This product is part of the Pardee RAND Graduate School (PRGS) dissertation series. PRGS dissertations are produced by graduate fellows of the Pardee RAND Graduate School, the world's leading producer of Ph.D.'s in policy analysis. The dissertation has been supervised, reviewed, and approved by the graduate fellow's faculty committee.

DISSERTATION

The Costs of Aging Aircraft

Insights from Commercial Aviation

Matthew Dixon

This document was submitted as a dissertation in September, 2005 in partial fulfillment of the requirements of the doctoral degree in public policy analysis at the Pardee RAND Graduate School. The faculty committee that supervised and approved the dissertation consisted of Bart Bennett (Chair), Ed Keating, and Greg Ridgeway.

RAND PARDEE RAND GRADUATE SCHOOL

The Pardee RAND Graduate School dissertation series reproduces dissertations that have been approved by the student's dissertation committee.

The RAND Corporation is a nonprofit research organization providing objective analysis and effective solutions that address the challenges facing the public and private sectors around the world. RAND's publications do not necessarily reflect the opinions of its research clients and sponsors.

RAND® is a registered trademark.

Published 2005 by the RAND Corporation
1776 Main Street, P.O. Box 2138, Santa Monica, CA 90407-2138
1200 South Hayes Street, Arlington, VA 22202-5050
201 North Craig Street, Suite 202, Pittsburgh, PA 15213-1516
RAND URL: http://www.rand.org/
To order RAND documents or to obtain additional information, contact
Distribution Services: Telephone: (310) 451-7002;
Fax: (310) 451-6915; Email: order@rand.org

Table Of Contents

TABLES AND FIGURES IX

ACKNOWLEDGEMENTS XI

CHAPTER 1 INTRODUCTION 1

1.1 OBJECTIVE 3

1.2 POLICY PROBLEM 3

1.3 RESEARCH QUESTIONS 4

1.4 MOTIVATION 6

1.4.1 There are Many AF Fleets that Contribute to the Policy Problem 7

1.4.2 The “Death Spiral” is Caused by Aging Fleets 9

1.4.3 Historical Events Changed Mission Focus 11

1.4.4 Repair Versus Replace Decisions Require Aging Estimates 13

1.4.5 Military Records May Not Provide Best Information 14

1.5 SUMMARY 16

CHAPTER 2 LITERATURE DISCUSSION AND PRIOR WORK 17

2.1 INTRODUCTION 19

2.2 CHRONOLOGY OF PRIOR WORK 20

2.2.1 Kamins (1970) Reasons for No Age Effect 21

2.2.2 Hildebrandt and Sze (1990) Find Small Positive Age Effects 22

2.2.3 Johnson (1993) and Stoll and Davis (1993) Find Evidence of Larger Age Effects 24

2.2.4 Ramsey, Sperry, and French (1998) Used Commercial Data to Estimate KC-135 Age Effects 24

2.2.5 The Center for Naval Analyses (CNA) Demonstrates Positive Age Effects for Navy Aircraft (2000 & 2002) 25

2.2.6 The Congressional Budget Office (CBO) Found Lower Aircraft Age Effects (2001) 27

2.2.7 RAND (Pyles, 2003) Found Specific Age Effects on Workloads and Material Consumption 27

2.2.8 Boeing Provides Maturity Curves for Cost Comparison Purposes 30

2.3 MILITARY DATA DO NOT PROVIDE A CLEAR COST PICTURE 33

2.4 SUMMARY 34

CHAPTER 3 DATA AND ANALYSIS METHODOLOGY 35

3.1 INTRODUCTION 37

3.2 DOT FORM 41 DATA CAPTURE A WEALTH OF KNOWLEDGE 37

3.3 THIS RESEARCH EXPLORES THE RELATIONSHIP BETWEEN AGE AND MAINTENANCE COSTS 39

3.3.1 Data Analysis 40

3.3.2 Development of Maturity Curves 40

3.3.3 Generalization to the AF 42

CHAPTER 4 RESULTS 45

4.1 OVERVIEW 47

4.2 INDUSTRY USES MATURITY CURVES TO UNDERSTAND AGE EFFECTS 48

4.3 THIS DISSERTATION FINDS THE EFFECTS OF AGE DECELERATE OVER THE LIFE OF A FLEET 50

4.3.1 Several Differences Exist Between Boeing's Maturity Curves and Figure 4.2 52

4.3.2 Simple OLS with Type and Year Fixed Effects Provides a Good Estimate of the Age Effects on Total Maintenance Costs ... 57

4.3.3 Type and Year Fixed Effects Improve Predictions and Reveal a More Accurate Age Effect ... 58

4.3.4 There are No Interactions or Airline Effects in the Fitted Model ... 60

4.3.5 In General, the Data Support the Fixed Effect Model without Interactions ... 60

4.3.5.1 Fixed Effects ... 61

4.3.5.2 Interactions ... 62

4.4 REGRESSION TREES TELL AN INTERESTING STORY ... 64

4.4.1 Warranties and D-checks are Significant Maintenance Cost Drivers ... 65

4.4.2 Era of Production Provides Homogeneous Separations ... 65

4.5 SUMMARY ... 67

CHAPTER 5 POTENTIAL BIASES IN ESTIMATED AGE EFFECT ... 69

5 FIVE ISSUES COULD BIAS ESTIMATED AGE EFFECTS ... 71

5.1 SELECTION BIAS ... 71

5.1.1 Lack of Evidence to Support Fleet Level Bias ... 72

5.1.2 Aircraft Selection Probably Does Not Bias Age Effect ... 77

5.2 NUMBER OF CYCLES ARE CONTROLLED FOR ... 78

5.3 OVERHEAD AND SUB-CONTRACTED EFFORTS ARE INCLUDED IN ANALYSIS ... 79

5.4 END OF WARRANTY PERIODS CAUSE DRAMATIC CHANGES IN MAINTENANCE COSTS ... 80

5.5 RETIRING CIVILIAN FLEETS DO NOT REQUIRE LESS MAINTENANCE ... 82

5.6 SUMMARY ... 83

CHAPTER 6 GENERALIZATIONS TO THE AIR FORCE 85

6 THESE RESULTS ARE USEFUL TO THE AF'S REPAIR VERSUS REPLACE DECISIONS 87

6.1 APPLICATION TO CURRENT AF FLEETS 87

6.1.1 The AF Flies Several Commercial Airliners 88

6.1.2 Results May Be Carefully Extended to Cargo and Bomber Aircraft 89

6.2 APPLICATION TO FUTURE AF FLEETS 90

6.3 ASSUMING MAINTENANCE COSTS INCREASE MAY BE INACCURATE 91

6.4 GENERALIZATION DIFFICULTIES 91

CHAPTER 7 CONCLUSIONS 93

7.1 AGE EFFECTS EXIST AND ARE SIGNIFICANT 95

7.2 AGE EFFECTS DECREASE OVER THE LIFE OF A FLEET 95

7.3 FLEETS AGE SIMILARLY 96

7.4 SELECTION BIAS DOES NOT APPEAR TO BE PRESENT 96

7.5 AF POLICY DECISIONS SHOULD CONSIDER COMMERCIAL AGE EFFECTS 97

REFERENCES 99

APPENDICES 103

A.1 REGRESSION TREE RESULTS 105

A.2 DERIVATION OF PERCENT INTERPRETATION 110

A.3 MODEL OUTPUT 112

A.3.1 Total Maintenance Cost per Flight Hour as Dependent Variable 113

A.3.2 Airframe, Engine, and Burden Maintenance Costs per Flight Hour as Dependent Variables 117

A.3.2.1 AIFRAME Costs 118

A.3.2.2 ENGINE Costs 120

A.3.2.3 BURDEN Costs 124

A.3.3 Age*Airline and Age*Type Interactions and Airline Fixed Effects 128

A.3.3.1 Age*Airline and Age*Type Interactions 128

A.3.3.2 Airline Fixed Effects 134

A.3.4 Short-Lived Fleets Removed 138

Tables and Figures

Diagram 1, Three Research Questions are Sequential 6

Figure 1.1, USAF Cargo and Support Aircraft are Old 9

Table 2.1, Summary of Literature Related to Aging Aircraft 20

Figure 2.1, Boeing's Maturity Curve 32

Figure 3.1, Data Sample; Thousands of Then Year Dollars 38

Figure 3.2, Distribution of Average Fleet Ages in Data 39

Figure 4.1, Boeing's Maturity Curve 48

Table 4.1, Boeing's Identification of Aircraft by Era of Production, Boeing (2004). 49

Figure 4.2, Age Effects Estimated with Form 41 Data 51

Figure 4.3, Effects of Age on Airframe Maintenance Costs Estimated with Form 41 Data 53

Figure 4.4, Sum of Airframe, Engine, and Burden Equal Total Maintenance Costs........ 53

Figure 4.5, Effects of Age on Engine Maintenance Costs Estimated with Form 41 Data 54

Figure 4.6, Effects of Age on Maintenance Burden Estimated with Form 41 Data 55

Figure 4.7, Airlines Deal with Aging Aircraft Differently 64

Table 4.3, Regression Tree Estimates of Most Homogenous Aircraft Type Separation .. 66

Table 5.1, Short-Lived Fleets 73

Figure 5.1, Age Effects of Fleets That Were Not Retired Before 20 Years of Age. 75

Figure 5.2, Original Maturity Curve 75

Table 6.1, COTS Aircraft Flown by the AF 89

Table A.1.1, Regression Tree Estimates of Most Homogenous Aircraft Type Separation 106

Figure A.1.1, Regression tree: Fitting age to predict log(Total Maint Cost per Flt Hr) . 107

Table A.3.1 Aircraft Type and Airline Labels in Output Below 112

Acknowledgements

I am grateful to the United States Air Force (AF), the AF Institute of Technology, and Colonels Diaz and Litwhiler of the AF Academy for providing the opportunity to study at the Pardee RAND Graduate School (PRGS). Natalie Crawford and Michael Kennedy of Project Air Force (PAF) at the RAND corporation have been very helpful and supportive.

Thank you to my committee members, Bart Bennett, Ed Keating, and Greg Ridgeway. A special thank you is due to Ed Keating for his mentorship, patience, and coaching during my three years at PRGS. Much of my success at PRGS is due to his support and diligence. The chairman, Bart Bennett, has also been a great help throughout my studies at PRGS and provides invaluable direction and encouragement for all the students. Greg Ridgeway has provided important help, feedback, and encouragement throughout this dissertation process. Thank you!

Thank you to Dan Abraham of the Boeing Corporation for valuable data, endless responses to questions, and insight into the commercial aviation world.

Finally, I am grateful to God; my wife, Anne; and my children, Hannah, Madi, Matt jr., Joe, and Emily for their love, encouragement, and joy!

Chapter 1

Introduction

1 Introduction

This chapter provides overall motivation for this research project, by discussing the objective, policy problem and the research questions. Specific motivation for the research and some background on the policy problem conclude this chapter.

1.1 Objective

This dissertation's objective is to assist the Air Force (AF) in making difficult yet necessary choices regarding its aging fleets in order to fulfill national security objectives at lowest cost.

Costs related to maintenance are a key component to the AF's decision-making process. In general, AF fleets are aging. This motivates the AF to want accurate maintenance cost forecasts. Forecasts of its current fleets and future replacement fleets are necessary.

This dissertation will use commercial airline data to help the AF make these difficult choices.

1.2 Policy Problem

The Air Force is deciding how to deal with its aging fleets while maintaining a high level of mission readiness. Current literature indicates that maintenance costs generally rise as aircraft age. At some unknown age it is more economical to replace a fleet than to continue maintaining it. This creates the classical repair or replace dilemma for senior government leaders.

In the past, age has not been a primary driver of replacement. Over the AF's short history, user requirements, changes in threats, obsolete technology and theater demand were primary drivers of weapons system replacement decisions. However, age has recently become one of the most important concerns facing the AF.

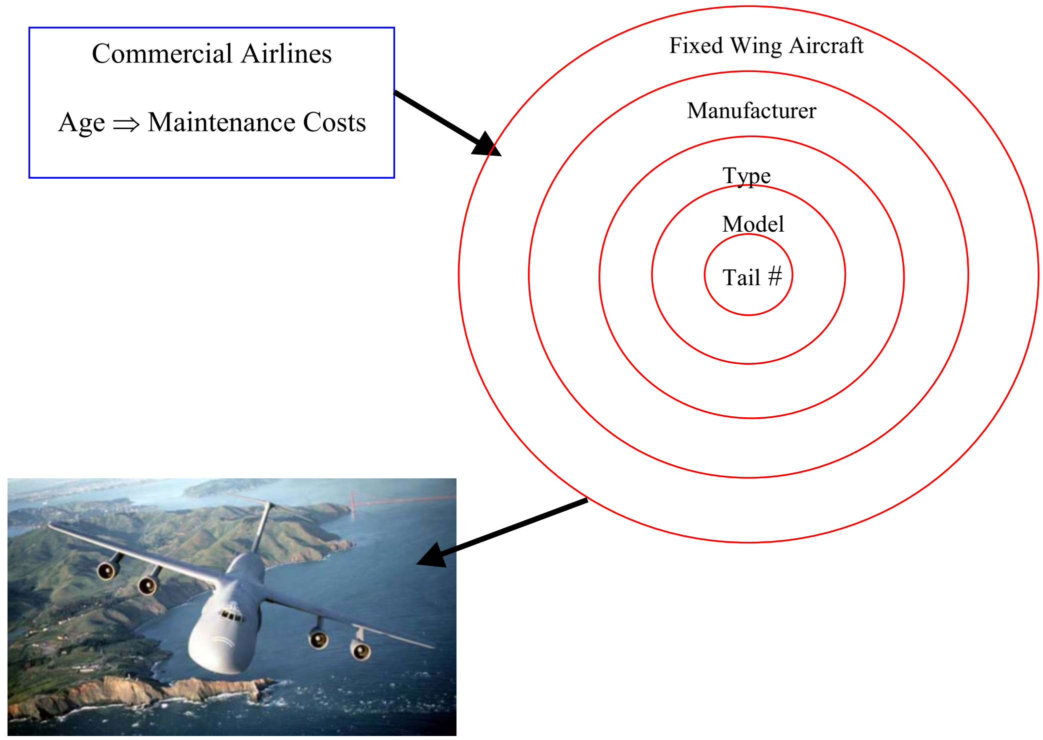
Furthermore, the problem age presents to policy decisions is not exclusive to fleets the AF currently flies. To make informed repair versus replace decisions, the AF must also understand how new replacements will age. Specifically, they must not only understand the purchase price of the replacement aircraft, but also how the costs of maintenance will change over the life of that fleet. So, understanding the effects of age on maintenance costs is a key element to AF repair versus replace decisions. These problems will only increase as the average age of the AF's fleets continue to rise. Specific examples of these issues will be discussed further in Section 1.4.

1.3 Research Questions

The AF has not kept sufficiently accessible aging and cost data to fully determine long-term aircraft maintenance costs. Analyses of military data that do exist have been on segments of a fleet's history, e.g., Pyles (2003). As a complement to analysis of AF aircraft, this dissertation will explore commercial airline data. US airlines are mandated by the Department of Transportation (DoT), through the Federal Aviation Act of 1958, to report multiple levels of information annually. From these commercial reports, we have gathered fleet level data describing maintenance costs and operational usage from 1965 to 2003. With this information, three research questions will be addressed:

1) Given the existing commercial airline data, can a relationship between age and maintenance cost be established?
2) At what level of generality (individual aircraft, model number, aircraft type, aircraft manufacturer, or aircraft generally) can age be linked with maintenance cost?
3) How do these relationships generalize to the AF?

These questions are illustrated in Diagram 1.



AF Factsheet available at http://www.af.mil

Diagram 1, Three Research Questions are Sequential

1.4 Motivation

This section describes the major motivating factors for this dissertation. It begins with current aging aircraft examples, then discusses the "death spiral" problem caused by aging aircraft. Then it moves into historical events that have contributed to the aging problem. Next, it introduces the necessity for estimating age effects. Finally, it discusses why military data may not provide the necessary information to make informed repair versus replace decisions.

1.4.1 There are Many AF Fleets that Contribute to the Policy Problem

The AF has many fleets that are suffering from age-related problems that affect policy decisions. One example of these policy issues is the KC-135 tanker fleet. There is Congressional debate over the future of this fleet and much of it centers on whether it should be replaced or repaired, based on cost. Air Mobility Command recently grounded 29 planes because of corrosion in the engine struts.[1] The repairs are still waiting approval as the repair versus replace debate continues. Included in this debate is the whether the AF should replace the KC-135 with a purchased or leased new aircraft.

The aging aircraft problem is not exclusive to the KC-135. Air Force policy makers are concerned also with repair versus replace decisions for many fleets because most have, or will, exceed their design service lives. The AF's versatile C-130 suffers age-related problems. Approximately 20% of the AF's C-130s are grounded or restricted due to wing cracks. Planes with more than 45,000 hours are grounded and planes with more than 38,000 hours are restricted[2]. None of these planes is available for deployment, which is a critical problem in light of the current conflict in Iraq.

---

[1] Rolfsen, 2005.
[2] Rolfsen, 2005.

Another example is the small fleet of C-32As the AF uses to transport VIPs, including the Vice President. These aircraft are on restriction for reasons not necessarily due to age, but nonetheless impact the repair versus replace decision.

The B-1B Lancer is under restriction for age-related problems. The B-1B's wings may create too much stress on the aircraft when the wings are extended in certain positions. The result is premature aging of the aircraft in the form of stress problems throughout the aircraft. The expected replacement date of these aircraft is 2038. Until then, their operating capacity is limited[3]. Figure 1.1 demonstrates the aging problem for all AF cargo and support fixed wing aircraft. The total average age of these aircraft is 29 years, with most being between 20 and 30 years old.

[3] Rolfsen, 2005.

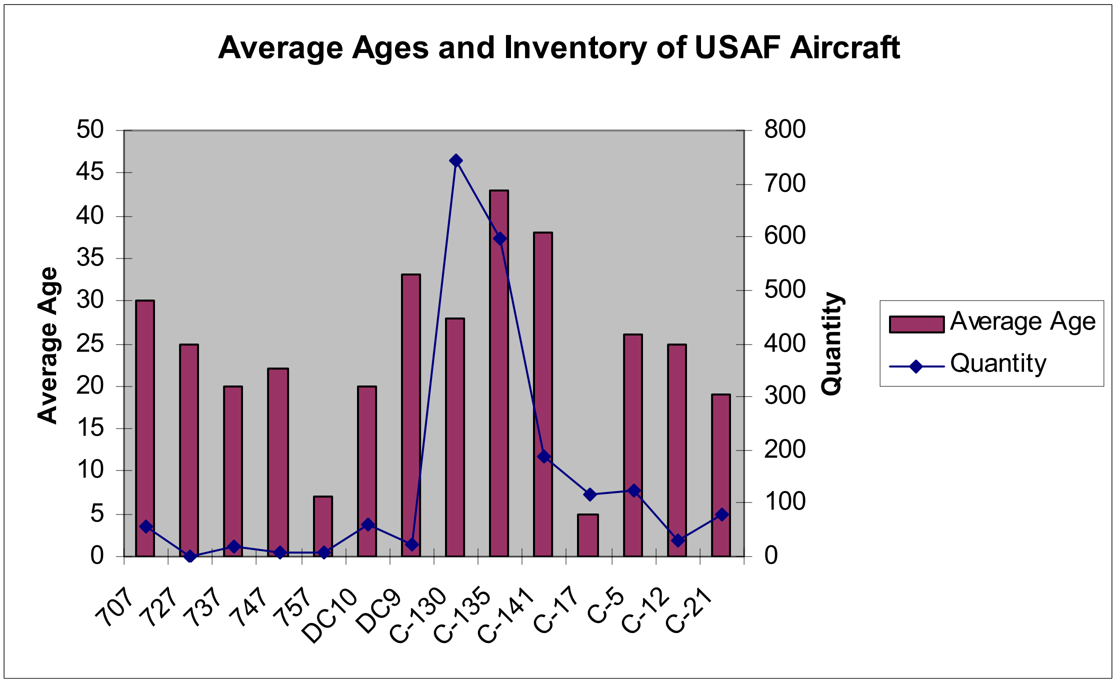


Figure 1.1, USAF Cargo and Support Aircraft are Old

1.4.2 The "Death Spiral" is Caused by Aging Fleets

The Air Force's mission is to defend the United States and protect its interests through air and space power[4], but many defense experts and senior military leaders believe the US military is in a "defense spending death spiral" that threatens to reduce the effectiveness of the AF and other services.[5] Decisions over the last decade and a half to reduce purchases of new equipment have left the AF with aging fleets that are increasingly expensive to maintain. This situation creates the spending "death spiral", a cycle in which older equipment require more funds to maintain, which, in turn, decreases the funds available for new weapon

[4] Department of the Air Force, *Mission Statement*.
[5] Kiley, 2001.

systems. The Congressional Budget Office (CBO) estimates spending on operation and maintenance for aircraft increases on average by one to three percent for every additional year of age, after adjusting for inflation.[6] These rough estimates may be understated, but still provide a grim picture of the future costs to maintain AF fleets. For example, the AF spent over $2 billion in 2003 to maintain approximately 660 KC-135s. This figure does not include the cost of military manpower. Understanding the rate at which this cost will change is critical to economically accomplishing the aerial refueling mission. These costs are not just realized costs but opportunity costs as well. Each percent increase in maintenance is $20 million -- money which is kept from other desirable programs.

The AF has a number of aging fleets. At a RAND briefing in 2001, the commander of the AF Materiel Command, Lieutenant General Lyles, referred to the aging aircraft problem as one of the biggest problems the AF currently faces. The AF is the youngest branch of the armed forces (57 years old) and some of its fleets have never been replaced. There is a wide range of ages among the aircraft in inventory. In 2001, the average age of all fleets was approximately 22 years[7]. The average age of the C-141 was 35 years while its companion aircraft, the C-17, had an average age of 4 years. Currently, the average age of the

[6] Kiley, 2001.
[7] Garamine, 2001.

B-52 is over 50 years, but the B-2 is only 10 years old.

Dr Eugene Covert, of the Massachusetts Institute of Technology who chaired an AF Scientific Advisor Board in the mid-1990's stated, "We have never tried to manage a fleet this old,…[the aircraft] are long past their design life"[8]. According to Covert, lack of planning has caused serious readiness problems. Understanding how maintenance costs change as fleets age is one of the critical components to maintaining high readiness.

1.4.3 Historical Events Changed Mission Focus

Another contributing factor to the aging aircraft problem was the end of the Cold War, which altered the military's focus. Although the Cold War officially ended over a decade and a half ago, the AF's role in national defense is still evolving. In 1997, the AF published a new doctrinal statement in which it established Air and Space Superiority as fundamental, but what is not clear is how this role will be maintained and with what technology. One result of this slow transformation has been the lack of procurement of new aircraft. This is a result of decreased procurement funds, changing political climates, and continually changing threats coupled with lack of agreement on how to counter them.

Other issues have also pulled attention away from aircraft replacement. Lately, much of the focus has been on

[8] Tirpak, 1996.

restructuring the force and repositioning forces from Europe to the Middle East. Different force locales coupled with a different threat has contributed to some aircraft procurement projects being reconsidered, scaled down, or cancelled. In attempts to save costs, the DoD has attempted to exploit the “joint” concept by acquiring one platform for multiple services, such as the Joint Strike Fighter. One downside of such acquisition projects is the extended length of time required to meet all the various needs of the different services. The aggregate result is fleets that are approaching, if not exceeding, their design service life.

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. 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. For example, a KC-135 manufactured in 1965 cost approximate $40 million in FY2000 dollars, while a potential replacement today may cost well over $100 million dollars each. 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.

1.4.4 Repair Versus Replace Decisions Require Aging Estimates

To maintain the current, and possibly higher, levels of readiness the expected future maintenance requirements of current fleets and the expected cost of maintaining potential replacement fleets must be understood. The optimal “replace versus repair” decision can be made only if the future maintenance costs of both the incumbent and potential replacement aircraft are known with a high degree of confidence. This requires analyzing historical data and understanding how the past relates to the future. The AF must understand how the current fleet will age. Procurement lead times for new aircraft can be anywhere from five to twenty years depending on the complexity of the project. The future maintenance cost of a fleet needs to be understood far in advance of the actual replacement date. Additionally, the expected maintenance costs of the replacement aircraft must also be understood. It clearly makes no sense to replace a fleet with a more expensive fleet, assuming the same capabilities. Currently the AF is deciding how to replace the KC-135, which is over 40 years old. This decision relies heavily on the expected maintenance costs of the new replacement aircraft.

Since the linkage between age and cost is a key component of the decision to replace aircraft, it is a natural next step to examine the data on the AF’s current and prior fleets. However, studying military aircraft may not be the best way to learn about the effect age has on AF maintenance for three main reasons discussed in the next section.

1.4.5 Military Records May Not Provide Best Information

RAND has used military data to gather insight into the effect age has on modification and maintenance costs. However, as author Ray Pyles discusses, there are significant gaps in the data, stating, "The AF has no comprehensive system for historical maintenance and material consumption data. Some historical data exist only as hard copy records kept in office file cabinets or in old reports archived sporadically."[9]

While there is insufficient AF data, Pyles also finds that there have been few studies published using airline data.[10] Boeing produces in-house estimates of the cost of aging and has found significant age effects. They have stated that much more work needs to be accomplished to understand the true age effect.[11]

Second, the AF does not specifically count maintenance costs in dollars, but in activities and materials and their cost accounting practices do not specifically attribute all costs to maintenance. In general, funds are distributed heavily based on prior years' expenditures. This leads to a

[9] Pyles, 2003.
[10] Pyles, 2003.
[11] In general, the term "age effect" refers to the change in costs due to one more year of age. In this dissertation the term "age effect" will refer to the *percent* change in *maintenance* costs due to one more year of age.

tendency for organizations to make certain all fiscal year funds are allocated before the end of the fiscal year. If an organization returns funds to its parent organization, there is a real threat of receiving reduced funds the next year regardless of the forecasted need. In years of fewer maintenance activities, this encourages units to use funds for activities of lower priority that may have been neglected in previous years. The result is a false picture of the true annual cost of maintenance because the dollars spent for maintenance activities will remain essentially constant, while the specific maintenance needs of each fleet fluctuate.

Third, the AF is concerned with mission capable rates and their objective is to be prepared for wartime sortie levels. This does not always lead to maintenance activities that are determined by the need of the aircraft. For example, a practice known as cannibalism is used. This involves taking parts of one aircraft to be used on another aircraft. This practice will skew the effect of age on maintenance because it may take up to twice the labor hours to use cannibalized parts as it does to use a new or refurbished part. Consider the time it takes to remove the broken part from an aircraft, remove the operable part from another aircraft, install the operable part on the initial aircraft, and then install another operable part on the cannibalized aircraft. So while the downtime of an aircraft is minimized, the number of maintenance hours may be increased. The AF maintains different types of data than the commercial sector and the objectives of the AF are different than the commercial sector.

1.5 Summary

The AF has a number of aging fleets that are facing repair versus replace decision. The AF must understand how its current fleets will age and how any potential replacement fleets will age in order to make informed and efficient repair versus replace decisions. This dissertation endeavors to understand how commercial aircraft fleets age and extends this to the AF’s problem.

Chapter 2

Literature Discussion and Prior Work

2.1 Introduction

This chapter discusses literature and prior work done relating to aging aircraft issues. Figure 2.1 below chronologically outlines a brief summary of previous studies. The age effect column has a "+" if the authors found a positive age effect. Most authors looked at multiple models and explanatory variables. Some combinations yielded no age effect and others did. The age effect column is only a "None" if the authors concluded that there was no age effect worth reporting in all their analysis. No author reported negative age effects. Each study will then be discussed individually.

Authors	Date	Age Effect	Data Level	Sector	Primary Dependent Variable	Data Type
Kamins (RAND)	1970	No	Multiple	AF & Commercial	Multiple	Cross-Sectional & Panel (2-period)
Hildebrandt & Sze	1990	+	Aircraft	AF	O&S / Aircraft	Panel
Johnson (NAMO)	1993	+	Aircraft	Navy	MTBF	Cross-Section
Stoll & Davis (NAMO)	1993	+	Multiple	Navy	Multiple	Cross-Section & Panel
Ramsey (OC-ALC), French, & Sperry (Boeing)	1998	+	Multiple	AF & Commercial	PDM Man-Hours	Panel
Francis and Shaw (CNA)	2000	+	Aircraft	Navy	Maintenance Man-hours	Panel
Kiley (CBO)	2001	+	Anecdotal	AF	Ops cost / Flight Hour	Panel
Jondrow (CNA)	2002	+	Aircraft	Navy	Repairs / Flight Hour	Panel
Pyles (RAND)	2003	+	Aircraft	AF	Workloads & Material Consumption	Cross-Section & Panel
Boeing	2004	+	Fleet	Commercial	Cost / Flight Hour	Panel

Table 2.1, Summary of Literature Related to Aging Aircraft

2.2 Chronology of Prior Work

Since the beginning of aviation maintenance, maintainers have been concerned with not only how to maintain aircraft but also how much aircraft will cost to maintain in the future. The AF is no different. Studies going back to the 1960's demonstrate the history of concern about the expected future cost of the AF's fleet maintenance.

2.2.1 Kamins (1970) Reasons for No Age Effect

In a RAND study published in 1970, Kamins cites ten different analyses that attempt to understand the age effect on maintenance cost. The cited works are dated in the 1960's and all the studies are based on small sample sizes of aircraft level data. He briefly critiques three studies that show a positive age effect, but argues that the studies are insufficient, primarily because the data are cross-sectional, the data points are few, and the representation of different aged aircraft is skewed and over-represented by older aircraft. In the early studies, the two aircraft of interest are the B-52 and the KC-135A.

Kamins then moves to seven studies he says prove there is no age effect. In fact, some of the studies seem to demonstrate that aircraft actually become more reliable as they age. One study uses accidents as the dependent variable, arguing that accident rates decreased as the aircraft got older, thus demonstrating a negative age effect. A second study, completed by RAND, summarized findings from United Airlines and Pan American Airlines, stating that due to process improvements in maintenance, maintenance requirements actually decreased as aircraft age. This does not indicate there is a zero age effect, but simply that the magnitude of the effect of the process improvements may have been greater than the magnitude of the age effect.

The studies used to justify no age effect have a small number of observations. Extrapolations of any results are nearly impossible. These studies were completed while aviation was still in its youth, when aircraft retired because of technological advances and not because of maintenance costs.

Kamins' paper demonstrates that aging aircraft are not unique to the military. The airlines and the manufacturers are equally, if not more, concerned than the AF with the cost of maintenance. However, most of the available literature regarding age effects focuses on the military fleets.

Later studies began to separate the effects of technology improvements, airframe design, and manufacturing process improvements from the age effect. Once these issues were better understood and descriptive covariates were controlled for, a positive age effect on maintainability and reliability began to emerge.[12]

2.2.2 Hildebrandt and Sze (1990) Find Small Positive Age Effects

Hildebrandt and Sze (1990) looked at the specific age effect on maintenance costs in the AF. Over a five year period of aggregate level data they found a very minimal age

[12] Pyles, 2003.

effect (0.5%). While they had access to longitudinal data, they faced challenges with the data since they did not have specific maintenance cost information and were forced to artificially allocate the dollars based on an assumed bathtub shape. Additionally, the results may have been underestimated due to allocation methods in the DoD. One inherent problem in government is the way that it allocates funds to different organizations. The problem with seeing an age effect on maintenance with military aircraft is that the funds will vary little.

Arguably, one of the reasons the AF wants to understand the age effect is to allocate funds more efficiently -- giving older aircraft more maintenance dollars than equivalent newer fleets, if appropriate. However, as discussed in Section 1.4.5, the readily apparent problem with using AF fleets to measure the cost of aging is the use of maintenance funds as an explanatory variable. This is similar to the rather mundane example of determining how much money a teenager needs for a trip to the mall based on how much he spent the last two trips. Since he is rewarded for spending more, the more he gets the more he will spend. While Hildebrandt and Sze estimated the allocation of the funds to specific maintenance costs, the commercial data used in this dissertation contain the actual dollars spent on labor, materials, and overhead for maintenance annually for a specific fleet.

While there are no military databases that capture the actual expended maintenance dollars, there are databases, such as REMIS (Reliability and Maintainability Information System) and MDC (Maintenance Data Collection), which attempt to capture actual maintenance workloads.

2.2.3 Johnson (1993) and Stoll and Davis (1993) Find Evidence of Larger Age Effects

Several studies completed over the last fifteen years demonstrate an increase in maintenance *efforts* as the age of aircraft increase. The Naval Aviation and Maintenance Office (Johnson, 1993), found significant age effects on total maintenance workloads in naval aircraft over a thirteen-year period. Also in 1993, Stoll and Davis (1993) found smaller naval aircraft age effects in on-equipment workloads over approximately the same period of time. Pyles (2003) provides a more lengthy discussion of these findings.

2.2.4 Ramsey, Sperry, and French (1998) Used Commercial Data to Estimate KC-135 Age Effects

Oklahoma City Air Logistics Center led a KC-135 Cost of Ownership IPT (Ramsey, Sperry, and French, 1998). The purpose of this study was to develop aging aircraft maintenance cost trends for the KC-135 based on a review of historical commercial and military data. They used military data from the AF combined with twelve years of commercial panel data from the DoT. They used aircraft types similar in structure, size, and composition to the KC-135. The KC-135 data are from the Maintenance Requirements Review Board and provide insight into the depot activities. They report commercial year effects of 3.5% to 9%.

2.2.5 The Center for Naval Analyses (CNA) Demonstrates Positive Age Effects for Navy Aircraft (2000 & 2002)

Francis and Shaw (2000) of the CNA analyzed the Navy's F/A-18 Hornets. They used two different datasets to gain information about F/A-18 maintenance costs. Both datasets have information on the individual tail numbers. The first dataset contains ten years' (1990-1999) worth of data about the utilization and organizational maintenance of every tail number of the F/A-18s in inventory. This information includes aircraft age, squadron manning numbers, maintenance time, deployment status, flight hours, and sorties. 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. Additionally, they found that the flight hours and deployment status were significant indicators of the man-hours required for maintenance.

The second dataset contains information about every sortie flown in one month with records of the surrounding maintenance activities. They employed a probit model to estimate the probability a F/A-18 would require unscheduled maintenance after a sortie. The independent variables were simply aircraft age, length of time since last depot-level maintenance, and an indicator for whether the sortie was carrier-based. The results estimated that a one-year gain in age significantly increased the probability of unscheduled maintenance by 0.8% and a carrier-based sortie significantly increased the probability estimate of needing unscheduled maintenance by 3.5%.

Another CNA study (Jondrow, 2002) found age effects for all types of Navy aircraft. They use a log-linear model with parameters estimated with weighted least squares. The independent variables used are the annual hours flown, the percent change in average age of a TMS (type, model, series, e.g., F-14A), and a categorization of the type of aircraft (carrier-based fixed wing, land-based fixed wing, or rotary wing). The dependent variable is the number of repairs per flight hour. Their goal was to help the Navy understand the effective cost of a new aircraft so that they can make informed repair versus replace decisions. At the mean aircraft age in the dataset, they found age effects of 1.9%, 1.7%, and 7.9% for the land-based aircraft, rotary-wing aircraft, and carrier-based aircraft, respectively.

They also found that some aircraft get significantly less expensive to maintain as they near retirement (the end of their service life). Readiness generally declines as aircraft age, but he found that as the F-14 and A-6 neared retirement, their readiness increased. Selective decommissioning is a cited reason for increased readiness near retirement. Another cited reason is that spare parts and maintainers do not drop proportional to the number of aircraft retired.[13]

2.2.6 The Congressional Budget Office (CBO) Found Lower Aircraft Age Effects (2001)

The CBO (Kiley, 2001) studied the age effects on all military equipment, including aircraft. Their purpose was to understand the rise in operating and support (O&S) costs of the military and discuss prior literature about the effects of age on O&S costs, which includes maintenance. They did no new analysis with raw data. However, they state, "Those studies typically found that the costs of operating and maintaining aircraft increase by 1 to 3 percent with every additional year of age after adjusting for inflation."[14]

2.2.7 RAND (Pyles, 2003) Found Specific Age Effects on Workloads and Material Consumption

A recent RAND study (Pyles, 2003) is the most comprehensive study of age effects on AF aircraft to date. This RAND study estimates multiple models calculating how AF

---

[13] Jondrow, 2002, slide 31.
[14] Kiley, 2001.

maintenance requirements change over time. Specifically, how aircraft age relates to maintenance and modification workloads and material consumption. He uses two conceptual models looking first at the material consumption and workload for maintenance and then modifications. Both models allow for varying effects at different ages, taking considerable effort to distinguish the actual age effect from other effects such as the obscure beginnings of an aircraft's life and exogenous events. He addressed the discrepancies found between linear estimates and non-linear estimates by accounting for acceleration in the growth rate.

He used regression analysis to address several questions about the age effects. These questions include understanding how a fleet ages, if and how platforms age differently, the future prospects of growth, and the age effect at different ages. He analyzed trends at many different levels including the on-equipment, line, depot, planned maintenance, and engine levels.

Pyles found several statistically significant results in the data. He found specific age-related growths of maintenance conditional on the age of the aircraft and the "fly-away" (a measure of aircraft complexity) costs. Furthermore, he also found that, in general, maintenance requirements increase as aircraft age and more expensive aircraft generally experience higher growth rates. He estimated that acceleration of growth rates occurs at least through age forty and honeymoon periods and infantile failures were both present, skewing the long-term growth rate estimates. Infantile periods caused the growth rates to be underestimated and honeymoon periods caused the rates to be overestimated. He also found that material consumption decelerated as the aircraft aged. The PDM (Programmed Depot Maintenance) workloads tended to accelerate beyond twenty years, stating that this is cause for significant concern. Pyles looked at many models searching for a relationship between age and proxies for maintenance costs. In some of these models he found effects and in others he did not. He found that growth was not uniform across fleets, flying hours, or flyaway costs. For example a $30 million fighter in the prime of its life, flying about 300 hours per year only increased in maintenance requirements by eighteen man-hours in a year, whereas a forty year old $100 million cargo aircraft's maintenance man-hours increased by about 1700 hours.[15]

In summary, Pyles found a positive age effect on maintenance requirements of nearly all activities. The number of man-hours required to perform the same task increased over time. Additionally, he found that more complex aircraft's maintenance requirements increase at a faster rate than do simpler aircraft. One important theme throughout the paper is that different tasks realize different age effects for the same airframe and the same tasks might experience different growth rates for different

[15] Pyles, 2004.

aircraft. There are many different covariates that help isolate the age effects. This research also suggests that the effect is correlated with the complexity of the airframe.

The research questions presented in Pyles' study are similar to the research questions this dissertation is answering. It will build on his in several ways. First, it will use a completely different dataset to test similar hypotheses. Second, it will measure maintenance costs in real dollar values as a rate (cost per flight hour). Third, it will generalize the results from civilian data to the AF.

Few publicly available studies show the age effect of commercial aircraft.

2.2.8 Boeing Provides Maturity Curves for Cost Comparison Purposes

Boeing is very interested in the effect of aging on maintenance. They benefit from supporting their current customers and potential purchasers of new and used aircraft. Understanding the implications of age will help users of their products understand the true cost of ownership. In their ongoing work on aging aircraft, the primary research objective is to understand how operating aircraft beyond their design service life will impact maintenance.[16]

Boeing separates an aircraft's life into three stages: the "Newness" period, "Mature" period, and "Aging" period.

[16] Boeing, 2004.

The Newness period generally is considered the first five to seven years of an aircraft's life. The second period, or the Mature period, ends at the second D-check. A D-check is a complete structural check and restoration. It is the most comprehensive scheduled maintenance. The Aging period is the period after the second D-check to the end of the aircraft's operational life[17]. These three periods combine to make a "Maturity Curve".

These Maturity Curves function to normalize the costs of various age aircraft so that their value can be equitably compared. The Mature period is assumed to be the comparison period -- the growth rate in this period is set to zero. The point of reference for age effects in the Newness and Aging periods is the Mature period. These maturity factors are used to adjust estimated maintenance costs of different age aircraft. These Maturity Curves are very similar to age effects discussed in this dissertation.

Figure 2.1 is adapted from a Boeing presentation and demonstrates estimates of the maturity factors for two different categories of aircraft types. They have aggregated the aircraft to the design type, estimating different maturity curves for two structurally different types of aircraft. They are labeled "pre-1980" and "post-1980". In a briefing presented at RAND in 2004, Boeing presented the idea that simply assuming one age effect for all aircraft types, as they have done in the past, is no

[17] Boeing, 2004.

longer viable. They suggest their previous approach overestimated the cost of future maintenance for new aircraft, but underestimates it for older aircraft. The new method will account for differences in aircraft types and eras by first normalizing the current cost of an aircraft then estimating the future maintenance cost. The accuracy of this method has not yet been proven. The most interesting effect is that in both situations the age effect is not constant over the aging period -- it increases, i.e., the curve is convex. Their research provides this dissertation with baseline expectations.

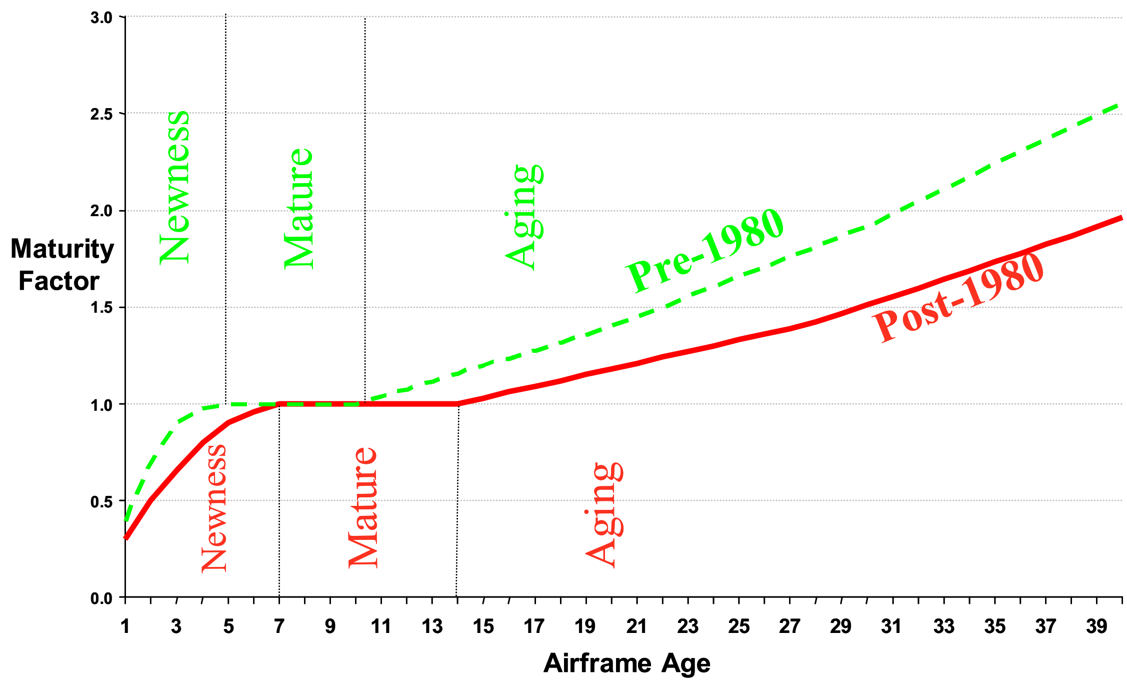


Figure 2.1, Boeing's Maturity Curve[18]

[18] Modified from Boeing, 2004.

However, there has not been a formal publication of this information nor is the statistical analysis presented. The standard errors, sample sizes, specific model, and assumptions are not supplied in the presentation. The analysis in this dissertation will build on this presentation in two ways. First, it will provide the statistical rigor to the estimation of commercial age effects, the corresponding models, and any assumptions. Second, this dissertation explores different age and aircraft separation to more accurately predict maintenance costs.

2.3 Military Data Do Not Provide A Clear Cost Picture

While several studies have been completed on military fleets, none has been able to use dollars as the dependent variable. The AF tracks maintenance by tasks completed, scheduled work, number of hours required for tasks, or materials used for modification and maintenance. Some of these measures can be translated into dollar figures, but it is not a direct one-to-one mapping. Air Force maintenance manpower costs are not entirely due to maintenance and therefore may be inflated. Additionally, there may be services used for maintenance that are completed by non-maintenance personnel and therefore will not be recorded. These include civil engineering tasks such as heating, air conditioning, or building maintenance that are not charged as maintenance expenses. Administration of the materials, manpower, and contracting will also not be accounted for by these measures of maintenance levels.[19] Isolating maintenance costs in the commercial industry is theoretically easier and more accurate.

2.4 Summary

In summary, most published literature discussing the effect of age on maintenance has been accomplished using military data. Earlier studies seem to suggest there was no age effect, but as the aviation industry and statistical techniques matured, age effects began to emerge.

[19] Pyles, 2004.

Chapter 3

Data and Analysis Methodology

3.1 Introduction

This chapter will include explanations of this dissertation research data and analysis methodology.

3.2 DoT Form 41 Data Capture a Wealth of Knowledge

The Department of Transportation maintains records on US airlines back to the early 1960s. In the 1990s RAND initially gathered these longitudinal data. After collecting and consolidating these RAND files, we were able to update the files through the year 2003 and add fleet ages to each line of data. The DoT refers to them as Form 41 files. The complete panel data used in this dissertation range from 1965 to 2003. There are no data for 1985 due to problems in the transition of collection methods. Pre-1985 data were collected at the annual level and post-1985 data were collected at the quarterly level. These data have been combined to form one dataset consisting of annual observations. When aggregated to the airline and type (737, A310, DC10, etc.) level, there are 1007 observations over 11 US airlines and 40 aircraft types spanning 38 years.

There are two main reasons the data are aggregated to the airline and type level. First, problems with accounting data are reduced when they are considered at a higher level. Second, age data were only available at the type level.

An observation consists of three kinds of fleet[20] (airline and type of aircraft) level variables: categorical variables describing the fleet, continuous variables recording maintenance costs, and continuous variables recording usage. The categorical variables describing a fleet are: airline, aircraft type, model, division, quarter, and year. The variables recording maintenance costs are separated down to the level of labor or material costs and then to the level of airframe, engine, contracted work or overhead costs. Finally, the four usage variables are: gallons of fuel, flight hours, days assigned to airline (operations days), and block hours (self powered hours, including flight time). Figure 3.1 below provides a sample of three observations.

					Labor		Outside Repair		Materials	
Airline	Yr	Qtr	Type	Model	Airframe	Engine	Airframe	Engine	Airframe	Engine
American	1992	1	727	200	9613	3614	966	1871	8021	6645
Delta	1990	2	767	200	746	299	367	946	878	1471
United	1997	4	A320	100/200	2621	134	622	2298	1487	65

Tot Dir Airframe	Tot Dir Engine	Tot Dir Maint.	Maint. Burden	Tot Flt Eq Maint	Tot Flt Hrs	Plane Ops Days	Block Hours	Fuel Gallons
18600	12130	30730	25379	56109	71151	10017	87707	107616515
1991	2716	4707	2366	7073	12812	1312	14949	20068729
4730	2497	7227	11969	19196	36649	3657	41371	34143558

Figure 3.1, Data Sample; Thousands of Then Year Dollars

Noticeably absent from the list of variables are the fleet inventory and average age. Average ages were acquired

[20] For the purposes of this dissertation, a "fleet" is a all individual tail numbers of the same aircraft type flown by an airline, e.g., all American Airline's 747s are a fleet, American Airline's 727s are a separate fleet, and Delta Airline's 727s are a third fleet.

separately from the SEC, individual airlines, and Boeing. Inventory was partially available from the airlines and DoT.

The average ages are distributed well from 0 to 25. The oldest recorded average fleet age is 33 years, but average ages beyond 25 are sparsely represented. Figure 3.2 demonstrates the age distributions.

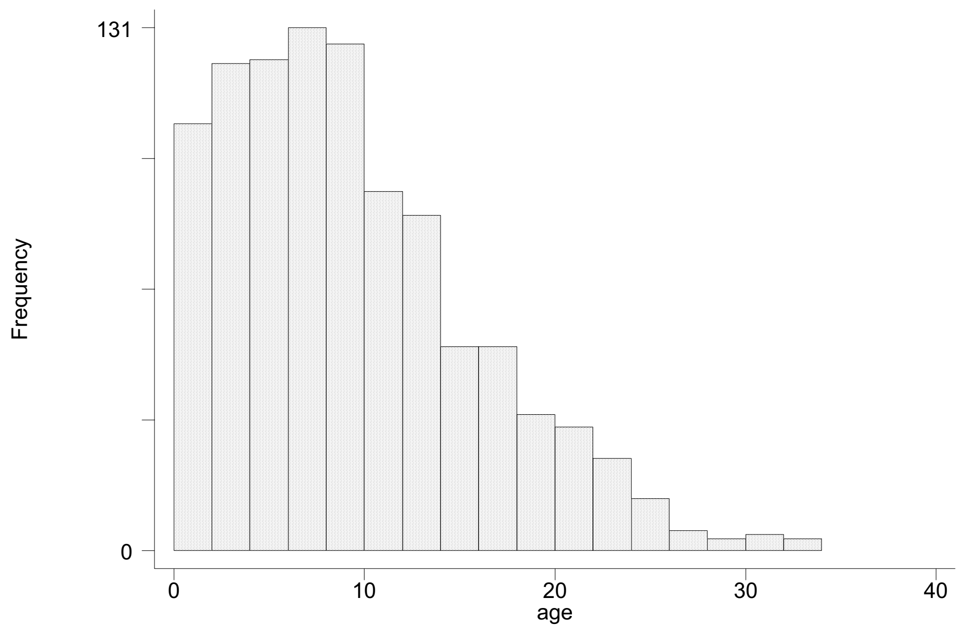


Figure 3.2, Distribution of Average Fleet Ages in Data

Since the ages are under-represented beyond 25 years, results in this dissertation cannot be directly applied to fleets that are much older on average than 25 years.

3.3 This Research Explores the Relationship Between Age and Maintenance Costs

The research approach consists of three steps:

- analyze the commercial data to understand how age impacts commercial airlines' maintenance costs,

- develop maturity curves and determine what level of generality these curves can be constructed, then
- extend the results to the AF.

3.3.1 Data Analysis

The first phase of research focuses on finding the general relationship between age and maintenance costs from the commercial data. The primary model is an ordinary least squares (OLS) model with fixed effects for different characteristics of a fleet that are constant over time. A fixed-effects model is appropriate because there likely exists heterogeneity bias, or one or more of the time invariant variables (airline, type, etc) are correlated with age.

Regression trees are used to test for the existence of better age and type separations. Boeing uses the maintenance schedule and era of production to identify age and type separations that may not be the most efficient. This dissertation uses regression trees to explore the data for patterns or trends that could provide more homogenous age or aircraft type separations. The hypothesis is that separations generated by regression trees will yield more accurate estimations of the age effects.

3.3.2 Development of Maturity Curves

This second phase uses the results from the first to develop maturity curves similar to Boeing's (as illustrated in Figure 2.1), provides academic rigor to the curve development process, and uses statistical tools to establish independent maturity curves. The same fixed-effects model will be used to estimate age effects for the different age and era of production categories Boeing uses. Then, regression trees are used to explore the potential for better age and type separations. Boeing assumes the second D-check is the beginning of the Aging period, however, *Aircraft Economics* state that this may not be readily accepted.

> "This year, aircraft built in 1985 enter the ageing aircraft category, if the norm of using 15 years as the milestone is accepted. Whether this arbitrary limit should be adhered to is a matter of some debate."[21]

Regression trees use binary decisions to minimize the squared errors. The decision nodes identify the critical ages; that is, they are the splits that provide the most homogenous age categorizations. Boeing separates the aircraft based on the era in which they were designed. While this appeals to intuition, it may not be the defining characteristic that clusters aircraft by similar aging effects. For example, grouping by aircraft size may yield a smaller sum of squared errors, $\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$, than design-era

[21] "Out with the Old", *Aircraft Economics*, 2000.

categorizations. Appendix A.1 discusses the model form of a regression tree.

3.3.3 Generalization to the AF

The third phase of this project generalizes the relationships from the civilian aircraft industry to the AF. This answers how age impacts AF maintenance costs and how this affects procurement and sustainment decisions. To do this, the fundamental differences between the two sectors must be understood. The AF and the civilian industry maintain, operate, and procure aircraft differently and have different objectives. For example, the use patterns are different. The AF flies fewer hours per year than the commercial sector.

A particular concern, selection bias with regard to the retirement of commercial aircraft, requires special attention and methodological rigor. Bias is believed to exist when airlines decide which *aircraft* in a fleet to sell; they may first sell their "lemons", or problem aircraft. Therefore, the data representing US airlines could have represented only the best aircraft available from the manufacturer. Ramsey, Sperry, and French summarize this problem well,

> "It should be recognized that selective replacement of high time commercial aircraft is a swift business decision. Typically commercial airlines have an ongoing fleet

> modernization program, constantly tailoring their fleet mix to present day flight routes and load factors. The military, however, cannot be as selective, they must maintain a fleet size as specified by a higher command, without the luxury to selectively retire individual high maintenance aircraft."[22]

Clearly if commercial airlines were able to get rid of aircraft, or entire fleets (if costs were prohibitive) then the age effect would be biased. This bias may also exist at the fleet level; some fleets may be jettisoned earlier due to unexpected problems or costs. The AF faces different, and probably greater, hurdles to prematurely rid itself of a problem fleet.

[22] Ramsey, Sperry, and French, 1998.

Chapter 4

Results

4.1 Overview

Analysis of Form 41 data yields several interesting results, which may change the way the AF views its aging fleets. First, as commercial fleets age up to 30 years the growth rate of total maintenance costs decreases, approaching a near-zero growth rate. (Costs continue to increase, but the rate of increase decreases.) Second, differences between airlines have an insignificant effect on the total maintenance costs. Third, the differences between the types of aircraft have a significant impact on total maintenance costs, but they have an insignificant impact on the *rate* at which these maintenance costs grow. So, changes in cost growth are not dependent on the aircraft operator or the aircraft type. Additionally, as surrogate measures for how and where aircraft are operated, there is some evidence that cost growth is invariant. These results mean that the age effects seen in commercial airlines may well be applicable to similar AF aircraft. Finally, regression trees demonstrate that warranty periods and the second D-check are pivotal points for changes in the cost of maintenance. In this chapter, each of these results will be described in more detail after a description of how one manufacturer imputes maintenance costs from age.

4.2 Industry Uses Maturity Curves to Understand Age Effects

Boeing is in the business of designing, manufacturing, selling, and supporting aircraft worldwide. To support key business decisions, they have developed maturity curves to help them and their customers understand how operating costs are affected by age. Figure 4.1 is a Boeing maturity curve describing how airframe maintenance costs change as aircraft age.

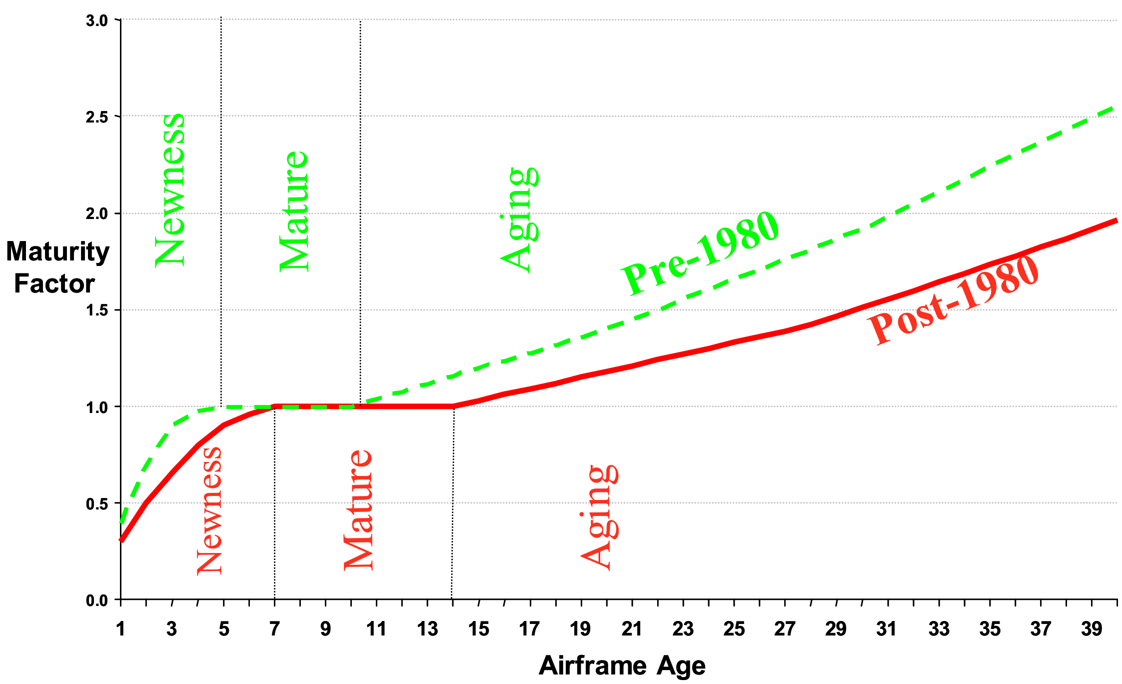


Figure 4.1, Boeing's Maturity Curve[23]

Boeing estimates unique maturity curves for different ages categories and eras of production. They label the

[23] Modified from Boeing, 2004.

three different age categories as "Newness", "Mature", and "Aging". The age categories are based on average maintenance schedules. The pre-1980 generations of aircraft are separated by the ages 5 and 10. The post-1985 aircraft are separated by the ages 7 and 14. These ages are approximately when the first and second D-checks are completed. A D-check is the most complete routine maintenance, which includes inspection for corrosion, cracks, and fatigue damage. It is generally completed after every 18,000 flight hours. The era of production refers to the time periods of manufacture and the maintenance schedules to which they are assigned. Table 4.1 below is how Boeing separates aircraft.

1968	1970	1972	1980	1988	1993
747	DC-10	Concorde	757	777	737-6/7/8/900
	L1011	A300	767	MD-11	A380
	737-3/4/500		747-400	A340	
	MD-80		A310		
			A320		

Table 4.1, Boeing's Identification of Aircraft by Era of Production, Boeing (2004).

Both maturity curves in Figure 4.1 have a "cubic" shape, without ever experiencing a negative slope. That is, the slope is always positive, but the second derivative is negative, then zero, and finally positive. This indicates the age effect is decreasing until it is zero and then it begins to increase.

4.3 This Dissertation Finds The Effects of Age Decelerate Over the Life of a Fleet

Using ordinary least squares regressions to estimate maturity curves on the Form 41 data take a noticeably different shape than Boeing's. Figure 4.2 demonstrates age effects estimated using Form 41 data. The standard errors are in parentheses. Model specification is provided in Section 4.3.2 and output is provided in Appendix A.3.1.

The estimated model is $\log(y_{itr}) = \alpha + \beta * Age_{itr} + \mu_t + \delta_r$, where μ_t are the aircraft type fixed effects, δ_r are the year fixed effects, i represents the airlines, β is the age effect, α is the intercept, and y is the total maintenance cost per flight hour. The specific value of β, multiplied by 100, is approximately the percent change in the costs (y) due to one year increase in age. These are the slopes provided in Figure 4.2. The justification for this model is provided in Sections 4.3 through 4.5 and diagnostics and assumptions are discussed in Appendix A.3. Throughout this dissertation only the fitted model is discussed, therefore the traditional "hat" notation over the parameters is dropped for simplicity.

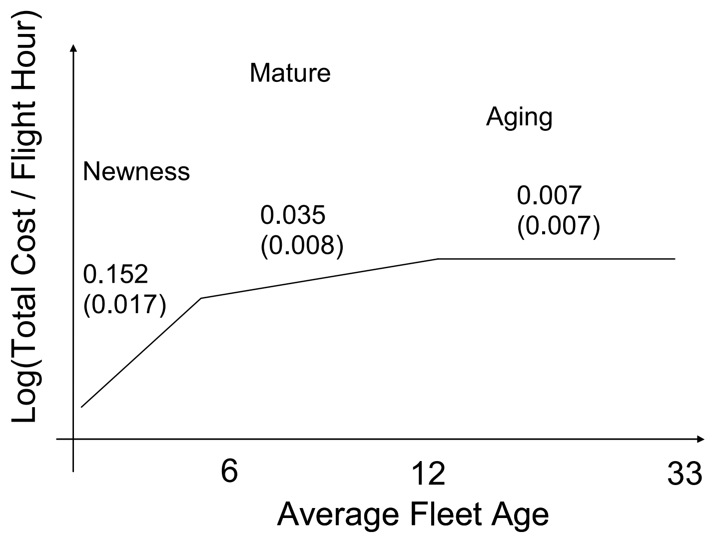


Figure 4.2, Age Effects Estimated with Form 41 Data

The most obvious difference between Figure 4.1 and Figure 4.2 is the shape. The maturity curve in Figure 4.2 does not have the same cubic shape. Within the age range of the data, the age effect decreases. Another way to say this is that the effects of age decelerate over the life of the fleet. This discovery coincides with a statement made in *Aircraft Economics* (2000) that it is hard to make a case for the replacement of older aircraft based purely on an economical or cost basis.

Since all generations of aircraft are analyzed together, the age categories are set as the median ages of Boeing’s categories whereas Boeing uses two separate analyses. Finally, the *y*-axis captures different costs in the two figures. Boeing’s maturity curves focus on direct airframe costs while Figure 4.2 focuses on the total maintenance costs.

4.3.1 Several Differences Exist Between Boeing's Maturity Curves and Figure 4.2

The vertical axis in Figure 4.2 is the log of the *total* maintenance cost per flight hour, while Boeing's vertical axis in Figure 4.1 only represents the *airframe* costs per flight hour. Figure 4.3 below demonstrates that the Form 41 generated maturity curves are similar in shape to Boeing's when the dependent variable is the log of the direct *airframe* maintenance costs per flight hour. The average composition of the total maintenance costs is provided in Figure 4.4. On average, airframe costs account for 34% of the total maintenance costs, while engine and burden account for 27% and 39%, respectively.

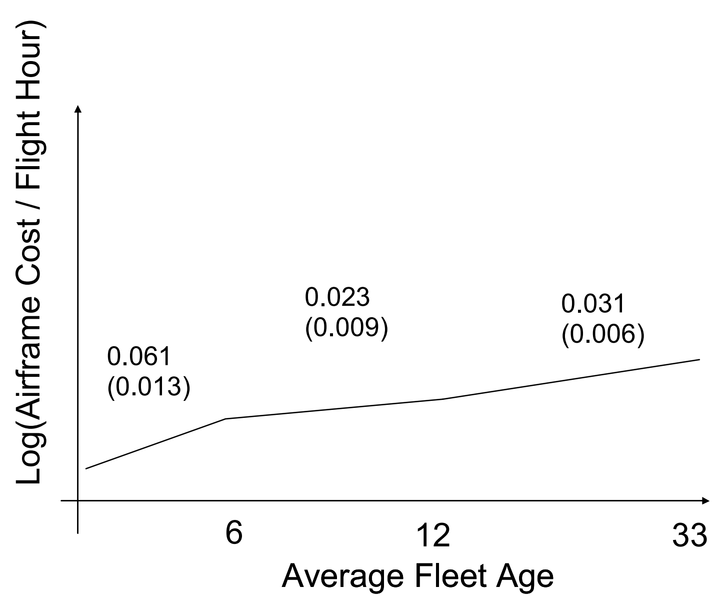


Figure 4.3, Effects of Age on Airframe Maintenance Costs Estimated with Form 41 Data

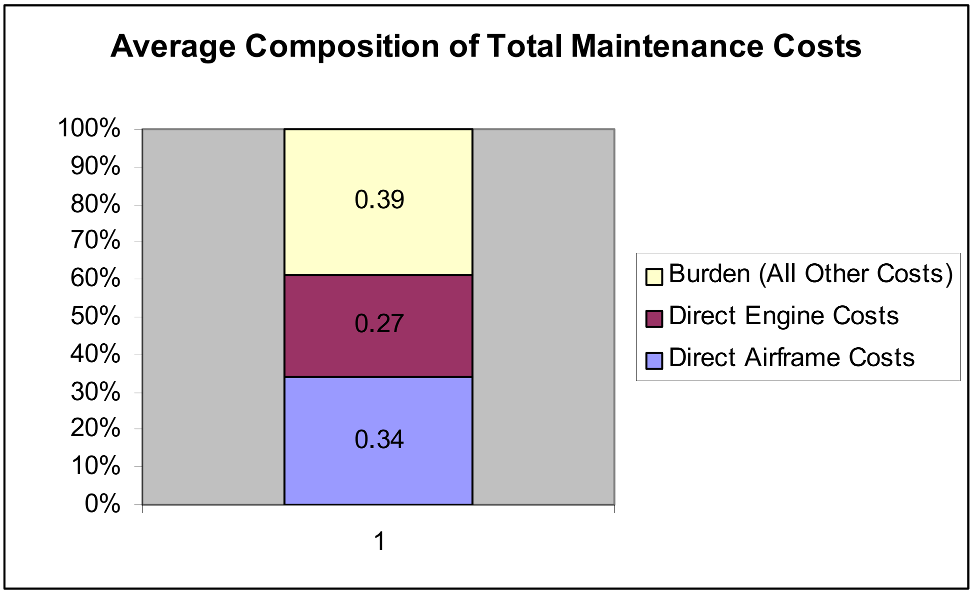


Figure 4.4, Sum of Airframe, Engine, and Burden Equal Total Maintenance Costs

Figure 4.3, using Form 41 data, is similar in shape to Boeing's maturity curves and it satisfies expectations. It is intuitive that the airframe should become increasingly more expensive as it ages.

In the Form 41 data, the total maintenance costs are the sum of the direct airframe costs, direct engine costs, and the burden. The direct costs include costs that are specifically attributable to the airframe or engine, including sub-contracted work. The burden is everything other than the direct engine and airframe maintenance costs, including airline overhead, cost for maintenance equipment and tools, cost to maintain these same items, and any other costs not identified as direct costs.

This dissertation finds age effects, or the percent change one year of age has on cost, on *airframe* maintenance costs grow as aircraft age but the age effect on *total* maintenance costs decrease. Since the age effects on *airframe* begin to increase in the Mature period, the continual decrease of the *total* maintenance costs must be due to the effects of age on the *burden* and direct *engine* costs. Figures 4.5 and 4.6 demonstrate the maturity curves of the engine and burden costs and model output is provided in Appendix A.3.2.

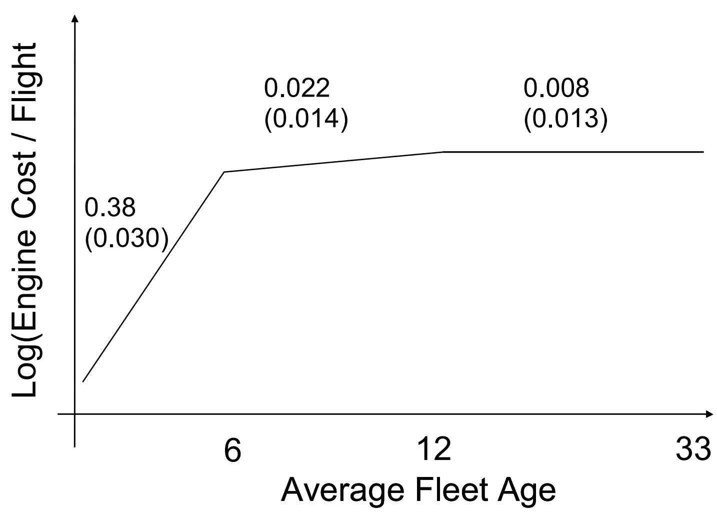


Figure 4.5, Effects of Age on Engine Maintenance Costs Estimated with Form 41 Data

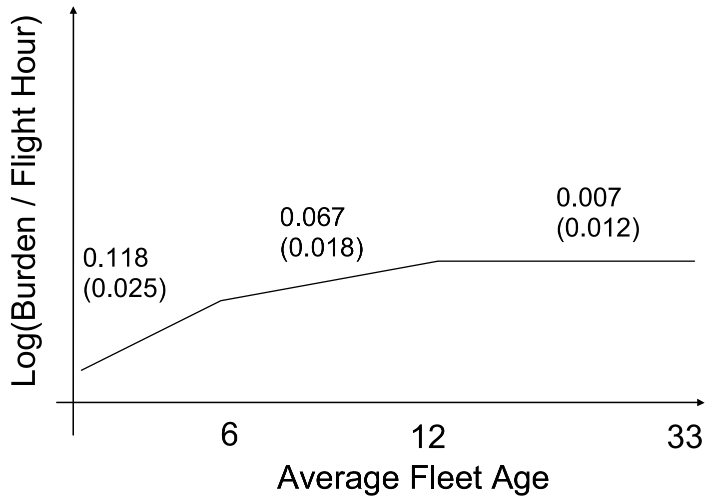


Figure 4.6, Effects of Age on Maintenance Burden Estimated with Form 41 Data

Engine maintenance costs experience decreasing rates of growth. After the first period, engine costs do not increase. Modern engines are very predictable and safe. It is understandable that the cost to maintain an engine does not continually grow over time. When engines are overhauled, nearly every part is either overhauled or replaced. The results are predictable and maintenance costs are approximately constant.

The age breaks used for airframe costs may not be the most appropriate for engine costs. Breaks determined by regression trees indicate that 2 and 12 years of age may yield more insight into how engines age. Using these year breaks, the Newness, Mature, and Aging periods experience an 80%, 8%, and 0% age effect, respectively. Regardless of which age breaks are used, the age effect continues to decrease over the life of the fleet. The large age effect in the Newness period is due to the extremely low costs to the airline in the first year of life. These low costs in the first year are due primarily to warranties. The direct engine maintenance costs reported in Form 41 data are actual net airline costs for maintenance. Therefore any repairs made under warranty are not reflected in the costs. The specific impacts of warranties will be discussed in Section 5.4.

The effects of age on burden costs also decrease as aircraft age. The burden is everything other than direct airframe and engine costs. This includes, but is not limited to, airline overhead and costs to repair and maintain equipment used in maintenance. Growth of overhead should not be related to age directly. It should be highly correlated with the growth of the airframe and engine maintenance costs. The cost to maintain equipment used for maintenance as well as the overhead should increase proportional to the direct costs of maintenance. Increases in the costs of airframe and engine maintenance should be associated with increase usage, and therefore failures, of maintenance equipment. These same increases in costs should also be associated with increases in the net overhead costs.

4.3.2 Simple OLS with Type and Year Fixed Effects Provides a Good Estimate of the Age Effects on Total Maintenance Costs

A good model for estimating the effects of age on total maintenance cost per flight hour is:

$\log(y_{itr}) = \alpha + \beta * Age_{itr} + \mu_t + \delta_r$ where μ_t are the aircraft type fixed effects, δ_r are the year fixed effects, i represents the airlines, β is the age effect, α is the intercept, and y is the total maintenance cost per flight hour. The specific value of β, multiplied by 100, is approximately the percent change in the costs (y) due to one year increase in age. Appendix A.2 discusses this approximation in more detail. There are several reasons this is a good model. These reasons are discussed in next three sections.

Fitting a model to predict the log of the total maintenance cost per flight hour is preferred over the strictly linear model for several reasons. The first is the convenient "percent" interpretation of the age effect. The appendix reviews the derivation of this interpretation and provides examples. Second, most literature using cost as the dependent variable employs a log model. Third, understanding the percent change in cost per flying hour is more meaningful to the AF than knowing the actual dollar increase an airline experiences with each year of age.

4.3.3 Type and Year Fixed Effects Improve Predictions and Reveal a More Accurate Age Effect

Some explanatory variables improve model prediction more than others. When these variables are not included in the model, prediction of the maintenance costs will be biased. This bias is called “omitted variable bias”. If these variables are available in the dataset, the simple solution is to include them in the model. However, these variables are not available and some adjustments must be made to account for this bias. Fixed effects are one approach, and are the best approach for this dataset.

A simple regression of total cost on the age is not only a poor fit, it also assumes there are no differences between the aircraft, the airlines, or the operating year. It also fails to make good use of the information available in the panel data. Including fixed effects for the airlines, aircraft types, or years accounts for constant differences between the airlines, aircraft types, or years. For example, the different airlines have different business plans, markets, routes, contracts, operating hubs, employee bases, and other things that may influence the cost of maintenance. However, information about these variables is not included in the data. If these variables remain constant over time and aircraft type, including airline fixed effects will account for the differences between airlines. This can be done with the aircraft type and year variables as well. Type fixed effects capture the differences between size, seating configurations, average flight times, manufacturer, or other variables that are different between the aircraft types but remain constant over time and airline. Year indicators are similar, except they assume there are constant (across all types and airlines) differences between the years that impact a shift in the total cost per flight hour.

Mathematically, these fixed effects, if non-zero, cause parallel shifts in the model but do not change the slope (age effect) of the model. (However, the slope will be different from the model without fixed effects.) The slope, or age effect, will only change within a model if interactions between age and another variable are included in the model. This is discussed in Section 4.3.4.

Including these fixed effects allows the slope, or age effect, to more accurately fit the data. For example, the model estimating the average age effect over the life of a fleet with no fixed effects explains only 13% of the variance in the log of the total cost per flight hour while the model with year and type fixed effects explains 69% (adjusted R^2) of the variance. This model makes the *Ceterus Paribus* assumption. Accounting for fixed differences between the aircraft types and years increases the legitimacy of this assumption and as well as the legitimacy of generalizations to the AF.

4.3.4 There are No Interactions or Airline Effects in the Fitted Model

General age effects are easier to extend to the AF. Including interactions in the model would confound the issue of extending the age effects to AF fleets. Having interactions between age and airline ("age*airline") or between age and type ("age*type") make the age effect unique only to the particular airline or aircraft type. An age effect that is general, as opposed to aircraft or airline specific, is more likely to also apply to the AF.

Year*age interactions would only be useful in understanding how aircraft age differently from year to year in the past. The only way a year*age interaction becomes useful is if a plausible argument is made equating a future year to a previous year.

4.3.5 In General, the Data Support the Fixed Effect Model without Interactions

Section 4.3.4 discussed the appeal of a fixed effects model without interactions. This same model is also statistically supported in all the age categories except the Aging period. The majority of all year and type fixed effects are *significant* in each age category. The majority of the age*type interactions are *insignificant* in each age category. The significance of the age*airline interactions are slightly more varied.

4.3.5.1 Fixed Effects

The large majority of all year and type fixed effects are significant in each of the three separate models estimating the age effects in each age category. The results of the aircraft type fixed effects are not surprising. It is certainly intuitive that aspects of aircraft types remain constant over time and across airlines. For example, the number of engines, weight capacities, ranges, routes, and usage patterns are constant over the life of a fleet and vary minimally between airlines. Additionally, these characteristics are also different enough between types causing the type fixed effects to be significant. As a specific example, characteristics of A300s are essentially the same throughout their lives. They are the same regardless of the operator. This is true also for 747s. However, characteristics of A300s and 747s are quite different and the cost to maintain each may be very different. Fixed effects will capture these constant differences.

Year fixed effects are also significant. There are characteristics of the years that remain constant across all airlines and types, yet change from year to year. Year effects may be significant for many reasons: deregulation of the airline industry in the late 1970s, the fuel crisis also of the 1970s (which would impact the cost of shipping), changes in labor wages, or catastrophic events. The differences created by these events cause different changes in maintenance costs between years but similar between airlines and types of aircraft.

Another possible explanation for the significance of the year effects is a potential shift in labor trends. Unfortunately, no wage indices were available and the pre-1985 data do not have cost information at the labor/materials level. Further research could compare labor trends to materials trends to determine if some of the age effect is due to labor cost trends. However, further analysis is only necessary if labor trends affect aircraft types and/or airlines differently. Otherwise, the year fixed effects should capture any labor trends. For example, if American Airlines experienced different changes in labor rates than United Airlines, then the labor rates will bias the estimated age effect. Or, if labor costs to maintain 737s changed at a different rate than labor costs for MD11s then the labor rates would bias the estimated age effect. However, if labor maintenance costs of all airlines and aircraft types experienced similar labor trends, then year fixed effects will account for this bias.

4.3.5.2 Interactions

The majority of the age*type interactions are insignificant in every age category, but the age*airline interactions vary in the Aging period. In the Newness and Mature periods, the age*airline interactions are insignificant, just like the age*type interactions. However, the differences between the airlines become important in the Aging period; the age*airline interactions and the airline fixed effects are significant in the Aging period. The airline fixed effects are insignificant when the age*airline interactions are not included in the model. The results are detailed in Appendix A.3.3.

So why are the airlines significant in the Aging period? Although airlines exist to maximize profits in a competitive environment, each operates under slightly different situations and constraints. These differences must compound over the life of the fleet. By the Aging period, these differences become significant enough to cause noticeably different costs per flight hour.

Another potential cause is the approach airlines have to dealing with aging tail numbers. Figure 4.7 is the average age of a few sample aircraft types in 2000 for each operating airline and demonstrates that the airlines have different approaches to dealing with aging aircraft. Some operate older aircraft while others prefer newer aircraft. It is not uncommon for aircraft to be sold immediately before needing a thorough overhaul, or a D-check[24], but clearly not all airlines approach this the same way. The differences between airlines in dealing with aging aircraft

[24] Meeting with Boeing on 29 June, 2005.

and specific maintenance tasks contributes to the significance of the age*airline interactions.

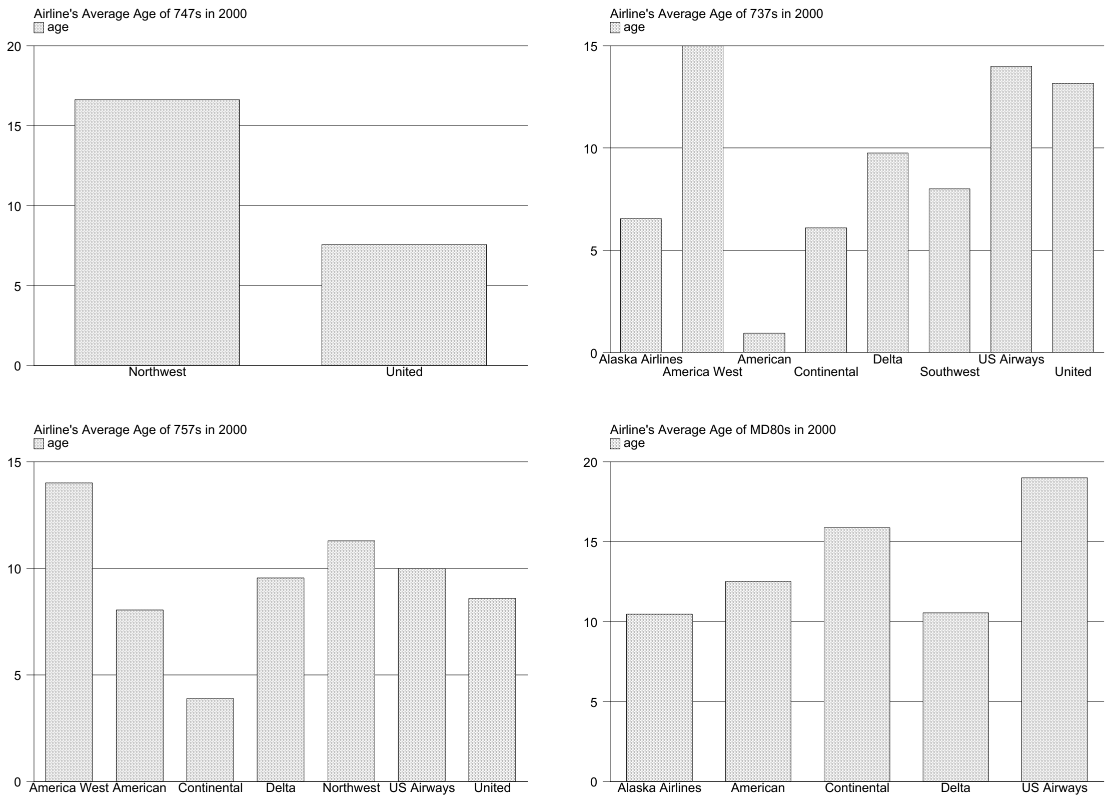


Figure 4.7, Airlines Deal with Aging Aircraft Differently

4.4 Regression Trees Tell an Interesting Story

Regression trees were used to determine if there are more homogenous splits of the data. These homogenous splits could be used to increase the explained variance of the cost per flight hour. The results would be increased accuracy of the estimated age effects over different age periods and types of aircraft. The results demonstrated that maintenance costs are driven by the warranty period, D-checks, and era of production. The regression tree methodolgy and results are discussed in more detail in Appendix A.1.

4.4.1 Warranties and D-checks are Significant Maintenance Cost Drivers

Regression trees were used to estimate the most homogenous age categories. Ages 3 and 12 were determined to be the most homogenous. Recall that the second D-check is completed after approximately the twelfth year of operation and the warranties expire after approximately three years[25]. These ages certainly make sense; the second D-check and warranty expiration are the two most costly maintenance events in the life of an aircraft.

These results are non-trivial. First, they indicate that the maintenance schedule is the best predictor of maintenance costs. Second, it shows that the unexpected costs are either less consistent than the scheduled maintenance costs, they are less in magnitude than the scheduled maintenance costs, or both. Finally, they lend credibility to the estimation approach, i.e., the estimates correspond to known events in an airplane's life.

4.4.2 Era of Production Provides Homogeneous Separations

Regression trees were also applied to the data with type as the explanatory variable to determine the most efficient separation of the aircraft. The results are

---

[25] Boeing, 2003.

strikingly similar to Boeing's separation along the era of production. Table 4.3 shows Boeing's separations and the aircraft in yellow cells are the first group determined by the regression trees. All other aircraft belong in the second group, excluding the Concorde, which is not in RAND's data. There are other aircraft that Boeing did not address in the table that belong in the second group, such as the 707 and 727.

1968	1970	1972	1980	1988	1993
747	DC-10	Concorde	757	777	737-6/7/8/900
	L1011	A300	767	MD-11	A380
	737-3/4/500		747-400	A340	
	MD-80		A310		
			A320		

Table 4.3, Regression Tree Estimates of Most Homogenous Aircraft Type Separation

The first group consists of the 747, DC-10, L1011, and A300. This is very similar to the groups Boeing established. The only aircraft it left out of the group is the MD80 and three models of the 737. The four aircraft in the first group (747, DC10, L1011, and A300) are all wide-body, long-range aircraft. The 737 is a mid-sized aircraft. The MD80 is a small, short range aircraft that began its delivery in 1980. The regression trees identify MD80s and 737s as belonging to the other group.

The regression tree results demonstrate that the era of production is the most important factor for separating the aircraft into their most homogenous types.

4.5 Summary

In summary, there are several results that may change the way the AF views its aged fleets. First, as fleets age the growth rate of total maintenance costs appears to slow. Second, airlines' fleets age similarly. Third, the differences between the types of aircraft have a significant impact on total maintenance costs, but not on the *rate* at which these costs grow. Finally, regression trees demonstrate that warranty periods and the second D-check are pivotal points for changes in the total cost of maintenance.

Chapter 5

Potential Biases in Estimated Age Effect

5 Five Issues Could Bias Estimated Age Effects

There are five primary issues that could bias estimated age effects. They are: selection bias, cycles, overhead and sub-contracted efforts, warranties, and retirement effects.

Potential selection bias and warranties biases became evident during this data analysis. Overhead, sub-contracted efforts, and cycles are items Boeing adjusts for in their maintenance cost estimating. Retirement effects were found in previous literature; Navy aircraft demonstrated retirement effects, as discussed in Section 2.2.5. This chapter will discuss these issues in detail.

5.1 Selection Bias

Airlines have the ability to rid themselves of economically inefficient fleets. If a fleet is too expensive to maintain early in life, or maintenance costs grow too quickly, it may be dropped from inventory earlier than most fleets. If this bias is present in the data, then the true age effect will be underestimated because only the most efficient fleets will be represented in the fitted model. The AF does not have this same luxury, nor is it motivated by the same objective (profit). It is interested in an age effect that is estimated by all fleets, not just the cheapest to maintain.

There is potential for bias at the aircraft level. Aircraft selection bias occurs when airlines discard their least efficient aircraft, or tail number, within a fleet.

5.1.1 Lack of Evidence to Support Fleet Level Bias

As this section will show, some fleets retired earlier than normal, but it does not appear to be a result of larger than normal age effects. The significance of this is important. For example, imagine a researcher interested in understanding the average grade point average of all eighth grade students in a school district. If the researcher was only able to sample 90% of the students (which is actually quite a lot), the researcher would want to be sure it was a random sample and not the best (or worst) 90%. Clearly, if it were the best 90% the average GPA of the district would be over estimated. Random selection is usually ideal, but rarely realistic. If the excluded 10% were not included for other reasons such as availability of data or illness, it would be desirable that these reasons have low correlation with GPA.

This analogy is equally applicable to the airline industry. If the maintenance cost data only include 90% of the best performing aircraft then the true age effects will be overestimated. Effects estimated from the sample are best generalized when the sample represents the population without bias.

Over the last forty years, 17 of 116 fleets in the data were retired earlier than normal ("short-lived fleets"). Table 5.1 summarizes these fleets.

Airline	Type	Retired Age Period	Average Age @ Retirement	Year of Retirement
American	707	Aging	14.1	1981
	720	Mature	11	1971
	747	Aging	12.7	1992
	MD11	Mature	8.75	2001
	MD90	Newness	4	2001
Delta	747	Newness	5.5	1976
	A310	Newness	4	1995
	CV880	Mature	12.3	1973
	DC10	Aging	13.9	1988
Northwest	707	Mature	9.4	1977
	720	Mature	9.5	1973
	L188	Mature	11	1970
	MD80	Aging	17.5	1999
United	720	Mature	11.75	1972
	SE210	Mature	9.2	1970
	V700	Aging	12.1	1968
US Airways	MD80	Aging	19.5	2001

Table 5.1, Short-Lived Fleets

These 17 fleets account for 158 of the 1007 data points. Comparison of these fleets to the complement (fleets still in service or retired after more than 20 years of service) shows no indication of a significant bias. The best way to determine if fleet level selection bias exists is to compare the age effects in the Mature period of fleets that lived a shortened life to those fleets that lived a full life. The Mature period is when the majority of the short-lived fleets retired or they were retired within one or two years into the Aging period. Fleets retired within the first year or two of the Aging period would have been considered for retirement in the Mature period.

Figure 5.1 illustrates age effects when short-lived fleets are removed from the sample. The result is a 0.5% decrease of the age effect in the Mature period. As expected, the Newness and Aging periods' growth rates are essentially unchanged, increasing by 0.1% and decreasing by 0.1%, respectively. Figure 5.2 is the original age effects demonstrated in Figure 4.2. The regression output is provided in Appendix A.3.4.

These insignificant differences in the Newness and Aging periods are not surprising even if a large bias exists. First, the warranties would mask most maintenance problems in the early years. Second, the Mature period is when the majority of the short-lived fleets were retired—leaving very few data points in the Aging period. There are only twenty observations in seven fleets that were removed from the Aging period.

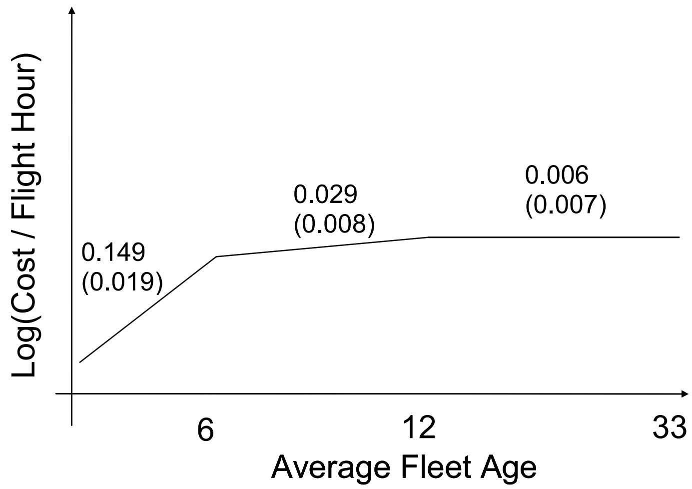


Figure 5.1, Age Effects of Fleets That Were Not Retired Before 20 Years of Age.

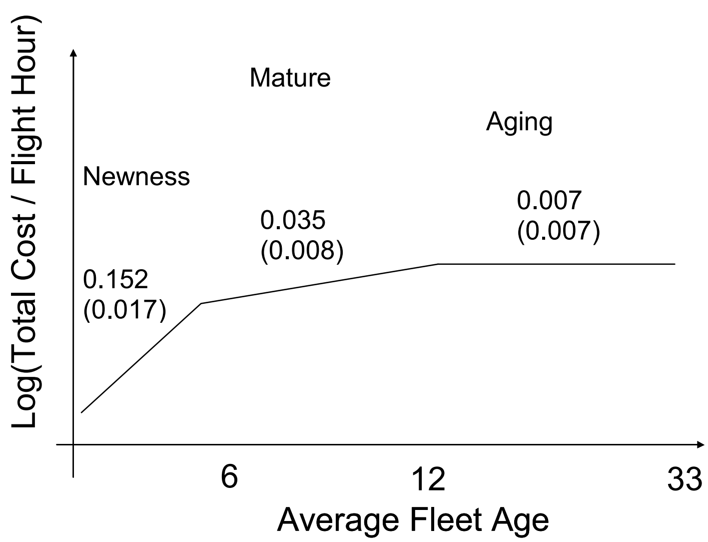


Figure 5.2, Original Maturity Curve

A simple model with an indicator variable for the short-lived fleets and an interaction term for these fleets and age tests for bias. The results indicate no significant difference between the age effects of the short-lived fleets and the non-short-lived fleets in either the Mature or the

Newness period. As noted, the lack of significance in the Newness period is not a surprise, but the lack of significance in the Mature period is interesting and powerful. The implication is that there is nothing significantly different about the short-lived fleets compared to the others as it pertains to age. The implication is that poor performing fleets in the Newness or Aging periods do not bias the age effect.

Neither the Newness period nor the Mature period demonstrate a significant difference in the age effects between the two types of fleets. The estimated model

$$\log(y_{itr}) = \alpha + \beta_1 * Age_{itr} + \beta_2 * short\_fleets + \beta_3 * age * short\_fleets + \mu_t + \delta_r$$

produced insignificant coefficients on "short_fleets" and the interaction between age and "short_fleets" in both age groups. The estimated model (with standard errors in parentheses) for the Newness period is

$$\log(y_{itr}) = \alpha + \underset{(0.018)}{0.148} * Age_{itr} + \underset{(0.166)}{0.261} * short\_fleets + \underset{(0.041)}{0.008} * age * short\_fleets + \mu_t + \delta_r$$

and the estimated model for the Mature period is

$$\log(y_{itr}) = \alpha + \underset{(0.008)}{0.036} * Age_{itr} + \underset{(0.199)}{0.150} * short\_fleets + \underset{(0.021)}{0.001} * age * short\_fleets + \mu_t + \delta_r.$$

The implication is that the cost per flight hour of these short-lived fleets did not increase (or decrease) any differently than other fleets that lived a full life or are still in service today.

So why were these fleets retired early? There may be several answers and the following model provides one answer. The model $\log(y_{itr}) = \alpha + \beta_1 * Age_{itr} + \beta_2 * short\_fleets + \mu_t + \delta_r$, which has no interaction term, has a significant positive coefficient on the term "short_fleets", β_2. In the Newness period the estimated model is

$$\log(y_{itr}) = \alpha + \underset{(0.017)}{0.149} * Age_{itr} + \underset{(0.110)}{0.286} * short\_fleets + \mu_t + \delta_r$$

and in the Mature period the estimated model is

$$\log(y_{itr}) = \alpha + \underset{(0.008)}{0.036} * Age_{itr} + \underset{(0.054)}{0.158} * short\_fleets + \mu_t + \delta_r$$

. The significant positive coefficients on the "short_fleet" indicator variable causes a parallel shift in the curve. It suggests that that the majority of these fleets were retired early because they were more expensive to maintain from their inception. The rate of growth in maintenance costs is growing at a similar rate as average fleets, but they began life costing significantly more to maintain than the average fleet, which is demonstrated by the positive parallel shift in the curve.

There may be other reasons these short lifespan fleets did not survive to 20 years. These reasons may include loss of consumer demand for this type of aircraft, regulation changes, an airline's shifting business plan, increase in operating costs, or others.

5.1.2 Aircraft Selection Probably Does Not Bias Age Effect

Selection bias may also occur at the aircraft level. Airlines could discard problematic tail numbers within a fleet. This dissertation does not explore aircraft selection bias in detail for two reasons.

First, some in the industry believe that airlines do not keep financial records at this level of detail. The airlines do indeed keep careful maintenance records, but they most likely do not keep detailed records of the cost of individual level repairs. Second, the AF may be equally able to also discard its more troublesome aircraft. The AF may be equitably able to identify tail numbers that continually require more maintenance and use those tail numbers less than more reliable aircraft. Some Navy aircraft are selectively retired[26].

5.2 Number of Cycles[27] are Controlled For

Maintenance may be driven by flight hours, cycle time, or calendar age. Similar to automobile oil changes, which are recommended every 3000 miles or 3 months, the number of hours between scheduled maintenance will vary by fleet.

Boeing adjusts for the number of cycles and the average hours per cycle. Fleets that fly short routes regularly may age differently than fleets that regularly fly long routes. Expensive maintenance events may be caused more by the number of cycles than by flight hours. This dissertation does not specifically address cycles because if the hours per cycle were significant, it would be captured

[26] Jondrow, 2002.
[27] A take-off and landing completes one "cycle".

by the type and airline fixed effects. Most likely differences in hours per cycles would be due to the type of aircraft, not the airline. These differences are captured in the type fixed effects, which are significant. Additionally, if hours per flight were a significant impact to the age effect, the interactions between age and type would have been significant; they are not.

5.3 Overhead and Sub-Contracted Efforts are Included in Analysis

Sub-contracted work is included in the direct airframe and direct engine costs. These sub-contracted efforts include the overhead of the sub-contractor. The airline's overhead is included in the burden variable. Since Boeing deals mostly with the direct costs, they make allowances for the overhead of the sub-contractors.

There are two reasons this dissertation does not differentially handle overhead and sub-contracted work. Overhead is one of the costs of doing business. The AF experiences similar costs in the forms of civil engineering, HVAC, and administration. Any organization will experience overhead-related costs. Second, and more importantly, since airlines are profit-driven, their decisions should maximize profit. Sub-contracted work can be treated as any other work performed in-house because it is assumed to be the most profitable means. A profit-driven firm would not knowingly continue to perform a task in a less-than-optimal way.

Therefore, there is no reason to control for sub-contracted efforts or overhead, even when dealing only with direct maintenance costs.

5.4 End of Warranty Periods Cause Dramatic Changes in Maintenance Costs

Warranties are generally in effect for the first three or four years of an aircraft's life[28]. In general, these warranties cover all systems, accessories, software, and parts. The scope of these warranties covers such things as non-conformance to specifications and defects in materials and/or workmanship.

Manufacturers factor warranty costs into the sale price.[29] Reclamation methods used by the airlines are different than methods employed by ordinary consumers. Usually an airline will fix the broken part or faulty system in-house and simply bill the manufacturer for the work.[30] The actual costs of the repairs are difficult to interpret. The airlines must maintain stores of spare parts and the equipment used to repair or update aircraft. The details of the accounting procedures may vary between airlines and manufacturers. The airlines incur some cost when repairs must be made in the warranty period, but it is only a fraction of the total repair bill.

---

[28] Boeing, 2003.
[29] Boeing, 2003.
[30] "Business Jet Warranties", 2004.

The majority of repair costs made in the warranty period will not be represented in these accounting data. Since the Newness period extends to the end of the sixth year, warranties are most likely the cause of the steep age effect in the Newness period. In the first 3 or 4 years the net maintenance costs to the airlines will be very low. However, the fourth or fifth year will show a great increase in the cost of maintenance as the airlines' net maintenance costs shoot up.

An insight provided by regression trees illustrates this point clearly. The most homogenous age breaks for total maintenance costs per flight hour are at ages 3 and 12. The twelfth year is the second D-check, while the third year is the end of the warranty period. The end of the warranty period "trumps" the cost of the first D-check, after the sixth year. Concerning maintenance costs, the two most decisive ages in the life of a fleet are after the warranty wears off and at the second D-check. Specifics are provided in Appendix A.1.

Since warranties cover a large amount of work done in the first few years, why is the age effect so low in the Newness period? One reason is that it is averaging the first six years; three are under warranty and three are not. Another reason is that any spare parts, equipment, or other costs that warranties do not cover will be positive net costs in the warranty period and will cause the age effect to be less. Remember that the existence of a positive age effect does not imply it is expensive to maintain, it simply implies costs are growing. A large growth rate could be associated with a very low initial maintenance costs.

The options for dealing with these warranty issues are beyond the scope of this dissertation. However, several interesting things can still be learned. First, the warranty bias primarily effects the Newness period. Second, this bias will lead to an overestimated age effect in the Newness period.

5.5 Retiring Civilian Fleets Do Not Require Less Maintenance

The decrease in the age effect over the life of a fleet is not due to fleets being neglected in the years just before retirement.

The F-14 and the A-6 actually became less costly per flight hour to fly as they approached retirement[31]. This apparent decrease in cost was attributed to the decline of maintenance as that fleet approached retirement. This does not appear to be the case with commercial fleets.

Reanalyzing the data without the last two years of a retired fleet's life yielded no significant change in the age effects. The age effect in the Newness period increased by only 0.1% (recall a few fleets retired in the first five years, e.g., Delta's A310s). The age effect of the Mature period decreases by 0.1%. The age effect in the Aging

[31] Jondrow, 2002.

period changes by 0.2%. None was statistically significant. Contrary to what Jondrow found for Navy aircraft, commercial aircraft do not appear to require less maintenance as they near retirement.

It should be noted, however, that selling aircraft immediately before a necessary D-check is a different issue. Older aircraft are generally sold first to cargo carriers. It may not be uncommon for aircraft to be sold immediately before needing a thorough overhaul, or a D-check[32]. The lack of an upward "spike" towards the end of a fleets life will certainly pull the age effect down and make the maintenance costs appear less than actual wear and tear necessitate. Further research should explore the flight hour trends relative to retirement of tail numbers.

5.6 Summary

There are five primary issues that could bias estimated age effects. They are: selection bias, cycles, overhead and sub-contracted efforts, warranties, and retirement effects. Some fleets are retired abnormally early, but it does not appear early retirements are being driven by large age effects. Therefore, there does not appear to be fleet level selection bias. The number of cycles should not bias the age effect estimates because the model will capture these if they are fixed effects. Since this dissertation deals mostly with the total maintenance costs per flight hour,

[32] Meeting with Boeing on 29 June, 2005.

overhead and sub-contracted efforts are included to avoid biasing the results. Warranties have significant effects on the cost of maintenance. They may bias the age effect estimate in the Newness period. Finally, commercial airlines do not appear to experience similar retirement effects found in some Navy aircraft.

Chapter 6

Generalizations to the Air Force

6 These Results are Useful to the AF’s Repair versus Replace Decisions

There are two ways to apply the preceding results to the AF. First, the results may be applied specifically to current AF fleets, which are younger than 30 years, to help refine estimates of the future maintenance costs. Second, the results can be used to understand how potential replacement fleets will age once they are in AF service. These results underscore that maintenance costs might *not* necessarily continue to rise as fleets age, at least in the first 25 or 30 years.

6.1 Application to Current AF Fleets

The results described in Chapters 4 and 5 are beneficial to the AF. They have shown that age and type interactions and age and airline interactions are not significant in explaining the increase in maintenance costs over time. Additionally, airline fixed effects are also insignificant. This means that the age effects are independent of the airline and type of aircraft. The age effects can be applied to any aircraft type and airline. Since commercial airline data do not allow for closer scrutiny of how and where the aircraft are operated, the results provide evidence, although not entirely conclusive, that the cost growth curves may also be applied to the AF’s fleets of similar aircraft with average ages less than 30 years.

These results can be applied at two levels. The first level of application is to fleets that are "Commercial, Off-The-Shelf" (COTS) aircraft. Differences on how and where the AF aircraft are flown may cause some deviation from the commercial aircraft results, but the lack of interaction of both the carrier and the aircraft type with age is evidence that the cost growth curves will at least approximate the age effect up to age 30. The second level is to other large aircraft that are specific to the AF, but have similar characteristics to commercial aircraft. Here, the generalization goes a step further and care should be taken in applying the commercial cost growth curves. In either case, the commercial results are an analytical step forward from other practices currently employed.

6.1.1 The AF Flies Several Commercial Airliners

Some of the AF's fleets are exactly the same aircraft the airlines fly. For example, the AF's C-32As, used to transport VIPs, are Boeing 757s and the AF's KC-10s are special versions of the DC-10. Table 6.1 summarizes the COTS aircraft the AF flies.

Aircraft	Primary AF Designation	Number
707	E-3 & E-8	58
727	C-22	1
737	T-43 & T-40	18
747	E-4B	7
757	C-32A	6
DC10	KC-10	60
DC9	C-9	23

Table 6.1, COTS Aircraft Flown by the AF

Because this dissertation has shown that the age effect is independent of aircraft type and airline, it is possible that the AF's fleets will age in the same way. On average, AF fleets that have an average age of 12 to 25 years can expect to show approximately zero growth in maintenance costs. Recall the age effect is estimated to be nearly zero in the Aging period. It is critically important to understand that this does not mean that the maintenance costs are zero or decreasing, but that maintenance costs are not expected to increase in the next year of operation, at least up to approximately age 25. It is also critically important to understand that *on average* these fleets are not expected to increase in maintenance costs. From year to year, some fleets will increase in total maintenance costs while others decrease, but on average, each year the total cost of maintaining a fleet should not increase. Additionally, each fleet, over the next several years should show an average of zero percent growth when costs are indexed for inflation.

6.1.2 Results May Be Carefully Extended to Cargo and Bomber Aircraft

In the absence of better estimates, the commercial age effects may be used to estimate age effects of other large aircraft in AF inventory. Since the age effects are generated from high-level data, the average age effects may also be applicable to cargo aircraft, bombers, and other aircraft that are not COTS aircraft. Bombers and cargo aircraft share some general characteristics with commercial aircraft. For example, both are generally large, some use the same engines (C-17 uses the same engines as 757), they may have similar ranges, operating speeds, capacities, and operating envelopes. However, the extensions should be done with care after considering all relevant factors.

6.2 Application to Future AF Fleets

If future AF fleets continue to be similar to current commercial fleets, then extensions of the age effects are pertinent and applicable. If future AF fleets are new designs, made with new composite materials, then extensions of the age effects may be less accurate.

The repair versus replace decision relies heavily on estimates of the cost to maintain the replacement fleet over the life of the fleet. The most relevant example is the debate over the KC-135's future. The Boeing and Airbus both have potential COTS replacements. The age effects estimated in this dissertation are specifically applicable to both aircraft.

6.3 Assuming Maintenance Costs Increase May be Inaccurate

Traditional thinking about aircraft assumed maintenance costs continue to rise as the fleet ages. This dissertation has demonstrated a lack of evidence for this in the commercial industry. Therefore, maintenance cost for AF aircraft may also slow as they age, at least up to approximately age 25. Possibly the most significant result of this dissertation, is the challenge of the assumption that aircraft get more expensive to maintain as they age.

6.4 Generalization Difficulties

There are complications when extending the results to the AF, but they should not detract from the results' significance. The two biggest generalization problems are age and utilization rates.

Extending the age effects from the commercial sector to the older aircraft such as the KC-135 or the B-52, which are approximately 45 and 55 years old, forces extrapolation beyond the range of the ages in the commercial data. However, these results are still useful to the KC-135 and B-52 repair versus replace decisions. The age effect of potential replacement aircraft is critical for this decision. Additionally, extending the results to fleets that are younger than 25 years should not be a problem. This includes some of the AF's cargo fleets such as the C-17.

Utilization rates are another possible issue. The annual flight hours of AF fleets are approximately 10% of commercial airlines. An average airline flies 3500 hours per aircraft annually. An AF KC-135 might only fly 400 hours per year, although dramatically more during war. This analysis attempts to capture this problem by using cost per flight hour as the dependent variable.

Boeing uses a separate proprietary model to forecast age effects for fleets that fly less than 1500 hours per year. There are no fleets in this data that averaged less than 1500 flight hours per year. Future work might analyze small business jet maintenance records to better understand specifically how low utilization rates impact the age effect.

Chapter 7

Conclusions

There are five main conclusions of this dissertation. Age effects exist and are significant. On average, fleets age the same regardless of the airline and type of aircraft. Surprisingly, age effects decrease over the life of a fleet. Lack of evidence exists for a fleet bias in the age effect estimate. AF policy should consider commercial age effects to better understand its repair versus replace decisions.

7.1 Age Effects Exist and Are Significant

Aircraft maintenance costs increase as fleets age. The data demonstrate significant age effects in the Newness and Mature periods. However, age effects are not significant in the Aging period. The Aging period begins after the second D-check, which is generally after the twelfth year of operation.

7.2 Age Effects Decrease Over the Life of a Fleet

Age effects, the changes in maintenance cost induced by an additional year of age, decrease as fleets age. The data demonstrate significant decreases in the age effects, as the fleets get older. This does not mean that fleets cost less to maintain, but the rate at which maintenance costs grow slows as they age. The age effect in the Newness period (first six years of life) is approximately 15%. The age effect in the second six years of life, or the Mature period, is only 3.4%. Both of these age effects are highly significant. Beyond the twelfth year, the age effect is only 0.7% and is statistically not different than zero.

7.3 Fleets Age Similarly

Age effects are the same regardless of the airline or the type of aircraft. Different age effects for different types of aircraft are statistically insignificant. For example, 747s, A300s, and MD80s experience approximately the same age effects. This does not mean that these aircraft cost the same to maintain, it means that their maintenance costs grow at similar rates. The same is true for the airlines. That is, aircraft age the same regardless of who is flying and maintaining them.

7.4 Selection Bias Does Not Appear to be Present

Selection bias, or the bias from airlines discarding the least efficient fleets, was a considerable concern. However, there does not appear to be fleet-level selection bias. Fleets that prematurely retire appear to have the same age effects (changes in maintenance costs) to those that do not. Prematurely retired, or short-lived, fleets appear to cost more to maintain initially, but did not grow at a significantly different rate than fleets that lived a full life or still in service.

7.5 AF Policy Decisions Should Consider Commercial Age Effects

The age effects learned from the commercial sector are useful to AF policy and planning. Repair versus replace decisions are a large piece of the budgeting puzzle. It is critical for AF optimal decision making and understanding age effects is an important component of this decision making process.

The results can be applied specifically to current AF fleets to help refine estimates of future maintenance costs. They can also be used to understand how potential replacement fleets will age once they are in AF service.

Finally, these results should be used in general to understand that maintenance costs might *not* necessarily continue to rise as fleets age and therefore the aging aircraft problem in the AF may not be as large as currently believed.

References

Boeing Corporation, *747 Scheduled Maintenance Cost Reductions*, No. 20, October, 2002.

Boeing Corporation, *2003 Annual Report*, available at www.boeing.com/companyoffices/financial/finreports/annual/03annualreport/f_ncfs_08.html.

Boeing Corporation, *The Basics of Maintenance Cost Forecasting*, www.boeing.com, October, 2001.

Boeing Corporation, "Airframe Maintenance Cost Analysis Methodology", 2004.

Bolkcom, Christopher, "The Air Force KC-767 Tanker Lease Proposal: Key Issues for Congress", *CRS Report for Congress*, 2003.

Breiman, Leo, Jerome H. Friedman, Richard A. Olshen, and Charles J. Stone, *Classification and Regression Trees*, Belmont, CA, Wadsworth International Group, 1984.

Bureau of Transportation Statistics, *Form 41 Data,* available at http://www.transtats.bts.gov/Databases.asp?Mode_ID=1&Mode_Desc=Aviation&Subject_ID2=0.

Bureau of Economic Analysis, "Implicit Price Deflators for Gross Domestic Product", December, 2004.

"Business Jet Warranties", *Warranty Weekly*, March 9, 2004, available at www.warrantyweek.com/archive/www20040309.html.

Department of the Air Force. *Fact Sheet: C-5 Galaxy* http://www.af.mil/factsheets/factsheet.asp?fsID=84, August 2003.

Department of the Air Force. *USAF mission statement*, available at: http://www.af.mil/main/welcome.asp.

DiDonato, Michael, and Gregory Sweers, *The Economic Considerations of Operating Post Production Aircraft Beyond Design Service Objectives*, Seattle, WA: Boeing, December 1997.

Francis, Peter and Geoff Shaw, "Effect of Aircraft Age on Maintenance Costs", briefing, Center for Naval Analyses, Alexandria, VA, 2000.

Garamone, Jim, "As equipment ages, readiness suffers, say DoD officials", *Hilltop Times*, Hill AFB, UT, July, 12,

2001. Available at www.hilltoptimes.com/archive/20010712/15.html.

General Accounting Office, “Aging Refueling Aircraft Are Costly to Maintain and Operate”, *Report to Congressional Committees*, Washington, DC, August 1996.

Genottin, Jean-Paul, “Maintenance Cost Analysis”, *Fast No. 25*, Airbus Industrie, April 2000.

Greenfield, Victoria A. and David M. Persselin, *An Economic Framework for Evaluating Military Aircraft Replacement*, Santa Monica, CA: RAND MR-1489-AF, 2002.

Hildebrandt, Gregory G. and Man-bing Sze, *An Estimation of USAF Aircraft Operating and Support Cost Relations*, Santa Monica, CA: RAND N-3062-ACQ, May, 1990.

Hsiao, Cheng, *Analysis of Panel Data*, New York, NY, Cambridge University Press, 1986.

Johnson, John, *Age Impacts on Operating and Support Costs: Navy Aircraft Age Analysis Methodology*, Patuxent River, MD: Naval Aviation Maintenance Office, August 1993.

Jondrow, James, Robert P. Trost, Michael Ye, John P. Hall, Rebecca L. Kirk, Laura J. Junor, Peter J. Francis, Geoffrey B. Shaw, Darlene E. Stanford, and Barbara H. Measell, *Support Costs and Aging Aircraft: Implications for Budgeting and Procurement*, CNA Corporation, January, 2002.

Keating, Edward G. and Matthew Dixon, *Investigating Optimal Replacement of Aging Air Force Systems*, Santa Monica, CA: RAND MR-1763-AF, 2003.

Kiley, Gregory T., *The Effects of Aging on the Costs of Maintaining Military Equipment*, Washington, DC: Congressional Budget Office, August 2001.

Maddalon, Dal V., *Estimating Airline Operating Costs*, Hampton, VA, NASA Technical Memorandum 78694, 1978.

Montgomery, Douglas C., Elizabeth A. Peck, and G. Geoffrey Vining, *Introduction to Linear Regression Analysis*, 3rd ed., New York, NY, Wiley and Sons, Inc., 2001.

National Materials Advisory Board, *Aging of US Air Force Aircraft: Final Report*, Washington, DC: National Academy Press NMAB-488-2, 1997.

“Out with the Old”, *Aircraft Economics*, No. 50, July/August, 2000.

Pyles, Raymond A., *Aging Aircraft: USAF Workload Consumption and Material Consumption Life Cycle Patterns*, Santa Monica, CA: RAND MR-1641, 2003.

Ramsey, Tom, Carl French, and Kenneth R. Sperry, "Airframe Maintenance Trend Analysis" briefing, Oklahoma City ALC (Ramsey) and Boeing (French and Sperry), 1998.

Rolfsen, Bruce, "Lockdown", *AF Times*, April 25, 2005.

Stoll, Lawrence, and Stan Davis, *Aircraft Age Impact on Individual Operating and Support Cost Elements*, Pauxuent Rver, MD: Naval Aviation Maintenance Office, July 1993.

Tirpak, John A., "The Aging of the Fleet", *AFA Magazine*, Vol 79, No. 06, June 1996. Available at www.afa.org/magazine/june1996/0696watch.asp.

United Airlines, *SEC Reports*, 1976-2003.

Wooldridge, Jeffrey M., *Introductory Econometrics: A Modern Approach*, 2nd ed., Mason, Ohio, South-Western, 2003.

Appendices

A.1 Regression Tree Results

This section provides detailed figures from the regression trees, which were used to explore different type and age separation from Boeing's. As described in the Section 4.4.2, the results show that the era of production separations are possibly the best and the maintenance schedule is a reasonable indicator of the best age separations. However, the end of a warranty appears to be a better point of separation in maintenance costs than the first D-check.

Regression trees use iterative binary separations of the data to determine the best regression equation that minimizes the sum of squared errors. A regression tree was fit to the data with only the type of aircraft as the explanatory variable. The response variable was the log of the total maintenance costs per flight hour. The first split grouped the 747, A300, DC10, and MD11 together. The second group consisted of all remaining aircraft types. This groups the aircraft types almost perfectly by era of production, very similarly to Boeing's groupings. Table A.1.1 demonstrates this. Boeing separated the aircraft types by era of production. Their two groups were pre- (green and yellow cells) and post-1980 (red cells). Boeing groups the yellow cells with the green cells, as they are all pre-1980.

1968	1970	1972	1980	1988	1993
747	DC-10	Concorde	757	777	737-6/7/8/900
	L1011	A300	767	MD-11	A380
	737-3/4/500		747-400	A340	
	MD-80		A310		
			A320		

Table A.1.1, Regression Tree Estimates of Most Homogenous Aircraft Type Separation

The regression tree groups slightly differently. It groups the red and green cells together and the yellow separate. The only real difference is the MD80 and 737. The Concorde is not included in RAND's Form 41 data. The 737 is split by Boeing according to model (-300s, -400s, and -500s in the pre-1980 group and the other models in the post-1980 group), but our data is aggregate to the type level. Furthermore, the 737 is a mid-sized jet while the "yellow" jets are all large-body jets. The MD80 is a small jet.

To explore the age categories, a regression tree was fit to the data with only the age of the fleet as the explanatory variable. The response variable was the log of the total maintenance costs per flight hour. Because the splits are binary, there are several different ways to interpret the results when looking for three age categories. Figure A.1.1 is an example of the age splits.

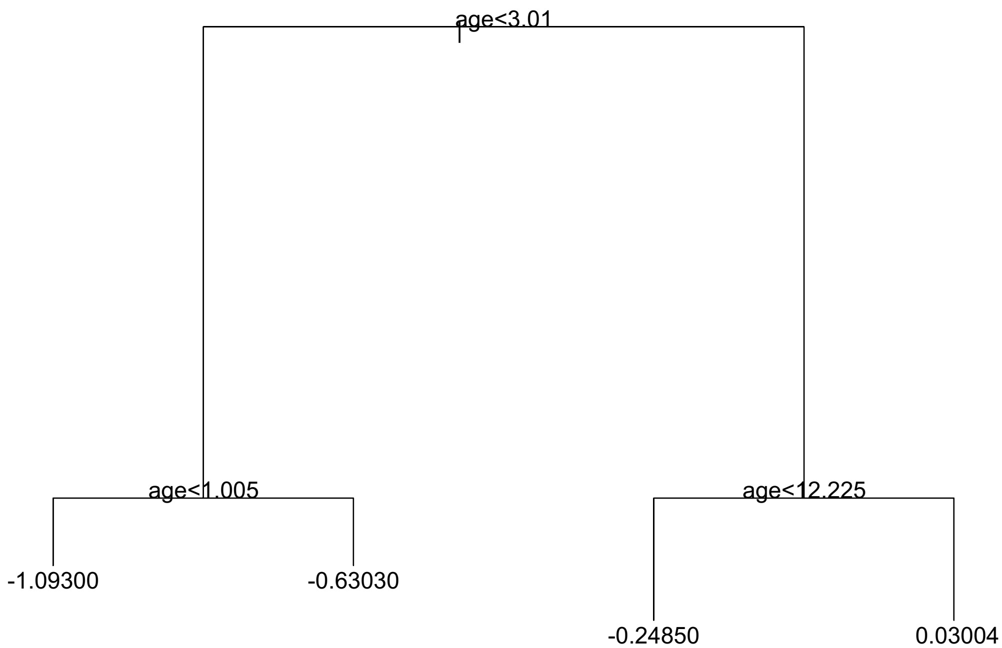


Figure A.1.1, Regression tree: Fitting age to predict log(Total Maint Cost per Flt Hr)

The first, and most significant split is at age 3, when the warranty period ends. The second most significant split is at 12 years old, at the second D-check. (The length of the "branches" signifies the relative importance of the splits.)

When the fixed effects model, $\log(y_{ity}) = \alpha + \beta * Age_{ity} + \mu_t + \gamma_y$, is applied to these age categories, the results show that splits 3 and 12 may not be any better than Boeing's splits of 6 and 12. These splits will be referred to as the "tree splits" and "Boeing's splits". The tree splits yield a slight higher mean F-statistic, but Boeing's splits yield a slightly larger combined R^2 value.

The FE model is fit to each age category and the F-statistics are averaged. The computation is

$$\overline{F}stat = \frac{Fstat_{Newness} * n_{Newness} + Fstat_{Mature} * n_{Mature} + Fstat_{Aging} * n_{Aging}}{n_{Newness} + n_{Mature} + n_{Aging}}$$

, where Newness refers to the first age category, Mature refers to the middle age category, and Aging refers to the last age category. The combined R^2 value computation is

$$Comb\ R^2 = 1 - \frac{SS_{\mathrm{Re}s\ \ Newness} + SS_{\mathrm{Re}s\ \ Mature} + SS_{\mathrm{Re}s\ \ Aging}}{SS_{Tot\ \ Newness} + SS_{Tot\ \ Mature} + SS_{Tot\ \ Aging}}$$

, where SS is the sum of square differences.

The mean F-statistic of the tree splits is 19.6 and the mean F-statistic of Boeing's splits is 17.5. However, the combined R^2 value (0.72) of the tree splits is slightly lower than the combined R^2 (0.74) for Boeing's splits. This is similar to saying that Boeing's splits allow 2% more of the variance in the total maintenance costs to be explained by the FE model. Regression trees are of the form

$$\log(y_i) = \beta_1 I_{N_1}(X) + \beta_2 I_{N_2}(X) I_{N_1}(X) + \beta_3 I_{N_3}(X)[1 - I_{N_1}(X)] + \\ ... + \beta_k I_{N_k}(X)[1 - I_{N_1}(X)][1 - I_{N_3}(X)][1 - I_{N_7}(X)],$$

where k is the number of nodes, I(X) is a binary indicator variable, and X is the vector of explanatory variables. β and $I_N(X)$ are determined by an exhaustive search of all possible splits to minimize $\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$.

All regression trees were estimated in S-Plus. Since the initial split is the primary consideration in both scenarios (age and era of production splits) pruning and the number of total nodes were not major concerns. However, experimenting with different tree parameters had little to no effect on the initial split in both scenarios. For more information regarding regression trees, see Breiman et al, 1984.

A.2 Derivation of Percent Interpretation

The term "age effect" is used throughout this dissertation to refer to the percent change in maintenance costs resulting from a one year increase in average age. This is approximately the interpretation of the coefficient on age in a regression model where age is the independent variable and the natural log of the maintenance costs is the dependent variable. When the coefficient is close to zero, the percentage change interpretation is extremely accurate. As the regression coefficient on age departs from zero the approximation breaks down and can no longer be interpreted as a percentage change. The estimated effects in this dissertation were always small enough to afford the percentage change interpretation. This section of the appendix briefly derives and reviews this interpretation.

Recall the model used throughout is $\log(y_{itr}) = \alpha + \beta * Age_{itr} + \mu_t + \delta_r$. The percent change in y is simply $\frac{\partial y}{y}$ *or* $\frac{y_1 - y_0}{y_0}$. Since $\log(y_{itr}) = \alpha + \beta * Age_{itr} + \mu_t + \delta_r$ then $y_{itr} = \exp\{\alpha + \beta * Age_{itr} + \mu_t + \delta_r\}$. So,

$$\frac{y_1 - y_0}{y_0} = \frac{\exp\{\alpha + \beta * Age_{1tr} + \mu_t + \delta_r\} - \exp\{\alpha + \beta * Age_{0tr} + \mu_t + \delta_r\}}{\exp\{\alpha + \beta * Age_{0tr} + \mu_t + \delta_r\}}$$

$$= \frac{\exp\{\alpha + \beta * Age_{1tr} + \mu_t + \delta_r\}}{\exp\{\alpha + \beta * Age_{0tr} + \mu_t + \delta_r\}} - 1$$

$$= \exp\{\beta * (Age_{1tr} - Age_{0tr})\} - 1$$

When the age increases by one year Age_{1tr}- Age_{0tr} = 1.

Therefore,

$$\frac{y_1 - y_0}{y_0} = \exp\{\beta\} - 1$$

$$\Rightarrow 100 * \frac{y_1 - y_0}{y_0} = 100 * (e^{\beta} - 1) \quad ,$$

$$\Rightarrow 100 * \frac{\partial y}{y_0} = 100 * (e^{\beta} - 1)$$

which implies the percent change in y is approximately equal to β when age increases by one and β is close to zero. For example, when β = .034, $100 * \frac{\partial y}{y_0} = 100 * (e^{0.034} - 1) = 3.46\%$.

A.3 Model Output

This appendix provides the statistical output of the referenced models in the body of this paper. The outputs are from Stata. Table A.3.1 is a key to the aircraft and airline labels.

Airline		Type					
air_dum_1	Alaska Airlines	type_dum_1	707	type_dum_11	A310	type_dum_24	DC10
air_dum_2	AmericaWest	type_dum_2	717	type_dum_12	A319	type_dum_27	DC8
air_dum_3	American	type_dum_3	720	type_dum_13	A320	type_dum_28	DC9
air_dum_4	Continental	type_dum_4	727	type_dum_14	A321	type_dum_29	F100
air_dum_5	Delta	type_dum_5	737	type_dum_15	A330	type_dum_31	L1011
air_dum_6	Northwest	type_dum_6	747	type_dum_16	BAC111	type_dum_34	L188
air_dum_7	Southwest	type_dum_7	757	type_dum_18	BAE146	type_dum_36	MD11
air_dum_9	United	type_dum_8	767	type_dum_21	CV880	type_dum_37	MD80
air_dum_10	US Airways	type_dum_9	777	type_dum_22	CV990	type_dum_38	MD90
		Type_dum_10	A300	type_dum_23	CVR580	type_dum_39	SE210
						type_dum_40	V700

Table A.3.1 Aircraft Type and Airline Labels in Output Below

The first section (A.3.1) provides the results from the estimated regressions for each age period in the maturity curves. The second section (A.3.2) provides the results from the estimated regressions for each age period in the maturity curves for airframe, engine, and burden maintenance costs. The third section (A.3.3) provides similar results for the maturity curves built with interactions and airline fixed effects. The final section (A.3.4) provides the results of the regression estimates when the short-lived fleets removed from the sample.

All the output below are from the software package Stata.

The assumptions of each model are the standard assumptions of an OLS fixed effects model[33]. The specific assumptions of concern are the assumptions that the errors are uncorrelated with age, the errors are normally distributed with mean of zero and a constant variance. The fixed effects model attempts to remove any correlation between age and the error terms due to traits related to the airline, type of aircraft, or the year. Diagnostics of the second two assumptions demonstrated that the variance of the error terms appears constant in all age periods. QQ-plots of error terms reveals that the normality assumption may be slightly weaker.

A.3.1 Total Maintenance Cost per Flight Hour as Dependent Variable

The estimated model is $\log(y_{itr}) = \alpha + \beta * Age_{itr} + \mu_t + \delta_r$, where μ_t are the aircraft type fixed effects, δ_r are the year fixed effects, *i* represents the airlines, β is the age effect, α is the intercept, and *y* is the total maintenance cost per flight hour. The fixed effects, δ_r and μ_t , are each a set of indicator variables with value 0 or 1, which have a coefficient before each. The coefficient for each indicator variable are listed in the regression outputs. For example, the type fixed effects, μ_t, are the set of indicators with

[33] Wooldridge, 2003.

the coefficients labeled type_dum_2 through type_dum_40 in the output below.

Age ≤ 6

```
reg logtotperflthr age type_dum_2-type_dum_40 y1966-y2003 if synth==0 & age<=6

      Source |       SS       df       MS              Number of obs =     359
-------------+------------------------------           F( 63,   295) =   11.25
       Model |  129.578038    63  2.05679425           Prob > F      =  0.0000
    Residual |  53.9101516   295  .182746276           R-squared     =  0.7062
-------------+------------------------------           Adj R-squared =  0.6434
       Total |   183.48819   358  .512536842           Root MSE      =  .42749

------------------------------------------------------------------------------
logtotperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .1520254   .0169867     8.95   0.000     .1185949    .1854559
  type_dum_2 |  (dropped)
  type_dum_3 |  -.1834181   .2159253    -0.85   0.396    -.6083673    .2415311
  type_dum_4 |    .188025   .1494521     1.26   0.209    -.1061024    .4821525
  type_dum_5 |   .1042732   .2078031     0.50   0.616    -.3046913    .5132377
  type_dum_6 |   1.358676   .1878177     7.23   0.000     .9890441    1.728309
  type_dum_7 |   .6075876   .2379582     2.55   0.011     .1392767    1.075898
  type_dum_8 |    .821424   .2338473     3.51   0.001     .3612036    1.281644
  type_dum_9 |   1.067786   .2502275     4.27   0.000     .5753291    1.560244
 type_dum_10 |   1.113176   .2829136     3.93   0.000     .5563914    1.669961
 type_dum_11 |   .8070161   .3017436     2.67   0.008     .2131732    1.400859
 type_dum_12 |  -.2169812   .2580517    -0.84   0.401    -.7248368    .2908744
 type_dum_13 |   .3958817   .2436541     1.62   0.105    -.0836388    .8754022
 type_dum_14 |  -.7896383   .3453463    -2.29   0.023    -1.469293   -.1099835
 type_dum_15 |   .4809608   .3094628     1.55   0.121    -.1280737    1.089995
 type_dum_16 |   .3476761   .2130635     1.63   0.104    -.0716409    .7669931
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |   .1671449   .3377289     0.49   0.621    -.4975185    .8318083
 type_dum_22 |     .62978    .282048     2.23   0.026     .0746989    1.184861
 type_dum_23 |  (dropped)
 type_dum_24 |   1.053128   .2042748     5.16   0.000      .651107    1.455148
 type_dum_25 |  (dropped)
 type_dum_26 |  (dropped)
 type_dum_27 |  -.0310058   .1839146    -0.17   0.866    -.3929566    .3309451
 type_dum_28 |  -.0639269   .1990098    -0.32   0.748    -.4555857    .3277319
 type_dum_29 |     .68704   .2885171     2.38   0.018     .1192273    1.254853
 type_dum_30 |  (dropped)
 type_dum_31 |   1.358532   .2269826     5.99   0.000     .9118213    1.805242
 type_dum_32 |  (dropped)
 type_dum_33 |  (dropped)
 type_dum_34 |  (dropped)
 type_dum_35 |  (dropped)
 type_dum_36 |    1.25247   .2561935     4.89   0.000     .7482713    1.756669
 type_dum_37 |   .0125561   .2589253     0.05   0.961    -.4970188     .522131
 type_dum_38 |   .7244682   .2755445     2.63   0.009     .1821862     1.26675
 type_dum_39 |  -.1224373   .3370399    -0.36   0.717    -.7857446      .54087
 type_dum_40 |  (dropped)
       y1966 |   -.179226    .163328    -1.10   0.273    -.5006618    .1422097
       y1967 |   -.236718   .1833606    -1.29   0.198    -.5975787    .1241428
       y1968 |  -.2776665   .1953957    -1.42   0.156    -.6622127    .1068797
       y1969 |  -.3747327   .1964732    -1.91   0.057    -.7613995     .011934
       y1970 |  -.4851141   .2013446    -2.41   0.017    -.8813678   -.0888603
       y1971 |  -.6854073   .2103557    -3.26   0.001    -1.099395   -.2714194
       y1972 |  -.6700233   .2190438    -3.06   0.002     -1.10111   -.2389367
       y1973 |  -.7671785   .2266709    -3.38   0.001    -1.213275   -.3210817
       y1974 |  -.6337951   .2320215    -2.73   0.007    -1.090422    -.177168
       y1975 |  -.7646594   .2429629    -3.15   0.002     -1.24282   -.2864992
       y1976 |  -.8505968   .2473012    -3.44   0.001    -1.337295   -.3638986
       y1977 |  -.9001101   .2764286    -3.26   0.001    -1.444132   -.3560881
       y1978 |  -1.068003    .291541    -3.66   0.000    -1.641766   -.4942387
       y1979 |  -1.063005   .3563914    -2.98   0.003    -1.764397    -.361613
       y1980 |  -1.144321   .3581303    -3.20   0.002    -1.849135   -.4395068
       y1981 |  -1.276831   .4945925    -2.58   0.010    -2.250208   -.3034542
       y1982 |  -1.105385    .372466    -2.97   0.003    -1.838413   -.3723581
       y1983 |   -1.26508   .3466295    -3.65   0.000     -1.94726      -.5829
       y1984 |  -1.276205   .2897241    -4.40   0.000    -1.846394   -.7060174
```

```
       y1985 |  (dropped)
       y1986 |  -1.238003   .2714261    -4.56   0.000     -1.77218   -.7038263
       y1987 |  -1.162129   .2810452    -4.14   0.000    -1.715237   -.6090219
       y1988 |  -1.262834   .2797971    -4.51   0.000    -1.813485   -.7121821
       y1989 |  -1.330083   .2713923    -4.90   0.000    -1.864194   -.7959731
       y1990 |  -1.255574   .2800928    -4.48   0.000    -1.806807   -.7043405
       y1991 |  -1.090405   .2700834    -4.04   0.000    -1.621939   -.5588703
       y1992 |  -1.238165   .2647694    -4.68   0.000    -1.759242   -.7170891
       y1993 |  -1.277326   .2712239    -4.71   0.000    -1.811105    -.743547
       y1994 |  -1.171733   .2819616    -4.16   0.000    -1.726645   -.6168222
       y1995 |  -1.303406   .2772298    -4.70   0.000    -1.849005   -.7578072
       y1996 |   -1.40351   .2879436    -4.87   0.000    -1.970194   -.8368263
       y1997 |  -1.317035   .2956644    -4.45   0.000    -1.898914   -.7351563
       y1998 |  -1.613473   .2868045    -5.63   0.000    -2.177915   -1.049031
       y1999 |   -1.22382   .2644652    -4.63   0.000    -1.744297   -.7033421
       y2000 |  -1.155318   .2671015    -4.33   0.000    -1.680984   -.6296525
       y2001 |   -1.12749   .2641957    -4.27   0.000    -1.647437   -.6075426
       y2002 |  -1.071134   .2697367    -3.97   0.000    -1.601986   -.5402815
       y2003 |   -.927218   .2638714    -3.51   0.001    -1.446527    -.407909
       _cons |  -.6030767    .174772    -3.45   0.001    -.9470347   -.2591187
------------------------------------------------------------------------------
```

<u>6 < Age ≤ 12</u>

```
. reg logtotperflthr age type_dum_2-type_dum_40 y1966-y2003 if synth==0 & age>6 & age<=12

      Source |       SS       df       MS              Number of obs =     349
-------------+------------------------------           F( 58,   290) =   23.84
       Model |  53.2013965    58  .917265456           Prob > F      =  0.0000
    Residual |  11.1578031   290  .038475183           R-squared     =  0.8266
-------------+------------------------------           Adj R-squared =  0.7920
       Total |  64.3591995   348  .184940229           Root MSE      =  .19615

------------------------------------------------------------------------------
logtotperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |    .035247   .0080315     4.39   0.000     .0194396    .0510545
  type_dum_2 |  (dropped)
  type_dum_3 |  -.1777469   .1030815    -1.72   0.086    -.3806296    .0251358
  type_dum_4 |  -.2583198   .0684604    -3.77   0.000    -.3930619   -.1235776
  type_dum_5 |  -.0674878   .0844864    -0.80   0.425    -.2337722    .0987965
  type_dum_6 |   .9767042   .0777289    12.57   0.000       .82372    1.129688
  type_dum_7 |   .2564413   .0909336     2.82   0.005     .0774679    .4354148
  type_dum_8 |    .359547   .0917214     3.92   0.000     .1790229    .5400711
  type_dum_9 |  (dropped)
 type_dum_10 |   .9644518    .118965     8.11   0.000     .7303076    1.198596
 type_dum_11 |  (dropped)
 type_dum_12 |  (dropped)
 type_dum_13 |   .0714602   .1093396     0.65   0.514    -.1437396    .2866599
 type_dum_14 |  (dropped)
 type_dum_15 |  (dropped)
 type_dum_16 |  (dropped)
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |   .1946102   .1237722     1.57   0.117    -.0489954    .4382159
 type_dum_22 |  (dropped)
 type_dum_23 |  (dropped)
 type_dum_24 |   .7127547   .0861256     8.28   0.000     .5432442    .8822651
 type_dum_25 |  (dropped)
 type_dum_26 |  (dropped)
 type_dum_27 |  -.0289882   .0783264    -0.37   0.712    -.1831485     .125172
 type_dum_28 |  -.4175196   .0951778    -4.39   0.000    -.6048464   -.2301929
 type_dum_29 |  -.2492503   .1652749    -1.51   0.133    -.5745407    .0760401
 type_dum_30 |  (dropped)
 type_dum_31 |   .6194062   .1079211     5.74   0.000     .4069982    .8318141
 type_dum_32 |  (dropped)
 type_dum_33 |  (dropped)
 type_dum_34 |  -.1271137   .1380701    -0.92   0.358    -.3988602    .1446327
 type_dum_35 |  (dropped)
 type_dum_36 |   .6641131   .1155114     5.75   0.000     .4367662    .8914601
 type_dum_37 |  -.0034889   .0928882    -0.04   0.970    -.1863093    .1793316
 type_dum_38 |   .3191898   .1467504     2.18   0.030     .0303588    .6080208
 type_dum_39 |  -.1387001   .1452385    -0.95   0.340    -.4245552     .147155
 type_dum_40 |  -.6207927   .1892237    -3.28   0.001    -.9932186   -.2483668
       y1966 |   .0276709   .1603578     0.17   0.863    -.2879418    .3432836
       y1967 |   .1578358    .146538     1.08   0.282    -.1305771    .4462486
       y1968 |   .0567883   .1550927     0.37   0.715    -.2484618    .3620383
```

```
        y1969 |   .0016787   .1635543     0.01   0.992    -.3202252    .3235826
        y1970 |   .0573885   .1626995     0.35   0.725    -.2628331      .37761
        y1971 |  -.1100051   .1748201    -0.63   0.530    -.4540821    .2340719
        y1972 |  -.2331197   .1778448    -1.31   0.191      -.58315    .1169105
        y1973 |  -.1169257   .1865148    -0.63   0.531      -.48402    .2501686
        y1974 |  -.0922038   .1921125    -0.48   0.632    -.4703154    .2859079
        y1975 |  -.1448726   .1944118    -0.75   0.457    -.5275096    .2377644
        y1976 |  -.1630714    .196962    -0.83   0.408    -.5507276    .2245848
        y1977 |   -.183115   .1985699    -0.92   0.357    -.5739359    .2077058
        y1978 |  -.2652678   .2000392    -1.33   0.186    -.6589804    .1284449
        y1979 |   -.366239   .2006108    -1.83   0.069    -.7610767    .0285986
        y1980 |  -.3152832   .2021804    -1.56   0.120    -.7132102    .0826439
        y1981 |   -.343458   .2026759    -1.69   0.091    -.7423602    .0554441
        y1982 |  -.5289319   .2060509    -2.57   0.011    -.9344767   -.1233871
        y1983 |  -.4789755   .2071951    -2.31   0.021    -.8867724   -.0711786
        y1984 |  -.5528463   .2152064    -2.57   0.011    -.9764108   -.1292818
        y1985 |  (dropped)
        y1986 |  -.5316973   .2223493    -2.39   0.017    -.9693203   -.0940742
        y1987 |  -.4358219   .2141068    -2.04   0.043    -.8572221   -.0144217
        y1988 |  -.4715845   .2126652    -2.22   0.027    -.8901474   -.0530216
        y1989 |  -.3970374   .2129556    -1.86   0.063    -.8161719     .022097
        y1990 |  -.3579971   .2120462    -1.69   0.092    -.7753418    .0593476
        y1991 |  -.3384942   .2173246    -1.56   0.120    -.7662276    .0892392
        y1992 |  -.5726609   .2218021    -2.58   0.010    -1.009207    -.136115
        y1993 |  -.5755859   .2242876    -2.57   0.011    -1.017024   -.1341481
        y1994 |   -.693964   .2097768    -3.31   0.001    -1.106842   -.2810859
        y1995 |   -.687401   .2098076    -3.28   0.001     -1.10034   -.2744624
        y1996 |  -.6974299   .2094237    -3.33   0.001    -1.109613   -.2852468
        y1997 |  -.6449764    .210843    -3.06   0.002    -1.059953   -.2299999
        y1998 |   -.631315   .2051501    -3.08   0.002    -1.035087    -.227543
        y1999 |  -.5934662   .2059775    -2.88   0.004    -.9988666   -.1880658
        y2000 |  -.4702716   .2064084    -2.28   0.023    -.8765201    -.064023
        y2001 |  -.3216325   .2064123    -1.56   0.120    -.7278885    .0846235
        y2002 |  -.3452757   .2082476    -1.66   0.098    -.7551439    .0645926
        y2003 |  -.4879048    .209962    -2.32   0.021    -.9011475   -.0746622
        _cons |  -.3553688   .1750887    -2.03   0.043    -.6999744   -.0107632
------------------------------------------------------------------------------
```

12 < Age

```
. reg logtotperflthr age type_dum_2-type_dum_40 y1966-y2003 if synth==0 & age>12

      Source |       SS       df       MS              Number of obs =     299
-------------+------------------------------           F( 40,   258) =   18.86
       Model |  45.7061516    40  1.14265379           Prob > F      =  0.0000
    Residual |  15.6281927   258   .06057439           R-squared     =  0.7452
-------------+------------------------------           Adj R-squared =  0.7057
       Total |  61.3343442   298  .205819947           Root MSE      =  .24612

------------------------------------------------------------------------------
logtotperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .0071536   .0071532     1.00   0.318    -.0069324    .0212397
  type_dum_2 |  (dropped)
  type_dum_3 |  (dropped)
  type_dum_4 |   .0200957   .1755294     0.11   0.909    -.3255571    .3657484
  type_dum_5 |   .0569096   .1823209     0.31   0.755    -.3021169    .4159362
  type_dum_6 |   .8450021   .1818079     4.65   0.000     .4869857    1.203018
  type_dum_7 |   .3792005   .2107728     1.80   0.073    -.0358534    .7942545
  type_dum_8 |   .2187794   .2192114     1.00   0.319     -.212892    .6504508
  type_dum_9 |  (dropped)
 type_dum_10 |   .7929224   .2408886     3.29   0.001     .3185644     1.26728
 type_dum_11 |  (dropped)
 type_dum_12 |  (dropped)
 type_dum_13 |  (dropped)
 type_dum_14 |  (dropped)
 type_dum_15 |  (dropped)
 type_dum_16 |  (dropped)
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |   .5565875    .348066     1.60   0.111    -.1288245    1.241999
 type_dum_22 |  (dropped)
 type_dum_23 |  -.0726067   .2510236    -0.29   0.773    -.5669227    .4217092
 type_dum_24 |   .8165709   .1759106     4.64   0.000     .4701676    1.162974
 type_dum_25 |  (dropped)
 type_dum_26 |  (dropped)
 type_dum_27 |   .2934111    .166963     1.76   0.080    -.0353727    .6221948
 type_dum_28 |  -.2273257   .1776425    -1.28   0.202    -.5771395    .1224882
```

type_dum_29	(dropped)					
type_dum_30	(dropped)					
type_dum_31	.5131647	.1906565	2.69	0.008	.1377236	.8886058
type_dum_32	(dropped)					
type_dum_33	(dropped)					
type_dum_34	(dropped)					
type_dum_35	(dropped)					
type_dum_36	(dropped)					
type_dum_37	.0107727	.1905487	0.06	0.955	-.364456	.3860013
type_dum_38	(dropped)					
type_dum_39	(dropped)					
type_dum_40	(dropped)					
y1966	(dropped)					
y1967	(dropped)					
y1968	(dropped)					
y1969	(dropped)					
y1970	(dropped)					
y1971	(dropped)					
y1972	(dropped)					
y1973	(dropped)					
y1974	(dropped)					
y1975	(dropped)					
y1976	(dropped)					
y1977	.4696218	.3445293	1.36	0.174	-.2088257	1.148069
y1978	.4062433	.3445018	1.18	0.239	-.2721501	1.084637
y1979	.5137359	.3051322	1.68	0.093	-.0871308	1.114603
y1980	.5007726	.3022149	1.66	0.099	-.0943493	1.095895
y1981	.4229993	.3007513	1.41	0.161	-.1692405	1.015239
y1982	.3243331	.3178035	1.02	0.308	-.3014859	.9501521
y1983	.1961327	.3158383	0.62	0.535	-.4258164	.8180818
y1984	.1364632	.3123723	0.44	0.663	-.4786607	.7515872
y1985	(dropped)					
y1986	.2675771	.3084798	0.87	0.387	-.3398817	.875036
y1987	.2532959	.3079489	0.82	0.412	-.3531175	.8597094
y1988	.2554133	.3089296	0.83	0.409	-.3529313	.863758
y1989	.3831108	.3111354	1.23	0.219	-.2295775	.9957991
y1990	.4217487	.3118607	1.35	0.177	-.1923678	1.035865
y1991	.467859	.3107548	1.51	0.133	-.1440797	1.079798
y1992	.4248003	.3122049	1.36	0.175	-.1899939	1.039595
y1993	.3279236	.3140178	1.04	0.297	-.2904407	.9462879
y1994	.3162355	.3132528	1.01	0.314	-.3006224	.9330934
y1995	.3276797	.31429	1.04	0.298	-.2912206	.9465799
y1996	.3713337	.3154902	1.18	0.240	-.2499301	.9925975
y1997	.3803769	.3153746	1.21	0.229	-.2406592	1.001413
y1998	.5410602	.3151575	1.72	0.087	-.0795484	1.161669
y1999	.5059551	.316364	1.60	0.111	-.1170294	1.12894
y2000	.5353239	.3176017	1.69	0.093	-.0900978	1.160746
y2001	.5583278	.318293	1.75	0.081	-.0684552	1.185111
y2002	.4559103	.3197419	1.43	0.155	-.173726	1.085546
y2003	.5051926	.3198934	1.58	0.116	-.1247419	1.135127
_cons	-.7967546	.2609895	-3.05	0.003	-1.310695	-.2828138

A.3.2 Airframe, Engine, and Burden Maintenance Costs per Flight Hour as Dependent Variables

The estimated model for the Engine and Burden costs is $\log(y_{itr}) = \alpha + \beta * Age_{itr} + \mu_t + \delta_r$, where μ_t are the aircraft type fixed effects, δ_r are the year fixed effects, *i* represents the airlines, β is the age effect, α is the intercept, and y is the total ENGINE or BURDEN Maintenance cost per flight hour.

The estimated model for the Airframe costs is $\log(y_{itr}) = \alpha + \beta * Age_{itr} + \mu_t + \tau_i$, where μ_t are the aircraft type fixed effects, τ_i are the airline fixed effects, *i* represents the airlines, β is the age effect, α is the intercept, and *y* is the total AIRFRAME Maintenance cost per flight hour.

A.3.2.1 AIFRAME Costs

<u>Age ≤ 6</u>

```
. reg logairperflthr age type_dum_2-type_dum_40 air_dum_2-air_dum_11 if synth==0 & age<=6

      Source |       SS       df       MS              Number of obs =     359
-------------+------------------------------           F( 32,   326) =   19.58
       Model |  88.8854081    32    2.777669           Prob > F      =  0.0000
    Residual |  46.2444324   326  .141854087           R-squared     =  0.6578
-------------+------------------------------           Adj R-squared =  0.6242
       Total |  135.129841   358  .377457655           Root MSE      =  .37664

------------------------------------------------------------------------------
logairperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .0609867   .0127606     4.78   0.000     .0358831    .0860902
  type_dum_2 |  (dropped)
  type_dum_3 |   .0222078   .1781828     0.12   0.901    -.3283254     .372741
  type_dum_4 |  -.1834154   .1265938    -1.45   0.148    -.4324592    .0656285
  type_dum_5 |  -.7585884   .1433728    -5.29   0.000    -1.040641   -.4765358
  type_dum_6 |   .6787458   .1339675     5.07   0.000     .4151959    .9422956
  type_dum_7 |  -.5366939   .1262942    -4.25   0.000    -.7851483   -.2882396
  type_dum_8 |  -.1064103   .1309731    -0.81   0.417    -.3640694    .1512488
  type_dum_9 |   .0140899   .1388025     0.10   0.919    -.2589718    .2871515
 type_dum_10 |   .4073412   .1816904     2.24   0.026     .0499075    .7647748
 type_dum_11 |   .3494449   .2083458     1.68   0.094     -.060427    .7593168
 type_dum_12 |  -1.027144   .1540994    -6.67   0.000    -1.330298   -.7239888
 type_dum_13 |  -.4780024   .1359426    -3.52   0.000    -.7454379   -.2105669
 type_dum_14 |  -1.416627   .2764124    -5.13   0.000    -1.960404     -.87285
 type_dum_15 |    .234253   .2272164     1.03   0.303    -.2127424    .6812485
 type_dum_16 |   .0957603   .1904703     0.50   0.615    -.2789457    .4704663
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |   .4528781   .2935765     1.54   0.124    -.1246654    1.030422
 type_dum_22 |   .4819749     .24484     1.97   0.050     .0003091    .9636408
 type_dum_23 |  (dropped)
 type_dum_24 |   .3585201   .1353188     2.65   0.008     .0923117    .6247284
 type_dum_25 |  (dropped)
 type_dum_26 |  (dropped)
 type_dum_27 |  -.0381801   .1667492    -0.23   0.819    -.3662204    .2898603
 type_dum_28 |  -.2752276    .181755    -1.51   0.131    -.6327883    .0823331
 type_dum_29 |  -.1538417   .1821118    -0.84   0.399    -.5121043    .2044208
 type_dum_30 |  (dropped)
 type_dum_31 |   .5187208   .1657773     3.13   0.002     .1925926     .844849
 type_dum_32 |  (dropped)
 type_dum_33 |  (dropped)
 type_dum_34 |  (dropped)
 type_dum_35 |  (dropped)
 type_dum_36 |   .2239803   .1456501     1.54   0.125    -.0625524     .510513
 type_dum_37 |  -.7417202   .1582996    -4.69   0.000    -1.053138   -.4303026
 type_dum_38 |  -.2440075    .170933    -1.43   0.154    -.5802785    .0922635
 type_dum_39 |  -.2385007   .2922193    -0.82   0.415    -.8133742    .3363728
 type_dum_40 |  (dropped)
   air_dum_2 |   .3628116   .2070957     1.75   0.081    -.0446012    .7702243
   air_dum_3 |   -.159188   .1135012    -1.40   0.162    -.3824753    .0640993
```

```
    air_dum_4 |  (dropped)
    air_dum_5 |  -.3010004   .1143565    -2.63   0.009    -.5259702   -.0760307
    air_dum_6 |  -.4252403   .1226638    -3.47   0.001    -.6665529   -.1839278
    air_dum_7 |  (dropped)
    air_dum_8 |  (dropped)
    air_dum_9 |  -.0277676   .1124382    -0.25   0.805    -.2489635    .1934284
   air_dum_10 |  -.3283926   .1720315    -1.91   0.057    -.6668245    .0100394
   air_dum_11 |  (dropped)
        _cons |  -1.436504   .1615929    -8.89   0.000      -1.7544   -1.118607
------------------------------------------------------------------------------
```

<u>6 < Age ≤ 12</u>

```
. reg logairperflthr age type_dum_2-type_dum_40 air_dum_2-air_dum_11 if synth==0 & age>6
& age<=12

      Source |       SS       df       MS              Number of obs =     349
-------------+------------------------------           F( 29,   319) =   28.11
       Model |  53.8541639    29  1.85704014           Prob > F      =  0.0000
    Residual |  21.0742754   319  .066063559           R-squared     =  0.7187
-------------+------------------------------           Adj R-squared =  0.6932
       Total |  74.9284393   348  .215311607           Root MSE      =  .25703

------------------------------------------------------------------------------
logairperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .0225745    .008801     2.56   0.011     .0052591    .0398899
  type_dum_2 |  (dropped)
  type_dum_3 |   .2446183   .0939873     2.60   0.010     .0597051    .4295316
  type_dum_4 |   -.178525   .0810716    -2.20   0.028    -.3380275   -.0190224
  type_dum_5 |   .0942023   .0891168     1.06   0.291    -.0811286    .2695331
  type_dum_6 |   .9583642   .0826867    11.59   0.000      .795684    1.121044
  type_dum_7 |  -.0348793   .0829889    -0.42   0.675     -.198154    .1283953
  type_dum_8 |   .3168677   .0866066     3.66   0.000     .1464755    .4872599
  type_dum_9 |  (dropped)
 type_dum_10 |   .8774693   .1268785     6.92   0.000     .6278449    1.127094
 type_dum_11 |  (dropped)
 type_dum_12 |  (dropped)
 type_dum_13 |   .0471914   .1231441     0.38   0.702    -.1950858    .2894685
 type_dum_14 |  (dropped)
 type_dum_15 |  (dropped)
 type_dum_16 |  (dropped)
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |   .7064722   .1337911     5.28   0.000     .4432478    .9696966
 type_dum_22 |  (dropped)
 type_dum_23 |  (dropped)
 type_dum_24 |   .5595962   .0899083     6.22   0.000     .3827081    .7364844
 type_dum_25 |  (dropped)
 type_dum_26 |  (dropped)
 type_dum_27 |   .2990043   .1039848     2.88   0.004     .0944216    .5035869
 type_dum_28 |   .1038207   .1277313     0.81   0.417    -.1474814    .3551228
 type_dum_29 |  -.2733577   .1959387    -1.40   0.164    -.6588531    .1121378
 type_dum_30 |  (dropped)
 type_dum_31 |   .9313501   .1208195     7.71   0.000     .6936464    1.169054
 type_dum_32 |  (dropped)
 type_dum_33 |  (dropped)
 type_dum_34 |   .5005767   .1067543     4.69   0.000     .2905454    .7106081
 type_dum_35 |  (dropped)
 type_dum_36 |   .7507331   .1222465     6.14   0.000     .5102219    .9912443
 type_dum_37 |  -.0227113   .0911203    -0.25   0.803    -.2019839    .1565613
 type_dum_38 |   .6521061   .1704478     3.83   0.000     .3167624    .9874498
 type_dum_39 |   .3045867   .1514921     2.01   0.045      .006537    .6026365
 type_dum_40 |   .0161189   .1689625     0.10   0.924    -.3163028    .3485406
   air_dum_2 |   .0452159   .1670818     0.27   0.787    -.2835055    .3739372
   air_dum_3 |  -.4103347   .0923364    -4.44   0.000        -.592   -.2286694
   air_dum_4 |  -.4678904   .1343182    -3.48   0.001    -.7321518   -.2036289
   air_dum_5 |  -.7361227   .0900208    -8.18   0.000    -.9132321   -.5590133
   air_dum_6 |  -.6597005   .0933907    -7.06   0.000      -.84344    -.475961
   air_dum_7 |  -.1754796   .1345202    -1.30   0.193    -.4401385    .0891792
   air_dum_8 |  (dropped)
   air_dum_9 |   -.497672   .0911019    -5.46   0.000    -.6769085   -.3184356
  air_dum_10 |  -.3623962   .1309391    -2.77   0.006    -.6200096   -.1047829
  air_dum_11 |  (dropped)
       _cons |  -1.291094    .133523    -9.67   0.000    -1.553791   -1.028398
------------------------------------------------------------------------------
```

12 < Age

```
. reg logairperflthr age type_dum_2-type_dum_40 air_dum_2-air_dum_11 if synth==0 & age>12

      Source |       SS       df       MS              Number of obs =     299
-------------+------------------------------           F( 22,   276) =   19.95
       Model |  41.0455213    22  1.86570551           Prob > F      =  0.0000
    Residual |  25.8129466   276  .093525169           R-squared     =  0.6139
-------------+------------------------------           Adj R-squared =  0.5831
       Total |  66.8584679   298  .224357275           Root MSE      =  .30582

------------------------------------------------------------------------------
logairperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .0312945   .0058054     5.39   0.000      .019866    .0427229
  type_dum_2 |  (dropped)
  type_dum_3 |  (dropped)
  type_dum_4 |   .1489375   .1873589     0.79   0.427    -.2198966    .5177716
  type_dum_5 |   .1576353    .193186     0.82   0.415    -.2226699    .5379405
  type_dum_6 |   .7725564   .1907803     4.05   0.000      .396987    1.148126
  type_dum_7 |   .3300024   .2354517     1.40   0.162    -.1335069    .7935117
  type_dum_8 |   .4526007   .2236447     2.02   0.044     .0123346    .8928669
  type_dum_9 |  (dropped)
 type_dum_10 |   1.054635   .2497038     4.22   0.000     .5630692    1.546201
 type_dum_11 |  (dropped)
 type_dum_12 |  (dropped)
 type_dum_13 |  (dropped)
 type_dum_14 |  (dropped)
 type_dum_15 |  (dropped)
 type_dum_16 |  (dropped)
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |   .3441019   .3604587     0.95   0.341    -.3654958      1.0537
 type_dum_22 |  (dropped)
 type_dum_23 |  -.0951103    .276661    -0.34   0.731    -.6397441    .4495235
 type_dum_24 |   .8017834   .1885571     4.25   0.000     .4305907    1.172976
 type_dum_25 |  (dropped)
 type_dum_26 |  (dropped)
 type_dum_27 |   .3112774   .1971161     1.58   0.115    -.0767647    .6993195
 type_dum_28 |  -.0427332   .2003789    -0.21   0.831    -.4371983    .3517319
 type_dum_29 |  (dropped)
 type_dum_30 |  (dropped)
 type_dum_31 |   .8012958   .2149662     3.73   0.000     .3781142    1.224477
 type_dum_32 |  (dropped)
 type_dum_33 |  (dropped)
 type_dum_34 |  (dropped)
 type_dum_35 |  (dropped)
 type_dum_36 |  (dropped)
 type_dum_37 |    .085181   .1945802     0.44   0.662    -.2978689    .4682309
 type_dum_38 |  (dropped)
 type_dum_39 |  (dropped)
 type_dum_40 |  -.1606523   .3583258    -0.45   0.654    -.8660511    .5447466
   air_dum_2 |   .4861191   .3378794     1.44   0.151     -.179029    1.151267
   air_dum_3 |  -.1322834   .3167146    -0.42   0.677    -.7557666    .4911998
   air_dum_4 |   .2927466   .3213425     0.91   0.363     -.339847    .9253403
   air_dum_5 |  -.2423148   .3181731    -0.76   0.447    -.8686692    .3840395
   air_dum_6 |  -.3405401   .3159549    -1.08   0.282    -.9625277    .2814474
   air_dum_7 |  (dropped)
   air_dum_8 |  (dropped)
   air_dum_9 |  -.1239246   .3170302    -0.39   0.696     -.748029    .5001799
  air_dum_10 |  -.0678278   .3240181    -0.21   0.834    -.7056887    .5700331
  air_dum_11 |  (dropped)
       _cons |  -1.822293    .368646    -4.94   0.000    -2.548008   -1.096578
------------------------------------------------------------------------------
```

A.3.2.2 ENGINE Costs

Age ≤ 6

```
. reg logengperflthr age type_dum_2-type_dum_40 y1966-y2003 if synth==0 & age<=6

      Source |       SS       df       MS              Number of obs =     359
-------------+------------------------------           F( 63,   295) =    9.65
```

Source	SS	df	MS			
Model	346.293794	63	5.49672688	Prob > F	=	0.0000
Residual	167.952983	295	.569332144	R-squared	=	0.6734
				Adj R-squared	=	0.6037
Total	514.246776	358	1.43644351	Root MSE	=	.75454

logengperf~r	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age	.3842729	.0299825	12.82	0.000	.3252662	.4432796
type_dum_2	(dropped)					
type_dum_3	-.8163739	.3811203	-2.14	0.033	-1.566433	-.0663146
type_dum_4	.6035849	.2637914	2.29	0.023	.0844334	1.122736
type_dum_5	.4490682	.3667843	1.22	0.222	-.2727771	1.170914
type_dum_6	2.56628	.3315088	7.74	0.000	1.913858	3.218702
type_dum_7	1.276406	.4200097	3.04	0.003	.4498106	2.103001
type_dum_8	1.101971	.4127536	2.67	0.008	.289656	1.914286
type_dum_9	1.842187	.4416657	4.17	0.000	.9729724	2.711402
type_dum_10	1.794233	.4993585	3.59	0.000	.8114768	2.77699
type_dum_11	1.397111	.5325945	2.62	0.009	.348945	2.445278
type_dum_12	.3216345	.4554758	0.71	0.481	-.5747592	1.218028
type_dum_13	1.072235	.4300632	2.49	0.013	.2258543	1.918616
type_dum_14	.4910625	.6095558	0.81	0.421	-.7085665	1.690691
type_dum_15	1.019742	.5462193	1.87	0.063	-.0552379	2.094723
type_dum_16	.2329673	.376069	0.62	0.536	-.5071508	.9730854
type_dum_17	(dropped)					
type_dum_18	(dropped)					
type_dum_19	(dropped)					
type_dum_20	(dropped)					
type_dum_21	-.4342732	.5961106	-0.73	0.467	-1.607442	.7388952
type_dum_22	.1291567	.4978306	0.26	0.795	-.8505928	1.108906
type_dum_23	(dropped)					
type_dum_24	2.254716	.3605565	6.25	0.000	1.545127	2.964305
type_dum_25	(dropped)					
type_dum_26	(dropped)					
type_dum_27	-.5902671	.3246196	-1.82	0.070	-1.229131	.0485965
type_dum_28	.1646259	.3512635	0.47	0.640	-.526674	.8559257
type_dum_29	1.097906	.509249	2.16	0.032	.095685	2.100128
type_dum_30	(dropped)					
type_dum_31	2.17372	.4006371	5.43	0.000	1.385251	2.962189
type_dum_32	(dropped)					
type_dum_33	(dropped)					
type_dum_34	(dropped)					
type_dum_35	(dropped)					
type_dum_36	2.13872	.452196	4.73	0.000	1.248781	3.028659
type_dum_37	.2950311	.4570178	0.65	0.519	-.6043974	1.19446
type_dum_38	2.10859	.4863516	4.34	0.000	1.151432	3.065749
type_dum_39	-.7848351	.5948944	-1.32	0.188	-1.95561	.3859397
type_dum_40	(dropped)					
y1966	-.3827859	.2882832	-1.33	0.185	-.9501381	.1845664
y1967	-.5713316	.3236419	-1.77	0.079	-1.208271	.0656079
y1968	-.8681337	.3448845	-2.52	0.012	-1.546879	-.189388
y1969	-1.00974	.3467863	-2.91	0.004	-1.692228	-.327251
y1970	-1.454432	.3553845	-4.09	0.000	-2.153843	-.755022
y1971	-1.843201	.3712896	-4.96	0.000	-2.573913	-1.112488
y1972	-1.974195	.3866247	-5.11	0.000	-2.735088	-1.213303
y1973	-2.115783	.4000868	-5.29	0.000	-2.903169	-1.328397
y1974	-1.996584	.409531	-4.88	0.000	-2.802556	-1.190611
y1975	-1.987182	.4288432	-4.63	0.000	-2.831161	-1.143202
y1976	-2.486259	.4365006	-5.70	0.000	-3.345309	-1.627209
y1977	-2.421043	.4879121	-4.96	0.000	-3.381272	-1.460813
y1978	-2.721582	.5145863	-5.29	0.000	-3.734308	-1.708857
y1979	-2.696316	.6290509	-4.29	0.000	-3.934312	-1.45832
y1980	-2.707553	.6321201	-4.28	0.000	-3.95159	-1.463517
y1981	-2.962619	.8729836	-3.39	0.001	-4.680684	-1.244554
y1982	-3.024344	.6574235	-4.60	0.000	-4.318179	-1.73051
y1983	-3.189045	.6118206	-5.21	0.000	-4.393131	-1.984959
y1984	-2.576566	.5113794	-5.04	0.000	-3.58298	-1.570152
y1985	(dropped)					
y1986	-2.285119	.4790824	-4.77	0.000	-3.227971	-1.342267
y1987	-2.012156	.4960605	-4.06	0.000	-2.988422	-1.03589
y1988	-1.922029	.4938577	-3.89	0.000	-2.89396	-.9500982
y1989	-2.521466	.4790227	-5.26	0.000	-3.464201	-1.578731
y1990	-2.512829	.4943796	-5.08	0.000	-3.485787	-1.539871
y1991	-2.153572	.4767124	-4.52	0.000	-3.09176	-1.215384
y1992	-2.601602	.4673329	-5.57	0.000	-3.521331	-1.681873
y1993	-2.5799	.4787255	-5.39	0.000	-3.52205	-1.63775
y1994	-2.487044	.4976781	-5.00	0.000	-3.466493	-1.507595
y1995	-2.731979	.4893262	-5.58	0.000	-3.694992	-1.768967
y1996	-3.11837	.5082366	-6.14	0.000	-4.118599	-2.118141
y1997	-3.190798	.5218643	-6.11	0.000	-4.217846	-2.163749
y1998	-3.396552	.5062261	-6.71	0.000	-4.392824	-2.400279

```
       y1999 |  -2.665607    .466796    -5.71   0.000    -3.584279   -1.746935
       y2000 |  -2.550513   .4714492    -5.41   0.000    -3.478343   -1.622684
       y2001 |  -2.531922   .4663203    -5.43   0.000    -3.449658   -1.614186
       y2002 |  -2.574269   .4761004    -5.41   0.000    -3.511253   -1.637285
       y2003 |  -2.516717    .465748    -5.40   0.000    -3.433327   -1.600107
       _cons |  -2.182874   .3084825    -7.08   0.000    -2.789979   -1.575769
------------------------------------------------------------------------------
```

6 < Age ≤ 12

```
. reg logengperflthr age type_dum_2-type_dum_40 y1966-y2003 if synth==0 & age>6 & age<=12

      Source |       SS       df       MS              Number of obs =     349
-------------+------------------------------           F( 58,   290) =   17.79
       Model |  126.320056    58  2.17793201           Prob > F      =  0.0000
    Residual |  35.4992546   290  .122411223           R-squared     =  0.7806
-------------+------------------------------           Adj R-squared =  0.7367
       Total |  161.819311   348   .46499802           Root MSE      =  .34987

------------------------------------------------------------------------------
logengperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |     .02163   .0143258     1.51   0.132    -.0065656    .0498256
  type_dum_2 |  (dropped)
  type_dum_3 |  -.2101143   .1838658    -1.14   0.254    -.5719949    .1517662
  type_dum_4 |  -.4409623   .1221123    -3.61   0.000     -.681301   -.2006235
  type_dum_5 |   -.244159   .1506979    -1.62   0.106    -.5407594    .0524413
  type_dum_6 |    1.22911   .1386445     8.87   0.000      .956233    1.501987
  type_dum_7 |   .8874642   .1621976     5.47   0.000     .5682304    1.206698
  type_dum_8 |   .5746838    .163603     3.51   0.001     .2526841    .8966835
  type_dum_9 |  (dropped)
 type_dum_10 |    1.39725   .2121971     6.58   0.000     .9796088    1.814892
 type_dum_11 |  (dropped)
 type_dum_12 |  (dropped)
 type_dum_13 |   .6896888   .1950283     3.54   0.000     .3058383    1.073539
 type_dum_14 |  (dropped)
 type_dum_15 |  (dropped)
 type_dum_16 |  (dropped)
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |   .2864735   .2207716     1.30   0.195    -.1480443    .7209913
 type_dum_22 |  (dropped)
 type_dum_23 |  (dropped)
 type_dum_24 |   .9358468   .1536216     6.09   0.000     .6334921    1.238202
 type_dum_25 |  (dropped)
 type_dum_26 |  (dropped)
 type_dum_27 |  -.2864925   .1397103    -2.05   0.041    -.5614671   -.0115178
 type_dum_28 |  -1.222932    .169768    -7.20   0.000    -1.557066   -.8887987
 type_dum_29 |   -.295688   .2947998    -1.00   0.317    -.8759064    .2845305
 type_dum_30 |  (dropped)
 type_dum_31 |   .2176314   .1924982     1.13   0.259    -.1612394    .5965021
 type_dum_32 |  (dropped)
 type_dum_33 |  (dropped)
 type_dum_34 |   .2261477   .2462747     0.92   0.359    -.2585648    .7108601
 type_dum_35 |  (dropped)
 type_dum_36 |   1.428158   .2060369     6.93   0.000     1.022641    1.833675
 type_dum_37 |   .1978629    .165684     1.19   0.233    -.1282328    .5239586
 type_dum_38 |    .827436   .2617578     3.16   0.002       .31225    1.342622
 type_dum_39 |  -.3943428   .2590609    -1.52   0.129    -.9042208    .1155352
 type_dum_40 |  -1.608049   .3375171    -4.76   0.000    -2.272343   -.9437555
       y1966 |  -.0959567   .2860292    -0.34   0.738     -.658913    .4669997
       y1967 |   .2220028   .2613789     0.85   0.396    -.2924374     .736443
       y1968 |   .1292154   .2766379     0.47   0.641    -.4152571     .673688
       y1969 |   .0342516   .2917308     0.12   0.907    -.5399264    .6084296
       y1970 |    .105689   .2902061     0.36   0.716    -.4654882    .6768662
       y1971 |  -.1651022   .3118255    -0.53   0.597    -.7788302    .4486258
       y1972 |  -.1473529   .3172207    -0.46   0.643    -.7716997    .4769938
       y1973 |   .2334502   .3326853     0.70   0.483    -.4213337     .888234
       y1974 |   .1807072   .3426699     0.53   0.598    -.4937281    .8551426
       y1975 |   .0997344   .3467711     0.29   0.774    -.5827728    .7822417
       y1976 |   .0758537   .3513198     0.22   0.829    -.6156062    .7673136
       y1977 |   .1177148   .3541878     0.33   0.740    -.5793898    .8148194
       y1978 |   -.064952   .3568086    -0.18   0.856    -.7672148    .6373108
       y1979 |  -.2007918   .3578281    -0.56   0.575    -.9050612    .5034777
       y1980 |  -.1035064   .3606279    -0.29   0.774    -.8132863    .6062735
       y1981 |  -.1931773   .3615116    -0.53   0.594    -.9046965    .5183419
       y1982 |  -.4769836   .3675317    -1.30   0.195    -1.200351    .2463841
```

```
       y1983 |  -.2685821   .3695727    -0.73   0.468    -.9959668    .4588026
       y1984 |   -.177434   .3838623    -0.46   0.644    -.9329432    .5780752
       y1985 |  (dropped)
       y1986 |  -.1894873   .3966031    -0.48   0.633    -.9700728    .5910982
       y1987 |  -.0239062   .3819009    -0.06   0.950    -.7755551    .7277427
       y1988 |  -.2097563   .3793295    -0.55   0.581    -.9563442    .5368316
       y1989 |  -.2847255   .3798475    -0.75   0.454    -1.032333     .462882
       y1990 |  -.1841728   .3782255    -0.49   0.627    -.9285879    .5602424
       y1991 |  -.4215689   .3876405    -1.09   0.278    -1.184514    .3413765
       y1992 |  -.6800827   .3956269    -1.72   0.087    -1.458747    .0985814
       y1993 |  -.5816385   .4000603    -1.45   0.147    -1.369028    .2057514
       y1994 |   -.798084   .3741776    -2.13   0.034    -1.534532    -.061636
       y1995 |  -.8123342   .3742324    -2.17   0.031     -1.54889   -.0757782
       y1996 |  -.8140455   .3735477    -2.18   0.030    -1.549254   -.0788371
       y1997 |   -.657061   .3760793    -1.75   0.082    -1.397252      .08313
       y1998 |  -.7711786    .365925    -2.11   0.036    -1.491384   -.0509732
       y1999 |  -.7381977   .3674008    -2.01   0.045    -1.461308   -.0150876
       y2000 |  -.7642373   .3681694    -2.08   0.039     -1.48886   -.0396144
       y2001 |  -.5322419   .3681762    -1.45   0.149    -1.256878    .1923944
       y2002 |  -.4796363   .3714499    -1.29   0.198    -1.210716    .2514431
       y2003 |  -.5962714    .374508    -1.59   0.112     -1.33337    .1408269
       _cons |  -1.697444   .3123045    -5.44   0.000    -2.312115   -1.082773
------------------------------------------------------------------------------
```

12 < Age

```
. reg logengperflthr age type_dum_2-type_dum_40 y1966-y2003 if synth==0 & age>12

      Source |       SS       df       MS              Number of obs =     299
-------------+------------------------------           F( 40,   258) =   16.88
       Model |  130.384462    40  3.25961155           Prob > F      =  0.0000
    Residual |  49.8198349   258  .193100135           R-squared     =  0.7235
-------------+------------------------------           Adj R-squared =  0.6807
       Total |  180.204297   298  .604712406           Root MSE      =  .43943

------------------------------------------------------------------------------
logengperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .0080284   .0127716     0.63   0.530    -.0171215    .0331782
  type_dum_2 |  (dropped)
  type_dum_3 |  (dropped)
  type_dum_4 |   .7320319   .3133983     2.34   0.020     .1148876    1.349176
  type_dum_5 |    .730061   .3255241     2.24   0.026     .0890384    1.371084
  type_dum_6 |   1.933426   .3246082     5.96   0.000     1.294207    2.572645
  type_dum_7 |   1.702777   .3763234     4.52   0.000     .9617203    2.443833
  type_dum_8 |   .8386985   .3913902     2.14   0.033     .0679724    1.609425
  type_dum_9 |  (dropped)
 type_dum_10 |   1.530878   .4300935     3.56   0.000     .6839373    2.377819
 type_dum_11 |  (dropped)
 type_dum_12 |  (dropped)
 type_dum_13 |  (dropped)
 type_dum_14 |  (dropped)
 type_dum_15 |  (dropped)
 type_dum_16 |  (dropped)
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |   1.579939   .6214531     2.54   0.012     .3561726    2.803705
 type_dum_22 |  (dropped)
 type_dum_23 |   .6763183   .4481891     1.51   0.133    -.2062562    1.558893
 type_dum_24 |   1.980112   .3140789     6.30   0.000     1.361627    2.598596
 type_dum_25 |  (dropped)
 type_dum_26 |  (dropped)
 type_dum_27 |   .5139641   .2981034     1.72   0.086    -.0730616     1.10099
 type_dum_28 |   .2823368   .3171711     0.89   0.374     -.342237    .9069106
 type_dum_29 |  (dropped)
 type_dum_30 |  (dropped)
 type_dum_31 |    1.17229    .340407     3.44   0.001     .5019597     1.84262
 type_dum_32 |  (dropped)
 type_dum_33 |  (dropped)
 type_dum_34 |  (dropped)
 type_dum_35 |  (dropped)
 type_dum_36 |  (dropped)
 type_dum_37 |   .8676601   .3402144     2.55   0.011     .1977095    1.537611
 type_dum_38 |  (dropped)
 type_dum_39 |  (dropped)
 type_dum_40 |  (dropped)
       y1966 |  (dropped)
       y1967 |  (dropped)
```

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
y1968	(dropped)					
y1969	(dropped)					
y1970	(dropped)					
y1971	(dropped)					
y1972	(dropped)					
y1973	(dropped)					
y1974	(dropped)					
y1975	(dropped)					
y1976	(dropped)					
y1977	1.468474	.6151385	2.39	0.018	.2571421	2.679805
y1978	1.449611	.6150894	2.36	0.019	.2383757	2.660845
y1979	1.590749	.544797	2.92	0.004	.5179338	2.663564
y1980	1.318244	.5395884	2.44	0.015	.2556861	2.380802
y1981	.8084878	.5369753	1.51	0.133	-.2489247	1.8659
y1982	.7119268	.567421	1.25	0.211	-.4054394	1.829293
y1983	.2237597	.5639122	0.40	0.692	-.886697	1.334216
y1984	.4060399	.5577239	0.73	0.467	-.6922308	1.504311
y1985	(dropped)					
y1986	1.028242	.5507741	1.87	0.063	-.0563433	2.112827
y1987	.974258	.5498262	1.77	0.078	-.1084606	2.056977
y1988	1.008643	.5515772	1.83	0.069	-.0775239	2.094809
y1989	1.124045	.5555155	2.02	0.044	.0301228	2.217967
y1990	1.048388	.5568106	1.88	0.061	-.0480841	2.14486
y1991	1.193446	.554836	2.15	0.032	.1008624	2.28603
y1992	1.048139	.557425	1.88	0.061	-.0495428	2.145821
y1993	.9421145	.5606619	1.68	0.094	-.1619417	2.046171
y1994	.8812817	.5592961	1.58	0.116	-.2200849	1.982648
y1995	.8232818	.5611479	1.47	0.144	-.2817314	1.928295
y1996	.9789826	.5632908	1.74	0.083	-.1302505	2.088216
y1997	.9874334	.5630844	1.75	0.081	-.1213931	2.09626
y1998	1.142477	.5626968	2.03	0.043	.0344138	2.25054
y1999	1.172767	.564851	2.08	0.039	.0604615	2.285072
y2000	1.175288	.5670608	2.07	0.039	.058631	2.291945
y2001	1.251861	.568295	2.20	0.028	.1327732	2.370948
y2002	1.049658	.570882	1.84	0.067	-.0745239	2.173839
y2003	1.124307	.5711524	1.97	0.050	-.0004071	2.249021
_cons	-3.616442	.4659827	-7.76	0.000	-4.534056	-2.698829

A.3.2.3 BURDEN Costs

<u>Age ≤ 6</u>

```
. reg logburdenperflthr age type_dum_2-type_dum_40 y1966-y2003 if synth==0 & age<=6
```

Source	SS	df	MS
Model	135.162272	63	2.14543288
Residual	113.136516	294	.384818081
Total	248.298787	357	.695514811

Number of obs	=	358
F(63, 294)	=	5.58
Prob > F	=	0.0000
R-squared	=	0.5444
Adj R-squared	=	0.4467
Root MSE	=	.62034

logburdenp~r	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age	.1178785	.0246502	4.78	0.000	.0693654	.1663916
type_dum_2	(dropped)					
type_dum_3	-.0911088	.313334	-0.29	0.771	-.7077706	.5255531
type_dum_4	.1021866	.2168731	0.47	0.638	-.3246339	.529007
type_dum_5	.3621061	.3015589	1.20	0.231	-.2313816	.9555937
type_dum_6	.8903091	.2725468	3.27	0.001	.3539192	1.426699
type_dum_7	.7205115	.3453405	2.09	0.038	.0408587	1.400164
type_dum_8	.9802902	.3393464	2.89	0.004	.3124342	1.648146
type_dum_9	.8645087	.363136	2.38	0.018	.1498333	1.579184
type_dum_10	.8675401	.4105634	2.11	0.035	.0595244	1.675556
type_dum_11	.2744777	.4378905	0.63	0.531	-.5873195	1.136275
type_dum_12	-.3012164	.3744842	-0.80	0.422	-1.038226	.4357931
type_dum_13	.2357824	.3536227	0.67	0.505	-.4601703	.9317351
type_dum_14	-1.041392	.5012212	-2.08	0.039	-2.027828	-.0549554
type_dum_15	.0840865	.4716493	0.18	0.859	-.8441504	1.012323
type_dum_16	.5405927	.3091808	1.75	0.081	-.0678954	1.149081
type_dum_17	(dropped)					
type_dum_18	(dropped)					
type_dum_19	(dropped)					
type_dum_20	(dropped)					
type_dum_21	.2702051	.4900856	0.55	0.582	-.6943156	1.234726

```
 type_dum_22 |   .9201849   .4092857     2.25   0.025     .1146837    1.725686
 type_dum_23 |  (dropped)
 type_dum_24 |   .5723929   .2964281     1.93   0.054    -.0109972    1.155783
 type_dum_25 |  (dropped)
 type_dum_26 |  (dropped)
 type_dum_27 |   .2329636   .2668823     0.87   0.383    -.2922783    .7582055
 type_dum_28 |   .0182206   .2887874     0.06   0.950    -.5501319     .586573
 type_dum_29 |    .693078   .4187055     1.66   0.099    -.1309618    1.517118
 type_dum_30 |  (dropped)
 type_dum_31 |   1.137203   .3293807     3.45   0.001     .4889602    1.785446
 type_dum_32 |  (dropped)
 type_dum_33 |  (dropped)
 type_dum_34 |  (dropped)
 type_dum_35 |  (dropped)
 type_dum_36 |    1.24964   .3718042     3.36   0.001     .5179044    1.981375
 type_dum_37 |   .2627842   .3757535     0.70   0.485    -.4767233    1.002292
 type_dum_38 |   .4847635   .4000413     1.21   0.227     -.302544    1.272071
 type_dum_39 |   .1408759   .4890857     0.29   0.774    -.8216769    1.103429
 type_dum_40 |  (dropped)
       y1966 |  -.1339863   .2370087    -0.57   0.572    -.6004349    .3324623
       y1967 |  -.2549181   .2660784    -0.96   0.339    -.7785779    .2687417
       y1968 |   -.229694   .2835431    -0.81   0.419    -.7877254    .3283374
       y1969 |  -.2997999   .2851068    -1.05   0.294    -.8609087     .261309
       y1970 |  -.2460575   .2921759    -0.84   0.400    -.8210789    .3289639
       y1971 |  -.4263203   .3052524    -1.40   0.164    -1.027077    .1744364
       y1972 |  -.2784839   .3178601    -0.88   0.382    -.9040535    .3470857
       y1973 |  -.4157877   .3289281    -1.26   0.207     -1.06314    .2315644
       y1974 |  -.1816215   .3366921    -0.54   0.590    -.8442537    .4810107
       y1975 |  -.4142151   .3525695    -1.17   0.241    -1.108095    .2796649
       y1976 |  -.3564569   .3588653    -0.99   0.321    -1.062727    .3498136
       y1977 |  -.4573087   .4011325    -1.14   0.255    -1.246764    .3321465
       y1978 |  -.5784963   .4230625    -1.37   0.173    -1.411111    .2541184
       y1979 |  -.5243443   .5171675    -1.01   0.311    -1.542164    .4934754
       y1980 |  -.6500717    .519691    -1.25   0.212    -1.672858    .3727143
       y1981 |  -.7379164   .7177149    -1.03   0.305    -2.150427    .6745936
       y1982 |  -.7554696   .5404958    -1.40   0.163    -1.819201    .3082616
       y1983 |  -1.005388   .5030049    -2.00   0.047    -1.995334   -.0154411
       y1984 |   -.993261   .4204297    -2.36   0.019    -1.820694   -.1658277
       y1985 |  (dropped)
       y1986 |  -1.485267   .3938847    -3.77   0.000    -2.260458   -.7100759
       y1987 |  -1.349598    .407846    -3.31   0.001    -2.152265   -.5469299
       y1988 |  -1.468515   .4060348    -3.62   0.000    -2.267618    -.669412
       y1989 |  -1.596181   .3938453    -4.05   0.000    -2.371294   -.8210676
       y1990 |  -1.493366   .4064721    -3.67   0.000     -2.29333   -.6934022
       y1991 |   -1.34396   .3919512    -3.43   0.001    -2.115345   -.5725739
       y1992 |  -1.333498    .384237    -3.47   0.001    -2.089702   -.5772944
       y1993 |  -1.233754   .3936051    -3.13   0.002    -2.008395   -.4591135
       y1994 |  -.9957105   .4091944    -2.43   0.016    -1.801032    -.190389
       y1995 |  -1.157144   .4023375    -2.88   0.004     -1.94897    -.365317
       y1996 |   -1.23391   .4178889    -2.95   0.003    -2.056343   -.4114771
       y1997 |  -1.077926   .4290927    -2.51   0.013    -1.922409   -.2334436
       y1998 |  -1.509633   .4162323    -3.63   0.000    -2.328805   -.6904601
       y1999 |  -1.538108    .383814    -4.01   0.000    -2.293479   -.7827364
       y2000 |   -1.04649   .3897972    -2.68   0.008    -1.813637    -.279344
       y2001 |  -.9428491   .3834163    -2.46   0.015    -1.697438   -.1882607
       y2002 |  -.8490814   .3914719    -2.17   0.031    -1.619524    -.078639
       y2003 |  -.7881991   .3832117    -2.06   0.041    -1.542385   -.0340134
       _cons |  -1.538375   .2536153    -6.07   0.000    -2.037507   -1.039244
------------------------------------------------------------------------------
```

<u>6 < Age ≤ 12</u>

```
. reg logburdenperflthr age type_dum_2-type_dum_40 y1966-y2003 if synth==0 & age>6 &
age<=12

      Source |       SS       df       MS              Number of obs =     349
-------------+------------------------------           F( 58,   290) =    4.94
       Model |  54.8584916    58  .945836063           Prob > F      =  0.0000
    Residual |  55.5685846   290  .191615809           R-squared     =  0.4968
-------------+------------------------------           Adj R-squared =  0.3961
       Total |  110.427076   348  .317319185           Root MSE      =  .43774

------------------------------------------------------------------------------
logburdenp~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .0666833   .0179235     3.72   0.000     .0314067    .1019599
  type_dum_2 |  (dropped)
  type_dum_3 |  -.3999554   .2300414    -1.74   0.083    -.8527178    .0528069
  type_dum_4 |  -.1824178   .1527793    -1.19   0.233    -.4831146    .1182791
```

type_dum_5	-.1155791	.1885438	-0.61	0.540	-.4866669	.2555087
type_dum_6	.7034916	.1734633	4.06	0.000	.3620849	1.044898
type_dum_7	.1886017	.2029315	0.93	0.353	-.2108037	.588007
type_dum_8	.501115	.2046898	2.45	0.015	.0982491	.9039809
type_dum_9	(dropped)					
type_dum_10	.8048907	.2654877	3.03	0.003	.2823636	1.327418
type_dum_11	(dropped)					
type_dum_12	(dropped)					
type_dum_13	-.4402434	.2440073	-1.80	0.072	-.9204931	.0400063
type_dum_14	(dropped)					
type_dum_15	(dropped)					
type_dum_16	(dropped)					
type_dum_17	(dropped)					
type_dum_18	(dropped)					
type_dum_19	(dropped)					
type_dum_20	(dropped)					
type_dum_21	.0630931	.2762157	0.23	0.819	-.4805484	.6067347
type_dum_22	(dropped)					
type_dum_23	(dropped)					
type_dum_24	.6019427	.1922018	3.13	0.002	.2236554	.98023
type_dum_25	(dropped)					
type_dum_26	(dropped)					
type_dum_27	.0354003	.1747968	0.20	0.840	-.3086308	.3794315
type_dum_28	-.2293729	.2124031	-1.08	0.281	-.6474199	.1886741
type_dum_29	-.008373	.3688351	-0.02	0.982	-.7343061	.71756
type_dum_30	(dropped)					
type_dum_31	.9378666	.2408418	3.89	0.000	.4638471	1.411886
type_dum_32	(dropped)					
type_dum_33	(dropped)					
type_dum_34	-.7128026	.3081235	-2.31	0.021	-1.319244	-.1063607
type_dum_35	(dropped)					
type_dum_36	.5531671	.2577805	2.15	0.033	.0458092	1.060525
type_dum_37	.0146605	.2072935	0.07	0.944	-.3933301	.422651
type_dum_38	.2349452	.3274951	0.72	0.474	-.4096233	.8795137
type_dum_39	-.1362053	.3241208	-0.42	0.675	-.7741327	.5017222
type_dum_40	-.7148604	.4222804	-1.69	0.092	-1.545983	.1162624
y1966	.0124879	.3578619	0.03	0.972	-.6918479	.7168237
y1967	.0750171	.327021	0.23	0.819	-.5686184	.7186526
y1968	-.1148061	.346112	-0.33	0.740	-.7960161	.566404
y1969	-.1591909	.3649953	-0.44	0.663	-.8775666	.5591847
y1970	-.1601116	.3630877	-0.44	0.660	-.8747329	.5545096
y1971	-.18324	.3901366	-0.47	0.639	-.9510981	.5846182
y1972	-.4434493	.3968867	-1.12	0.265	-1.224593	.3376943
y1973	-.4684959	.4162351	-1.13	0.261	-1.28772	.3507288
y1974	-.3987316	.4287272	-0.93	0.353	-1.242543	.4450798
y1975	-.4769629	.4338584	-1.10	0.273	-1.330873	.3769475
y1976	-.5083845	.4395494	-1.16	0.248	-1.373496	.356727
y1977	-.5536353	.4431377	-1.25	0.213	-1.425809	.3185385
y1978	-.5462951	.4464166	-1.22	0.222	-1.424922	.3323323
y1979	-.6699347	.4476922	-1.50	0.136	-1.551073	.2112032
y1980	-.6654871	.4511951	-1.47	0.141	-1.553519	.2225451
y1981	-.6418946	.4523008	-1.42	0.157	-1.532103	.2483137
y1982	-.8397376	.4598326	-1.83	0.069	-1.74477	.0652948
y1983	-.9191252	.4623862	-1.99	0.048	-1.829183	-.0090669
y1984	-1.16303	.4802645	-2.42	0.016	-2.108276	-.2177844
y1985	(dropped)					
y1986	-1.014884	.4962051	-2.05	0.042	-1.991504	-.0382642
y1987	-1.411796	.4778106	-2.95	0.003	-2.352212	-.4713795
y1988	-1.251803	.4745934	-2.64	0.009	-2.185887	-.3177186
y1989	-1.170892	.4752415	-2.46	0.014	-2.106251	-.2355319
y1990	-1.17452	.4732122	-2.48	0.014	-2.105885	-.2431539
y1991	-.9632574	.4849915	-1.99	0.048	-1.917807	-.0087078
y1992	-.8784915	.4949837	-1.77	0.077	-1.852707	.0957245
y1993	-.9233916	.5005305	-1.84	0.066	-1.908525	.0617414
y1994	-1.084942	.4681476	-2.32	0.021	-2.00634	-.1635442
y1995	-1.18577	.4682163	-2.53	0.012	-2.107302	-.2642368
y1996	-1.143159	.4673596	-2.45	0.015	-2.063006	-.2233126
y1997	-1.160809	.470527	-2.47	0.014	-2.086889	-.2347278
y1998	-1.246436	.4578225	-2.72	0.007	-2.147512	-.34536
y1999	-1.156003	.4596689	-2.51	0.012	-2.060713	-.2512929
y2000	-1.15659	.4606306	-2.51	0.013	-2.063193	-.2499867
y2001	-.8061615	.4606391	-1.75	0.081	-1.712781	.1004581
y2002	-.9216583	.4647349	-1.98	0.048	-1.836339	-.0069774
y2003	-.9895008	.468561	-2.11	0.036	-1.911712	-.0672895
_cons	-1.157355	.3907359	-2.96	0.003	-1.926393	-.3883175

12 < Age

```
. reg logburdenperflthr age type_dum_2-type_dum_40 y1966-y2003 if synth==0 & age>12

      Source |       SS       df       MS              Number of obs =     299
-------------+------------------------------           F( 40,   258) =    5.93
       Model |  43.470777    40  1.08676942           Prob > F      =  0.0000
    Residual | 47.2560025   258   .1831628           R-squared     =  0.4791
-------------+------------------------------           Adj R-squared =  0.3984
       Total | 90.7267795   298   .30445228           Root MSE      =  .42798

------------------------------------------------------------------------------
logburdenp~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .0073923   .0124387     0.59   0.553    -.0171019    .0318865
  type_dum_2 |  (dropped)
  type_dum_3 |  (dropped)
  type_dum_4 |  -.1369378   .3052277    -0.45   0.654    -.7379926    .4641171
  type_dum_5 |  -.1662784   .3170374    -0.52   0.600    -.7905889    .4580321
  type_dum_6 |   .6642374   .3161454     2.10   0.037     .0416835    1.286791
  type_dum_7 |  -.8406305   .3665123    -2.29   0.023    -1.562367    -.118894
  type_dum_8 |   .2873658   .3811863     0.75   0.452    -.4632668    1.037998
  type_dum_9 |  (dropped)
 type_dum_10 |    .842085   .4188806     2.01   0.045     .0172247    1.666945
 type_dum_11 |  (dropped)
 type_dum_12 |  (dropped)
 type_dum_13 |  (dropped)
 type_dum_14 |  (dropped)
 type_dum_15 |  (dropped)
 type_dum_16 |  (dropped)
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |   .4624159   .6052513     0.76   0.446    -.7294457    1.654277
 type_dum_22 |  (dropped)
 type_dum_23 |  -.4174977   .4365044    -0.96   0.340    -1.277063    .4420674
 type_dum_24 |    .424581   .3058906     1.39   0.166    -.1777791    1.026941
 type_dum_25 |  (dropped)
 type_dum_26 |  (dropped)
 type_dum_27 |   .2755033   .2903316     0.95   0.344    -.2962182    .8472247
 type_dum_28 |  -.3716761   .3089022    -1.20   0.230    -.9799667    .2366145
 type_dum_29 |  (dropped)
 type_dum_30 |  (dropped)
 type_dum_31 |    .378361   .3315323     1.14   0.255    -.2744928    1.031215
 type_dum_32 |  (dropped)
 type_dum_33 |  (dropped)
 type_dum_34 |  (dropped)
 type_dum_35 |  (dropped)
 type_dum_36 |  (dropped)
 type_dum_37 |  -.0675428   .3313447    -0.20   0.839    -.7200272    .5849416
 type_dum_38 |  (dropped)
 type_dum_39 |  (dropped)
 type_dum_40 |  (dropped)
       y1966 |  (dropped)
       y1967 |  (dropped)
       y1968 |  (dropped)
       y1969 |  (dropped)
       y1970 |  (dropped)
       y1971 |  (dropped)
       y1972 |  (dropped)
       y1973 |  (dropped)
       y1974 |  (dropped)
       y1975 |  (dropped)
       y1976 |  (dropped)
       y1977 |   .3890536   .5991013     0.65   0.517    -.7906975    1.568805
       y1978 |   .2932389   .5990534     0.49   0.625    -.8864179    1.472896
       y1979 |   .4291575   .5305937     0.81   0.419    -.6156883    1.474003
       y1980 |   .4785379   .5255208     0.91   0.363    -.5563185    1.513394
       y1981 |   .4607183   .5229759     0.88   0.379    -.5691265    1.490563
       y1982 |   .3441043   .5526278     0.62   0.534    -.7441312     1.43234
       y1983 |   .2472067   .5492105     0.45   0.653    -.8342994    1.328713
       y1984 |   .1104803   .5431836     0.20   0.839    -.9591575    1.180118
       y1985 |  (dropped)
       y1986 |  -.0435749   .5364149    -0.08   0.935    -1.099884    1.012734
       y1987 |  -.0213029   .5354918    -0.04   0.968    -1.075794    1.033188
       y1988 |  -.0684693   .5371971    -0.13   0.899    -1.126319    .9893799
       y1989 |   .0835139   .5410328     0.15   0.877    -.9818885    1.148916
       y1990 |   .1863351    .542294     0.34   0.731    -.8815509    1.254221
       y1991 |   .2121498   .5403709     0.39   0.695    -.8519493    1.276249
       y1992 |   .1931025   .5428924     0.36   0.722    -.8759619    1.262167
       y1993 |   .2205703    .546045     0.40   0.687    -.8547022    1.295843
       y1994 |   .1974372   .5447147     0.36   0.717    -.8752158     1.27009
```

```
        y1995 |   .2528022   .5465183     0.46   0.644    -.8234022    1.329007
        y1996 |    .233798   .5486054     0.43   0.670    -.8465163    1.314112
        y1997 |   .1787968   .5484043     0.33   0.745    -.9011216    1.258715
        y1998 |   .2015332   .5480268     0.37   0.713     -.877642    1.280708
        y1999 |   .1812303   .5501248     0.33   0.742    -.9020762    1.264537
        y2000 |    .179073    .552277     0.32   0.746    -.9084716    1.266618
        y2001 |   .1591726   .5534791     0.29   0.774    -.9307391    1.249084
        y2002 |   .0366055   .5559986     0.07   0.948    -1.058268    1.131479
        y2003 |   .2031507    .556262     0.37   0.715    -.8922411    1.298543
        _cons |  -1.347699   .4538341    -2.97   0.003     -2.24139   -.4540084
------------------------------------------------------------------------------
```

A.3.3 Age*Airline and Age*Type Interactions and Airline Fixed Effects

A.3.3.1 Age*Airline and Age*Type Interactions

The estimated model is

$\log(y_{itr}) = \alpha + \beta * Age_{itr} + \mu_t + \delta_r + \tau_i + \beta_i * Age_{itr} * \tau_i + \beta_t * Age_{itr} * \mu_t$, where μ_t are the aircraft type fixed effects, δ_r are the year fixed effects, τ_i are the airline fixed effects, β is the age effect, β_i is the effect of the age*airline interaction, β_t is the effect of the age*type interactions, α is the intercept, and y is the total maintenance cost per flight hour.

<u>Age ≤ 6</u>

```
. reg logtotperflthr age type_dum_2-type_dum_40 y1966-y2003 agetype2-agetype40 air_dum_2-
air_dum_11 ageair2-ageair11 if synth==0 & age<=6

      Source |       SS       df       MS              Number of obs =     359
-------------+------------------------------           F(100,   258) =   10.90
       Model |  148.364632   100  1.48364632           Prob > F      =  0.0000
    Residual |  35.1235574   258  .136137819           R-squared     =  0.8086
-------------+------------------------------           Adj R-squared =  0.7344
       Total |   183.48819   358  .512536842           Root MSE      =  .36897

------------------------------------------------------------------------------
logtotperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |  -.1872358   .1307534    -1.43   0.153    -.4447156    .0702441
  type_dum_2 |  (dropped)
  type_dum_3 |  -.5029913   1.109806    -0.45   0.651    -2.688422    1.682439
  type_dum_4 |  -.2500227   .3734271    -0.67   0.504    -.9853759    .4853305
  type_dum_5 |  -.7951175   .4392545    -1.81   0.071    -1.660098    .0698629
  type_dum_6 |   .5166693   .4687924     1.10   0.271    -.4064773    1.439816
  type_dum_7 |  -.5627834   .4690155    -1.20   0.231    -1.486369    .3608025
  type_dum_8 |  -.0452738   .4949701    -0.09   0.927     -1.01997     .929422
  type_dum_9 |   .0477023   .4655002     0.10   0.918    -.8689612    .9643658
 type_dum_10 |  -.4480859   .5441488    -0.82   0.411    -1.519624    .6234526
```

type_dum_11	-.0335691	.5752009	-0.06	0.954	-1.166255	1.099117
type_dum_12	-1.832897	.4777419	-3.84	0.000	-2.773667	-.8921272
type_dum_13	-.4831834	.468057	-1.03	0.303	-1.404882	.4385151
type_dum_14	-2.426423	.7585655	-3.20	0.002	-3.920191	-.9326548
type_dum_15	-.4577029	.5349881	-0.86	0.393	-1.511202	.5957964
type_dum_16	-.4168678	.4764154	-0.88	0.382	-1.355026	.5212901
type_dum_17	(dropped)					
type_dum_18	(dropped)					
type_dum_19	(dropped)					
type_dum_20	(dropped)					
type_dum_21	-.981028	2.835639	-0.35	0.730	-6.564973	4.602917
type_dum_22	-.5754495	1.415823	-0.41	0.685	-3.36349	2.212591
type_dum_23	(dropped)					
type_dum_24	-.0716719	.4758943	-0.15	0.880	-1.008803	.8654597
type_dum_25	(dropped)					
type_dum_26	(dropped)					
type_dum_27	-.0278745	.9201928	-0.03	0.976	-1.839919	1.78417
type_dum_28	-.9635372	.4582997	-2.10	0.036	-1.866022	-.0610528
type_dum_29	.0110355	.5158126	0.02	0.983	-1.004703	1.026774
type_dum_30	(dropped)					
type_dum_31	.1205838	.5507172	0.22	0.827	-.9638893	1.205057
type_dum_32	(dropped)					
type_dum_33	(dropped)					
type_dum_34	(dropped)					
type_dum_35	(dropped)					
type_dum_36	.2830036	.4855284	0.58	0.560	-.6730996	1.239107
type_dum_37	-1.404255	.5018498	-2.80	0.006	-2.392498	-.4160117
type_dum_38	-.6165372	.4919918	-1.25	0.211	-1.585368	.3522937
type_dum_39	.0709286	2.638398	0.03	0.979	-5.124609	5.266466
type_dum_40	(dropped)					
y1966	-.1236737	.170072	-0.73	0.468	-.4585798	.2112324
y1967	-.1445654	.190422	-0.76	0.448	-.5195447	.2304139
y1968	-.1534409	.1998144	-0.77	0.443	-.5469157	.2400339
y1969	-.1879729	.2097945	-0.90	0.371	-.6011006	.2251548
y1970	-.2086989	.2429096	-0.86	0.391	-.6870368	.269639
y1971	-.3247305	.2680029	-1.21	0.227	-.8524822	.2030212
y1972	-.2563996	.2848533	-0.90	0.369	-.817333	.3045339
y1973	-.3724923	.278704	-1.34	0.183	-.9213167	.176332
y1974	-.2793689	.2841268	-0.98	0.326	-.8388718	.2801339
y1975	-.4031177	.2887165	-1.40	0.164	-.9716587	.1654232
y1976	-.4534955	.3018666	-1.50	0.134	-1.047932	.1409405
y1977	-.6050616	.3172879	-1.91	0.058	-1.229865	.0197421
y1978	-.7220626	.3339925	-2.16	0.032	-1.379761	-.0643642
y1979	-.6296395	.3741328	-1.68	0.094	-1.366382	.1071034
y1980	-.6486192	.3853705	-1.68	0.094	-1.407491	.1102529
y1981	-.9022313	.4877537	-1.85	0.065	-1.862716	.0582539
y1982	-.9785722	.4008074	-2.44	0.015	-1.767843	-.1893018
y1983	-1.181264	.3884035	-3.04	0.003	-1.946109	-.4164193
y1984	-1.093639	.3303876	-3.31	0.001	-1.744238	-.4430389
y1985	(dropped)					
y1986	-.8367896	.3056643	-2.74	0.007	-1.438704	-.234875
y1987	-.697367	.3110444	-2.24	0.026	-1.309876	-.084858
y1988	-.7373928	.311892	-2.36	0.019	-1.351571	-.1232148
y1989	-.8085176	.305746	-2.64	0.009	-1.410593	-.2064421
y1990	-.8018337	.308661	-2.60	0.010	-1.409649	-.194018
y1991	-.7195593	.3010027	-2.39	0.018	-1.312294	-.1268244
y1992	-.8732008	.2944	-2.97	0.003	-1.452934	-.293468
y1993	-.9517891	.2959161	-3.22	0.001	-1.534507	-.3690708
y1994	-.9409033	.3005569	-3.13	0.002	-1.53276	-.3490463
y1995	-1.078837	.293908	-3.67	0.000	-1.657601	-.5000724
y1996	-1.153481	.2964965	-3.89	0.000	-1.737343	-.5696201
y1997	-1.069274	.3016012	-3.55	0.000	-1.663187	-.4753601
y1998	-1.187687	.3023294	-3.93	0.000	-1.783035	-.5923397
y1999	-.7749482	.2837934	-2.73	0.007	-1.333795	-.2161018
y2000	-.8303948	.2814589	-2.95	0.003	-1.384644	-.2761457
y2001	-.7569353	.2781191	-2.72	0.007	-1.304608	-.2092628
y2002	-.7716655	.2786999	-2.77	0.006	-1.320482	-.2228492
y2003	-.686073	.2725347	-2.52	0.012	-1.222749	-.1493972
agetype2	(dropped)					
agetype3	.1131486	.2236729	0.51	0.613	-.3273083	.5536056
agetype4	.0405583	.1010396	0.40	0.688	-.158409	.2395256
agetype5	.1063603	.1095584	0.97	0.333	-.1093822	.3221028
agetype6	.132332	.1196309	1.11	0.270	-.1032452	.3679092
agetype7	.2209686	.1083033	2.04	0.042	.0076976	.4342396
agetype8	.1303581	.1149656	1.13	0.258	-.0960324	.3567485
agetype9	.1823907	.1184747	1.54	0.125	-.0509099	.4156913
agetype10	.3544747	.1397098	2.54	0.012	.079358	.6295913
agetype11	.1437309	.1346627	1.07	0.287	-.1214471	.4089089
agetype12	.5525354	.1370956	4.03	0.000	.2825666	.8225042
agetype13	.1872798	.1119245	1.67	0.095	-.0331222	.4076817
agetype14	.6199	.3027109	2.05	0.042	.0238013	1.215999

```
   agetype15 |   .3239911   .2116344     1.53   0.127    -.0927596    .7407418
   agetype16 |   .1386935   .1269756     1.09   0.276    -.1113471     .388734
   agetype17 |  (dropped)
   agetype18 |  (dropped)
   agetype19 |  (dropped)
   agetype20 |  (dropped)
   agetype21 |   .2859057   .5574646     0.51   0.608    -.8118543    1.383666
   agetype22 |   .2676042   .3150676     0.85   0.396    -.3528274    .8880358
   agetype23 |  (dropped)
   agetype24 |    .217524   .1183587     1.84   0.067     -.015548    .4505961
   agetype25 |  (dropped)
   agetype26 |  (dropped)
   agetype27 |   .0155498   .1999563     0.08   0.938    -.3782043    .4093039
   agetype28 |   .1456269   .1322726     1.10   0.272    -.1148445    .4060984
   agetype29 |    .053349   .1363725     0.39   0.696     -.215196     .321894
   agetype30 |  (dropped)
   agetype31 |    .235187   .1352881     1.74   0.083    -.0312225    .5015965
   agetype32 |  (dropped)
   agetype33 |  (dropped)
   agetype34 |  (dropped)
   agetype35 |  (dropped)
   agetype36 |   .1588966    .117067     1.36   0.176    -.0716319    .3894252
   agetype37 |   .2789981   .1178537     2.37   0.019     .0469204    .5110757
   agetype38 |   .2858204   .1271426     2.25   0.025     .0354511    .5361898
   agetype39 |   -.026547   .5573736    -0.05   0.962    -1.124128    1.071034
   agetype40 |  (dropped)
   air_dum_2 |   1.269187   .4215661     3.01   0.003     .4390383    2.099335
   air_dum_3 |   .6014233   .2522183     2.38   0.018     .1047547    1.098092
   air_dum_4 |  (dropped)
   air_dum_5 |   .9411214   .2720263     3.46   0.001     .4054468    1.476796
   air_dum_6 |   .0853047   .2897431     0.29   0.769    -.4852577    .6558671
   air_dum_7 |  (dropped)
   air_dum_8 |  (dropped)
   air_dum_9 |   1.027108   .2556779     4.02   0.000     .5236268    1.530589
  air_dum_10 |   .9615498   .3657704     2.63   0.009     .2412743    1.681825
  air_dum_11 |  (dropped)
     ageair2 |  (dropped)
     ageair3 |   .1969183   .0980044     2.01   0.046     .0039278    .3899087
     ageair4 |   .3182748   .1163085     2.74   0.007       .08924    .5473095
     ageair5 |   .0902012   .0997248     0.90   0.367     -.106177    .2865794
     ageair6 |   .2347916   .0893252     2.63   0.009     .0588923    .4106908
     ageair7 |  (dropped)
     ageair8 |  (dropped)
     ageair9 |   .1036558   .0940593     1.10   0.271    -.0815658    .2888775
    ageair10 |  -.0907479   .1263304    -0.72   0.473    -.3395178    .1580221
    ageair11 |  (dropped)
       _cons |  -.6113463   .4518937    -1.35   0.177    -1.501216    .2785234
------------------------------------------------------------------------------
```

6 < Age ≤ 12

```
. reg logtotperflthr age type_dum_2-type_dum_40 y1966-y2003 agetype2-agetype40 air_dum_2-
air_dum_11 ageair2-ageair11 if synth==0 & age>6 & age<=12

      Source |       SS       df       MS              Number of obs =     349
-------------+------------------------------           F( 94,   254) =   22.46
       Model |  57.4487436    94  .611156846           Prob > F      =  0.0000
    Residual |  6.91045598   254  .02720652            R-squared     =  0.8926
-------------+------------------------------           Adj R-squared =  0.8529
       Total |  64.3591995   348  .184940229           Root MSE      =  .16494

------------------------------------------------------------------------------
logtotperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .0084701   .0463079     0.18   0.855    -.0827262    .0996664
  type_dum_2 |  (dropped)
  type_dum_3 |    -.016322   .6623999   -0.02   0.980    -1.320818    1.288174
  type_dum_4 |  -.6092816   .2911694    -2.09   0.037    -1.182695   -.0358679
  type_dum_5 |  -.6411536    .350807    -1.83   0.069    -1.332015    .0497073
  type_dum_6 |   .2599165   .3437142     0.76   0.450    -.4169762    .9368092
  type_dum_7 |  -.3543986   .3393081    -1.04   0.297    -1.022614     .313817
  type_dum_8 |   -.137286   .3624175    -0.38   0.705     -.851012    .5764401
  type_dum_9 |  (dropped)
 type_dum_10 |   .8876048   .4783029     1.86   0.065    -.0543398    1.829549
 type_dum_11 |  (dropped)
 type_dum_12 |  (dropped)
 type_dum_13 |  -.9064557   .5412064    -1.67   0.095    -1.972279    .1593677
 type_dum_14 |  (dropped)
 type_dum_15 |  (dropped)
 type_dum_16 |  (dropped)
```

type_dum_17	(dropped)					
type_dum_18	(dropped)					
type_dum_19	(dropped)					
type_dum_20	(dropped)					
type_dum_21	.5280632	.7410006	0.71	0.477	-.9312246	1.987351
type_dum_22	(dropped)					
type_dum_23	(dropped)					
type_dum_24	.5751115	.3675923	1.56	0.119	-.1488055	1.299028
type_dum_25	(dropped)					
type_dum_26	(dropped)					
type_dum_27	-.4637783	.3929591	-1.18	0.239	-1.237651	.3100946
type_dum_28	-.8857062	.453243	-1.95	0.052	-1.778299	.0068868
type_dum_29	4.801683	2.281161	2.10	0.036	.3092844	9.294081
type_dum_30	(dropped)					
type_dum_31	-.0787781	.4535576	-0.17	0.862	-.9719906	.8144344
type_dum_32	(dropped)					
type_dum_33	(dropped)					
type_dum_34	-2.036567	1.018818	-2.00	0.047	-4.042975	-.0301598
type_dum_35	(dropped)					
type_dum_36	2.063211	.6416945	3.22	0.001	.799491	3.32693
type_dum_37	-.478875	.3640342	-1.32	0.190	-1.195785	.2380348
type_dum_38	.4250979	.9350449	0.45	0.650	-1.41633	2.266526
type_dum_39	-.7428744	.9213724	-0.81	0.421	-2.557377	1.071628
type_dum_40	-2.123832	2.087375	-1.02	0.310	-6.234598	1.986934
y1966	-.1329638	.1761735	-0.75	0.451	-.4799107	.2139831
y1967	-.3251818	.2818584	-1.15	0.250	-.8802589	.2298953
y1968	-.4678795	.3265511	-1.43	0.153	-1.110972	.1752132
y1969	-.5017888	.3748599	-1.34	0.182	-1.240018	.2364405
y1970	-.4133491	.4257952	-0.97	0.333	-1.251888	.4251896
y1971	-.4916782	.4466278	-1.10	0.272	-1.371243	.3878872
y1972	-.5630941	.4574509	-1.23	0.219	-1.463974	.3377857
y1973	-.4152286	.4518428	-0.92	0.359	-1.305064	.4746069
y1974	-.383486	.4621894	-0.83	0.407	-1.293698	.5267254
y1975	-.4201078	.4655269	-0.90	0.368	-1.336892	.4966764
y1976	-.4221112	.4692582	-0.90	0.369	-1.346244	.5020211
y1977	-.397716	.4679057	-0.85	0.396	-1.319185	.523753
y1978	-.5168514	.4674097	-1.11	0.270	-1.437343	.4036407
y1979	-.6181258	.468206	-1.32	0.188	-1.540186	.3039345
y1980	-.5618112	.4688526	-1.20	0.232	-1.485145	.3615226
y1981	-.5892689	.4681296	-1.26	0.209	-1.511179	.332641
y1982	-.743272	.4699587	-1.58	0.115	-1.668784	.1822399
y1983	-.6620345	.472568	-1.40	0.162	-1.592685	.268616
y1984	-.6861875	.4752564	-1.44	0.150	-1.622132	.2497575
y1985	(dropped)					
y1986	-.6695673	.4759334	-1.41	0.161	-1.606846	.2677111
y1987	-.6143666	.4726361	-1.30	0.195	-1.545151	.3164181
y1988	-.6761197	.4725843	-1.43	0.154	-1.606802	.2545629
y1989	-.6519124	.4720548	-1.38	0.168	-1.581552	.2777276
y1990	-.6111481	.4716634	-1.30	0.196	-1.540017	.317721
y1991	-.6083487	.4733615	-1.29	0.200	-1.540562	.3238646
y1992	-.7377999	.4767903	-1.55	0.123	-1.676766	.2011658
y1993	-.752508	.4766121	-1.58	0.116	-1.691123	.1861069
y1994	-.9445257	.472302	-2.00	0.047	-1.874652	-.0143989
y1995	-.9549037	.4714243	-2.03	0.044	-1.883302	-.0265054
y1996	-.944662	.4707759	-2.01	0.046	-1.871783	-.0175406
y1997	-.8856596	.4703848	-1.88	0.061	-1.812011	.0406915
y1998	-.8972144	.4676703	-1.92	0.056	-1.81822	.0237909
y1999	-.8680056	.4674255	-1.86	0.064	-1.788529	.0525176
y2000	-.7485326	.4674574	-1.60	0.111	-1.669119	.1720535
y2001	-.6067831	.4672256	-1.30	0.195	-1.526913	.3133465
y2002	-.6440565	.467555	-1.38	0.170	-1.564835	.2767217
y2003	-.7465398	.4689558	-1.59	0.113	-1.670077	.176997
agetype2	(dropped)					
agetype3	.0003061	.066741	0.00	0.996	-.1311302	.1317424
agetype4	.035311	.0325514	1.08	0.279	-.0287939	.099416
agetype5	.058461	.0381216	1.53	0.126	-.0166137	.1335357
agetype6	.0741797	.0370999	2.00	0.047	.0011171	.1472423
agetype7	.0730297	.0368169	1.98	0.048	.0005244	.1455351
agetype8	.0520114	.0388234	1.34	0.182	-.0244453	.1284681
agetype9	(dropped)					
agetype10	-.0062728	.0520461	-0.12	0.904	-.1087696	.096224
agetype11	(dropped)					
agetype12	(dropped)					
agetype13	.1396646	.0679413	2.06	0.041	.0058645	.2734648
agetype14	(dropped)					
agetype15	(dropped)					
agetype16	(dropped)					
agetype17	(dropped)					
agetype18	(dropped)					
agetype19	(dropped)					
agetype20	(dropped)					

```
   agetype21 |  -.0090283   .0744736    -0.12   0.904    -.1556927    .1376361
   agetype22 |  (dropped)
   agetype23 |  (dropped)
   agetype24 |    .002976   .0408319     0.07   0.942    -.0774361    .0833881
   agetype25 |  (dropped)
   agetype26 |  (dropped)
   agetype27 |   .0545664   .0421899     1.29   0.197    -.0285201    .1376529
   agetype28 |   .0577445   .0504746     1.14   0.254    -.0416576    .1571465
   agetype29 |  -.4812135   .2161566    -2.23   0.027    -.9069009   -.0555261
   agetype30 |  (dropped)
   agetype31 |    .073193   .0503898     1.45   0.148     -.026042     .172428
   agetype32 |  (dropped)
   agetype33 |  (dropped)
   agetype34 |   .2418287   .0999409     2.42   0.016     .0450103    .4386471
   agetype35 |  (dropped)
   agetype36 |  -.1769285   .0760937    -2.33   0.021    -.3267835   -.0270735
   agetype37 |   .0484671    .038978     1.24   0.215    -.0282941    .1252283
   agetype38 |  -.0202158   .1259428    -0.16   0.873    -.2682409    .2278093
   agetype39 |   .0852853   .1072485     0.80   0.427    -.1259242    .2964948
   agetype40 |   .1430413   .1864515     0.77   0.444    -.2241466    .5102291
   air_dum_2 |   .0810698   .5071868     0.16   0.873    -.9177572    1.079897
   air_dum_3 |   .0603883   .3323372     0.18   0.856    -.5940992    .7148758
   air_dum_4 |  -.4584944   .8914644    -0.51   0.607    -2.214098    1.297109
   air_dum_5 |   .0949921   .3137801     0.30   0.762    -.5229499    .7129341
   air_dum_6 |  -.2986779   .3350386    -0.89   0.374    -.9584854    .3611296
   air_dum_7 |   -.184389   .8592775    -0.21   0.830    -1.876605    1.507827
   air_dum_8 |  (dropped)
   air_dum_9 |   .2915379   .3268258     0.89   0.373    -.3520957    .9351715
  air_dum_10 |   .1019779   .5690547     0.18   0.858    -1.018689    1.222644
  air_dum_11 |  (dropped)
     ageair2 |    -.04313   .0572121    -0.75   0.452    -.1558005    .0695405
     ageair3 |   -.016124   .0370658    -0.44   0.664    -.0891195    .0568715
     ageair4 |   .0658657   .1307077     0.50   0.615    -.1915433    .3232746
     ageair5 |   -.039531   .0356198    -1.11   0.268    -.1096787    .0306168
     ageair6 |  -.0032191   .0371566    -0.09   0.931    -.0763934    .0699551
     ageair7 |  -.0015212   .0995139    -0.02   0.988    -.1974986    .1944561
     ageair8 |  (dropped)
     ageair9 |  -.0451208   .0368406    -1.22   0.222    -.1176727    .0274311
    ageair10 |  -.0458698   .0577122    -0.79   0.427    -.1595251    .0677856
    ageair11 |  (dropped)
       _cons |   .3492874   .5852453     0.60   0.551     -.803264    1.501839
------------------------------------------------------------------------------
```

<u>12 < Age</u>

```
. reg logtotperflthr age type_dum_2-type_dum_40 y1966-y2003 agetype2-agetype40 air_dum_2-
air_dum_11 ageair2-ageair11 if synth==0 & age>12

      Source |       SS       df       MS              Number of obs =     299
-------------+------------------------------           F( 65,   233) =   16.51
       Model |  50.3954711    65  .775314939           Prob > F      =  0.0000
    Residual |  10.9388732   233  .046947953           R-squared     =  0.8217
-------------+------------------------------           Adj R-squared =  0.7719
       Total |  61.3343442   298  .205819947           Root MSE      =  .21667

------------------------------------------------------------------------------
logtotperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |  -.2118865   .2800838    -0.76   0.450    -.7637069     .339934
  type_dum_2 |  (dropped)
  type_dum_3 |  (dropped)
  type_dum_4 |   -5.73717   3.575648    -1.60   0.110     -12.7819    1.307562
  type_dum_5 |  -6.560152   3.612491    -1.82   0.071    -13.67747    .5571692
  type_dum_6 |  -4.488536   3.589067    -1.25   0.212    -11.55971    2.582636
  type_dum_7 |  -6.474543   3.767274    -1.72   0.087    -13.89682    .9477312
  type_dum_8 |  -5.433442   3.841408    -1.41   0.159    -13.00177     2.13489
  type_dum_9 |  (dropped)
 type_dum_10 |  -6.166132   4.131944    -1.49   0.137    -14.30688    1.974614
 type_dum_11 |  (dropped)
 type_dum_12 |  (dropped)
 type_dum_13 |  (dropped)
 type_dum_14 |  (dropped)
 type_dum_15 |  (dropped)
 type_dum_16 |  (dropped)
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |  (dropped)
 type_dum_22 |  (dropped)
```

type_dum_23	-10.01763	5.175031	-1.94	0.054	-20.21347	.1781985
type_dum_24	-4.671619	3.578431	-1.31	0.193	-11.72184	2.378597
type_dum_25	(dropped)					
type_dum_26	(dropped)					
type_dum_27	-5.038716	3.529255	-1.43	0.155	-11.99205	1.914613
type_dum_28	-5.392942	3.583811	-1.50	0.134	-12.45376	1.667873
type_dum_29	(dropped)					
type_dum_30	(dropped)					
type_dum_31	-4.278442	3.601163	-1.19	0.236	-11.37345	2.816561
type_dum_32	(dropped)					
type_dum_33	(dropped)					
type_dum_34	(dropped)					
type_dum_35	(dropped)					
type_dum_36	(dropped)					
type_dum_37	-5.566041	3.595268	-1.55	0.123	-12.64943	1.517347
type_dum_38	(dropped)					
type_dum_39	(dropped)					
type_dum_40	(dropped)					
y1966	(dropped)					
y1967	(dropped)					
y1968	(dropped)					
y1969	(dropped)					
y1970	(dropped)					
y1971	(dropped)					
y1972	(dropped)					
y1973	(dropped)					
y1974	(dropped)					
y1975	(dropped)					
y1976	(dropped)					
y1977	.0557071	.2167649	0.26	0.797	-.3713625	.4827768
y1978	(dropped)					
y1979	.0261974	.2116717	0.12	0.902	-.3908376	.4432324
y1980	.1353026	.1996812	0.68	0.499	-.2581088	.5287141
y1981	.0797521	.2029579	0.39	0.695	-.3201152	.4796193
y1982	-.125048	.2053104	-0.61	0.543	-.52955	.279454
y1983	-.2493719	.2071419	-1.20	0.230	-.6574823	.1587385
y1984	-.2885594	.2089932	-1.38	0.169	-.7003172	.1231985
y1985	(dropped)					
y1986	-.0998338	.2115909	-0.47	0.637	-.5167097	.3170421
y1987	-.1144215	.2118515	-0.54	0.590	-.5318108	.3029678
y1988	-.1348602	.2156537	-0.63	0.532	-.5597406	.2900201
y1989	.0130911	.2169473	0.06	0.952	-.414338	.4405202
y1990	.0548365	.2181174	0.25	0.802	-.3748978	.4845709
y1991	.0870971	.2160735	0.40	0.687	-.3386103	.5128046
y1992	.053161	.2145663	0.25	0.805	-.369577	.475899
y1993	-.0228066	.2162601	-0.11	0.916	-.4488817	.4032686
y1994	.0023508	.2150432	0.01	0.991	-.4213268	.4260285
y1995	.0135039	.2155086	0.06	0.950	-.4110906	.4380985
y1996	.0603495	.2163016	0.28	0.780	-.3658074	.4865064
y1997	.0798924	.2157868	0.37	0.712	-.3452502	.505035
y1998	.2064475	.2169556	0.95	0.342	-.2209979	.633893
y1999	.1943921	.2178407	0.89	0.373	-.2347972	.6235814
y2000	.191022	.218731	0.87	0.383	-.2399213	.6219652
y2001	.2015107	.2201414	0.92	0.361	-.2322113	.6352328
y2002	.098522	.2216623	0.44	0.657	-.3381966	.5352405
y2003	.113805	.2223378	0.51	0.609	-.3242445	.5518544
agetype2	(dropped)					
agetype3	(dropped)					
agetype4	.4325233	.2655354	1.63	0.105	-.0906338	.9556804
agetype5	.4956641	.2684821	1.85	0.066	-.0332987	1.024627
agetype6	.4074423	.2666115	1.53	0.128	-.117835	.9327196
agetype7	.5126089	.2782855	1.84	0.067	-.0356686	1.060886
agetype8	.4248565	.286071	1.49	0.139	-.1387598	.9884729
agetype9	(dropped)					
agetype10	.5202328	.3089694	1.68	0.094	-.0884979	1.128964
agetype11	(dropped)					
agetype12	(dropped)					
agetype13	(dropped)					
agetype14	(dropped)					
agetype15	(dropped)					
agetype16	(dropped)					
agetype17	(dropped)					
agetype18	(dropped)					
agetype19	(dropped)					
agetype20	(dropped)					
agetype21	-.0111338	.0348138	-0.32	0.749	-.0797238	.0574562
agetype22	(dropped)					
agetype23	.56572	.2898586	1.95	0.052	-.0053587	1.136799
agetype24	.417627	.2656485	1.57	0.117	-.1057531	.9410071
agetype25	(dropped)					
agetype26	(dropped)					

```
   agetype27 |    .409796   .2633876     1.56   0.121    -.1091297    .9287217
   agetype28 |   .4094451   .2658411     1.54   0.125    -.1143144    .9332047
   agetype29 |  (dropped)
   agetype30 |  (dropped)
   agetype31 |   .3806783   .2666007     1.43   0.155    -.1445779    .9059344
   agetype32 |  (dropped)
   agetype33 |  (dropped)
   agetype34 |  (dropped)
   agetype35 |  (dropped)
   agetype36 |  (dropped)
   agetype37 |   .4095206   .2669071     1.53   0.126    -.1163391    .9353804
   agetype38 |  (dropped)
   agetype39 |  (dropped)
   agetype40 |  -.0646876   .0373166    -1.73   0.084    -.1382087    .0088335
   air_dum_2 |  (dropped)
   air_dum_3 |    2.49234   1.076815     2.31   0.022     .3708025    4.613878
   air_dum_4 |   3.104568   1.133756     2.74   0.007     .8708443    5.338292
   air_dum_5 |   2.187025   1.077803     2.03   0.044     .0635404     4.31051
   air_dum_6 |   2.205043   1.075922     2.05   0.042     .0852636    4.324823
   air_dum_7 |  (dropped)
   air_dum_8 |  (dropped)
   air_dum_9 |    1.98096   1.066988     1.86   0.065    -.1212162    4.083136
  air_dum_10 |   .9737842   1.128565     0.86   0.389    -1.249713    3.197281
  air_dum_11 |  (dropped)
     ageair2 |  -.0586459   .0272407    -2.15   0.032    -.1123154   -.0049763
     ageair3 |  -.2177753   .0913478    -2.38   0.018    -.3977485   -.0378021
     ageair4 |  -.2343213   .0927612    -2.53   0.012    -.4170792   -.0515634
     ageair5 |  -.2068682   .0913476    -2.26   0.024    -.3868411   -.0268953
     ageair6 |  -.2101676   .0910378    -2.31   0.022    -.3895301   -.0308052
     ageair7 |  (dropped)
     ageair8 |  (dropped)
     ageair9 |  -.1875877   .0906835    -2.07   0.040    -.3662521   -.0089232
    ageair10 |  -.1130299   .0937145    -1.21   0.229     -.297666    .0716061
    ageair11 |  (dropped)
       _cons |   2.944055   3.704222     0.79   0.428    -4.353994     10.2421
------------------------------------------------------------------------------
```

A.3.3.2 Airline Fixed Effects

The estimated model is $\log(y_{itr}) = \alpha + \beta * Age_{itr} + \mu_t + \delta_r + \tau_i$, where μ_t are the aircraft type fixed effects, δ_r are the year fixed effects, τ_i are the airline fixed effects, β is the age effect, α is the intercept, and y is the total maintenance cost per flight hour.

<u>Age ≤ 6</u>

```
. reg logtotperflthr age type_dum_2-type_dum_40 y1966-y2003 air_dum_2-air_dum_11 if
synth==0 & age<=6

      Source |       SS       df       MS              Number of obs =     359
-------------+------------------------------           F( 69,   289) =   13.26
       Model |  139.447635    69  2.02098022           Prob > F      =  0.0000
    Residual |  44.0405544   289  .152389462           R-squared     =  0.7600
-------------+------------------------------           Adj R-squared =  0.7027
       Total |   183.48819   358  .512536842           Root MSE      =  .39037

------------------------------------------------------------------------------
logtotperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .1421294   .0157578     9.02   0.000     .1111149     .173144
  type_dum_2 |  (dropped)
```

type_dum_3	-.2492666	.1978635	-1.26	0.209	-.6387027	.1401695
type_dum_4	.0120394	.1388309	0.09	0.931	-.2612085	.2852873
type_dum_5	-.2417639	.1975783	-1.22	0.222	-.6306389	.1471111
type_dum_6	1.199668	.1755322	6.83	0.000	.8541844	1.545152
type_dum_7	.3569839	.227524	1.57	0.118	-.0908302	.804798
type_dum_8	.4953972	.2239063	2.21	0.028	.0547035	.936091
type_dum_9	.72776	.2393767	3.04	0.003	.2566172	1.198903
type_dum_10	.8160263	.2664602	3.06	0.002	.2915777	1.340475
type_dum_11	.511669	.2825144	1.81	0.071	-.0443777	1.067716
type_dum_12	-.4439497	.261312	-1.70	0.090	-.9582657	.0703663
type_dum_13	.1953393	.2415075	0.81	0.419	-.2799974	.6706759
type_dum_14	-.9404033	.3531065	-2.66	0.008	-1.63539	-.2454169
type_dum_15	.3716474	.3142982	1.18	0.238	-.2469564	.9902512
type_dum_16	.122089	.1995054	0.61	0.541	-.2705787	.5147567
type_dum_17	(dropped)					
type_dum_18	(dropped)					
type_dum_19	(dropped)					
type_dum_20	(dropped)					
type_dum_21	-.0438914	.317246	-0.14	0.890	-.6682971	.5805142
type_dum_22	.4298476	.261403	1.64	0.101	-.0846474	.9443426
type_dum_23	(dropped)					
type_dum_24	.8771489	.1922492	4.56	0.000	.4987628	1.255535
type_dum_25	(dropped)					
type_dum_26	(dropped)					
type_dum_27	-.3329763	.1767158	-1.88	0.061	-.6807895	.0148369
type_dum_28	-.322777	.1924635	-1.68	0.095	-.7015849	.056031
type_dum_29	.4197264	.2693641	1.56	0.120	-.1104377	.9498906
type_dum_30	(dropped)					
type_dum_31	1.078476	.2115793	5.10	0.000	.6620443	1.494908
type_dum_32	(dropped)					
type_dum_33	(dropped)					
type_dum_34	(dropped)					
type_dum_35	(dropped)					
type_dum_36	.959609	.2382754	4.03	0.000	.4906339	1.428584
type_dum_37	-.2450151	.2426003	-1.01	0.313	-.7225024	.2324723
type_dum_38	.3992202	.2576399	1.55	0.122	-.1078683	.9063086
type_dum_39	-.48016	.3136084	-1.53	0.127	-1.097406	.1370861
type_dum_40	(dropped)					
y1966	-.1728015	.1491597	-1.16	0.248	-.4663786	.1207755
y1967	-.1899204	.1675655	-1.13	0.258	-.5197238	.139883
y1968	-.2591667	.1784917	-1.45	0.148	-.6104751	.0921417
y1969	-.3512454	.1795075	-1.96	0.051	-.7045533	.0020625
y1970	-.4588352	.184242	-2.49	0.013	-.8214616	-.0962089
y1971	-.6304406	.1926454	-3.27	0.001	-1.009607	-.2512746
y1972	-.6475405	.2018852	-3.21	0.001	-1.044892	-.2501889
y1973	-.7532541	.2107176	-3.57	0.000	-1.16799	-.3385183
y1974	-.6222594	.2181193	-2.85	0.005	-1.051563	-.1929555
y1975	-.7275274	.2257132	-3.22	0.001	-1.171777	-.2832772
y1976	-.8088716	.2312902	-3.50	0.001	-1.264098	-.3536449
y1977	-.8557423	.2573516	-3.33	0.001	-1.362263	-.3492212
y1978	-1.006182	.2712065	-3.71	0.000	-1.539972	-.4723913
y1979	-1.049587	.3315019	-3.17	0.002	-1.702051	-.3971227
y1980	-1.126004	.3332099	-3.38	0.001	-1.78183	-.4701784
y1981	-1.205391	.4558	-2.64	0.009	-2.102499	-.3082826
y1982	-1.104342	.342652	-3.22	0.001	-1.778752	-.4299324
y1983	-1.226527	.3218426	-3.81	0.000	-1.859979	-.5930739
y1984	-1.213063	.271908	-4.46	0.000	-1.748234	-.6778916
y1985	(dropped)					
y1986	-1.096684	.2536623	-4.32	0.000	-1.595943	-.5974239
y1987	-1.003949	.2648639	-3.79	0.000	-1.525256	-.4826419
y1988	-1.152635	.2647426	-4.35	0.000	-1.673703	-.6315666
y1989	-1.20929	.257282	-4.70	0.000	-1.715674	-.7029054
y1990	-1.131405	.2647546	-4.27	0.000	-1.652496	-.6103131
y1991	-.9821483	.2549741	-3.85	0.000	-1.48399	-.4803066
y1992	-1.160687	.2495275	-4.65	0.000	-1.651809	-.6695656
y1993	-1.198045	.2554562	-4.69	0.000	-1.700836	-.6952548
y1994	-1.112618	.2643139	-4.21	0.000	-1.632842	-.5923937
y1995	-1.255927	.2592875	-4.84	0.000	-1.766259	-.7455958
y1996	-1.34844	.2687936	-5.02	0.000	-1.877481	-.8193985
y1997	-1.2996	.2755317	-4.72	0.000	-1.841903	-.7572965
y1998	-1.460412	.2718157	-5.37	0.000	-1.995401	-.9254225
y1999	-1.070169	.2526194	-4.24	0.000	-1.567376	-.5729623
y2000	-1.046365	.254484	-4.11	0.000	-1.547242	-.5454875
y2001	-.9921263	.2524531	-3.93	0.000	-1.489006	-.4952466
y2002	-.9256326	.2583022	-3.58	0.000	-1.434025	-.4172406
y2003	-.7902603	.2518218	-3.14	0.002	-1.285897	-.294623
air_dum_2	.3080761	.2233458	1.38	0.169	-.1315145	.7476667
air_dum_3	.2463435	.1329667	1.85	0.065	-.0153625	.5080495
air_dum_4	(dropped)					
air_dum_5	.2778805	.1392803	2.00	0.047	.0037482	.5520128
air_dum_6	-.1502726	.1485618	-1.01	0.313	-.4426728	.1421276

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
air_dum_7	(dropped)					
air_dum_8	(dropped)					
air_dum_9	.4210043	.1355665	3.11	0.002	.1541814	.6878272
air_dum_10	.0509689	.1848661	0.28	0.783	-.3128857	.4148235
air_dum_11	(dropped)					
_cons	-.6227627	.2070141	-3.01	0.003	-1.030209	-.2153162

6 < Age ≤ 12

```
reg logtotperflthr age type_dum_2-type_dum_40 y1966-y2003 air_dum_2-air_dum_11 if
synth==0 & age>6 & age<=12
```

Source	SS	df	MS
Model	55.863786	66	.846421001
Residual	8.4954135	282	.03012558
Total	64.3591995	348	.184940229

Number of obs	=	349
F(66, 282)	=	28.10
Prob > F	=	0.0000
R-squared	=	0.8680
Adj R-squared	=	0.8371
Root MSE	=	.17357

logtotperf~r	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age	.0328693	.0076732	4.28	0.000	.0177652	.0479734
type_dum_2	(dropped)					
type_dum_3	-.1364218	.0927417	-1.47	0.142	-.3189758	.0461321
type_dum_4	-.2856827	.061977	-4.61	0.000	-.4076789	-.1636865
type_dum_5	-.1213484	.0778159	-1.56	0.120	-.2745221	.0318253
type_dum_6	.9424385	.0711761	13.24	0.000	.8023347	1.082542
type_dum_7	.2936505	.0854762	3.44	0.001	.1253981	.461903
type_dum_8	.330743	.0860207	3.84	0.000	.1614188	.5000671
type_dum_9	(dropped)					
type_dum_10	.8546537	.1094012	7.81	0.000	.639307	1.07
type_dum_11	(dropped)					
type_dum_12	(dropped)					
type_dum_13	.1755834	.112683	1.56	0.120	-.0462231	.3973899
type_dum_14	(dropped)					
type_dum_15	(dropped)					
type_dum_16	(dropped)					
type_dum_17	(dropped)					
type_dum_18	(dropped)					
type_dum_19	(dropped)					
type_dum_20	(dropped)					
type_dum_21	.3192126	.1162346	2.75	0.006	.0904151	.5480102
type_dum_22	(dropped)					
type_dum_23	(dropped)					
type_dum_24	.6460238	.0782187	8.26	0.000	.4920573	.7999904
type_dum_25	(dropped)					
type_dum_26	(dropped)					
type_dum_27	-.0205002	.0743009	-0.28	0.783	-.166755	.1257546
type_dum_28	-.3578625	.0902763	-3.96	0.000	-.5355633	-.1801616
type_dum_29	-.3369725	.1503577	-2.24	0.026	-.6329383	-.0410067
type_dum_30	(dropped)					
type_dum_31	.5919032	.0989604	5.98	0.000	.3971084	.7866981
type_dum_32	(dropped)					
type_dum_33	(dropped)					
type_dum_34	.0015496	.1246709	0.01	0.990	-.2438541	.2469532
type_dum_35	(dropped)					
type_dum_36	.6622267	.1062353	6.23	0.000	.4531118	.8713415
type_dum_37	-.0316911	.0838163	-0.38	0.706	-.1966761	.133294
type_dum_38	.3902379	.1345724	2.90	0.004	.125344	.6551318
type_dum_39	-.1499169	.1317336	-1.14	0.256	-.4092229	.109389
type_dum_40	-.5802724	.1718148	-3.38	0.001	-.9184746	-.2420702
y1966	.0300486	.1419246	0.21	0.832	-.2493175	.3094147
y1967	.1704925	.1298293	1.31	0.190	-.0850651	.4260501
y1968	.0991469	.1376591	0.72	0.472	-.1718229	.3701168
y1969	.0715043	.145575	0.49	0.624	-.2150472	.3580557
y1970	.1365971	.1451516	0.94	0.347	-.149121	.4223152
y1971	-.0410498	.155948	-0.26	0.793	-.3480197	.2659201
y1972	-.1311912	.1593356	-0.82	0.411	-.4448292	.1824468
y1973	.0157717	.1674959	0.09	0.925	-.3139291	.3454726
y1974	.0273809	.1724079	0.16	0.874	-.3119888	.3667506
y1975	-.0232827	.1747912	-0.13	0.894	-.3673438	.3207783
y1976	-.039442	.1774247	-0.22	0.824	-.3886869	.3098029
y1977	-.054195	.1789062	-0.30	0.762	-.4063562	.2979662
y1978	-.1525778	.1800657	-0.85	0.398	-.5070213	.2018658
y1979	-.2279109	.1809755	-1.26	0.209	-.5841453	.1283235
y1980	-.1719605	.1826678	-0.94	0.347	-.531526	.1876049
y1981	-.1912194	.1833749	-1.04	0.298	-.5521767	.1697379
y1982	-.3639488	.1868768	-1.95	0.052	-.7317993	.0039018

```
       y1983 |  -.2983391   .1882512    -1.58   0.114     -.668895    .0722169
       y1984 |  -.3363185   .1962673    -1.71   0.088    -.7226534    .0500163
       y1985 |  (dropped)
       y1986 |  -.3246884   .2025341    -1.60   0.110    -.7233589    .0739821
       y1987 |  -.2539003   .1946676    -1.30   0.193    -.6370864    .1292857
       y1988 |  -.2978073   .1927557    -1.54   0.123    -.6772299    .0816153
       y1989 |  -.2434694   .1926973    -1.26   0.207    -.6227771    .1358382
       y1990 |  -.1930935   .1920821    -1.01   0.316    -.5711901    .1850031
       y1991 |  -.1907953   .1961565    -0.97   0.332    -.5769121    .1953214
       y1992 |  -.3681118     .20065    -1.83   0.068    -.7630738    .0268501
       y1993 |  -.3690218   .2032633    -1.82   0.071    -.7691277    .0310841
       y1994 |  -.5571941   .1911097    -2.92   0.004    -.9333768   -.1810114
       y1995 |  -.5506601   .1915082    -2.88   0.004     -.927627   -.1736931
       y1996 |   -.551388   .1914641    -2.88   0.004    -.9282681   -.1745079
       y1997 |  -.5092424   .1934104    -2.63   0.009    -.8899537   -.1285312
       y1998 |  -.5132125   .1889777    -2.72   0.007    -.8851984   -.1412265
       y1999 |  -.4762985   .1892825    -2.52   0.012    -.8488844   -.1037127
       y2000 |  -.3480547   .1907846    -1.82   0.069    -.7235974    .0274879
       y2001 |  -.2103573   .1909999    -1.10   0.272    -.5863238    .1656092
       y2002 |  -.2305074   .1933649    -1.19   0.234    -.6111293    .1501144
       y2003 |   -.379098   .1962701    -1.93   0.054    -.7654384    .0072423
   air_dum_2 |  -.2330849   .1190905    -1.96   0.051    -.4675041    .0013343
   air_dum_3 |  -.0650174   .0699523    -0.93   0.353    -.2027124    .0726776
   air_dum_4 |  -.0633293   .0921496    -0.69   0.492    -.2447176     .118059
   air_dum_5 |  -.2315704   .0652719    -3.55   0.000    -.3600524   -.1030884
   air_dum_6 |  -.2928124   .0721139    -4.06   0.000    -.4347623   -.1508625
   air_dum_7 |  -.1758598   .0911272    -1.93   0.055    -.3552357    .0035161
   air_dum_8 |  (dropped)
   air_dum_9 |  -.0874944    .068651    -1.27   0.204    -.2226279     .047639
  air_dum_10 |  -.2933314   .0927584    -3.16   0.002    -.4759181   -.1107447
  air_dum_11 |  (dropped)
       _cons |  -.2892963   .1693533    -1.71   0.089    -.6226535    .0440608
------------------------------------------------------------------------------
```

<u>12 < Age</u>

```
. reg logtotperflthr age type_dum_2-type_dum_40 y1966-y2003 air_dum_2-air_dum_11 if
synth==0 & age>12

      Source |       SS       df       MS              Number of obs =     299
-------------+------------------------------           F( 47,   251) =   19.03
       Model |  47.8931125    47  1.01900239           Prob > F      =  0.0000
    Residual |  13.4412317   251  .053550724           R-squared     =  0.7809
-------------+------------------------------           Adj R-squared =  0.7398
       Total |  61.3343442   298  .205819947           Root MSE      =  .23141

------------------------------------------------------------------------------
logtotperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .0042335   .0071656     0.59   0.555    -.0098789    .0183458
  type_dum_2 |  (dropped)
  type_dum_3 |  (dropped)
  type_dum_4 |   .0862873   .1679383     0.51   0.608    -.2444605     .417035
  type_dum_5 |  -.0057654    .175104    -0.03   0.974    -.3506257     .339095
  type_dum_6 |   .9062576   .1743385     5.20   0.000     .5629049     1.24961
  type_dum_7 |   .2371086   .2089011     1.14   0.257    -.1743138     .648531
  type_dum_8 |   .1162392   .2099911     0.55   0.580      -.29733    .5298083
  type_dum_9 |  (dropped)
 type_dum_10 |   .7724591   .2285854     3.38   0.001     .3222693    1.222649
 type_dum_11 |  (dropped)
 type_dum_12 |  (dropped)
 type_dum_13 |  (dropped)
 type_dum_14 |  (dropped)
 type_dum_15 |  (dropped)
 type_dum_16 |  (dropped)
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |  (dropped)
 type_dum_22 |  (dropped)
 type_dum_23 |   .1475584   .2454898     0.60   0.548     -.335924    .6310409
 type_dum_24 |   .8714429   .1679596     5.19   0.000     .5406531    1.202233
 type_dum_25 |  (dropped)
 type_dum_26 |  (dropped)
 type_dum_27 |   .3448456   .1647381     2.09   0.037     .0204005    .6692908
 type_dum_28 |  -.0820898   .1742705    -0.47   0.638    -.4253086    .2611289
 type_dum_29 |  (dropped)
 type_dum_30 |  (dropped)
 type_dum_31 |   .6108653   .1880613     3.25   0.001     .2404862    .9812445
```

type_dum_32	(dropped)					
type_dum_33	(dropped)					
type_dum_34	(dropped)					
type_dum_35	(dropped)					
type_dum_36	(dropped)					
type_dum_37	-.0141239	.182156	-0.08	0.938	-.372873	.3446251
type_dum_38	(dropped)					
type_dum_39	(dropped)					
type_dum_40	(dropped)					
y1966	(dropped)					
y1967	(dropped)					
y1968	(dropped)					
y1969	(dropped)					
y1970	(dropped)					
y1971	(dropped)					
y1972	(dropped)					
y1973	.6615441	.3311784	2.00	0.047	.0093013	1.313787
y1974	(dropped)					
y1975	(dropped)					
y1976	(dropped)					
y1977	.4712496	.3278291	1.44	0.152	-.1743967	1.116896
y1978	.4083528	.3277825	1.25	0.214	-.2372018	1.053907
y1979	.5203111	.2909567	1.79	0.075	-.0527166	1.093339
y1980	.5220371	.2875962	1.82	0.071	-.0443721	1.088446
y1981	.433678	.2863031	1.51	0.131	-.1301845	.9975405
y1982	.3240338	.3030871	1.07	0.286	-.2728842	.9209519
y1983	.1880053	.3007102	0.63	0.532	-.4042315	.7802421
y1984	.1172766	.2974408	0.39	0.694	-.4685213	.7030744
y1985	(dropped)					
y1986	.2819	.2936509	0.96	0.338	-.2964336	.8602337
y1987	.2691003	.2932157	0.92	0.360	-.3083764	.846577
y1988	.2787624	.2945142	0.95	0.345	-.3012716	.8587965
y1989	.3906686	.2957247	1.32	0.188	-.1917494	.9730867
y1990	.4316161	.2963809	1.46	0.147	-.1520942	1.015326
y1991	.4921854	.2957752	1.66	0.097	-.0903322	1.074703
y1992	.443977	.2972526	1.49	0.137	-.1414503	1.029404
y1993	.3569529	.2985829	1.20	0.233	-.2310944	.9450001
y1994	.3630267	.2976869	1.22	0.224	-.2232558	.9493092
y1995	.3767688	.2986592	1.26	0.208	-.2114285	.9649661
y1996	.4228487	.2997972	1.41	0.160	-.16759	1.013287
y1997	.4416148	.2998384	1.47	0.142	-.1489051	1.032135
y1998	.5235341	.3000214	1.74	0.082	-.0673462	1.114414
y1999	.4906728	.3012087	1.63	0.105	-.1025457	1.083891
y2000	.5371173	.3025731	1.78	0.077	-.0587883	1.133023
y2001	.5619164	.3032213	1.85	0.065	-.035266	1.159099
y2002	.4964988	.3051336	1.63	0.105	-.1044496	1.097447
y2003	.5588504	.3054629	1.83	0.069	-.0427467	1.160447
air_dum_2	.1136707	.2648154	0.43	0.668	-.4078726	.635214
air_dum_3	-.0597653	.2486102	-0.24	0.810	-.5493933	.4298627
air_dum_4	.124709	.2524603	0.49	0.622	-.3725015	.6219196
air_dum_5	-.1549973	.2477984	-0.63	0.532	-.6430263	.3330318
air_dum_6	-.2303487	.2470428	-0.93	0.352	-.7168897	.2561923
air_dum_7	(dropped)					
air_dum_8	(dropped)					
air_dum_9	-.0504787	.2484984	-0.20	0.839	-.5398863	.4389289
air_dum_10	.0857714	.2534694	0.34	0.735	-.4134264	.5849693
air_dum_11	(dropped)					
_cons	-.7108254	.3431575	-2.07	0.039	-1.38666	-.0349903

A.3.4 Short-Lived Fleets Removed

Short-lived fleets, as described in Section 5.1.1, are removed from sample. The estimated model is $\log(y_{itr}) = \alpha + \beta * Age_{itr} + \mu_t + \delta_r$, where μ_t are the aircraft type fixed effects, δ_r are the year fixed effects, *i* represents the airlines, β is the age effect, α is the intercept, and y is the total maintenance cost per flight hour.

<u>Age ≤ 6</u>

```
. reg logtotperflthr age type_dum_2-type_dum_40 y1966-y2003 if synth==0 & age<6

      Source |       SS       df       MS              Number of obs =     297
-------------+------------------------------           F( 56,   240) =   10.09
       Model |  104.292295    56  1.86236241           Prob > F      =  0.0000
    Residual |   44.311301   240  .184630421           R-squared     =  0.7018
-------------+------------------------------           Adj R-squared =  0.6322
       Total |  148.603596   296  .502039176           Root MSE      =  .42969

------------------------------------------------------------------------------
logtotperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .1486109   .0186681     7.96   0.000     .1118366    .1853853
  type_dum_2 |  (dropped)
  type_dum_3 |  (dropped)
  type_dum_4 |   .2458212   .1731066     1.42   0.157    -.0951811    .5868235
  type_dum_5 |   .2133228   .2203425     0.97   0.334    -.2207293     .647375
  type_dum_6 |   1.281184   .2074631     6.18   0.000     .8725029    1.689865
  type_dum_7 |   .6971824    .252484     2.76   0.006     .1998147     1.19455
  type_dum_8 |   .9173583   .2506593     3.66   0.000     .4235852    1.411131
  type_dum_9 |   1.207513   .2599338     4.65   0.000     .6954702    1.719556
 type_dum_10 |   1.197212   .2958398     4.05   0.000     .6144378    1.779986
 type_dum_11 |  (dropped)
 type_dum_12 |  -.0656015   .2666785    -0.25   0.806     -.590931    .4597279
 type_dum_13 |   .5166463   .2561302     2.02   0.045      .012096    1.021197
 type_dum_14 |  -.6375841   .3528199    -1.81   0.072    -1.332603    .0574351
 type_dum_15 |   .6286443   .3163695     1.99   0.048     .0054288     1.25186
 type_dum_16 |  (dropped)
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |  (dropped)
 type_dum_22 |  (dropped)
 type_dum_23 |  (dropped)
 type_dum_24 |   1.060583   .2126646     4.99   0.000      .641656    1.479511
 type_dum_25 |  (dropped)
 type_dum_26 |  (dropped)
 type_dum_27 |   .0467862   .2244204     0.21   0.835    -.3952989    .4888714
 type_dum_28 |  (dropped)
 type_dum_29 |   .7551685    .299294     2.52   0.012       .16559    1.344747
 type_dum_30 |  (dropped)
 type_dum_31 |   1.335494   .2440756     5.47   0.000     .8546897    1.816297
 type_dum_32 |  (dropped)
 type_dum_33 |  (dropped)
 type_dum_34 |  (dropped)
 type_dum_35 |  (dropped)
 type_dum_36 |   1.434481    .285602     5.02   0.000     .8718745    1.997088
 type_dum_37 |   .1101808   .2808694     0.39   0.695    -.4431032    .6634648
 type_dum_38 |   .4110095   .3057698     1.34   0.180    -.1913256    1.013345
 type_dum_39 |  (dropped)
 type_dum_40 |  (dropped)
       y1966 |   -.063678   .2618968    -0.24   0.808     -.579588    .4522319
       y1967 |  -.1929805    .262338    -0.74   0.463    -.7097595    .3237985
       y1968 |  -.2741883   .2555898    -1.07   0.284    -.7776741    .2292975
       y1969 |  -.3772825   .2562827    -1.47   0.142    -.8821332    .1275681
       y1970 |  -.4453673    .268886    -1.66   0.099    -.9750453    .0843106
       y1971 |   -.619974   .2716803    -2.28   0.023    -1.155156   -.0847915
       y1972 |   -.625077   .2641729    -2.37   0.019     -1.14547   -.1046835
       y1973 |  -.7678783   .2755142    -2.79   0.006    -1.310613   -.2251435
       y1974 |  -.6049067   .2854599    -2.12   0.035    -1.167233   -.0425798
       y1975 |  -.6431478   .2879497    -2.23   0.026    -1.210379   -.0759164
       y1976 |   -.748762   .2921654    -2.56   0.011    -1.324298   -.1732261
       y1977 |  -.8032097   .3124593    -2.57   0.011    -1.418722   -.1876968
       y1978 |  -.9706091   .3260411    -2.98   0.003    -1.612877   -.3283416
       y1979 |  -.9716656   .3848881    -2.52   0.012    -1.729856   -.2134755
       y1980 |  -1.051291   .3868074    -2.72   0.007    -1.813262   -.2893203
       y1981 |  -1.143009   .5205589    -2.20   0.029    -2.168457   -.1175612
       y1982 |  -1.038578   .3995491    -2.60   0.010    -1.825649   -.2515075
       y1983 |  -1.264605   .3790488    -3.34   0.001    -2.011292   -.5179179
       y1984 |  -1.249417   .3238843    -3.86   0.000    -1.887436   -.6113982
       y1985 |  (dropped)
```

```
       y1986 |  -1.301871   .3266318    -3.99   0.000    -1.945302   -.6584397
       y1987 |  -1.145385    .321983    -3.56   0.000    -1.779659   -.5111115
       y1988 |  -1.254424   .3178931    -3.95   0.000     -1.88064   -.6282067
       y1989 |  -1.324769    .310439    -4.27   0.000    -1.936302   -.7132362
       y1990 |   -1.24806    .318427    -3.92   0.000    -1.875328   -.6207913
       y1991 |  -.9331592   .3133305    -2.98   0.003    -1.550388   -.3159302
       y1992 |  -1.192885   .3070562    -3.88   0.000    -1.797755    -.588016
       y1993 |  -1.300929   .3146232    -4.13   0.000    -1.920704   -.6811534
       y1994 |  -1.240278   .3272198    -3.79   0.000    -1.884867   -.5956884
       y1995 |   -1.28458   .3228121    -3.98   0.000    -1.920487   -.6486735
       y1996 |  -1.369158   .3289887    -4.16   0.000    -2.017232   -.7210845
       y1997 |  -1.246706   .3370229    -3.70   0.000    -1.910607   -.5828058
       y1998 |  -1.634071   .3268623    -5.00   0.000    -2.277957   -.9901861
       y1999 |   -1.26591    .304454    -4.16   0.000    -1.865653   -.6661666
       y2000 |  -1.218219     .30657    -3.97   0.000    -1.822131   -.6143078
       y2001 |   -1.22484   .3050339    -4.02   0.000    -1.825726   -.6239544
       y2002 |  -1.100901   .3083331    -3.57   0.000    -1.708286   -.4935163
       y2003 |  -.9547438    .302648    -3.15   0.002    -1.550929   -.3585582
       _cons |  -.6967543   .2586087    -2.69   0.008    -1.206187   -.1873216
------------------------------------------------------------------------------
```

<u>6 < Age ≤ 12</u>

```
. reg logtotperflthr age type_dum_2-type_dum_40 y1966-y2003 if synth==0 & age>6 & age<=12

      Source |       SS       df       MS              Number of obs =     273
-------------+------------------------------           F( 47,   225) =   25.62
       Model |  39.5633933    47  .841774326           Prob > F      =  0.0000
    Residual |  7.39163417   225  .032851707           R-squared     =  0.8426
-------------+------------------------------           Adj R-squared =  0.8097
       Total |  46.9550275   272  .172628778           Root MSE      =  .18125

------------------------------------------------------------------------------
logtotperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .0286767   .0082329     3.48   0.001     .0124533    .0449002
  type_dum_2 |  (dropped)
  type_dum_3 |  (dropped)
  type_dum_4 |   .0139414   .1454107     0.10   0.924    -.2725996    .3004824
  type_dum_5 |   .1919845   .1354796     1.42   0.158    -.0749867    .4589557
  type_dum_6 |   1.178849   .1420714     8.30   0.000     .8988886     1.45881
  type_dum_7 |   .5192042   .1349588     3.85   0.000     .2532594     .785149
  type_dum_8 |   .6299952   .1369363     4.60   0.000     .3601535    .8998368
  type_dum_9 |  (dropped)
 type_dum_10 |   1.237309   .1540877     8.03   0.000     .9336691    1.540948
 type_dum_11 |  (dropped)
 type_dum_12 |  (dropped)
 type_dum_13 |   .3174982    .144223     2.20   0.029     .0332976    .6016988
 type_dum_14 |  (dropped)
 type_dum_15 |  (dropped)
 type_dum_16 |  (dropped)
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |  (dropped)
 type_dum_22 |  (dropped)
 type_dum_23 |  (dropped)
 type_dum_24 |   .9910414   .1504834     6.59   0.000     .6945044    1.287578
 type_dum_25 |  (dropped)
 type_dum_26 |  (dropped)
 type_dum_27 |   .2681946   .1606686     1.67   0.096    -.0484129    .5848022
 type_dum_28 |   -.137172   .1586947    -0.86   0.388    -.4498901     .175546
 type_dum_29 |  (dropped)
 type_dum_30 |  (dropped)
 type_dum_31 |   .8586461   .1616136     5.31   0.000     .5401764    1.177116
 type_dum_32 |  (dropped)
 type_dum_33 |  (dropped)
 type_dum_34 |  (dropped)
 type_dum_35 |  (dropped)
 type_dum_36 |   .6885191   .1593515     4.32   0.000     .3745069    1.002531
 type_dum_37 |    .288097   .1407153     2.05   0.042     .0108087    .5653854
 type_dum_38 |   .5527352   .1684258     3.28   0.001     .2208415    .8846288
 type_dum_39 |  (dropped)
 type_dum_40 |  (dropped)
       y1966 |  (dropped)
       y1967 |  (dropped)
       y1968 |  (dropped)
```

```
       y1969 |  (dropped)
       y1970 |   .3292589   .1936929     1.70   0.091    -.0524252     .710943
       y1971 |   .2661281   .1913836     1.39   0.166    -.1110054    .6432616
       y1972 |   .3145245   .1651946     1.90   0.058    -.0110019    .6400508
       y1973 |   .2757858   .1445011     1.91   0.058    -.0089628    .5605343
       y1974 |   .3236181   .1352435     2.39   0.018     .0571123     .590124
       y1975 |   .3043564   .1338506     2.27   0.024     .0405954    .5681174
       y1976 |   .3063262   .1328238     2.31   0.022     .0445885    .5680639
       y1977 |   .2254211    .130374     1.73   0.085    -.0314892    .4823314
       y1978 |   .1404721    .127998     1.10   0.274     -.111756    .3927002
       y1979 |   .0894216   .1251234     0.71   0.476    -.1571421    .3359852
       y1980 |   .1054808   .1267553     0.83   0.406    -.1442985    .3552602
       y1981 |   .0783557   .1264882     0.62   0.536    -.1708973    .3276088
       y1982 |  -.0721707   .1255878    -0.57   0.566    -.3196494    .1753081
       y1983 |  -.0252409   .1239436    -0.20   0.839    -.2694795    .2189978
       y1984 |  -.0957503    .133501    -0.72   0.474    -.3588225    .1673219
       y1985 |  (dropped)
       y1986 |  -.0610115    .139167    -0.44   0.662    -.3352489     .213226
       y1987 |  (dropped)
       y1988 |   .0519404   .1392084     0.37   0.709    -.2223786    .3262594
       y1989 |   .0673192   .1361898     0.49   0.622    -.2010515    .3356899
       y1990 |   .1092848   .1329934     0.82   0.412     -.152787    .3713566
       y1991 |   .0322664    .158854     0.20   0.839    -.2807655    .3452984
       y1992 |  -.1762234   .1589337    -1.11   0.269    -.4894123    .1369655
       y1993 |  -.0459914   .1581384    -0.29   0.771    -.3576132    .2656304
       y1994 |  -.2615749   .1404194    -1.86   0.064    -.5382802    .0151304
       y1995 |  -.2517654    .137664    -1.83   0.069    -.5230411    .0195103
       y1996 |  -.2616714   .1356818    -1.93   0.055     -.529041    .0056983
       y1997 |  -.2065061   .1358025    -1.52   0.130    -.4741134    .0611013
       y1998 |  -.1837698   .1252491    -1.47   0.144     -.430581    .0630415
       y1999 |  -.1570237   .1258565    -1.25   0.213    -.4050319    .0909845
       y2000 |  -.0334033   .1250755    -0.27   0.790    -.2798724    .2130658
       y2001 |   .1341259   .1251748     1.07   0.285     -.112539    .3807907
       y2002 |   .1259377   .1253437     1.00   0.316      -.12106    .3729353
       y2003 |  -.0099653   .1266296    -0.08   0.937    -.2594969    .2395663
       _cons |   -1.00978   .2005672    -5.03   0.000    -1.405011   -.6145502
------------------------------------------------------------------------------
```

12 < Age

```
. reg logtotperflthr age type_dum_2-type_dum_40 y1966-y2003 if synth==0 & age>12

      Source |       SS       df       MS              Number of obs =     279
-------------+------------------------------           F( 37,   241) =   20.04
       Model |  42.6362645    37  1.15233147           Prob > F      =  0.0000
    Residual |  13.8590709   241  .057506518           R-squared     =  0.7547
-------------+------------------------------           Adj R-squared =  0.7170
       Total |  56.4953354   278  .203220631           Root MSE      =  .23981

------------------------------------------------------------------------------
logtotperf~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .0064973   .0073269     0.89   0.376    -.0079356    .0209301
  type_dum_2 |  (dropped)
  type_dum_3 |  (dropped)
  type_dum_4 |  -.7843716   .1640968    -4.78   0.000    -1.107619   -.4611246
  type_dum_5 |  -.7405951   .1519358    -4.87   0.000    -1.039887   -.4413034
  type_dum_6 |    .009769   .1577832     0.06   0.951    -.3010412    .3205791
  type_dum_7 |  -.4142725   .1672116    -2.48   0.014    -.7436553   -.0848896
  type_dum_8 |   -.573218   .1701321    -3.37   0.001    -.9083539   -.2380822
  type_dum_9 |  (dropped)
 type_dum_10 |  (dropped)
 type_dum_11 |  (dropped)
 type_dum_12 |  (dropped)
 type_dum_13 |  (dropped)
 type_dum_14 |  (dropped)
 type_dum_15 |  (dropped)
 type_dum_16 |  (dropped)
 type_dum_17 |  (dropped)
 type_dum_18 |  (dropped)
 type_dum_19 |  (dropped)
 type_dum_20 |  (dropped)
 type_dum_21 |  (dropped)
 type_dum_22 |  (dropped)
 type_dum_23 |  -.8581476   .2852443    -3.01   0.003    -1.420038   -.2962572
 type_dum_24 |    .010279   .1687896     0.06   0.951    -.3222122    .3427702
 type_dum_25 |  (dropped)
```

type_dum_26	(dropped)					
type_dum_27	-.4752826	.1867116	-2.55	0.012	-.8430776	-.1074875
type_dum_28	-1.023314	.1863231	-5.49	0.000	-1.390343	-.656284
type_dum_29	(dropped)					
type_dum_30	(dropped)					
type_dum_31	-.2970295	.1723511	-1.72	0.086	-.6365363	.0424773
type_dum_32	(dropped)					
type_dum_33	(dropped)					
type_dum_34	(dropped)					
type_dum_35	(dropped)					
type_dum_36	(dropped)					
type_dum_37	-.7360046	.1550587	-4.75	0.000	-1.041448	-.4305612
type_dum_38	(dropped)					
type_dum_39	(dropped)					
type_dum_40	(dropped)					
y1966	(dropped)					
y1967	(dropped)					
y1968	(dropped)					
y1969	(dropped)					
y1970	(dropped)					
y1971	(dropped)					
y1972	(dropped)					
y1973	(dropped)					
y1974	(dropped)					
y1975	(dropped)					
y1976	(dropped)					
y1977	(dropped)					
y1978	-.0632703	.2398082	-0.26	0.792	-.535658	.4091174
y1979	-.0036263	.2398989	-0.02	0.988	-.4761925	.46894
y1980	-.0275797	.2219766	-0.12	0.901	-.4648417	.4096823
y1981	.0438086	.2115372	0.21	0.836	-.3728892	.4605064
y1982	-.1997557	.2124181	-0.94	0.348	-.6181889	.2186775
y1983	-.3110271	.2083197	-1.49	0.137	-.721387	.0993328
y1984	-.3386872	.2020025	-1.68	0.095	-.7366031	.0592287
y1985	(dropped)					
y1986	-.170397	.195027	-0.87	0.383	-.5545721	.213778
y1987	-.1839631	.1948829	-0.94	0.346	-.5678544	.1999282
y1988	-.189028	.1974493	-0.96	0.339	-.5779747	.1999186
y1989	-.0493837	.2002021	-0.25	0.805	-.443753	.3449857
y1990	-.0102266	.2016716	-0.05	0.960	-.4074907	.3870375
y1991	.038109	.2007306	0.19	0.850	-.3573014	.4335194
y1992	.0003302	.2042957	0.00	0.999	-.402103	.4027633
y1993	-.0968503	.2060797	-0.47	0.639	-.5027977	.3090972
y1994	-.0849012	.2061889	-0.41	0.681	-.4910637	.3212614
y1995	-.0919086	.2080676	-0.44	0.659	-.5017717	.3179546
y1996	-.0808603	.2102093	-0.38	0.701	-.4949423	.3332217
y1997	-.0110132	.210066	-0.05	0.958	-.4248131	.4027866
y1998	.1296983	.2102208	0.62	0.538	-.2844065	.543803
y1999	.0836403	.2123361	0.39	0.694	-.3346313	.5019119
y2000	.0844001	.2146882	0.39	0.695	-.3385048	.507305
y2001	.1150868	.2161862	0.53	0.595	-.310769	.5409426
y2002	.0123632	.2193865	0.06	0.955	-.4197966	.444523
y2003	.0571896	.2201966	0.26	0.795	-.3765661	.4909454
_cons	.4497095	.2328757	1.93	0.055	-.009022	.9084411