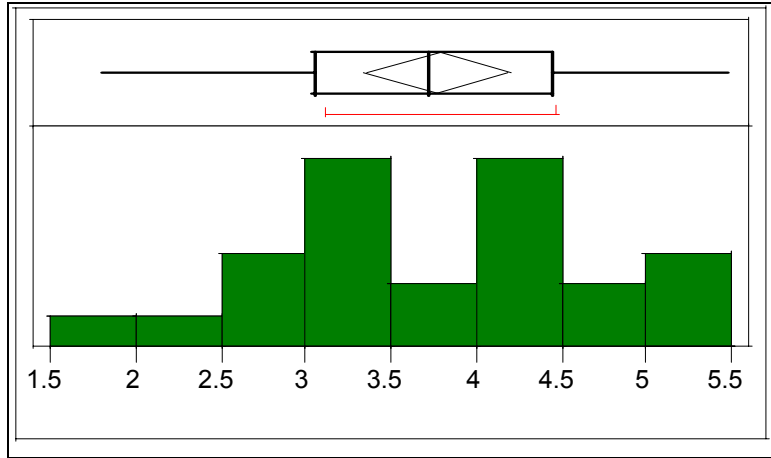


Figure 31. Continuous Data Histogram for Basic Airframe

The next step is to determine the overall predictive capability of the model. As shown in Table 17, the p-value is $<.0001$ indicating that at least one of the model parameters has predictive capability.

Table 17. ANOVA Table for Basic Airframe

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	21.000082	5.25002	85.4912
Error	19	1.166792	0.06141	Prob > F
C. Total	23	22.166874		$<.0001$

A plot of Cook's D is the diagnostic for influential data points. As shown in Figure 32, there is one major influential data point above the 0.5 threshold level. Removing that data point and re-running the model resulted in two other influential data points. These points are also removed from the model.

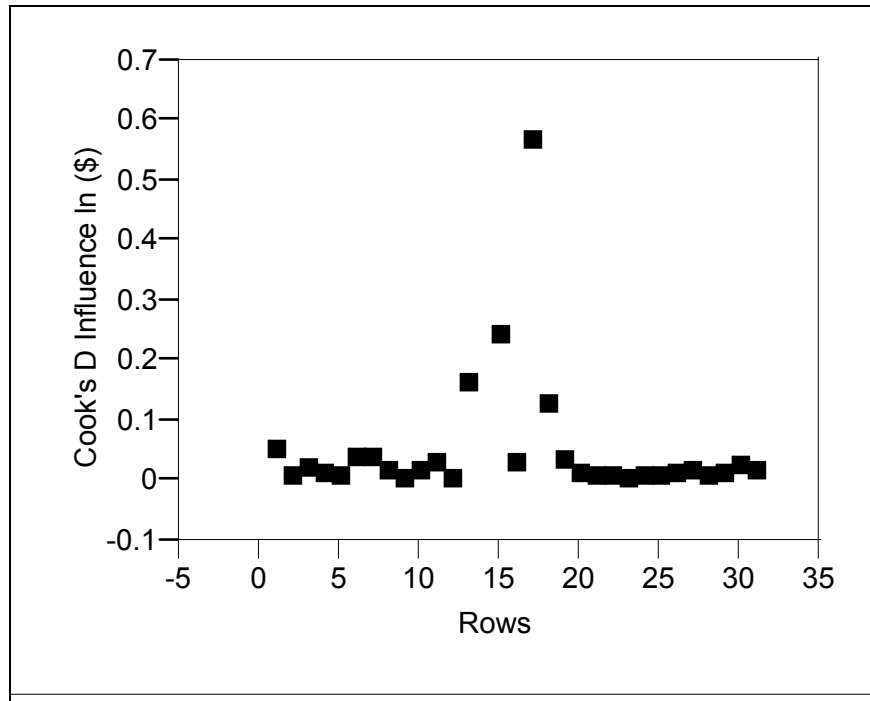


Figure 32. Cook's D Influence for Basic Airframe

A final plot of Cook's D Influence (see Figure 33) shows a uniform spread of the data, with each value below 0.25. Thus, the final model does not include influential data points.

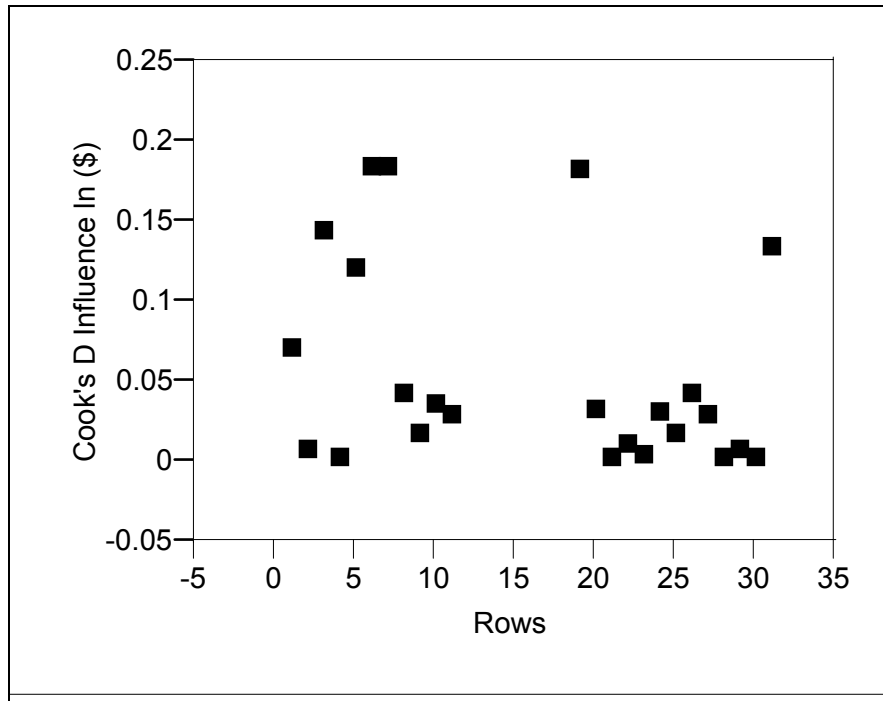


Figure 33. Revised Cook's D Influence for Basic Airframe

An examination of the Summary of Fit table (see Table 18) and Parameter Estimates shows that the independent variables do an excellent job of explaining the variability of the dependent variable. This is confirmed by the R^2 value of 0.947 and adjusted R^2 value of 0.936. Additionally, the independent variables are significant with each having a p-value less than the $\alpha = 0.10$ threshold. The VIF scores are also well below the threshold of ten, verifying that multi-collinearity does not exist.

Table 18. Summary of Fit and Parameter Estimates for Basic Airframe

RSquared	0.947363
RSquared Adj	0.936282
Root Mean Square Error	0.247811
Mean of Response	3.7751
Observations (or Sum Wgts)	24

Summary of Fit

Term	Estimate	Std Error	t Ratio	Prob> t 	VIF
Intercept	4.5174542	0.079756	56.64	<.0001	.
Category[1]	0.8095095	0.101365	7.99	<.0001	2.5655289
Category[2]	0.7282849	0.145753	5.00	<.0001	3.4449211
Category[3]	-1.436094	0.107786	-13.32	<.0001	2.577618
Cum Qty	-0.017515	0.001677	-10.44	<.0001	1.1791086

Parameter Estimates

The three assumptions of normality, independence, and constant variance must be satisfied before accepting the model. Figure 34 shows a plot of the studentized residuals to test for normality. The visual plot exhibits some bell shaped characteristics that would be expected from a normal distribution. However, the dip in the middle leaves some doubt. For a more robust indicator, the Shapiro-Wilk test is applied and a p-value of 0.84 is returned. Thus, the assumption of normality is validated.

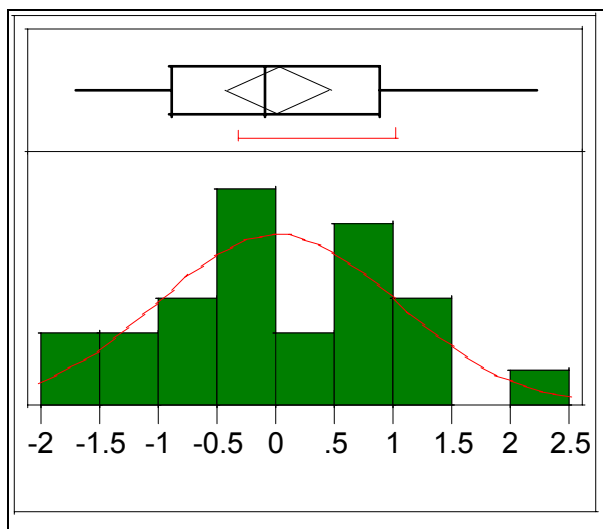


Figure 34. Normality Histogram for Basic Airframe

The studentized residuals are also used to check for outliers. As shown in Table 19, the furthest value from zero is 2.21. Therefore, it can be concluded that there are no outliers in this model.

Table 19. Quartiles for Basic Airframe

100.0%	maximum	2.210
99.5%		2.210
97.5%		2.210
90.0%		1.282
75.0%	quartile	0.895
50.0%	median	-0.083
25.0%	quartile	-0.886
10.0%		-1.414
2.5%		-1.681
0.5%		-1.681
0.0%	minimum	-1.681

The autocorrelation function is analyzed to check for independence. As shown in Figure 35, the autocorrelation plot dies down quickly. Also, there is only one spike above the critical lines. The assumption of independence is thus met.

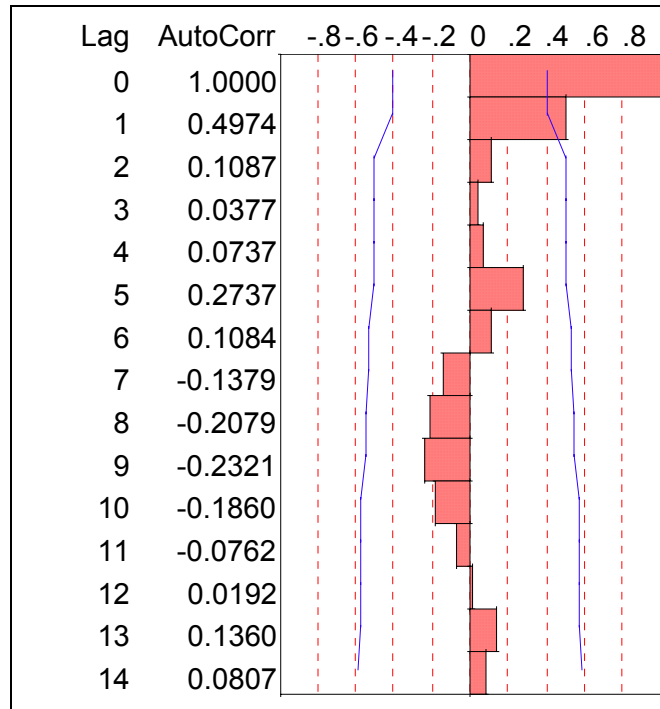


Figure 35. Autocorrelation Function for Basic Airframe

The final assumption to verify is constant variance. The residual by predicted plot (see Figure 36) is used as the descriptive measure. The data points have a relatively even spread, but a potential megaphone pattern is present. An application of the more robust Breusch-Pagan test results in a χ^2 statistic of 0.783, as calculated below.

$$\frac{\frac{.01007851}{5}}{\left(\frac{1.166792}{23}\right)^2} = 0.783$$

The p-value associated with the χ^2 statistic is 0.94, thereby satisfying the assumption of constant variance.

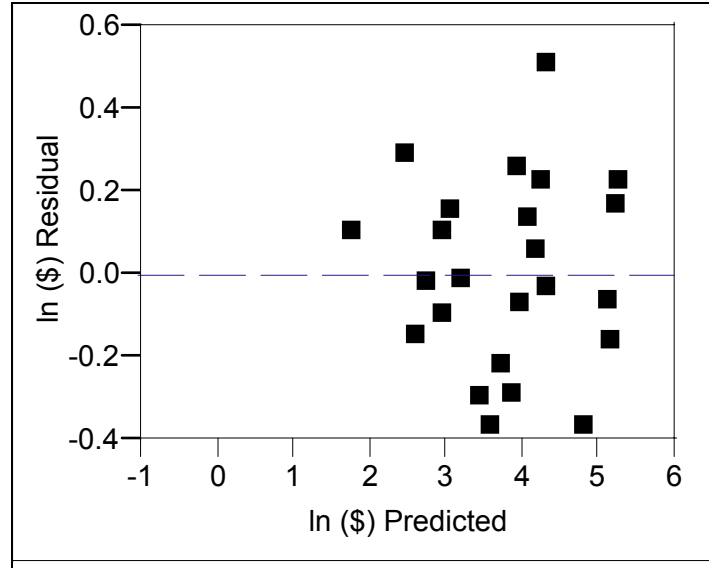


Figure 36. Residual by Predicted for Basic Airframe

The Basic Airframe model is complete and has passed all the required diagnostics. The resulting equation is:

$$Y = 4.517 + 0.809 * Cat(1) + 0.728 * Cat(2) - 1.44 * Cat(3) - 0.0178 * CumQty + \varepsilon \quad (7)$$

The error term is the item of interest to perform the macro versus micro comparison. The underlying distribution of the residuals is shown in Figure 37. The residuals are Normally Distributed with $\mu = 0$ and $\sigma = 0.225$. The Kolmogorov-Smirnov Test returns a p-value of >0.15 , validating the normal distribution fit. This distribution is critical as an input to the Bootstrap technique that will be used to perform the macro versus micro comparison.

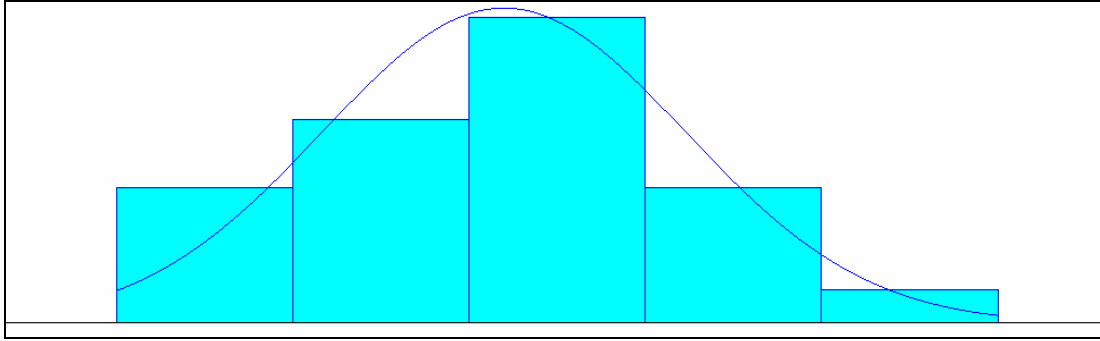


Figure 37. Plot of Residuals for Basic Airframe

Other Air Vehicle Model

A plot of the dependent variable (see Figure 38) confirms that the data is continuous. There are no gaps or major spikes in the data.

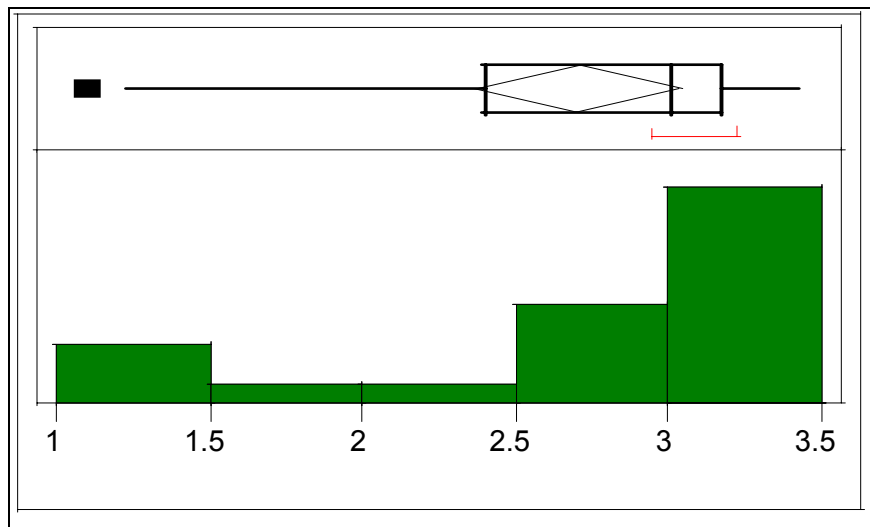


Figure 38. Continuous Data Histogram for Other Air Vehicle

The overall predictive capability of the model is shown in the ANOVA Table (see Table 20). The p-value associated with the F-statistic is $<.0001$. This is lower than the $\alpha = 0.1$ threshold. From this it can be concluded that at least one of the parameters in the model has predictive capability.

Table 20. ANOVA Table for Other Air Vehicle

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	8.895078	2.96503	34.0974
Error	17	1.478279	0.08696	Prob > F
C. Total	20	10.373357		<.0001

The plot of Cook's D checks for influential data points (see Figure 39). There is one data point above the 0.50 threshold level. An analysis of the impact of this data point reveals little change in the R^2 and adjusted R^2 values. Additionally, the significance of neither the parameter estimate values nor their associated VIF scores changes dramatically with the removal of the data point. Therefore, because the data point's value of 0.506 is close to the threshold value and it does not appear to dramatically change the model, it remains in the final model.

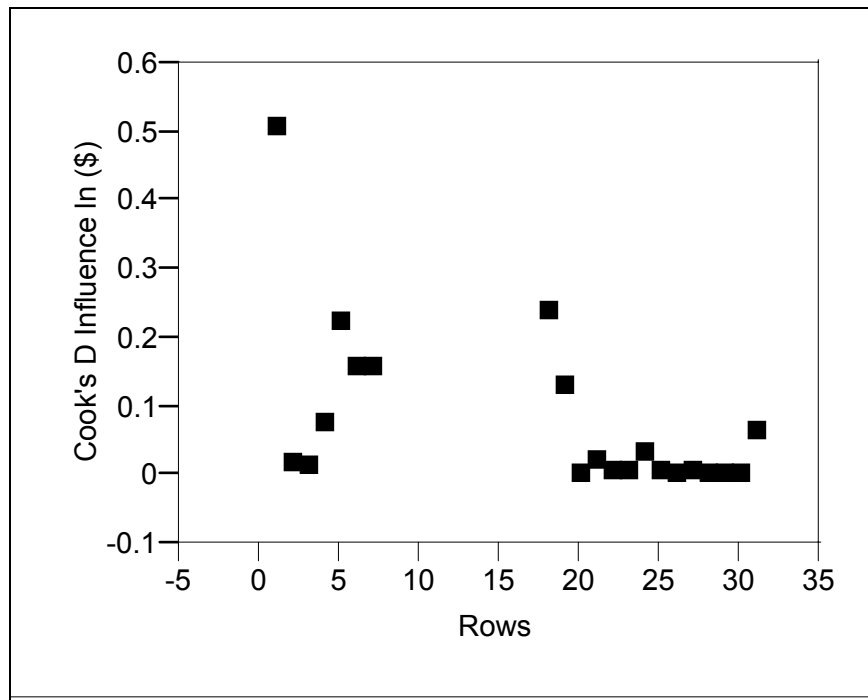


Figure 39. Cook's D Influence for Other Air Vehicle

The Summary of Fit table and Parameter Estimates (see Table 21) confirms that the model does a good job of explaining the variability in the dependent variable. This is

verified through the R^2 value of 0.857 and adjusted R^2 value of 0.832. All of the parameter estimates are below the $\alpha = 0.10$ threshold except for the cumulative quantity parameter. The cumulative quantity parameter serves two purposes: to capture the learning curve effect, and to represent the element of time due to consecutive production lot buys. An analysis of the raw data does not indicate a natural decline of lot cost over time, as would be expected from a learning curve. This lack of learning curve effect is a likely cause of the high p-value. An analysis of the effects of removing the cumulative quantity parameter results in a 0.001 decrease in the adjusted R^2 value. Thus, due to the dual purpose of the variable and the fact that it does not adversely affect the outputs of the model, it remains in the final model.

Table 21. Summary of Fit and Parameter Estimates for Other Air Vehicle

RSquare	0.857493
RSquare Adj	0.832344
Root Mean Square Error	0.294886
Mean of Response	2.706801
Observations (or Sum Wgts)	21

Summary of Fit

Term	Estimate	Std Error	t Ratio	Prob> t 	VIF
Intercept	2.6529963	0.10428	25.44	<.0001	.
Category[1]	-1.019602	0.116718	-8.74	<.0001	2.3723415
Category[2]	0.5212374	0.157098	3.32	0.0041	2.5948719
Cum Qty	-0.002204	0.002069	-1.07	0.3017	1.146707

Parameter Estimates

The three underlying assumptions are tested for compliance before accepting the model. Figure 40 shows a histogram of the studentized residuals. The shape of the histogram appears to be bell-shaped. The Shapiro-Wilk test returns a p-value of 0.3679. Thus, the assumption of normality is satisfied.

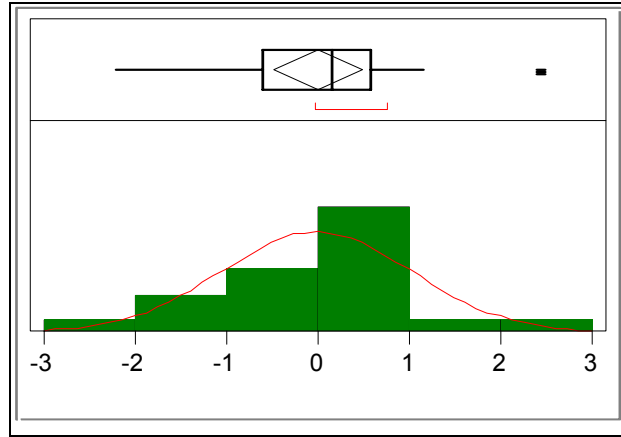


Figure 40. Normality Histogram for Other Air Vehicle

Outliers are also examined with the studentized residuals. As shown in Figure 40, all the data points are between negative three and three. Table 22 shows the quartiles for the Other Air Vehicle model. The maximum value of 2.45 in the quartiles table confirms the visual diagnostic that outliers are not present in the model.

Table 22. Quartiles for Other Air Vehicle

100.0%	maximum	2.450
99.5%		2.450
97.5%		2.450
90.0%		1.085
75.0%	quartile	0.567
50.0%	median	0.139
25.0%	quartile	-0.602
10.0%		-1.689
2.5%		-2.227
0.5%		-2.227
0.0%	minimum	-2.227

The autocorrelation function (see Figure 41) indicates that the assumption of independence is satisfied. The spikes dampen quickly and remain within the critical values.

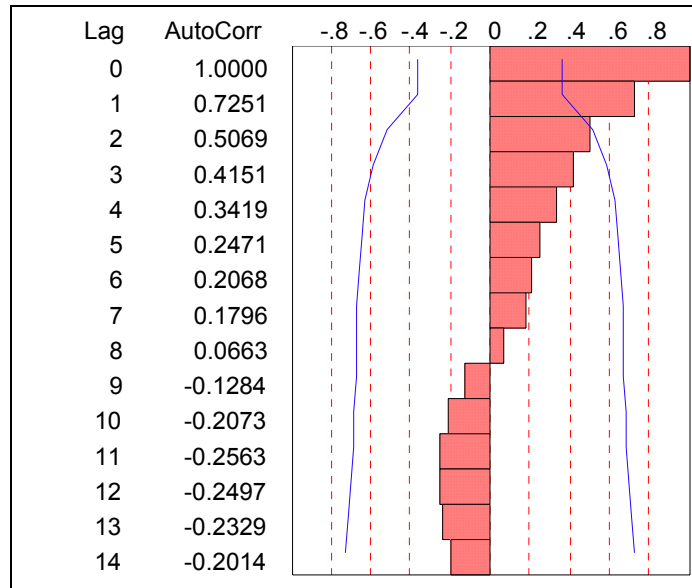


Figure 41. Autocorrelation Function for Other Air Vehicle

The residual by predicted plot (see Figure 42) has a uniform spread of the data around zero. This indicates constant variance of the residuals. The Breusch-Pagan test returns a χ^2 statistic of 3.296.

$$\frac{\frac{.06532}{4}}{\left(\frac{1.4782}{21}\right)^2} = 3.296$$

The p-value associated with this test statistic is 0.348. This confirms the visual diagnostic of constant variance.

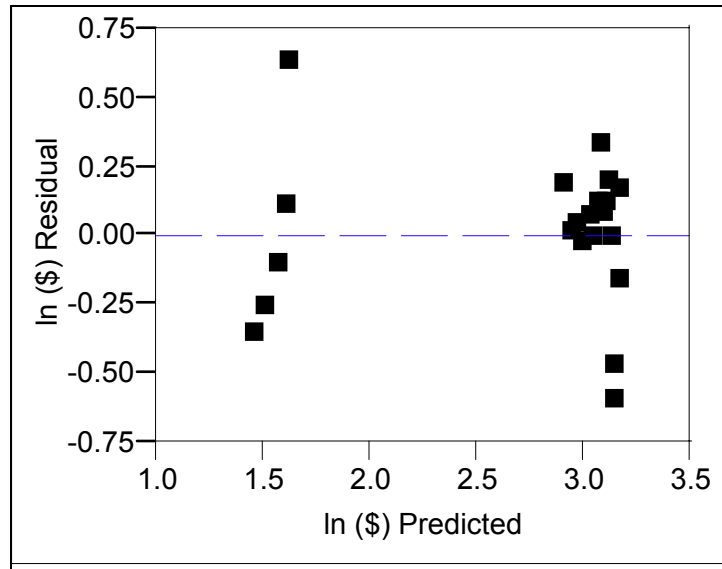


Figure 42. Residual by Predicted Plot for Other Air Vehicle

The Other Air Vehicle model passes all the necessary diagnostics. The resulting equation is:

$$Y = 2.653 - 1.019 * Cat(1) + 0.521 * Cat(2) - 0.0022 * Cum Qty + \varepsilon \quad (8)$$

The error term is the item of interest to perform the micro versus macro comparison. The underlying distribution of the residuals is shown in Figure 43. The residuals are Normally Distributed with a $\mu = 0$ and $\sigma = 0.272$. The Kolmogorov-Smirnov Test returns a p-value of >0.15 , validating the normal distribution fit. This distribution is the critical input for the Bootstrap technique.

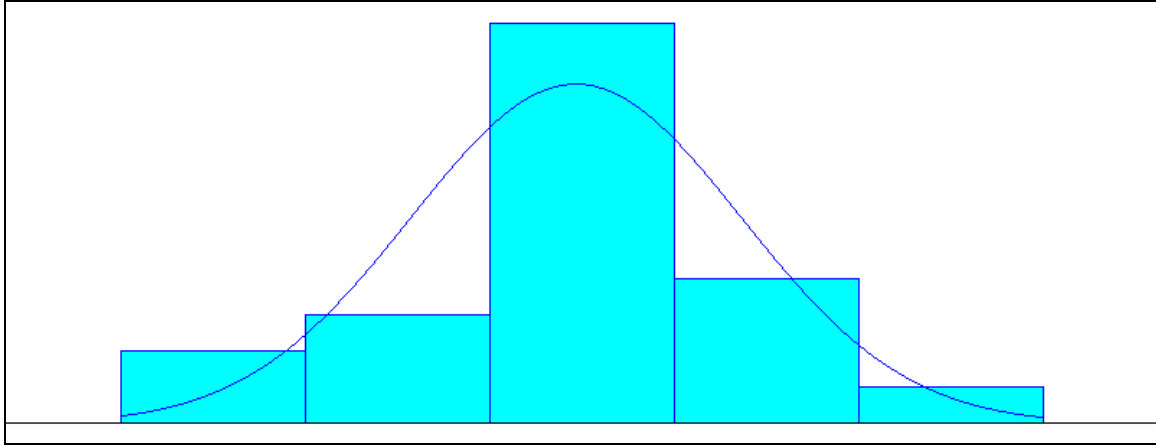


Figure 43. Plot of Residuals for Other Air Vehicle

Flyaway Cost Model

A histogram of the dependent variable (see Figure 44) reveals that there are no gaps in the data. Additionally, no bins of data exist that would indicate a split distribution. Thus, it can be concluded that the data is continuous.

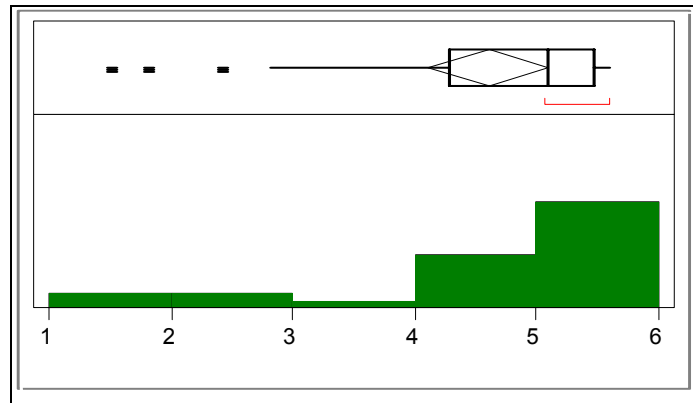


Figure 44. Continuous Data Histogram for Flyaway Cost

The ANOVA table (see Table 23) indicates that the overall model has predictive capability. This is demonstrated by the p-value associated with the F-statistic of $<.0001$.

Table 23. ANOVA Table for Flyaway Cost

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	35.224151	8.80604	187.4490
Error	21	0.986545	0.04698	Prob > F
C. Total	25	36.210695		<.0001

A plot of Cook's D found two influential data points in the model. These points are removed and Cook's D is re-analyzed. Figure 45 shows the new plot. Although all the data points are below the threshold level, there is one data point that is separated from the rest. An analysis of this data point, to include the effect on the adjusted R^2 values and parameter estimates, verifies that this point is not influential.

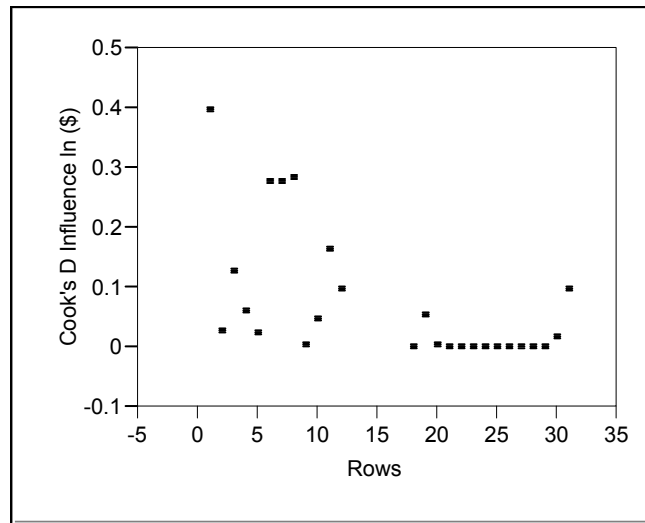


Figure 45. Cook's D Influence for Flyaway Cost

The independent variables explain most of the variability in the model with a R^2 of 0.972 and an adjusted R^2 of 0.967. The independent variables in the model are also significant as each is below the $\alpha = 0.10$ threshold. Multi-collinearity is not an issue as all the VIF scores are below ten. These results are shown in Table 24.

Table 24. Summary of Fit and Parameter Estimates for Flyaway Cost

RSquare	0.972755
RSquare Adj	0.967566
Root Mean Square Error	0.216745
Mean of Response	4.598784
Observations (or Sum Wgts)	26

Summary of Fit

Term	Estimate	Std Error	t Ratio	Prob> t 	VIF
Intercept	4.7262224	0.06626	71.33	<.0001	.
Category[1]	0.3233277	0.086936	3.72	0.0013	2.5555149
Category[2]	0.6178742	0.126029	4.90	<.0001	3.5370266
Category[3]	-1.867154	0.089858	-20.78	<.0001	2.7301896
Cum Qty	-0.008976	0.001117	-8.03	<.0001	1.1097917

Parameter Estimates

Before accepting the model, the three underlying assumption must be validated. Figure 46 shows a histogram of the studentized residuals. The data shows a bell-shape that indicates a normal distribution. This is confirmed by the Shapiro-Wilk p-value of 0.64. Thus, the assumption of normality is satisfied.

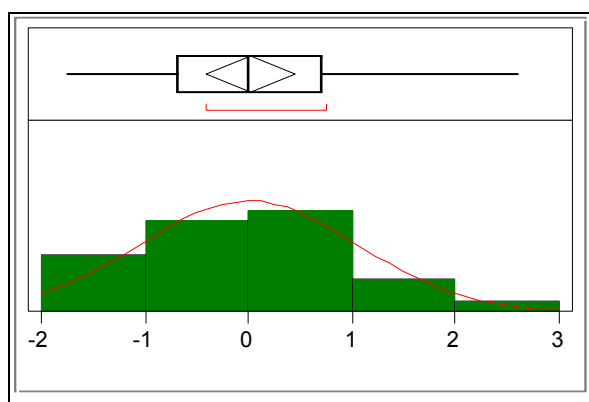


Figure 46. Normality Histogram for Flyaway Cost

Outliers are also identified by the studentized residuals. Figure 46 does not show any outliers. The quartiles table confirms this visual result (see Table 25). The furthest data point from zero is 2.59. Therefore, outliers are not present in the model.

Table 25. Quartiles for Flyaway Cost

100.0%	maximum	2.599
99.5%		2.599
97.5%		2.599
90.0%		1.577
75.0%	quartile	0.709
50.0%	median	-0.013
25.0%	quartile	-0.688
10.0%		-1.520
2.5%		-1.745
0.5%		-1.745
0.0%	minimum	-1.745

The autocorrelation function (see Figure 47) confirms independence in the model.

The function dampens quickly and does not have spikes outside the critical values.

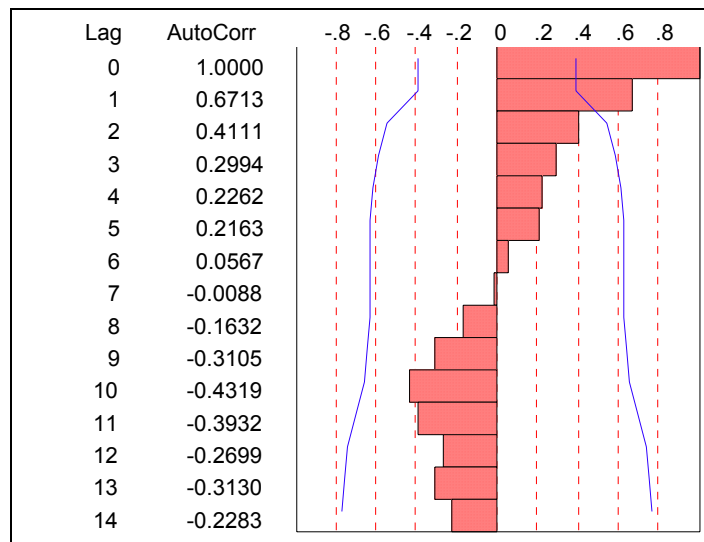


Figure 47. Autocorrelation Function for Flyaway Cost

The last diagnostic is constant variance. Figure 48 shows a plot of the residuals by predicted. This visual plot shows a uniform spread around zero, indicating constant variance. The Breusch-Pagan test quantitatively confirms this visual conclusion. The χ^2 statistic value is 2.931.

$$\frac{\frac{.0211}{5}}{\left(\frac{.9865}{26}\right)^2} = 2.931$$

The p-value associated with the χ^2 statistic is 0.57. Thus, the assumption of constant variance is validated.

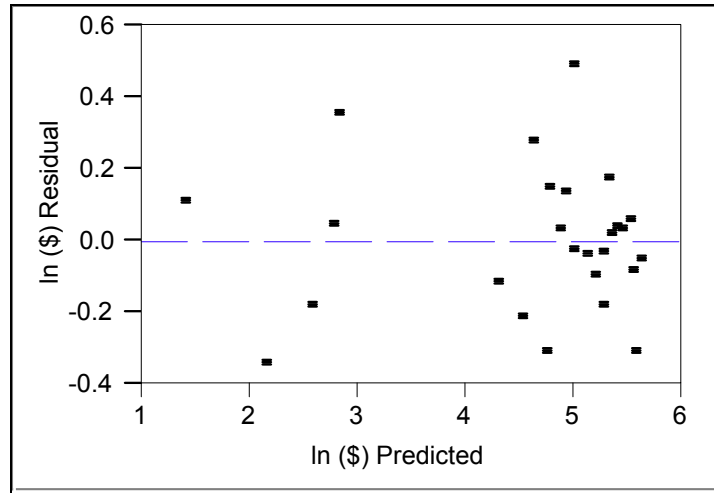


Figure 48. Residual by Predicted Plot for Flyaway Cost

The Flyaway Cost model is complete and has passed all the diagnostics. The resultant equation is:

$$Y = 4.726 + 0.323*Cat(1) + 0.618*Cat(2) - 1.867*Cat(3) - 0.0089*CumQty + \varepsilon \quad (9)$$

The error term is the required input for the Bootstrap technique to perform the micro versus macro comparison. Figure 49 shows the resulting distribution of the residuals. The residuals are Normally Distributed with a $\mu = 0$ and $\sigma = 0.199$. The Kolmogorov-Smirnov returns a p-value of >0.15 , validating the normal distribution fit.

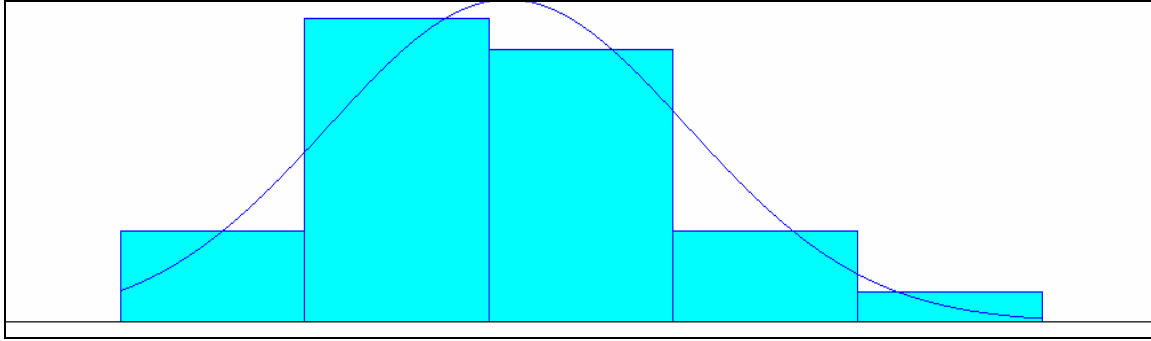


Figure 49. Plot of Residuals for Flyaway Cost

Bootstrap Comparison for Flyaway Versus Basic Airframe

Fixed X, residual re-sampling is the next step in the analysis. Starting with the Flyaway Cost regression equation, Crystal Ball performs the Bootstrap technique. This is accomplished by defining the assumption cell as a Normal (0, 0.119) Distribution. This distribution represents the residuals as determined from the regression equation. 200 bootstrap samples are generated, with 1000 iterations occurring within each sample. The frequency histogram for the standard deviation from these trials is shown in Figure 50. As anticipated, the majority of the trials are around the 0.20 value, with a relatively tight range from 0.19 to 0.21.

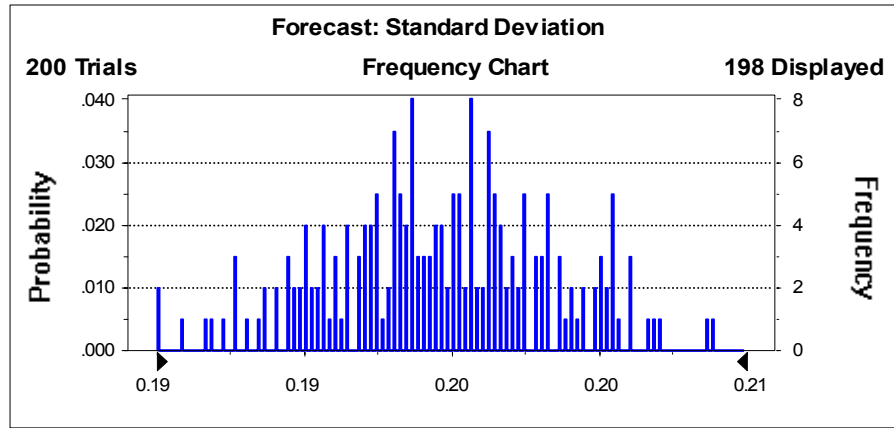


Figure 50. Frequency Chart of Flyaway Bootstrap Data

The process is repeated for the Basic Airframe data. The primary change in the application of the Bootstrap technique is the residuals are modeled as a Normal (0, 0.225) distribution, as determined from the regression equation. The resulting Bootstrap standard deviation frequency chart is shown below (see Figure 51). One characteristic that is noticeably different from the Flyaway Cost frequency chart is the spread of the data. The Basic Airframe has a wider spread, by 0.01. This may be a significant indicator of a difference between estimating the two error components.

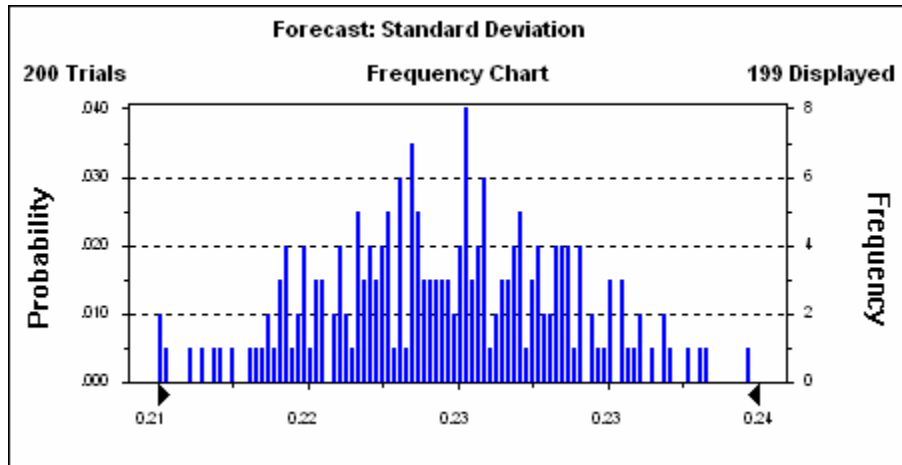


Figure 51. Frequency Chart of Basic Airframe Bootstrap Data

The standard error of the 200 Bootstrap samples from the Flyaway cost and Basic Airframe are paired and differenced. Appendix C shows the 200 trials and differenced data. The resulting distribution is the critical component to perform the macro versus micro comparison. A histogram of this distribution is shown in Figure 52.

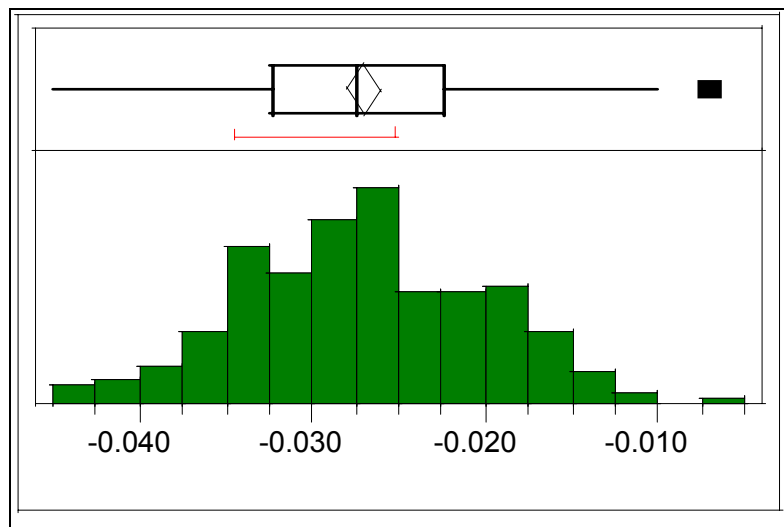


Figure 52. Differenced Flyaway vs. Basic Airframe Data

The mean of the distribution is -0.027 . The 95% confidence interval is -0.026 to -0.028 . This interval does not contain zero. Therefore, it can be concluded that there is a

statistical difference in the error risk between estimating at the Flyaway level versus the Basic Airframe level.

Bootstrap Comparison for Flyaway Versus Other Air Vehicle

The Bootstrap technique is applied in an identical manner for the Other Air Vehicle data as it was for the Flyaway and Basic Airframe components. The only difference is the residuals are modeled as a Normal (0, 0.272) Distribution, as determined from the regression equation. The frequency chart of the standard deviation from the Bootstrap data is shown in Figure 53. The range of values for the Other Air Vehicle component is 0.26 to 0.29, which is wider by 0.01 than the range from the Flyaway component. This may be an indication that there is a difference in the error components.

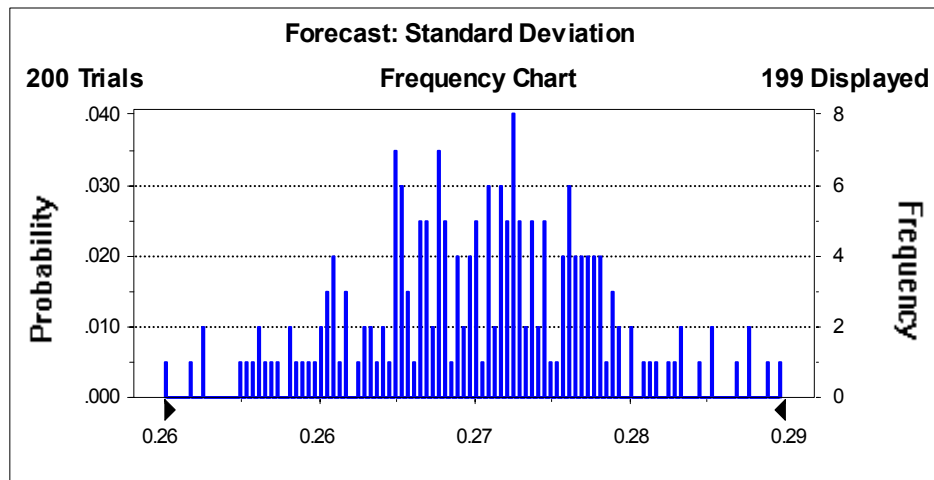


Figure 53. Frequency Chart of Other Air Vehicle Bootstrap Data

The resulting 200 standard deviation samples from the Flyaway and Other Air Vehicle data are differenced. See Appendix C for the raw and differenced data. A histogram of the differenced data is shown in Figure 54.

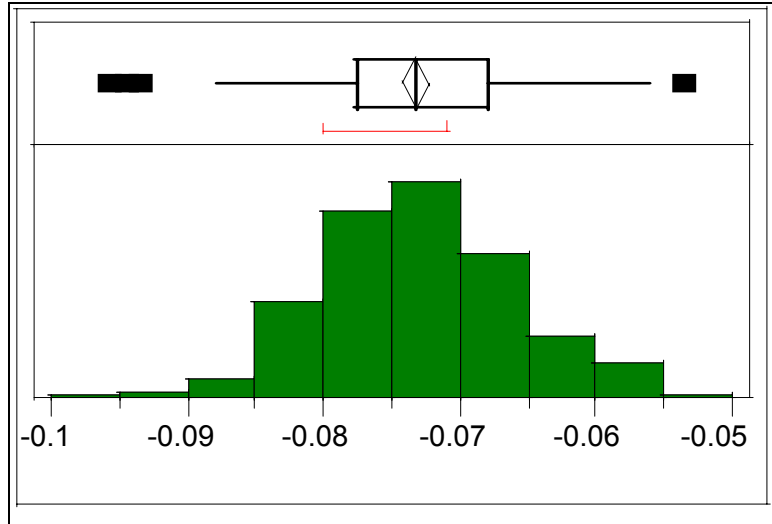


Figure 54. Differenced Flyaway vs. Other Air Vehicle Data

The mean of the distribution is -0.0732 . The 95% confidence interval is -0.0722 to -0.0742 . This interval does not contain zero. Therefore, it can be concluded that there is a statistical difference in the error risk between estimating at the Flyaway level versus the Other Air Vehicle level.

Summary

This chapter has shown the analysis of the data required to perform the micro versus macro comparison. Regression equations and Bootstrap samples were developed for both categories of data. This data was then differenced and paired to form a distribution. The four resulting distributions (see Figure 55) are the basis for the conclusions drawn in Chapter 5.

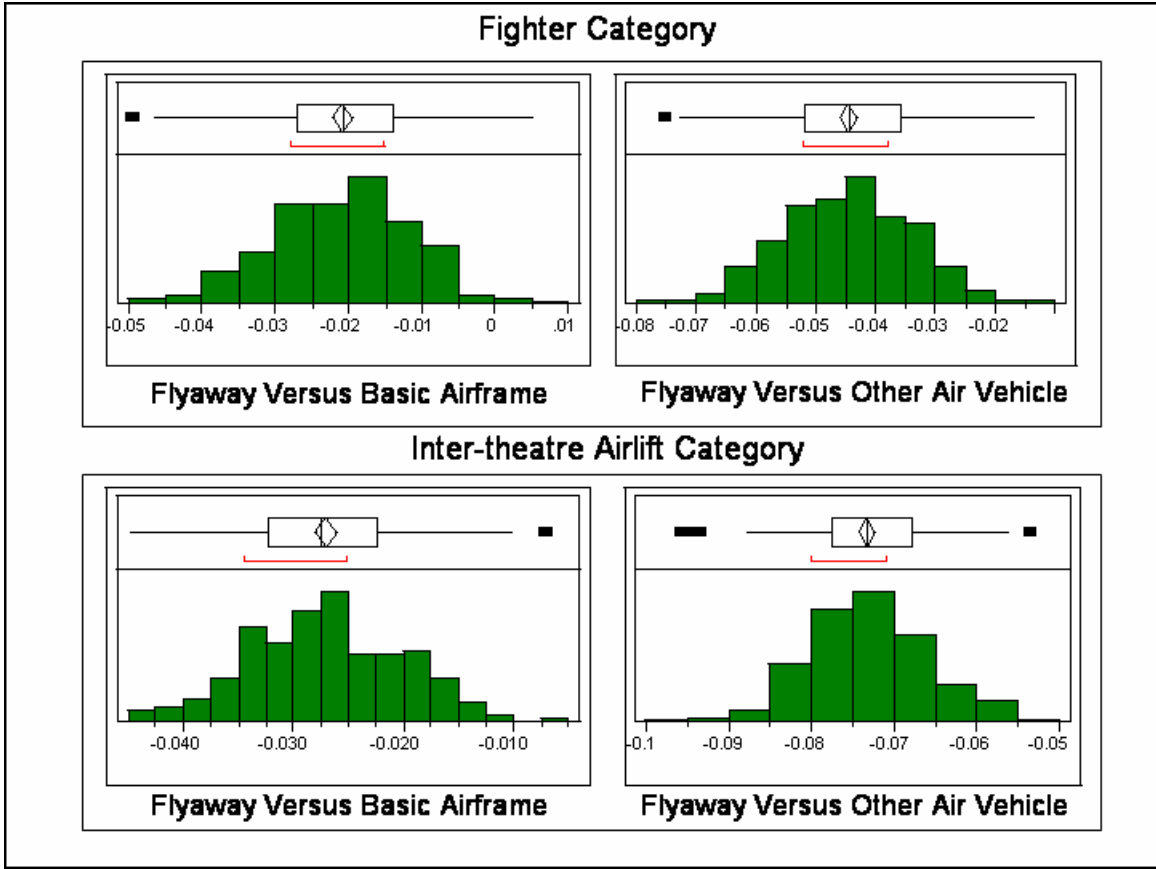


Figure 55. Distributions from Macro vs. Micro Comparisons

V. Conclusions

Importance of Findings

This research is important for several reasons. First, the cost analysis career field is shrinking. As demonstrated by the ASC example in Chapter 1, there has been a dramatic reduction in cost authorizations over the past decade. Cost analysts are therefore becoming a scarce resource. When confronted with the challenge of developing a cost estimate, program managers need to know how to optimize this resource. By understanding the advantages and disadvantages from an estimation error risk perspective of estimating at differing WBS level, optimal allocation of cost analysis resources can be achieved. Second, in order to achieve cycle time reduction goals, the time to develop a cost estimate is compressed. As a result, cost estimates need to be developed more quickly while still maintaining a satisfactory level of fidelity. This lends to the conclusion that using the time consuming grass-roots techniques will not be possible. Rather, estimation will occur at the highest WBS level possible, while still achieving a satisfactory level of confidence in the estimate. This research provides the analysis necessary to understand the tradeoffs implicit in estimating at the differing WBS levels. When making resource allocation decisions under a constrained environment, program managers can then apply this information.

Limitations

There are several limitations to this research. First, only recurring data is considered in the analysis. The estimation error risk of non-recurring data is not

considered. Second, the weapons systems analyzed are limited to aircraft systems, specifically fighters and inter-theatre airlift aircraft. To extrapolate the results of the analysis to data outside of aircraft weapons systems is inappropriate. Likewise, to extrapolate the results to other categories of aircraft, such as bombers is inappropriate. Third, the WBS level comparison is limited to level one versus level two. Conclusions about lower WBS levels are not considered. Finally, the WBS level two breakdown is not a pure MIL-HDBK-881 breakout. Conclusions can only be drawn about a level one versus level two comparison with regards to the breakout of WBS level two into the Basic Airframe and Other Air Vehicle components.

Discussion of Results

Starting with the Fighter category, there is a statistically significant difference between estimating at the Flyaway Cost level versus the Basic Airframe and the Other Air Vehicle level. This is confirmed by the 95% confidence intervals around the mean of the differenced distribution, which do not contain zero for either model comparison. For the Flyaway Cost versus Basic Airframe model, the mean of the distribution is -0.0208 with a 95% confidence interval of (-0.0195, -0.0222). For the Flyaway Cost versus Other Air Vehicle model, the mean is -0.0445 with a 95% confidence interval of (-0.0429, -0.046). Several additional conclusions can be drawn from this. First, there is clearly more error risk in the estimation of the Other Air Vehicle model than the Basic Airframe model. This indicates that program managers should allocate more time and resource to the development of the Other Air Vehicle estimate than to the Basic Airframe estimate if the estimate is being developed at WBS level two. The second conclusion was one not

anticipated when this research began. The differenced distributions are calculated by subtracting the WBS level two data from the WBS level one data. As shown above, the mean and resultant 95% confidence intervals of both these distributions are negative. This leads to the conclusion that estimating at WBS level one has less error risk than estimating at WBS level two. There are several possible reasons for this. It could be that when estimating at the lower levels, the details of the estimate cloud the bigger picture, leading to inaccurate or inappropriate model inputs from experts. In other words, it may be harder to breakdown an estimate to the individual components without adding additional error. Another possible explanation is that the positive and negative error risks in the individual components cancel each other out as they accumulate at higher levels. Although this research cannot conclude with any certainty why the WBS level one error risk is less than the WBS level two error risk, the above possibilities are reasonable explanations.

The results from the Inter-theatre Airlift category are similar. There is a statistically significant difference in the estimating error between estimating at WBS level one and level two. The mean of the distribution for the Flyaway Cost versus Basic Airframe is -0.027 with a 95% confidence interval of (-0.026, -0.028). The mean of the distribution for the Flyaway Cost versus Other Air Vehicle is -0.0732 with a 95% confidence interval of (-0.0722, -0.0742). As neither confidence interval encompasses zero, it is appropriate to say that there is a statistical difference between the two. Like the Fighter category conclusions, there is more estimation error risk in the Other Air Vehicle model than the Basic Airframe. This indicates that program managers should allocate more resources to the Other Air Vehicle portion of their estimates. Also, as with the

Fighter category results, it is determined that there is more estimation error risk when estimating at WBS level two than at WBS level one. The same rationale explained for the Fighter category is applicable to the Inter-theatre Airlift results.

Practical versus Statistical Significance

Despite the conclusions above regarding the statistically significant differences between estimating at the varying WBS levels, there is a practical application perspective to consider. The estimation errors from the models are extremely small considering the multi-million dollar costs of aircraft weapon systems. Quantitatively, the dollar amount differences are shown in Table 26.

Table 26. Practical Significance of WBS Estimation Levels

Category	Fighter	Inter-theatre Airlift
Flyaway vs. Basic Airframe	\$44,137.60	\$68,682.90
Flyaway vs. Other Air Vehicle	\$124,097.40	\$157,584.96

These dollar amounts are so small that although there is a statistically significant difference, there is little difference from a practical standpoint. In most cases, the error risk is simply not large enough for program managers to be overly concerned when allocating resources. As a result, it is anticipated that program managers will allocate resources based on other considerations, such as time constraints or desired level of visibility into the estimate.

Future Research

There are several areas related to the methodology of this research that can be explored in future research. First, an examination of the non-recurring estimating error between differing WBS levels could be examined. This is a natural extension of the

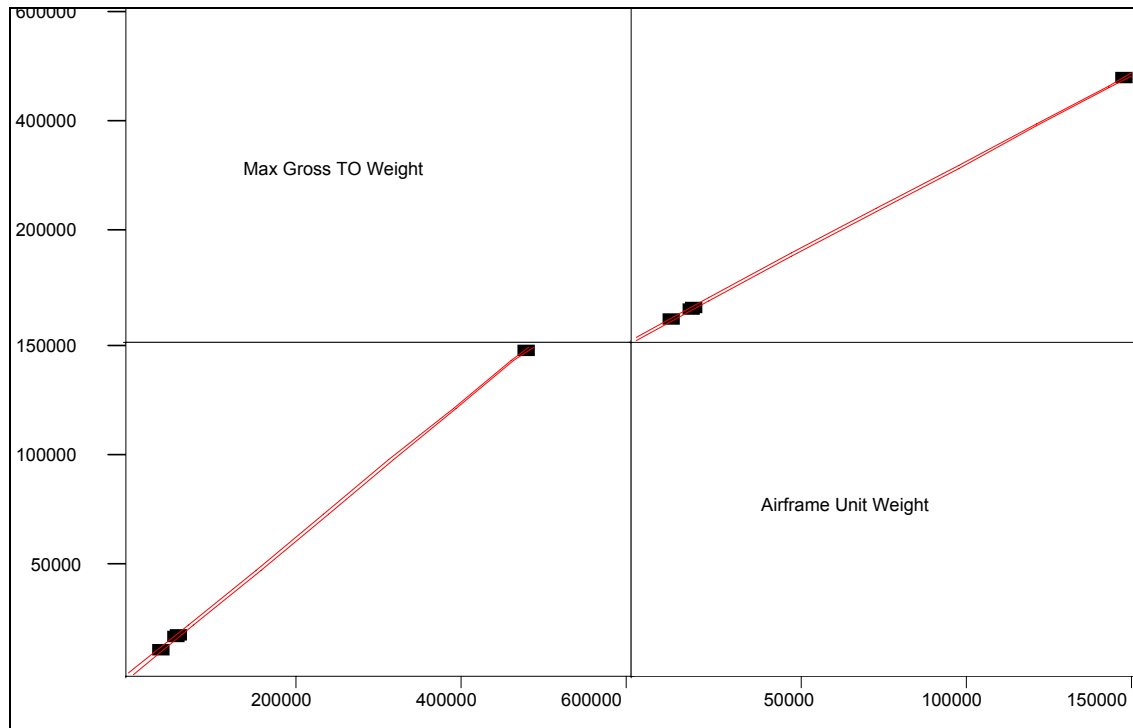
recurring estimation error analyzed in this research. Second, a comparison of the estimation error difference at WBS level two versus WBS level three could be explored. Although other variations of WBS level comparisons could be made, a level two versus level three would be most useful to the practitioner. Third, this methodology could be applied to different weapon systems than aircraft. These future research areas would be a natural bridge to the limitations described above.

Appendix A. Basic Airframe Regression Model at Quantity 100

Each aircraft's cost is calculated at quantity 100. The Delta Research Corporation database includes the learning curve percentage and quantity 100 costs calculated for the four aircraft under consideration. Under this approach all of the physical, performance, and technical independent variables are able to be considered in the regression model. Due to the fact that only four data points are used for the model, a maximum of only two parameters can be included in the model. Through a multitude of regression analysis runs, two variables are found to be significant: Airframe Unit Weight (AUW), and Max Gross Take-Off Weight. This result is shown below.

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	2.4681831	0.06634	37.20	0.0171
Airframe Unit Weight	0.001279	0.00012	10.62	0.0598
Max Gross TO Weight	-0.00039	0.000037	-10.47	0.0606

However, the VIF scores for the two parameters are greater than 31,000. The multivariate plot below confirms this multi-collinearity problem.



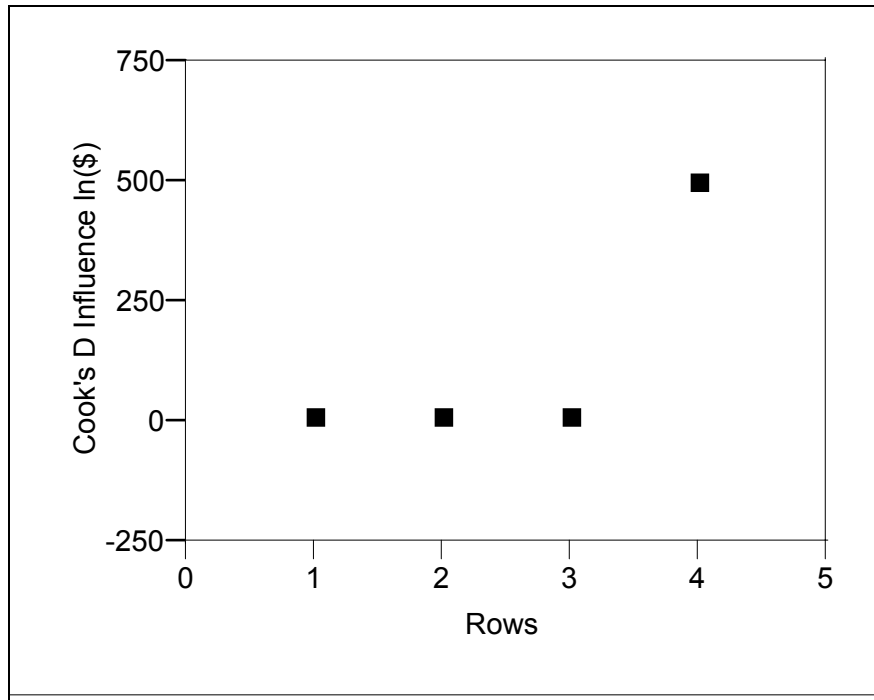
Due to the multi-collinearity problem with the two parameters, a new model must be developed. The results of this analysis lead to a one-parameter model. Airframe unit weight is selected as the independent variable. The selection of AUW as the independent variable is consistent with the RAND studies. The ANOVA output for this model is shown below.

RSquare	0.871481
RSquare Adj	0.807221
Root Mean Square Error	0.584932
Mean of Response	2.916314
Observations (or Sum Wgts)	4

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	2.0250211	0.379622	5.33	0.0334
Airframe Unit Weight	0.0000187	0.000005	3.68	0.0665

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	4.6401337	4.64013	13.5619
Error	2	0.6842920	0.34215	Prob > F
C. Total	3	5.3244257		0.0665

The R^2 value is high at 0.87. Additionally, the independent variable is significant. However, a plot of Cook's D Influence shows that the B-1 data point is highly influential. Because the B-1 is such a highly influential data point, the result above cannot be considered accurate. This problem, plus the fact that the original methodology results in a more parsimonious model, is the primary reason this methodology is not selected.



Appendix B: Bootstrap Data for Fighter Category

Bootstrap Sample	Flyaway Std. Dev.	Basic Airframe Std. Dev.	Differenced Distribution	Flyaway Std. Dev.	Other Air Vehicle Std. Dev.	Differenced Distribution
1	0.31200	0.34725	-0.03525	0.31200	0.36313	-0.05113
2	0.31691	0.33221	-0.01530	0.31691	0.35786	-0.04095
3	0.30899	0.32262	-0.01363	0.30899	0.38152	-0.07253
4	0.32144	0.35048	-0.02904	0.32144	0.36832	-0.04688
5	0.31060	0.33852	-0.02792	0.31060	0.36794	-0.05733
6	0.32390	0.33068	-0.00678	0.32390	0.37039	-0.04649
7	0.32115	0.33535	-0.01420	0.32115	0.36314	-0.04199
8	0.32144	0.34780	-0.02636	0.32144	0.36734	-0.04590
9	0.31761	0.33342	-0.01582	0.31761	0.36945	-0.05185
10	0.33090	0.33719	-0.00629	0.33090	0.35523	-0.02434
11	0.30494	0.34121	-0.03627	0.30494	0.35503	-0.05009
12	0.32175	0.33623	-0.01448	0.32175	0.35915	-0.03740
13	0.32275	0.34568	-0.02293	0.32275	0.37205	-0.04930
14	0.30876	0.34927	-0.04052	0.30876	0.36581	-0.05705
15	0.31089	0.34404	-0.03314	0.31089	0.37517	-0.06427
16	0.31643	0.33874	-0.02230	0.31643	0.35587	-0.03943
17	0.30911	0.33771	-0.02860	0.30911	0.35914	-0.05003
18	0.31497	0.33389	-0.01892	0.31497	0.36791	-0.05294
19	0.31639	0.33421	-0.01783	0.31639	0.37894	-0.06255
20	0.30953	0.34693	-0.03741	0.30953	0.36575	-0.05622
21	0.31620	0.32341	-0.00721	0.31620	0.37226	-0.05607
22	0.31514	0.34193	-0.02679	0.31514	0.35051	-0.03537
23	0.30959	0.34085	-0.03125	0.30959	0.35214	-0.04255
24	0.31481	0.34234	-0.02753	0.31481	0.35565	-0.04084
25	0.32020	0.33532	-0.01512	0.32020	0.35418	-0.03398
26	0.31022	0.33156	-0.02133	0.31022	0.36775	-0.05753
27	0.31440	0.34376	-0.02936	0.31440	0.37363	-0.05923
28	0.31226	0.33411	-0.02184	0.31226	0.36216	-0.04989
29	0.30466	0.32629	-0.02163	0.30466	0.36154	-0.05688
30	0.31337	0.34028	-0.02691	0.31337	0.36413	-0.05076
31	0.30748	0.33379	-0.02631	0.30748	0.35938	-0.05190
32	0.31895	0.34812	-0.02917	0.31895	0.35751	-0.03856
33	0.32049	0.32818	-0.00769	0.32049	0.36510	-0.04461
34	0.31276	0.33671	-0.02396	0.31276	0.35511	-0.04235
35	0.32324	0.33999	-0.01674	0.32324	0.35549	-0.03224
36	0.32502	0.35018	-0.02516	0.32502	0.35225	-0.02723
37	0.31024	0.32606	-0.01582	0.31024	0.35423	-0.04399
38	0.31650	0.34334	-0.02684	0.31650	0.35091	-0.03441
39	0.31673	0.32940	-0.01267	0.31673	0.36816	-0.05144

Bootstrap Sample	Flyaway Std. Dev.	Basic Airframe Std. Dev.	Differenced Distribution	Flyaway Std. Dev.	Other Air Vehicle Std. Dev.	Differenced Distribution
40	0.32122	0.32633	-0.00511	0.32122	0.35948	-0.03826
41	0.31769	0.35776	-0.04008	0.31769	0.36256	-0.04487
42	0.31995	0.34330	-0.02334	0.31995	0.36664	-0.04669
43	0.29852	0.33740	-0.03888	0.29852	0.37376	-0.07524
44	0.31292	0.34310	-0.03018	0.31292	0.35478	-0.04186
45	0.32016	0.34913	-0.02896	0.32016	0.36492	-0.04476
46	0.30334	0.32906	-0.02572	0.30334	0.35748	-0.05414
47	0.32800	0.32296	0.00504	0.32800	0.36038	-0.03237
48	0.31997	0.35307	-0.03310	0.31997	0.35525	-0.03528
49	0.33155	0.32845	0.00310	0.33155	0.36164	-0.03010
50	0.32328	0.33848	-0.01520	0.32328	0.36489	-0.04161
51	0.31389	0.33485	-0.02096	0.31389	0.34483	-0.03094
52	0.32569	0.34792	-0.02223	0.32569	0.36104	-0.03535
53	0.31654	0.33669	-0.02015	0.31654	0.36494	-0.04840
54	0.32609	0.34379	-0.01770	0.32609	0.36919	-0.04310
55	0.31557	0.34124	-0.02567	0.31557	0.35355	-0.03798
56	0.32774	0.33493	-0.00720	0.32774	0.36090	-0.03316
57	0.32098	0.34480	-0.02383	0.32098	0.36833	-0.04735
58	0.31970	0.33828	-0.01858	0.31970	0.37385	-0.05415
59	0.31184	0.32851	-0.01666	0.31184	0.35632	-0.04447
60	0.30860	0.33486	-0.02625	0.30860	0.35470	-0.04610
61	0.32152	0.33658	-0.01506	0.32152	0.35300	-0.03148
62	0.31312	0.33150	-0.01839	0.31312	0.34268	-0.02956
63	0.31799	0.33669	-0.01870	0.31799	0.36650	-0.04851
64	0.30535	0.32727	-0.02192	0.30535	0.35430	-0.04894
65	0.32738	0.33648	-0.00909	0.32738	0.35810	-0.03072
66	0.31790	0.33688	-0.01897	0.31790	0.35134	-0.03344
67	0.31679	0.34501	-0.02822	0.31679	0.35999	-0.04320
68	0.33066	0.33598	-0.00532	0.33066	0.35576	-0.02510
69	0.29733	0.34369	-0.04636	0.29733	0.35739	-0.06005
70	0.32770	0.33981	-0.01210	0.32770	0.35280	-0.02510
71	0.32092	0.33439	-0.01347	0.32092	0.35076	-0.02984
72	0.31177	0.34487	-0.03310	0.31177	0.35580	-0.04403
73	0.30838	0.33953	-0.03114	0.30838	0.35389	-0.04551
74	0.31052	0.33034	-0.01982	0.31052	0.36200	-0.05148
75	0.30705	0.33448	-0.02743	0.30705	0.36828	-0.06123
76	0.32065	0.33703	-0.01638	0.32065	0.35407	-0.03341
77	0.31785	0.33104	-0.01319	0.31785	0.36992	-0.05207
78	0.31782	0.33658	-0.01876	0.31782	0.35710	-0.03928
79	0.30985	0.33846	-0.02861	0.30985	0.35061	-0.04077
80	0.30855	0.34161	-0.03306	0.30855	0.35946	-0.05092
81	0.31402	0.34283	-0.02881	0.31402	0.35643	-0.04241

Bootstrap Sample	Flyaway Std. Dev.	Basic Airframe Std. Dev.	Differenced Distribution	Flyaway Std. Dev.	Other Air Vehicle Std. Dev.	Differenced Distribution
82	0.32530	0.33825	-0.01295	0.32530	0.35975	-0.03446
83	0.31430	0.33854	-0.02424	0.31430	0.38047	-0.06617
84	0.31819	0.33226	-0.01407	0.31819	0.36775	-0.04956
85	0.32115	0.33356	-0.01240	0.32115	0.36294	-0.04179
86	0.31805	0.34462	-0.02658	0.31805	0.35965	-0.04161
87	0.32785	0.34047	-0.01262	0.32785	0.35567	-0.02783
88	0.31280	0.33944	-0.02664	0.31280	0.36332	-0.05053
89	0.31895	0.34130	-0.02234	0.31895	0.35703	-0.03808
90	0.32154	0.33789	-0.01634	0.32154	0.37491	-0.05336
91	0.31921	0.32578	-0.00657	0.31921	0.36347	-0.04426
92	0.31657	0.33497	-0.01841	0.31657	0.35339	-0.03683
93	0.31643	0.35217	-0.03574	0.31643	0.35657	-0.04013
94	0.32654	0.33996	-0.01342	0.32654	0.36079	-0.03425
95	0.32764	0.33910	-0.01146	0.32764	0.35942	-0.03178
96	0.31822	0.33753	-0.01931	0.31822	0.37284	-0.05462
97	0.31599	0.33884	-0.02284	0.31599	0.35010	-0.03411
98	0.31138	0.33393	-0.02255	0.31138	0.37135	-0.05997
99	0.30675	0.33189	-0.02514	0.30675	0.35724	-0.05048
100	0.31774	0.32709	-0.00935	0.31774	0.36143	-0.04369
101	0.31392	0.33523	-0.02131	0.31392	0.35599	-0.04207
102	0.32351	0.33759	-0.01407	0.32351	0.35383	-0.03031
103	0.32326	0.34224	-0.01898	0.32326	0.37019	-0.04693
104	0.31237	0.34182	-0.02945	0.31237	0.36268	-0.05031
105	0.32726	0.34258	-0.01533	0.32726	0.36654	-0.03928
106	0.31281	0.33436	-0.02155	0.31281	0.36340	-0.05059
107	0.31970	0.33671	-0.01701	0.31970	0.36018	-0.04048
108	0.31700	0.34109	-0.02409	0.31700	0.36445	-0.04745
109	0.31536	0.35052	-0.03515	0.31536	0.34669	-0.03133
110	0.31354	0.32475	-0.01121	0.31354	0.37750	-0.06396
111	0.32650	0.32965	-0.00315	0.32650	0.34893	-0.02243
112	0.31230	0.33212	-0.01981	0.31230	0.36230	-0.05000
113	0.32620	0.34032	-0.01412	0.32620	0.34926	-0.02306
114	0.30902	0.34564	-0.03663	0.30902	0.35209	-0.04308
115	0.31358	0.34014	-0.02656	0.31358	0.36786	-0.05428
116	0.32298	0.32597	-0.00299	0.32298	0.36827	-0.04528
117	0.30955	0.33630	-0.02675	0.30955	0.34791	-0.03836
118	0.32674	0.33990	-0.01316	0.32674	0.37309	-0.04635
119	0.33086	0.33600	-0.00514	0.33086	0.36378	-0.03292
120	0.32873	0.33146	-0.00273	0.32873	0.36933	-0.04060
121	0.31670	0.32662	-0.00992	0.31670	0.36237	-0.04567
122	0.31083	0.33692	-0.02610	0.31083	0.36045	-0.04963
123	0.31358	0.32608	-0.01250	0.31358	0.34145	-0.02787

Bootstrap Sample	Flyaway Std. Dev.	Basic Airframe Std. Dev.	Differenced Distribution	Flyaway Std. Dev.	Other Air Vehicle Std. Dev.	Differenced Distribution
124	0.31008	0.33485	-0.02477	0.31008	0.35525	-0.04517
125	0.31006	0.33571	-0.02565	0.31006	0.36191	-0.05185
126	0.30724	0.33807	-0.03082	0.30724	0.37023	-0.06299
127	0.30356	0.33367	-0.03011	0.30356	0.36783	-0.06427
128	0.30193	0.33541	-0.03347	0.30193	0.36094	-0.05900
129	0.30953	0.35377	-0.04424	0.30953	0.37181	-0.06228
130	0.31707	0.33449	-0.01743	0.31707	0.36180	-0.04473
131	0.33137	0.33939	-0.00803	0.33137	0.35478	-0.02341
132	0.32301	0.33363	-0.01062	0.32301	0.36100	-0.03799
133	0.31911	0.32650	-0.00739	0.31911	0.35954	-0.04043
134	0.31803	0.32735	-0.00932	0.31803	0.36048	-0.04245
135	0.30785	0.33431	-0.02646	0.30785	0.36444	-0.05659
136	0.30344	0.32326	-0.01982	0.30344	0.36723	-0.06379
137	0.30994	0.33582	-0.02588	0.30994	0.36526	-0.05532
138	0.31387	0.33413	-0.02026	0.31387	0.36862	-0.05474
139	0.32242	0.34147	-0.01905	0.32242	0.36427	-0.04185
140	0.32036	0.35839	-0.03803	0.32036	0.35496	-0.03460
141	0.31301	0.34916	-0.03614	0.31301	0.35479	-0.04178
142	0.32124	0.32798	-0.00674	0.32124	0.36852	-0.04728
143	0.30961	0.34433	-0.03472	0.30961	0.36825	-0.05865
144	0.31667	0.33274	-0.01606	0.31667	0.35759	-0.04092
145	0.30951	0.33741	-0.02790	0.30951	0.36901	-0.05950
146	0.30075	0.33404	-0.03329	0.30075	0.36498	-0.06423
147	0.30963	0.33841	-0.02878	0.30963	0.34470	-0.03507
148	0.31433	0.33400	-0.01967	0.31433	0.36110	-0.04677
149	0.31682	0.34762	-0.03079	0.31682	0.35873	-0.04190
150	0.31871	0.33686	-0.01815	0.31871	0.35951	-0.04080
151	0.30887	0.33165	-0.02278	0.30887	0.37641	-0.06754
152	0.31205	0.34679	-0.03474	0.31205	0.35137	-0.03933
153	0.32351	0.35072	-0.02721	0.32351	0.37138	-0.04787
154	0.32136	0.33686	-0.01550	0.32136	0.35970	-0.03834
155	0.30833	0.34728	-0.03895	0.30833	0.37671	-0.06838
156	0.31694	0.34892	-0.03198	0.31694	0.37336	-0.05642
157	0.31752	0.33471	-0.01720	0.31752	0.36546	-0.04795
158	0.32313	0.32956	-0.00643	0.32313	0.34931	-0.02618
159	0.30526	0.32490	-0.01964	0.30526	0.34441	-0.03915
160	0.32692	0.33807	-0.01115	0.32692	0.34624	-0.01933
161	0.31750	0.33726	-0.01975	0.31750	0.36832	-0.05082
162	0.31244	0.33477	-0.02233	0.31244	0.35993	-0.04749
163	0.32330	0.34273	-0.01943	0.32330	0.35956	-0.03626
164	0.33213	0.33915	-0.00702	0.33213	0.34559	-0.01346
165	0.32447	0.33460	-0.01013	0.32447	0.36010	-0.03563

Bootstrap Sample	Flyaway Std. Dev.	Basic Airframe Std. Dev.	Differenced Distribution	Flyaway Std. Dev.	Other Air Vehicle Std. Dev.	Differenced Distribution
166	0.32037	0.33266	-0.01229	0.32037	0.36659	-0.04622
167	0.31660	0.33480	-0.01821	0.31660	0.35821	-0.04162
168	0.32574	0.33931	-0.01358	0.32574	0.35513	-0.02939
169	0.30844	0.33172	-0.02328	0.30844	0.36539	-0.05695
170	0.31425	0.33261	-0.01836	0.31425	0.36263	-0.04837
171	0.31516	0.33920	-0.02405	0.31516	0.36677	-0.05162
172	0.30846	0.32965	-0.02120	0.30846	0.34936	-0.04090
173	0.31933	0.34307	-0.02374	0.31933	0.35787	-0.03854
174	0.30425	0.32601	-0.02176	0.30425	0.36387	-0.05962
175	0.31931	0.33094	-0.01163	0.31931	0.37014	-0.05082
176	0.31774	0.34012	-0.02238	0.31774	0.37425	-0.05652
177	0.31132	0.32747	-0.01615	0.31132	0.36534	-0.05402
178	0.31382	0.33303	-0.01921	0.31382	0.34550	-0.03168
179	0.31997	0.34700	-0.02703	0.31997	0.34705	-0.02707
180	0.31540	0.33203	-0.01663	0.31540	0.36840	-0.05300
181	0.32519	0.34236	-0.01717	0.32519	0.36081	-0.03563
182	0.31170	0.33428	-0.02258	0.31170	0.35419	-0.04249
183	0.30592	0.35539	-0.04946	0.30592	0.35692	-0.05100
184	0.31692	0.33899	-0.02207	0.31692	0.36264	-0.04571
185	0.31836	0.33735	-0.01899	0.31836	0.35376	-0.03540
186	0.31830	0.34194	-0.02364	0.31830	0.35261	-0.03431
187	0.30369	0.34021	-0.03652	0.30369	0.36737	-0.06367
188	0.31340	0.33636	-0.02296	0.31340	0.36087	-0.04748
189	0.31423	0.34639	-0.03216	0.31423	0.37019	-0.05595
190	0.32382	0.33478	-0.01096	0.32382	0.35952	-0.03570
191	0.31780	0.34145	-0.02366	0.31780	0.35267	-0.03488
192	0.32166	0.33170	-0.01004	0.32166	0.35204	-0.03038
193	0.30073	0.33082	-0.03009	0.30073	0.35909	-0.05835
194	0.32396	0.33425	-0.01030	0.32396	0.34914	-0.02518
195	0.32501	0.34170	-0.01668	0.32501	0.36358	-0.03857
196	0.31899	0.33209	-0.01310	0.31899	0.35922	-0.04023
197	0.32858	0.33768	-0.00910	0.32858	0.38175	-0.05317
198	0.33390	0.33117	0.00273	0.33390	0.36473	-0.03084
199	0.32065	0.32605	-0.00540	0.32065	0.35585	-0.03520
200	0.31518	0.34611	-0.03092	0.31518	0.36030	-0.04512

Appendix C: Bootstrap Data for Inter-theatre Airlift Category

Bootstrap Sample	Flyaway Std. Dev.	Basic Airframe Std. Dev.	Differenced Distribution	Flyaway Std. Dev.	Other Air Vehicle Std. Dev.	Differenced Distribution
1	0.19824	0.21628	-0.01804	0.1982	0.2749	-0.07665
2	0.20725	0.22963	-0.02238	0.2072	0.2796	-0.07232
3	0.19749	0.22174	-0.02425	0.1975	0.2677	-0.07024
4	0.19079	0.22375	-0.03295	0.1908	0.2699	-0.07915
5	0.19971	0.22338	-0.02366	0.1997	0.2736	-0.07384
6	0.20026	0.22884	-0.02859	0.2003	0.2735	-0.07322
7	0.19705	0.22876	-0.03171	0.1970	0.2822	-0.08513
8	0.19739	0.22797	-0.03058	0.1974	0.2634	-0.06600
9	0.20051	0.22370	-0.02319	0.2005	0.2744	-0.07390
10	0.20073	0.22658	-0.02585	0.2007	0.2652	-0.06448
11	0.20384	0.22195	-0.01811	0.2038	0.2719	-0.06804
12	0.19762	0.22284	-0.02522	0.1976	0.2667	-0.06911
13	0.19859	0.22985	-0.03126	0.1986	0.2705	-0.07193
14	0.20087	0.22123	-0.02036	0.2009	0.2854	-0.08448
15	0.20078	0.22310	-0.02232	0.2008	0.2704	-0.06960
16	0.19987	0.21869	-0.01882	0.1999	0.2769	-0.07704
17	0.19027	0.22289	-0.03262	0.1903	0.2861	-0.09584
18	0.20059	0.23422	-0.03363	0.2006	0.2767	-0.07615
19	0.18703	0.22152	-0.03449	0.1870	0.2658	-0.07873
20	0.20276	0.22581	-0.02305	0.2028	0.2766	-0.07385
21	0.18987	0.22027	-0.03040	0.1899	0.2774	-0.08751
22	0.19153	0.22689	-0.03536	0.1915	0.2743	-0.08279
23	0.19735	0.22351	-0.02616	0.1973	0.2658	-0.06845
24	0.20260	0.22469	-0.02208	0.2026	0.2766	-0.07395
25	0.19680	0.22039	-0.02359	0.1968	0.2646	-0.06783
26	0.20338	0.22773	-0.02435	0.2034	0.2687	-0.06529
27	0.19701	0.22436	-0.02734	0.1970	0.2621	-0.06507
28	0.19565	0.23187	-0.03622	0.1956	0.2724	-0.07677
29	0.20953	0.22540	-0.01588	0.2095	0.2845	-0.07500
30	0.19912	0.22654	-0.02742	0.1991	0.2741	-0.07494
31	0.19539	0.22434	-0.02895	0.1954	0.2696	-0.07416
32	0.19522	0.22878	-0.03356	0.1952	0.2732	-0.07801
33	0.19240	0.22645	-0.03405	0.1924	0.2750	-0.08260
34	0.19978	0.21820	-0.01841	0.1998	0.2683	-0.06855
35	0.19328	0.23340	-0.04013	0.1933	0.2776	-0.08430
36	0.19822	0.21369	-0.01547	0.1982	0.2703	-0.07211
37	0.19301	0.21891	-0.02590	0.1930	0.2701	-0.07707
38	0.20694	0.22738	-0.02043	0.2069	0.2718	-0.06481
39	0.19927	0.21977	-0.02051	0.1993	0.2683	-0.06899

Bootstrap Sample	Flyaway Std. Dev.	Basic Airframe Std. Dev.	Differenced Distribution	Flyaway Std. Dev.	Other Air Vehicle Std. Dev.	Differenced Distribution
40	0.19194	0.21821	-0.02627	0.1919	0.2736	-0.08161
41	0.19672	0.23042	-0.03370	0.1967	0.2699	-0.07315
42	0.20609	0.22621	-0.02012	0.2061	0.2719	-0.06579
43	0.19733	0.22483	-0.02750	0.1973	0.2642	-0.06682
44	0.19940	0.22454	-0.02514	0.1994	0.2650	-0.06565
45	0.19736	0.22383	-0.02647	0.1974	0.2774	-0.08004
46	0.19586	0.22854	-0.03269	0.1959	0.2723	-0.07641
47	0.19745	0.22047	-0.02303	0.1974	0.2711	-0.07361
48	0.19482	0.22959	-0.03477	0.1948	0.2710	-0.07618
49	0.19726	0.22582	-0.02856	0.1973	0.2705	-0.07322
50	0.19755	0.22258	-0.02503	0.1976	0.2717	-0.07416
51	0.20246	0.22460	-0.02214	0.2025	0.2789	-0.07647
52	0.19520	0.22424	-0.02904	0.1952	0.2652	-0.07002
53	0.19682	0.22765	-0.03082	0.1968	0.2679	-0.07110
54	0.20192	0.23637	-0.03445	0.2019	0.2735	-0.07161
55	0.20005	0.21405	-0.01401	0.2000	0.2681	-0.06801
56	0.19587	0.22430	-0.02843	0.1959	0.2684	-0.07255
57	0.20281	0.22932	-0.02651	0.2028	0.2642	-0.06138
58	0.19308	0.22682	-0.03374	0.1931	0.2763	-0.08319
59	0.19813	0.22726	-0.02913	0.1981	0.2695	-0.07141
60	0.19817	0.22396	-0.02579	0.1982	0.2687	-0.07055
61	0.19664	0.22935	-0.03271	0.1966	0.2775	-0.08084
62	0.19868	0.23244	-0.03376	0.1987	0.2684	-0.06976
63	0.20622	0.22485	-0.01863	0.2062	0.2785	-0.07225
64	0.19932	0.22864	-0.02932	0.1993	0.2681	-0.06880
65	0.21280	0.22642	-0.01362	0.2128	0.2692	-0.05640
66	0.20044	0.22527	-0.02483	0.2004	0.2812	-0.08081
67	0.19872	0.21992	-0.02119	0.1987	0.2749	-0.07613
68	0.20374	0.21955	-0.01581	0.2037	0.2693	-0.06552
69	0.19791	0.23014	-0.03223	0.1979	0.2827	-0.08477
70	0.20065	0.22665	-0.02599	0.2007	0.2647	-0.06402
71	0.19959	0.22709	-0.02750	0.1996	0.2725	-0.07291
72	0.18715	0.23131	-0.04416	0.1871	0.2747	-0.08752
73	0.20935	0.22598	-0.01663	0.2093	0.2846	-0.07522
74	0.20095	0.22225	-0.02129	0.2010	0.2739	-0.07299
75	0.19542	0.23583	-0.04041	0.1954	0.2713	-0.07592
76	0.20148	0.21982	-0.01834	0.2015	0.2782	-0.07671
77	0.20537	0.22645	-0.02107	0.2054	0.2701	-0.06476
78	0.19700	0.22722	-0.03022	0.1970	0.2732	-0.07625
79	0.20252	0.22943	-0.02691	0.2025	0.2700	-0.06743
80	0.20403	0.22123	-0.01719	0.2040	0.2745	-0.07051
81	0.19423	0.23113	-0.03690	0.1942	0.2737	-0.07946

Bootstrap Sample	Flyaway Std. Dev.	Basic Airframe Std. Dev.	Differenced Distribution	Flyaway Std. Dev.	Other Air Vehicle Std. Dev.	Differenced Distribution
82	0.19659	0.23081	-0.03422	0.1966	0.2710	-0.07445
83	0.20502	0.22191	-0.01689	0.2050	0.2718	-0.06678
84	0.19576	0.23380	-0.03804	0.1958	0.2617	-0.06590
85	0.19289	0.22265	-0.02976	0.1929	0.2731	-0.08016
86	0.19386	0.22276	-0.02891	0.1939	0.2691	-0.07529
87	0.19391	0.22309	-0.02918	0.1939	0.2740	-0.08012
88	0.19479	0.21983	-0.02504	0.1948	0.2669	-0.07216
89	0.19014	0.21794	-0.02780	0.1901	0.2745	-0.08432
90	0.19391	0.22055	-0.02665	0.1939	0.2739	-0.07996
91	0.18817	0.23294	-0.04478	0.1882	0.2828	-0.09459
92	0.19742	0.22451	-0.02708	0.1974	0.2774	-0.08000
93	0.19978	0.23027	-0.03049	0.1998	0.2590	-0.05919
94	0.19566	0.22635	-0.03070	0.1957	0.2736	-0.07792
95	0.20610	0.21894	-0.01284	0.2061	0.2811	-0.07501
96	0.19566	0.21674	-0.02108	0.1957	0.2750	-0.07937
97	0.19864	0.23823	-0.03959	0.1986	0.2648	-0.06613
98	0.20037	0.22802	-0.02765	0.2004	0.2761	-0.07576
99	0.19914	0.22711	-0.02797	0.1991	0.2729	-0.07381
100	0.19520	0.22499	-0.02979	0.1952	0.2728	-0.07755
101	0.20498	0.22824	-0.02326	0.2050	0.2774	-0.07246
102	0.20554	0.22518	-0.01965	0.2055	0.2762	-0.07062
103	0.19135	0.22527	-0.03392	0.1914	0.2720	-0.08061
104	0.20336	0.21894	-0.01558	0.2034	0.2666	-0.06323
105	0.20152	0.22103	-0.01951	0.2015	0.2702	-0.06865
106	0.19369	0.22877	-0.03508	0.1937	0.2730	-0.07932
107	0.19391	0.22109	-0.02718	0.1939	0.2763	-0.08234
108	0.20069	0.22654	-0.02585	0.2007	0.2769	-0.07624
109	0.20342	0.21376	-0.01033	0.2034	0.2769	-0.07344
110	0.20196	0.23004	-0.02808	0.2020	0.2729	-0.07090
111	0.19953	0.22721	-0.02768	0.1995	0.2676	-0.06802
112	0.20047	0.23483	-0.03436	0.2005	0.2756	-0.07509
113	0.19237	0.22638	-0.03401	0.1924	0.2759	-0.08350
114	0.19706	0.22717	-0.03012	0.1971	0.2653	-0.06827
115	0.20541	0.23094	-0.02554	0.2054	0.2637	-0.05830
116	0.19985	0.22499	-0.02514	0.1998	0.2731	-0.07323
117	0.20292	0.21754	-0.01463	0.2029	0.2777	-0.07474
118	0.19264	0.21900	-0.02636	0.1926	0.2709	-0.07827
119	0.19676	0.23047	-0.03371	0.1968	0.2737	-0.07694
120	0.19994	0.22120	-0.02126	0.1999	0.2574	-0.05741
121	0.20153	0.23212	-0.03059	0.2015	0.2689	-0.06735
122	0.19803	0.23073	-0.03270	0.1980	0.2748	-0.07675
123	0.20125	0.22431	-0.02307	0.2012	0.2725	-0.07130

Bootstrap Sample	Flyaway Std. Dev.	Basic Airframe Std. Dev.	Differenced Distribution	Flyaway Std. Dev.	Other Air Vehicle Std. Dev.	Differenced Distribution
124	0.19261	0.22417	-0.03156	0.1926	0.2701	-0.07748
125	0.20059	0.22962	-0.02903	0.2006	0.2762	-0.07563
126	0.20549	0.22265	-0.01716	0.2055	0.2622	-0.05671
127	0.19634	0.22674	-0.03040	0.1963	0.2695	-0.07313
128	0.20526	0.22800	-0.02274	0.2053	0.2728	-0.06758
129	0.19984	0.23076	-0.03092	0.1998	0.2627	-0.06285
130	0.19589	0.23255	-0.03665	0.1959	0.2784	-0.08254
131	0.19600	0.23915	-0.04315	0.1960	0.2608	-0.06482
132	0.20537	0.22213	-0.01676	0.2054	0.2653	-0.05990
133	0.20182	0.22819	-0.02637	0.2018	0.2791	-0.07724
134	0.19028	0.22661	-0.03633	0.1903	0.2839	-0.09366
135	0.19889	0.22610	-0.02721	0.1989	0.2679	-0.06906
136	0.19448	0.22569	-0.03121	0.1945	0.2778	-0.08329
137	0.19672	0.23372	-0.03700	0.1967	0.2807	-0.08400
138	0.20493	0.23046	-0.02553	0.2049	0.2648	-0.05985
139	0.19968	0.22663	-0.02695	0.1997	0.2711	-0.07145
140	0.19552	0.21780	-0.02228	0.1955	0.2723	-0.07679
141	0.20087	0.22340	-0.02253	0.2009	0.2590	-0.05811
142	0.19628	0.23067	-0.03439	0.1963	0.2631	-0.06682
143	0.19930	0.22899	-0.02970	0.1993	0.2763	-0.07704
144	0.20486	0.22231	-0.01746	0.2049	0.2687	-0.06389
145	0.20278	0.22265	-0.01987	0.2028	0.2685	-0.06569
146	0.19554	0.23131	-0.03577	0.1955	0.2799	-0.08438
147	0.19849	0.22825	-0.02976	0.1985	0.2745	-0.07603
148	0.19836	0.22998	-0.03162	0.1984	0.2781	-0.07969
149	0.20577	0.22370	-0.01794	0.2058	0.2759	-0.07015
150	0.19736	0.21974	-0.02238	0.1974	0.2693	-0.07194
151	0.20085	0.21859	-0.01775	0.2008	0.2734	-0.07259
152	0.18903	0.22506	-0.03603	0.1890	0.2616	-0.07255
153	0.20074	0.21915	-0.01841	0.2007	0.2668	-0.06611
154	0.19484	0.21927	-0.02444	0.1948	0.2680	-0.07319
155	0.20279	0.22058	-0.01779	0.2028	0.2758	-0.07301
156	0.20475	0.22761	-0.02285	0.2048	0.2584	-0.05369
157	0.21509	0.22215	-0.00706	0.2151	0.2736	-0.05848
158	0.19603	0.21558	-0.01955	0.1960	0.2738	-0.07776
159	0.19843	0.22439	-0.02596	0.1984	0.2716	-0.07319
160	0.19661	0.23493	-0.03832	0.1966	0.2705	-0.07386
161	0.20237	0.23627	-0.03390	0.2024	0.2772	-0.07479
162	0.19984	0.22214	-0.02230	0.1998	0.2696	-0.06973
163	0.19692	0.22551	-0.02858	0.1969	0.2610	-0.06410
164	0.20170	0.22325	-0.02155	0.2017	0.2766	-0.07486
165	0.20187	0.23018	-0.02830	0.2019	0.2657	-0.06381

Bootstrap Sample	Flyaway Std. Dev.	Basic Airframe Std. Dev.	Differenced Distribution	Flyaway Std. Dev.	Other Air Vehicle Std. Dev.	Differenced Distribution
166	0.19789	0.22549	-0.02760	0.1979	0.2723	-0.07436
167	0.20121	0.22839	-0.02718	0.2012	0.2671	-0.06586
168	0.20248	0.23013	-0.02765	0.2025	0.2769	-0.07444
169	0.19911	0.21876	-0.01965	0.1991	0.2723	-0.07317
170	0.19470	0.22691	-0.03221	0.1947	0.2731	-0.07843
171	0.19784	0.23182	-0.03398	0.1978	0.2731	-0.07531
172	0.19911	0.22336	-0.02425	0.1991	0.2684	-0.06929
173	0.19353	0.23257	-0.03904	0.1935	0.2803	-0.08674
174	0.19763	0.22948	-0.03185	0.1976	0.2698	-0.07213
175	0.19935	0.22300	-0.02365	0.1994	0.2776	-0.07825
176	0.19656	0.22373	-0.02717	0.1966	0.2751	-0.07854
177	0.19286	0.22033	-0.02747	0.1929	0.2703	-0.07741
178	0.19341	0.22162	-0.02821	0.1934	0.2693	-0.07589
179	0.20739	0.22322	-0.01583	0.2074	0.2733	-0.06589
180	0.20515	0.22454	-0.01939	0.2052	0.2715	-0.06637
181	0.20173	0.21946	-0.01772	0.2017	0.2649	-0.06313
182	0.20429	0.23061	-0.02632	0.2043	0.2676	-0.06329
183	0.18940	0.22234	-0.03294	0.1894	0.2614	-0.07205
184	0.20044	0.22861	-0.02817	0.2004	0.2737	-0.07322
185	0.20016	0.22845	-0.02829	0.2002	0.2814	-0.08125
186	0.20422	0.21497	-0.01075	0.2042	0.2752	-0.07098
187	0.19401	0.22931	-0.03530	0.1940	0.2569	-0.06289
188	0.19439	0.22304	-0.02864	0.1944	0.2765	-0.08206
189	0.19304	0.23292	-0.03989	0.1930	0.2662	-0.07319
190	0.20366	0.23467	-0.03102	0.2037	0.2679	-0.06428
191	0.19184	0.23131	-0.03947	0.1918	0.2715	-0.07961
192	0.19431	0.22639	-0.03207	0.1943	0.2699	-0.07563
193	0.19305	0.23327	-0.04021	0.1931	0.2759	-0.08284
194	0.20254	0.22136	-0.01881	0.2025	0.2695	-0.06699
195	0.19916	0.22366	-0.02450	0.1992	0.2632	-0.06406
196	0.19713	0.23299	-0.03586	0.1971	0.2782	-0.08112
197	0.19241	0.22728	-0.03487	0.1924	0.2761	-0.08373
198	0.19641	0.22451	-0.02810	0.1964	0.2717	-0.07524
199	0.20193	0.21616	-0.01423	0.2019	0.2681	-0.06617
200	0.19131	0.23183	-0.04052	0.1913	0.2767	-0.08536

Bibliography

AFSC Cost Estimating Handbook Series. Reading, MA. Prepared for the U.S. Air Forces Systems Command. n. pag.
<https://fmfweb.wpafb.af.mil/fmweb/fmc/estimatinghandbooks/estimatinghandbooks.htm>. 1986.

Air Force Material Command. *AFMC – Price Estimating Suite 2000*. n. pag.
<http://web2.deskbook.osd.mil/valhtml/2/2B/2B4/2B4S03.htm>. April 2001.

Cho, George, Hans Jerrel, and William Landley. *Program Management 2000: Know the Way – How Knowledge Management Can Improve DoD Acquisitions*. Ft Belvoir VA: Defense Systems Management College Report of the Military Research Fellows, January 2000.

Ciccotello, Conrad S., Steve G. Green, and Martin J. Hornyak. “Rethinking Twenty-First Century Acquisition: Emerging Trends for Efficiency Ends,” *Acquisition Review Quarterly*, (Winter 1997).

“Cohen Reports to Vice President,” *Program Manager*, (May-June 2000).

Cohen, William. *Annual Report to the President and the Congress*. Washington: GPO, 2000.

Davison, Anthony and D.V. Hinkley. *Bootstrap Methods and their Applications*. New York: Cambridge University Press, 1997.

Delta Research Corporation. *Cost Estimating Systems Volume 2, Aircraft Cost Handbook, Book 1: Aircraft*. Report Prepared for the Air Force Cost Analysis Agency, November 1987.

Department of Defense (a). *Mandatory Procedures for Major Defense Acquisition Programs (MDAPs) and Major Automated Information Systems (MAIS) Acquisition Programs*. DoD Regulation 5000.2.R. Washington, 15 March 1996.

Department of Defense (b). *Department of Defense Handbook: Work Breakdown Structure*. MIL-HDBK-881. Washington, 2 January 1998.

Department of Defense (c). *Parametric Cost Estimating Handbook*. 14 September 1995.

Department of Defense (d). *National Defense Budget Estimates for FY 2001 Budget (Green Book)*. n. pag. <http://www.dtic.mil/comptroller/fy2001budget/>. March 2001.

Deputy Assistant Secretary of Cost and Economics. *Annual Report 1998-1999*. Washington DC: SAF/FMC, 1999.

Devore, Jay L. *Probability and Statistics for Engineering and the Sciences 5th Edition*. Pacific Grove CA: Duxbury, 2000.

Druyun, Darlene. "A Blueprint for Action: Final Report," *Proceedings of the AIAA Defense Reform Conference*. Washington DC: 14-15 February 2001.

Flemming, Quentin W. and Joel M. Koppelman. *Earned Value Project Management, 2nd Edition*. Newton Square PA: Project Management Institute, 2000.

Garamone, Jim (a). "DoD to Combat Effects of Civilian Downsizing," *Program Manager*, (July-August 2000).

Garamone, Jim (b). "Chiefs Tell Senate DoD Needs Money for Modernization," *Armed Forces Press Service*, 29 September 2000.

Garamone, Jim (c). "Rumsfeld Details DoD Goals, Objectives in Testimony," *Program Manager*, (January-February 2001).

Grier, Peter. "The Winning Combination of Air & Space," *Air Force Magazine*, 85: 1 (January 2002).

Hall, Peter. *The Bootstrap and Edgeworth Expansion*. New York: Springer-Verlag, 1992.

Hess, Ronald and H.P. Romanoff. *Aircraft Airframe Cost Estimating Relationships*. Santa Monica, CA: RAND, R-3255-AF, 1987.

Institute for Defense Analysis. *Cost Estimating for Next Generation Aircraft*. Volume 7, No. 2, Fall 2000.

Large, J.P., H.G. Campbell, and D. Cates. *Parametric Equations for Estimating Aircraft Airframe Costs*. Santa Monica, CA: RAND, R-1693-1-PA&E, 1976.

Levenson, G.S. and Stephen Barro. *Cost Estimating Relationships for Aircraft Airframes*. Santa Monica, CA: RAND, R-0761-AF, 1966.

Long, John A. "Parametric Cost Estimating in the New Millennium," *ISPA SCEA Joint International Conference Papers*, 2000.

Makridakis, Spyros, Steven C. Wheelwright, and Rob J. Hyndman. *Forecasting Methods and Applications 3rd Edition*. New York: John Wiley & Sons Inc., 1998.

Makridakis, Spyros, Steven Wheelwright, and Victor McGee. *Forecasting, Methods and Applications*. New York: Wiley, 1983.

“Multicollinearity in Logistic Regression.” Excerpt from University of Kentucky Regression Class. n. pag. <http://www.uky.edu/ComputingCenter/SSTARS/MulticollinearityinLogisticRegression.htm>. 24 September 2002.

Nelson, Peter. “Introduction to Monte Carlo Methods.” Excerpt from Computational Science Education Project. n. pag. http://csep1.phy.ornl.gov/gif_figures/mcfl.gif 10 December 1997.

Neter, John, Michael Kutner, Christopher Nachtsheim, and William Wasserman. *Applied Linear Statistical Models*. USA: McGraw-Hill, 1996.

Niederreiter, Harold. *Random Number Generation and Quasi-Monte Carlo Methods*. Philadelphia: Society for Industrial and Applied Mathematics, 1992.

Nhysoft Inc. “A Brief History of Parametric Estimating”, Excerpt from company website. n. pag. www.nhysoft.com/history.htm. 13 August 2002.

Office of the Deputy Director of Defense Procurement for Cost, Pricing, and Finance. *Contract Pricing Reference Guides, Vol 2-Quantitative Techniques for Contract Pricing*. Washington, 19 June 2000.

Osborne, Jason A. and Elaine Waters. “Four Assumption of Multiple Regression that Researchers Should Always Test,” *Practical Assessment, Research, & Evaluation*, Volume 8(2), 2002.

PMI Standards Committee. *A Guide to the Project Management Body of Knowledge (PMBOK® Guide)*, Newton Square PA, 1996.

Ragsdale, Cliff T. *Spreadsheet Modeling and Decision Analysis 3rd Edition*. United States of America: South-Western College Publishing, 2001.

Rester, Susan A., Curt Rogers, and Ronald Hess. *Advanced Airframe Structural Materials: A Primer and Cost Estimating Methodology*. Santa Monica, CA: RAND, R-4016-AF, 1991.

Robbins, J.L. and J.C. Daneman. “Parametric Estimating & the Stepwise Statistical Technique,” *National Estimator*, (Spring 1999).

Ruffner, Kathy. “Growing Cost Estimators.” Presentation to SAF/FM, Wright Patterson AFB OH, 9 January 2002.

Seibel, Mike. Chief, Research Section, Acquisition Cost Division, Aeronautical System Center. Electronic Message. August 2002.

Stine, Robert. Class handout, "Bootstrap Resampling," ICPSR Blalock Lectures. Department of Statistics, Wharton School, 2002.

Woller, Joy. Class notes. Chem 484, The Basics of Monte Carlo Simulations. University of Nebraska-Lincoln, n. pag. <http://www.chem.unl.edu/zeng/joy/mclab/mcintro.html>. Spring 1996.

Younassi, Obaid, Michael Kennedy, and John Graser. *Military Aircraft Costs: The Effects of Advanced Materials and Manufacturing Processes*, Santa Monica CA: RAND, 2001.

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14. ABSTRACT A shrinking workforce, unstable budgets, and rapidly changing objectives under stricter time constraints characterize today's cost analysis and acquisition environment. In concert with this environment, cost analyst positions have been rapidly decreasing as demonstrated by Aeronautical Systems Centers 54% decline in total authorized slots from 1992 to 2001. The purpose of this research is to investigate and measure the risks associated with taking a macro versus micro approach to aircraft cost estimation. By analyzing the fidelity of a cost estimate developed at the flyaway cost level versus a cost estimate developed at the individual components level, this research provides guidelines for appropriate allocation of cost analyst resources. This objective is accomplished by looking at the cost estimation error risk of recurring costs at level one of the Work Breakdown Structure (WBS) and at level two of the WBS. Results show that there is a statistically significant difference between estimating at the differing WBS levels. However, from a practical standpoint, the difference in dollar terms is too small to be considered significant. As a result, program manager should allocate resources based on other constraints such as time allotted to complete the estimate or required level of visibility into the estimate.					
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