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Forecasting the KC-135 Cost Per Flying Hour: A Panel Data Analysis

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THESIS

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AFIT/GCA/ENV/07-M2

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Abstract

This thesis developed models to forecast the KC-135R monthly Consumables (CONS) and Depot Level Reparable (DLR) Cost per Flying Hour (CPFH) for each U.S. Air Force service component. Using data for each operating location from FY1998 to FY2004, the models were constructed using panel data analysis, a form of regression that adds a cross-sectional and time-series dimension.

In addition to including factors previously identified as prime contributors to CPFH, the models added new elements that may influence maintenance costs and be of interest to policymakers. These elements included mission capable rates, airframe operating hours, and climatology factors. An interaction variable for utilization rate and combat flying hours is also included.

The results reveal that utilization rate can be a major factor to determine if the CPFH increases or decreases when a wing is flying combat hours. Furthermore, mission capable rates have an inverse relationship on the KC-135R CPFH, while average airframe hours have a positive relationship. Average airframe hours is an alternative measure to aircraft age, although this measure is better suited for quarterly or yearly models. Overall, this research extends knowledge of the KC-135R CPFH program and provides a tool for planners, programmers, and decision makers at all levels.

To my wife and two daughters, the most beautiful ladies in the world.

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First of all, I thank God for giving me the drive, motivation, and wisdom necessary to successfully complete this research effort. I also could have never accomplished this immense task without the unwavering love and support from the three lovely ladies in my life, my wife and two daughters. Even though my priorities were wrong at times, their understanding and patience allowed me to reach greater accomplishments.

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I. Introduction

Military planners have tried for centuries to accurately predict the cost of military operations. In the 5th Century BC, Sun Tzu, a Chinese General and military strategist, observed:

> In the operations of war, where there are in the field a thousand swift chariots, a thousand heavy chariots, and a hundred thousand mail-clad soldiers…the expenditure at home and at the front, including entertainment of guests, small items such as glue and paint, and sums spent on chariots and armor, will reach the total of a thousand ounces of silver per day (Tzu, 1996:15).

While Sun Tzu may have been able to successfully predict the cost of war, more recently, poor forecasting methods in the Department of Defense (DoD) have been exposed. Models used to forecast spare parts during Operation DESERT STORM over predicted by more than 200 percent (Wallace, 2000). In 1995, airlift support in the former Yugoslavia to implement the Dayton Peace Accords was estimated to be several million dollars. However, data from Air Mobility Command indicated costs of $82 million (GAO, 1996). Additionally, a new study reveals that the cost of the Iraq war could top $2 trillion, more than four times what the war was expected to cost through 2006 (Bilmes & Stiglitz, 2006).

Accurate forecasting is hindered, to a large extent, by lack of dependable data. In a Government Accountability Office (GAO) (1996) report on funding issues with supplemental appropriations, it was noted that the DoD's financial systems cannot reliably determine costs. Financial systems are classified as high risk and cannot easily capture actual incremental costs. Only the total obligations are captured by the accounting systems. The GAO recommended methodological improvements to the cost estimating process to include the development of independent cost models to better reflect incremental costs.

To add fuel to the fire, GAO (2000) noted that the Air Force does not give operation and support (O&S) cost management the same high priority it assigns to other program concerns, such as weapon performance during system development or improved combat capability after fielding. O&S costs are defined as the costs of owning and operating a military system, including the costs of personnel, consumables, goods and services, and sustaining investment (OSD, 1992). Poor visibility of operating and support costs has been a key factor inhibiting management of operating costs (GAO, 2000).

Background

According to the Congressional Budget Office (CBO) (2006), about two-thirds of the defense budget is devoted to O&S funding. Excluding inflation, O&S costs grew 13 percent from $190B in 1997 to $215B in 2005, a 1.8 percent annual increase. While this amount is not excessive, O&S costs for certain weapon systems have escalated at higher rates. For example, O&S costs for the KC-135 have increased from $1.75B in 2002 to $2.16B in 2005, a 5.3 percent annual increase.

In light of recent growth of O&S costs, Congress and DoD leaders have become increasingly concerned. Speaking during his last week as Air Force Chief of Staff, General John Jumper said the issue that concerns him the most is an aging fleet of combat and support aircraft that is becoming more costly to maintain (Grossman, 2005). USAF aircraft are an average of over 23 years old. In particular, the inventory of tanker aircraft averages over 41 years old, and the C-130 tactical airlifters average over 25 years old

(CBO, 2006). Echoing General Jumper's concerns, Air Force Secretary Michael Wynne and Chief of Staff General Moseley (2006) recently noted that "as our equipment ages, it requires more frequent maintenance and replacement of parts; meanwhile, increased OPSTEMPO accelerates wear and tear on our equipment…and exposes our equipment to extreme conditions".

The advanced age and growing O&S costs are largely a result of failing to replace equipment purchased during the Cold War. Dixon (2005) notes that during the height of the Cold War aircraft were replaced every 20 years on average, but today most fleets are expected to be active well beyond the twenty-year mark. Although modifications and refurbishments of fleets assist in maintaining reliability, operating aircraft of this age is unfamiliar territory and the sustainability and maintainability implications are unknown. Additionally, the cost of new aircraft is dramatically greater than the cost during the Cold War period. This higher procurement cost of new aircraft combined with decreasing budgets and long procurement lead times have mandated that older aircraft remain in service longer than originally planned.

One of the oldest aircraft in the military inventory is the KC-135 Stratotanker. In a recent study, the GAO (2004) highlights the U.S. Air Force's dependence on the KC-135 aircraft. The KC-135 aircraft represents 90 percent of the Air Force's aerial refueling capability. Furthermore, many aircraft will likely remain in service until 2030. As a result, some aircraft could be 70 to 80 years old when replaced, well beyond their initial design life. A fleet of this age is unprecedented in aviation history. Thus, accurate estimates of future costs will be paramount to ensure uninterrupted financial support of this critical air power asset. Inaccurate forecasts causes funding to be taken from weapons procurement to cover shortfalls further delaying modernization.

Purpose

The military has little or no experience operating and maintaining aircraft past 40 years, and no commercial airline fleets of a comparable age exist (Kiley, 2001). As a result, cost prediction errors are likely to grow when considering aircraft of this age (Pyles, 2003). Further, extrapolating beyond the range of experience with aging aircraft can lead to erroneous decisions for budget planners. As O&S cost issues receive increased interest by senior leadership, the purpose of this research is to better understand the maintenance cost impacts on operating the KC-135R beyond its intended life so this information can be used during the budgeting process as well as in estimates of life-cycle operating costs for new aircraft. A secondary purpose will be to determine the relationship of new elements that may influence maintenance costs and be of interest to policymakers. These elements include mission capable rates, average airframe operating hours, and climatology factors.

In fulfilling this purpose, this research will investigate the impact of aircraft characteristics and operational, economic, and environmental factors on Depot Level Reparable (DLR) and Consumables (CONS) costs for the KC-135R. This data will then be used to build a defendable and easily used cost per flying hour (CPFH) forecasting model. This model will be developed using panel data analysis, a form of regression that adds a spatial and temporal dimension to the model. The specific variables for the model will be discussed further in Chapters Two and Three.

This research builds upon the previous forecasting model for F-15 aircraft developed by Armstrong (2006). While Armstrong's model was only applied to active duty aircraft, this research seeks to apply the model to both of the Air Force's reserve components as well, the Air National Guard and Air Force Reserve Command. Furthermore, applying this model to the KC-135 will help determine the model's relevance in the context of other types of aircraft besides fighters. From a practical standpoint, differences in missions, flying patterns, and operating locations could impact the model's forecasting ability.

Research Questions

The following research questions will be addressed in the body of this thesis:

1. Does the dew point impact the KC-135R CPFH?
2. Is there a relationship between the annual O&M budget cycle and the CPFH for the KC-135R fleet?
3. Do mission capable rates impact the KC-135R CPFH?
4. Is average airframe operating hours an accurate predictor of the KC-135R CPFH?
5. Does the KC-135R CPFH significantly change during deployments?
6. Do the variables included in the models affect the active and reserve components differently?

Scope

Due to availability of data, the models constructed for this research will be limited to the DLR and CONS elements of the CPFH structure. DLR items are parts that can be repaired at a maintenance facility and are used in direct support of aircraft maintenance.

CONS are generally defined as non-repairable supply items used by maintenance personnel in direct support of aircraft maintenance. Data for CONS items procured with the Government Purchase Card were not available and will not be included. Although DLR and CONS items do not constitute a large portion of aircraft O&S costs, instability in forecasting these parts has caused much concern among flying commands (GAO, 1999).

The forecasting models will be limited to the R model of the KC-135. This model represents the majority of the KC-135 fleet. Older E models are still in operation, but are likely to be the first aircraft that are retired. Also, the data available for this research is limited to fiscal years 1998 to 2005. Finally, the forecasting models will be constructed for active, reserve, and Air National Guard aircraft.

Summary

Inaccurate cost estimating and forecasting threatens the integrity of the budget planning process and places considerable risk on the execution of the US Air Force mission. This research focuses on developing DLR and CONS cost factors for the KC-135 aircraft. This weapon system was chosen for two primary reasons: 1) the US Air Force's heavy reliance on this aircraft for aerial refueling and 2) the unique circumstance of never having operated an aircraft for this length of time.

The KC-135 cost model will be developed using the same fundamental methodology as the F-15 model developed by Armstrong. The goal of this research is to build upon the previous aircraft O&S cost research and develop a comprehensive KC-135 model that will be implemented into budget exercises for more accurate accounting and greater visibility of maintenance costs.

II. Literature Review

Air Force CPFH Program

The CPFH program encompasses part of the overall O&S cost structure. O&S costs include all costs of operating, maintaining, and supporting a fielded system. These costs cover personnel, consumable and repairable materials, organizational and depot maintenance; facilities, and sustaining investment (OSD, 1992). All of the main elements that comprise O&S costs are described in Table 1 below.

Table 1. Main O&S Cost Element Definitions

Category		Defintion
Personnel		Pay and allowances of officer and enlisted personnel required to operate, maintain, and support an aircraft
CPFH		
	DLRs	Spare parts that, when removed from an aircraft, are tracked individually by an item number and returned to a central maintenance facility for repair and reuse
	Consumables	Items purchased for one-time use, such as filters, brackets, and bolts and then discarded when they must be replaced
	Av Fuel	Fuel expended during flight
Civilian Personnel		Pay and allowances of civilian personnel required to maintain and support an aircraft
Depot Maintenance		Labor, material, and overhead incurred in performing major overhauls on aircraft and their components at centralized repair depots and contractor repair facilities
Sustaining Engineering		Labor, material, and overhead costs incurred in providing continued systems engineering and program management oversight
Software Maintenance		Effort required to design, code, test, and produce embedded weapon system and associated test system software after establishment of an initial software production baseline
Contract Services		Contractual services incurred in providing all or part of the logistics support required by an aircraft system
Other		Direct O&S funding not captured in one of the above categories including various base support services

Source: OSD Cost Analysis Improvement Group O&S Cost-Estimating Guide

The scope of research conducted in the past has ranged from analyzing one O&S element of one aircraft such as DLRs (Hawkes, 2005) to analyzing total O&S costs across multiple types of aircraft (Kiley, 2001). Furthermore, dependent variables such as maintenance man-hours and workload have been used as proxies for O&S costs (Pyles, 2003). The reasons for this variation are due to the nature of the research question being asked and availability of data.

The scope of this research is on DLR and Consumables CPFH for the KC-135R. This study will build upon a model developed for forecasting F-15 DLR and Consumables CPFH to determine its applicability to other aircraft; aviation fuel will not be investigated. As noted by Armstrong (2006), forecasting this element has been relatively accurate and has limited problems.

Significance of CPFH Program

Although the CPFH program is a relatively small part of the overall O&S cost structure, the CPFH program represents a large percentage of a MAJCOM's and wing's Operations and Maintenance (O&M) budget and provides funding for the core mission of the Air Force (Rose, 1997). Furthermore, many of the cost elements external to the CPFH program are relatively fixed. The elements of the CPFH program are more variable and subject to prediction errors.

As another significant factor, the CPFH rates developed form the basis of a wing's flying hour funding. For instance, the number of programmed flying hours is multiplied by the projected CPFH rate to determine total funding levels. Thus, accurate forecasts of CPFH rates are critical during the budgeting process. The rates comprise the three elements defined in Table 1: DLRs, consumable supplies, and aviation fuel. The specific analysis of previous research related to these rates and broader O&S costs will be discussed in the next section as each independent variable is explored.

CPFH Predictors

As noted, several studies have explored the extent to which certain factors influence O&S costs. These variables fall into four general categories, namely, aircraft characteristics, operational factors, economic factors, and environmental factors. Aircraft characteristics capture the effects of aircraft age, percent engine type, percent block, and the interaction of age and purchase price. Operational factors include basic mission area of the aircraft, average sortie duration, utilization rate, and deployments. Economic factors are aircraft purchase price, jet fuel prices, policy changes, and seasonal dummy variables. Finally, environmental factors include variables that influence the setting in which the aircraft is maintained and operated, for instance, climatology dynamics. Table 2 represents variables used in previous research and those which will be incorporated into this study.

Table 2. Independent Variables Used in Previous Research

Independent Variable	Research Study					
	Armstrong (2006)	Francis-Shaw (2000)	Hawkes (2005)	Hildebrandt-Sze (1990)	Kiley (2001)	Pyles (2003)
Aircraft Characteristics						
Average Aircraft Age	X	X	X	X	X	X[2]
Percent Engine Type			X			
Percent Block			X			
Age-Purchase Price Interaction						X
Operational Factors						
Basic Mission Area						X
Average Sortie Duration*	X		X			
Utilization Rate*		X[1]	X	X	X	
Deployment*	X	X	X			
Economic Factors						
Aircraft Purchase Price		X				
Jet Fuel Prices*	X					
Seasonal*	X					
Policy Change*	X				X	X
Environmental Factors						
MAJCOM			X			X
Climatology*	X					

* Indicates variables that will be utilized in this research

[1] Francis and Shaw use flight hours in their model of maintenance man-hours

[2] Pyles uses average fleet age due to the nature of his analysis

The rationale for not including average aircraft age is discussed in the final section in this chapter. Percent engine type is not applicable to this research as the KC-135R does not have multiple types of engines. Percent block was used by Hawkes (2006) to capture the effects of different versions of the F-16C/D. These aircraft are assigned a block number that represents a specific version. Again, this variable is not applicable to the KC-135R. Aircraft purchase price is used as a proxy for the different types of aircraft being pooled in studies with multiple weapon systems (Kiley, 2001). Basic mission area is also used in a model that includes different types of aircraft. Finally, the MAJCOM variable cannot be used in the model for this research as this variable does not change over time. The remainder of this section will discuss the relevant independent variables to this research and the findings from previous studies.

Aircraft Characteristics. As noted, aircraft age is the variable most frequently linked to O&S costs. In fact, the first research that explored the relationship between aircraft age and maintenance costs was conducted in the 1960s. By and large, these studies failed to find a positive relationship between aircraft age and maintenance costs. According to Dixon (2005), these findings were inconclusive because the researchers failed to account for other factors such as process improvements and policy changes which may have confounded the age effect. Also, these studies were based on extremely small numbers of observations (less than 15) which made any extrapolation very difficult. Furthermore, these studies were conducted when the average age of aircraft was relatively low compared to today's fleet. According to Pyles (2003), later studies began to separate the effects of technology improvements and airframe design from the age effect. After these issues were better understood, a positive age effect on maintenance cost and reliability began to emerge.

In 1990, Hildebrandt and Sze used average aircraft age in the development of cost estimating relationships for total O&S costs. They found a 1.7 percent annual age-related increase in total O&S costs of USAF aircraft based on cost data from 1981 through 1986. However, when fuel and personnel costs were excluded, the increase changed to .5 percent.

The Congressional Budget Office (CBO) (Kiley, 2001) analyzed three sets of data on O&M and O&S costs for military aircraft using Hildebrandt and Sze's 1990 model. For clarification, the only difference between O&S and O&M is that O&S includes military personnel costs. Those analyses provide estimates of the effects of the average age of a particular type of aircraft on its O&S and O&M costs while taking into account the effects of other variables, including the pace of operations, the purchase price of the aircraft, and the calendar year. The first set of data included 17 Air Force fighter, attack, bomber, cargo, and helicopter aircraft from 1996 to 1999. For this group, O&S and O&M costs increased by 1 percent for each additional year of aircraft age. The second set of data included 13 Navy fighter, attack, cargo, and helicopter aircraft from 1986 to 1999. O&S costs increased by 2.4 percent and O&M costs increased by 2.6 percent for each additional year of aircraft age in this group. The third set of data included 20 Navy and Air Force fighter, attack, and bomber aircraft from 1976 to 1999. In this grouping, the O&M costs increased by 2.5 percent for each additional year of aircraft age.

One of the most extensive studies on the effects of age on aircraft maintenance was conducted by Pyles (2003) for the RAND Corporation. Pyles applied ordinary least squares multiple regression techniques to 13 different workload and material-consumption categories spanning multiple weapon systems. His findings suggested that no single, constant growth rate can adequately represent the fluctuation of maintenance and modification workloads over an aircraft's life cycle, and that other factors may also affect workloads and material costs. These factors include changes in operational requirements, maintenance organization, training, and incentives. Furthermore, Pyles concludes that different aircraft experience different growth rates for the same maintenance workload, and that different workloads have different growth rates for the same aircraft. At least part of those differences may be due to the complexity or size of the aircraft. In summary, Pyles suggests that maintenance and modification workloads and material consumption generally grow as aircraft age, but not without limit, providing an argument to the previous studies that imply that the historical workload and material consumption growth will not change (Pyles, 2003).

One weakness in these studies was the use of pooled aircraft data. That is, both different years and data for different types of aircraft were combined. That approach increases the number of observations and permitted the effects of the equipment's age to be distinguished from the effects of other variables, but it also assumed that each type of aircraft is associated with the same age-related costs. For these reasons, studies with pooled data may appear to be comprehensive but can be less reliable than those that concentrate on individual systems (Kiley, 2001).

Francis and Shaw (2000) of the Center for Naval Analysis analyzed the Navy’s F/A-18 Hornets. The dataset for this research contained ten years’ (1990-1999) worth of data about the utilization and organizational maintenance of every tail number for each the F/A-18 in the inventory. Their regression model used the log of maintenance man-hours as the dependent variable and several variables including number of flight hours, deployment status, personnel variables, and age as the independent variables. They find a significant age effect. The age effect was 6.5% to 8.9% per calendar year of age.

Hawkes (2005) uses multiple linear regression to forecast yearly DLR CPFH rates for the F-16C/D. Based on data for 40 aircraft fighter wings from 1998-2004, Hawkes concludes that the DLR rate increases with the age of the aircraft for active duty fighter wings, but not for Air National Guard fighter wings. This research estimates that for every additional year in the average age of the F-16C/D in an active duty fighter wing, the expected DLR rate increase is $70 per flying hour.

In contrast to much of the previous research, Armstrong (2006) did not find conclusive evidence that average aircraft age effects flying program costs. Armstrong specifically analyzed the DLR and CONS CPFH rates for F-15CD and F-15E aircraft. This analysis was conducted using a form of regression known as panel data analysis. Monthly data including average aircraft age was compiled from every applicable location in building the model. The results indicated the average age of an aircraft was not statistically significant in the F-15CD CONS and F-15E DLR models while significant in the F-15CD DLR and F-15E CONS models. Nevertheless, in these last two models that found average age to be statistically significant, the economic magnitudes of the coefficients was only significant in the F-15CD DLR model.

One explanation for the results is the short period of analysis (2001-2005). As previously pointed out by Pyles, growth rates can fluctuate over a weapon system's life cycle. The time frame used by Armstrong could have been a period of no growth. Furthermore, Armstrong's models were based on monthly data, a relatively short time period when considering aircraft maintenance costs. A more significant relationship between age and maintenance costs might exist when analyzing longer time periods such as years. The results of the previous analyses are summarized in Table 3 below.

Table 3. Studies on Effects of Aircraft Age on O&S and O&M Costs

Author/Date	Equipment Examined	Estimated Effect of an Additional Year of Age
RAND Corporation/1990	Up to 74 types and versions of Air Force aircraft from 1981 to 1986	O&S costs (O&M costs plus the costs of military personnel) increased by 1.7 percent
Francis-Shaw/2000	F/A-18 Hornet from 1990-1999	Maintenance man-hours increase by 6.5 to 8.9 percent
CBO/2001	(a) 17 Air Force fighter, attack, bomber, cargo, and helicopter aircraft from 1996 to 1999	(a) O&S and O&M costs increased by 1 percent
	(b) 13 Navy fighter, attack, cargo, and helicopter aircraft from 1986 to 1999	(b) O&S costs increased by 2.4 percent, and O&M costs increased by 2.6 percent
	(c) 20 Navy and Air Force fighter, attack, and bomber aircraft from 1976 to 1999	(c) O&M costs increased by 2.5 percent
Pyles/2003	61 versions of Air Force Aircraft from 1993 to 1999	Maintenance workload growth varies over an aircraft's life cycle
Hawkes/2005	F-16 C/D from 1998 to 2004	DLR rate increases by $70 per flying hour for active duty aircraft
Armstrong/2006	F-15 C/D and F-15 E from 2001 to 2005	F-15 C/D DLR rate increases $199 per flying hour; F-15E Consumables rate increase $4 per flying hour

Operational Factors. Average sortie duration (ASD) is simply the total number of sorties divided by the total number of hours flown. The popular theory pertaining to this variable is that the longer the sortie the less maintenance actions that will be required (Armstrong, 2006). Assuming constant flying hours in a given period, reducing the ASD will require more maintenance effort to generate additional sorties. In turn, the additional sorties create added stress on the aircraft from increased take-offs and landings and starts and stops.

Six out of seven studies conducted in the 1970s indicate that average sortie duration does not influence flying hour costs (Hawkes, 2005). Hawkes' (2005) research indicates that ASD has no effect on the DLR rate for F-16C/Ds, while Armstrong's (2006) research indicates average sortie duration has a significant impact on DLR and CONS rates for both the F-15C/D and E models. Armstrong's (2006) research shows increasing the ASD by one hour decreases the monthly CONS CPFH rate by $234 to $238 and decreases the monthly DLR CPFH rate by $964 to $1943.

The utilization rate as used in previous research is defined as the number of flight hours per period per aircraft. Although slightly similar to ASD, utilization rate is intended to quantify the impact of operations tempo, whereas ASD attempts to quantify the impact of sortie length. Issues related to collinearity will be addressed in Chapter 4. Hawkes (2005) found utilization rate to be significant in his research, although the magnitude was small. The coefficients in the model indicated an inverse relationship between the utilization rate and the F-16CD DLR CPFH. An increase in one flight hour per aircraft reduces the DLR CPFH rate by $3.66 and $5.71 for active duty aircraft and ANG aircraft, respectively.

The CBO study results conflict with the results from the Hawkes study. However, the scope of the two studies is different. While Hawkes focuses specifically on DLR rates for the F-16CD, the CBO examines total O&S and O&M costs for multiple USAF and Navy aircraft by pooling aircraft in three separate models. Again, pooling aircraft together can mask the effects of utilization rate on individual aircraft. The CBO findings indicate that an increase in utilization rate of 10% will increase O&S costs by 5.8 to 7.4 percent. The results of each study are displayed in Table 4.

Table 4. Findings of Utilization Rate Effect on Maintenance Costs

Author/Date	Equipment Examined	Estimated Effect of Increase in Utilization Rate
CBO/February 2001	(a) 17 Air Force fighter, attack, bomber, cargo, and helicopter aircraft from 1996 to 1999	(a) 10% increase results in 5.8% increase in O&S costs
	(b) 13 Navy fighter, attack, cargo, and helicopter aircraft from 1986 to 1999	(b) 10% increase results in 7.4% increase in O&S costs
	(c) 20 Navy and Air Force fighter, attack, and bomber aircraft from 1976 to 1999	(c) 10% increase results in 6.2% increase in O&M costs
Hawkes/2005	F-16 C/D from 1998 to 2004	Increase in one flight hour per aircraft reduces DLR rate by $3.66 and $5.71 per hr. for active duty aircraft and ANG aircraft, respectively

This research will add a variable for utilization rate to determine its effect on KC-135R aircraft. Analysis of the KC-135 data reveals increased utilization rates since the start of the Global War on Terror.

A related research question in this study is to determine if there is a difference in maintenance costs during deployments. Fewer budget constraints and increased criticality of generating sorties in a deployed environment can potentially affect maintenance costs. Armstrong (2006) included a binary variable for the start of OIF in his research; however, this variable only accounts for the basic trend in maintenance costs after OIF. This variable was not statistically significant beyond the 20 percent level, but the magnitude of the coefficients was significant. Including a variable that accounts specifically for deployed flying hours can add greater visibility into maintenance costs during deployed periods.

Hawkes (2005) included a variable for percent deployed in his research. Percent deployed is the annual amount of combat hours flown divided by the total annual number of hours flown. Hawkes did not find any evidence that the F-16C/D DLR CPFH changes during contingencies. A variable similar to percent deployed will be incorporated into this research to further investigate this area's effect on the KC-135R aircraft. However, this variable will be based on monthly data.

Economic Factors. Armstrong (2006) used consumer jet fuel prices as a proxy variable to account for the fluctuations and impact the petroleum industry has on the aerospace industry. As reported by Armstrong (2006), Hicks notes that oil price fluctuations not only affect the cost of aviation fuel, but also the cost of acquiring other goods such as aircraft parts. This impact is mainly seen in the transportation and manufacturing costs of end items used in aircraft from consumables to DLRs. This variable was statistically significant in the F-15CD DLR model, but the magnitude was minor. Since this economic variable has not been used in other analyses, this variable will be included to expand the research in this area.

Seasonal cycles are binary variables that represent the months of the year and measure the seasonality or business cycles within the data. Armstrong (2006) discovered a seasonal cycle for the F-15 CPFH rate in three out of four of his models. To illustrate, the coefficients for these variables were largest in the fourth quarter of the fiscal year and the second quarter was higher than the third quarter. This pattern matches the USAF O&M budget cycle. A majority of the expenditures occur in the fourth quarter along with "fall-out" money and bases usually receive budget authority for the new fiscal year at the start of the second quarter.

Binary variables for each year are also used in previous research to capture the effects that annual budgets and changes in accounting policies or practices over time may have had on costs, independent of other factors in the model (Armstrong, 2006; Kiley, 2004; Pyles, 2003). One example is the change in the method of allocating costs for certain aircraft consumables. Previously, only items that were directly attached to the aircraft were considered flying program expenses. After the policy change, all consumable items directly related to aircraft, aircraft maintenance and the production of sorties and flying operations were considered flying program expenses, whether they were on the aircraft or stored off the aircraft (SAF/FMC, 2003). These variables are statistically significant in the previous studies cited; however, the magnitudes of the effects are relatively small (Armstrong, 2006; Kiley, 2004; Pyles, 2003). This research will also include binary variables for policy change to understand its effect specific to the KC-135R.

Environmental Factors. Armstrong (2006) was also the first to apply climatic variables to the area of O&S costs. This insight was motivated by previous research (Guo, 2004) indicating that temperature and salinity have a great impact on corrosion of aluminum alloy in Navy aircraft. Corrosion is viewed as a large contributor to maintenance costs (GAO, 2003). Indeed, a recent GAO report (2003) identifies corrosion as the reason for over 50 percent of the maintenance needed on the KC-135 aircraft.

Armstrong (2006) used the average monthly mean temperature difference of each applicable location as the climatology variable. The average monthly difference in temperature variable was significant in three of the four models with the magnitude of the variable being significant. Counter-intuitively, the sign of the coefficient was negative indicating that an increase in the average monthly mean temperature difference decreased the CPFH rate.

This research proposes to add another climatology variable for the amount of moisture in the atmosphere since this factor has also been identified as a contributor to corrosion (GAO, 2003). In fact, most KC-135 aircraft are scheduled for depot maintenance every 5 years; however, aircraft based in locations subject to increased humidity or a salt air environment are generally scheduled every 4 years (GAO, 2004). Dew point rather than relative humidity will be used to represent this variable as dew point is a more accurate measure of moisture content in the air. Relative humidity indicates how close the air is to becoming saturated, whereas dew point indicates the actual quantity of water vapor in the air. (National Oceanic & Atmoshperic Administation, 2006).

Motivation for Additional Variables

The previous research has identified several critical factors that impact aircraft O&S costs; however, there are other potential variables to investigate. As noted, average aircraft age is used frequently as a predictor of aircraft maintenance costs. Nevertheless, this measure may not always be accurate if the number of flying hours varies or if changes occur to flying patterns. To illustrate, suppose a fleet averaged 100 flying hours during a period of analysis and then increased to 150 flying hours after the analysis period. The maintenance costs would likely increase when the flying hours increased, but an age variable would not capture this effect. This research proposes an alternative measure such as airframe operating hours to capture this effect. Essentially, this measure is the equivalent of analyzing mileage rather than age.

Another area that can impact maintenance costs is aircraft availability. Availability in this research is expressed as a mission capable rate. This rate is simply the percentage of wing possessed aircraft capable of flying at least one specified mission (Hart & Mitchell, 2003).   The inclusion of this variable is a combination of intuition and observations from other researchers. It seems probable that lower availability of aircraft leads more required maintenance actions and associated costs. Indeed, Hart and Mitchell (2003) note that while mission capable rates have decreased in recent years, O&S costs have increased.

Lastly, interaction variables can provide valuable information when included in a model. An interaction variable is the product of two independent variables. The inclusion of an interaction variable is referred to as non-additive, meaning that the effect of one independent variable on the dependent variable varies according to the value of a second independent variable. In normal regression the effect of the independent variable on a dependent variable is constant regardless of the value of any other independent variable. Furthermore, the constituent variables of the interaction model should always be included regardless of whether they are significant (Jaccard and others, 1990). It is noted that including an interaction variable can increase the level of collinearity; accordingly, the models will be evaluated for statistical problems associated with this effect.

The interaction variable included in the models for this study will be the product of percent combat hours and utilization rates. This term was chosen because it is believed that utilization rates during deployments have an effect on DLR and Consumable rates.

Summary

This chapter described the components the make up the CPFH program and how they relate to broader level aircraft O&S costs. Additionally, the significance of the CPFH program was discussed along with the relationship to a MAJCOM's and wing's

O&M budget. The CPFH program does not represent a majority of O&S costs; however, this is a highly visible program due to the variable nature of expenditures.

In addition, previous research pertaining to O&S costs was analyzed along with the motivation for selecting the specific variables for this model. There are many variables that have been used to forecast costs and related factors for aircraft maintenance; however, some of these variables are not applicable for the model being used in this research.

Finally, the rationale was offered for including variables not previously used in similar research. These variables are average airframe operating hours, mission capable rate, and a utilization-percent combat hours interaction term.

III. Methodology

Description of Databases

The primary automated information systems used to collect data on the dependent and independent variables in this research are the Air Force Total Ownership Cost (AFTOC) database, Air Force Reliability and Maintainability Information System (REMIS), Multi-Echelon Resource and Logistics Information Network (MERLIN) and the Air Force Combat Climatology Center (AFCCC) database. AFTOC is a repository of operation and support cost data since 1996 for all Air Force weapon systems. This database receives feeds from other databases that collect cost data as well as data on operations, for instance, the hours flown or the equipment in inventory. AFTOC uses Automated Budget Interactive Data Environment System (ABIDES), Command On-Line Accounting & Reporting System (COARS), and Standard Base Supply System (SBSS). AFTOC is the best available source of detailed information on the costs of operating and maintaining Air Force equipment (Kiley, 2001).

The AFTOC data were provided by the Air Force Cost Analysis Agency and it contained the DLR and CONS costs for each base that operates the KC-135 aircraft. The data were provided in current year dollars for each month from 1996 to 2005 and adjusted to 2006 constant year dollars using SAF/FMC provided inflation factors. An example of this data is provided in Appendix A.

The AFCCC uses historical weather data to develop and produce special weather-impact information used in planning and executing DoD worldwide military operations and in engineering weapon system design and employment. The AFCCC has a repository of climatology observations for over 10,000 locations (Rabayda, 1998).

Included within the database are the surface observations such as temperature and relative humidity for individual stations (e.g., Grand Forks AFB, Altus AFB). The center provided all of the climatology data used in this research. An example of this data is shown in Appendix A.

The aircraft characteristics and operational factors for this model were obtained from REMIS. REMIS consists of an integrated database containing weapon system and equipment inventory, operational status, configuration management and reliability and maintainability analysis data. An example of the REMIS data is provided in Appendix A.

The aircraft mission capable rates were obtained from MERLIN. MERLIN is a web-based reporting and analysis tool that provides access to a variety of logistics data including availability of weapon systems. An example of the MERLIN data is also provided in Appendix A.

Description of Dependent Variables

DLR CPFH. This variable is the sum of the DLR net costs for the period divided by the flying hours for the period. This data was obtained from the AFTOC database in then year dollars. All costs were converted to FY2006 dollars.

CONS CPFH. This variable is the sum of the Consumables net costs for the period divided by the flying hours for the period. This data was obtained from the AFTOC database in then year dollars. All costs were converted to FY2006 dollars.

Description of Independent Variables

Average Sortie Duration. This variable is defined as the number of flying hours divided by the number of sorties. It is computed directly from the REMIS data.

Average Airframe Operating Hours. This is the cumulative average operating hours of the KC-135Rs in each location. It is computed by taking the value from the previous period and making adjustments based on the current period's flying hours. It is computed directly from the REMIS data.

Utilization Rate. This explanatory variable is defined as the number of sorties flown divided by the number of aircraft. It is computed directly from the REMIS data.

Jet Fuel Prices. The consumer jet fuel prices are being used as a proxy variable to account for the fluctuations and impact the petroleum industry has on the aerospace industry. The historical data for jet fuel prices was obtained from the Energy Information Administration.

Policy Change Dummy Variable (DV). This binary variable accounts for changes in the items that are considered aircraft CPFH expenses. This policy change was enacted on 1 October 2003. This variables is only included in the CONS model as it primarily affected non-reparable items.

Percent Combat Hours. This variable represents the number of hours flown in support of contingency operations such as OIF and OEF divided by the total number of hours flown. Combat hours were determined from the mission symbols contained in the REMIS data.

Seasonal DVs. These binary variables represented the months of the year, except for November which is the base month, and they will measure the seasonality within the data.

Mission Capable Rates. This variable is the percentage of wing possessed aircraft capable of flying at least one specified mission. This data was obtained from the MERLIN database.

Climatology. The mean temperature and dew point (degrees Farenheit) are being used to quantify the impact of climatology factors on corrosion. This data was supplied by the AFCCC.

Percent Combat Hours-Utilization Rate. This variable is the product of percent combat hours and utilization rate and was included to determine the effect of the interaction of these two terms.

Methods

Panel Model. This research applies panel data analysis to KC-135R DLR and CONS CPFH data. According to Yaffee (2003), panel data analysis is a method of studying a particular subject within multiple sites, periodically observed over a defined time frame. Panel data analysis is a form of regression that adds a spatial and temporal dimension to the model. The spatial dimension pertains to a set of cross-sectional units of observation. The temporal dimension pertains to periodic observations of a set of variables characterizing these cross-sectional units over a particular time span. The combination of time series with cross-sections can enhance the quality and quantity of data in ways that would be impossible using only one of these two dimensions.

Furthermore, while it is possible to use ordinary multiple regression techniques on panel data, they may not be optimal. The estimates of coefficients derived from regression may be subject to omitted variable bias, a problem that arises when there is some unknown variable or variables that cannot be controlled for that affect the dependent variable. With panel data, it is possible to control for some types of omitted variables even without observing them, by observing changes in the dependent variable over time. This controls for omitted variables that differ between cases but are constant over time (Yaffee, 2003).

There are two main types of panel data analytical models, fixed effects models and random effects models. The key assumption for the fixed effects model is that minimal time-series effect on the dependent variables exists. There are significant differences among the cross-sections, bases in this case. Conversely, the random effects model assumes there are unique, time constant attributes of groups that are the results of random variation and do not correlate with the individual regressors (Yaffee, 2003).

According to Yaffee (2003), the generally accepted way of choosing between fixed and random effects is running a Hausman test. The Hausman test tests the null hypothesis that the coefficients estimated by the random effects model are the same as the ones estimated by the fixed effects model. If the coefficients are the same, then the random effects model should be used. The predominant method in use is fixed effects. This method was used in the previous thesis by Armstrong (2006) and will also be used in building the models for this research.

A common panel regression model takes the form of $y_{it} = a + bx_{it} + \varepsilon_{it}$, where i and t are indices for units and time. The fixed-effects panel model notation is:

$y_{it} = x_{it}\beta + \alpha_i + e_{it}$,

where it is the ith base in the tth time period, β is the vector of coefficients, x_{it} is a vector of regressors, α_i is a base specific constant, and e_{it} is the error term. The model proposed in this research is that DLR and consumables cost per flying hour are a function of aircraft characteristics, and operational, economic, and environmental factors such that:

$$DLR_{Rate} = f(ConsumableRate + AverageSortieDuration + AverageAirframeHrs + PercentCombatHrs - UtilizationRate + JetFuel + MissionCapableRate + MeanDew + MeanTemp + PercentCombatHrs + UtilizationRate + MonthlyDVs) \quad (1)$$

$$Consumable_{Rate} = f(DLRRate + AverageSortieDuration + AverageAirframeHrs + PercentCombatHrs - UtilizationRate + JetFuel + MissionCapableRate + MeanDew + MeanTemp + PercentCombatHrs + PolicyChange + UtilizationRate + MonthlyDVs) \quad (2)$$

A separate model will be constructed for each service component to identify the differences in these organizations.

A few assumptions with panel data and regression analysis need to be addressed, to include stationarity of the dependent variable, heteroskedasticity, normality of the error terms, and collinearity. These assumptions and the tests to identify them will be specifically addressed in Chapter 4.

Summary

This chapter provided an overview of the four main databases from which information was obtained to construct the forecasting models: AFTOC, REMIS, MERLIN, and the AFCCC database. It also described the dependent and independent variables. Next, a description of the panel model, its variations, and the advantages of using this type of analysis was offered. Finally, the specified notations for the DLR and CONS models were given along with the anticipated effects of the independent variables on the dependent variables.

IV. Analysis and Results

Model Specification

One of the first steps in specifying a model is to check for correlation of the independent variables. Correlation can lead to collinearity resulting in the following problems: small changes in the data produce wide swings in parameter estimates and coefficients may have the incorrect sign or implausible magnitudes (Greene, 2003). A correlation of +1 or -1 indicates a perfect correlation, while a number close to either +1 or -1 indicates a strong correlation. The correlation matrices can be found in Appendix B. Average sortie duration was moderately correlated with both percent combat hours and the utilization-percent combat hours interaction variable in all of the matrices. Thus, average sortie duration was removed from the model specification since this variable was correlated with more than one variable. Also, mean temperature and mean dew point were strongly correlated. Mean temperature was removed from the model as this thesis seeks to investigate the effect of other climatology variables beyond temperature. Because percent combat hours is part of the utilization rate-combat hours interaction variable, these two terms were strongly correlated. However, both of these terms were used in the final model; their inclusion did not cause the model to exhibit any of the statistical problems associated with collinearity. Finally, the policy change variable was correlated with average airframe hours, but both variables were included as there is no casual relationship between these elements.

After including the aforementioned adjustments to the independent variables, the specified notations for the equations are as follows (sign represents the anticipated affect of the independent variable on the dependent variable):

$$DLR_{it} = \alpha_i + \alpha_{i+1} base_i + \beta_1 AvgAirframeHrs_{1it} + \beta_2 PercentCombatHrsUtilRate_{2it} + \beta_3 PercentCombatHrs_{3it} + \beta_4 JetFuel_{4it} - \beta_5 MCrate_{5it} + \beta_6 MeanDewPoint_{6it} + \beta_7 ConsumableRate_{7it} - \beta_8 UtilizationRate_{8it} + \beta_{9-19} MonthlyDVs_{9-19it} \quad (3)$$

$$CONS_{it} = \alpha_i + \alpha_{i+1} base_i + \beta_1 AvgAirframeHrs_{1it} + \beta_2 PercentCombatHrsUtilRate_{2it} + \beta_3 PercentCombatHrs_{3it} + \beta_4 JetFuel_{4it} - \beta_5 MCrate_{5it} + \beta_6 MeanDewPoint_{6it} + \beta_7 DLRRate_{7it} - \beta_8 UtilizationRate_{8it} + \beta_9 PolicyChange + \beta_{10-20} MonthlyDVs_{10-20it} \quad (4)$$

The next step is ensuring stationarity of the dependent variable. A stationary process has the property that the mean, variance, and autocorrelation structure do not change over time (Greene, 2003). Non-stationarity of the dependent variable could result in spurious relationships. A Fisher test for panel unit root was used to determine if the dependent variables in each model were stationary or contained a unit root (non-stationary). Fisher's test assumes that all series are non-stationary under the null hypothesis against the alternative that at least one series in the panel is stationary. The results of the Fisher tests indicate that all dependent variables are stationary. For more detailed information on the Fisher tests for each data set see Appendix C.

An appropriate lag structure for the dependent and independent variables also had to be determined for each model. Lag length was selected using a statistical criterion known as the Akaike Information Criterion (AIC). Under this goodness of fit measure, the optimal lag length is achieved when the AIC is minimized.

For each model constructed in this research, the AIC values continually decreased as the number of lags were increased. These results indicate there is no apparent lag structure for any of the variables. Furthermore, there is no theoretical lag structure in the previous literature to follow. Specific AIC values for each model are listed in Appendix D.

Before the results are presented, a discussion of the post-estimation and model specification tests is necessary to explain the rationale behind choosing each model. There were six models constructed to investigate the research questions identified in Chapter 1, a DLR and CONS CPFH model for each USAF total force component: ANG, AFR, and active duty. Analysis of the results will follow the description of the diagnostic post-estimation tests.

Panel Model Determination. As explained in Chapter 3, there are two main types of panel models, a fixed effects and random effects model. The generally accepted way of choosing between fixed effects and random effects is running a Hausman test. Under the null hypothesis, the coefficients estimated by the two models are the same. If the coefficents are the same (p-value greater than .05), then the random effects model can be used. Two of the models in this case favored the use of a random effects model. However, the fixed effects model was used in favor of random effects because the fixed effects model always gives consistent results and is the main technique for analysis of panel data (Greene, 2003). Moreover, for these data sets, it is believed there are more cross-sectional differences rather than significant time-series effects. Results of the Hausman tests can be found in Appendix E.

Normality Assumption. In order to check the assumption of normally distributed error terms, a Shapiro Wilk W test was performed and a histogram with a normal density plot laid over the top was created. Shapiro Wilk's W test is based on the null hypothesis that the distribution is normal and the alternative hypothesis that the residuals are not normally distributed. Thus, a large p-value is needed to fail to reject the null hypothesis. The histograms and test results are displayed in Appendix D. A visual inspection of the histogram and results of the Shapiro Wilk W test indicate that none of the error terms in the models are normally distributed.

Calculation of confidence intervals is based on the assumption of normally distributed errors. However, in this case, failing to meet the normality assumption is only a problem when conducting hypothesis testing and does not impact the results of the models presented in this chapter (Greene, 2003).

Homoskedasticity Assumption. When variance of the error terms is not constant, too much weight may be given to the subset of data where the error variance was largest when estimating coefficients. Heteroskedasticity does not invalidate the analysis, but the analysis is weakened. A common tool in econometrics to handle potential non-constant variance is heteroskedasticity-robust standard errors. In regression with robust standard errors, the coefficients are the same but the estimates of the standard errors are more robust to failure to meet the assumption of constant variance of the residuals. If errors are homoskedastic and robust standard errors are used, the results of the regression are still valid (Greene, 2003). All models in this research were developed with the robust standard errors option.

Independence Assumption. Non-independence of the error terms is referred to as autocorrelation. This condition can lead to an upward bias in estimates of the statistical significance of coefficients. The traditional test for the presence of autocorrelation is the Durbin-Watson statistic. Ideally, the Durbin Watson statistic should be close to 2 if no autocorrelation is present. Based on the number of observations and independent variables used in this research's models, an acceptable range for the Durbin Watson statistic is between 1.57 and 2.43. Two of the models in this research, the AFR and AD

CONS, indicated that autocorrelation was present with Durbin Watson statistics near 1.4. The dependent variable in these models was lagged and added as an explanatory variable to correct the autocorrelation. However, when lagged values of the dependent variable are added to the model, the Durbin Watson statistic is no longer appropriate (Greene, 2003). An alternative to the Durbin Watson statistic, the Woolridge test was performed and indicated that two lags of the dependent variable were the proper number of lags to correct for autocorrelation. The specific values for each Durbin Watson test are displayed with the results of the models while the Woolridge test results are displayed in Appendix E.

Panel Model Results

In this section, the results of each model are thoroughly analyzed, interpreted, and compared. The models are organized by service component. The ANG models are presented first.

Table 5. KC-135R ANG DLR Model Regression Results

KC-135R ANG DLR Model				
Fixed-effects (within) regression		Number of obs =		881
Group variable (i): base		Number of groups =		12
R-sq: within = 0.1498		Obs per group: min =		20
between = 0.0063		avg =		73.4
overall = 0.1339		max =		84
		F(19,850) =		5.14
		Prob > F =		0.000
ANG DLR Rate	Coefficient	Robust Std. Err.	t-stat	P>|t|
October	29.08075	89.55256	0.32	0.745
December	53.82951	85.28308	0.63	0.528
January	124.0411	102.6311	1.21	0.227
February	138.1228	78.78246	1.75	0.08
March	-29.20053	74.89745	-0.39	0.697
April	-4.05731	80.01636	-0.05	0.96
May	-30.52316	86.09286	-0.35	0.723
June	-153.9192	108.5392	-1.42	0.157
July	-67.84821	116.7886	-0.58	0.561
August	4.407552	125.5644	0.04	0.972
September	24.19628	133.224	0.18	0.856
Average Airframe Hours	0.0324195	0.0247839	1.54	0.123
Mission Capable Rate	-6.429171	2.002618	-3.21	0.001
Jet Fuel Price	-0.6970817	0.3703168	-1.88	0.06
Utilization Rate	-31.7439	10.74693	-2.95	0.003
Percent Combat Hours	0.2568591	2.741696	0.09	0.925
Mean Dew Point	4.019604	3.361701	1.20	0.232
CONS Rate	0.1922816	0.0608924	3.16	0.002
Util.-Combat Hrs. Interaction	0.0355432	0.2176636	0.16	0.87
Constant	651.1599	439.8729	1.48	0.139
Durbin Watson Statistic	**1.964**			

While this model only explains a small part of the variation in the DLR CPFH, the model still reveals some important points to discuss. First, there does not appear to be a strong seasonal trend to the data as February is the only month with any statistical significance. Further, airframe operating hours per aircraft is a valid predictor of the DLR rate; however, the magnitude of the coefficient is small. An increase in the average total operating hours by 100 hours will only increase the DLR rate by $3 per hour. Analyzing the raw data for average total operating hours indicates this measure increases by an average of 366 hours per year. Thus, the DLR rate increases by an average of $11 per year holding all other variables constant. The sign of the coefficient on mission capable rate is consistent with its anticipated effect on the DLR rate. For this model, as the mission capable rate decreases by 10 percent, the DLR rate increases by \$60. The utilization rate is also inversely related to the DLR rate; this finding is consistent with the previous research by Hawkes. Another inverse relationship exists between jet fuel prices and the DLR rate; however, this finding is counterintuitive. One would expect the DLR rate to increase as jet fuel prices increase because higher petroleum prices tend to increase the cost of acquiring aircraft parts. A possible explanation for this finding is a missing lag structure. Finally, the Consumables rate shows a strong correlation with the DLR rate. An increase in the Consumables rate by \$100 will increase the DLR rate by \$19. This relationship stems from the fact that many consumable items are replaced at the same time as DLRs.

Table 6. KC-135R ANG CONS Model Regression Results

KC-135R ANG CONS Model				
Fixed-effects (within) regression		Number of obs =		881
Group variable (i): base		Number of groups =		12
R-sq: within = 0.3963		Obs per group: min =		20
between = 0.0038		avg =		73.4
overall = 0.3548		max =		84
		F(20,849) =		7.58
		Prob > F =		0.000
ANG CONS Rate	Coefficient	Robust Std. Err.	t-stat	P>|t|
October	103.1704	47.0572	2.19	0.029
December	94.17633	48.00832	1.96	0.05
January	161.1735	52.17051	3.09	0.002
February	108.5298	49.25414	2.2	0.028
March	189.0472	43.51067	4.34	0.000
April	116.061	43.94056	2.64	0.008
May	50.85559	52.91552	0.96	0.337
June	92.24588	77.57172	1.19	0.235
July	72.8344	85.42328	0.85	0.394
August	206.7738	83.51247	2.48	0.013
September	1079.029	139.6646	7.73	0.000
Policy Change	-66.08418	57.30232	-1.15	0.249
Average Airframe Hours	0.1030809	0.0389335	2.65	0.008
Mission Capable Rate	-3.060918	1.836276	-1.67	0.096
Jet Fuel Price	-0.4784045	0.3979198	-1.2	0.23
Utilization Rate	-49.50905	10.9867	-4.51	0.000
Percent Combat Hours	-4.161795	2.77754	-1.5	0.134
Mean Dew Point	3.904036	2.56032	1.52	0.128
DLR Rate	0.188095	0.0635163	2.96	0.003
Util.-Combat Hrs. Interaction	0.3327438	0.2156027	1.54	0.123
Constant	-709.3592	612.9614	-1.16	0.247
Durbin Watson Statistic	**1.706**			

The ANG CONS model explains more of the variation in the dependent variable than the DLR model. The CONS model also exhibits more of a seasonal cycle with the CONS rate increasing significantly during the last two months of the fiscal year. This occurrence coincides with end of year fiscal closeout. During this time, fall out money is frequently used to replenish bench stock items. This event affects consumables more than DLRs and is reflected by the difference in the coefficients between the two models.

Similar to the previous model, the mission capable rate is inversely related to the CONS rate. However, the magnitude of the coefficient is 50 percent smaller. This variance is likely a reflection of the higher costs inherent in DLRs. The utilization rate is also inversely related to the CONS rate; increasing the sorties per aircraft by one decreases the CONS rate by $50.

Unexpectedly, this model indicates that as percent combats hours increases the CONS rate decreases, although the coefficient is marginally significant and the magnitude is relatively small. It was anticipated that percent combat hours would have a positive relationship with the CONS rate. However, a discussion of the interaction variable is necessary to fully understand the impact of percent combat hours. The interaction of percent combat hours and the utilization rate creates a different impact on the dependent variable. With the interaction variable in the model, the effect of percent combat hours can be interpreted as $\beta_1 + (\beta_2 X_2)$ where β_1 = coefficient for percent combat hours, β_2 = coefficient for interaction term and X_2 = the utilization rate. In this case, assuming a utilization rate of 9 (mean value), a one percent increase in percent combat hours will decrease the CONS rate by $1.17, a relatively insignificant amount. The effect still remains fairly small even at bigger increases in percent combat hours. The utilization rate would have to increase above 12.5 in order for percent combat hours to have a positive relationship with the CONS rate. Thus, both the direction and size of effect for percent combat hours is dependent upon the value of the utilization rate.

The mean dew point is also statistically significant in this model. With a coefficient of 3.9, the CONS rate will increase by $39 if the mean dew point increases 10 degrees. A change in the dew point in 10 degrees is quite common at most of the ANG locations, especially during the changing of seasons. In fact, the dew point typically fluctuates about 50 degrees during the year.

Table 7. KC-135R AD DLR Model Regression Results

KC-135R AD DLR Model				
Fixed-effects (within) regression		Number of obs =		723
Group variable (i): base		Number of groups =		9
R-sq:	within = 0.1523	Obs per group: min =		57
	between = 0.3011	avg =		80.3
	overall = 0.1603	max =		84
		F(19,695) =		6.99
		Prob > F =		0
Active Duty DLR Rate	Coefficient	Robust Std. Err.	t-stat	P>|t|
October	-38.0383	95.78927	-0.4	0.691
December	-10.46584	95.99126	-0.11	0.913
January	-187.2645	101.9208	-1.84	0.067
February	-93.68534	93.21298	-1.01	0.315
March	-166.2037	92.39126	-1.8	0.072
April	-45.62605	92.46952	-0.49	0.622
May	-69.75883	92.58228	-0.75	0.451
June	-10.92035	112.2155	-0.1	0.923
July	8.934365	115.7093	0.08	0.938
August	19.22458	98.07923	0.2	0.845
September	82.47522	108.8999	0.76	0.449
Average Airframe Hours	0.0068299	0.0183486	0.37	0.71
Mission Capable Rate	-13.06002	2.378881	-5.49	0.000
Jet Fuel Price	-0.1154729	0.3065764	-0.38	0.707
Utilization Rate	-45.70671	10.982	-4.16	0.000
Percent Combat Hours	-6.038601	2.179167	-2.77	0.006
Mean Dew Point	-1.889957	2.776544	-0.68	0.496
CONS Rate	0.0671804	0.079502	0.85	0.398
Util.-Combat Hrs. Interaction	0.3428123	0.1797629	1.91	0.057
Constant	2228.748	355.8323	6.26	0.000
Durbin Watson Statistic	**1.903**			

Similar to the ANG DLR model, the active duty DLR model does not exhibit any seasonal trend. January and March are the only months that are statistically significant. Mission capable rate and utilization rate also have the same relationships with the dependent variable as in the previous models, although the magnitude of the coefficients is larger than the ANG DLR model.

In addition, both percent combat hours and the interaction variable are statistically significant in this model. The coefficients reveal that deployments impact active duty aircraft similarly to ANG aircraft. Taking into account the interaction with the utilization rate (mean value of 11.56), an increase in percent combat hours by one percent decreases the DLR rate by $2. The utilization rate would have to increase to 17.5 in order for percent combat hours to have a positive relationship with the DLR rate. Furthermore, percent combat hours must fluctuate by a large amount to have a significant impact because of the small coefficient.[1]

[1] It is noted that the utilization rate and percent combat hours are both negative, but the interaction of these terms is positive. This relationship is a result of the interaction of these variables capturing an effect on the dependent variable that is not captured by the individual variables themselves. The coefficients for utilization rate and percent combat hours can still be negative depending upon their magnitude along with the magnitude of the interaction term.

Table 8. KC-135R AD CONS Model Regression Results

KC-135R AD CONS Model				
Fixed-effects (within) regression		Number of obs =		705
Group variable (i): base		Number of groups =		9
R-sq:	within = 0.2047	Obs per group: min =		55
	between = 0.0848	avg =		78.3
	overall = 0.1835	max =		82
		F(21,675) =		9.04
		Prob > F =		0

Active Duty CONS Rate	Coefficient	Robust Std. Err.	t-stat	P>|t|
October	-4.222171	30.09862	-0.14	0.888
December	-19.55028	33.83363	-0.58	0.564
January	31.88195	35.78692	0.89	0.373
February	-24.63393	28.10874	-0.88	0.381
March	29.75907	28.12279	1.06	0.29
April	56.75873	41.52492	1.37	0.172
May	107.3622	39.5154	2.72	0.007
June	111.9389	59.34857	1.89	0.06
July	89.43941	45.56736	1.96	0.05
August	109.9491	42.57331	2.58	0.01
September	301.9646	68.80352	4.39	0
Policy Change	7.134768	32.52924	0.22	0.826
Average Airframe Hours	-0.0085684	0.0141005	-0.61	0.544
Mission Capable Rate	1.15335	1.511687	0.76	0.446
Jet Fuel Price	0.2084067	0.1623516	1.28	0.2
Utilization Rate	-26.08483	10.2632	-2.54	0.011
Percent Combat Hours	-2.856871	1.473773	-1.94	0.053
Mean Dew Point	-2.395323	1.558862	-1.54	0.125
DLR Rate	0.0076753	0.0200429	0.38	0.702
Util.-Combat Hrs. Interaction	0.1551209	0.129789	1.2	0.232
CONS rate (2 lags)	0.0921681	0.0390036	2.36	0.018
Constant	602.6198	250.6568	2.4	0.016
Durbin Watson (non-lagged model)	**1.462**			

The initial active duty CONS model constructed suffered from autocorrelation so the CONS rate was lagged and added as an independent variable to correct this problem. The Woolridge test for autocorrelation in panel data is displayed in Appendix E. The model presented in Table 8 represents the final model with the lagged dependent variable.

The active duty CONS model demonstrates a seasonal/business cycle during the last five months of the fiscal year with the CONS rate increasing by $300 per hour during

September. The coefficients for utilization rate and percent combat hours are consistent with the previous models discussed; however, the interaction term is not statistically significant so these two variables can be interpreted separately in this model. While the coefficient of -2.86 for percent combat hours seems small, a decrease in this variable of 50 percent could increase the CONS rate by $143 per hour.

The mean dew point in this model behaves differently. The coefficient for mean dew point suggests that as the dew point decreases the CONS rate increases. This relationship is the opposite of that in the ANG CONS model. This variation is possibly due to the difference in locations between the service components. Furthermore, this finding may suggest that extremely dry air affects Consumables cost more than moist air due to the type of materials.

The lag of the dependent variable can be interpreted as the rate at which the CONS rate two months ago contributes to the current month's CONS rate. In this case, if the CONS rate was $500 two months ago, the current month's rate would increase by $45, or 9 percent.

Table 9. KC-135R AFR DLR Model Regression Results

KC-135R AFR DLR Model				
Fixed-effects (within) regression		Number of obs	=	360
Group variable (i): base		Number of groups	=	7
R-sq: within = 0.3596		Obs per group: min	=	8
between = 0.8085		avg	=	51.4
overall = 0.4521		max	=	82
		F(19,334)	=	2.29
		Prob > F	=	0.0018
AFR DLR Rate	Coefficient	Robust Std. Err.	t-stat	P>|t|
October	-75.53453	277.2874	-0.27	0.785
December	-129.131	193.6215	-0.67	0.505
January	-161.2256	171.7797	-0.94	0.349
February	69.96621	202.682	0.35	0.73
March	-94.99663	240.4643	-0.4	0.693
April	-139.5902	245.0765	-0.57	0.569
May	-147.5129	313.5153	-0.47	0.638
June	-289.7503	388.0282	-0.75	0.456
July	-294.6881	422.989	-0.7	0.486
August	-499.8689	439.3411	-1.14	0.256
September	-751.2571	503.5779	-1.49	0.137
Average Airframe Hours	0.0160926	0.0460754	0.35	0.727
Mission Capable Rate	-21.10568	6.505295	-3.24	0.001
Jet Fuel Price	-0.3584056	0.7495636	-0.48	0.633
Utilization Rate	-38.04797	19.76803	-1.92	0.055
Percent Combat Hours	-7.789749	4.249957	-1.83	0.068
Mean Dew Point	9.006375	10.80964	0.83	0.405
CONS Rate	0.8517382	0.2966254	2.87	0.004
Util.-Combat Hrs. Interaction	0.9331242	0.4244533	2.2	0.029
Constant	1884.838	961.4453	1.96	0.051
Durbin Watson Statistic	**1.816**			

Upon analyzing this model, the r-squared values are significantly higher than the other models. Also, this model accounts for the variation between the bases much better than the variation within the bases.

The lack of seasonal/business cycle in this model is comparable to the other service component DLR models. These findings suggest that DLRs for the KC-135R are not impacted by the annual O&M budget cycle. This conclusion is certainly plausible as flying operations typically receive top priority and are less likely to be impacted by the budget pattern. Armstrong found a strong seasonal trend in three of the four models developed. However, a DLR model was the one model without a seasonal trend.

The mission capable rate and utilization rate variables are also consistent with the other service component DLR models in terms of size and direction of effect. Conversely, the interaction term coefficient is three times larger in this model compared to the active duty DLR model. As a result, percent combat hours has a positive relationship with the DLR rate at the mean utilization rate of 9.88. A one unit increase in percent combat hours increases the DLR rate by $1.43. The utilization rate would have to decrease to 8.35 or lower in order for percent combat hours to have a negative relationship with the DLR rate. Nevertheless, similar to the other models, big fluctuations in percent combat hours are necessary for this variable to have a significant impact.

Table 10. KC-135R AFR CONS Model Regression Results

KC-135R AFR CONS Model				
Fixed-effects (within) regression		Number of obs	=	346
Group variable (i): base		Number of groups	=	7
R-sq:	within = 0.3731	Obs per group: min	=	6
	between = 0.4902	avg	=	49.4
	overall = 0.3942	max	=	80
		F(21,318)	=	4.44
		Prob > F	=	0.000

AFR CONS Rate	Coefficient	Robust Std. Err.	t-stat	P>|t|
October	151.7526	74.2156	2.04	0.042
December	155.0142	120.0876	1.29	0.198
January	77.55042	85.0716	0.91	0.363
February	80.50283	69.99708	1.15	0.251
March	167.0873	71.48236	2.34	0.02
April	135.1577	67.51706	2	0.046
May	226.8088	102.7816	2.21	0.028
June	265.2155	122.6992	2.16	0.031
July	375.8015	141.2983	2.66	0.008
August	565.7582	142.5751	3.97	0.000
September	993.073	185.3714	5.36	0.000
Policy Change	-11.75268	57.83555	-0.2	0.839
Average Airframe Hours	0.0449935	0.0310276	1.45	0.148
Mission Capable Rate	-4.095902	2.819248	-1.45	0.147
Jet Fuel Price	0.2661803	0.4319078	0.62	0.538
Utilization Rate	-22.19428	11.67087	-1.9	0.058
Percent Combat Hours	-2.637553	2.216926	-1.19	0.235
Mean Dew Point	-5.122094	4.672469	-1.1	0.274
DLR Rate	0.0651674	0.0445072	1.46	0.144
Util.-Combat Hrs. Interaction	0.1746599	0.1933797	0.9	0.367
CONS rate (2 lags)	0.0892516	0.0595396	1.5	0.135
Constant	96.45637	571.8541	0.17	0.866
Durbin Watson (non-lagged model)	**1.411**			

The initial AFR CONS model constructed suffered from autocorrelation so the CONS rate was lagged and added as an independent variable to correct this problem. The Woolridge test for autocorrelation in panel data is displayed in Appendix E. The model presented in Table 10 represents the final model with the lagged dependent variable. The AFR CONS model demonstrates a strong seasonal/business cycle with nine of the twelve months being statistically significant. September is the most notable month with a coefficient of $993.

The coefficients for utilization rate and mission capable rate are consistent with the previous models in terms of sign and size of the coefficient. Furthermore, average airframe hours is statistically significant in this model as in the ANG models. However, a comparison of the coefficient reveals this variable has 50 percent less of an impact in the AFR CONS model than the ANG CONS model. This variance does not appear to be a result of the difference in the average aircraft operating hours between the AFR and ANG aircraft. The mean value of this variable during the study period was 15,086 hours for the ANG aircraft as opposed to 15,561 hours for the AFR aircraft. The variance could likely be a result of different maintenance procedures between the two service components. Moreover, as identified in previous research, maintenance growth rates will likely fluctuate during an aircraft's lifecycle which would also contribute to this difference.

The CONS rate with two lags was added to correct for autocorrelation. Again, this variable can be interpreted as the rate at which the CONS rate two months ago contributes to the current month's CONS rate. In this case, the CONS rate two months ago increases the current month's rate by 8.9 percent.

It should also be noted that the policy change variable was not statistically significant in this model or any of the other models. This finding suggests that the policy change had no impact on the KC-135R CONS rate. In Armstrong's research, this variable was significant in one of the two CONS models developed for the F-15 aircraft.

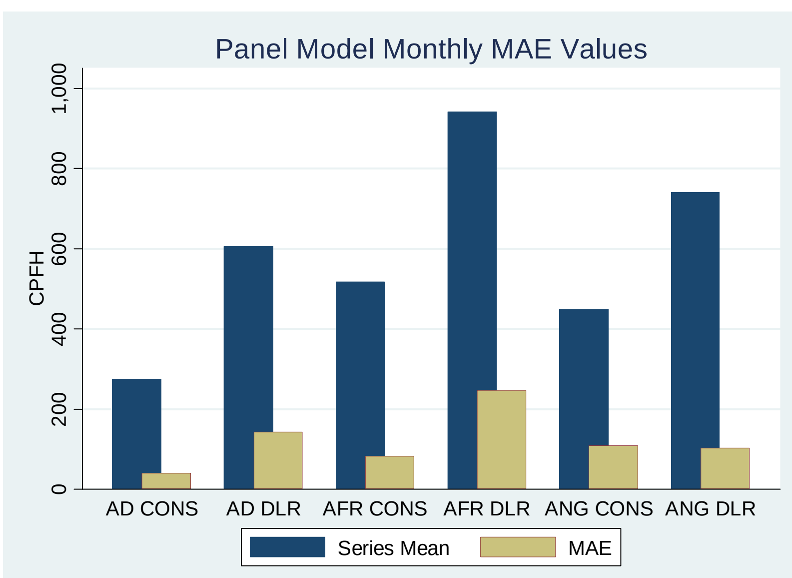
Validation Testing for Panel Data Models

In order to determine the accuracy of the models, the data for 2005 was withheld and reestimated. The models were then used to forecast 2005 values and compared to actual values. In addition to the monthly models presented in this chapter, quarterly models were generated to evaluate their accuracy in relation to the monthly models.

Two measures used in practice to calculate the overall forecast error are the Mean Absolute Error (MAE) and the Mean Absolute Percent Error (MAPE). The MAE is calculated by taking the sum of the absolute values of the individual forecast errors and dividing by the number of periods. One drawback with the MAE is that the value depends on the magnitude of the item being forecast. If the forecast item is measured in large units, the MAE value can be large. To avoid problems with interpretation of the MAE, the MAPE can be used. The MAPE expresses the error as a percentage of the actual values.

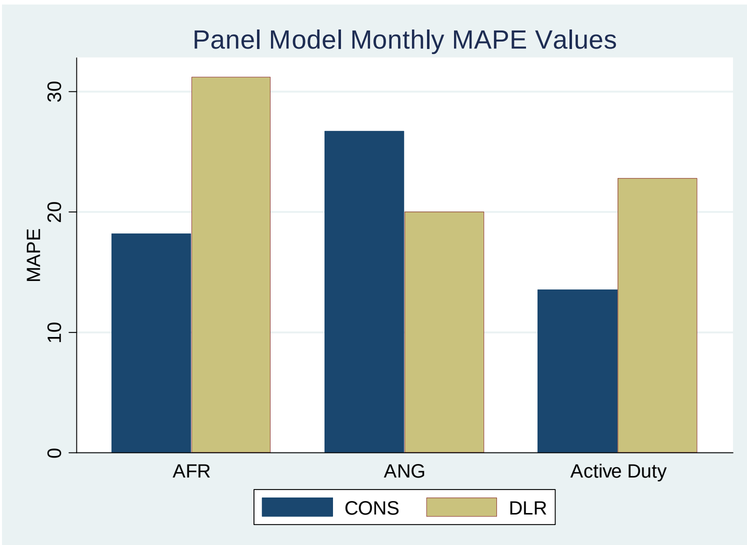
The MAE for the monthly models is presented in Figure 1. Each series mean value is displayed to provide a perspective of the magnitude of the MAE. Overall, one of the models had a MAE that was greater than 25 percent of the series mean. Also, the CONS models performed slightly better than the DLR models.

Figure 1. Panel Model Monthly MAE Values



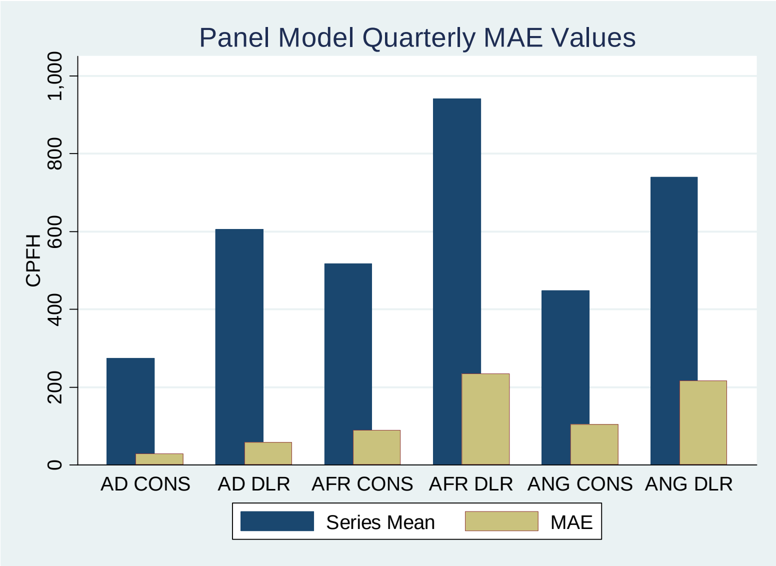
The MAPE for the monthly models is present in Figure 2. Except for the ANG, the CONS models performed better than DLR models. Comparing the service components, the AD models performed the best followed by the ANG and then the AFR. Although these accuracy measures may seem poor, these forecasts are for monthly predictions, a relatively short time period.

Figure 2. Panel Model Monthly MAPE Values



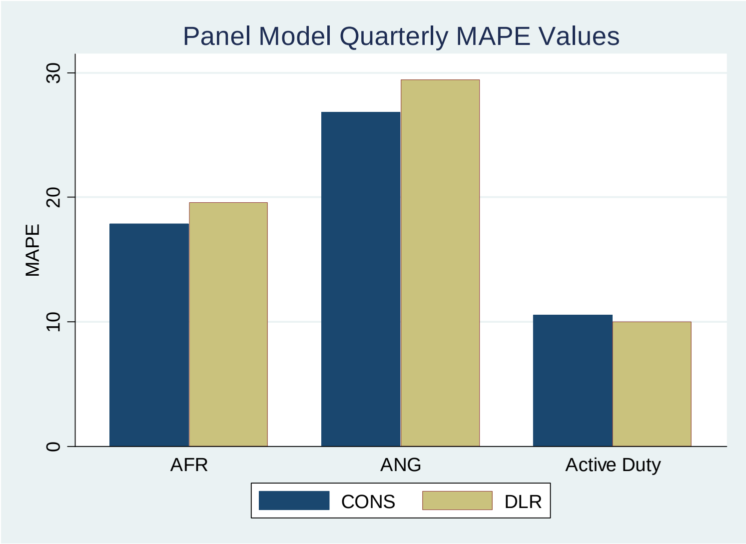
The MAE for the quarterly models is presented in Figure 3Figure 1. Overall, the forecast error for the quarterly models was the same or smaller compared to the monthly models. The only exception is the ANG DLR model. Also, all the models had a MAE that was 29 percent or less of the series mean.

Figure 3. Panel Model Quarterly MAE Values



The MAPE for the quarterly models is present in Figure 4. Similar to the monthly models, the AD models have a lower forecasting error than the other service components. However, the AFR models perform better than the ANG models unlike the monthly models. Also, as observed in the monthly models, the CONS models performed better than DLR models.

Figure 4. Panel Model Quarterly MAPE values



The accuracy measures presented in this chapter indicate the quarterly and monthly models are both valid tools for forecasting the KC-135R CPFH. Although some of the measures may seem poor, they are similar to the forecast accuracy in Hawkes' and Armstrong's models. The annual MAPE for Armstrong's CONS models ranged from 7 to 11 percent and the DLR models ranged from 12 to 16 percent, while Hawkes' DLR model had a MAPE of 15 percent. The monthly MAPE for Armstrong's models was much higher at 26 to 131 percent. The new models presented in this research confirm the volatile nature of the KC-135 data and its difficulty in forecasting.

Summary

The procedures used to specify each model were discussed in this chapter. The first procedure was to determine correlation of the independent variables. After this step, the notation for the equations was proposed along with the anticipated effect of each independent variable. An explanation of testing for an appropriate lag structure and stationarity of the dependent variable was then presented. Also, the ability of the models to meet the basic assumptions of regression and adjustments to the models were summarized. Next, the results of each model were analyzed and interpreted in detail. Finally, the accuracy of the models was determined by forecasting the values for 2005 and computing the MAE and MAPE.

V. Conclusions and Recommendations

Chapter Overview

This chapter integrates the regression results from Chapter Four by using this data to answer the research questions posed in Chapter One. Also, the significance of the research and its potential applications are summarized. Finally, recommendations are provided for future research areas related to this subject.

Discussion of Research Questions

Does the dew point impact the KC-135R CPFH?

As mentioned in Chapter Two, KC-135 aircraft based in humid air locations receive depot maintenance more often due to an increase in corrosion. Thus, the amount of moisture in the air impacts maintenance costs. However, this research is not able to answer with certainty if the dew point is an accurate predictor of the KC-135 CPFH. The dew point was only statistically significant in the ANG and AD CONS models. Moreover, the sign of the coefficient was different in these models. A possible explanation is missing lag structure to this variable. That is, corrosion occurs over a period of a time longer than one month. Accordingly, the dew point from last month or several months ago affect maintenance costs this month. This issue is further complicated by parts corroding and requiring replacement at different intervals. Another possible explanation is that corrosion primarily affects the components that are repaired or replaced during programmed depot maintenance and not the components handled during daily maintenance activities.

Is there a relationship between the annual O&M budget cycle and the CPFH for the KC-135R fleet?

The regression results indicate more of a relationship for the CONS models than the DLR models, which suggest that the KC-135R DLR CPFH is not impacted by the annual USAF O&M budget cycle. This cycle is typically calendar driven, resulting in an increase in spending during the second fiscal quarter as bases receive their budget authority. Spending also increases during the fourth quarter, September in particular, as bases receive "fall-out" funding. For the three CONS models developed in this research, the CONS CPFH increased by an average of $790 in September, a highly significant amount considering the mean CONS CPFH of $415. Most of the monthly DVs were not significant in the three DLR models. However, the models do imply that the DLR CPFH can actually decrease in the fourth quarter. Furthermore, these findings reveal the DLR CPFH is insulated from the fluctuations in spending inherent during the fiscal year. This conclusion is consistent with funding prioritization; repairable items for flying operations typically receive top priority and are not as affected by any funding shortages or changes to budgets.

In Armstrong's research, both CONS models exhibited a calendar trend and one of the two DLR models exhibited a calendar trend. This outcome raises an important issue: is the relationship between the budget cycle and DLR CPFH the same across weapon systems?

Do mission capable rates impact the KC-135R CPFH?

This variable had never been investigated in previous research. The mission capable rate was statistically significant in all of the models except the AD CONS model. The size of the coefficients indicates this variable has the biggest impact on the DLR CPFH. Among the three total force components, the AFR seems to be effected the greatest, with coefficients of -4 and -21 for the CONS and DLR models, respectively. Furthermore, the sign of the coefficients reveals the anticipated inverse relationship between mission capable rates and the CPFH. At a minimum, this relationship is a function of the math. In other words, as aircraft are deemed non-mission capable, flying hours would decrease thereby increasing the CPFH. However, even if flying hours remained constant, increased maintenance costs are likely during this time to upgrade aircraft to mission capable status.

Is average airframe operating hours an accurate predictor of the KC-135R CPFH?

This research sought to find an alternative measure to aircraft age. As noted in previous research, many studies using this variable assume the same age related maintenance costs over an aircraft's lifecycle. The airframe operating hours variable was designed to account for the variation in maintenance costs over the lifecycle by taking into consideration cumulative flying hours for the aircraft. This variable was statistically significant in three of the models (ANG CONS/DLR, and AD CONS). Interestingly, the results indicate that the CONS CPFH increases just as much if not more than the DLR CPFH as an aircraft progresses through its service life.

This researcher believes that this variable might be better suited for use with quarterly or annual data. Again, a month is a relatively short period of time for aircraft maintenance costs. Basic trends and relationships are likely to be more evident during longer time periods. Thus, analyzing longer time periods is required to reveal more conclusive evidence pertaining to the impact of this variable.

Does the KC-135R CPFH significantly change during deployments?

The effect of deployments on the CPFH was captured by the percent combat hours variable and interaction term created from the product of utilization rate and percent combat hours. The interaction term captures an effect that is not captured by the individual variables. The percent combat hours variable was statistically significant in four of the models. The interaction variable was statistically significant in three of these models. In general terms, the results indicate that percent combat hours has a positive relationship with the CPFH at high utilization rates and a negative relationship at lower utilization rates. Nevertheless, the magnitude of the relationship is relatively small. Percent combat hours must change by a large amount to have a significant impact on the CPFH. Thus, the change in the CPFH will likely be significant during the deployment or redeployment of the majority of a wing's aircraft.

Upon closer inspection of the data provided for total costs and flying hours, total costs tend to increase during support of contingency operations overseas, but so does flying hours. Consequently, the unit cost remains relatively constant.

Do the variables included in the models affect the active and reserve components differently?

In terms of the relationship between the budget cycle and CPFH, the service components behave in a similar manner. The service components demonstrate a calendar trend more for the CONS models than the DLR models. Within the CONS models, the AFR and ANG are more impacted by fiscal year end closeout than the active component. The CONS CPFH increases by 900 to 1000 in September for the ANG and AFR compared to $300 for active duty.

When comparing the effect of percent combat flying hours, this variable appears to be positively related to the CPFH for the AFR and negatively related for the other two service components. However, it is difficult to generalize the findings of this variable due to the interaction with the utilization rate. Differences in this area could be the result of aircraft age, maintenance procedures, personnel, and organizational factors. When analyzing age, the AFR fleet is the oldest which possibly explains the positive relationship to the CPFH.

The effect of mission capable rates is similar between the service components. The rates have more of an impact on the DLR CPFH than the CONS CPFH. However, mission capable rates have more of an effect on the AFR than the other components. One explanation for this result is the smaller number of aircraft located at AFR locations. A non-mission capable aircraft at an AFR wing will have more of an impact than another wing with more aircraft.

Significance of Research

This research made many significant contributions to the existing literature in this area. First, this research revealed that the interaction of utilization rate and percent combat hours captures an effect that is not captured by the individual variables. The utilization rate can be a major factor to determine if the CPFH increases or decreases when a wing is flying combat hours.

Furthermore, this research quantified the impact of two variables that had never been investigated: mission capable rate and average airframe hours. Mission capable rates have an inverse relationship on the KC-135R cost per flying hour while average airframe hours have a positive relationship. Average airframe hours is an alternative measure to aircraft age, although this measure is better suited for quarterly or yearly models.

From a broader perspective, this research has also made important contributions. Since the start of the Global War on Terror, O&S costs have received greater attention from senior leadership, including Congress. This research has expanded the knowledge of O&S costs with respect to the KC-135R aircraft. Specifically, this research has developed models for forecasting DLR and CONS CPFH for small time periods. These models can be used by anyone from a base level analyst to an Air Staff analyst to better manage the CPFH program. This information can be valuable to analysts when budgeting and planning for the incremental costs associated with contingencies or any change in operations. In addition, this added knowledge of KC-135R maintenance costs can be applied to lifecycle cost estimates of new aircraft. More importantly, some of the relationships between the independent variables and CPFH that have been identified can be applied when performing cost risk analyses. Finally, this research discovered important similarities and differences between the service component CPFH factors, another useful tool for planning budgets and forecasting.

Recommendations for Future Research

This research along with Armstrong's and Hawkes' previous research has provided much more insight and knowledge into the base level CPFH program. However, there are other potential areas related to this topic that need to be addressed.

First, the Air Force is centralizing the programming, budgeting, and execution of the CPFH program under Air Force Materiel Command. MAJCOM and base level organizations will no longer be players in this process. Determining the impact of this move would be extremely valuable for future decision making. The CPFH program was previously centralized so data may be available from this time period to use in the analysis.

Second, many aging aircraft such as the KC-135 have had extensive modifications to extend their service life. No previous studies have investigated the growth in modification costs as aircraft age or the effect of modifications on other items such as DLRs and Consumables. Research in these areas is needed.

Third, depot maintenance costs constitute a major part of an aircraft's overall O&S costs. A model to forecast programmed depot maintenance is warranted as previous research has focused on aggregate level O&S costs or smaller components of O&S costs. Further, the depots have implemented many business process improvement initiatives in recent years. The impact of these changes on depot maintenance costs could be studied.

Finally, manning and experience levels of maintenance personnel play an important role in the CPFH program. Although no empirical evidence is offered, Pyles (2003) notes that personnel changes can confound the effects of age-related maintenance cost growth. In light of the recent Force Shaping initiatives, an analysis of personnel effects on maintenance costs would be valuable. In particular, the difference in manning and experience levels between the different service components.

Summary

Six panel models were developed to forecast the KC-135R monthly CONS and DLR CPFH using aircraft characteristics, and operational, economic, and environmental factors. This data was collected for each service component operating location from

FY1998 to FY2004. This research contributed new information regarding the effect of mission capable rates, average airframe hours, mean dew point, and the interaction of utilization rates with combat flying hours. Also, the external validity of variables used in previous research is evaluated. These variables include utilization rate, policy change, jet fuel prices, and monthly dummy variables. In summary, this research extends our knowledge of the KC-135R CPFH program and provides a tool for decision makers at various levels.

Appendix A. Examples of Data Collected From Automated Information Systems

Table 11. Example of Cost Data from AFTOC Database

Fiscal Year	FY_Month	MD_CPFH	Data_Type	Command_CPFH	Unit	Base	Net_Cost	EEIC
2000	03	KC-135R	MSD	AETC	97th AMW	ALTUS AFB (OK)	($3,053.69)	644
2000	03	KC-135R	MSD	AETC	97th AMW	ALTUS AFB (OK)	$2,341.23	644
2000	02	KC-135R	MSD	AETC	97th AMW	ALTUS AFB (OK)	$1,501.41	644
2000	07	KC-135R	MSD	AETC	97th AMW	ALTUS AFB (OK)	$1,325.72	644
2000	08	KC-135R	MSD	AETC	97th AMW	ALTUS AFB (OK)	$12,480.85	644
2000	08	KC-135R	MSD	AETC	97th AMW	ALTUS AFB (OK)	$3,595.79	644
2000	07	KC-135R	MSD	AETC	97th AMW	ALTUS AFB (OK)	$1,712.40	644

Table 12. Example of Data provided by AFCCC

Base	Year	Month	meanmax temp	meanmin temp	mean temp	meanmax dew point	meanmin dew point	mean dew point
Robins	1997	10	67	47	56	51	40	45
	1997	11	52	38	44	40	30	35
	1997	12	47	31	38	34	23	29
	1998	1	49	35	41	38	28	33
	1998	2	49	34	42	37	28	33

Table 13. Example of Data provided by REMIS

Aircraft_ID	FY	Fscl_Month	Tail_Number	Possessing_Agency	Possessed_Base	Mission_Symbol	Mission	FH	Sorties	Assigned_Org
KC135R	FY2001	3	62003516	AET	ALTUS AFB (OK)	T2T	Training	28.2	5	0097MBYWG
KC135R	FY2000	1	63008037	AET	ALTUS AFB (OK)	T2T	Training	72.2	20	0097MBYWG
KC135R	FY2000	1	63008045	AET	ALTUS AFB (OK)	T2T	Training	64.2	15	0097MBYWG
KC135R	FY2001	3	62003516	AET	ALTUS AFB (OK)	T3T	Training	4.2	1	0097MBYWG
KC135R	FY2000	7	63008023	AET	ALTUS AFB (OK)	T2T	Training	32.4	6	0097MBYWG
KC135R	FY2000	2	63008045	AET	ALTUS AFB (OK)	T2T	Training	35.7	7	0097MBYWG
KC135R	FY2000	3	63008045	AET	ALTUS AFB (OK)	T2T	Training	61.8	15	0097MBYWG

Table 14. Example of Data Provided by MERLIN

YEAR	MONTH	BASE	UNIT	MDS	MAJCOM	MC
1997	Sep	Lincoln	155ARFWG	KC-135R	ANG	63.7
1997	Oct	Lincoln	155ARFWG	KC-135R	ANG	50.2
1997	Nov	Lincoln	155ARFWG	KC-135R	ANG	57.9
1997	Dec	Lincoln	155ARFWG	KC-135R	ANG	77.6
1998	Jan	Lincoln	155ARFWG	KC-135R	ANG	70.4

Appendix B. Correlation Matrices for Independent Variables

Table 15. Correlation Matrix for KC-135R ANG Data

Correlation Matrix KC-135R ANG Data

	DLR Rate	Policy Change	Avg. Airframe Hrs.	Avg. Sortie Duration	Mission Cap. Rate	Jet Fuel Price	Utilization Rate	Percent Combat Hrs.	Mean Temp	Mean Dew Point	CONS Rate	Util.-Combat Hrs. Interaction
DLR Rate	1.000											
Policy Change	0.011	1.000										
Avg. Airframe Hrs.	0.034	-0.069	1.000									
Avg. Sortie Duration	-0.112	-0.082	0.004	1.000								
Mission Cap. Rate	-0.106	-0.166	0.149	0.155	1.000							
Jet Fuel Price	-0.001	0.349	0.310	-0.101	-0.153	1.000						
Utilization Rate	-0.221	0.014	0.143	-0.046	0.054	0.020	1.000					
Percent Combat Hrs.	-0.072	-0.174	0.190	0.459	0.314	-0.118	0.196	1.000				
Mean Temp	0.061	-0.005	0.066	0.090	-0.022	0.153	-0.017	-0.031	1.000			
Mean Dew Point	0.071	-0.009	0.045	0.096	-0.007	0.140	-0.021	-0.017	0.975	1.000		
CONS Rate	0.295	-0.012	0.060	-0.156	-0.086	0.057	-0.253	-0.088	0.098	0.103	1.000	
Util.-Combat Hrs. Interaction	-0.101	-0.120	0.208	0.400	0.292	-0.071	0.374	0.938	-0.013	-0.001	-0.201	1.000

Table 16. Correlation Matrix for KC-135R AD Data

Correlation Matrix KC-135R AD Data

	DLR Rate	Policy Change	Avg. Airframe Hrs.	Avg. Sortie Duration	Mission Cap. Rate	Jet Fuel Price	Utilization Rate	Percent Combat Hrs.	Mean Temp	Mean Dew Point	CONS Rate	Util.-Combat Hrs. Interaction
DLR Rate	1											
Policy Change	-0.0642	1										
Avg. Airframe Hrs.	-0.0929	0.6377	1									
Avg. Sortie Duration	-0.2558	0.2687	0.2719	1								
Mission Cap. Rate	-0.2485	0.1911	0.2553	0.1818	1							
Jet Fuel Price	0.014	0.3227	0.2577	0.0141	-0.1505	1						
Utilization Rate	-0.2396	0.1645	0.3268	0.1782	0.0723	0.1162	1					
Percent Combat Hrs.	-0.2937	0.3356	0.3109	0.58	0.2157	0.0106	0.3171	1				
Mean Temp	0.085	0.0134	0.1281	-0.1784	-0.0208	0.1653	0.1038	-0.1475	1			
Mean Dew Point	0.0692	0.0417	0.1645	-0.1308	0.0114	0.1395	0.0664	-0.0918	0.9257	1		
CONS Rate	0.125	-0.0647	-0.0592	-0.2423	-0.0967	0.0585	-0.2203	-0.262	0.0938	0.1158	1	
Util.-Combat Hrs. Interaction	-0.3023	0.3281	0.3383	0.5382	0.2079	0.0316	0.5366	0.9323	-0.094	-0.0623	-0.275	1

Table 17. Correlation Matrix for KC-135R AFR Data

Correlation Matrix KC-135R AFR Data

	DLR Rate	Policy Change	Avg. Airframe Hrs.	Avg. Sortie Duration	Mission Cap. Rate	Jet Fuel Price	Utilization Rate	Percent Combat Hrs.	Mean Temp	Mean Dew Point	CONS Rate	Util.-Combat Hrs. Interaction
DLR Rate	1											
Policy Change	0.2074	1										
Avg. Airframe Hrs.	0.1767	0.5106	1									
Avg. Sortie Duration	-0.2752	0.0583	0.2325	1								
Mission Cap. Rate	-0.3053	-0.0283	0.0461	0.3389	1							
Jet Fuel Price	0.1164	0.3994	0.2604	-0.1054	-0.1048	1						
Utilization Rate	-0.2732	-0.0807	-0.0695	0.0231	-0.0948	0.0752	1					
Percent Combat Hrs.	-0.1649	0.1191	0.0453	0.6877	0.3297	-0.0785	0.0868	1				
Mean Temp	-0.0242	-0.078	0.1475	-0.0654	0.1403	0.184	0.0428	-0.0137	1			
Mean Dew Point	-0.0058	-0.0616	0.092	-0.089	0.1086	0.2122	0.0407	0.0036	0.9465	1		
CONS Rate	0.6111	0.2064	0.1372	-0.2517	-0.272	0.1503	-0.2595	-0.1603	0.0797	0.0867	1	
Util.-Combat Hrs. Interaction	-0.1587	0.1126	0.049	0.6488	0.3219	-0.0827	0.2458	0.9487	-0.04	-0.02	-0.168	1

Appendix C. Fisher Test for Panel Unit Root Using Augmented Dickey Fuller Test

Fisher's test assumes that all series are non-stationary under the null hypothesis against the alternative that at least one series in the panel is stationary. Based on the p-values, the null hypothesis can be rejected and the alternative accepted.

Table 18. Fisher Test Results

Model	Chi-squared	Probability>chi squared
KC-135R ANG DLR	694.0463	0.000
KC-135R ANG CONS	523.5076	0.000
KC-135R AFR DLR	276.7481	0.000
KC-135R AFR CONS	214.295	0.000
KC-135R Active DLR	450.3525	0.000
KC-135R Active CONS	340.143	0.000

Appendix D. AIC Values for Lag Structure Determination

AIC values for ANG DLR Model

Lag	DLR rate	Mean Dew Point	Jet Fuel	Miss. Cap. Rate
0	N/A	13409.95	13409.95	13409.95
1	13238.43	13236.61	13234.1	13245.74
2	13046.33	13047.44	13045.68	13058.95
3	12788.52	12787.98	12786	12802.52
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
12	11137.96	11130.47	11134.82	11152.72

AIC values for ANG CONS Model

Lag	CONS rate	Mean Dew Point	Jet Fuel	Miss. Cap. Rate
0	N/A	13379.93	13379.93	13379.93
1	13192.52	13196.71	13200.65	13203.67
2	13016	13001.18	13012.12	13013.72
3	12833.25	12826.4	12828.18	12834.42
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
12	11204.79	11210.4	11183.04	11207.29

AIC values for AD CONS Model

Lag	CONS rate	Mean Dew Point	Jet Fuel	Miss. Cap. Rate
0	N/A	9837.448	9837.448	9837.448
1	9680.25	9711.058	9714.483	9713.419
2	9588.923	9593.064	9592.499	9592.912
3	9462.416	9469.239	9468.258	9464.636
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
12	8242.548	8239.555		8243.06

AIC values for AD DLR Model

Lag	DLR rate	Mean Dew Point	Jet Fuel	Miss. Cap. Rate
0	N/A	10943.1	10943.1	10943.1
1	10799.33	10806.39	10805.73	10840.9
2	10651.1	10667.23	10666.67	10693.32
3	10531.21	10535.44	10535.97	10562.87
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
12	9325.502	9322.035	9321.445	9342.691

AIC values for AFR CONS Model				
Lag	DLR rate	Mean Dew Point	Jet Fuel	Miss. Cap. Rate
0	N/A	5211.582	5211.582	5211.582
1	5122.845	5136.681	5135.403	5137.138
2	5065.5	5063.015	5063.933	5064.887
3	4996.917	4995.319	4995.627	4993.386
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
12	4362.324	4360.834	4356.504	4359.378

AIC values for AFR DLR Model				
Lag	DLR rate	Mean Dew Point	Jet Fuel	Miss. Cap. Rate
0	N/A	5463.302	5463.302	5463.302
1	5387.932	5391.107	5390.677	5398.002
2	5317.661	5317.945	5318.041	5324.004
3	5247.219	5244.347	5245.584	5252.665
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
12	4538.353	4536.381	4535.373	4545.423

Appendix E. Hausman Specification Test Results

Table 19. KC-135R ANG DLR Hausman Specification Test

KC-135R ANG DLR Hausman Specification Test				
	Coefficients			
	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
October	112.3178	186.8662	-74.54845	19.72116
December	103.7408	36.30106	67.43973	17.21213
January	197.2184	102.0242	95.19419	24.71291
February	132.9878	64.6775	68.31031	15.59795
March	186.8702	154.0195	32.85074	.
April	117.7026	163.0749	-45.37228	9.741144
May	47.21209	176.3808	-129.1687	36.66511
June	69.59189	269.8068	-200.2149	56.37326
July	65.27	301.523	-236.253	66.37748
August	216.0343	441.7425	-225.7082	63.92816
September	1120.23	1302.558	-182.3281	48.51399
Avg Total Hrs	0.115099	0.0748276	0.0402709	0.024809
Mission Cap Rate	-4.37786	-4.334503	-0.0433568	0.4578931
Jet Fuel	-0.593511	-0.559886	-0.0336248	.
Utilization Rate	-56.55307	-49.17852	-7.374558	2.979229
Percent Combat Hrs	-4.250303	-3.883933	-0.36637	.
Mean Dew Point	4.557438	-4.132044	8.689481	2.461298
DLR CPFH	0.018523	0.018093	0.0004294	0.000983
Utilization-Percent Combat Hrs Interaction	0.349358	0.3095748	0.0397829	0.0070184

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(17) = (b-B)'[(V_b-V_B)^(-1)](b-B)

= 15.89

Prob>chi2 = 0.5317

(V_b-V_B is not positive definite)

Table 20. KC-135R ANG CONS Hausman Specification Test

KC-135R ANG CONS Hausman Specification Test				
	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	Fixed	Random	Difference	S.E.
October	112.3178	186.8662	-74.54845	19.72116
December	103.7408	36.30106	67.43973	17.21213
January	197.2184	102.0242	95.19419	24.71291
February	132.9878	64.6775	68.31031	15.59795
March	186.8702	154.0195	32.85074	.
April	117.7026	163.0749	-45.37228	9.741144
May	47.21209	176.3808	-129.1687	36.66511
June	69.59189	269.8068	-200.2149	56.37326
July	65.27	301.523	-236.253	66.37748
August	216.0343	441.7425	-225.7082	63.92816
September	1120.23	1302.558	-182.3281	48.51399
Policy Change	-73.69693	-49.22215	-24.47478	23.97182
Avg Total Hrs	0.115099	0.0748276	0.0402709	0.024809
Mission Cap Rate	-4.37786	-4.334503	-0.0433568	0.4578931
Jet Fuel	-0.593511	-0.559886	-0.0336248	.
Utilization Rate	-56.55307	-49.17852	-7.374558	2.979229
Percent Combat Hrs	-4.250303	-3.883933	-0.36637	.
Mean Dew Point	4.557438	-4.132044	8.689481	2.461298
DLR CPFH	0.018523	0.018093	0.0004294	0.000983
Utilization-Percent Combat Hrs Interaction	0.349358	0.3095748	0.0397829	0.0070184

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(17) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 51.89
Prob>chi2 = 0.0000
(V_b-V_B is not positive definite)

Table 21. KC-135R AD DLR Hausman Specification Test

KC-135R Active Duty DLR Hausman Specification Test				
	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	Fixed	Random	Difference	S.E.
October	112.3178	186.8662	-74.54845	19.72116
December	103.7408	36.30106	67.43973	17.21213
January	197.2184	102.0242	95.19419	24.71291
February	132.9878	64.6775	68.31031	15.59795
March	186.8702	154.0195	32.85074	.
April	117.7026	163.0749	-45.37228	9.741144
May	47.21209	176.3808	-129.1687	36.66511
June	69.59189	269.8068	-200.2149	56.37326
July	65.27	301.523	-236.253	66.37748
August	216.0343	441.7425	-225.7082	63.92816
September	1120.23	1302.558	-182.3281	48.51399
Avg Total Hrs	0.115099	0.0748276	0.0402709	0.024809
Mission Cap Rate	-4.37786	-4.334503	-0.0433568	0.4578931
Jet Fuel	-0.593511	-0.559886	-0.0336248	.
Utilization Rate	-56.55307	-49.17852	-7.374558	2.979229
Percent Combat Hrs	-4.250303	-3.883933	-0.36637	.
Mean Dew Point	4.557438	-4.132044	8.689481	2.461298
DLR CPFH	0.018523	0.018093	0.0004294	0.000983
Utilization-Percent Combat Hrs Interaction	0.349358	0.3095748	0.0397829	0.0070184

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(17) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 30.36
Prob>chi2 = 0.0239
(V_b-V_B is not positive definite)

Table 22. KC-135R AD CONS Hausman Specification Test

KC-135R Active Duty CONS Hausman Specification Test				
	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	Fixed	Random	Difference	S.E.
October	112.3178	186.8662	-74.54845	19.72116
December	103.7408	36.30106	67.43973	17.21213
January	197.2184	102.0242	95.19419	24.71291
February	132.9878	64.6775	68.31031	15.59795
March	186.8702	154.0195	32.85074	.
April	117.7026	163.0749	-45.37228	9.741144
May	47.21209	176.3808	-129.1687	36.66511
June	69.59189	269.8068	-200.2149	56.37326
July	65.27	301.523	-236.253	66.37748
August	216.0343	441.7425	-225.7082	63.92816
September	1120.23	1302.558	-182.3281	48.51399
Policy Change	-73.69693	-49.22215	-24.47478	23.97182
Avg Total Hrs	0.115099	0.0748276	0.0402709	0.024809
Mission Cap Rate	-4.37786	-4.334503	-0.0433568	0.4578931
Jet Fuel	-0.593511	-0.559886	-0.0336248	.
Utilization Rate	-56.55307	-49.17852	-7.374558	2.979229
Percent Combat Hrs	-4.250303	-3.883933	-0.36637	.
Mean Dew Point	4.557438	-4.132044	8.689481	2.461298
DLR CPFH	0.018523	0.018093	0.0004294	0.000983
Utilization-Percent Combat Hrs Interaction	0.349358	0.3095748	0.0397829	0.0070184

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(19) = (b-B)'[(V_b-V_B)^(-1)](b-B)

= 145.42

Prob>chi2 = 0.0000

(V_b-V_B is not positive definite)

Table 23. KC-135R AFR DLR Hausman Specification Test

KC-135R AFR DLR Hausman Specification Test				
	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	Fixed	Random	Difference	S.E.
October	112.3178	186.8662	-74.54845	19.72116
December	103.7408	36.30106	67.43973	17.21213
January	197.2184	102.0242	95.19419	24.71291
February	132.9878	64.6775	68.31031	15.59795
March	186.8702	154.0195	32.85074	.
April	117.7026	163.0749	-45.37228	9.741144
May	47.21209	176.3808	-129.1687	36.66511
June	69.59189	269.8068	-200.2149	56.37326
July	65.27	301.523	-236.253	66.37748
August	216.0343	441.7425	-225.7082	63.92816
September	1120.23	1302.558	-182.3281	48.51399
Avg Total Hrs	0.115099	0.0748276	0.0402709	0.024809
Mission Cap Rate	-4.37786	-4.334503	-0.0433568	0.4578931
Jet Fuel	-0.593511	-0.559886	-0.0336248	.
Utilization Rate	-56.55307	-49.17852	-7.374558	2.979229
Percent Combat Hrs	-4.250303	-3.883933	-0.36637	.
Mean Dew Point	4.557438	-4.132044	8.689481	2.461298
DLR CPFH	0.018523	0.018093	0.0004294	0.000983
Utilization-Percent Combat Hrs Interaction	0.349358	0.3095748	0.0397829	0.0070184

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(19) = (b-B)'[(V_b-V_B)^(-1)](b-B)

= 72.53

Prob>chi2 = 0.000

(V_b-V_B is not positive definite)

Table 24. KC-135R AFR CONS Hausman Specification Test

KC-135R AFR CONS Hausman Specification Test				
	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	Fixed	Random	Difference	S.E.
October	112.3178	186.8662	-74.54845	19.72116
December	103.7408	36.30106	67.43973	17.21213
January	197.2184	102.0242	95.19419	24.71291
February	132.9878	64.6775	68.31031	15.59795
March	186.8702	154.0195	32.85074	.
April	117.7026	163.0749	-45.37228	9.741144
May	47.21209	176.3808	-129.1687	36.66511
June	69.59189	269.8068	-200.2149	56.37326
July	65.27	301.523	-236.253	66.37748
August	216.0343	441.7425	-225.7082	63.92816
September	1120.23	1302.558	-182.3281	48.51399
Policy Change	-73.69693	-49.22215	-24.47478	23.97182
Avg Total Hrs	0.115099	0.0748276	0.0402709	0.024809
Mission Cap Rate	-4.37786	-4.334503	-0.0433568	0.4578931
Jet Fuel	-0.593511	-0.559886	-0.0336248	.
Utilization Rate	-56.55307	-49.17852	-7.374558	2.979229
Percent Combat Hrs	-4.250303	-3.883933	-0.36637	.
Mean Dew Point	4.557438	-4.132044	8.689481	2.461298
DLR CPFH	0.018523	0.018093	0.0004294	0.000983
Utilization-Percent Combat Hrs Interaction	0.349358	0.3095748	0.0397829	0.0070184

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

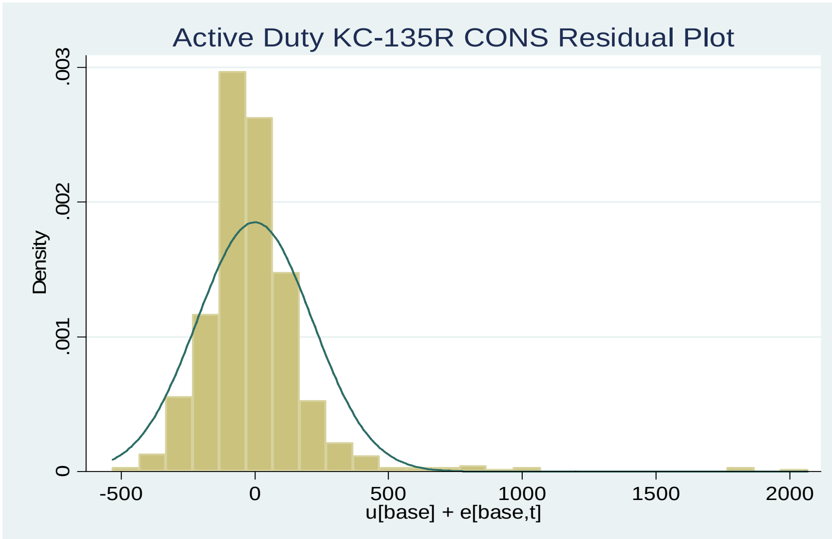
chi2(19) = (b-B)'[(V_b-V_B)^(-1)](b-B)

= 15.75

Prob>chi2 = 0.5417

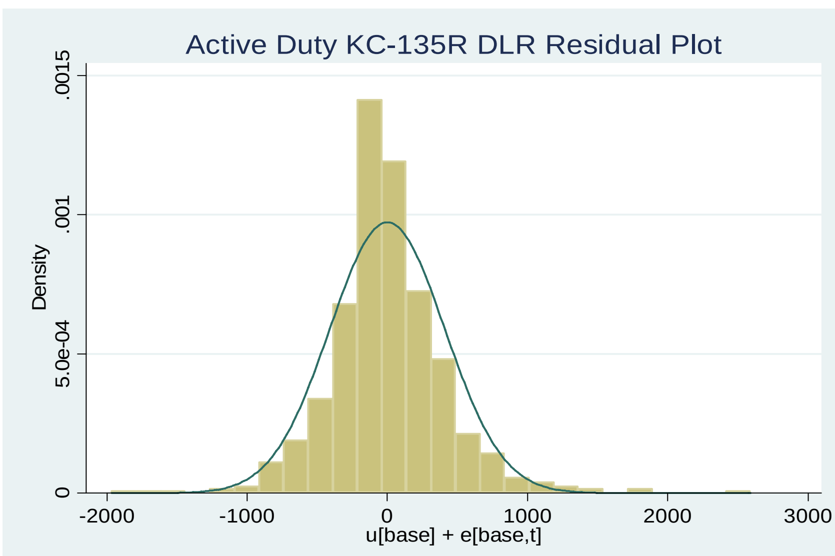
(V_b-V_B is not positive definite)

Appendix F. Shapiro-Wilk W Test Results and Histogram of Residuals



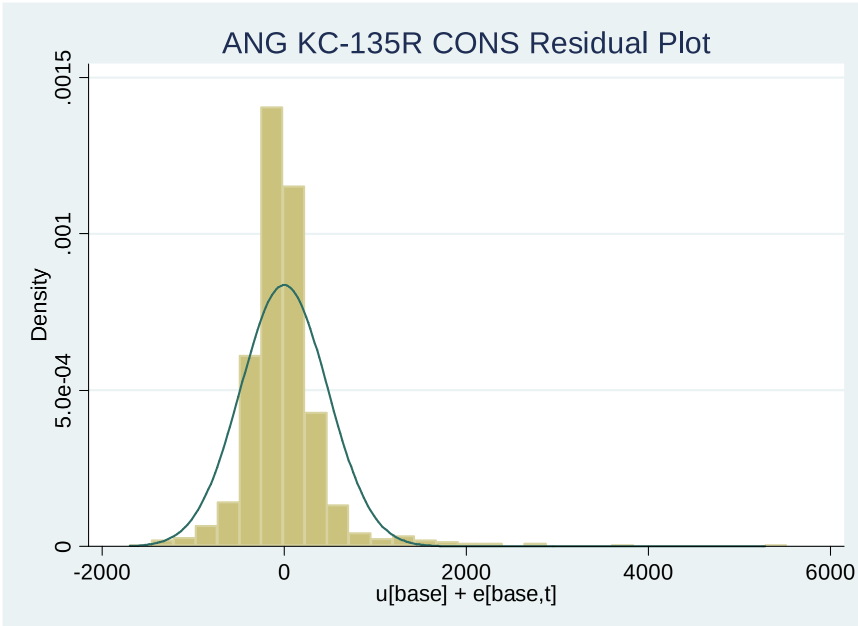
Shapiro Wilk W Test for Normal Data					
Variable	**Obs**	**W**	**V**	**z**	**Prob>z**
CONS Residuals	705	0.74861	115.38	11.588	0.000

Figure 5. Histogram Plot of Residuals for KC-135R Active Duty CONS Model



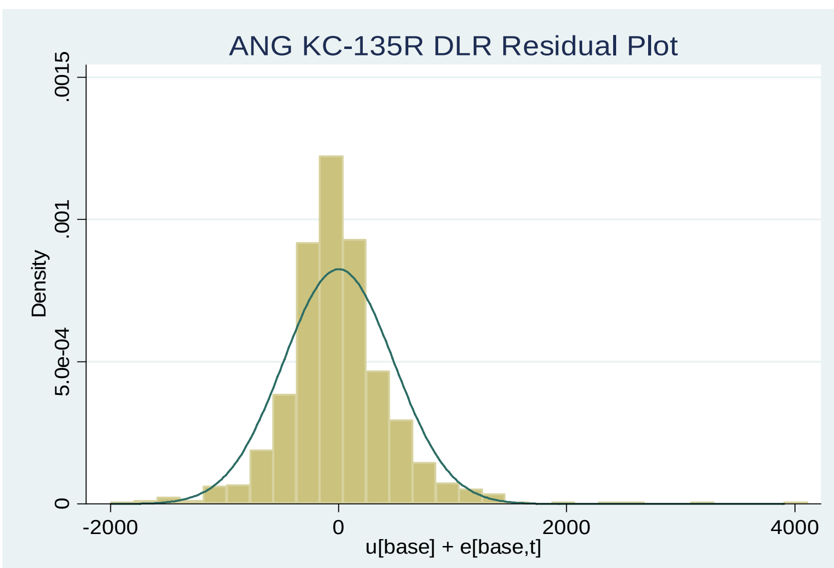
Shapiro Wilk W Test for Normal Data					
Variable	**Obs**	**W**	**V**	**z**	**Prob>z**
DLR Residuals	723	0.94372	26.429	8	0.000

Figure 6. Histogram Plot of Residuals for KC-135R Active Duty DLR Model



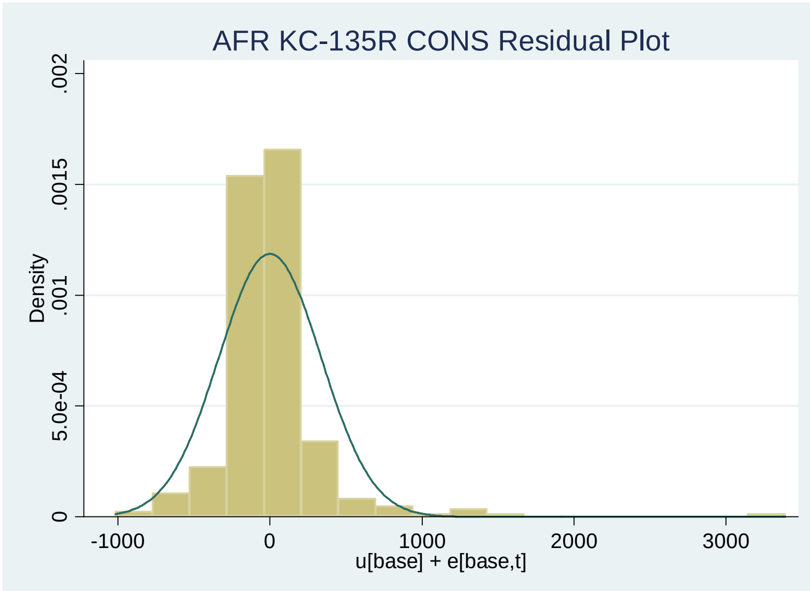
Shapiro Wilk W Test for Normal Data					
Variable	**Obs**	**W**	**V**	**z**	**Prob>z**
CONS Residuals	881	0.7683	130.617	12.005	0.000

Figure 7. Histogram Plot of Residuals for KC-135R ANG CONS Model



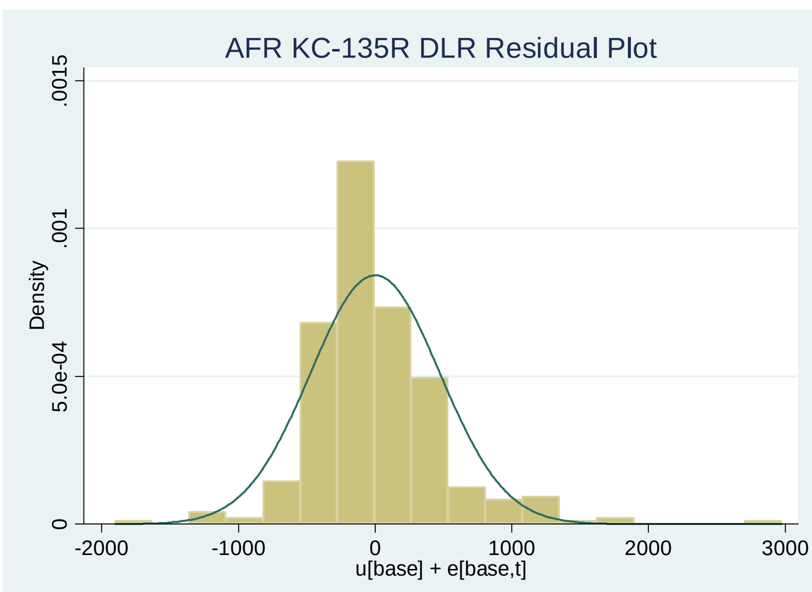
Shapiro Wilk W Test for Normal Data					
Variable	**Obs**	**W**	**V**	**z**	**Prob>z**
DLR Residuals	723	0.94372	26.429	8	0.000

Figure 8. Histogram Plot of Residuals for KC-135R ANG DLR Model



Shapiro Wilk W Test for Normal Data					
Variable	**Obs**	**W**	**V**	**z**	**Prob>z**
CONS Residuals	346	0.73445	64.554	9.852	0.000

Figure 9. Histogram Plot of Residuals for KC-135R AFR CONS Model



Shapiro Wilk W Test for Normal Data					
Variable	**Obs**	**W**	**V**	**z**	**Prob>z**
DLR Residuals	360	0.90857	22.794	7.401	0.000

Figure 10. Histogram Plot of Residuals for KC-135R ANG DLR Model

Appendix G. Woolridge Test for Autocorrelation in Panel Data

The null hypothesis for the Woolridge test is that there is no first-order autocorrelation. Since the p-value at two lags is greater than α = .05 for each model, we can accept the null hypothesis at this number of lags.

Table 25. Woolridge Test for KC-135R AFR CONS Model

Wooldridge test for autocorrelation in panel data (H_0: no first-order autocorrelation)		
Lags	Test-statistic	p-value
1 lag	37.806	0.0003
2 lags	0.737	0.4156

Table 26. Woolridge Test for KC-135R AD CONS Model

Wooldridge test for autocorrelation in panel data (H_0: no first-order autocorrelation)		
Lags	Test-statistic	p-value
1 lag	214.295	0.0001
2 lags	6.34	0.0655

Appendix H. List of Acronyms

ABIDES	Automated Budget Interactive Data Environment System
AD	Active Duty
AFCCC	Air Force Combat Climatology Center
AFR	Air Force Reserve
AFTOC	Air Force Total Ownership Cost
AIC	Akaike Information Criterion
ANG	Air National Guard
ASD	Average Sortie Duration
AVFUEL	Aviation Fuel
CBO	Congressional Budget Office
COARS	Command On-Line Accounting & Reporting System
CONS	Consumables
CPFH	Cost Per Flying Hour
DLR	Depot Level Reparable
DV	Dummy Variable
GAO	Government Accountability Office
MAE	Mean Absolute Error
MAJCOM	Major Command
MAPE	Mean Absolute Percent Error
MERLIN	Multi-Echelon Resource and Information Network
O&M	Operations and Maintenance
O&S	Operation and Support
OEF	Operation Enduring Freedom
OIF	Operation Iraqi Freedom
OPSTEMPO	Operations Tempo
REMIS	Reliability and Maintenance Information System
SBSS	Standard Base Supply System

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Vita

Captain Michael T. Bryant graduated from Southwest High School in Fort Worth, Texas. He entered undergraduate studies at Texas State University in San Marcos, Texas where he graduated Cum Laude with a Bachelor of Arts in International Studies in December 1992. After spending a couple of years in the private sector, he enlisted in the United States Air Force in 1995. He served in the 75th Aerospace Medicine Squadron, Hill AFB, Utah as a Bioenvironmental Engineering Technician until 1999 when he was accepted to attend Air Force Officer Training School at Maxwell AFB, Alabama. He graduated Officer Training School and received his commission in January 2000.

His first assignment as an officer was at the 4th Comptroller Squadron, Seymour Johnson AFB, North Carolina, as the Deputy Budget Officer and later that tour served as the Financial Services Officer. In 2003, he accepted his next assignment as a Cost Analyst with the Comptroller Directorate, Ogden Air Logistics Center, Hill AFB, Utah. In August 2005, he entered the Graduate School of Engineering and Management, Air Force Institute of Technology, to obtain his Masters in Cost Analysis. Upon graduation, he will be assigned to the Air Force Cost Analysis Agency in Crystal City, Virginia.

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14. ABSTRACT
This thesis developed models to forecast the KC-135R monthly Consumables (CONS) and Depot Level Reparable (DLR) Cost per Flying Hour (CPFH) for each U.S. Air Force service component. Using data for each operating location from FY1998 to FY2004, the models were constructed using panel data analysis, a form of regression that adds a cross-sectional and time-series dimension. In addition to including factors previously identified as prime contributors to CPFH, the models added new elements that may influence maintenance costs and be of interest to policymakers. These elements included mission capable rates, airframe operating hours, and climatology factors. An interaction variable for utilization rate and combat flying hours is also included. The results reveal that utilization rate can be a major factor to determine if the CPFH increases or decreases when a wing is flying combat hours. Furthermore, mission capable rates have an inverse relationship on the KC-135R CPFH while average airframe hours have a positive relationship. Average airframe hours is an alternative measure to aircraft age, although this measure is better suited for quarterly or yearly models. Overall, this research extends knowledge of the KC-135R CPFH program and provides a tool for planners, programmers, and decision makers at all levels.

15. SUBJECT TERMS Cost analysis, Cost per Flying Hour, KC-135, forecasting, panel data, time series analysis, O&M Costs, O&S Costs, DLR, Consumables, interaction variable, aging aircraft, utilization rate, combat flying hours, airframe operating hours, mission capable rates, cross-sectional, longitudinal

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