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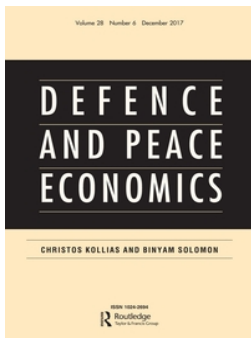
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THE LONG TERM EFFECTS OF AN AGING FLEET ON OPERATIONAL AVAILABILITY AND COST: EVIDENCE FROM THE U.S. COAST GUARD

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This paper empirically examines whether the aging of a fleet affects operational availability and operating cost using a unique data-set on the 117 47-foot Motor Lifeboats (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; Coastguard; Fleet

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

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 Lifeboat (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

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decision-makers determine when the current MLB fleet should be replaced or undergo a Service Life Extension Program (SLEP¹). To analyze the effects of the aging MLB fleet, we utilize a unique data-set 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. Hildebrandt and Sze 1990; Stoll and Davis 1993; Kiley 2001; Keating and Dixon 2004; 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 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 data-set). 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.

¹In 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.

²Related 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; Keating et al. 2014; see Maybury 2015 for a thorough review of this literature).

2. INSTITUTIONAL DETAILS

The USCG conducts maritime safety, security, and stewardship operations in and around the US and around the world to protect American security and economic interests. The USCG uses specially designed and constructed boats to conduct operations in areas of rough surf and heavy weather. The primary surface asset used in these areas is the 47-foot MLB. This MLB is unique to the coastguard because it is designed to operate in the open ocean in seas up to 30 feet, surf up to 20 feet and is self-righting within 30 seconds without any loss of operational capabilities in the event of a roll over. It is exceptionally useful in search and rescue missions since it is a multi-mission asset and conducts operations in all the coastguard mission areas.

Typically, there is only one to three 47-foot MLBs assigned to boat stations across the US (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. 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 h in seas less than 4 feet, 8 h in seas greater than 4 feet but less than 8 feet, and 6 h for seas greater than 8 feet. A standby crew would be called in if the 8 h timeframe is exceeded. The boat can hold a maximum of 34 passengers in addition to the crew.

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. 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.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 also considered that the coastguard 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

³Textron also sold versions of the 47-foot MLB to Canada, Egypt, and Mexico.

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 to 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

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 10 separate coastguard 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 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

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

⁵Of 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.

TABLE I Summary Statistics

	Mean	Standard deviation		Mean	Standard deviation
<i>Outcome variables</i>			<i>Boat mission</i>		
Annual cost	\$35,266	\$45,433	Station	0.2205	0.4146
Operational availability	0.7781	0.1981	Surf and PWCS level 1	0.0427	0.2023
			Surf	0.3094	0.4622
			HWX and PWCS Level 1	0.1487	0.3558
<i>Boat age</i>					
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	<i>Coastguard district</i>		
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 contain 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 to 2014 (i.e. a balanced panel data-set of the 117 boats).

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 data-sets, 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

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

⁷Of 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.

mission type complete the port, waterways, and coastal security mission. These MLBs are responsible for escorting large, 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, Hildebrandt 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 (Hildebrandt and Sze 1990; Kiley 2001) have included controls, data restrictions have precluded the inclusion of controls in other studies (Keating and Dixon 2004; 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, Magee, and Robb (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 follows:

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

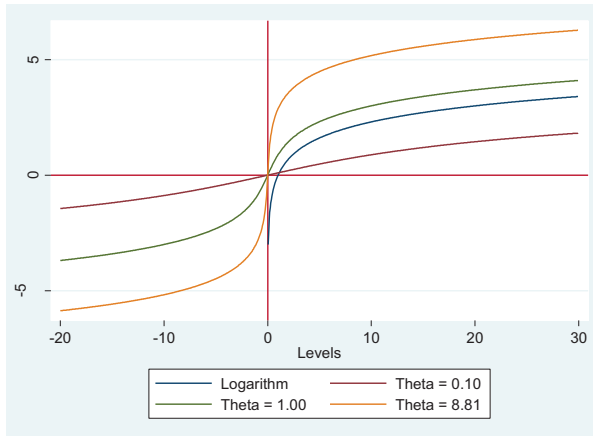


FIGURE 1 Logarithm and inverse hyperbolic sine transformations

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

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 $\theta \geq 0$. 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, Magee, and Robb (1988) note that for large values of $|\theta y_t|$, the IHS becomes similar to the transformation:

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

⁹Burbidge, Magee, and Robb (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.

¹⁰As 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.

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

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

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, Magee, and Robb (1988) and use l'Hopital's rule and the derivative of g to show that:

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

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

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

Following Burbidge, Magee, and Robb (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 follows:

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

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

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

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 $\theta = 1$.¹¹

Lastly, we turn to the interpretation of the estimated coefficients. The interpretation of the level and logarithm transformation is well known. With regards to the IHS, we note that

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

since $y = \text{IHS}(A) = X\beta + u$, 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 (MacKinnon 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:

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

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

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. Hildebrandt and Sze 1990; Stoll and Davis 1993; Kiley 2001; Keating and Dixon 2004; Sokri 2011). This model is shown below:

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

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 \mathbf{X} is a set of control variables including binary indicator variables for each of the individual coastguard 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 v_{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 availability 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:

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

where Y , \mathbf{X} , μ , λ , and v 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, Y_8 , 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 Y_9 through Y_{17} , 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. Y_8, Y_9, \dots, Y_{17}) instead of just one (i.e. *age*). As an illustrative example, a negative coefficient on say, Y_{17} , would indicate the negative impact of a 17-year-old boat on operational availability or cost in comparison to being a 7-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. $\beta_1, \beta_2, \dots, \beta_9$) 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 vs. 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 vs. the

¹²We 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.

TABLE II The Effect of Boat Age on Operational Availability (OA)

	(1)	(2)	(3)	(4)	(5)	(6)
	OA	OA	Log(OA)	Log(OA)	IHS(OA)	IHS(OA)
Age	-0.016** (0.0047)	-0.0095* (0.0048)	-0.018* (0.0081)	-0.0083 (0.0086)	-0.0046** (0.0013)	-0.0028* (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: All models have the full set of controls, and report the heteroscedastically robust standard errors in parentheses. Full estimates available upon request.

*Significance at 5%.

**Significance at 1%.

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 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 7-year-old MLBs (i.e. the youngest boats in our data-set).

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

¹³To 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.

¹⁴We 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.

TABLE III 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 (0.059)	-0.040 (0.061)	-0.100 (0.093)	-0.084 (0.099)	-0.011 (0.010)	-0.0098 (0.011)
Y9	-0.032 (0.052)	-0.0044 (0.055)	-0.027 (0.073)	0.0054 (0.078)	-0.0026 (0.0083)	-0.0008 (0.009)
Y10	-0.017 (0.05)	0.015 (0.054)	-0.015 (0.07)	0.027 (0.077)	-0.0006 (0.0079)	0.0013 (0.0089)
Y11	-0.063 (0.058)	-0.023 (0.064)	-0.083 (0.087)	-0.029 (0.093)	-0.011 (0.010)	-0.0062 (0.012)
Y12	-0.038 (0.053)	0.0062 (0.057)	-0.049 (0.077)	0.013 (0.081)	-0.0038 (0.0087)	0.0023 (0.010)
Y13	-0.073 (0.056)	-0.023 (0.059)	-0.100 (0.081)	-0.031 (0.086)	-0.013 (0.0098)	-0.0057 (0.011)
Y14	-0.037 (0.056)	0.018 (0.062)	-0.035 (0.080)	0.045 (0.090)	-0.007 (0.010)	0.0019 (0.012)
Y15	-0.16* (0.069)	-0.099 (0.074)	-0.23 ⁺ (0.120)	-0.14 (0.130)	-0.043** (0.016)	-0.031 ⁺ (0.016)
Y16	-0.23* (0.092)	-0.16 ⁺ (0.097)	-0.21 ⁺ (0.120)	-0.11 (0.130)	-0.065* (0.026)	-0.049 ⁺ (0.026)
Y17	-0.21 ⁺ (0.120)	-0.13 (0.130)	-0.31 (0.220)	-0.19 (0.230)	-0.040 ⁺ (0.024)	-0.018 (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: All models have the full set of controls, and report the heteroscedastically robust standard errors in parentheses. Full estimates available upon request.

⁺Significance at 10%.

*Significance at 5%.

**Significance at 1%.

from approximately 1.9 to 3.1% per year.¹⁵ Five of the six specifications show the age coefficient to 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

¹⁵The 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 $\hat{\theta}\beta = -0.045$ and $\hat{\theta}\beta = -0.025$, 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: $\frac{1}{2}(e^{\hat{\theta}y} + e^{-\hat{\theta}y})\hat{\beta} = -0.031$ 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.

TABLE IV 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** (876.6)	1736.8 ⁺ (1017.7)	0.0781** (0.0298)	0.00329 (0.0382)	0.00887** (0.00338)	0.000373 (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: All models have the full set of controls, and report the heteroscedastically robust standard errors in parentheses. Full estimates available upon request.

⁺Significance at 10%.

**Significance at 1%.

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, 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

¹⁶Removing 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 -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.

¹⁷The 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: $\frac{1}{2}(e^{\hat{\theta}y} + e^{-\hat{\theta}y})\hat{\beta} = -0.215$. Additional calculations are available upon request.

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

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

TABLE V 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	12,856.9 (13,751)	11,099.8 (13,556.9)	0.44 (0.763)	0.203 (0.761)	0.05 (0.0866)	0.0231 (0.0864)
Y9	11,626.1 (10,976.7)	15,713.5 (11,644.1)	0.722 (0.609)	0.644 (0.628)	0.082 (0.0692)	0.0731 (0.0712)
Y10	17,835.6 (13,056.1)	18,274.5 (13,431.4)	0.722 (0.619)	0.495 (0.640)	0.0819 (0.0703)	0.0562 (0.0726)
Y11	19,649.2* (9830.2)	16,664.7 (10,947.2)	0.964 ⁺ (0.565)	0.598 (0.593)	0.109 ⁺ (0.0641)	0.0679 (0.0673)
Y12	18,052.9 (11,692.2)	14,357.7 (12,792.3)	0.863 (0.595)	0.455 (0.627)	0.0979 (0.0675)	0.0516 (0.0712)
Y13	28,424.1* (11,371)	24,136.0 ⁺ (13,131.9)	1.249* (0.591)	0.821 (0.639)	0.142* (0.0671)	0.0932 (0.0725)
Y14	12,913 (11,365.5)	6512.5 (13,355.2)	0.816 (0.593)	0.314 (0.644)	0.0926 (0.0673)	0.0356 (0.0731)
Y15	40,826.8** (14,082.5)	31,139.7* (15,465.6)	1.166 ⁺ (0.621)	0.556 (0.678)	0.132 ⁺ (0.0705)	0.0631 (0.0769)
Y16	48,684.2* (23,134.8)	36,224.6 (23,688.3)	1.026 (0.698)	0.337 (0.747)	0.116 (0.0792)	0.0383 (0.0848)
Y17	37,515.9 (28,782.8)	25,747.5 (29,429.1)	1.462 ⁺ (0.761)	0.829 (0.810)	0.166 ⁺ (0.0864)	0.0941 (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: All models have the full set of controls, and report the heteroscedastically robust standard errors in parentheses. Full estimates available upon request.

⁺Significance at 10%.

*Significance at 5%.

**Significance at 1%.

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, 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 and 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) may be correlated with our variables of interest. This could bias the results one way or another. We cannot completely rule out these concerns. It is stated that 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 7-year-old MLBs (i.e. the youngest boats in our data-set).

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 coastguard 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.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

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²⁰These estimates are available upon request.

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