



NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

**BASIC ALLOWANCE FOR HOUSING RESOURCE
ALLOCATION: A DEPENDENT-BASED MODEL**

by

Aaron J. Chamberlain

June 2023

Thesis Advisor:
Second Reader:

Ruriko Yoshida
Ross J. Schuchard

Approved for public release. Distribution is unlimited.

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE			<i>Form Approved OMB No. 0704-0188</i>	
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington, DC 20503.				
1. AGENCY USE ONLY (Leave blank)		2. REPORT DATE June 2023		3. REPORT TYPE AND DATES COVERED Master's thesis
4. TITLE AND SUBTITLE BASIC ALLOWANCE FOR HOUSING RESOURCE ALLOCATION: A DEPENDENT-BASED MODEL			5. FUNDING NUMBERS	
6. AUTHOR(S) Aaron J. Chamberlain				
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A			10. SPONSORING / MONITORING AGENCY REPORT NUMBER	
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.				
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.			12b. DISTRIBUTION CODE A	
13. ABSTRACT (maximum 200 words) <p>Basic Allowance for Housing (BAH) is intended to cover 95 percent of a service member's housing costs, including rent and utilities. However, our research indicates that the assigned BAH at 35 percent of military sites is below the U.S. Department of Housing and Urban Development (HUD) standards for adequacy. Furthermore, we found that the shortages and surpluses are normally distributed with a mean above zero. This finding implies that most sites experience a surplus, and that by bringing the tails closer to the mean, the problem could be alleviated. In this work, we focus on E4-and-below service members and we develop a dependent-based model to optimize BAH, maximizing the BAH over the rates set by HUD as standards of adequacy. The basic assertion is that service members should be able to afford housing at a standard that meets at least HUD levels of adequacy, and exceeds those standards if budgetary constraints allow for it. The data leveraged in this research suggests that this is very attainable, given some reasonable changes to the current BAH calculation methodology.</p>				
14. SUBJECT TERMS basic allowance for housing, BAH, servicemember finances, housing, military families, retention			15. NUMBER OF PAGES 69	
			16. PRICE CODE	
17. SECURITY CLASSIFICATION OF REPORT Unclassified	18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified	19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified	20. LIMITATION OF ABSTRACT UU	

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. Z39-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release. Distribution is unlimited.

**BASIC ALLOWANCE FOR HOUSING RESOURCE ALLOCATION:
A DEPENDENT-BASED MODEL**

Aaron J. Chamberlain
Lieutenant, United States Navy
BA, Alma College, 2006
M.S.Ed, Arkansas State University, Jonesboro, 2011
MBA, University of Michigan at Flint, 2018

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

**NAVAL POSTGRADUATE SCHOOL
June 2023**

Approved by: Ruriko Yoshida
Advisor

Ross J. Schuchard
Second Reader

W. Matthew Carlyle
Chair, Department of Operations Research

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

Basic Allowance for Housing (BAH) is intended to cover 95 percent of a service member's housing costs, including rent and utilities. However, our research indicates that the assigned BAH at 35 percent of military sites is below the U.S. Department of Housing and Urban Development (HUD) standards for adequacy. Furthermore, we found that the shortages and surpluses are normally distributed with a mean above zero. This finding implies that most sites experience a surplus, and that by bringing the tails closer to the mean, the problem could be alleviated. In this work, we focus on E4-and-below service members and we develop a dependent-based model to optimize BAH, maximizing the BAH over the rates set by HUD as standards of adequacy. The basic assertion is that service members should be able to afford housing at a standard that meets at least HUD levels of adequacy, and exceeds those standards if budgetary constraints allow for it. The data leveraged in this research suggests that this is very attainable, given some reasonable changes to the current BAH calculation methodology.

THIS PAGE INTENTIONALLY LEFT BLANK

Table of Contents

1	Introduction	1
2	Background	5
2.1	Purpose and Goal of BAH	5
2.2	BAH Data Collection for Setting Annual Rates	5
2.3	SAFMR Background, Purpose, and Process	7
2.4	Dataset	8
2.5	Literature Review	10
3	Methodology and Optimization Model	15
3.1	Military Installation Data	15
3.2	HUD SAFMR Data, BAH Data and MHA Data	17
3.3	BAH and MHA Data	19
3.4	EDA	20
3.5	Optimizing BAH Allocation	26
4	Results	35
4.1	Results of the Optimization Model	35
5	Findings	39
5.1	Discussion	39
5.2	Recommendations	40
5.3	Future Work	41
5.4	Conclusion.	42
	List of References	45
	Initial Distribution List	49

THIS PAGE INTENTIONALLY LEFT BLANK

List of Figures

Figure 1.1	Maslow’s Hierarchy of Needs	2
Figure 3.1	Distribution for BAH across All Observations in the Data Set. . .	21
Figure 3.2	Multivariate Scatterplot for BAH Difference and Zip Code. . . .	22
Figure 3.3	Elbow Plot From Our Geographical Data for K-Means Clustering	23
Figure 3.4	Optimization Model Output Holding Percent-over SAFMR Equal.	32
Figure 3.5	Tuning the Model to Find Optimality.	33
Figure 4.1	Final BAH Percent-Over SAFMR Model Results	36
Figure 4.2	Final BAH Dollars-Over SAFMR Model Results	37

THIS PAGE INTENTIONALLY LEFT BLANK

List of Tables

Table 3.1	Sample Installations to Provide a Reasonable Estimate of BAH Costs.	26
Table 3.2	Decision Variables and User Inputs for BAH Allocation Model . .	31
Table 4.1	Comparing BAH Models to Current BAH	38

THIS PAGE INTENTIONALLY LEFT BLANK

List of Acronyms and Abbreviations

ACS	American Community Survey
BAH	Basic Allowance for Housing
CSV	Comma Separated Value
DoD	Department of Defense
EDA	Exploratory Data Analysis
FMR	Fair Market Rent
HUD	the Department of Housing and Urban Development
MHA	Military Housing Area
MLS	Multiple Listing Service
NaN	Not a Number
NPS	Naval Postgraduate School
PCS	Permanent Change of Station
SAFMR	Small Area Fair Market Rent
USMC	United States Marine Corps
USN	United States Navy
WCSS	Within Cluster Sum of Squares
ZCTA	Zip Code Tabulation Area
ZIP	Zone Improvement Plan

THIS PAGE INTENTIONALLY LEFT BLANK

Executive Summary

In 2022, 35 percent of military sites in the U.S. demonstrated a BAH shortfall for E4-and-below service members when compared to HUD SAFMR rates as a level of adequacy.

Ensuring that housing needs of U.S. military service members are met is a part of the responsibility that the Department of Defense (DoD) has assumed to ensure its members are adequately cared for while they are in service to their country. The method by which the DoD executes their responsibility for providing adequate member housing is through an allowance known as BAH. BAH is intended to cover 95 percent of members rent and utility costs near their duty station. According to recent reports by Blue Star Families, though, there is increasing sentiment that the allowance provided to service members — especially members with families — is not meeting the needs of the member or the objectives of the allowance. Members are needing to either live above their means, commute further, or sacrifice opportunities for their families (e.g., quality schools, personal safety, etc.). Our EDA demonstrated that service members assigned to over 35 percent of military sites would garner BAH that is below SAFMR.

This research explores a new dependent-based model for allocating DoD funds for BAH by considering not only the presence of dependents but also whether a member has one dependent, or more than one. This allows for the creation of new dependent categories for which adequate housing can be determined. The model works within budgetary constraints and leverages HUD SAFMR data as an indicator of adequacy. What we found is that despite 35 percent of military sites falling short of SAFMR, it is possible for every military site to receive BAH that is as much as 18.75 percent above SAFMR for E4-and-below service members.

The findings of this research for E4-and-below service members could be expanded to analyze the situation for other ranks or the entirety of the force. We believe there is the potential to see similar results for all service members. If the expanded version of this scenario provides similar results, this model could be used to restructure how BAH is allocated in the future.

THIS PAGE INTENTIONALLY LEFT BLANK

Acknowledgments

There are countless people to acknowledge for their contributions to any success I have had while at the Naval Postgraduate School, so I would be remiss to try to name them all. However, there are some that deserve personal acknowledgement.

My thesis advisor Dr. Ruriko Yoshida was instrumental in ensuring I stayed on task and continued to move forward with my work. She was supportive and an invaluable resource. I take pride in the research represented in this thesis, but I could not have done it without her.

The Operations Research curriculum at NPS is incredibly challenging, and I faced my fair share of challenges during my time. While I had several outstanding professors, there were a few that made an incredible impact on me during my time here. One in particular was LTC Ross Schuchard, who recognized I was struggling early in this program and offered support. I needed that support, and his impact on my time here cannot be overstated.

Furthermore, I cannot describe the impact made on me by my fellow students. One of the turning points in my time at NPS was when I began working more closely with the students in my cohort. In doing so, I was provided support and encouragement to achieve what was in front of us. What I was also shown, though, is how much talent lies within the ranks of the Department of Defense (DoD). If the next generation of leaders in the DoD are coming from the ranks of those I was able to work with at NPS, the DoD is in good hands.

The greatest thanks, however, needs to go to my family. My brother, LCDR Derek Chamberlain, who encouraged me to apply to this program, my parents for allowing me to complain without judgment, and especially my wife, Lauren, and children, Avery and Harvey. At home I was absent as much as I was present over the last two years, and while I am sure it was inconvenient at best, I felt nothing but support and understanding. They probably don't even fully understand how much I appreciate them, and how much more difficult this would have been without them.

Looking back on the last two years, Monterey and the Naval Postgraduate School have left an indelible mark on me, and it would not have been possible without the support of so many others, so thank you to all who have had a hand in it.

THIS PAGE INTENTIONALLY LEFT BLANK

CHAPTER 1:

Introduction

Basic Allowance for Housing (BAH) is an entitlement provided to United States military service members. The following work will provide background and analysis as to the allocation of BAH. The goal is to provide insights as to how to better allocate Department of Defense (DoD) funds.

BAH is an entitlement intended to provide service members with an allowance to obtain adequate housing near their duty location (Department of Defense 2022). While the purpose of BAH is noble, the execution of its allocation is creating unstable situations for service members, as they undergo Permanent Change of Station (PCS) transitions from one duty station to another. Recent Blue Star Families survey results indicate that finding adequate housing in the local market is challenging; highlighted in a survey response from an anonymous active duty spouse: “This area is way too expensive. Most houses with 3 or 4 bedrooms that are close enough to the base and still have a good school district and safe area are about \$500 over BAH” (Families et al. 2023).

The above quotation seems rooted in reasonable concerns, as the family was looking for a house in a safe neighborhood with good schools, enough room for their family, and one that is close enough to the base, presumably, so that traveling to base for groceries, health care appointments, etc. is not seen as difficult or, worse yet, prohibitive. Many installations provide a number of amenities to service members but when adequate housing cannot be found within a reasonable distance of those amenities, the value of the amenities to the service member is diminished. As highlighted above, families are having a difficult time finding housing that meets their needs and is within a reasonable distance from the installation. While this may be considered merely an inconvenience, the stress this places on the service member — be it directly or indirectly — could potentially have a negative mission impact as the the member is either adding stress to his or her own life by facing a longer, more expensive commute, or additional worry for the safety and welfare of his or her family.

While all service members take an oath and carry out their duties. Their ability to perform is

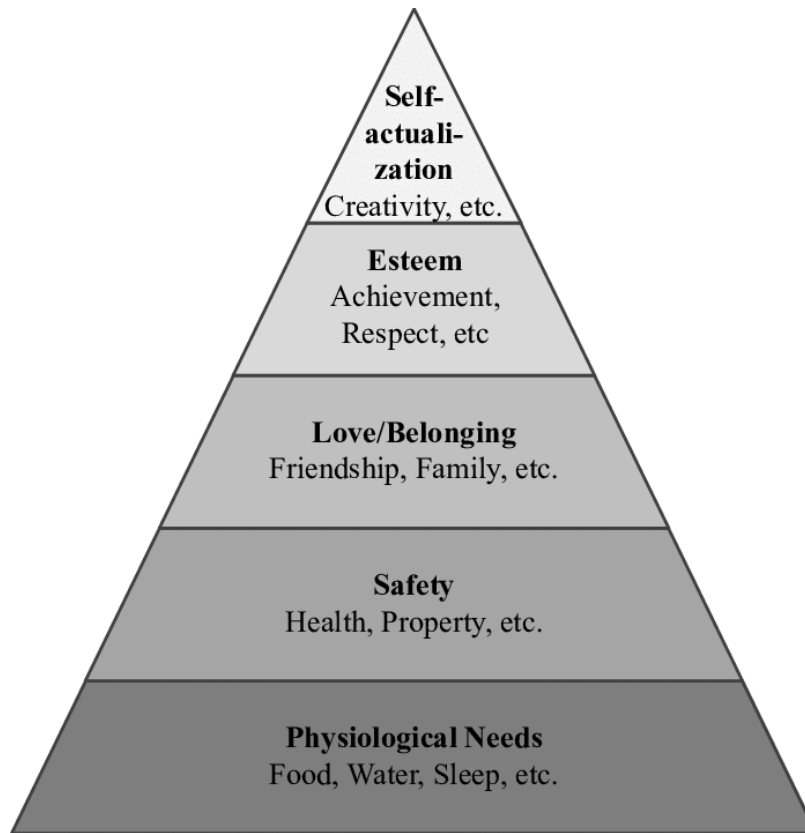


Figure 1.1. As seen in Maslow's Hierarchy of Needs, one's physiological and safety needs are more foundational — thus fundamentally more important to them — than “esteem” or “self-actualization,” which is where service members would need to be within the hierarchy to make the greatest impact. Source: Praktijnjo et al. (2011).

impacted by their ability to take care of their needs. As demonstrated in Maslow's Hierarchy of Needs (Figure 1.1), individuals place greater importance on their physiological needs, their personal safety, and their family needs before their needs for achievement, respect, or self-actualization are even considered. This is relevant, because if the DoD wants to maximize the effectiveness of its force, it needs to consider all manners in which to maximize performance at an individual level. Ensuring a service member and his or her family has their basic needs adequately met needs to be a priority.

While the easiest solution may be to simply increase BAH across the board, that may not be a realistic solution. Given the significant expenditure on BAH by the DoD, increasing it

equally across all situations until those suffering from extreme shortages in BAH have their needs met would be a large investment by the DoD. Establishing a baseline to compare BAH to determine whether a shortage exists may also prove troublesome. For those reasons, we explored this problem from the perspective of maintaining the current budgetary constraints to see if a feasible solution could be reached. This thesis explores specifically the situation of E4-and-below service members with dependents, leveraging Small Area Fair Market Rent (SAFMR) values established by the Department of Housing and Urban Development (HUD) as the minimum threshold for adequate housing. The goal is to optimize BAH allocation and ensure no service member is needing to exceed their BAH cost-share to cover their off-base housing costs.

In Chapter 2, we introduce some of the necessary background information, specifically focusing on BAH and SAFMR. We examine the purpose behind each of them and their data collection processes. This information helps the reader better understand how these data points are related later in the thesis where they are included in an optimization model. Furthermore, we explore previous related research to better understand the existing body of work and how our research adds value to what is already available.

In Chapter 3, we step through the methodology of this thesis and examine the process by which the research was conducted. We reveal where all of the data was obtained, how it was cleaned, why it was important to have, and eventually how it was put together to conduct the necessary analysis. We provide insights from our Exploratory Data Analysis (EDA) and discuss how those insights are related to the direction of the thesis. Lastly, Chapter 3 guides the reader through the optimization model developed to support the thesis, including alternative models evaluated during the process.

Chapter 4 is where the reader can see the output of the optimization model, as it presents the results and walks the reader through them. The reader can not only see the results but better understand what those results reveal about the problem at hand. Lastly, it allows the reader to compare the alternative optimization models him or herself, so he or she can determine which model, if either, should be implemented.

In Chapter 5, we discuss the results from Chapter 4 and make considerations and recommendations as to the implementation of this research. We also explore areas for future work

that could expand upon this research and provide even greater value to the DoD.

CHAPTER 2: Background

In Chapter 2, we introduce insights from background literature for better understanding BAH, its intended use, how it is determined, and how it is allocated to service members. Likewise, Chapter 2 examines SAFMR, its purpose and how it is allocated.

2.1 Purpose and Goal of BAH

According to the BAH Primer published by the DoD, “[W]hen government quarters are unavailable, BAH rates serve as a form of compensation to help members find adequate rental housing near their duty location” (Department of Defense 2022). The BAH program is designed to adequately compensate the service member — at 95 percent, with a 5 percent service member cost-share — for median local rent and mean utility costs, aligning these costs with civilian counterparts in the same locality. Based on analysis of the private sector rental housing costs for each permanent duty station, BAH is set based on a member’s duty station, pay grade, and dependency status. The DoD and its services have designed the BAH program to monitor the market rent and utility costs across the U.S., and rates are established to offset a large proportion of those costs (Department of Defense 2022).

2.2 BAH Data Collection for Setting Annual Rates

The DoD annually collects data on the median local rental housing costs and average utility costs (e.g., electricity, heating fuel, water and sewer) for approximately 300 geographic localities across the U.S., including Alaska and Hawaii. Each of the geographic localities is considered a Military Housing Area (MHA), which represent the housing market surrounding military installations where at least 100 active BAH recipients reside. The data collection is typically done during the spring and summer months, since the rental market is typically most active, and it is collected for different housing profiles (e.g., apartments, townhouses/duplexes, and single-family homes of varying bedroom counts) (Department

of Defense 2022).

The DoD leverages multiple sources for collecting data in an effort to ensure their BAH rates are suitable by providing a system of “checks and balances” against the data collected. Data is gathered from online Multiple Listing Service (MLS), subscription services for rental housing data, and major online real estate platforms that serve the rental market (e.g., Zillow (Zillow Group 2023b), Trulia (Zillow Group 2023a), etc.). Beyond the aforementioned online data collected, the DoD also contact subject matter experts (e.g., real estate professionals and landlords) in each MHA to validate the figures gathered. Once the data is collected and verified, there is an additional process where properties are screened by a contracted independent housing consultant. The consultant assesses units for availability, current rental rates, rental inclusions (e.g., electric, water, sewer, etc.) and adjusts the lease terms to reflect a 12-month lease. Furthermore, the consultant eliminates houses that are deemed inadequate or unavailable to service members, such as efficiency apartments, mobile homes, income-subsidized complexes, age-restricted facilities, seasonal units, furnished units, and housing in high-crime neighborhoods (Department of Defense 2022).

In collecting data in the above-described manner, the DoD is attempting to have enough data to capture an estimate — with 95 percent statistical confidence — within 10 percent of the true median local rent market. The multi-step data collection process described typically yields 30-75 units per housing profile, per sample, per MHA; there are six data samples in each MHA, providing insights into different market segment and housing profiles. While most of the MHA reach the target for sample size, there are exceptions in more remote areas or areas with few available rental properties. To combat this issue, the DoD conducts some trend analysis on housing profiles where they have sufficient data in the same geographic area to help determine a prediction for the housing profile for where they do not have sufficient data. For instance, if there is sufficient data for 2-bedroom and 4-bedroom single family homes but not 3-bedroom single family homes, they would evaluate the historical trends for a relationship among the 2-, 3-, and 4-bedroom single family homes to derive a prediction for the current 3-bedroom homes where there is insufficient data for. To include the utility costs, the DoD uses the U.S. Census Bureau’s American Community Survey to set average utility expenses for each of the housing profiles in each MHA (Department of Defense 2022).

There are only a few variables impacting how much BAH a service member will receive: pay grade, location, and whether or not the service member has dependents. In our analysis we are controlling for the first variable by scoping our analysis down to junior enlisted pay grades of E4 and below, and analyzing the impacts of duty station location and dependent status. An intriguing decision made in the BAH rate-setting calculation is to look at dependent status as a binary variable — either the service member has dependents or he or she does not. However, the service member’s housing needs do not follow the same binary outcomes. It is reasonable for one to expect a single service member and a service member with a spouse but no children to have similar housing needs; they are both likely looking at units with 1-2 bedrooms within reasonable commuting distance of their duty station. However, a service member with children — or planning on having children — regardless of their marital status, is likely looking for a unit with more bedrooms — probably one bedroom for the service member and one for each child dependent, if that can be obtained within their budget. Adequate housing, therefore, could be dependent on the number of dependents and not merely their binary consideration (Department of Defense 2022).

2.3 SAFMR Background, Purpose, and Process

According to the Center for Budget Policies and Priorities, Fair Market Rents are set to establish a mark to which low-income families can be subsidized up to, ensuring they can secure adequate housing (Center on Budget and Policy Priorities 2018). Typically, a family receiving a voucher would contribute 30 percent of their household income toward housing costs, and they would receive a voucher for the difference between the fair market rent value and that 30 percent value (U.S. Department of Housing and Urban Development 2023). For instance, if we were to create an example where an eligible family’s monthly household income is \$2,500, 30 percent of that is \$750. If the fair market rent for the area and their situation (e.g., needing three bedrooms) is set to \$1,500, this family would be eligible for a voucher to help them afford the adequate housing priced at \$1,500. Small Area Fair Market Rents were introduced by HUD to provide greater opportunities for people receiving vouchers (Center on Budget and Policy Priorities 2018). The SAFMR allows higher opportunity areas to have rates set higher than areas that are lower opportunity and less desirable. Leaning on our previous example, where 30 percent of household monthly

income is \$750, but we look at it through the lens of SAFMR where a SAFMR is set by the Zone Improvement Plan (ZIP) code and may be \$2,000 instead of \$1,500. This provides a larger voucher and greater opportunities for the families receiving them.

When determining the number of bedrooms a family receiving a voucher qualifies for, a simple calculation is made considering the number of dependents. The determination is made by assigning a requirement of one bedroom for the head of household and his or her spouse (if applicable), then an additional bedroom for every two additional members of the house, regardless of age or sex (Keating 1998). For example, a family with two parents and three children would qualify for a 3-bedroom unit and would be subsidized up to that level. There are opportunities for the public housing agencies to provide more bedrooms than this when the situation when calls for it, but the Keating Memo established two per-bedroom as the expectation (Keating 1998). This manner of adjusting for number of dependents provides evidence that it is worth considering the difference between units of varying sizes and how they compare to the BAH provided to service members in a given area.

HUD collects the SAFMR data by analyzing the gross rents provided by the U.S. Census Bureau for Zip Code Tabulation Area (ZCTA). The data gathered from the Census Bureau is assessed for statistical reliability, ensuring the margins of error are acceptable and they are based on at least 100 observations. (Office of the Assistant Secretary for Policy Development and Research, HUD 2020) HUD prioritizes using similar bedroom count units to create the SAFMR for the ZCTA, however, when there are not sufficient observations available for that unit size, HUD will then consider different size units within the same ZCTA then consider the same size units in bordering ZCTA as proxies, weighting the information across the neighboring ZCTA to provide an appropriate estimate (Office of the Assistant Secretary for Policy Development and Research, HUD 2020). Furthermore, HUD leverages American Community Survey (ACS) data rolling averages to promote year over year rate stability (Office of the Assistant Secretary for Policy Development and Research, HUD 2020).

2.4 Dataset

The consolidated dataset upon which our analysis was conducted was 49,749 data points comprised of 69 variables and 721 observations.

Each of the 721 observations is a different military site within the United States, including Hawaii and Alaska. The observations are military installations representing all possible sites ranging in service member population from zero to several thousand at each installation. The military site data was pulled from open source data, before it was culled to include only sites found within the United States.

Of the 69 variables in the final dataset, seven of them were part of the original military site data set: Latitude, Longitude, Component, Site Name, State Terr, Country, and Oper Stat. The latitude and longitude are quantitative variables that provide geographic coordinates for each of the military sites (e.g. 34.01821, -77.9732). The component variable is a categorical variable telling us to which branch of service (e.g., Army Active, Navy Active, Air Force Reserve, etc.) each site belongs to. Site Name is a categorical variable that provides the name of the military site the observation is referring to (e.g., Pease ANGB). The “Country” variable is a categorical variable that was limited to only values that had “United States”, as the data was constrained to sites within the United States. Lastly, the “Oper Stat” variable is a categorical variable that describes the operation status of the site, and this was constrained to “Active” sites to ensure we were not building in data from a site that was no longer active.

Six of the remaining 62 variables are identifying what zip code each military site was in and what zip codes are within given radii surrounding each site. “Zip Code” is actually a quantitative value that we add leading zeros to and convert to a categorical during the processing of the data to determine the surrounding zip codes. The remaining zip code related data are lists of string values that comprise a list of zip codes within a given radius. The radii that we looked at were five, ten, fifteen, twenty and twenty-five miles from the zip code assigned to each observation.

Thirty of the remaining 56 variables were created during our process of determining mean and median SAFMR data for two-, three-, and four-bedroom units within a given radius of a military site’s zip code. The Mean 2BR in Radius 5 Miles, Median 2BR in Radius 5 Miles, Mean 3BR in Radius 5 Miles, Median 3BR in Radius 5 Miles, Mean 4BR in Radius 5 Miles, and Median 4BR in Radius 5 Miles variables are all then repeated for the 10-mile, 15-mile, 20-mile, and 25-mile radii. The values represent the mean and median SAFMR value for the respective unit size; the mean and median are generated from the list of zip codes generated for each observation in “Zips in Radius: 5 Miles” (or, . . . 10 Miles, 15

Miles, etc.).

Two of the 26 variables that are left in the dataset are categorical data that provide information about which MHA the military site is in presently. “MHA” is a categorical data point that gives the MHA code (e.g., NC186 or MA039) the site is currently assigned to. “MHA_NAME” is a categorical data point that provides a more intelligible name — providing a geographic reference — for better understanding of what area(s) the MHA covers.

The final 24 variables are all quantitative, and they are comprised of the 2023 BAH rates for each of the ranks. The most important rates for our research, after scoping, were the “E01” to “E04” rates, however, we did not discard the remaining rates as we felt they could prove useful for extensions of the research. Each of the values in the data set for these variables are quantitative and used as such to calculate shortages and surpluses in our EDA as well as to ensure our optimization model has a baseline to work from as a budgetary constraint.

2.5 Literature Review

In this section, we outline related previous work and then we compare and contrast similarity and difference from this research.

2.5.1 Heidt and Sanchez: Cost Savings of Taxing Lower-Ranking, Non-Dependent Members Basic Allowance for Housing for Collocated Military Couples

In the Naval Postgraduate School (NPS) thesis LCDR Heidt and LTJG Sanchez completed in December 2022, they analyzed the cost savings created by taxing the lower-ranking member’s BAH as if it was income instead of being viewed as an allowance (Heidt and Sanchez 2022). This research was a novel way of considering the dual-military situation and ways in which the U.S. government can consider cutting costs. According to Heidt and Sanchez (2022), the U.S. government could recapture approximately \$151.4 million to \$284.5 million dollars annually, based on the BAH figures for Fiscal Year 2022 (Heidt and Sanchez 2022). The range provided is based on the manner in which the tax is imposed: whether the tax rate is only on the members’ total BAH, or if it is on the sum of the

members' BAH and basic pay. Essentially, if the tax rate is based only on the allowance — viewing it as separate from the member's basic pay — the U.S. government would recapture approximately \$151.4 million dollars, whereas approximately \$284.5 million dollars would be recaptured if the tax rate from the combination of basic pay and BAH was used to tax the lower-ranking member's BAH (Heidt and Sanchez 2022).

Heidt and Sanchez (2022) differs from our work in that its focus was on the dual-military scenario in which there are two members of the household, presumably spouses, both drawing BAH, while our work was focused on optimizing the allocation of BAH with a model that was directly based on the number of dependents in the household. Heidt and Sanchez (2022) and our work, however, are not mutually exclusive. If the two were to be combined, it could be done by leveraging our model — introduced in Chapter 3 — on the higher-ranking member's BAH and considering the number dependents in the in household — which would not include the lower-ranking member, since they are not considered a dependent (Heidt and Sanchez 2022) — the lower-ranking member would then be taxed on their BAH but could still buoy the household BAH to accommodate for their presence in the household.

2.5.2 Vaden: Process Analysis of Basic Allowance for Housing BAH Withing the Military Personnel, Marine Corps (MPMC) Appropriation

In the research completed in March 2005 by United States Marine Corps (USMC) Captain Dillon D. Vaden, he details the process by which BAH was determined at that time, which included a more service-specific methodology than is currently employed by the DoD (Vaden 2005). One of the areas explored in Vaden (2005) was the presence of “information gaps” in the methodology used to set BAH rates (Vaden 2005). The work demonstrated that the BAH rates were missing recent data in dynamic housing markets, and that the BAH allocated to service members was most accurate in steady markets or those experiencing slow and consistent growth (Vaden 2005). These “information gaps” help provide a reason for why the BAH levels aren't necessarily reflecting current housing costs in an area; Vaden (2005) establishes that setting rates based on data gathered before the rate-setting process begins suggests that in a volatile market could either overestimate or underestimate actual

costs in a given market.

Vaden (2005) differs from our work in that it focused on gaps in methodology, specifically in the problems stemming from poor estimates, whereas our research is focused on allocating the funds available most efficiently based on the available rates from HUD. That isn't to say our model wouldn't also be susceptible to similar issues as discussed by Vaden (2005), but it also could be paired to a dynamic data collection process based on real-time rental costs to help off-set the impact of market volatility. Whether the real-time component was a weighted input to work with the SAFMR rates from HUD or completely replaces it would be worth considering in future work. However, given that the HUD SAFMR rates are a measure of adequacy upon which our model works the model would simply consider the live rates in the same way. This would be an interesting extension for application of our model to determine if leveraging the model in a rolling model to correct for market changes could help provide a better overall application of it.

2.5.3 Griner: Forecasting USMC Basic Allowance for Housing Utilizing Historical Dependency Rates

In his 2020 thesis, USMC Major Michael S. Griner conducted analysis on dependent rates amongst service members to better forecast BAH costs to the DoD. The premise of Major Griner's research is that service members with dependents have a greater cost to the DoD than do service members without dependents (Griner 2020). While the Griner (2020) dataset had the number of dependents for each service member in his data set, he converted that to a binary of with or without dependent status to be more relevant for the current manner in which BAH is determined. Griner (2020) indicates a 2.82 percent increase amongst service members with dependents — 3.28 percent increase for enlisted service members and 8.44 percent decline for officers — from 1980 to 2019.

Griner (2020) work provides evidence of increased number of service members with dependents, working in concert with civilian counterparts (Griner 2020). This research is related to our work in that it is useful in combination with our work to forecast future BAH costs. It is different in its purpose, however. Griner (2020) focused on forecasting service member dependent rates, whereas our research focuses on optimizing the allocation of BAH dollars within multiple BAH categories. Further research with Griner's dataset — or an updated

version thereof — would provide greater insights as to future costs, if the DoD were to employ the BAH model suggested in our research.

2.5.4 The Effect of Zoning Laws on Housing Prices and BAH Rates

The 2014 thesis work of LCDR William Fitzkee expanded upon the work of economists Edward Glaeser and Joseph Gyourko, considering the impacts of zoning laws on housing costs (Fitzkee 2014). Fitzkee (2014) expands the work beyond housing and rent costs to also consider the impact a reduction or elimination of zoning laws would have on BAH rates for service members. Fitzkee (2014) concludes that the existing zoning laws are beneficial for existing homeowners and create a fundamental disadvantage for renters. This implies that military families are placed at a disadvantage in the housing market due to their transient nature and consistent status as a renter.

Fitzkee (2014) provides evidence of the need to ensure that BAH resources are responsibly allocated, as his conclusions imply a fundamental disadvantage for service members in the housing market (Fitzkee 2014). Our research, however, is focused on how to allocate the available funds, as opposed to why the housing costs are high in given areas. As we have seen with the previous work, our model and the suggestions from Fitzkee (2014) are not mutually exclusive. Our model could continue to be utilized if the suggestions of zoning law reduction or elimination set forth in Fitzkee (2014) were to be enacted.

2.5.5 Hofmann and Worcester — Navy family housing: an analysis of adequacy standards and their relationship to the Variable Housing Allowance

The 1991 NPS thesis work of Tracy D. Hofmann and James A. Worcester provides an in-depth analysis of United States Navy (USN) standards of housing adequacy versus civilian standards of housing adequacy (Hofmann and Worcester 1991). While it is admitted that much of what was written in 1991 may have changed, however, there are critical aspects of Hofmann and Worcester (1991) that are still relevant. Specifically, there is discussion of space requirements that are outlined with great attention to detail for housing built and/or maintained by the Navy, but there exists much less for those service members forced to rent

privatized housing in the community (Hofmann and Worcester 1991). Reconciling the 1991 adequacy requirements from Hofmann and Worcester (1991), we found in the DoD Manual for Housing Management that “installation commanders should make a reasonable attempt to assign one bedroom for each dependent (Carter 2018).”

Our work leverages some of the adequacy standards that Hofmann and Worcester (1991) asserts should be extended to civilian housing rented by service members by taking into account the need for a certain number of bedrooms based on the number of dependents the service member has. The bedroom requirements cited from the DoD Manual for Housing Management provides a firm foundation for the exploration of a model that leverages the number of dependents as an input as opposed to the binary method of with or without dependents presently in use.

CHAPTER 3:

Methodology and Optimization Model

In Chapter 3, we will explore the process undertaken throughout the data collection, cleaning, processing, and modeling. This chapter will provides specifics in regard to the data sources, packages, and methods used to interact with the data. Furthermore, the mathematical formulation for our optimization models — and a discussion differentiating them — can be found near the end.

3.1 Military Installation Data

The data was sourced from the OpenDataSoft (Military Bases – Opendatasoft) website via a Comma Separated Value (CSV) download. (U.S. Department of Transportation 2019) Our primary use for this data was to use the latitude and longitude coordinates for each of the military installations to be able to match the installation locations with ZIP codes within the United States to align with HUD SAFMR data, which is presented by ZIP code (U.S. Housing and Urban Development 2022). Once the installation and SAFMR data was married, we could leverage that connection to compare BAH data with SAFMR data for each installation.

Using Python, we imported Pandas (Reback et al. 2020) and GeoPandas (Jordahl et al. 2020), then read the CSV into a GeoPandas data frame. The data frame consisted of 776 rows and 15 columns of data, which provided information regarding military installations in the United States, Guam and Puerto Rico. We used the “GeoPoint” data included in the dataset – this is essentially a coordinate pair – to create independent latitude and longitude columns (increasing the column count to 17). Once that was done, we dropped all sites not in the United States and any sites marked as “inactive,” dropping our row count from 776 to 721 sites.

When we originally read in the military bases CSV into GeoPandas, it lacked the “geometry” required for GeoPandas to work as intended. From “shapely.geometry” we imported “Point” and “Polygon” to be able to define the geometry for this data frame and a subsequent one.

Using the latitude and longitude obtained previously by deconstructing the GeoPoint, we were able to create a “point” at the coordinates provided to add to the “geometry” column in GeoPandas; this allows GeoPandas to conduct the geocoding we desired. Eventually, these points will be matched to ZIP codes, which will allow us to work with the HUD SAFMR data.

Before we can match the points created in the previous GeoPandas data frame, we need to define the ZIP codes in a manner that GeoPandas will recognize. Therefore, the next step is to read in the ZIP code shape file as a GeoPandas data frame (U.S. Census Bureau 2022). This file was pulled from U.S. Census data and creates polygon shape for each ZIP code in the United States. The “geometry” in this data frame is not a point, as it was in the military bases data frame, but rather a polygon defining the edges or borders of each ZIP code shape. Once this GeoPandas data frame was read into the Python environment, we were able to use the “sjoin” method to bring the two data frames together, matching points to a polygon inside which it was found; this ultimately assigns a ZIP code to each point it was able to.

However, upon evaluating the data frame the “sjoin” method produced, we noticed it only had 659 rows, as opposed to the 721 rows we had previously. What this told us is that 62 installations were unable to be geocoded using GeoPandas, so another method would need to be used to assign these ZIP codes. Before we can assign ZIP codes to these sites, however, we would need to identify which sites weren’t geocoded by GeoPandas. To solve this problem, we created a list of sites from the original data frame of active U.S. sites (721) and a list of sites that were geocoded in the GeoPandas data frame (659), then compared the two lists by using a “not in” conditional inside a for loop for sites in the original data frame of all 721 sites originally, appending each site not found to a new list. Essentially, we looked at each site in the original data frame and asked whether it was in the new one; if it wasn’t, we stored it in a list we could reference. From this list, we needed to build a data frame of the sites that were dropped when geocoding. To complete this task, we created an empty data frame, then used a for loop to iterate through the list of 62 sites that were dropped, created a temporary data frame of one row inside the loop for each site, then appended that single-site data frame to the empty data frame we created. Each iteration of the for loop appended another site to the bottom of the data frame, and at the end all 62 sites were included in this data frame. This data frame was then appended to the existing data frame of 659 sites, which gave us a complete data frame of 721 sites. However, all of the data that

wasn't known for 62 sites appended are simply Not a Number (NaN) values. Fortunately, the only data we would be needing is the ZIP code for each site.

To add the ZIP code for each of the 62 sites, we then manually searched the sites using internet search engines to see if a ZIP code could be found for the site. If a ZIP code was found, we would look at the state, latitude and longitude for that ZIP code using the website zipdatamaps.com to ensure that state matched what was in our data frame and the coordinates were reasonable for our site. However, if a ZIP code could not be found, we used the state associated with the site from the data frame and an interactive ZIP code map (zipmap.net) to basically chase latitude/longitude coordinate pairs to find the closest pair we could to what was given for the site in the data frame. We understand this is imperfect, but for the sake of how we would be working from a ZIP code centroid (which are also the ZIP code coordinates used to manually hunt for sites), — this can be thought of as the ZIP code's center of mass — finding the ZIP code centroid closest to installation would work well. A reasonable solution was found for each of the missing ZIP codes; there were a few ZIP codes where the solution was admittedly imperfect, but they were reasonable, and they were sites that will have smaller overall weighting on the analysis and closer hands-on evaluation could be done to remedy any issues that arise from our method. The ZIP code was updated in the data frame using the “at” method, essentially updating a cell by using its index and column identifiers and assigning a new value to that location.

After adding the missing ZIP codes manually, we identified what columns would be useful and dropped the rest from the data frame; we were left with 721 rows and eight columns: ZIP Code, Latitude, Longitude, Component (i.e., military branch), Site Name, State Terr, Country, and Operating Status (i.e., Active or Inactive site). This made the data frame much easier to digest and very intuitive to work with.

3.2 HUD SAFMR Data, BAH Data and MHA Data

The data for the SAFMR and county-level Fair Market Rent (FMR) values came from HUDuser.gov, where they have a portal for data dissemination. (U.S. Housing and Urban Development 2022) The SAFMR data was needed to drill down to small geographic areas for considering the cost to live in specific localities. The SAFMR is setup to provide fair

market rent rates for the ZIP codes within metropolitan areas, as opposed to the county-level FMR data.

The SAFMR data was read into a Pandas data frame, resulting in a data frame of 27,331 rows and 18 columns. Once the data was in the Pandas data frame, the ZIP code was set as the index, then the data frame was reconciled to ensure each ZIP code was only listed once. This was done by using the “groupby” method within Pandas to group these like values. Since the SAFMR values are set by ZIP code, these common ZIP code entries had the same values for both entries, so we were able to simply take one of them and treat both entries as one. Ultimately, this reduced our row count to 24,681 and our column count to 17, since we made one of the existing columns our index.

Once the data frame was established and reconciled for duplicate ZIP code entries, we looped through the ZIP codes within a given radius for each installation, finding the mean and median SAFMR for 2-, 3-, and 4-bedroom units. The mean and median SAFMR for each radius from each installation was then added to the data frame in a new column. Essentially, each installation now has the SAFMR for each of the unit sizes for 5-, 10-, 15-, 20-, and 25-mile radii. Once these were added to the data frame, we reorganized the columns so the new mean and median values would be adjacent to the respective radius for easier viewing.

The only problem we ran into with the data was that SAFMR do not exist for every installation. Since some installations are in very remote or rural areas, there may not be a SAFMR within the radii we used for our analysis. We found this to be the case for 122 of the 721 installations, or approximately 17 percent. To solve the problem of missing SAFMR values, we considered what SAFMR values are and what would serve as the next best data point for those missing SAFMR values. In essence, the SAFMR values take the FMR values and use greater granularity, so what we did was use the greatest granularity available, which for some installations was merely the county-level FMR data. This process was a manual data input process, as we took the CSV file, then filtered for missing mean and median SAFMR values in the CSV, then conducted an internet search to find the county that ZIP code fell in. We then looked in the HUD FMR data set, which we had in CSV format, copied the 2-, 3-, and 4-bedroom values for that county, then pasted those values into a python function we had written to replace the missing values for the given ZIP code in our data frame. We started with the 25-mile radius, replacing all missing values, then 20-mile

radius, 15-mile, etc. As mentioned, this was a very manual process and took about six hours to complete; each missing value took about 3-5 minutes to look up, verify, and enter, but since some ZIP codes had multiple installations, we were able to complete the process on the lower end of that range, overall.

3.3 BAH and MHA Data

The MHA by ZIP code was provided in Heidt and Sanchez (2022), which analyzed the impact of taxing the BAH of collocated service members. While the BAH data was downloaded from the Defense Travel Management Office website (Defense Travel Management Office 2023). The MHA data obtained from Heidt and Sanchez (2022) was important for us to be able to apply the current BAH values to ZIP codes for comparison with the SAFMR rates, while the BAH Data allows us to compare FMR to current BAH rates for that ZIP code.

After the SAFMR data was added to the data frame, and the data frame was organized, we added the MHA that each ZIP code is found in, as found in the work from Heidt and Sanchez. The MHA were added by completing a ‘left’ merge onto the ‘bases_df’ by merging on the ZIP code. Once the MHA were part of the ‘bases_df’ data frame, we added the 2023 BAH rates for each installation.

To add the BAH rates for each installation, we needed to read in the rates. We had split the with and without dependent rates into individual CSV files to make the process more straightforward. We read in two files, one for BAH with dependents and one for BAH without dependents. Each of these was merged with ‘bases_df’ - on the MHA criterion - to create new data frames; ‘bases_df’ did not change, but it was used to create new data frames with all of its information, plus the 2023 BAH rates for – one with dependents and one without.

We found two installations that were not assigned an MHA via our merge operation. To solve the problem of missing MHA designations, we simply looked the MHA up for those two installations and input them manually, ensuring they matched the syntax for the others and would be able to work similarly to the others in the data frame.

3.4 EDA

Once the data was compiled into a single data set, we could start to conduct our EDA to better understand our data and see if any interesting insights could be gleaned from it. The very first thing we did was merely determine if there were in fact shortfalls in BAH at any of the installations across our data set. What we found from a quick look was that using just 2-bedroom and 3-bedroom median SAFMR for each installation through the lens of the E4 and below service members, we found that just over 1 percent of the installations had a shortage for 2-bedroom units whereas over 35 percent of installations experience a BAH shortage for 3-bedroom units. Further analysis of this would be warranted, as the average overage was \$554.74 across 713 installations, versus an average shortfall of \$96.62 across 254 installations. As some of these installations may merely be training sites with very few or even zero people assigned to them and some of these are undoubtedly very large installations with tens of thousands of service members attached to them, it would be necessary to have service member population numbers by rank for each of the installations to truly have actionable data. The initial insights, though, are thought provoking in that the funds needed to improve the situation may already be being allocated across the enterprise.

Visualizing the data seemed like a logical next step, so we leveraged the power of the JMP Statistical Software to visually evaluate the data for any insights that could be gained from seeing what we were working with, see Figure 3.1. The first thing we did was look at the distribution of the BAH difference across all the observations in the data set. What we found was that the observations were normally distributed, which may seem comforting, but what it really means is we need to explore the impact of the tails. Assessing the five greatest BAH shortfalls, we found that three of the five sites are — from greatest to least — Navy Annex Monterey (Zip Code: 93940) at -\$1,583, Presidio of Monterey (Zip Code: 93944) at -\$1,483, and Naval Support Activity Monterey (Zip Code; 93943) at -\$713; these three represented numbers one, two, and five with three and four being Air Force sites in Alaska (one of which is Eilson AFB at -\$832).

Given that BAH varies with duty station location, the next thought was to examine the impact of zip codes on BAH difference. This can be numerically, because zip codes are assigned in a manner that generally works from east to west. In general the zip codes

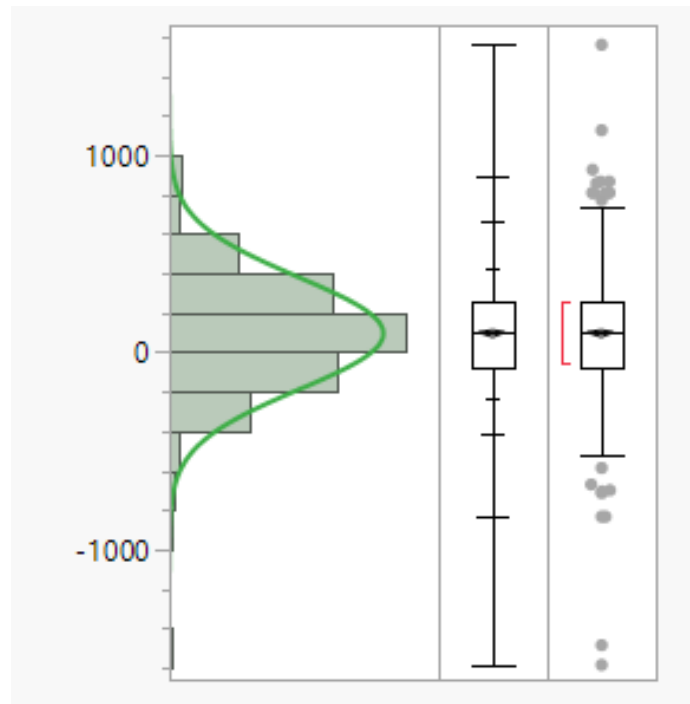


Figure 3.1. Creating a histogram of the BAH difference for each of the observations suggests a normal distribution, but it is important to understand the outliers in this distribution can be looked at as service members and they are living two very different lives based on where their orders took them.

assigned to eastern areas are smaller than those assigned to western areas, which allows us gain some insights from looking at the scatterplot of the those two variables. As can be seen in Figure 3.2, the upper-right quadrant has a slight leftward lean. This lean indicates that as zip codes increase (y-axis) the BAH difference becomes more negative (x-axis). One other thing worth noting is a slightly conical shape — wider at the top — indicating greater variance in BAH difference in duty stations found in western areas — especially those zip codes starting with nine.

The next form of EDA conducted was to look at installations for any insights that could be gained from separating them geographically. To do this, we used K-Means clustering techniques leveraging latitude and longitude data for each installation. Clustering, in general, is a data analysis technique that breaks the data into clusters of data. The clusters themselves are groups of data points that possess similarities. The more clusters the data set is segmented into, the more similar they will be. In theory, one could take the installations data set of 721

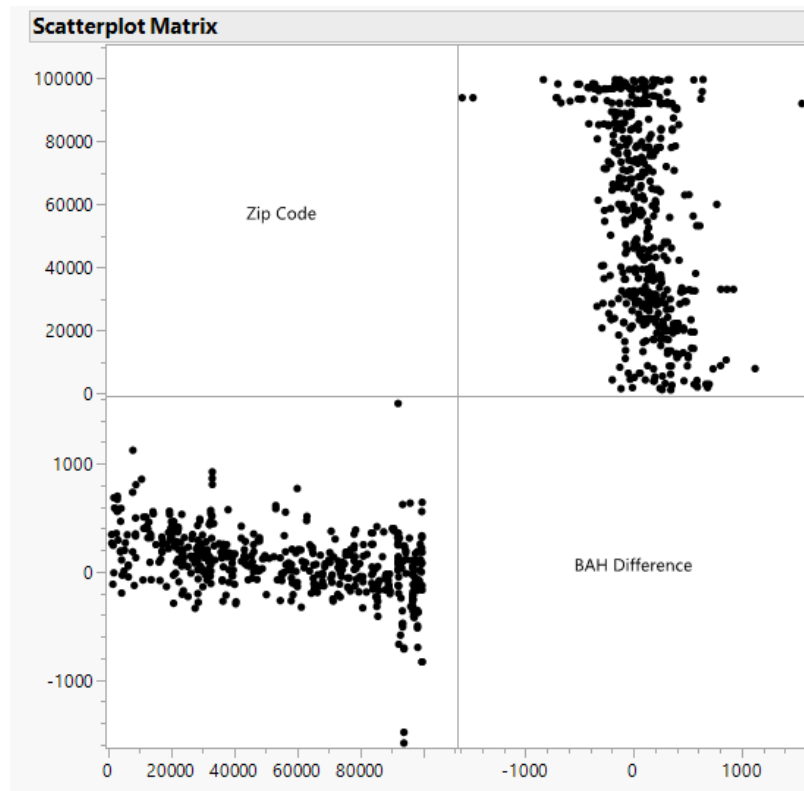


Figure 3.2. Zip codes are generally assigned east to west, so we can treat their numerical value as a general indicator of their east-west position in the United States. The upper right quadrant leans slightly left, indicating a greater shortfall at higher zip codes (i.e., zip codes in the western United States).

installations, choose a K-value of 721 — dividing the data into 721 individual clusters — and end up with the same data, rendering the clustering useless. Therefore, when using the K-Means clustering technique, identifying the appropriate number of clusters is important.

The “elbow plot” shown in Figure 3.3 is a very common way to approach determining the appropriate number of clusters (Kaloyanova 2023). The elbow plot provides a graphical representation of the Within Cluster Sum of Squares (WCSS) on the y-axis and the number of clusters on the x-axis, allowing the analyst to assess the change in the WCSS when adding an additional cluster (Kaloyanova 2023). The WCSS is the total sum of squared Euclidean distances within each cluster, so the analyst is looking for the point at which the WCSS starts to flatten when a new cluster is added (Kaloyanova 2023). That signals that adding that

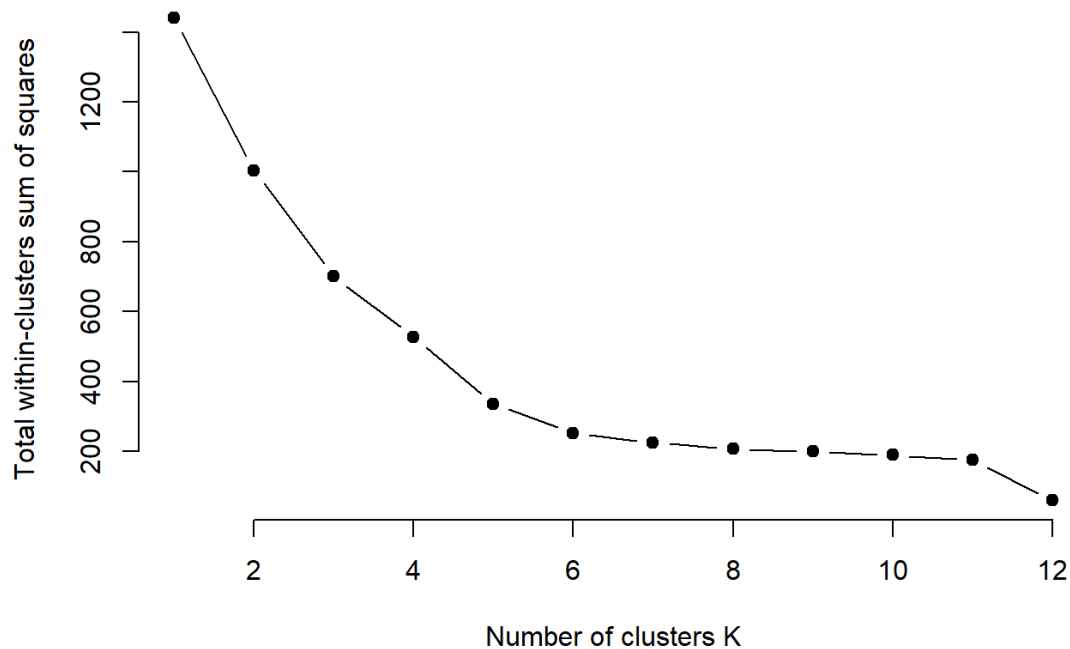


Figure 3.3. Elbow plot from our geographical data for k-means clustering: The x-axis is the number of clusters for k-means clustering method and the y-axis represents the total sum of squares of all pairwise distances within each cluster.

cluster provides minimal marginal value to the analysis. In our analysis of the installation data for geographical clustering, we found that six clusters did a nice job of clustering the data points. In looking at the elbow plot from our geographical data, one can see how it flattens out and marginal value from additional clusters is diminishing.

The data point(s) for which one is clustering the data on is what they are analyzing the impact of. In our data set we wanted to see if there were geographic insights that could be gained from simple K-Means clustering of latitude and longitude. We determined that six clusters would be best by examining the elbow plot. The geographic clusters determined to best represent the duty stations, along with their BAH and BAH to SAFMR relationship, according to their latitude and longitude were:

- Cluster 1: A mean latitude and longitude of 63.327, -149.226, which was comprised of 13 sites primarily in Alaska with a mean E4 and below BAH of \$1946.08; seven-of-fifteen of our distance-bedroom combinations experienced a shortfall in BAH.
- Cluster 2: A mean latitude and longitude of 21.238, -157.776, which was comprised of 37 sites in Hawaii with a mean E4 and below BAH of \$2942.43; ten-of-fifteen of our distance-bedroom combinations experienced a shortfall in BAH.
- Cluster 3: A mean latitude and longitude of 40.123, -78.998, which was comprised of 252 sites across the Northeast United States with a mean E4 and below BAH of \$1897.26; five-of-fifteen of our distance-bedroom combinations experienced a shortfall in BAH.
- Cluster 4: A mean latitude and longitude of 31.794, -88.201, which was comprised of 215 sites across the Southeastern United States with a mean E4 and below BAH of \$1653.25; five-of-fifteen of our distance-bedroom combinations experienced a shortfall in BAH.
- Cluster 5: A mean latitude and longitude of 45.157, -111.260, which was comprised of 80 sites across the Pacific Northwest and the Northern Rocky Mountains with a mean E4 and below BAH of \$1677.41; ten-of-fifteen of our distance-bedroom combinations experienced a shortfall in BAH.
- Cluster 6: A mean latitude and longitude of 35.017, -114.798, which was comprised of 124 sites from California and the Southwestern United States with a mean E4 and below BAH of \$2396.93; ten-of-fifteen of our distance-bedroom combinations experienced a shortfall in BAH.

Considering what we saw in the scatter plot in Figure 3.2, what we see in the clusters provides some further validation that western areas are experiencing greater shortfalls. Clusters 1, 2, 5, and 6 are the clusters that best represent the western installation observations with 254 observations amongst them. Thirty-seven of the sixty bedroom (2-, 3-, and 4-bedroom) and distance (5-, 10-, 15-, 20-, and 25-mile radius) observations experienced shortfalls, meaning — assuming the E4-and-below servicemembers are house shopping by need — in nearly 62 percent of the scenarios servicemembers found themselves in a situation where their BAH did not cover their needs.

In looking at the BAH and SAFMR data we had compiled, it became apparent that with what we had we could do little more than describe if there might be an issue with members

suffering BAH shortages when compared to SAFMR. In fact, we did find that that BAH for approximately 35 percent of zip codes where military installations existed in our dataset experienced a shortage. That, however, did not provide us with enough information to determine if the issue could be readily resolved, or provide any insight as to how it might be accomplished. Since we had the data for BAH and SAFMR for each installation, the missing piece of data was the population at each installation. Acquiring this data would allow us to look at the total costs and for BAH and perhaps examine how to effectively reallocate it.

The first data source we considered was capturing the actual data from was the Defense Manpower Data Center. However, in an attempt not to run into any classification issues, we turned to arguably the most open-source tool for acquiring this information; we simply asked OpenAI's ChatGPT tool to provide us with the answer (OpenAI 2023). By asking for the twenty USN installations with the greatest number of active duty service members, we were able to have what we found to be reasonable estimates of the information. From the list, we eliminated one joint base, two foreign bases, and the United States Naval Academy, leaving us with sixteen bases comprising roughly 78 percent of the navy's overall active duty force at 266,600 of 343,223 active duty USN service members. The final list of installations can be found in Figure 3.1 for further inspection.

Since we were working with only E4-and-below, we pulled the breakdown of navy personnel by rank to estimate how many E4-and-below sailors were stationed at each. Since E4-and-below generally do not receive BAH unless they have dependents, we then referenced the same demographic report for the percentage of this population to have at least one dependent and then at least two dependents. Multiplying the total active duty personnel by the navy-wide percentage of E4-and-below then by the dependent categories provided us data to work with (Department of Defense 2022) we had a reasonable estimate of the population we sought without having to use any sensitive information; our process yielded an estimate of 102,108 E4-and-below service members within our sample. Since all eligible E4-and-below service members (generally those with dependents) rate the same BAH, calculating the BAH allocated to these service members was as simple as multiplying the E4-and-below estimate by the E4-and-below BAH for a given installation. Extrapolating the data from our sample to be representative of the entire USN, we found an estimate of \$48.31 million allocated to this service member population segment monthly, or approximately \$579.73 million annually for BAH.

	Total	Represented
Navy Active Duty Population	343,223	78%

Installation	Military Population Est.	E4 and Below Pop.	E4 Pop. 1+ Dep.	E4 Pop. 2+ Dep.	BAH/Mbr.	Total BAH Allocated
NAVSTA Norfolk	53,800	20,605	3,359	1,875	\$ 1,914	\$ 6,428,513.90
NAS Jacksonville (FL)	28,000	10,724	1,748	976	\$ 2,088	\$ 3,649,849.06
NAVBASE San Diego	24,000	9,192	1,498	836	\$ 3,639	\$ 5,452,299.14
NAVBASE Coronado	22,000	8,426	1,373	767	\$ 3,639	\$ 4,997,940.88
NAVBASE Kitsap	17,500	6,703	1,093	610	\$ 2,136	\$ 2,333,596.02
NAVSTA Mayport	15,000	5,745	936	523	\$ 2,088	\$ 1,955,276.28
NAS Lemoore	14,000	5,362	874	488	\$ 1,866	\$ 1,630,895.20
NSA Mid-South	12,500	4,788	780	436	\$ 1,956	\$ 1,526,389.05
NAS Whidbey Island	12,400	4,749	774	432	\$ 1,692	\$ 1,309,810.36
NSA Bethesda	12,000	4,596	749	418	\$ 2,655	\$ 1,988,987.94
NAS Oceana	11,400	4,366	712	397	\$ 1,914	\$ 1,362,175.81
NAS Pensacola	10,500	4,022	656	366	\$ 1,683	\$ 1,103,214.07
NSA Hampton Roads	10,000	3,830	624	349	\$ 1,914	\$ 1,194,891.06
NAS Patuxent River	9,000	3,447	562	314	\$ 2,040	\$ 1,146,196.44
NAS Fallon	7,500	2,873	468	261	\$ 1,329	\$ 622,261.06
NAVSTA Great Lakes	7,000	2,681	437	244	\$ 1,884	\$ 823,313.65
TOTAL	266,600	102,108			Sample/Mo. \$	37,525,609.93
					Total/Mo. \$	48,310,774.25
					Total/Year \$	579,729,291.02

Table 3.1. A sample of sixteen installations representing 78 percent of the USN active duty population. This is used to estimate E4-and-below with dependent BAH costs in order to build an optimization model to better allocate the dollars spent.

3.5 Optimizing BAH Allocation

Now that we have a budget for this, using Microsoft Excel (Microsoft Corporation 2023) and the native Excel Solver, we looked at optimizing the allocation of these funds. The goal in this effort was to see if a feasible solution could be obtained, maximizing the amount of BAH paid over SAFMR while ensuring no service member category (i.e., pay-grade/location/dependent-status) realized a shortfall in BAH versus SAFMR. The thought process behind this objective was rooted in the assumption that if SAFMR is used to determine a baseline for adequate housing, each dollar spent on BAH above SAFMR would indicate a higher quality of living for service members.

Before diving into building an optimization model to address BAH allocation, we had to determine the best way to address the dependent scenario. Presently, BAH calculations treat dependents as a binary: either you have dependents or you do not (Defense Travel Management Office 2023). While this is a very simple way to address the issue of dependents,

it does not address the housing concerns raised by dependents. We assert it is important to consider not only the presence of dependents but also some consideration of the number of dependents. For this reason, we chose to create two very simple dependent categories to assess the difference in making a simple adjustment. The two categories created we referred to as “BAH 1” and “BAH 2+”, which was merely a reference to the number of dependents in the category: “BAH 1” indicated there was one dependent, whereas “BAH 2+” indicated there were two or more dependents.

When applying the new dependent categories — “BAH 1” and “BAH 2+” — to the optimization model, we needed to convert the dependent category in manner relating it to data we have available. The logical conversion was to translate the dependent category to the bedroom needs of the service member and his or her family. Making that leap, we applied an assumption that a “BAH 1” classification would rate a two-bedroom unit, and a “BAH 2+” classification would rate a three-bedroom unit. The basis for making this determination was to allow for single parent or outlier scenarios to be properly allocated without having to unnecessarily complicate the model to account for them. In essence, we are not making the assumption any of the dependents are spouses sharing a bedroom with the service member. If that is that is the situation of a service member, they will benefit from their BAH being calculated at a higher bedroom count.

The optimization model seeks to maximize an objective function that brings together considerations of the average percentage over SAFMR an installation’s BAH is while maintaining similar percentages across all the installations. For instance, if SAFMR for an installation is \$1,000 and BAH is \$1,250, then the percentage over SAFMR is \$1,250 minus \$1,000 divided by \$1,000 or 25 percent. In order to try to maintain similar increases across the installations, we built in a penalty by multiplying the average percentage over SAFMR by one minus the range of the percentages for both two bedroom and three bedroom scenarios. For instance, assuming the 25 percent scenario from before is representative of the average across all installations, if the range for two-bedroom scenarios is two percent (e.g., 24 percent minimum to 26 percent maximum) and it is four percent (e.g., 23 percent minimum to 27 percent maximum) for the three-bedroom scenarios, we would multiply 25 percent by 0.98 and 0.96 (one minus two percent and four percent, respectively).

The constraints in the model provide the user with “knobs” they can use to tune the outcome

based on their inputs. The primary tuning mechanism is addressing the percentage over SAFMR that BAH needs to be for each installation. If additional research indicates that the baseline living conditions for a service member in a given location need to be greater there than at other locations, that floor can be raised for an individual duty station vice having to raise it for all. This can lead to some infeasible solutions due to the constraint on the range, though. The range constraint is there to ensure that no single duty station has a significantly greater living standard (based on the percentage over SAFMR their BAH is) than other duty stations; the range can be changed to adapt to the user preferences, but it is a check-and-balance to help ensure no duty station is receiving undue preferences. The range considers the difference between the maximum and minimum percentages over SAFMR to ensure there is a semblance of balance amongst them; there is a range constraint for each of the BAH categories. Additionally, there is a constraint that ensures that no installation has a BAH that falls below SAFMR. This is merely a safety-switch, though, as this is also accomplished by establishing the BAH floors above SAFMR; the only time this constraint would be violated would be in the event a negative value was input for a floor value.

We analyzed two different ways to constrain this model to assess differences in its output. The first model formulation is found below, and the second model formulation follows.

Sets:	Variables:	Data:
		1. S_{2BR}^i = SAFMR value for 2 bedroom unit for an installation $i \in I$.
	1. B_1^i = BAH 1 for an installation $i \in I$.	2. S_{3BR}^i = Set of SAFMR value for 3 bedroom unit for an installation $i \in I$.
1. I = Set of installations	2. B_{2+}^i = BAH 2+ for an installation $i \in I$.	

$$\max_{B_1^i, B_{2+}^i} \frac{1}{n} \left(\sum_{i \in I} P_1^i + \sum_{i \in I} P_{2+}^i \right) (1 - R_1)(1 - R_{2+})$$

such that

$$n = |I|,$$

$$P_1^i = \frac{B_1^i - S_{2BR}^i}{S_{2BR}^i} \quad \forall i \in I,$$

$$P_{2+}^i = \frac{B_{2+}^i - S_{3BR}^i}{S_{3BR}^i} \quad \forall i \in I,$$

$$P_1^i \leq 1 \quad \forall i \in I$$

$$P_{2+}^i \leq 1 \quad \forall i \in I$$

$$B_1^i \geq S_{2BR}^i \quad \forall i \in I$$

$$B_{2+}^i \geq S_{3BR}^i \quad \forall i \in I$$

$$B_1^i \leq B_{2+}^i \quad \forall i \in I,$$

$$R_1 = \max_{i \in I} (P_1^i) - \min_{i \in I} (P_1^i),$$

$$R_{2+} = \max_{i \in I} (P_{2+}^i) - \min_{i \in I} (P_{2+}^i),$$

$$P_1^i = P_{2+}^i, \quad \forall i \in I.$$

Second formulation:

Sets:

Variables:

Data:

1. I = Set of installations

1. B_1^i = BAH 1 for an installation $i \in I$.
2. B_{2+}^i = BAH 2+ for an installation $i \in I$.

1. S_{2BR}^i = SAFMR value for 2 bedroom unit for an installation $i \in I$.
2. S_{3BR}^i = Set of SAFMR value for 3 bedroom unit for an installation $i \in I$.

$$\max_{B_1^i, B_{2+}^i} \frac{1}{n} \left(\sum_{i \in I} P_1^i + \sum_{i \in I} P_{2+}^i \right) (1 - R_1)(1 - R_{2+})$$

such that

$$n = |I|,$$

$$P_1^i = \frac{B_1^i - S_{2BR}^i}{S_{2BR}^i} \quad \forall i \in I,$$

$$P_{2+}^i = \frac{B_{2+}^i - S_{3BR}^i}{S_{3BR}^i} \quad \forall i \in I,$$

$$P_1^i \leq 1 \quad \forall i \in I$$

$$P_{2+}^i \leq 1 \quad \forall i \in I$$

$$B_1^i \geq S_{2BR}^i \quad \forall i \in I$$

$$B_{2+}^i \geq S_{3BR}^i \quad \forall i \in I$$

$$B_1^i \leq B_{2+}^i \quad \forall i \in I,$$

$$R_1 = \max_{i \in I} (P_1^i) - \min_{i \in I} (P_1^i),$$

$$R_{2+} = \max_{i \in I} (P_{2+}^i) - \min_{i \in I} (P_{2+}^i),$$

$$B_1^i - S_{2BR}^i = B_{2+}^i - S_{3BR}^i, \quad \forall i \in I.$$

Comparing the two formulations, the difference really lies in the last constraint. In the first formulation, the percent over SAFMR that BAH was held constant across the two BAH dependent categories. This was done with an eye toward the percentage over SAFMR would be representative of the quality of housing one would be able to afford in the area. Since the two BAH categories were not equally valued, though, the percentages produced larger financial gains for those in the “BAH 2+” category than the “BAH 1” category. We saw this as a potential issue in service members feeling they are being treated unfairly compared to their peers, so the second model was tried to hold the average dollars BAH is above SAFMR across the two dependent categories. This creates an equal financial benefit above SAFMR for their respective housing units.

	BAH w/ 1 Dep.	BAH w/ 2+ Dep.	Min % Over SAFMR	
Installation	BAH 1	BAH 2+	BAH 1 Floor	BAH2 Floor
NAVSTA Norfolk	\$ 1,576.28	\$ 2,058.50	15.0%	15.0%
NAS Jacksonville (FL)	\$ 1,582.88	\$ 1,897.50	15.0%	15.0%
NAVBASE San Diego	\$ 3,047.88	\$ 3,892.75	15.0%	15.0%
NAVBASE Coronado	\$ 3,065.35	\$ 3,898.50	15.0%	15.0%
NAVBASE Kitsap	\$ 2,316.08	\$ 2,886.50	15.0%	15.0%
NAVSTA Mayport	\$ 1,924.81	\$ 2,242.50	15.0%	15.0%
NAS Lemoore	\$ 1,652.35	\$ 2,104.50	15.0%	15.0%
NSA Mid-South	\$ 1,332.73	\$ 1,587.00	15.0%	15.0%
NAS Whidbey Island	\$ 1,962.53	\$ 2,518.50	15.0%	15.0%
NSA Bethesda	\$ 2,406.08	\$ 2,737.00	15.0%	15.0%
NAS Oceana	\$ 1,936.30	\$ 2,432.25	15.0%	15.0%
NAS Pensacola	\$ 1,460.87	\$ 1,817.00	15.0%	15.0%
NSA Hampton Roads	\$ 1,640.28	\$ 2,058.50	15.0%	15.0%
NAS Patuxent River	\$ 1,999.09	\$ 2,380.50	15.0%	15.0%
NAS Fallon	\$ 1,355.79	\$ 1,729.60	15.0%	15.0%
NAVSTA Great Lakes	\$ 2,037.53	\$ 2,323.00	15.0%	15.0%



Table 3.2. The decision variables are found in the columns “BAH 1” and “BAH 2+” which are pointed to by the white arrows. The user inputs for a minimum percentage over SAFMR for each installation are pointed to by the black arrows.

When considering the first model, where the BAH percentage over SAFMR is held equal for both categories, we found less predictable results based on the user input of changing the “BAH Floor”. One thing worth noting is when we varied the BAH Floor, we changed it so that the floor was the same for every installation in the sample data. For instance, we did not change Naval Base San Diego’s to be greater than Naval Station Norfolk’s or any other equivalent scenario. We simply changed the floor to be consistent across all installations. The output can be seen in Figure 3.4, where we see that as the floor is raised the BAH Floor is raised, we initially see a large jump in the range. The model given so much freedom could create a large enough average percentage BAH over to mitigate the impact of the range penalty in the objective function, and raised NSA Mid-South to nearly

BAH Floor	Average \$ BAH1 Over 2BR SAFMR	% BAH1 Over 2BR SAFMR	Range for BAH1	Average \$ BAH2+ Over 3BR SAFMR	% BAH2+ Over 3BR SAFMR	Range for BAH2+
0.15	302	18.91	29.64	406.39	18.91	29.64
0.155	320.52	22.21	78.49	429.87	22.21	78.49
0.16	305	19.86	22.34	410.19	19.86	22.34
0.165	303.15	20.02	11.93	408.55	20.02	11.93
0.17	300.14	19.76	11.74	404.5	19.76	11.74
0.175	301.89	19.77	11.8	406.95	19.77	11.8
0.18	293.16	18.99	1.3	396.31	18.99	1.3
0.185	291.99	18.99	7.73	394.58	18.99	7.73

Figure 3.4. The output of the optimization model, varying the BAH Floor — the minimum the BAH needs to exceed SAFMR — while holding the percentage over SAFMR equal across the two “with dependent” BAH categories. The problem became infeasible at a BAH Floor of 19 percent.

94 percent over SAFMR while holding nearly every other installation to just over the floor of 15.5 percent. After that, we see that raising the floor initially raises the percentage over SAFMR (compared to the initial floor of 15 percent) and generally compresses the range until the floor is increased to 18.5 percent. At that point, we see the percentage over SAFMR hold steady at 18.99 percent but the range increases, indicating a sub-optimal result. When running the problem is a BAH floor of 19 percent, the problem was infeasible.

By manually varying the BAH Floor, we had identified a very good result with a floor of 18 percent, but there was still more that we could get from this. With that in mind, we added the floor as an additional decision variable with a constraint of being at least 0.18 to ensure we were seeing at point between 18- and 19 percent (where we found the problem to be infeasible) the optimal results are actually found. The BAH outputs from this model can be seen in Figure 3.5. The BAH at each installation is at least 18.75 percent above SAFMR — actual is just below 18.75 percent, which can be seen in the box adjacent to “BAH % Over SAFMR Floor” in Figure 3.5 — and the range across those is zero.

This led us to a new formulation that would require fewer iterations of user input to reach optimality. Instead of manually varying the minimum BAH over SAFMR floor, the model will handle that directly for the user. The user will set the minimum acceptable threshold to assess whether that qualitative decision presents a feasible solution. For instance, a user input of 20 percent would return an error that a solution is infeasible, as previously discussed.

Installation	BAH w/ 1 Dep.	BAH w/ 2+ Dep.	Min % Over SAFMR	
	BAH 1	BAH 2+	BAH 1 Floor	BAH2 Floor
NAVSTA Norfolk	\$ 1,519.94	\$ 2,125.54	18.75%	18.75%
NAS Jacksonville (FL)	\$ 1,519.94	\$ 1,959.30	18.75%	18.75%
NAVBASE San Diego	\$ 2,938.95	\$ 4,019.53	18.75%	18.75%
NAVBASE Coronado	\$ 2,944.88	\$ 4,025.47	18.75%	18.75%
NAVBASE Kitsap	\$ 2,208.66	\$ 2,980.51	18.75%	18.75%
NAVSTA Mayport	\$ 1,804.93	\$ 2,315.53	18.75%	18.75%
NAS Lemoore	\$ 1,531.81	\$ 2,173.04	18.75%	18.75%
NSA Mid-South	\$ 1,234.95	\$ 1,638.68	18.75%	18.75%
NAS Whidbey Island	\$ 1,828.68	\$ 2,600.52	18.75%	18.75%
NSA Bethesda	\$ 2,256.16	\$ 2,826.14	18.75%	18.75%
NAS Oceana	\$ 1,798.99	\$ 2,511.46	18.75%	18.75%
NAS Pensacola	\$ 1,353.70	\$ 1,876.18	18.75%	18.75%
NSA Hampton Roads	\$ 1,519.94	\$ 2,125.54	18.75%	18.75%
NAS Patuxent River	\$ 1,852.43	\$ 2,458.03	18.75%	18.75%
NAS Fallon	\$ 1,256.33	\$ 1,785.93	18.75%	18.75%
NAVSTA Great Lakes	\$ 1,888.05	\$ 2,398.65	18.75%	18.75%



DECISION VARIABLES

USER
INPUT



BAH % Over SAFMR Floor	0.18745283
---------------------------	------------

Figure 3.5. Finding optimality by adding the BAH Floor as an additional decision variable yielded a better result, as the model was able to find an optimal point within the range from 18- to 19 percent.

A modified version of this formulation will also be used for the previously introduced formulation for holding dollars vice percent over SAFMR equal across all installations by substituting the final constraint as was done previously. This will allow us to compare the BAH results directly for the two formulations to allow the decision maker to consider the qualitative decision regarding which formulation would be in the best interest of the organization. The results will be discussed in Chapter 4 where the two models will be compared to gain further insights.

Sets:

1. I = Set of installations

Variables:

1. B_1^i = BAH 1 for an installation $i \in I$.
2. B_{2+}^i = BAH 2+ for an installation $i \in I$.
3. S_{2BR}^i = SAFMR value for 2 bedroom unit for an installation $i \in I$.
4. S_{3BR}^i = Set of SAFMR value for 3 bedroom unit for an installation $i \in I$.

$$\max_{B_1^i, B_{2+}^i} \frac{1}{n} \left(\sum_{i \in I} P_1^i + \sum_{i \in I} P_{2+}^i \right) (1 - R_1)(1 - R_{2+})$$

such that

$$n = |I|,$$

$$P_1^i = \frac{B_1^i - S_{2BR}^i}{S_{2BR}^i} \quad \forall i \in I,$$

$$P_{2+}^i = \frac{B_{2+}^i - S_{3BR}^i}{S_{3BR}^i} \quad \forall i \in I,$$

$$P_1^i \leq 1 \quad \forall i \in I$$

$$P_{2+}^i \leq 1 \quad \forall i \in I$$

$$B_1^i \geq S_{2BR}^i \quad \forall i \in I$$

$$B_{2+}^i \geq S_{3BR}^i \quad \forall i \in I$$

$$B_1^i \leq B_{2+}^i \quad \forall i \in I,$$

$$R_1 = \max_{i \in I} (P_1^i) - \min_{i \in I} (P_1^i),$$

$$R_{2+} = \max_{i \in I} (P_{2+}^i) - \min_{i \in I} (P_{2+}^i),$$

$$B_1^i - S_{2BR}^i = B_{2+}^i - S_{3BR}^i, \quad \forall i \in I.$$

CHAPTER 4:

Results

In Chapter 4, we will examine the results from the optimization model proposed in Chapter 3. In Figures 4.1 and 4.2, we compare the output from both optimization formulations previously introduced. Lastly, we compare both optimization formulation outputs to current BAH rates for each installation in our sample to consider the changes at each.

4.1 Results of the Optimization Model

During the EDA, we saw normally distributed BAH differences, which led us to believe there is a reasonable expectation to ensure that none of the duty stations would have BAH at less than the SAFMR for their location. For the EDA, however, we did not consider the number of service members assigned to each of the duty stations, but instead we looked at them weighted equally — as if only one service member (or an equal number) was assigned to each of them. Since this is an unrealistic assumption, we built our optimization model to work with the sample installations. The sample installations comprise a significant proportion of the active duty population, representing 78 percent of the active duty USN population. The installations are all also large enough for us to make the assumption that each of them is representative of the overall navy rank structure breakdown, so we can apply the navy-wide proportion of E4-and-below and the portion of that population that has at least one dependent as well as those who have two or more dependents.

We assessed optimizing BAH allocation by considering two different situations. For the first model, where the optimization model held the percentage BAH exceeded the SAFMR for the area equal. This meant that whatever percentage the “BAH 1” category’s BAH exceeded the two-bedroom SAFMR by the “BAH 2+” category would also exceed the three-bedroom SAFMR by. Then, for the second model, where we held the actual dollars, the BAH exceeded the the respective SAFMR by — two-bedroom units for “BAH 1” and three-bedroom units for “BAH 2+”. Figure 4.1 shows the output from that optimization model. Looking at the user input when we ran this, we can see that all our input into the model was that BAH had

Installation	BAH w/ 1 Dep.	BAH w/ 2+ Dep.	Min % Over SAFMR	
	BAH 1	BAH 2+	BAH 1 Floor	BAH2 Floor
NAVSTA Norfolk	\$ 1,519.94	\$ 2,125.54	18.75%	18.75%
NAS Jacksonville (FL)	\$ 1,519.94	\$ 1,959.30	18.75%	18.75%
NAVBASE San Diego	\$ 2,938.95	\$ 4,019.53	18.75%	18.75%
NAVBASE Coronado	\$ 2,944.88	\$ 4,025.47	18.75%	18.75%
NAVBASE Kitsap	\$ 2,208.66	\$ 2,980.51	18.75%	18.75%
NAVSTA Mayport	\$ 1,804.93	\$ 2,315.53	18.75%	18.75%
NAS Lemoore	\$ 1,531.81	\$ 2,173.04	18.75%	18.75%
NSA Mid-South	\$ 1,234.95	\$ 1,638.68	18.75%	18.75%
NAS Whidbey Island	\$ 1,828.68	\$ 2,600.52	18.75%	18.75%
NSA Bethesda	\$ 2,256.16	\$ 2,826.14	18.75%	18.75%
NAS Oceana	\$ 1,798.99	\$ 2,511.46	18.75%	18.75%
NAS Pensacola	\$ 1,353.70	\$ 1,876.18	18.75%	18.75%
NSA Hampton Roads	\$ 1,519.94	\$ 2,125.54	18.75%	18.75%
NAS Patuxent River	\$ 1,852.43	\$ 2,458.03	18.75%	18.75%
NAS Fallon	\$ 1,256.33	\$ 1,785.93	18.75%	18.75%
NAVSTA Great Lakes	\$ 1,888.05	\$ 2,398.65	18.75%	18.75%



DECISION VARIABLES

USER
INPUT



Range	0.05	MODEL OUTPUT	
BAH % Over SAFMR Floor	0	BAH % Over SAFMR Floor	0.187452821

Figure 4.1. The optimal results when using the final formulation presented in Chapter 3 while holding the percentage over SAFMR equal across the two “with dependent” BAH categories with the user selecting the minimum the BAH needs to exceed SAFMR and the acceptable range of percent-over.

to be at least equal to SAFMR (i.e., at least 0 percent greater), and that the range needed to be within 5 percent (e.g., if the installation with the greatest increase above SAFMR was 20 percent, the lowest needed to be at least 15 percent). Under “Model Output” in Figure 4.1, we can see the actual percentage over SAFMR that the model found, or we can see it rounded to two decimal places in the table at 18.75 percent. This yielded ranges of 0 percent across the installations for both “BAH 1” and “BAH 2+”, meaning that no installation was preferential to any other in terms of BAH, as we measured it in terms of a percentage over SAFMR.

	BAH w/ 1 Dep.	BAH w/ 2+ Dep.	Min % Over SAFMR	
Installation	BAH 1	BAH 2+	BAH 1 Floor	BAH2 Floor
NAVSTA Norfolk	\$ 1,576.56	\$ 2,086.56	16.57%	16.57%
NAS Jacksonville (FL)	\$ 1,553.37	\$ 1,923.37	16.57%	16.57%
NAVBASE San Diego	\$ 3,035.82	\$ 3,945.82	16.57%	16.57%
NAVBASE Coronado	\$ 3,041.65	\$ 3,951.65	16.57%	16.57%
NAVBASE Kitsap	\$ 2,275.85	\$ 2,925.85	16.57%	16.57%
NAVSTA Mayport	\$ 1,843.07	\$ 2,273.07	16.57%	16.57%
NAS Lemoore	\$ 1,593.19	\$ 2,133.19	16.57%	16.57%
NSA Mid-South	\$ 1,268.64	\$ 1,608.64	16.57%	16.57%
NAS Whidbey Island	\$ 1,902.83	\$ 2,552.83	16.57%	16.57%
NSA Bethesda	\$ 2,294.31	\$ 2,774.31	16.57%	16.57%
NAS Oceana	\$ 1,865.41	\$ 2,465.41	16.57%	16.57%
NAS Pensacola	\$ 1,401.77	\$ 1,841.77	16.57%	16.57%
NSA Hampton Roads	\$ 1,576.56	\$ 2,086.56	16.57%	16.57%
NAS Patuxent River	\$ 1,902.95	\$ 2,412.95	16.57%	16.57%
NAS Fallon	\$ 1,307.18	\$ 1,753.18	16.57%	16.57%
NAVSTA Great Lakes	\$ 1,924.67	\$ 2,354.67	16.57%	16.57%



DECISION VARIABLES

USER
INPUT



Range	0.05	MODEL OUTPUT	
BAH % Over SAFMR Floor	0	BAH % Over SAFMR Floor	0.165677697

Figure 4.2. The optimal results when using the final formulation presented in Chapter 3 while holding the dollars over SAFMR equal across the two “with dependent” BAH categories with the user selecting the minimum the BAH needs to exceed SAFMR and the acceptable range of percent-over.

Comparing the second model where the dollars over SAFMR are held equal to the previously introduced model of holding the percentage over SAFMR equal, as one might expect, we find different results. The results can be seen in Figure 4.2, where we see that, given the same user inputs, the optimal floor to two decimal places is 16.57 percent. One difference found here, though, is there is a range of 2.81 percent (20.75- to 23.56 percent) across the installations. Also worth noting is the “BAH 1” dependent category is about four- to seven percent above the floor, while the “BAH 2+” dependent category has a range of zero and is equal to the 16.57 percent floor.

Installation	Dollars Equal		Percent Equal		Current BAH	Dollars Equal vs. Current		Percent Equal vs. Current	
	BAH w/ 1 Dep.	BAH w/ 2+ Dep.	BAH w/ 1 Dep.	BAH w/ 2+ Dep.	BAH w/ Dependents	BAH w/ 1 Dep.	BAH w/ 2+ Dep.	BAH w/ 1 Dep.	BAH w/ 2+ Dep.
	BAH 1	BAH 2+	BAH 1	BAH 2+		BAH 1	BAH 2+	BAH 1	BAH 2+
NAVSTA Norfolk	\$ 1,576.56	\$ 2,086.56	\$ 1,519.94	\$ 2,125.54	\$ 1,914.00	\$ (337.44)	\$ 172.56	\$ (394.06)	\$ 211.54
NAS Jacksonville (FL)	\$ 1,553.37	\$ 1,923.37	\$ 1,519.94	\$ 1,959.30	\$ 2,088.00	\$ (534.63)	\$ (164.63)	\$ (568.06)	\$ (128.70)
NAVBASE San Diego	\$ 3,035.82	\$ 3,945.82	\$ 2,938.95	\$ 4,019.53	\$ 3,639.00	\$ (603.18)	\$ 306.82	\$ (700.05)	\$ 380.53
NAVBASE Coronado	\$ 3,041.65	\$ 3,951.65	\$ 2,944.88	\$ 4,025.47	\$ 3,639.00	\$ (597.35)	\$ 312.65	\$ (694.12)	\$ 386.47
NAVBASE Kitsap	\$ 2,275.85	\$ 2,925.85	\$ 2,208.66	\$ 2,980.51	\$ 2,136.00	\$ 139.85	\$ 789.85	\$ 72.66	\$ 844.51
NAVSTA Mayport	\$ 1,843.07	\$ 2,273.07	\$ 1,804.93	\$ 2,315.53	\$ 2,088.00	\$ (244.93)	\$ 185.07	\$ (283.07)	\$ 227.53
NAS Lemoore	\$ 1,593.19	\$ 2,133.19	\$ 1,531.81	\$ 2,173.04	\$ 1,866.00	\$ (272.81)	\$ 267.19	\$ (334.19)	\$ 307.04
NSA Mid-South	\$ 1,268.64	\$ 1,608.64	\$ 1,234.95	\$ 1,638.68	\$ 1,956.00	\$ (687.36)	\$ (347.36)	\$ (721.05)	\$ (317.32)
NAS Whidbey Island	\$ 1,902.83	\$ 2,552.83	\$ 1,828.68	\$ 2,600.52	\$ 1,692.00	\$ 210.83	\$ 860.83	\$ 136.68	\$ 908.52
NSA Bethesda	\$ 2,294.31	\$ 2,774.31	\$ 2,256.16	\$ 2,826.14	\$ 2,655.00	\$ (360.69)	\$ 119.31	\$ (398.84)	\$ 171.14
NAS Oceana	\$ 1,865.41	\$ 2,465.41	\$ 1,798.99	\$ 2,511.46	\$ 1,914.00	\$ (48.59)	\$ 551.41	\$ (115.01)	\$ 597.46
NAS Pensacola	\$ 1,401.77	\$ 1,841.77	\$ 1,353.70	\$ 1,876.18	\$ 1,683.00	\$ (281.23)	\$ 158.77	\$ (329.30)	\$ 193.18
NSA Hampton Roads	\$ 1,576.56	\$ 2,086.56	\$ 1,519.94	\$ 2,125.54	\$ 1,914.00	\$ (337.44)	\$ 172.56	\$ (394.06)	\$ 211.54
NAS Patuxent River	\$ 1,902.95	\$ 2,412.95	\$ 1,852.43	\$ 2,458.03	\$ 2,040.00	\$ (137.05)	\$ 372.95	\$ (187.57)	\$ 418.03
NAS Fallon	\$ 1,307.18	\$ 1,753.18	\$ 1,256.33	\$ 1,785.93	\$ 1,329.00	\$ (21.82)	\$ 424.18	\$ (72.67)	\$ 456.93
NAVSTA Great Lakes	\$ 1,924.67	\$ 2,354.67	\$ 1,888.05	\$ 2,398.65	\$ 1,884.00	\$ 40.67	\$ 470.67	\$ 4.05	\$ 514.65

Table 4.1. Comparing each model to the current BAH, we can see that, in order to optimize the allocation overall — regardless of model, it would require reallocating some resources from members with one dependent to those with more than one.

When comparing the models directly, we see the logical and expected outcomes based on the constraints applied. When dollars are held equal, we see greater values for the “BAH 1” category than when percent-over-SAFMR is held equal. Similarly, when percent is held equal, we see it is advantageous for those members in “BAH 2+”. When comparing the models’ assigned BAH to the current BAH, we see that in general the “BAH 1” category sees a reduction in their BAH whereas the “BAH 2+” category generally sees an increase. This makes sense as well, given the SAFMR is higher for 3-bedroom units than for 2-bedroom units, which is what the “BAH 2+” and “BAH 1” categories are tied to, respectively. Furthermore, by adding the budget constraint, we have created a zero-sum game, where not everyone can see an increase, because there would not be enough resources to cover.

CHAPTER 5: Findings

In Chapter 5, we consider the findings from the results explored in Chapter 4, considering specifically the impacts to E4-and-below service members. Recommendations are made to the DoD to improve its current BAH methodology, as our model has demonstrated it is reasonable to believe all installations can be assigned BAH above SAFMR. Lastly, we propose areas for future work related to this topic, as we understand our work to be only the stepping off point in what could be a very fruitful research series directly impacting service members.

5.1 Discussion

The results from our optimization model can be found in 4, but the primary takeaway is that if the DoD is willing to reconsider how BAH is calculated there is an opportunity to help ensure that service members have the housing allowance they need to secure adequate housing within a reasonable commute. By adding an additional dependent category, we were able to ensure that service member BAH was significantly greater than the SAFMR for the installation's zip code; depending on which constraints we have active in the formulation, each installation was at least 16.57 percent or 18.75 percent over SAFMR. This suggests that it is reasonable to expect that no E4-and-Below service member should be expected to live in housing near SAFMR, let alone below it.

The importance of these findings are that there are currently service members assigned to areas like Monterey, California that would need to pay approximately half their basic pay in addition to their BAH in order to secure housing at SAFMR levels. With their basic pay being approximately \$3,000 per month (Service 2023), and needing to pay over \$1,500 of it in some scenarios to meet SAFMR. The DoD orders service members to the installations at which they work and near which they need to obtain adequate housing; service members are not like civilians in this context, as they do not always have the ability to choose where they are going to live and work. With that in mind, being assigned to high priced areas

like Monterey could be seen as financially detrimental to service members, resulting in an annual cost of nearly \$20,000 to the junior enlisted ordered to serve there.

According to the Blue Star Families 2022 Report, “BAH/Off-base Housing” is a top-five concern amongst survey respondents for the first time (Families et al. 2023). This suggests that BAH is not only about ensuring service members have adequate housing to be able to focus on the mission, but it is also a serious consideration for service member retention; furthermore, it suggests it is more concerning now than it has been in the past. In a time when meeting recruitment numbers has proven challenging for the services, the DoD needs to make a concerted effort to remove reasons for current service members to separate.

5.2 Recommendations

We recommend the DoD expand the dependent categories in the BAH calculation from the binary — with dependents or without — system presently used to the two dependent categories: service members with one dependent and service members with two-or-more dependents. This provides a necessary distinction in the housing needs of service members based on their dependent situation, instead of a member’s rank determining the type of housing their BAH is set to afford them (Department of Defense 2022).

The recommended action need not come at an additional cost to the DoD or the U.S. taxpayer, as our model looks at the problem through the lens of maintaining current budgetary constraints and merely optimizing the allocation of funds more responsibly. New policy discussions are considering the the removal of the five percent cost share that service members have in their housing cost. While removing the cost share for service members in the BAH calculation is one avenue to help mitigate shortfalls, it comes at a cost of the DoD. Our work demonstrates that, while removing the cost-share to the service member could still be evaluated, it is not necessarily needed to mitigate the problem currently faced by service members. Our model suggests that service members can live comfortably above SAFMR through responsible allocation of the current BAH budget.

The implementation of our recommendation will need to be considered, as a drastic change could have civilian-military relations ramifications. In fleet- or force-concentration areas

where a disproportionately high military population is present, a large shift in BAH could disrupt the larger rental market. The focus of our research was not on the implementation of our recommended approach to the solution, but we do understand that considerations need to be made to ensure proper implementation and fostering of civilian-military relations in the cities that host our installations.

5.3 Future Work

While this research was scoped to look specifically at E4-and-below service members with dependents, there is an opportunity to expand the current work to examine how the DoD could implement this model to make its BAH calculations across all ranks and dependent statuses. The primary issue to be explored, from our perspective, is how to scale the floor above SAFMR for each rank. There are several ways one could approach this, so it would be an interesting problem and one that could take the current work and make it much more valuable in terms of its immediate applicability.

In addition to scaling across ranks and dependent statuses, we can incorporate more geospatial analysis into this research. More specifically, we might be able to incorporate commuting distances and estimated commuting costs into the model using road networks with the Python package OSMnx (Boeing 2017). This approach would take into account more accurate data for establishing a reasonable commuting distance, and potentially modify the model to penalize for commuting distance beyond national average by compensating the member for additional travel time. In areas where housing inventory within the immediate area of the duty location is extremely low, this could be one way to look at the problem. The additional resources allocated could serve as both a way to help ensure service members are assigned sufficient BAH and also serve as an incentive and potential a signal as to where the DoD should consider looking for privatized housing partners to help mitigate this overspending.

Additional research could be done to set BAH rates for service members with more recent data to provide something closer to live rate setting. This work would help to protect against the issues mentioned in Vaden (2005), and also help protect against underpaying or overpaying in more volatile markets. A moving average could be used to analyze appropriate window size for setting rates, which could be an effective study in itself. Implementation of

this would take some finesse, as it may not be prudent to set rates in a fixed manner for a member's duration at a duty station if using a method to compensate for volatile markets. We could see this analysis done to protect against volatile markets by establishing a market protection measure that is added to BAH when needed. Creating the funds to be leveraged for this market protection measure could be done by enacting policy that pays 100 percent of the housing costs in an area, while the member only receives 95 percent — still with a five percent cost share — and the DoD allocates the five percent it is now budgeting for to fund this protection measure. It would also require it to be distributed separately from BAH as it shouldn't be protected for the duration of a member's time at a duty station and should be reactive to the market conditions with annual evaluation for the individual member.

Looking specifically at the impact of BAH shortages and surpluses through the lens of service member retention would be an interesting study to link the two more concretely than the recent surveys have (Families et al. 2023). One way to approach this would be to look at survival analysis of service members at different BAH shortfalls and surpluses over their career. If the researcher were to establish a direct linkage from BAH shortfall to early separation of the member, then a cost-benefit analysis should be conducted to determine the cost of recruiting, training, and placing new members — along with the loss of experience from the separating member — versus the increased cost in BAH necessitated to arrive at an acceptable retention rate.

As demonstrated, there is significant work that can be done. Shining additional light on the impact that BAH has as part of a member's compensation package is important, so that it can be utilized appropriately. The DoD needs to look at the issue of BAH through lenses other than matching housing allowance to area rents, and start looking at it for what it really is: one of the ways a member perceives his or her value to the DoD.

5.4 Conclusion

Keeping the limited scope of this research in mind, the findings that optimizing BAH allocation in the manner we did can ensure that all E4-and-below service members with dependents could receive BAH that is over 16 percent above SAFMR without the DoD spending additional funds is significant. The significance lies in the fact that the limiting

factor in ensuring service members are living above HUD SAFMR standards is not limited by available resources, it is create by misguided resource allocation. We are in no way implying that the solution to this problem is is simple or void of issues, but it certainly does appear that the solution is feasible.

THIS PAGE INTENTIONALLY LEFT BLANK

List of References

- Boeing G (2017) OSMnx: A Python package to work with graph-theoretic openstreetmap street networks. *Journal of Open Source Software* 2(12), URL <http://dx.doi.org/doi:10.21105/joss.00215>.
- Carter A (2018) *DoD Housing Management, Change 2*. Department of Defense, Washington, DC.
- Center on Budget and Policy Priorities (2018) A guide to small area fair market rents (SAFMRs). Accessed March 20, 2023, <https://www.cbpp.org/research/housing/a-guide-to-small-area-fair-market-rents-safmrs>.
- Defense Travel Management Office (2023) Basic allowance for housing rate lookup. Accessed December 24, 2022, <https://www.travel.dod.mil/Allowances/Basic-Allowance-for-Housing/BAH-Rate-Lookup/>.
- Department of Defense (2022) Basic Allowance for Housing (BAH): bah data collection and rate-setting process overview. Electronic publication, Department of Defense, November, accessed March 3, 2023 <https://media.defense.gov/2022/Jun/23/2003023204/-1/-1/0/BAH-PRIMER.PDF>.
- Families BS, for Veterans DI, Families M (2023) Military Family Lifestyle Survey: 2022 Comprehensive Report. Blue Star Families, Encinitas, CA, https://bluestarfam.org/wp-content/uploads/2023/03/BSF_MFLS_Spring23_Full_Report_Digital.pdf.
- Fitzkee W (2014) *The Effect of Zoning Laws on Housing Prices and BAH Rates*. Master's thesis, Department of Defense Management, Naval Postgraduate School, Monterey, CA.
- Griner M (2020) *Forecasting USMC Basic Allowance for Housing Utilizing Historical Dependency Rates*. Master's thesis, Department of Military Studies, USMC Command and Staff College, Quantico, VA.
- Heidt M, Sanchez M (2022) *Cost Savings of Taxing Lower-Ranking, Non-Dependent Members' Basic Allowance for Housing for Collocated Military Couples*. Master's thesis, Department of Defense Management, Naval Postgraduate School, Monterey, CA.
- Hofmann T, Worcester J (1991) *Navy family housing: an analysis of adequacy standards and their relationship to the Variable Housing Allowance*. Master's thesis, Department of Defense Management, Naval Postgraduate School, Monterey, CA.

- Jordahl K, den Bossche JV, Fleischmann M, Wasserman J, McBride J, Gerard J, Tratner J, Perry M, Badaracco AG, Farmer C, Hjelle GA, Snow AD, Cochran M, Gillies S, Culbertson L, Bartos M, Eubank N, maxalbert, Bilogur A, Rey S, Ren C, Arribas-Bel D, Wasser L, Wolf LJ, Journois M, Wilson J, Greenhall A, Holdgraf C, Filipe, Leblanc F (2020) geopandas/geopandas: v0.8.1. URL <http://dx.doi.org/10.5281/zenodo.3946761>.
- Kaloyanova E (2023) What is k-means clustering? Accessed April 26, 2023, <https://365datascience.com/tutorials/python-tutorials/k-means-clustering/>.
- Keating F (1998) Fair Housing Enforcement Policy: Occupancy Cases. *Federal Register* 63(245), https://www.hud.gov/sites/documents/DOC_7780.PDF.
- Microsoft Corporation (2023) Microsoft Excel. URL <https://office.microsoft.com/excel>.
- Office of the Assistant Secretary for Policy Development and Research, HUD (2020) Fair Market Rents for the Housing Choice Voucher Program, Moderate Rehabilitation Single Room Occupancy Program, and Other Programs Fiscal Year 2021. *Federal Register* 85(158), <https://www.govinfo.gov/content/pkg/FR-2020-08-14/pdf/2020-17717.pdf>.
- OpenAI (2023) "What are the 20 us navy installations with the highest active duty population?" Accessed March 8, 2023, <https://chat.openai.com/chat>.
- Praktiknjo A, Hähnel A, Erdmann G (2011) Assessing energy supply security: Outage costs in private households. *Energy Policy* 39:7825–7833, URL <http://dx.doi.org/10.1016/j.enpol.2011.09.028>.
- Reback J, jbrockmendel, McKinney W, den Bossche JV, Augspurger T, Cloud P, Hawkins S, Roeschke M, gflyoung, Sinhrks, Klein A, Petersen T, Hoefler P, Tratner J, She C, Ayd W, Naveh S, Garcia M, Darbyshire J, Schendel J, Hayden A, Shadrach R, Saxton D, Gorelli ME, Li F, Zeitlin M, Jancauskas V, McMaster A, Battiston P, Seabold S (2020) pandas-dev/pandas: Pandas. URL <http://dx.doi.org/10.5281/zenodo.3509134>.
- Service DFA (2023) Military basic/drill pay tables 2023. Accessed April 8, 2023, https://www.dfas.mil/Portals/98/Documents/militarymembers/militarymembers/pay-tables/2023%20AC_RC%20Pay%20Table1.pdf?ver=NUrUfCrNLYPqk6TT20HCXw%3d%3d.
- U.S. Census Bureau (2022) Series information for 2020 census 5-digit zip code tabulation area (zcta5) national tiger/line shapefiles, current. Accessed December 12, 2022, <https://catalog.data.gov/dataset/series-information-for-2020-census-5-digit-zip-code-tabulation-area-zcta5-national-tiger-line-s>.
- U.S. Department of Housing and Urban Development (2023) Housing Choice Vouchers Fact Sheet. Accessed March 20, 2023, https://www.hud.gov/topics/housing_choice_voucher_program_section_8.

U.S. Department of Transportation (2019) Military bases. Accessed November 12, 2022, <https://public.opendatasoft.com/explore/dataset/military-bases/export/>.

U.S. Housing and Urban Development (2022) Fair market rents (40th percentile rents). Accessed December 4, 2022, https://www.huduser.gov/portal/datasets/fmr.html#2023_data.

Vaden D (2005) *Process Analysis of Basic Allowance for Housing (BAH) Within the Military Personnel, Marine Corps (MPMC) Appropriation*. Master's thesis, Department of Defense Management, Naval Postgraduate School, Monterey, CA.

Zillow Group (2023a) Trulia. Accessed March 20, 2023, <https://www.trulia.com/>.

Zillow Group (2023b) Zillow. Accessed March 20, 2023, <https://www.zillow.com/>.

THIS PAGE INTENTIONALLY LEFT BLANK

Initial Distribution List

1. Defense Technical Information Center
Ft. Belvoir, Virginia
2. Dudley Knox Library
Naval Postgraduate School
Monterey, California



DUDLEY KNOX LIBRARY

NAVAL POSTGRADUATE SCHOOL

WWW.NPS.EDU

WHERE SCIENCE MEETS THE ART OF WARFARE