Does Money Matter?
Examining the Relationships Between Federal Funding & Population Trends for ESA-Listed Marine Species

By

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Abstract

The Endangered Species Act (ESA) is widely regarded as one of the world's most impactful conservation policies. However, much of its success is dependent on the financial support it receives from the federal government. In recent years, there has been increasing debate surrounding the effectiveness of the ESA, with underfunding and inequity of allocated resources cited as key issues. While burgeoning conservation finance research has measured the impact of funding levels on terrestrial conservation, much remains unknown about the impact of conservation funding on ESA-listed marine species. To address this gap, this study examines the relationship between federal funding and population trends for ESA-listed marine species. Through the use of regression modelling techniques, I find no statistically significant relationship between the total federal funding (cumulative USD since listing date species^{-1} year^{-1}) and the likelihood that a species will have an increasing population trend. However, I do find that the total length of time a species is funded is significantly correlated with likelihood of population recovery, with species receiving twenty or more years of funding showing a higher likelihood of population recovery. These findings highlight the importance of long-term investment in marine conservation. Policymakers should prioritize species-specific recovery plans, equitable financial resource distribution, and improved data transparency to enhance future conservation outcomes.

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Introduction

Biodiversity is an important component of Earth's many ecosystems and has a direct impact on human society (Dirzo & Raven, 2003). However, global biodiversity has been decreasing at an alarming rate, with scientific consensus pointing to human activity as the overarching driver of species extirpation (Wilcove et al., 1998). Current estimates of species extinction project that over 99% of the 4 billion species to have evolved on Earth over the last 3.5 million years have gone extinct, leading researchers to believe that Earth is currently in its 6th ongoing extinction event sometimes called the "Anthropocene Era" (Barnosky et al., 2011; Crutzen, 2002). A wide variety of human activities contribute to the accelerated extinction of Earth's biodiversity including climate change, habitat alteration and destruction, species overexploitation, and the introduction of invasive species into fragile ecosystems (Dueñas et al., 2021). It is due to the combination and complexity of these drivers that species such as Kirtland's Warbler (*Dendroica kirtlandii*) experienced a 60% decline in overall population density over a 10 year period from 1961 to 1971 (Wilcove & Terborgh, 1984). However, this aggressive population decline is not limited to avian species, nor is it confined to a specific geographic region, leaving flora and fauna worldwide vulnerable to extinction in an ever-changing world. Consequently, as human-driven development, nature extraction, and climate change continue, species face increasing pressures to adapt. This trend emphasizes the need for countries to take accountability and implement protective measures for these imperiled species. Ultimately, this is where legislation such as the United States' Endangered Species Act (ESA) becomes critical to combatting biodiversity loss.

Established in 1973, the Endangered Species Act (ESA) was one of the world's first comprehensive regulatory frameworks aimed at the protection and rehabilitation of the United States' imperiled species and their respective habitats. Congress passed the ESA to help combat the global biodiversity crisis and strengthen overall U.S. conservation policy, expanding species protections beyond fish and mammals to include birds, plants, and taxonomic groups below the subspecies level (Doremus, 2010; Schwartz, 2008). Beyond adding to the definition of protected species, the ESA also imposed a thorough conservation mandate on all federal agencies, ensuring that their actions do not pose a threat to the imperiled populations of ESA-listed species (Doremus, 2010). This regulatory expansion increased the robustness of conservation policy within the United States and cemented the ESA as one of the most effective environmental policies in the world (Schwartz, 2008). Implementation of the ESA is controlled by two federal agencies, the U.S. Fish & Wildlife Service (USFWS) and the National Marine Fisheries Service (NMFS), both of which either solely or jointly manage the populations of the country's endangered species. Through adaptive management, these two agencies work together to utilize data from previously implemented conservation actions to develop future strategies, ensuring that all recovery efforts are guided by reliable science and research (Evansen et al., 2021; Murphy & Weiland, 2016).

Conservation actions can take many forms, including habitat restoration and protection, captive breeding, regulatory monitoring, and law enforcement; however, each of these tasks comes with a fiscal cost. Thus, the efficacy of the ESA, and completion of planned recovery tasks, hinges on the overall federal funding that each species' recovery plan receives.
Federally funding the Endangered Species Act has historically been a difficult task, requiring cooperation amongst diverse economic, political, social, and environmental stakeholders. Since

the ESA's inception, chronic underfunding has forced difficult decisions pertaining to which species receive prioritization for recovery, and which are left behind. Previous research has shown that approximately 20% of what is required to adequately rehabilitate the United States' endangered species is being allocated to the Endangered Species Act (Miller et al., 2002).

Despite shortfalls in ESA funding, financial investment per species has been identified as one of the best predictors for a species recovery and rehabilitation, with previous research showing positive correlations between investment and recovery progress (Adamo et al., 2022; Gerber, 2016). Other environmental sectors and regulations also demonstrate a strong link between financial investment and environmental outcomes. For example, the Inflation Reduction Act (IRA) of 2022 introduced a significant increase in federal investment to climate change mitigation across a variety of sectors when compared to its predecessor, the Infrastructure Investment and Jobs Act (IIJA) of 2021. Previous research identified that when federal funding in climate mitigation was increased from $184 billion under the IIJA to $390 billion under the IRA, the potential decrease in greenhouse gas (GHG) emissions increased to 47-83% below 2005 levels by 2030 (Bistline et al., 2023; Gurule, 2024). More importantly, it was also found that 38-80% of the GHG reduction projection was directly attributable to the implementation of the IRA and increased climate mitigation funding (Bistline et al., 2023). In sum, previous research on the effects of increased funding in adjacent environmental sectors broadly suggests that species conservation might be more effective under increased funding. However, even with increased financial support, a glaring issue remains: the ESA must develop more effective mechanisms for allocating the funds it does receive.

Current federal funding allocation within the Endangered Species Act shows evidence of vastly disproportionate allocation of financial resources across the listed species (Hayashi, 2023).

From 1998 to 2012, over 80% of all federal funding allocated to endangered species recovery targeted just 5% of the total ESA-listed species, while 80% of the listed species shared a mere 5% of the federal budget. This extremely disproportionate allocation was funneled to just 15 species of fish, including 7 salmonid and 8 sturgeon species (Evans et al., 2016). Furthermore, marine species are considerably more underfunded when compared to terrestrial species (Luther & Gentry, 2019). This emphasizes the extreme disparity between financial resources allocated to conserving ESA-listed species and highlights the need to clarify factors that influence funding distribution. Potential drivers for the disproportionate allocation of funds are competing economic and social interests, challenges in comparing the costs and benefits of conservation efforts, difficulty in assessing the efficacy of conservation actions, and heightened interest in protecting charismatic species (Gerber et al., 2018). However, despite these potential drivers, understanding the broader context as to why specific species receive higher financial resources is largely difficult to track due to inadequate record keeping within the USFWS and the NMFS. Additionally, existing recovery plans often lack detailed assessments of how politically, economically, or logistically feasible it would be to implement the recommended recovery actions for each species (Miller et al., 2002). This highlights the need to not only improve the management and record keeping practices of both the USFWS and NMFS, but also to further investigate the efficacy of current funding allocation strategies.

Much of the current literature in this field takes a broad economic approach to analyzing the ESA's effectiveness and rarely considers the role of species-specific ESA financial investments in ecosystem- or species-level recovery (Luther & Gentry, 2019). In addition, existing research typically focuses on terrestrial species (Echols et al., 2019; Epanchin-Niell & Boyd, 2020; Main et al., 1999; Miller et al., 2002), and as a result conservation finance for marine species is severely under-researched (Bos et al., 2015). Thus, there is an urgent gap in understanding how federal investments affect population trends for ESA-listed marine species. Ultimately, this emphasizes the importance of investigating marine conservation finance and understanding how federal financial investment can influence the survival and recovery of imperiled marine species, in order to effectively guide future conservation efforts and marine policy decisions.

This research aims to explore these identified gaps in current literature by employing a more granular, species-level approach to marine conservation finance. Specifically, I analyze the impact of federal investment on population trends in ESA-listed marine species. This study aims to answer two questions: (1) To what extent is there a relationship between federal funding and population recovery for ESA-listed marine species?, and (2) What administrative and species-specific factors are correlated with the total amount of federal funding marine species receive? Through exploring these questions, this research contributes to the growing body of literature on marine conservation finance and supports the development of more informed, equitable, and effective conservation strategies and marine policy decisions.

Methods

Building the Dataset

Species Compilation

In order to examine the relationships between U.S. federal funding and population trends for the threatened and endangered marine species listed under the Endangered Species Act (ESA), I constructed a dataset utilizing data from multiple sources such as government and non-governmental organizations (NGOs). The sources included the U.S. Fish & Wildlife Service's (USFWS) Environmental Conservation Online System (ECOS) species reports, the International Union for Conservation of Nature's (IUCN) Red List of Threatened Species, the National Oceanic and Atmospheric Administration's (NOAA) National Marine Fisheries Service (NMFS) species directory, and NatureServe Explorer's species profiles.

To begin, I gathered a list of all the ESA-listed marine species identified on both the NMFS and ECOS public databases. The use of both of these databases was important, as marine species protected under the ESA have the unique condition of being managed solely or jointly by either the USFWS or the NMFS. Some species, such as *Ursus maritimus* (polar bear), are solely managed by the USFWS, whereas others like *Megaptera novaeangliae* (humpback whale), are managed only by the NMFS. However, there are some cases, such as *Salmo salar* (Atlantic salmon), where the species is jointly managed by both federal agencies.

Through this search, I identified a total of 110 potential marine species, with the majority coming from the NMFS database (n = 105), and a few species who were solely under USFWS management coming from the ECOS database (n = 5). After building this species list, I used the "Region" identifier within the NMFS species directory to further refine the species, ensuring that only species within U.S. jurisdiction were included in the final dataset. I filtered out species that were exclusively beyond the U.S. Exclusive Economic Zone and territorial waters (tagged as "foreign"), as well as species who were listed without a region identifier (tagged as "—"). This left only the 5 USFWS managed species from the ECOS database, as well as 58 NMFS managed species who were categorized within a U.S. region (n = 63).

Attribute Collection

Once I had finalized a list of species, various attributes were pulled from both the NMFS species directory and the ECOS species reports. The first, species type, was derived from the "Species Category" identifier within the NMFS database. Each species within the final dataset was assigned to a category based on their taxonomy: marine fissipeds, cetaceans, pinnipeds, sirenians, birds, corals, gastropods, fish, sea turtles, or other invertebrates. This variable, containing the species type, was included to allow for later analysis based on taxonomic groups.

I then identified the year that each species was listed as threatened or endangered under the Endangered Species Act. In most cases, the listing year was sourced from the database where the species was managed (e.g. , *Megaptera novaeangliae* on the NMFS species directory). In cases where species were listed within both databases, indicating dual management, the listing year was typically identical. However, in the case where a discrepancy occurred for these species, the earliest year of listing was coded into the dataset. Additionally, in cases where a species has multiple distinct population segments (DPS) listed in either or both databases, the earliest year across all DPS was coded into the dataset (e.g., *Caretta caretta* listed in 1978 on ECOS and 2011 on NMFS was selected as 1978 for the dataset). This was done in order to account for the entire history of a species' threats and endangerment. Once this was completed, I constructed a secondary year variable that calculated the number of years since the species' initial listing using the formula: "*YearsSinceListing* = 2020 - *ListingYear*." The year 2020 was chosen as the endpoint for this analysis, as it represents the most recent publicly available expenditure report from the USFWS at the time of this study, providing the latest data for calculations.

The next variable, recovery plan publication year, indicated the year that each recovery plan was published by species on the databases for public record. As with previous variables, the recovery plan publication year was typically available within the database for the managing agency, however this was not always the case. In situations where a species was cross-listed and had conflicting publication dates (e.g., *Salmo salar* shows a recovery plan publication of 2009 on ECOS and 2000 on NMFS), the earliest publication date was coded into the dataset. Similarly, if a species had multiple publication dates due to updated recovery plans, the earliest year was also selected. Two additional categories were also used: "Under development" and "N/A." These two categories were used in the cases where a species was either noted to have a recovery plan in development, or if a species had no mention of a recovery plan at all. Once complete, I constructed an additional, binary variable that took the value of "1" if a species had a recovery plan publication date or plan under development, and "0" if the species did not have a recovery plan.

The current listing status of each species was also derived from both the ECOS and NMFS databases. Due to every species in this study having a listing status of "threatened" or "endangered", the variable containing the species' listing status in the final dataset only contains those two factors. As with previous variables, if a species had conflicting listing statuses across both databases due to joint management, or multiple DPS across one or both databases, the most severe of the statuses was coded into the final dataset (e.g., endangered status takes precedence over threatened).

The final attribute sourced directly from these two databases, was the number of NMFS-identified regions that the species inhabits. The National Oceanic and Atmospheric Administration's NMFS species directory tags species with up to 5 unique region identifiers (for species under sole U.S. jurisdiction): New England/Mid-Atlantic, Southeast, West Coast, Pacific Islands, and Alaska. For the purposes of this study, I quantified the number of region tags a species possessed and coded it numerically (e.g., *Balaenoptera musculus* was tagged with all five NMFS regions and therefore was assigned a value of “5”). For the species solely managed by the USFWS within the ECOS database, I referenced their critical habitat profiles and matched the range maps to the corresponding NMFS regions. For example, *Ursus maritimus*’s critical habitat range map indicates that it occupies the region to the north and east of Alaska, and was therefore assigned the “Alaska” NMFS region tag. Once all qualifying region tags were assigned, they were then quantified and coded numerically in the same manner as before.

Financial Data Integration

I aggregated financial data sourced from the U.S. Fish & Wildlife Service’s *Endangered and Threatened Species Expenditure Reports*, which were publicly available documents available on the ECOS website. For this study, I focused on a time scale spanning from 1990 to 2020. This range allowed for 30 years of marine conservation federal funding to be included, in order to best model the relationship federal funding has on population trends over time.

To collect this data I downloaded all 30 expenditure reports from the ECOS website, and extracted financial values from *Table 1: Reported Expenditures for Endangered and Threatened Species, Not Including Land Acquisition* for each fiscal year. I coded the reported expenditures within this table for each available species within the final dataset. If a species was not listed within this table in a given year, it was coded as “N/A”. When complete, I calculated the total value that each species received over the 30 year time series, and coded that amount into the total federal funding variable.

Once the financial data was finalized, I constructed a variable that calculated the total number of years that a species received funding within the dataset's time series. This was determined by summing the total number of years that a species had received a funding amount of greater than zero dollars, as some species had reported a value of zero within a given year. Similarly, years with a value of "N/A" were excluded from the summation.

At the end of the financial data aggregation, it became evident that two species would need to be removed from the final dataset due to various inconsistencies in their funding reports. Specifically, *Eubalaena glacialis* (North Atlantic Right Whale) and *Eubalaena japonica* (North Pacific Right Whale). These species were originally reported as a single species, "Right Whale", within the *Endangered and Threatened Species Expenditure Reports* until 1997. In 1997, the USFWS reclassified these cetaceans into two separate species, "North Atlantic Right Whale" and "Right Whale," with the latter encompassing all U.S.-domestic and foreign right whale species. However, it was not until 2011 that the "North Pacific Right Whale" was officially recognized as its own distinct species within the expenditure reports. This ultimately meant that the funding for the U.S. right whales was aggregated under various versions of broader species names for much of the study's time series, with no clear identifiable way of how much funding went to either species. Due to this, I chose to exclude these two cetaceans from the final dataset, reducing the total number of species to 61 (n = 61).

Population Trend Extraction

Population trends for the ESA-listed species are often reported in varying formats across different databases and studies, which can make direct comparisons challenging. To address this variability, I defined a population trend variable based on available data from the IUCN Red List of Threatened Species and NatureServe Explorer's species profiles.

This variable prioritized IUCN population trend data, and thus I compared the IUCN population trend with the short-term population trend anecdote on the NatureServe Explorer species profile for each species. If the short-term population trend anecdote for a species contained any U.S.-specific information, the information was matched with an IUCN population trend category (either “Increasing,” “Decreasing,” “Stable,” or “Unknown”) and that category was coded into the dataset. This category would take precedence over the original IUCN trend, even if IUCN had identified a more severe population trend originally. Conversely, if no U.S.-specific information was present in the anecdote, then the IUCN population trend category was used. Additionally, if the IUCN trend was categorized as “Unknown” and NatureServe contained a population trend with no U.S.-specific information, the entry was coded as “Unknown.” To standardize this process, all negative NatureServe anecdotes were categorized as “Decreasing,” all positive anecdotes were categorized as “Increasing,” and all anecdotes related to population stability were categorized as “Stable.” If multiple DPSs were identified to have varying population trends, then the most severe population trend was coded into the dataset, defaulting to “Decreasing” in the case of ambiguity.

Incorporation of Additional Variables

After all other variables were constructed, I extracted some final pieces of information from the IUCN Red List of Threatened Species database. This resulted in the creation of 2 more variables: the number of IUCN-classified threats to species and whether the marine species inhabits both land and sea (binary).*e*. The number of IUCN-classified threats to species was generated by counting the number of threats listed under the header “Threats” on the species profiles and coding that numerically in the dataset. As was done with other variables, if no threats were identified under this header, then “N/A” was coded into the dataset. Finally, whether the species inhabits both the land and sea was constructed as a binary identifier that took on the value of "1" if a species' profile identified "Terrestrial" or "Marine Intertidal" habitats, or "0" if neither of these habitats were identified.

Statistical Analysis

To analyze this dataset, I used RStudio version 2024.12.1+563 to conduct statistical modeling aimed at evaluating (1) the relationship between federal funding and population trends for ESA-listed marine species, and (2) the administrative and species-specific factors correlated with the total amount of federal funding marine species receive.

Data Cleaning & Correlation Testing

Prior to conducting my statistical analysis, I cleaned the dataset by removing unnecessary columns, converting data types, and standardizing my numeric variables. Several columns were identified to be unnecessary due to the difficulties they would present when including them in statistical models, and thus were ultimately dropped from the dataset. This was important as it helped to retain as many complete observations as possible that were available for the regression analyses.

Similarly, two variables were converted to binary indicators to allow for their inclusion in logistic regressions. Both the IUCN-skewed population trend and species' listing status variables were converted to binary form. For the IUCN-skewed population trend, original categories took on the value of "1" if the population trend was "Increasing", and "0" if the population trend was "Decreasing," "Stable," or "Unknown." The species' listing status variable was re-coded so that "1" identified species that were listed as "Endangered," and "0" represented species who were listed as "Threatened."

Finally, all numeric variables were standardized using z-scores, which meant that every numeric variable had a mean of 0 and a standard deviation of 1. This transformation on the variables was important as it assisted with coefficient interpretation, as the numeric variables were all on different scales originally. Standardizing ensured that variables with larger scales, such as total federal funding, did not disproportionately influence the regression models compared to smaller-scale variables like the number of IUCN-classified threats.

Once the dataset was cleaned and ready for analysis, I tested for potential correlations between the independent variables using a combination of Pearson's correlations, Point-Biserial correlations, and Chi-squared tests. Pearson's correlations were calculated through the creation of a correlation matrix with coefficient values (*see Appendix, Figure 1*), and used to identify potential multicollinearity between the continuous variables. A standard threshold of $|r| > 0.7$ was used to determine significant relationships where independent variables with $|r| > 0.7$ were not included in the same regression.

Point-Biserial correlation tests were then conducted to examine the relationship between the continuous and binary variables within the dataset. The continuous variables included in these tests were the total federal funding, the total number of years a species was funded, the year they were federally listed, the number of years since their federal listing, the total number of IUCN-classified threats, and the total number of NMFS-identified regions the species inhabits, and they were tested against the binary variables for whether or not a species has a recovery plan, the species' listing status, the IUCN-skewed population trend, and whether the species inhabited both the land and sea. A p-value threshold of 0.05 ($p < 0.05$) was used to determine significant relationships between the variables. Any significant relationship involving the IUCN-skewed population trend was determined to be unproblematic, as this variable served as a dependent variable in our later regression analyses.

Finally, Chi-squared tests were conducted on the remaining categorical variables (the species' scientific name, common name, type) to assess potential associations. These tests have a similar role to Pearson's correlations in examining relationships between categorical predictor variables.

Analysis of Variance (ANOVA)

Once the correlation tests were complete, I conducted one-way analysis of variance (ANOVA) tests to explore the possible significant differences in federal funding allocations across several categorical variables within the dataset. Specifically, I ran the ANOVA tests using the total federal funding as the dependent variable, with the species type, the species' listing status, and whether or not the species inhabited both the land and sea as the independent variables. These variables were specifically chosen as I was interested in exploring whether federal funding allocations differed based on a species type, listing status, or habitat designations. Each ANOVA test was conducted and examined using a standard significance threshold of 0.05 ($p < 0.05$).

As these tests were exploratory in nature, I did not conduct assumption diagnostics such as homogeneity of variance and normality, as the ANOVA tests were not designed to test hypotheses that rely on these assumptions. Each ANOVA test was run to assist in providing insights into potential relationships or differences between key variables for further analysis. The results of these ANOVA tests were also visualized using violin and box plots to support interpretation and assess the variance across the groups (*see Appendix*, *Figures 2-4*).

Logistic Regression Modeling

Logistic regression analysis was conducted on the dataset in order to evaluate the primary research question of the study: evaluating the relationship between federal funding and population trends for threatened and endangered ESA-listed marine species. I began by identifying the potential covariates to include in the logistic regressions, and created a subset data frame containing the dependent variable for the IUCN-skewed population trend, along with the independent variables for the total federal funding, the total number of years a species was funded, the year they were federally listed, the number of years since their federal listing, whether or not a species has a recovery plan, the species' listing status, the total number of IUCN-classified threats, the total number of NMFS-identified regions the species inhabits, and whether or not the species inhabits both the land and sea. I then omitted all missing values in order to preserve as many complete observations as possible for the analyses, leaving a final total of 53 observations to be included in the logistic regressions (n = 53).

I first constructed a base logistic regression that contained all the independent variables in the subset, except for the year the species was federally listed and the number of years since the species' federal listing. These two variables were omitted from the base model due to their correlations with the variable for the total number of years a species was funded that were identified in the Pearson's correlation matrix. A second model was then created that used a best-subset selection approach based on an exhaustive search method and the Akaike Information Criterion (AIC) value as the primary model selection criteria. This method estimated all possible combinations of the independent variables to identify the model of best fit that had the lowest AIC value, while still balancing the potential model's fit with its complexity, rather than relying on a monodirectional model selection approach. Utilizing this best subset selection approach resulted in a model that contained the IUCN-skewed population trend as the dependent variable, as well as the total federal funding and the total number of years a species was funded as the independent variables.

I then tested the goodness-of-fit of the final logistic model generated by the best-subset selection. To do so, I conducted a Hosmer-Lemeshow test that evaluated how well the model's predicted probabilities align with the observed data points. For this diagnostic test, an insignificant p-value ($p < 0.05$) indicates a model of good fit for the data. Additionally, I created a confusion matrix to evaluate the model's classification performance. This allowed for assessment of the model's accuracy and specificity by indicating the correct and incorrect predictions made by the final model. In this test, a higher number of true positives and true negatives indicate good model performance. Lastly, I plotted the final logistic model for both independent variables (*see Appendix, Figures 5-6*) to help visualize how well the predicted probabilities matched up with the actual outcomes, and to better interpret the behavior of the covariates within the model.

Linear Regression Modeling

The final analysis conducted on this dataset was a series of linear regressions aimed at evaluating the secondary research question in this study: evaluating the various additional administrative and species-specific factors that are correlated with the total amount of federal funding a marine ESA-listed species receives. To begin, I identified the potential variables that could be included in the linear regression, and created a subset of the original unscaled data frame containing those variables. The original unscaled data was used for this subset in order to preserve the interpretability and magnitude of the regression coefficients, which allowed the model to reflect the true scale and impact of each covariate. While scaled data is generally recommended during regression modeling to account for differences in variable magnitudes, unscaled data was used in this instance for interpretability. Future versions of this research will incorporate scaled data during model construction and reserve unscaled variables for post-modeling interpretation and visualization. This linear subset included the dependent variable for total federal funding, as well as the independent variables for the total number of years a species was funded, the species' listing status, whether or not a species has a recovery plan, the total number of IUCN-classified threats, the total number of NMFS-identified regions the species inhabits, and whether or not species inhabits both the land and sea. Just as I did with the logistic regression subset, I removed the missing values from the linear regression subset in order to preserve as many complete observations as possible for the analyses. This left a final total of 53 observations to be included in the linear regressions (n = 53).

As before, I first constructed a base linear model that contained all the independent variables in the subset. This initial regression output produced estimates and standard errors in the hundreds of thousands, which made interpretation extremely challenging. Upon examining the distribution of the dependent variable for the total amount of federal funding, it was found to be extremely right-skewed. To help alleviate this issue, I applied a log-transformation, and re-ran the base model. This log-transformation was applied to stabilize the variance and assist in coefficient interpretation, with the regression coefficients now representing approximate proportional change in federal funding associated with a one-unit change in each dependent variable.

I then performed a best-subset selection that used an exhaustive search method and the AIC value as the primary model selection criteria. This approach estimated all possible combinations of the independent variables to identify the model of best fit, identified by the lowest AIC value, as was previously done with the logistic regression. Utilizing this best subset selection approach resulted in a model that contained the total federal funding as the dependent variable, as well as the total number of years a species was funded and whether or not the species has a recovery plan as the independent variables. Once the model of best fit was selected, I visually assessed the diagnostic plots (*see Appendix, Figures 7-10*) to evaluate whether the assumptions of linear regressions were met.

Results

Based on the statistical models used in this study, these are the key results from the analyses. To begin, the Pearson's correlation matrix of continuous covariates (*see Appendix, Figure 1*) identified 3 specific variables that were heavily correlated with one another, each with absolute r values above the acceptable threshold of 0.7 ($|r| > 0.7$). The correlated variables were the total number of years a species was funded, the year the species was federally listed, and the number of years since the species' federal listing. All other correlations tested in the Pearson's correlation matrix were determined to be unproblematic, and possessed absolute r values below the acceptable threshold. The Point-Biserial correlations identified varying levels of correlations between the continuous-numeric and binary variables in the dataset. For instance, the total number of years a species was funded, the year the species was federally listed, and the number of years since the species' federal listing all showed evidence of weak to moderate correlations between nearly all 4 binary variables. In contrast, the total number of IUCN-classified threats, the total number of NMFS-identified regions that the species inhabits, and the total federal funding showed weak to no correlations with any of the binary variables. The final set of correlation tests, the Chi-squared tests, indicated that there were no significant associations between any of the three categorical non-binary variables: the species' scientific name, common name, type.

As mentioned previously, the ANOVA tests conducted were exploratory in nature, and diagnostic tests were not run to verify the validity of their results. As such, these findings should be interpreted with caution. While each ANOVA test resulted in a p-value greater than the standard significance threshold of 0.05, suggesting no statistically significant differences across the tested groups, these results are not conclusive. Specifically, there is insufficient statistical evidence from these exploratory tests to suggest that species type, listing status, or land use designation has a measurable effect on the amount of federal funding a species receives. Therefore, we do not reject the idea that funding may be roughly equivalent across these groups, though further validated testing would be required to support such a conclusion. Nonetheless, the ANOVA plots suggest there may be meaningful variation in how funding is distributed within each group. For example, across species types, taxa such as fish and pinnipeds display a much wider range of funding allocations compared to taxa like gastropods or sea turtles (*see Appendix, Figure 2*). A similar pattern appears when comparing listing status and land use designation, where endangered species and species without a terrestrial habitat tend to show more variability in funding allocations (*see Appendix, Figures 3–4*).

Table 1. *Summary of regression model results examining factors influencing ESA-listed marine species' population trends and federal funding allocations. Models 1 and 2 are logistic regressions with the IUCN-skewed population trend (IUCNSkewPop) as the dependent variable; Models 3 and 4 are linear regressions with total federal funding (FedFundingTotal) as the dependent variable. Models 1 and 3 represent base models including all covariates; Models 2 and 4 reflect best subset models selected via AIC. The dependent variable in Models 3 and 4 was log-transformed due to right skew.*

Table 1: Logistic & Linear Regression Models

	Dependent variable:			
	IUCNSkewPop		FedFundingTotal	
	logistic		*OLS*	
	(1)	(2)	(3)	(4)
FedFundingTotal	-0.553	-1.035		
	(1.086)	(1.547)		
YearsFunded	4.454**	2.444***	0.136***	0.130***
	(1.908)	(0.812)	(0.023)	(0.018)
ListingStatus	-3.714**		0.846*	
	(1.870)		(0.448)	
RecoveryPlanBinary	-2.231		1.267**	1.289**
	(1.662)		(0.609)	(0.586)
IUCNThreats	-0.813		0.079	
	(0.729)		(0.105)	
NOAARegions	0.259		-0.283	
	(0.543)		(0.213)	
LandUse	-0.237		-0.177	
	(1.012)		(0.422)	
Constant	-0.242	-2.813***	13.031***	13.428***
	(1.782)	(0.929)	(0.870)	(0.612)
AIC	42.78	40.78	188.15	186.57
Null Deviance	56.7	56.7		
Residual Deviance	26.78	34.78		
Observations	53	53	53	53
R^2			0.610	0.560
Adjusted R^2			0.559	0.542
Log Likelihood	-13.391	-17.390		
Residual Std. Error			1.318 (df = 46)	1.343 (df = 50)
F Statistic			11.985*** (df = 6; 46)	31.770*** (df = 2; 50)
Note:				*p<0.1; **p<0.05; ***p<0.01

Most important to this study are the results of the logistic and linear regression models. For starters, when looking at the results of base logistic regression that contained all the potential covariates, two variables were identified to be significant at the 95% confidence level: the total number of years a species was funded (p = 0.0196) and the species' listing status (p = 0.0470). After model selection and AIC comparison, the best fitting model regressed the variables for the total federal funding and the total number of years a species was funded on the IUCN-skewed population trend. The results from this final fitted model show that total federal funding is not statistically significant, while the total number of years a species was funded is statistically significant (p = 0.00260) with an effect size of 2.444 units. We can see that for each additional 1-unit (scaled) increase in the years an ESA-listed marine species receives federal funding, the odds of the species' population trend being "Increasing" are $e^{2.444}$ times higher, holding all else constant. Also, when comparing the AIC values across the base and fitted models, we can see that the AIC decreases from 42.78 to 40.78, indicating that the model is a better fit for the data.

Turning to the linear regression models, the original base linear model identified three covariates to be statistically significant in predicting total federal funding. The significant variables are as follows: the species' listing status (p = 0.065), whether or not the species has a recovery plan (p = 0.043), and the total number of years a species was funded (p = $5.51e^{-07}$). After model selection, and AIC & F-statistic comparison, the model of best fit regressed the variables for the total number of years a species was funded and whether or not the species has a recovery plan on total federal funding. The results from this final fitted linear model show that the total number of years a species was funded (p = $1.52e^{-09}$) and whether or not the species has a recovery plan (p = 0.0323) were both statistically significant, but remove the covariate of the species' listing status. For each additional year that an ESA-listed species receives funding, there is an approximate 13% increase in the total federal funding that they receive, holding all else constant. Likewise, when a species has a published recovery plan, it is associated with an approximate 129% increase in the total federal funding a species receives holding all else constant. When comparing test statistics to the base linear model, the adjusted R^2 value is 0.542, meaning that the fitted model accounts for approximately 54% of the variability in federal funding. Additionally, the F-statistic of 31.77 ($p = 1.246e^{-09}$) is highly significant at the 99% confidence level, indicating that the model is a good fit for the data.

Discussion

This study is, to our knowledge, the first analysis of the relationship between population trends and federal funding for threatened and endangered marine species listed on the Endangered Species Act. While federal funding is a crucial tool that can aid in the recovery of imperiled species, there is a considerable lack of research on how funding affects population trend outcomes, particularly for marine species. This paper helps to fill that gap by providing new insight into how federal funding and other conservation-related factors influence population trends, in order to inform more effective conservation planning in the future.

Ultimately, the total amount of federal funding that an imperiled marine species receives is not correlated with whether its population is likely to increase. However, the length of time that a species receives federal investment is positively correlated with population growth. This novel result suggests that sustained long-term support is more effective for recovery than short-term, one-time payouts. This pattern may reflect the benefits of consistent recovery planning and long-term conservation efforts. At the same time, it raises questions about equity in how federal Endangered Species Act funding is distributed. If only certain species receive long-term support, regardless of ecological needs or threat levels, this could signal imbalances in prioritization and point to structural inequities in funding allocation across species.

One possible explanation for this pattern is that meaningful population recovery depends on thorough, long-term conservation planning. In contrast, short-term funding appears to be less effective, which may be due in part to biological factors (i.e. generational timescales of some mammalian species) that delay visible recovery. However, it is also possible that short-term investments, even when attached to a recovery plan, lack the strategic depth and follow-through needed for meaningful impact. While this study found that the presence of a recovery plan was not significantly correlated with population trends, this may point towards the need for more robust, adaptive, and comprehensive recovery planning. Simply allocating funding to a species without a clear plan for how it will be used is unlikely to result in any significant recovery outcomes. Previous studies, such as Miller et al., (2002), found that the ESA is persistently underfunded and that species that have a higher proportion of available funding tend to show signs of greater species recovery. However, they also noted constraints when accounting for broader economic and social factors that influence species recovery, which are also often overlooked by current recovery plans. Paired together, their findings and the results of this study suggest a pressing need for updated recovery plans that are not only well-funded but are also comprehensive and include greater socio-economic, ecological, and management factors into their reports. Species recovery is inherently slow and iterative, requiring adaptive management and the best available science (Evans et al., 2016; Murphy & Weiland, 2016). These results support the argument that short-term, sporadic support is not adequate to achieve meaningful conservation goals for marine species. What is truly needed is long-term sustained commitments.

Another possible explanation for this pattern is that federal funding may be inconsistently allocated across marine species, with some species receiving far more funding than others. While this study did not verify the results of the ANOVA tests statistically, the plotted distribution of federal funding by species type still identifies considerable differences in the ranges of funding different marine species types receive. Similarly, Evans et al. (2016) noted that approximately 80% of the federal ESA budget was allocated to just 15 species of fish, which highlights just how disproportionate this allocation can be. This result is echoed in the ANOVA plot of this study (*see Appendix, Figure 2*), with fish having the widest range of total federal funding values compared to all other marine species groups. This allocation imbalance may stem from certain species being more charismatic, publicly visible, or economically viable leading to them receiving higher levels of support (Petersen, 1999). The second regression model in this study also supports this interpretation, showing that higher amounts of total federal funding are positively correlated with longer durations of funding, albeit with a relatively low effect size of approximately 13%. However, this still suggests that once a species begins to receive funding, it may continue to do so, which reinforces existing allocation patterns and leaves less charismatic yet ecologically important species behind. It is also worth considering whether there might be a threshold effect in the relationship between funding and population recovery, as revealed by the regression models. Specifically, additional funding might not produce proportional improvements once a certain level of funding is reached, particularly if the funding is not effectively allocated or managed. In this case, the regression could show diminishing returns where higher amounts of funding beyond a threshold have less impact on population trends.

While we did find that total federal funding is not correlated with predicting imperiled marine species population trends (*see Table 1*), we did further analyze which conservation factors are associated with the total federal investment a species receives. Interestingly, along with longer durations of funding, a species having a published federal recovery plan had a significant effect on total federal funding. In fact, species with recovery plans were associated with a 129% increase in funding over the time series of this study. This suggests that recovery plans act as gateways to species receiving greater federal investment. However, the direction of this relationship is still unclear and would require further analysis to explain. It is just as likely that species with more funding are more likely to receive updated recovery plans, as it is that having a recovery plan leads to increased funding. Either way, the connection between recovery planning and funding highlights the importance of strategic conservation efforts that ensure recovery resources are equitably and effectively distributed amongst imperiled marine species.

It is also important to acknowledge the limitations of this study when interpreting its results. First, the best available financial data was sourced from the USFWS regarding the annual expenditures for each ESA-listed marine species. However, these reports only identify expenditures at the state and federal levels, and do not account for investments made at the county, private, or NGO levels. This means that the true expenditures for some species may be ultimately underreported. Additionally, the accuracy of these reports is unknown, as reporting to the USFWS database is voluntary. This could introduce bias towards certain species in the results, if certain agencies or projects are more likely to report funding for certain species (Luther & Gentry, 2019). Further research should aim to include more granular funding data to accurately incorporate these additional sources and gain a deeper understanding of total investment into species conservation. Second, species population trends can vary depending on the source and methodology. In this study, a unique categorization system was developed, which could have resulted in some trends being over simplified or misclassified due to data constraints.

Future studies could benefit from the use of species-specific monitoring data or more standardized population metrics to increase accuracy and comparability. Additionally, future research could account for non-binary population trend data, moving beyond just whether or not a species' population trend increased, but also measuring the degree to which population trends have decreased or increased. This would provide a more nuanced understanding of species recovery and potentially reveal patterns not captured in a simplified binary framework.

Conclusion

This study set out to answer the seemingly simple but important question: does money matter when it comes to rehabilitation of imperiled marine species? The short answer is "partially", but the reality is far more nuanced. Importantly, this study suggests that funding duration, rather than just total dollars, may play a role in influencing marine conservation outcomes in terms of population trends. Current funding strategies for marine species appear to be too short-term and unevenly distributed among the taxonomic groups. To be more effective, marine policy should prioritize long-term sustained investment models that allow for multi-generational, long-term trajectories in population recovery, giving species the time they need for recovery to succeed.

The presence of recovery plans may be key entry points for funding, suggesting that these plans require more dedicated support. Future marine policies should focus on strengthening and expanding species recovery plan development, as a dual strategy: to improve both conservation planning methodology and resource allocation methods within federal agencies.

I also recommend that federal agencies take considerable action going forward when protecting our marine species. First, I stress the importance of creating comprehensive recovery plans. These plans commit federal agencies to rehabilitating imperiled species over longer periods of time, rather than intervening sporadically when it is already too late. Second, I urge the need for targeted, consistent investment in marine conservation, especially in species that are considered less charismatic or economically valuable. Truly equitable conservation allows all species the chance to survive and prosper, instead of leaving us to decide which ones deserve to live and which do not. This is especially important given that many non-charismatic species, such as *Pycnopodia helianthoides* (sunflower sea star), are often ecologically vital and play critical roles in maintaining ecosystem balances. Third, I call for better data transparency, reporting, and standardization in reporting both funding and population trends. Increased accountability on this front will enable more accurate research and more informed conservation planning. Ultimately, the successful recovery of imperiled marine species will depend on significant collaboration between federal agencies, scientists, and NGOs.

Appendix

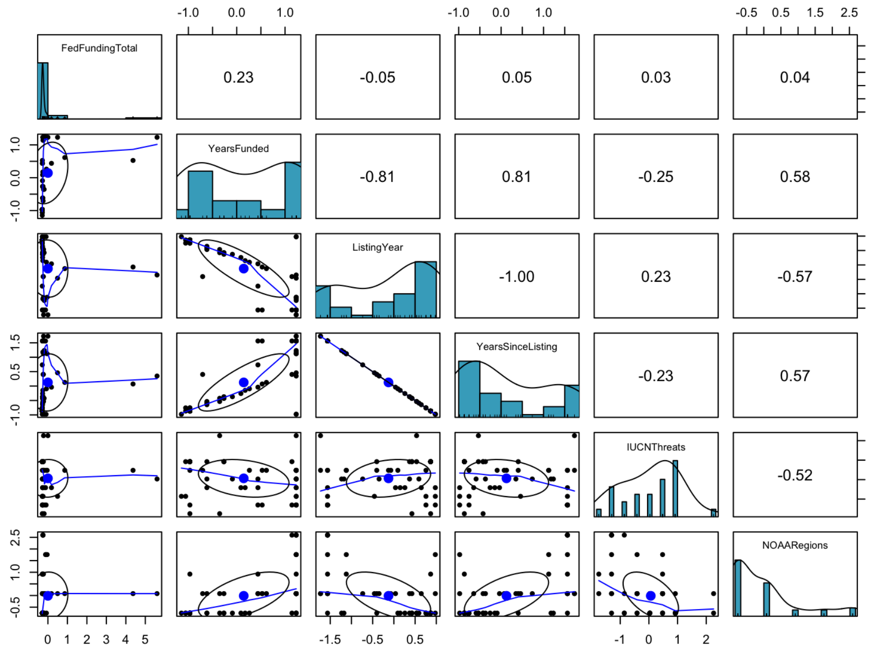

Figure 1: Pearson's correlation matrix of continuous variables.

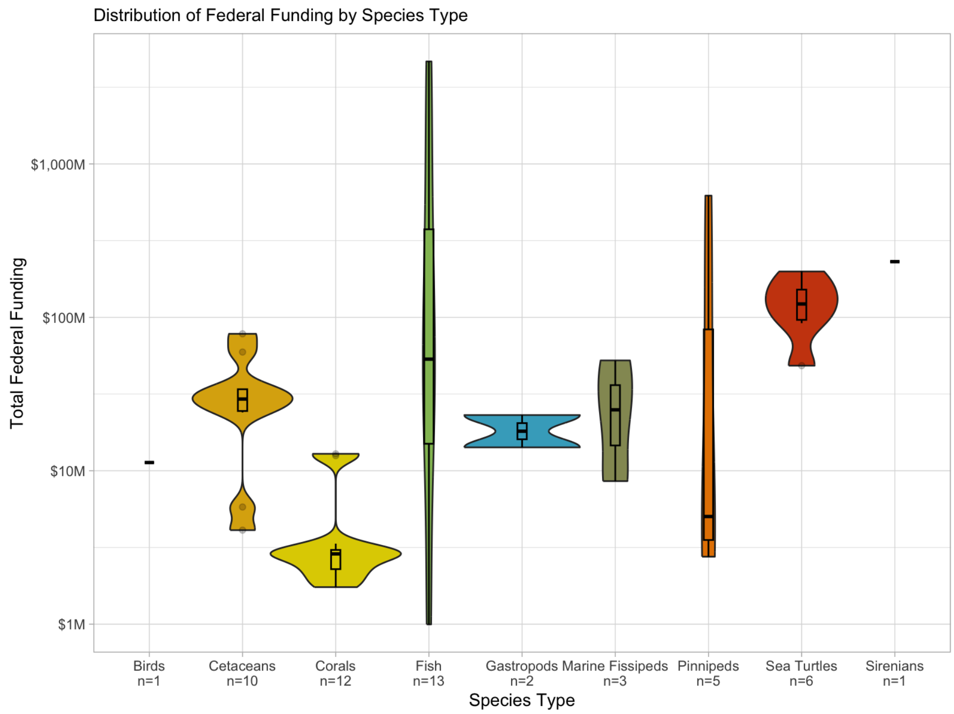

Figure 2: ANOVA plot showing variation in federal funding by species type.

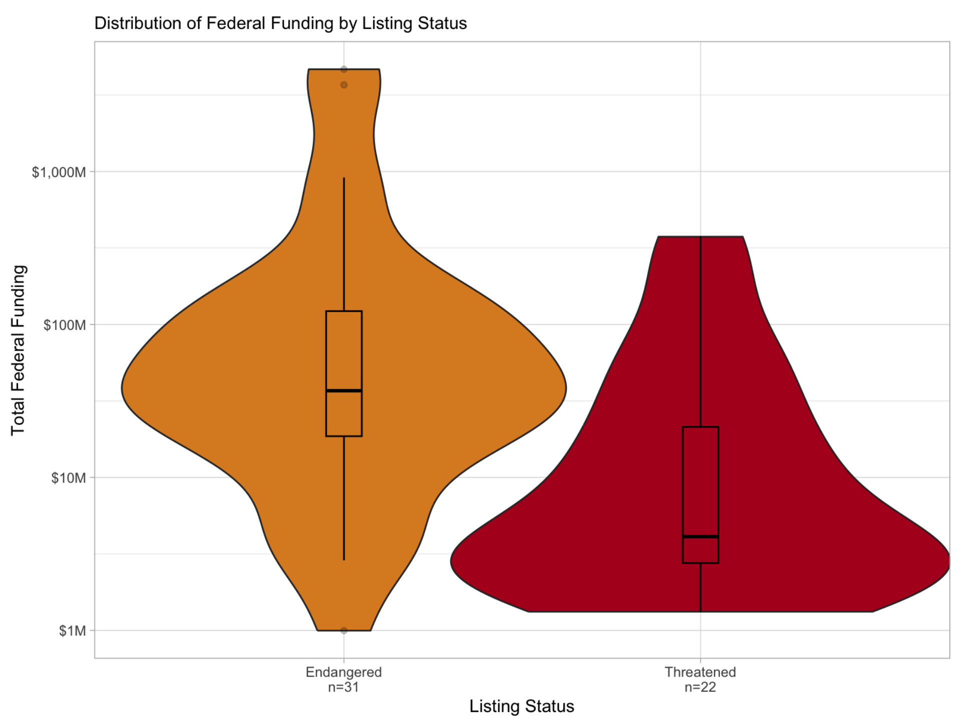

Figure 3: ANOVA plot showing variation in federal funding by listing status.

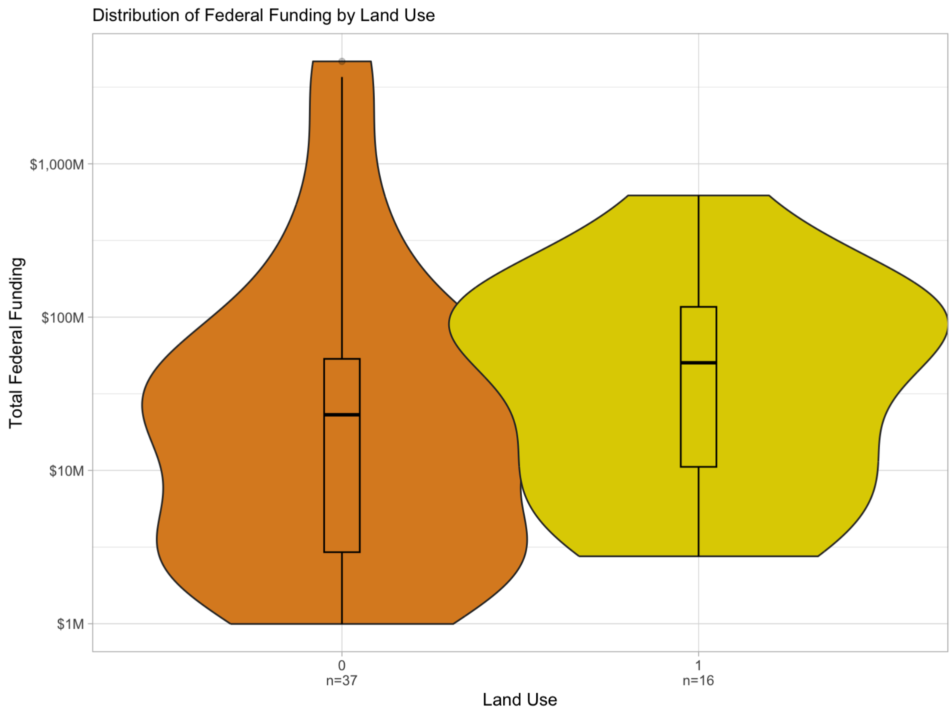

Figure 4: ANOVA plot showing variation in federal funding by land use designation.

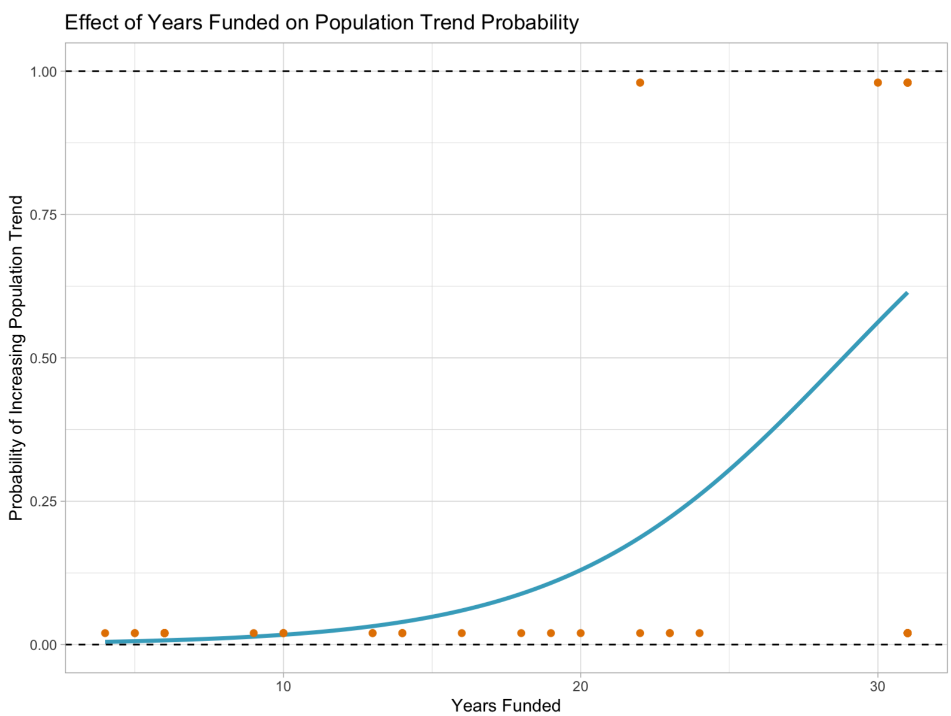

Figure 5: Fitted logistic regression model predicting population trend based on years funded.

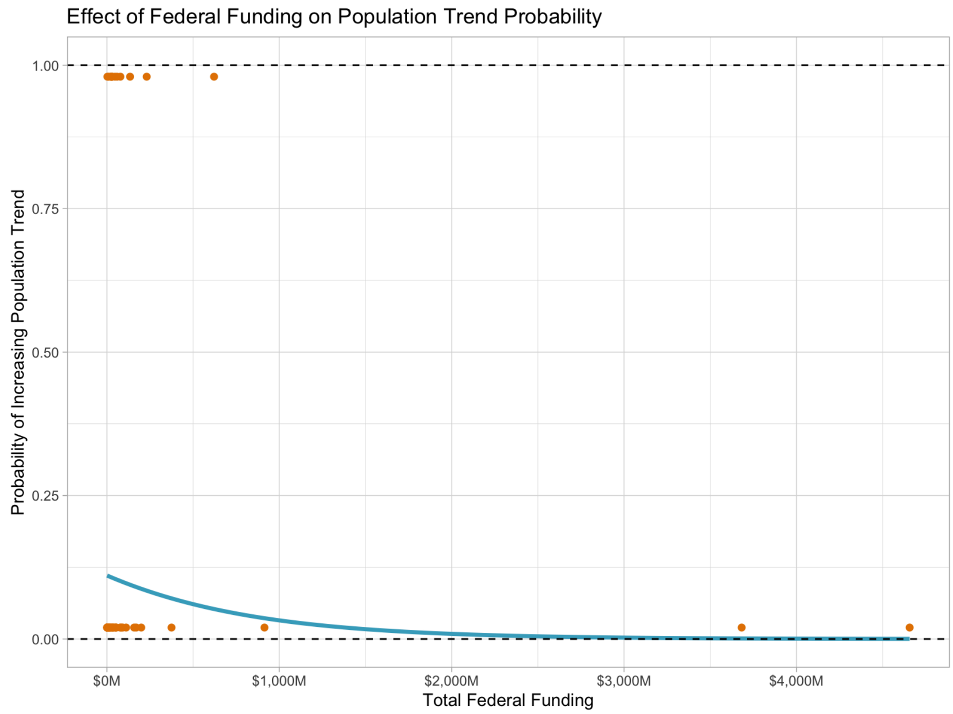

Figure 6: Fitted logistic regression model predicting population trend based on federal funding.

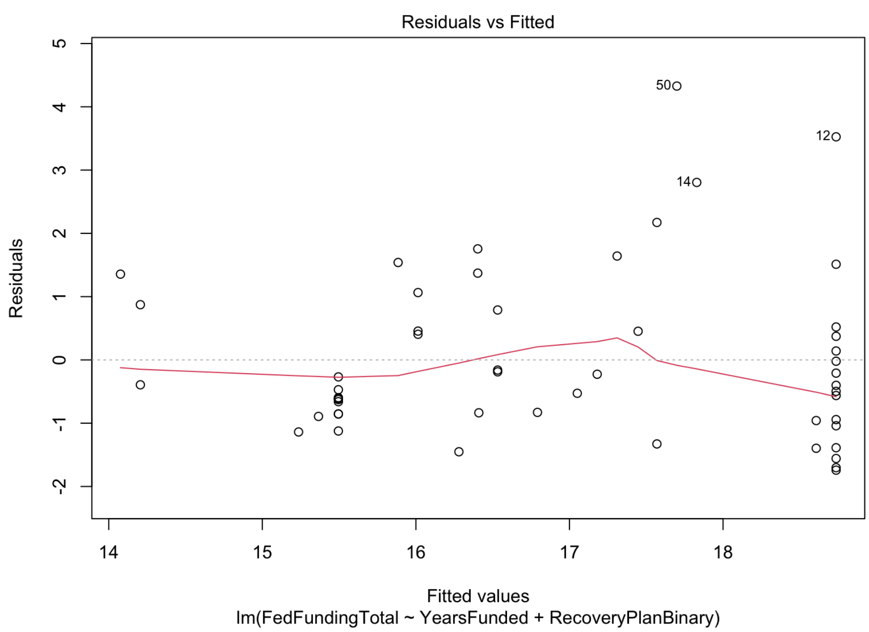

Figure 7: Linear diagnostic plot: Residuals vs. Fitted.

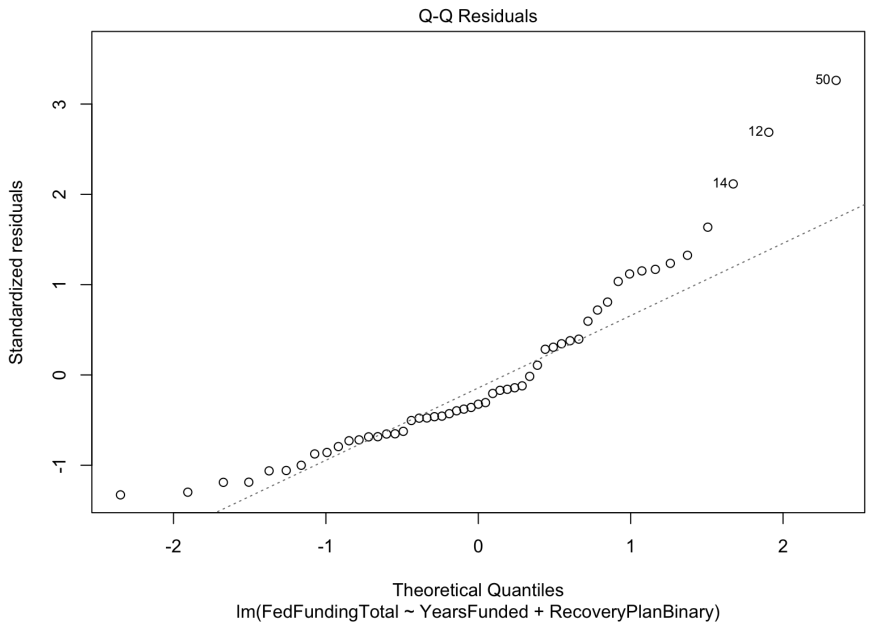

Figure 8: Linear diagnostic plot: Q-Q Residuals.

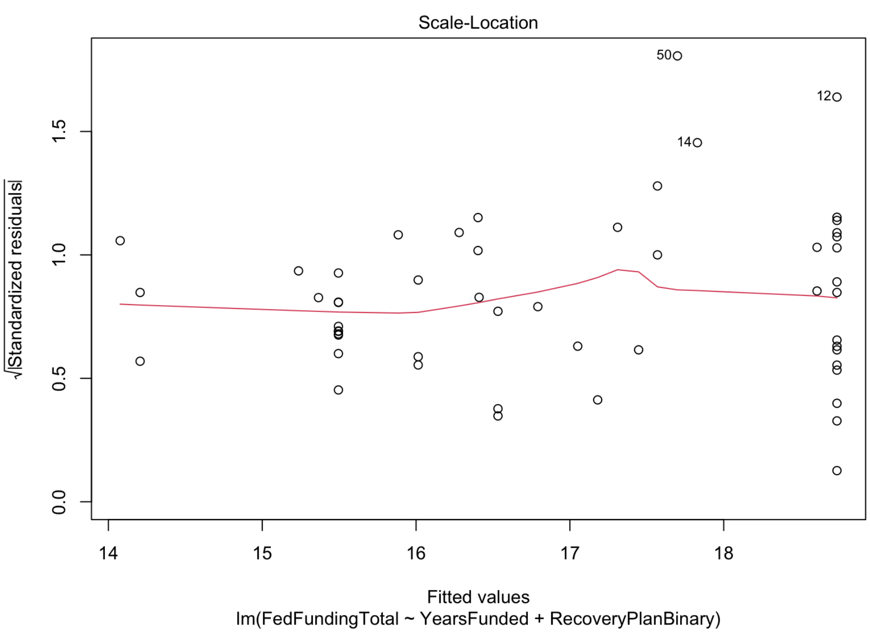

Figure 9: Linear diagnostic plot: Scale-Location.

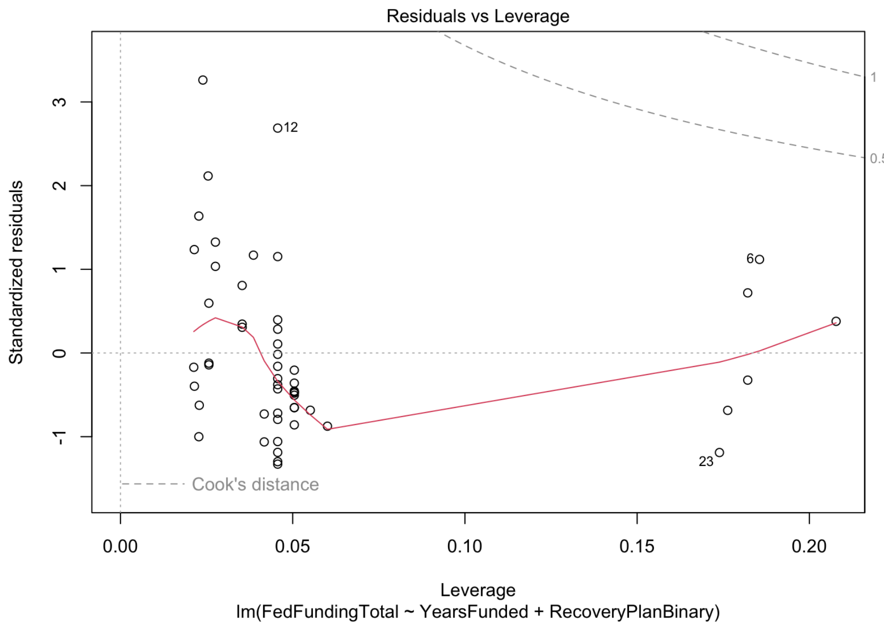

Figure 10: Linear diagnostic plot: Residuals vs. Leverage.

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