The Long Term Effects of an Aging Fleet on Operational Availability and Cost: Evidence from the U.S. Coast Guard

Christopher W. Lavin
United States Coast Guard
Office of Surface Acquisition
Washington D.C.
chris.lavin@uscg.mil

Robert M. McNab
Strome College of Business
Old Dominion University
2110 Constant Hall
Norfolk, VA 23529
rmcnab@odu.edu

Ryan S. Sullivan (contact author)*
Naval Postgraduate School
205 Halligan Hall
Monterey, CA 93943
rssulliv@nps.edu

Abstract

This paper empirically examines whether the aging of a fleet affects operational availability and operating cost using a unique dataset on the 117 47-foot Motor Life Boats (MLBs) of the United States Coast Guard (USCG). Procured from 1997 to 2003, the 47-foot MLB is the standard lifeboat of the USCG and all 117 MLBs remain in service. The aging of the MLB fleet has resulted in higher annual operating costs and lower operational availability, although the nature of this relationship remains unclear. Our estimation strategy utilizes an error components estimator to examine these issues. We employ three variants of the dependent variables (i.e., the standard logarithmic transformation as is most commonly seen in the literature, inverse hyperbolic sine (IHS), and level outcomes). The point estimates from the standard logarithmic model finds operational availability for the MLBs decreases at a rate between 0.83% and 1.8% per year and cost increases at a rate between 0.33% and 7.81% per year. Similar effects are shown with the IHS and level outcome specifications. In terms of nonlinearity effects, we find the most pronounced changes in operational availability and cost occur for MLBs aged 15 years or more (in comparison to younger MLBs).

Keywords: Operational Availability, Program Cost, Coast Guard, Fleet

JEL Classifications: D23, H41, H56, H57, L98

***** The views expressed in this document are those of the authors and do not reflect the official policy or position of the Department of Defense, Department of Homeland Security or the U.S. Government. Distribution for this article is unlimited. Special thanks to Jesse Cunha for helpful comments and the U.S. Coast Guard Surface Forces Logistics Center Small Boat Product Line and the U.S. Coast Guard Office of Boat Forces for providing data and comments as well.

1. Introduction

The United States Coast Guard (USCG) performs heavy weather rescue operations in winds up to, and including, hurricane force winds using the 47-foot Motor Life Boat (MLB). Produced from 1997 to 2003, 117 MLBs are now in service and the MLB is the standard lifeboat of the USCG. Furthermore, the USCG expects to continue to operate the MLBs in the medium-term even through reliability issues and operating cost are increasingly a concern. Whether (and when) an aging fleet affects reliability and cost remains an unanswered question.

This paper empirically examines whether the aging of the 47-foot MLB fleet affects operational availability and operating cost. Understanding these connections is critical in helping decision makers determine when the current MLB fleet should be replaced or undergo a Service Life Extension Program (SLEP[1]). To analyze the effects of the aging MLB fleet, we utilize a unique dataset on the operational availability and annual operating costs for each of the MLBs produced and currently operated by the USCG. We control for geographical location, mission type, as well as individual boat effects, and time fixed effects to investigate the influence of an aging fleet on operational availability and cost.

We contribute to a growing body of research that examines the relationship between aging military equipment and operational availability and cost (e.g., Hildbrandt and Sze, 1990; Stoll and Davis, 1993; Kiley, 2001; Keating and Dixon, 2004; and Sokri; 2011).[2] While most of the previous research has generally focused on aircraft, the methods displayed in the literature (e.g., theoretical models, regression analysis, and simulations) provide context for broader

[1] In February 2015, the USCG issued a Request for Information regarding a SLEP for the 47-foot MLBs, primarily focusing on a one-to-one replacement of equipment in the boats. The operating characteristics of the boats are expected to remain the same after the proposed SLEP. See U.S. Coast Guard (2015) for more details.
[2] Related to this line of research are other studies more specifically focused on calibrating the optimal time to replacement of military equipment (e.g., Dixon, 2005; Francis and Shaw, 2000; Greenfield and Persselin 2002, 2003; Jondrow *et al*., 2002; and Keating *et al*., 2014 ; see Maybury, 2015 for a thorough review of this literature).

military applications in other areas such as the replacement of other systems, including tactical vehicles, helicopters, frigates, among others. We extend this literature to now focus specifically on the USCG MLB program. To the best of our knowledge, this is the first time that the effect of aging has been empirically investigated with regards to this USCG MLB fleet.

We expect, *a priori*, that operational availability should decrease and cost should increase as the age of an MLB increases. What is of particular interest, however, is whether age linearly affects availability and cost or whether there is a discontinuity at which availability and cost suffer adversely. For the USCG, this behavior is a continuing concern for policy makers with regards to managing scarce resources, determining whether or not to proceed with a specific SLEP (or complete replacement of the boats), and the optimal usage of MLBs over time.

Our estimation strategy utilizes an error components estimator to examine these issues. We employ three variants of the dependent variables: the standard logarithmic transformation as is most commonly seen in the literature, levels, and the inverse hyperbolic sine (IHS) transformation. The logarithmic point estimates suggest that operational availability for MLBs decreases at a rate between 0.83% and 1.8% per year and cost increases at a rate between 0.33% and 7.81% per year. We find similar estimates for the IHS and levels specifications. In terms of nonlinearity effects, we find the most pronounced changes in operational availability and cost occurs for MLBs aged 15 years or more in comparison to seven-year-old MLBs (i.e., the youngest boats in our dataset). To the best of our knowledge, this is the first use of the IHS transformation in the literature with regards to the impact of aging on operational availability and cost.

The remainder of paper is structured as follows. In the following section, we briefly review the institutional background of the MLB program. In the third section, we discuss the data. We then present the empirical methodology of the study in the fourth section. The fifth section discusses our results, limitations of the study, and possible extensions. The last section concludes the paper.

2. Institutional Details

The USCG conducts maritime safety, security and stewardship operations in and around the United States (U.S) and around the world to protect American security and economic interests (U.S. Coast Guard, 2014). The USCG uses specially designed and constructed boats to conduct operations in areas of rough surf and heavy weather (Textron Systems, 2011). The primary surface asset used in these areas is the 47 foot MLB. This MLB is unique to the Coast Guard because it is designed to operate in the open ocean in seas up to thirty feet, surf up to twenty feet and is self-righting within thirty seconds without any loss of operational capabilities in the event of a roll over (Textron Systems, 2011). It is exceptionally useful in search and rescue missions since it is a multi-mission asset and conducts operations in all the Coast Guard mission areas (CG-731, 2007).

Typically there are only one to three 47 foot MLBs assigned to boat stations across the U.S. (depending on the requirements of the individual station). These stations are generally geographically isolated from other stations and thus, the MLBs often work alone or in very small numbers on their patrols. For some stations such as those operating in surf or heavy weather operating environments, the MLBs will have the support of an additional small response boat (RB-S) (CG-7, 2013) for their duties.

The minimum boat crew for a 47 foot MLB consists of a qualified coxswain, engineer and one boat crew member, although additional crew members are required for heavy weather, surf and Port Waterways Coastal Security (PWCS) missions (CG-731, 2013). The boat crew is usually on duty for two days and off duty for two days. The boat crew typically conducts a patrol of the station's area of responsibility each duty day and then may be underway for additional time depending on operations. The commandant's policy limits underway time depending on the length of the boat and the sea conditions. The 47 foot MLB crew has a limit of 10 hours in seas less than four feet, eight hours in seas greater than four feet but less than eight feet, and six hours for seas greater than eight feet (CG-731, 2013). A standby crew would be called in if the eight hour timeframe is exceeded. The boat can hold a maximum of 34 passengers in addition to the crew (CG-731, 2007).

The Coast Guard Engineering Logistics Center completed the preliminary design of the 47 foot MLB in the 1980s. Textron Marine and Land Systems completed the detailed design and produced the first prototype in 1990. Textron went on to produce five pre-production variants in 1993 and 1994 for testing (CG-731, 2007). Full-rate production began in 1997 and ended in 2003 (CG-731, 2014) at a unit cost of $1,214,300 per copy in 2003 dollars (U.S. Coast Guard Thirteenth District, 2003).[3] The projected design life of an MLB is 25 years with an operational availability of 0.8. While all 117 MLBs remain in service, operational availability for the fleet has witnessed a steady decline since 2009 and fell below 0.8 after 2012 (CG-9325, 2014).

Given a fixed fleet size, the decline in operational availability is of significant concern given its potential to adversely impact the ability of the USCG to conduct missions. In 2014, an Alternatives Analysis (AA) was completed by the Boats Acquisition Program, CG-9325, and the AA attributed the decline in operational ability to equipment casualties to the main propulsion system, electrical generation system and steering system (CG-9325, 2014). The CG-9325 report

[3] Textron also sold versions of the 47 foot MLB to Canada, Egypt and Mexico (Textron Systems, 2011)

also considered that the Coast Guard could "do nothing", provide a SLEP for the existing fleet, purchase a new fleet (not necessarily the same types of boats currently used), or a combination of a SLEP and new fleet purchase. In 2015, the USCG issued a Request for Information for the conduct of a SLEP of the existing fleet of MLBs.

Given the usefulness of the fleet of MLBs, decline in operational availability, and increases in operating cost, this paper examines how the aging of the MLB fleet affects availability and cost. If the USCG conducts a SLEP of the existing fleet, the question remains when should an MLB be part of the SLEP program? Too early and the USCG may waste scarce resources upgrading a boat that does not require an upgrade. Too late and the USCG will waste scarce resources due to increased operating cost and decrease availability. This paper seeks to estimate the impact of aging on operational availability and cost to help in addressing these questions.

3. Data

We gathered unclassified data on the 117 MLBs in the USCG from 2010-2014. We gather annual cost data from the Fleet Logistics System (FLS) and the Asset Maintenance Management Information System (AMMIS) databases. The cost data presented here are an aggregated version of the micro-level data and includes information on planned maintenance costs, time compliance technical orders, transportation costs, consumables for organizational level planned maintenance, and repair of items that are within the organization's capabilities that are not mission limiting, or replacement of outfit items.[4]

[4] See the online Appendix (available at: http://my.nps.edu/web/drmi/working-papers) for a detailed description of these data.

We use the Asset Logistics Management Information System (ALMIS) to obtain operational availability data. ALMIS tracks when a boat is available for operations. As is typical in the literature, we define operational availability as mission capable time divided by total measured time (Jones 2006). The difference between mission capable time and total measured time is the time lost due to preventative maintenance, corrective maintenance, and administrative and logistics delays (Jones 2006). We average the monthly data to obtain annual operating availability data.[5]

The USCG tracks operational performance with the Abstract of Operations (AOPS) database. The AOPS database contains information on every small boat station, to include information on the dominant operating environment or mission. Each station is denoted through the use of a Unit Identification Code (UIC). We use the AOPS database to capture each MLB's dominant mission type for the purposes of this analysis. As each MLB is assigned to a USCG district, we also include geographical location in the database.

The MLBs are located in ten separate Coast Guard districts (Table 1). We label these districts as Northeast (i.e., the Northeast district includes the states of ME, NH, VT, MA, NJ, CT, and part of NY), mid-East Coast (i.e., DE, MD, VA, NC, Washington D.C., and part of PA), Southeast (i.e., SC and most of GA and FL), Central States (i.e., WY, ND, SD, IA, NE, CO, KS, NM, TX, OK, MO, AR, LA, MS, AL, TN, KY, and parts of MN, IL, IN, OH, PA, WV, GA, and FL), Northern Great Lakes (i.e., WI, MI, and parts of MN, IL, IN, OH, PA, and NY), Southwest (i.e., CA, NV, UT, and AZ), Northwest (i.e., WA, OR, MT, and ID), Hawaii, Alaska, and the National Motor Lifeboat School. The National Motor Lifeboat School is technically located in

[5] Of note, the Great Lakes boats were routinely unavailable in January, February, and March due to freezing conditions. Thus, we modified the annual operational availability data for boats located on the Great Lakes to ignore those zero values and calculated their values based on the remaining nine months.

the Northwest district, but has its own "district" for data purposes because their concept of operations is so different from other boat stations. Boats at the National Motor Lifeboat School have a different operational profile because they seek out rough, surf conditions to give students experience. This is different from a normal unit that encounters rough conditions only when required by operations. The increased operations in surf conditions may lead to decreased operational availability and increased maintenance costs. We keep the National Motor Lifeboat School as a separate district from the Northwest due to its unique features.[6]

Combining these datasets, we obtain a strongly balanced panel data set of 585 observations for the 2010-2014 period. For the 117 MLBs, mean annual operating cost was approximately $35,000 and mean operational availability was 0.78 over the period of analysis (Table 1).[7] The MLBs range in age from 7 to 17 years old with a median age of 12 years old.

With regards to mission types, we note that the surf mission type was the most common for the period of analysis with approximately 31% of the observations (Table 1). Surf mission boats primarily conduct search and rescue operations. Following surf missions, heavy weather missions (HWX) were the next most common with approximately 28% of the observations. These boats operate in areas that frequently experience heavy weather conditions and primarily conduct search and rescue operations. Boats with the PWCS Level 1 mission type complete the port, waterways and coastal security mission. These MLBs are responsible for escorting large,

---

[6] We find little difference between the estimates presented in this paper and those that combine the Northwest and Training districts.

[7] Of note, the cost data contained an unusually high number of observations (108 out of 585) equal to zero, suggesting there was zero operating cost for these observations. We had detailed discussions with numerous operators and data analysts to understand this peculiarity in the data. In the end, it was determined that a changeover in accounting systems may have led to inputting zeros where there were missing cost data. Thus, there appears to be a considerable amount of measurement error within these 108 observations. Due to this concern, we decided to exclude these observations in our final analysis. Policy makers should be aware of this limitation when making decisions in regards to our cost results. That stated, discussions with the same military personnel lead us to believe that this was not a problem with the operational availability data. Thus, those results should be completely free from any measurement error or selection bias.

high-value vessels or high-capacity passenger vessels in busy ports and guarding critical infrastructure and key resources like oil and natural gas terminals, bridges and nuclear power plants. Boats with the surf and PWCS Level 1 missions are located in a surf environment and have PWCS responsibilities. Station Golden Gate in San Francisco is an example of one of these areas. MLBs with the HWX and PWCS Level 1 missions are located in heavy weather environments and have PWCS responsibilities. Station Southwest Harbor in Maine is an example of one of these areas. Lastly, boats with the station mission do not have any special weather requirements or special security responsibilities.

Geographically, we find that the highest number of boats resides in the Northeast district with a total of 29.4% of the observations located there. The next four highest percentages of boats by district are in the Northwest (20.2%), mid-East Coast (16.1%), Northern Great Lakes (12.7%), and the Southwest (11.6%), respectively. The rest of the individual districts all have less than 5% (each) of the total number of observations.

4. Methodology

4.1. Previous Literature

As stated previously, the literature has employed a variety of techniques to analyze the effects of aging on operational availability and cost, with a particular focus on aircraft. Some additional work has analyzed the effects of aging on other types of military vehicles and hardware, although the research in these areas has been much more limited in nature. In this section, we present a review of the literature most pertinent to this article (i.e., specific studies which measure the impact of aging on cost or operational availability). We refer readers to see Maybury (2015) for a further, comprehensive review of the literature on this topic and others related to it.

In early work on the subject, Hildbrandt and Sze (1990) estimate the effect of an aging aircraft fleet on operating and support cost. The authors estimate a log-linear model where the logarithm of total operating and support cost per aircraft is a function of age, type of aircraft, a linear time trend, and the logarithms of average flying hours and number of aircraft. They find that a one year increase in the mission design fleet age increases total operating and support cost per aircraft by about 1.7%.

Stoll and Davis (1993) examine the impact of aging on a variety of cost measures using aircraft data from the 1980s and early 1990s. The authors primarily use an Ordinary Least Squares (OLS) estimator in levels where cost is specified as a function of age or fiscal year. Additional estimates explored whether the percentage change rates in costs were a function of age or fiscal year. Their estimates vary depending upon specification, however, the authors generally find that direct labor, overhead, direct material, and total costs all have projected increases over time as the aircraft age.

Kiley (2001) examines the relationship between aging and the cost of operating and maintaining military equipment such as major battle force ships, tanks, Bradley fighting vehicles, helicopters and other aircraft. The most detailed analysis in Kiley's study is presented on aircraft. The author employs a one-way fixed time effects estimator where the logarithm of cost is a function of age, year fixed effects, and the logarithms of annual flying hours and procurement unit average unit cost. Kiley finds a positive relationship between cost and age; an additional year of average age is associated with an increase in operational and maintenance costs between 1% and 3% per year.

Keating and Dixon (2004) provide estimates on the effects of aging on maintenance hours and operational availability for the KC-135 aircraft. The authors estimate the logarithm of maintenance hours on age. We note that the authors did not include specific control variables. A similar model is used to estimate the effects of age on operational availability. The authors find a positive, statistically significant relationship between age and cost and a negative, statistically significant relationship between age and operational availability.

Sokri (2011) takes a similar approach to Kiley in analyzing the impact of aircraft age on cost. Using an OLS estimator, the author estimates a model where the logarithm of operating and maintenance cost is a function of age. We again note the absence of control variables. Sokri finds a positive coefficient for age which is statistically significant at the 5% level, suggesting a robust relationship between age and cost increases over time.

The literature has, to this point, typically estimated a linear model either in levels or with the logarithmic transform of the dependent variables and some of the regressors of interest. While some studies (Hildbrandt and Sze (1990) and Kiley (2001)) have included controls, data restrictions have precluded the inclusion of controls in other studies (Keating and Dixon (2004) and Sokri (2011)). Most of the studies have shown standard aging effects to be in the 1-6% per annum range for cost or operational availability, with some outliers.

To date, no study has utilized an IHS transformation, relying instead on levels or the logarithmic transformation. We acknowledge the literature by specifying models in levels and logarithms, but also advance the literature by comparing and contrasting these results with those of the IHS transformation. As the properties of the level and logarithmic transformation are well known, we briefly discuss the standard characteristics of the IHS transformation next and then outline the formal empirical models utilized in our estimation strategy in section 4.3.

4.2. The Inverse Hyperbolic Sine

The IHS can, depending on the value of the scaling parameter, approximately either the level or the logarithmic transformation. The IHS transformation, however, is defined for those boats with zero availability or cost in a given year, unlike the logarithmic transformation. As is widely understood by statisticians, the logarithmic transformation comes at a cost as observations with zero cost or availability must be dropped from the analysis. While some have argued that arbitrarily "small" values can be added to the observations with zero value to enable the logarithmic transformation of these observations, the arbitrary nature of what is "small" leaves much to be desired.[8] If observations with zero for cost or availability contain valuable information (e.g., these boats did not perform any missions or generate any cost), then we may bias our estimates by arbitrarily excluding or transforming these observations. The IHS transformation provides an established methodology to estimate percentage change specifications without eliminating observations with zero value.

Johnson (1949) suggested the use of an IHS transformation for univariate and multivariate cases, respectively. Burbidge et. al. (1988) applied the transformation in the univariate case and illustrated the potential superiority of the IHS relative to the logarithmic and Box-Cox transformations. The IHS of a variable y with scaling parameter θ can be specified as:

$$g(y_t, \theta) = \frac{ln\left(\theta y_t + \sqrt{(y_t^2\theta^2 + 1)}\right)}{\theta} = \frac{sinh^{-1}(\theta y_t)}{\theta}$$

[8] The wealth literature, for example, has extensively discussed how to handle households with negative or zero assets and we draw inspiration from the literature.

Unlike the logarithmic or the Box-Cox transformation[9], the IHS is defined over all θ even though most statistical programs explicitly assume that θ is equal to one. While the IHS and Box-Cox transformations compress extremes toward the other transformed observations, the damping effect of the IHS is superior to that of the Box-Cox transformation. The linearity of the IHS transformation through the origin is also appealing.[10] Figure 1 illustrates the shape of the IHS transformation at different values of θ to illustrate the importance of estimating, rather than assuming, the value of the scaling parameter.

As the function g is symmetric about 0 in θ and is linear about the origin, we consider those cases where θ≥0. The value of the scaling parameter is important as it defines the proportion of the function's domain that is approximately linear and the proportion that the function is approximately logarithmic. We do note that as the parameter θ approaches 0, the value of the IHS transformation of y approaches y. Thus, if the true value of the scaling parameter is 0, the transformed observations and estimation approximate the original values of the observation and estimation in levels.

Burbidge et.al. (1988) note that for large values of $|\theta y_t|$, the IHS becomes similar to the transformation:

$$g(y_t, \theta) \approx \frac{sign(\theta y_t)\log(2|\theta y_t|)}{\theta}$$

Likewise, Pence (2006) notes that, for large y, the function is a vertical displacement of the logarithm as:

[9] Burbidge et.al. (1988) note that while the Box-Cox and IHS have linear models that are defined for positive and negative values, the Box-Cox transformation is not defined at zero. Also as the scaling parameter approaches zero for the Box-Cox transformation, negative observations are transformed into infinitely large negative values. These issues raise concerns about the validity of the Box-Cox transformation when observations with zero value are observed in the data.

[10] As noted by Pence (2006) with regards to wealth data, the logarithmic transformation treats a $1 to $2 increase in wealth equivalent to a $10,000 to $20,000 increase in wealth and that result may not be appealing to wealth researchers. With regards to cost data, a $1 to $2 increase in cost would be, in our opinion, viewed much differently than a $10,000 to $20,000 increase in cost.

$$\ln\left(\theta y + (y_t^2\theta^2 + 1)^{\frac{1}{2}}\right) \approx ln2\theta + y_t$$

Using:

$$\frac{\delta \sinh(x)^{-1}}{\delta y_t} = (1 + \theta^2 y_t^2)^{-1/2}$$

An examination of the derivative yields two properties of interest. First, if θ is large relative to *y*, the derivative becomes an approximation of the derivative of the logarithm for most positive values of *y*. On the other hand, if *y* is large relative to θ, the derivative is approximately one and the function is approximately linear (Pence, 2006).

We continue to follow Burbidge et.al. (1988) and use l'Hopital's rule and the derivative of *g* to show that:

$$\lim_{n\to\infty} g_t = y_t$$

Given that *g(θ)* is an n-vector having element *t* of g_t, the IHS model can be specified as:

$$g(\theta) = X\beta + u, u \sim N(0, \sigma^2 I)$$

Following Burbidge et. al. (1988) and MacKinnon and Magee (1990), we assume that the errors are normally distributed so that the log-likelihood function with *n* observations can be expressed as:

$$L(\theta, \beta, \sigma) = -\frac{n}{2} ln2\pi - \frac{n}{2} ln\sigma^2 - \frac{1}{2\sigma^2}(g(\theta) - X\beta)^T (g(\theta) - X\beta) - \frac{1}{2}\sum_{t=1}^{n} \ln(\theta^2 y_t^2 + 1)$$

Let $M = I - X(X^T X)^{-1} X^T$, then the concentrated log-likelihood can be expressed as:

$$L(\theta) = -\frac{n}{2} ln2\pi - \left(\frac{n}{2}\right) \ln g(\theta)^T M g(\theta) - \frac{1}{2}\sum_{t=1}^{n} \ln(\theta^2 y_t^2 + 1)$$

Given that *g* is symmetric about 0 in θ, we following Pence (2006) in conducting a careful search over possible values of θ to maximize the concentrated log-likelihood function. We obtain a bootstrap estimate of $\hat{\theta} = 8.810$. This estimate illustrates the need to obtain an estimate of $\hat{\theta}$ and not to rely on the assumption that θ = 1.[11]

Lastly, we turn to the interpretation of the estimated coefficients. The interpretation of the level and logarithm transformation are well known. With regards to the IHS, we note that since $y = IHS(A) = X\beta + u$, then $\frac{\delta A}{\delta x} = \frac{\delta A}{\delta y}\frac{\delta y}{\delta x} = \frac{\delta A}{\delta y}\beta = \frac{1}{2}(e^{\theta y} + e^{-\theta y})\beta$ (Pence, 2006). For sufficiently large *y*, $\theta\beta$ approximates the marginal effect of a one unit change in *x* on the percentage change of y (McKinnon and MaGee, 1990; Pence, 2006). This interpretation is notable in that it is akin to a regression where the dependent variable is a logarithmic transform. Of course, this approximation is useful for where the IHS transformation approximates the logarithm. Following Pence (2006), the approximation is:

$$\beta = \frac{\delta IHS(y)}{\delta x} = \frac{1}{\sqrt{1+\theta^2 y^2}}\frac{\delta y}{\delta x} \approx \frac{1}{\theta y}\frac{\delta y}{\delta x} = \frac{1}{\theta}\frac{1}{y}\frac{\delta y}{\delta x} = \frac{1}{\theta}\frac{\delta \ln(y)}{\delta x}$$

$$\theta\beta \approx \frac{\delta \ln(y)}{\delta x}$$

4.3. Empirical Models and Tests

To test the aging effects of the MLB fleet, we first use individual boat variation in operational availability and cost over time as a function of age, which is analogous to previous studies on this topic (e.g., Hildbrandt and Sze, 1990; Stoll and Davis, 1993; Kiley, 2001; Keating and Dixon, 2004; and Sokri; 2011). This model is shown below:

$$Y_{it} = \alpha + \beta_1 age_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \mu_i + \lambda_t + v_{it} \tag{1}$$

[11] For example, for the a value *Operational Availability* of 0.8796, the logarithm is -0.1386. The IHS transformation with θ = 1 is equal to 0.7869. Using the estimate of $\hat{\theta} = 8.810$, the IHS transformation is equal to 0.3104.

where the outcome variables, *Operational Availability* (i.e., mission capable time divided by total measured time) and *Cost* (i.e., annual aggregation of monthly operating cost) for boat *i* in year *t* are denoted by Y_{it}. Of note, this model is estimated by using six different specifications of Y_{it} in our final analysis including: the level effects of *Operational Availability*, log of *Operational Availability*, IHS of *Operational Availability*, level effects of *Cost*, log of *Cost*, and IHS of *Cost*. The vector **X** is a set of control variables including binary indicator variables for each of the individual coast guard districts and binary indicator variables for primary boat mission type. In addition, μ_i and λ_t represent the unobservable individual boat and time effects, respectively, and υ_{it} is a white noise error term. The variable of interest in Equation 1 is age_{it} and represents the age of boat *i* in year *t*.

Equation 1 provides standard measures of the impact of age on operational availability and cost. Interpreting the results from Equation 1 is relatively straightforward. A positive coefficient for β_1 can be interpreted as a positive impact on operational availabliity or cost due to a one-year increase in the age of an MLB (ceterus paribus). Next, we present a model that examines whether specific ages significantly affect operational availability or operating cost (which is new to the literature). This model is displayed below:

$$\begin{aligned} Y_{it} = \alpha + \beta_1 Y8_{it} + \beta_2 Y9_{it} + \beta_3 Y10_{it} + \beta_4 Y11_{it} + \beta_5 Y12_{it} + \beta_6 Y13_{it} + \beta_7 Y14_{it} \\ + \beta_8 Y15_{it} + \beta_9 Y16_{it} + \beta_{10} Y17_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \mu_i + \lambda_t + \upsilon_{it} \end{aligned} \tag{2}$$

where Y, **X**, μ, λ, and υ are the same as those defined in Equation 1. The key difference in this equation is that the variable age in Equation 1 has been replaced by dummy variables for each of the years in the data. More specifically, we create dummy variables that coincide with the age of a specific boat during a given year. We define, for example, *Y8*, as a dummy variable that is equal to one for those MLBs that are eight years old during a specific year in the sample and zero otherwise. Following this methodology, we similarly define years 9 through 17 as *Y9* through *Y17*, respectively.

The interpretation of the results from Equation 2 is somewhat different in comparison to Equation 1 since we use binary indicator variables for specific ages (instead of a continuous variable for age) in this model. For Equation 2, we leave out boats that are 7 years-old as our baseline boats to use as a comparison group. We also have 10 specific variables of interest (i.e., $Y8$, $Y9$, …, $Y17$) instead of just one (i.e., age). As an illustrative example, a negative coefficient on say, *Y17*, would indicate the negative impact of a 17 year old boat on operational availability or cost in comparison to being a seven year old boat (ceteris paribus). A positive coefficient would indicate the opposite. Similar interpretation of the results can be done with the other coefficients of interest (i.e., β_1, β_2, …, β_9) in comparison to seven year old boats.

Before estimating Equations 1 and 2, we exercise caution and examine whether the variables of interest suffer from a unit root; whether the pooled OLS estimator, random effects Generalized Least Squares (GLS) estimator or fixed effects Within estimator is appropriate; whether the effects are jointly significant, and lastly, whether the residuals are heteroscedastic. Each of these issues either renders the estimators inconsistent (unit root), inefficient (whether the time and individual effects are statistically significant), or biases the standard errors of the estimated coefficients (heteroscedasticity). We, of course, take the appropriate correction action when an issue is determined to be present.

We first examine whether the variables of interest suffer from a unit root. If so, this would render the empirical estimators inconsistent and increase the likelihood of spurious results. Following Maddala and Wu (1999), we can examine the null hypothesis that all the panels exhibit a unit root against the alternative that at least one panel is stationary. We use the

Augmented Dickey-Fuller and Philipps-Perron variants of the Fisher-type test. We also examine whether the inclusion of a linear time trend affects the results of the test and test of each of the variants of the dependent variables of interest. We strongly reject the null hypothesis of non-stationarity at the 1% level of significance for each of the dependent variables of interest.[12]

Under specific assumptions about the lack of individual boat and time specific effects, the pooled OLS estimator is consistent and efficient relative to the error components estimators (Baltagi, 2008). If there are individual boat or time effects, however, then an error components estimator is consistent and efficient relative to the pooled OLS estimator. We examine whether the individual effects are jointly significant and reject the null hypothesis that the individual effects are jointly equal to zero at the 1% level of significance. We then examine the appropriateness of a random effects GLS estimator versus a fixed effects Within estimator for each of the dependent variables. If the effects are orthogonal to the regressors, then the random effects GLS estimator is consistent and efficient relative to the fixed effects Within estimator. On the other hand, if the effects are correlated with the regressors, the GLS estimator is inconsistent while the Within estimator is consistent and efficient. For the *Availability* and *Cost* variables, we fail to reject the null hypotheses of the Hausman test that there are not systemic differences between the random effects GLS estimator versus the fixed effects Within estimator.[13] The random effects GLS estimator is consistent and relatively efficient to the fixed effects Within estimator. We also unambiguously reject the null hypotheses of

---

[12] We strongly reject the null hypothesis at 1% level of significance for *Availability* with a Chi-squared test statistic of 1450.96. We also strongly reject the null hypothesis at the 1% level of significance for *Cost* with a Chi-squared test statistic of 1354.21. Full results of all the unit root tests are available upon request.

[13] To calculate the Hausman test, we compare the random and fixed effects estimates with individual effects, time effects, mission controls, and district controls. For *Availability* as the dependent variable, the Chi-squared test statistics with 25 degrees of freedom is 17.72. For *Cost* as the dependent variable, the Chi-squared test statistics with 25 degrees of freedom is 15.44. We also conduct tests for the logarithmic and inverse hyperbolic sine transformations of the dependent variables. In all cases we fail to reject the null hypothesis of no systemic differences between the random and fixed effects estimators. Full results are available upon request.

homoscedasticity.[14] We thus estimate and compare the one-way individual effects, and two-way individual and time effects estimates with robust standard errors in the next section.

5. Results

Overall, we find that *Age* statistically, significantly, and negatively impacts *Operational Availability*. This result is consistent across all specifications and almost all transformations of the *Operational Availability* variable. We also find evidence to suggest that *Age* statistically, significantly, and positively affects *Cost*. This result, however, appears to be fragile to the inclusion of time effects and may also be dependent upon sample selection. In terms of nonlinearity effects, we find the most pronounced changes in *Operational Availability* and *Cost* occurs for MLBs aged 15 years or more in comparison to seven-year-old MLBs (i.e., the youngest boats in our dataset).

Table 2 presents our estimates for the impact of *Age* on *Operational Availability* as described in Equation 1. In general, we find a statistically significant, negative, and mostly robust relationship between *Age* and *Operational Availability*. The point estimates from the standard logarithmic model in columns 3 and 4 finds operational availability for the MLBs decreases at a rate between 0.83% and 1.8% per year. A similar result is suggested for the levels specification. With regards to the IHS transformation, the estimated impact ranges from approximately 1.9% to 3.1% per year.[15] Five of the six specifications show the age coefficient to

[14] We use a Breusch-Pagan test to examine the null hypothesis of homoscedasticity. With *Availability* as the dependent variable, the Chi-squared test statistic with one degree of freedom is 106.04. With *Cost* as the dependent variable, the Chi-squared test statistics with one degree of freedom is 91.10. We also conduct Breusch-Pagan tests for the logarithmic and inverse hyperbolic sine transformations of the dependent variables. In all cases we reject the null hypothesis of homoscedasticity. Full results are available upon request.

[15] The estimated coefficients for *Age* are -0.0046 and -0.0028 for the IHS transformation of *Availability* (Columns 5 and 6). This yields two marginal estimates of $\hat{\theta}\hat{\beta} = -0.045$ and $\hat{\theta}\hat{\beta} = -0.025$, respectively. We also evaluate the inverse hyperbolic sine at the mean value of *Availability* of 0.778 which yields two estimates of the marginal effects:

be negative and statistically significant, with the lone exception being the logarithmic specification with time effects (which is shown to be negative and insignificant in column 4).

Next, we turn our attention to estimates showing the impact of specific years on *Operational Availability* from Equation 2. These results are shown in Table 3. We find empirical evidence to indicate that, relative to 7-year old MLBs, 15 and 16-year-old MLBs are less available across the sample period and some suggestive evidence for similar effects for 17-year-old MLBs. For the *Y15* variable, all of the estimated coefficients are negative with four of the six specifications being statistically significant at the conventional levels. Columns 2 and 4 show that the *Y15* results are fragile to the inclusion of time effects for the levels and logarithm specifications. For the *Y16* variable, the estimated coefficients are all statistically significant, with the lone exception of the logarithmic transformation which includes of time effects (as presented in column 4). The *Y17* coefficients are the only other coefficients (besides *Y15* and *Y16*) in Table 3 showing any evidence of statistical significance. All of the *Y17* coefficients are negative; however, only columns 1 and 5 display statistically significant results at the conventional levels.

Of note, discussions with data analysts lead us to believe that the nine observations with zeroes for operational availability (which were left out of the regressions in columns 3 and 4 in Table 3) were actually not available and thus the logarithmic transformation may result in a biased sample that understates the impact of age on availability. Regarding the other year dummies in Table 3, these appear to be either fragile to the inclusion of the time effects or statistically insignificant across specifications.[16] For 15-year-old boats, our results suggest that,

---

$\frac{1}{2}\left(e^{\hat{\theta}y} + e^{-\hat{\theta}y}\right)\hat{\beta} = -0.031$ and $-\ 0.019$. We use the lower estimate as it should be more precise as *Availability* is bounded between 0 and 1. These calculations are available upon request.

[16] Removing the observations with zero *Availability* yields smaller estimated coefficients for the regressors of interest. The estimated coefficients for the levels and inverse hyperbolic sine specifications for *Y15*, for example, are

all else being equal, 15-year old boats are between 16 and 21% less available than 7-year-old boats, though this result is fragile to specification choice.[17] Our results suggest that, all else being equal, 16-year-old boats are between 16% and 34% less available than 7-year-old boats, depending on the specification and transformation of the dependent variable.[18] The point estimates for the 17-year-old boats, while somewhat imprecise, suggest that 17-year-old boats are between 21% and 27% less available than 7-year-old boats.[19]

Turning to the question of the impact of age on cost, we recognize that while only 9 observations have zeros with regards to availability (and we are fairly confident that these zeros actually represent zero availability), 108 observations have zeros with regards to operational cost. We note that the average *Availability* of an observation with zero *Cost* is 83.9%, suggesting that non-zero cost was incurred but not captured in the accounting system. We suspect, *a priori*, that some MLBs had zero cost but also understand that a change in accounting systems may have resulted in missing data. Unfortunately, as discussed previously, we do not know whether the zeroes contain information or are merely missing data. *For the purposes of exploring the impact of Age on Cost, we reduce the sample to those observations that reported non-zero Cost.*

Table 4 presents our estimates for the impact of *Age* on *Cost* as described in Equation 1. All six of the specifications show positive values for the *Age* coefficients. Four of the six specifications are statistically significant at the standard conventional levels. The two exceptions,

---

-0.11 and 0.025, respectively and are statistically significant at the 10% level of significance. This would yield a marginal impact of between 11% and 17%, respectively. These regressions and calculations are available upon request.

[17] The estimated coefficient for *Y15*, for example, is -0.031 for the IHS transformation of *Availability* (Column 6). Evaluating the inverse hyperbolic sine at the mean value of *Availability* of 0.778 yields: $\frac{1}{2}\left(e^{\hat{\theta}y} + e^{-\hat{\theta}y}\right)\hat{\beta} = -0.215$. Additional calculations are available upon request.

[18] The estimated coefficient for Y16 is -0.049 (Column 6). Evaluating the inverse hyperbolic sine at the mean value of *Availability* of 0.778 is: $\frac{1}{2}\left(e^{\hat{\theta}y} + e^{-\hat{\theta}y}\right)\hat{\beta} = -0.339$. Additional calculations are available upon request.

[19] The estimated coefficient for Y17 is -0.040 (Column 5). Evaluating the inverse hyperbolic sine at the mean value of *Availability* of 0.778 is: $\frac{1}{2}\left(e^{\hat{\theta}y} + e^{-\hat{\theta}y}\right)\hat{\beta} = -0.277.$ The estimates are based upon Columns (1) and (5) of Table (3).

as shown in columns 4 and 6, indicate fragility of the results for the logarithmic and IHS specifications when time effects are included in the regressions. Noting this, we observe that an increase in *Age* by one year increases predicted *Cost* by approximately \$1736 to \$3365 for the levels specification. For the logarithmic specification, the point estimates suggests *Cost* increases at a rate between 0.33% and 7.81% per year. As we argued previously, the IHS transformation approximates the logarithm for large values of the transformed variable; the IHS estimates show *Cost* increasing at a rate between 0.32% to 7.82% per year.

The estimates for the effect of specific years on *Cost* in Table 5 appear to be much more fragile to the changes in specification (in comparison to the *Operational Availability* results in Table 3). While the estimated coefficient for *Y15* is statistically significant in the levels specification (as shown in columns 1 and 2), it appears to be fragile to the inclusion of time effects for the logarithmic and IHS transformations (as shown in columns 4 and 6, respectively). The estimated coefficients suggest that, relative to 7-year-old MLBs, 15-year-old MLBs are approximately 116% more expensive.

One of the primary limitations of this study (and others like it) is that it is incredibly difficult to plausibly identify the effect that aging has on operational availability and cost given Department of Homeland Security (DHS) policy and data constraints. For instance, it is possible that omitted variables (e.g., different crews, usage rates, etc.) may be correlated with our variables of interest. This could bias the results one way or another. We cannot completely rule out these concerns. That stated, we do believe that the random effects and unique control variables used in our estimation strategy should rule out most of this bias (if not all of it). However, it is possible that some of the variation is not being picked up. Thus, policy makers should be aware of this limitation of the study in determining future courses of action.

The reduced form effects shown in this study simply predict the overall effect of age on operational availability and cost with this given set of controls and fixed effects. Other methods may be better suited to handle such questions such as randomized control trials. Unfortunately these methods are often impossible to implement in military settings which is why we advocate and use this particular methodology outlined in this study. It is our belief that we provide the best estimates possible given the constraints of DHS policy and data available.

6. Conclusion

This paper combines numerous unclassified data from the U.S. DHS to empirically estimate the effect that an aging fleet has on operational availability and annual cost. We utilize an error components estimator to examine these effects and employ three variants of the dependent variables (i.e., the standard logarithmic transformation, IHS, and level outcomes) in our models.

The point estimates from the standard logarithmic model finds operational availability for the MLBs decreases at a rate between 0.83% and 1.8% per year and cost increases at a rate between 0.33% and 7.81% per year. Similar effects are shown with the IHS and level outcome specifications. Of note, the estimates for cost (in contrast to the operational availability results) appear to be much more fragile to the inclusion of time effects and may also be less precise due to sample selection bias. In terms of nonlinearity effects, we find the most pronounced changes in operational availability and cost occurs for MLBs aged 15 years or more in comparison to seven-year-old MLBs (i.e., the youngest boats in our dataset).

The results of this study have a number of policy implications for officials within the U.S. Coast Guard. First, it does not appear that taking a “do nothing” approach with the fleet is a viable option. The aging of the current fleet of 47 foot MLBs is on a clear downward trajectory in terms of operational availability. The projections for annual costs appear to be just as discouraging and will undoubtedly continue to increase as the fleet ages. Thus, we suggest a couple of specific policy proposals based off of our results.

If policy makers choose to stay with the current fleet, then it probably makes sense to have a service life extension program around year 15 for each of the boats in service. Some of the estimates not directly presented here (such as estimates on mission type and district effects) could also be of use in these decisions.[20] The estimates in this paper strongly advocate support of such an overhaul strategy if new procurement of boats is deemed to be too expensive.

Alternatively, the U.S. Coast Guard could take a hybrid approach to overhauling the fleet with some MLBs receiving an overhaul around the 15 year mark and some being completely replaced by new boats. We recommend an extension of this study if the Coast Guard chooses to procure an entire new fleet since our focus has been on the operational availability and cost of the current fleet. Regardless of the higher level policy decision implemented; the data, estimates, and methodology presented here provides a sound basis not only for the current U.S. Coast Guard procurement or boat overhaul guidance, but for U.S. DHS (and her allies) future decisions in general.

[20] These estimates are available upon request.

References

Baltagi, B. (2008). *Econometric analysis of panel data* (Vol. 1). Chichester, England: John Wiley & Sons.

Burbidge, J. B., Magee, L., & Robb, A. L. (1988). Alternative transformations to handle extreme values of the dependent variable. *Journal of the American Statistical Association*, *83* (401), 123-127.

CG-7. (2013). Decision Memo - Shore-Based Boat Sitting Plan. Washington, DC.

CG-731. (2007). 47FT MOTOR LIFEOBAT OPERATOR'S HANDBOOK. Washington, DC: U.S. Coast Guard.

CG-731. (2013). U.S. Coast Guard Boat Operations and Training (BOAT) Manual Volume I. *COMDTINST M16114.32C*. Washington, DC.

CG-731. (2014). Annual Operational Hours Data. Washington, DC: U.S. Coast Guard.

CG-9325. (2014). Preliminary Alternatives Analysis (AA) for the 47' Motor Life Boat (MLB). Washington, DC: U.S. Coast Guard.

Dixon, M. (2005). The costs of aging aircraft: Insights from commercial aviation. RAND Dissertation, Pardee RAND Graduate School.

Francis, P. and G. Shaw (2000). Effect of Aircraft Age on Maintenance Costs. Center for Naval Analyses, Alexandria VA.

Greenfield, V. and D. Persselin (2002). An Economic Framework for Evaluating Military Aircraft Replacement. Santa Monica, CA: RAND MR-1489-AF.

Greenfield, V. and D. Persselin (2003). How old is too old? An economic approach to replacing military aircraft. *Defence and Peace Economics 14* (5), 357–368.

Hildebrandt, G. G., & Sze, M. B. (1990). An estimation of USAF aircraft operating and support cost relations. RAND CORP Santa Monica, CA: RAND/N-3062-ACQ.

Johnson, N. L. (1949). Systems of frequency curves generated by methods of translation. *Biometrika*, *36* (1/2), 149-176.

Jondrow, J., R. Toast, M. Ye, J. Hall, P. Francis, and B. Measell (2002). Support costs and aging aircraft: Implications for budgeting and procurement. CNA Corporation.

Jones, J. V. (2006). *Integrated Logistics Support Handbook.* New York: Sole Logistics Press.

Keating and Dixon, M. (2004). Investigating optimal replacement of aging Air Force systems. *Defence and Peace Economics*, *15*(5), 421-431.

Keating, E. G., Blickstein, I., Boito, M., Chandler, J., and Peetz, D. (2014). Investigating the Desirability of Navy Aircraft Service Life Extension Programs. *Defence and Peace Economics*, *25* (3), 271-280.

Kiley, G. (2001). The effects of aging on the costs of maintaining military equipment. Washington DC: Congressional Budget Office.

MacKinnon, J. G., and Magee, L. (1990). Transforming the dependent variable in regression models. *International Economic Review*, 315-339.

Maddala, G. S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and statistics*, *61* (S1), 631-652.

Maybury, D. W. (2015). Chapter 12: Extensions of the Greenfield–Persselin optimal fleet replacement model. In Melese, F, Richter, A., & Solomon B. (Eds.), *Military Cost–Benefit Analysis: Theory and Practice*. New York, NY. Routledge.

Pence, K. M. (2006). The role of wealth transformations: An application to estimating the effect of tax incentives on saving. *The BE Journal of Economic Analysis & Policy*, *5* (1).

Sokri, A. (2011). Optimal replacement of military aircraft: an economic approach. *Defence and Peace Economics*, *22*(6), 645-653.

Stoll, L. and S. Davis (1993). Aircraft age impact on individual operating and support cost elements. Patuxent River MD: Naval Aviation Maintenance Office.

Textron Systems. (2011). *Textron Systems Motor Lifeboat.* Retrieved from Textron Systems: http://www.textronsystems.com/sites/default/files/pdfs/product-info/tmls-motor-life-boat.pdf (Access date: 13 April 2016).

U.S. Coast Guard. (2015). 47' Motor Life Boat Service Extension Program. Retrieved from FEDBIZOPPS.GOV: https://www.fbo.gov/index?s=opportunity&mode=form&id=0bf3a2536758661a7c9d3003afb563a1&tab=core&_cview=1 (Access date: 13 April 2016).

U.S. Coast Guard. (2014). Coast Guard Publication 1. *Doctrine for the U.S. Coast Guard*. Washington, DC: U.S. Coast Guard.

U.S. Coast Guard Thirteenth District. (2003). *47-Foot Motor LIfeboat (MLB) Fact Sheet.* Retrieved from U.S. Coast Guard: http://www.uscg.mil/d13/docs/factsheets/47.pdf (Access date: 13 April 2016).

Figure 1: Logarithm and Inverse Hyperbolic Sine Transformations

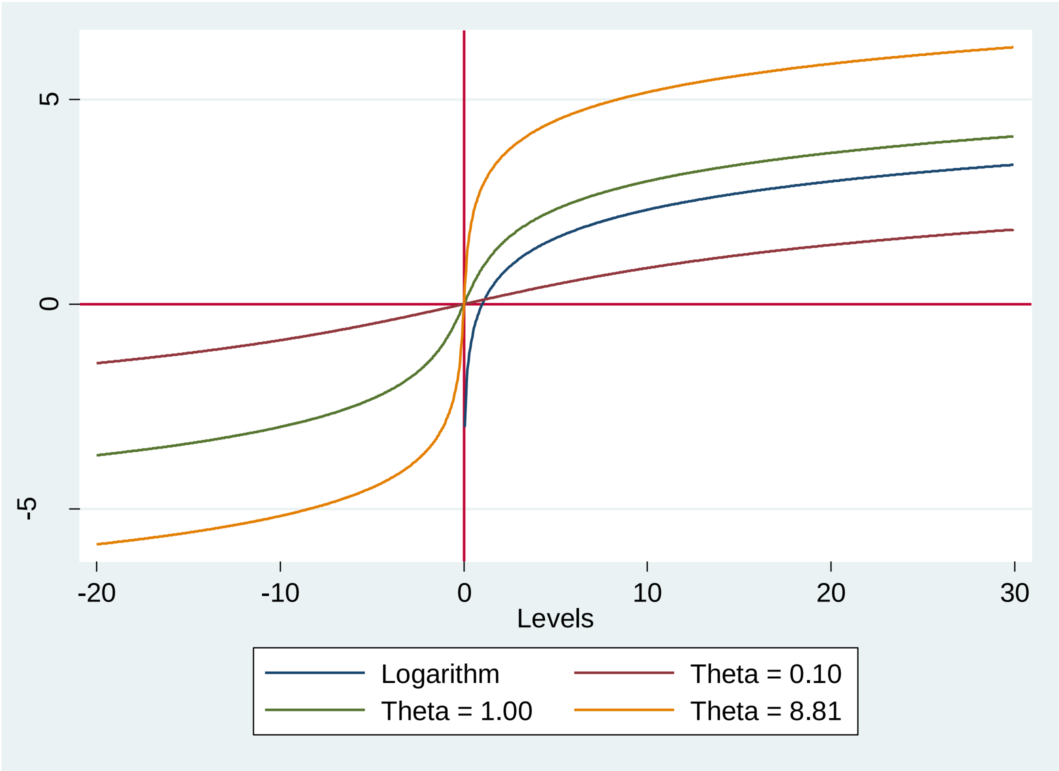

Table 1: Summary Statistics

	Mean	Standard Deviation		Mean	Standard Deviation
Outcome Variables			*Boat Mission*		
Annual Cost	\$35,266	\$45,433	Station	0.2205	0.4146
Operational Availability	0.7781	0.1981	Surf & PWCS Level 1	0.0427	0.2023
			Surf	0.3094	0.4622
Boat Age			HWX & PWCS Level 1	0.1487	0.3558
7 Years Old	0.0239	0.1528	HWX	0.2752	0.4466
8 Years Old	0.0581	0.2340	PWCS Level 1	0.0034	0.0584
9 Years Old	0.0940	0.2919			
10 Years Old	0.1299	0.3362	*Coast Guard District*		
11 Years Old	0.1658	0.3719	Northeast	0.2940	0.4556
12 Years Old	0.1675	0.3734	Mid-East Coast	0.1607	0.3672
13 Years Old	0.1419	0.3489	Southeast	0.0222	0.1474
14 Years Old	0.1060	0.3078	Central States	0.0017	0.0413
15 Years Old	0.0701	0.2553	Northern Great Lakes	0.1265	0.3324
16 Years Old	0.0342	0.1817	Southwest	0.1162	0.3205
17 Years Old	0.0085	0.0921	Northwest	0.2017	0.4013
			Hawaii	0.0171	0.1296
			Alaska	0.0171	0.1296
			Training School	0.0427	0.2023

Notes: The data contains 585 observations that have information on each of the variables presented. The years are evenly split with 20% of the observations shown in each year from 2010 through 2014 (i.e., a balanced panel dataset of the 117 boats).

Table 2: The Effect of Boat Age on Operational Availability (OA)

	(1) OA	(2) OA	(3) Log(OA)	(4) Log(OA)	(5) IHS(OA)	(6) IHS(OA)
Age	-0.016**	-0.0095*	-0.018*	-0.0083	-0.0046**	-0.0028*
	(0.0047)	(0.0048)	(0.0081)	(0.0086)	(0.0013)	(0.0012)
Observations	585	585	576	576	585	585
Estimator	GLS	GLS	GLS	GLS	GLS	GLS
Time Effects	No	Yes	No	Yes	No	Yes
R^2	0.101	0.108	0.054	0.060	0.110	0.136

Notes: **,*,+ denote significance at the 1%, 5%, and 10% level respectively. All models have the full set of controls, and report the heteroscedastically robust standard errors in parentheses. Full estimates available upon request.

Table 3: The Effect of Specific Boat Years on Operational Availability (OA)

	(1) OA	(2) OA	(3) Log(OA)	(4) Log(OA)	(5) IHS(OA)	(6) IHS(OA)
Y8	-0.057	-0.040	-0.100	-0.084	-0.011	-0.0098
	(0.059)	(0.061)	(0.093)	(0.099)	(0.010)	(0.011)
Y9	-0.032	-0.0044	-0.027	0.0054	-0.0026	-0.0008
	(0.052)	(0.055)	(0.073)	(0.078)	(0.0083)	(0.009)
Y10	-0.017	0.015	-0.015	0.027	-0.0006	0.0013
	(0.05)	(0.054)	(0.07)	(0.077)	(0.0079)	(0.0089)
Y11	-0.063	-0.023	-0.083	-0.029	-0.011	-0.0062
	(0.058)	(0.064)	(0.087)	(0.093)	(0.010)	(0.012)
Y12	-0.038	0.0062	-0.049	0.013	-0.0038	0.0023
	(0.053)	(0.057)	(0.077)	(0.081)	(0.0087)	(0.010)
Y13	-0.073	-0.023	-0.100	-0.031	-0.013	-0.0057
	(0.056)	(0.059)	(0.081)	(0.086)	(0.0098)	(0.011)
Y14	-0.037	0.018	-0.035	0.045	-0.007	0.0019
	(0.056)	(0.062)	(0.080)	(0.090)	(0.010)	(0.012)
Y15	-0.16*	-0.099	-0.23+	-0.14	-0.043**	-0.031+
	(0.069)	(0.074)	(0.120)	(0.130)	(0.016)	(0.016)
Y16	-0.23*	-0.16+	-0.21+	-0.11	-0.065*	-0.049+
	(0.092)	(0.097)	(0.120)	(0.130)	(0.026)	(0.026)
Y17	-0.21+	-0.13	-0.31	-0.19	-0.040+	-0.018
	(0.120)	(0.130)	(0.220)	(0.230)	(0.024)	(0.026)
Observations	585	585	576	576	585	585
Estimator	GLS	GLS	GLS	GLS	GLS	GLS
Time Effects	No	Yes	No	Yes	No	Yes
R^2	0.133	0.139	0.078	0.084	0.157	0.174

Notes: **,*,+ denote significance at the 1%, 5%, and 10% level respectively. All models have the full set of controls, and report the heteroscedastically robust standard errors in parentheses. Full estimates available upon request.

Table 4: The Effect of Boat Age on Cost

	(1) Cost	(2) Cost	(3) Log(Cost)	(4) Log(Cost)	(5) IHS(Cost)	(6) IHS(Cost)
Age	3364.8**	1736.8+	0.0781**	0.00329	0.00887**	0.000373
	(876.6)	(1017.7)	(0.0298)	(0.0382)	(0.00338)	(0.00433)
Observations	477	477	477	477	477	477
Estimator	GLS	GLS	GLS	GLS	GLS	GLS
Time Effects	No	Yes	No	Yes	No	Yes
R^2	0.097	0.141	0.091	0.156	0.091	0.156

Notes: **,*,+ denote significance at the 1%, 5%, and 10% level respectively. All models have the full set of controls, and report the heteroscedastically robust standard errors in parentheses. Full estimates available upon request.

Table 5: The Effect of Specific Boat Years on Cost

	(1) Cost	(2) Cost	(3) Log(Cost)	(4) Log(Cost)	(5) IHS(Cost)	(6) IHS(Cost)
Y8	12856.9	11099.8	0.44	0.203	0.05	0.0231
	(13751)	(13556.9)	(0.763)	(0.761)	(0.0866)	(0.0864)
Y9	11626.1	15713.5	0.722	0.644	0.082	0.0731
	(10976.7)	(11644.1)	(0.609)	(0.628)	(0.0692)	(0.0712)
Y10	17835.6	18274.5	0.722	0.495	0.0819	0.0562
	(13056.1)	(13431.4)	(0.619)	(0.640)	(0.0703)	(0.0726)
Y11	19649.2*	16664.7	0.964+	0.598	0.109+	0.0679
	(9830.2)	(10947.2)	(0.565)	(0.593)	(0.0641)	(0.0673)
Y12	18052.9	14357.7	0.863	0.455	0.0979	0.0516
	(11692.2)	(12792.3)	(0.595)	(0.627)	(0.0675)	(0.0712)
Y13	28424.1*	24136.0+	1.249*	0.821	0.142*	0.0932
	(11371)	(13131.9)	(0.591)	(0.639)	(0.0671)	(0.0725)
Y14	12913	6512.5	0.816	0.314	0.0926	0.0356
	(11365.5)	(13355.2)	(0.593)	(0.644)	(0.0673)	(0.0731)
Y15	40826.8**	31139.7*	1.166+	0.556	0.132+	0.0631
	(14082.5)	(15465.6)	(0.621)	(0.678)	(0.0705)	(0.0769)
Y16	48684.2*	36224.6	1.026	0.337	0.116	0.0383
	(23134.8)	(23688.3)	(0.698)	(0.747)	(0.0792)	(0.0848)
Y17	37515.9	25747.5	1.462+	0.829	0.166+	0.0941
	(28782.8)	(29429.1)	(0.761)	(0.810)	(0.0864)	(0.0919)
Observations	477	477	477	477	477	477
Estimator	GLS	GLS	GLS	GLS	GLS	GLS
Time Effects	No	Yes	No	Yes	No	Yes
R^2	0.097	0.141	0.091	0.156	0.091	0.156

Notes: **,*,+ denote significance at the 1%, 5%, and 10% level respectively. All models have the full set of controls, and report the heteroscedastically robust standard errors in parentheses. Full estimates available upon request.

Appendix

Cost Data

Cost data is from fiscal years 2010-2014 and is recorded in two tracking systems: FLS and AMMIS. FLS cost data comes in the following categories: CASREP, CASREP MODERN, CSMP, Planned Maintenance, TCTO and Transportation. A CASREP is a casualty report message that a unit releases to inform their operational commander an asset is unable to perform or partially perform a primary or secondary mission. The CASREP message also notifies the support community of the casualty and requests assistance such a parts, labor or technical guidance. CASREP costs are funds expended to correct the discrepancies.

CASREP MODERN costs are funds expended to correct a discrepancy with a planned equipment modernization project instead of the original system. A CSMP is a current ship's maintenance project. CSMP costs fix materiel or configuration discrepancies that do not limit the boat's ability to complete the mission (do not require a CASREP) and are above the organizational capability level. Planned maintenance is preventive maintenance that is part of the boat class maintenance plan. A TCTO is a time compliance technical order; these costs are typically planned changes to the entire fleet to upgrade or replace obsolete equipment or provide a new capability. Transportation costs are to hire a hauling company or licensed commercial vessel captain to move a boat between units or to complete maintenance availability at another location.

AMMIS cost data is money spent on a boat that does not fall into one of the other categories, discussed above. These costs may include consumables for organizational level planned maintenance, repair of items that are within the organization's capabilities that are not mission limiting, or replacement of outfit items.

The Coast Guard switched to a new finance and logistics system between 2009 and 2012 so cost data during this time is incomplete. FLS data is available from 2010 to June 2014, when we received the data, and AMMIS data is available from 2011 to June 2014. In 2011, two percent of boats had AMMIS costs recorded. That number jumped to 81 percent in 2012, 93 percent in 2013 and 94 percent in 2014. Table 1AX shows the annual average amount of money spent per boat, the standard deviation and the total amount.

AMMIS data has been tracked since 2012 for most units, though there is no AMMIS data for six boats, hull numbers as follows: 47233, 47249, 47279, 47301, 47316 and 47322. All these boats are at stations within the Sector Long Island Sound area of responsibility. This suggests the sector has a problem logging their costs in AMMIS. We have notified SFLC SBPL of this issue.

Figure 1AX: Standard 47 foot Motor Life Boat

Notes: Photograph courtesy of the U.S. Coast Guard, 2012

Figure 2AX: Distribution of Support Costs for the Fleet of 47 foot MLBs

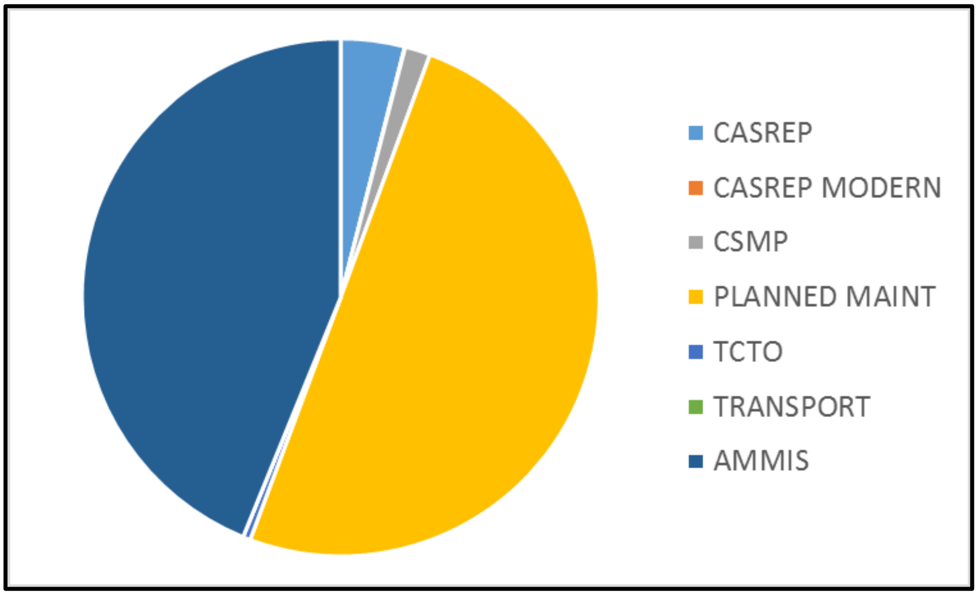

Table 1AX: Annual Average Cost per Boat

	FY10	FY11	FY12	FY13	FY14	Total
Ave.	$23,056	$20,594	$24,567	$54,486	$59,833	$184,013
St. Dev.	$33,736	$33,372	$31,729	$53,846	$101,029	$110,160
Total	$2,720,711	$2,430,162	$2,898,944	$6,429,402	$7,060,361	$21,529,521