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Risk of Food Insecurity in the U.S. Military: Definitions, Distributions, and Solutions

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RISK OF FOOD INSECURITY IN THE U.S. MILITARY:

DEFINITIONS, DISTRIBUTIONS, AND SOLUTIONS

by

Dr. Jennifer A. Heissel & Dr. Diane W. Schanzenbach

October 2023

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Takeaway 1: Having a larger family size and if the head of house is a woman, divorced, Black, or Hispanic are associated with a higher probability of being food insecure (risk factors).

Takeaway 2: Being from a military family, being married, having more education, and more income are associated with a lower probability of being food insecure (protective factors).

Takeaway 3: Few service members have income levels at or below BNA eligibility criteria.

Takeaway 4: The FY2023 NDAA's method of eligibility for the BNA will not significantly reduce military food insecurity.

Takeaway 5: We estimate that 6.9% of the military is likely to be food insecure.

Takeaway 6: Moderate increases in benefits or income will not eliminate food insecurity.

We take our results as an indication that food insecurity is a multi-faceted issue that will not be solved with money alone. Military members—and their families—should not face food insecurity. The current BNA will not change much about current rates of food insecurity. Indeed, moderate tweaks to pay are unlikely to have a meaningful effect on rates of food insecurity. Instead, a more comprehensive approach to food insecurity is needed.

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ABSTRACT

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We take our results as an indication that food insecurity is a multi-faceted issue that will not be solved by money alone. Military members—and their families—should not face food insecurity. The current BNA will not change much about current rates of food insecurity. Indeed, moderate tweaks to pay are unlikely to have a meaningful effect on rates of food insecurity. Ultimately, a more comprehensive approach to food insecurity is needed.

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I. INTRODUCTION

Food insecurity is a military readiness concern, but it is not obvious how widespread military food insecurity is. Defense Secretary Austin issued a 2021 memo to reiterate Department of Defense (DoD) commitment to the economic security of the Force. The memo included a directive for the Under Secretary of Defense for Personnel and Readiness to define a strategy and implementation roadmap for strengthening food security for service members.

A household's food insecurity is typically determined based on their responses to a scientifically validated survey. Two households with the same income can have different food security statuses due to a range of factors that are difficult to directly measure. One family may be food insecure because they had an expensive car repair bill that month, or because their housing rental costs take up too large a share of their budget. Another family with the same income may be food secure because they have a homemaker who carefully budgets and prepares inexpensive meals from scratch. Some factors—like high rent—are more easily observable to predict food insecurity, while others—like unexpected emergency costs and time available to plan, purchase and prepare food—are harder to measure.

Food insecurity cannot be measured directly from available DoD data. We know a Sailor's income but not whether they are able to manage that income to be food secure—or how patterns of food security change as the income, family structure, or the geographic location of a Sailor changes.

The present study explores ways that the Department of the Navy can define and measure risk of food insecurity, from rough-cut measures ("income less than 150% of the poverty line") to detailed machine learning-based projections based on largescale administrative data. This research examines how widespread the risk of food insecurity is and how that risk assessment depends on the measure used. We specifically pursue four research questions:

1. What are some of the contributing factors influencing food insecurity?
2. How can the Navy/Marine Corps define the risk of food insecurity?

3. How widespread is the risk of food insecurity, and who is most at risk of food insecurity?
4. Which policies most effectively mitigate the risk of food insecurity?

Understanding food security matters for many reasons. Food insecurity affects physical and cognitive outcomes. From the military perspective, a prevalence of food insecurity in the force could harm recruitment, readiness, and retention. It is hard to recruit service members if there is a perception of widespread food insecurity. Service members distracted by a food insecure family—or who are hungry themselves—may also be less focused on their mission. Those who have faced bouts of food insecurity in their first contract may be less likely to reenlist.

This report proceeds as follows. The Background section provides a brief overview of relevant definitions and options for combatting food insecurity. The Data section provides an overview of the data used in this report. The subsequent section answers the four research questions, and the Conclusion section provides some broader perspectives on the findings.

II. BACKGROUND

A. DEFINING FOOD INSECURITY

Food insecurity is defined as a lack of consistent access "by all people at all times to enough food for an active, healthy life" (USDA, 2023). Food insecurity is a household-level socioeconomic condition. Food insecurity is different from hunger, which USDA defines as an individual-level physiological condition that may follow food insecurity (2022). Food insecurity may reflect excessive worry about having adequate resources for food or not being able to afford to eat balanced meals.

Unlike height or blood pressure, there is no clinical way to measure food insecurity. Instead, food security status is always measured through a self-reported survey. USDA's Economic Research Service monitors civilian food security levels via an 18-item module included as part of the Current Population Survey (CPS) each December. USDA categorizes households into four groups (see Table 1). In the 2021 report on Household Food Security in the United States, 10.2 percent of households were food insecure, meaning that they experienced low or very low food security (Coleman-Jensen et al., 2022). For our research, we group individuals into "food secure" and "food insecure," based on the USDA categories.

Table 1. Ranges of Food Security and Food Insecurity

USDA category	Category	Description
High food security	Food secure	No reported indications of food access problems or limitations.
Marginal food security	Food secure	One or two reported indications—typically of anxiety over food sufficiency or shortage of food in the house. Little or no indication of changes in diets or food intake.
Low food security	Food insecure	Reports of reduced quality, variety, or desirability of diet. Little or no indication of reduced food intake.
Very low food security	Food insecure	Reports of multiple indications of disrupted eating patterns and reduced food intake.

Source: United States Department of Agriculture, Economic Research Service (2022).

B. FACTORS AFFECTING CIVILIAN FOOD INSECURITY

Many factors are associated with higher rates of food insecurity. Factors that predict less income per household member or less disposable income—that is, money available to purchase food after paying rent, utilities, medical bills and other necessities—also predict the likelihood of food insecurity. These factors include income levels below 185% of the federal poverty line and children in the household (particularly children under the age of six). Households headed by single women and/or single parents, and households from racial/ethnic minority groups are also more likely to experience food insecurity than other groups (Coleman-Jensen et al., 2022). Geography is associated with food insecurity, with higher rates in the south and southwest regions of the country (Bonanno & Li, 2015; Coleman-Jensen et al., 2022; Gundersen et al., 2021). Large cities and rural areas also have higher rates of food insecurity than the national average (Bonanno & Li, 2015; Coleman-Jensen et al., 2022). Higher food prices and housing costs are associated with higher food insecurity (Gregory & Coleman-Jensen, 2013), which may explain some of the geographic variation. Childcare costs also differ by location (Women's Bureau, Department of Labor, 2020). Below, we will use factors that predict food insecurity among civilians to predict food insecurity in the military. Appendix A discusses the geographic distribution of civilian food insecurity.

C. EFFECTS OF FOOD INSECURITY ON THE MILITARY

Food insecurity may be problematic for recruiting to the extent that the potential recruiting pool believes that service members are not paid enough to support themselves or their families, either overall or at certain bases. However, there is little research that addresses the direct effect of the risk of food insecurity on recruiting.

Research has examined the relationship between food insecurity, military readiness, and retention. Food insecurity is associated with a variety of poor health outcomes, including sleep disorders, depression, and anxiety (Arenas et al., 2019; Beymer et al., 2021; Gundersen & Ziliak, 2015; Reeder et al., 2022; Seligman et al., 2010). Beymer at al. (2021) studied a sample of U.S. Army soldiers and found that food insecurity was associated with anxiety, depression, and suicidal ideation, which in turn were associated with a higher intention to leave the Army. Thus, addressing food insecurity in the military may improve force readiness and increase retention.

D. CURRENT ESTIMATES OF MILITARY FOOD INSECURITY

There is not a comprehensive, direct measure of food insecurity in the military. We also do not know how the risk of food insecurity changes as the income, family structure, or geographic location of a service member changes. The Office of People Analytics (OPA) runs surveys for the DOD that have attempted to estimate the extent of food insecurity. The 2020 Status of Forces Survey of Active Duty Members (SOFS-A) survey and 2021 Active Duty Spouse Survey (ADSS) indicate that 24% of military respondents and 25% of military spouses report either low or very low food security (OPA, 2022a, 2022b). There are similar numbers in civilian-run military family advocacy organizations; the Military Family Advisory Network indicates that 23.3% of respondents in enlisted families are food insecure, with an overall rate of 16.6% across all military and veteran families (L'Esperance et al., 2022).

An important shortcoming of these existing measurement approaches is that those who choose to take the survey are not necessarily representative of the full population. This is a particular concern when surveys are not distributed randomly or participation rates are low. Response rates were 12% in the 2020 SOFSA and 21% in the 2021 ADSS. Those particularly concerned about food insecurity may be more likely to participate in a survey about food insecurity; alternatively, those who are food insecure may be too busy or distracted to take a survey. Moreover, we need different tools to project what would happen to food security in the future if policy changed. Below, we explore ways to predict food insecurity from existing data without deploying new, comprehensive surveys.

E. CURRENT PROGRAMS TO COMBAT FOOD INSECURITY

A variety of civilian and military-specific programs seek to reduce households' and individuals' rates of food insecurity. The Supplementary Nutrition Assistance Program (SNAP) and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) are the two largest programs targeting food insecurity in the United States. SNAP generally provides additional resources to food to households with total incomes below 130% of the federal poverty line (130% FPL) and net incomes (i.e., after deductions for certain expenses) below 100% FPL. This calculation does not count in-kind housing as part of income, but it does count the military's Basic Allowance for Housing (BAH). This distinction means that many military families receiving BAH are ineligible for SNAP (Asch et al., 2023; London & Heflin, 2015). WIC, on the other hand, has a higher income limit at 185% FPL and does not count BAH as income, but is limited to expectant and postpartum mothers and children ages zero through four (Asch et al., 2023; Hodges & Todd, 2023). The higher income threshold and exclusion of BAH from the income calculation allows more military families to access WIC than SNAP. About a third of DoD and Coast Guard families with children five and under report ever using WIC (Asch et al., 2023). Appendix A includes additional information on other support programs.

The FY2022 NDAA created the Basic Needs Allowance (BNA). The eligibility threshold was originally set at 130% FPL but was revised to 150% FPL under the FY2023 NDAA. BNA allocates additional monthly pay to bring the service members' gross household income up to 150% FPL, for service members with at least one dependent. Service members without dependents are ineligible. Like SNAP, BNA includes BAH as part of the income calculation, although the statute allows the Secretary of Defense to exclude any portion of BAH from a household's income for those who reside in areas with a high cost of living (37 USC § 402b, 2022).[1]

In practice, very few military families qualify for the BNA: under the 130% FPL guideline, the Navy, Marine Corps, Air Force and Space Force combined identified 85 service members who may have been eligible (Jowers, 2023). Military family advocates argue that BNA should exclude BAH to increase access to the benefit (Bushatz, 2022).

F. PREDICTING THE RISK OF FOOD INSECURITY

No DOD-wide measure exists to determine which members are food insecure. However, it is useful to mathematically model the risk of food insecurity to predict how proposed policy changes are likely to impact food insecurity. In cases where researchers or policymakers do not have a survey measure of food insecurity for their population of interest, they may instead use other data to predict the *risk* of food insecurity. This differs from food insecurity itself in that it is predicting who *is likely to be* food insecure.

Predicting the risk of food insecurity will be the focus of the remainder of this report. Specifically, we use several methods to identify the risk of food insecurity, ranging from relatively simple calculations (e.g., the share with income less than 150% FPL) to complex machine-learning methods. We use these methods to compare predicted

[1] Specifically, if eligible, the monthly BNA payment is the difference between the current year's BNA eligibility threshold and the preceding year's gross household income divided by twelve. For instance, if the relevant 150% FPL level for the current year is $45,000, and the gross household income was $39,000 last year and $41,000 this year, the service member would receive a BNA of ($45,000-$39,000)/12=$500 per month. For additional details, see https://www.dfas.mil/MilitaryMembers/payentitlements/bna/.

risk of food insecurity by a variety of characteristics (e.g., number of children, local cost of living, branch of service).

III. DATA

A. CIVILIAN DATA

The Department of Health and Human Services (DHHS) produces annual federal poverty levels (FPL) and supplemental poverty measures (SPM). FPL increases with each additional family member. The level is the same for the 48 contiguous states and Washington, DC, with higher levels for Alaska and Hawaii. SPM varies geographically, adjusting for local cost of consumer expenditures on shelter, food, clothing, and utilities for below-median income families; it also calculates available financial resources differently (Congressional Research Service, 2022; U.S. Census Bureau, 2021).

Our primary information on civilian characteristics comes from the Food Security Supplement (FSS) of the Current Population Survey (CPS) from the Census Bureau. FSS occurs every December and includes demographic variables, family income bins, and county, state, and/or metro location. For a subsample of the FSS sample, we also have the Annual Social and Economic Supplement (ASEC) to the CPS, which occurs in March and has comprehensive data on household income. We use the FSS-ASEC overlap subsample for an analysis of the SPM, as it requires more detailed income/location data than the general FSS allows.

We also use estimates of local price differences across metropolitan regions (called regional price parity) from the Bureau of Economic Analysis, housing costs from the Department of Housing and Urban Development, childcare costs from the Department of Labor, and food cost data from Feeding America's Map the Meal Gap program; see Appendix A for details.

B. DEERS DATA

Our DMDC active-duty master demographic DEERS files include descriptive information (age, gender, race/ethnicity, grade, ZIP, county-state) on all active-duty individuals in the data from January 2010 through December 2021 at the monthly level. We use this information to identify marital status, total number of children, and number of children under various ages. This also allows us to calculate the total number of members of the family, which we top-code at 11 (service member plus up to 10 dependents). We take these characteristics as of September of each year.

C. EARNINGS

DMDC active duty pay files include basic pay, special and incentive pay (e.g., language bonuses), and allowances (e.g., basic allowance for housing or BAH) at the monthly level from 2012-2021. Active-duty individuals in the United States who are not provided government housing (e.g., barracks) are provided BAH. BAH is standardized by rank, with a higher rate if a member has at least one dependent. BAH is adjusted using a DOD-calculated cost of living adjustment (COLA) for a few high-cost areas.

We create an annualized income for each person as of September of each year that includes military pay and allowances. Supplementary analyses remove BAH from the total earnings for some calculations to match what military family advocates propose as a revision to the BNA. When BAH is included, mean (median) 2021 annualized military wage was \$65,333 (\$60,690), with the fifth percentile making \$24,348 and the 95th percentile making \$132,331. Mean (median) annualized income excluding BAH is \$50,187 (\$43,123), with a fifth percentile of \$23,901 and a 95th percentile of \$104,250.

We do not have income data for the *family members* of military service members. For unmarried individuals, we assume the only income comes from the service member's military pay. For dual military families, we link spouses' total income and assume the only family income comes from their combined military pay. We keep both individuals in the data so that the data is at the service member level, not the family level. For service members married to a civilian, we take several steps to impute income; see Appendix A for details. Note that the imputation will certainly have errors, does not allow for underemployment or differences in employment probability by education level, and does not allow for nuance in, say, probability of employment by whether a family has recently had a permanent change of station (PCS). We are likely to be incorrect in the estimate for any given individual family, but, on net, these individual-level errors will even out as we estimate a population-level risk of food insecurity. Despite drawbacks, incorporating spouse pay provides a more realistic assessment of the resources available to provide food for a family than only including military pay.

Mean (median) estimated family pay is \$80,702 (\$71,760), with a fifth percentile of \$24,496 and a 95th percentile of \$183,039. In most analyses, we exclude families with income below \$15,000 (0.7% of the data) and top-code high earners to the 99th percentile.

IV. RESULTS

A. Q1: WHAT CONTRIBUTING FACTORS INFLUENCE THE RISK OF FOOD INSECURITY?

This section explores factors that increase and decrease the risk of food insecurity in the civilian CPS sample. We will use insights from this relationship to build a model to predict food insecurity in the military sample.

1. Q1 Methods

We use a linear probability regression model to identify which factors predict food insecurity (or a lack thereof) in the civilian CPS data, implementing the model in increasingly restricted samples.

All models include a basic set of variables. If the head of household (HOH) or spouse is in the military, we designate it as a military family. Note that only military families that include a civilian adult would be included in the CPS data, which does not sample military-only families. As a result, single, divorced, and dual-military families are not included. This coefficient can thus be interpreted as a comparison between civilian families and families with one military and one civilian adult. All models also include variables for gender, age and age-squared, race/ethnicity (Black, Hispanic, and other non-White compared to White), education level (no high school degree, some college or college relative to a high school degree), marital status (married or divorced relative to single), and number of children in the household. The number of children in the household is entered as a linear variable, and each additional child in the household would be predicted to increase by the same amount (or decrease, if the coefficient is negative) the probability that a family is food insecure. The models also include various costs of living values (local family meal cost, housing costs, and childcare costs), whether the individual lives in a non-metropolitan area, and a year-specific effect.

Model (1) includes all civilian data, but it is likely that many civilians are not a good representation of military families. For instance, elderly civilians, those with no high school degree, or those who are not employed are more likely to be food insecure than others, but the military population does not include these groups. If relationships between other variables (e.g., cost of living) and food insecurity vary by these characteristics, then we may misestimate the effects of the other variables on the risk of food insecurity if we include these groups in the analysis. Thus, Model (2) limits the data to only those aged 18-50 and not living in group quarters. Model (3) further limits the sample to those with at least a high school diploma. The final two models also include controls for the number of people in the family who are employed and in the CPS annual income category. Model (5) limits the sample to households with at least one working adult and incomes of at least $15,000 to resemble the military population more closely.

The outcome for this analysis is the actual reported food insecurity level in the CPS. We define a respondent as food insecure if they have low or very low food security.

2. Q1 Results

Table 6 in Appendix A displays the results from these various models. Results are fairly consistent across all models. Holding all other variables constant, risk factors are those that increase the predicted probability of being food insecure—that is, the positive coefficients. Protective factors are the reverse. Holding the other variables constant, military families in the CPS tend to have a lower probability of reporting being food insecure than other families.[2] Imagine two families who are the same on every characteristic listed—the families have the same number of children, same income, etc.—except that one has a civilian adult married to a military member and one has two married civilians. Holding other factors constant, military families have a 5.4 percentage point lower likelihood of being food insecure than otherwise-similar, non-military families in the final model. Recall, however, as described above, we can only measure a military vs. non-military difference among married couples in which one spouse is in the military and one spouse is a civilian; we cannot directly measure the protective effect of military service on unmarried, divorced, or dual-military couples.

Other protective characteristics include having a college degree (relative to a high school diploma) and being married. In the final two models, in columns (4) and (5), every categorical increase in family income is related to a lower risk of food insecurity, holding the other variables constant. Having at least one adult working is also protective, even

[2] Military families in our CPS data report a 5.0% rate of food insecurity, with an additional 7.0% identifying as marginally food secure. Rates are 4.8% food insecure and 7.0% marginally food secure when using CPS-FSS weights.

holding income level constant; in the DOD sample, all individuals will de facto have at least one working adult (i.e., the service member). Risk factors include if the head of household is female (relative to male), non-white (relative to white), or divorced (relative to single). Those in their 30s have a higher risk than younger or older individuals; peak predicted risk is at 35 in the final model, holding other factors constant. The risk of food insecurity increases as the number of children in the household increases. In early models, having a child under age five is predicted to increase the chance of food insecurity. However, that risk is driven by employment patterns among those with young children; once we account for income and employment status in the final models, child age is no longer an additional risk factor. In the first two models, having an education level less than a high school diploma is associated with a higher probability of food insecurity, compared with those with a high school diploma. However, the military sample will not accrue this risk because all service members have at least a high school diploma.

Comparing models in columns (3) and (4), the coefficients on several variables decrease in magnitude once we control for income. For instance, the coefficient on having a college degree is cut in half. This occurs because college education is associated with higher income. When we statistically control for both education and income, we can somewhat separate the two relationships. However, even when statistically comparing two people with the same income (and other characteristics) in Models (4) and (5), those with a college degree have a lower predicted risk of food insecurity than those with only a high school degree. Overall, then, there are several factors—above and beyond income—that are associated with food insecurity, even after we statistically account for income and employment.

Takeaway 1: Having a larger family size and if the head of house is a woman, divorced, Black, or Hispanic are associated with a higher probability of being food insecure (risk factors).

Takeaway 2: Being from a military family, being married, having more education, and more income are associated with a lower probability of being food insecure (protective factors).

B. Q2: HOW SHOULD THE NAVY/MARINE CORPS DEFINE RISK OF FOOD INSECURITY?

This section outlines several potential methods for predicting the risk of food insecurity in the military.

1. 150% of the Federal Poverty Line

One potentially attractive tactic to define risk of food security is related to whether a household's income is below some multiple of the federal poverty level (FPL). SNAP and free school meals use 130% FPL for identifying eligibility and funding levels. Implicitly, this indicates that the federal government assesses that those below 130% FPL are at higher risk of food insecurity. The FY2022 NDAA used 130% FPL to identify which military families are eligible for the BNA, and the FY2023 NDAA updated it to a somewhat more generous 150%. The updated 150% level came into effect in July 2023 (Defense Finance and Accounting Service, 2023). Using this method, we identify a family as being at risk of food insecurity if their predicted family income falls below 150% FPL.

To be eligible for the BNA, they must have at least one dependent and earn less than 150% FPL. Almost no one in the military earns less than 150% FPL, with or without including BAH. In 2021, 5.6% of service members fell below 150% FPL when excluding BAH; the rate was 3.6% when adding imputed spouse income and 1.2% when also adding BAH. Many of those under the 150% FPL threshold had no dependents. As a result, we estimate that only about 0.3% of service members are eligible for the BNA – and that fewer than 0.1% of Navy Sailors are eligible.

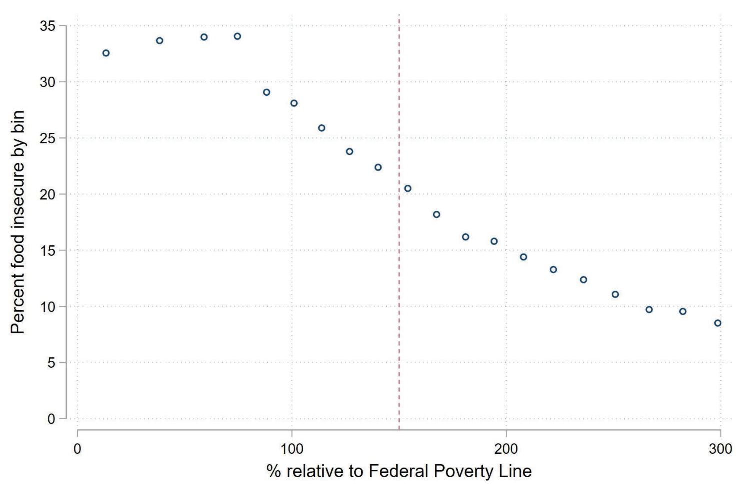
Table 2. Rates of income <150% FPL using various measures

	Category	Military pay without BAH	Add imputed spouse income	Add BAH and imputed spouse income
DOD	<150% FPL	5.6%	3.6%	1.2%
	And HH>1	4.5%	2.5%	0.3%
Navy	<150% FPL	4.0%	2.7%	1.2%
	And HH>1	2.8%	1.5%	0.1%

Notes: Fraction of service members/Sailors who fell into a given category (rows) by various wage measurements (columns) in 2021. BNA eligibility requires both an income under 150% FPL and at least one dependent (HH>1).

Takeaway 3: Few service members have income levels at or below BNA eligibility criteria.

We next assess whether having income below 150% FPL is a good marker of reported food insecurity. Figure 1 displays the fraction of civilians that report food insecurity by their income, relative to the federal poverty line, broken into 20 population-weighted bins for the bottom half of the U.S. population, relative to the poverty line. Each bin represents about 2.5% of the civilian population. The dashed vertical line indicates 150% FPL. The figure illustrates that 150% FPL is not a good indicator of food insecurity risk. The bottom five bins, representing about 12.5% of civilians, have incomes below 100% of the poverty line and have a 30–35% chance of being food insecure. As income increases relative to the poverty line, the likelihood of food insecurity among civilians declines, but remains substantial. At 150% FPL, about 20% are food insecure, and at 200% FPL, around 15% are food insecure. Given these patterns, using a sharp cutoff as a predictor of food insecurity — such as 150% FPL — misses food insecurity at higher income levels in the civilian setting, and, by extension, would likely understate food insecurity in the military setting. Thus, a policy guaranteeing income to 150% FPL is likely to provide no additional resources to many food-insecure families and will not substantially reduce nor eliminate food insecurity in the Navy or DoD overall.



Notes: For this analysis, we use the full CPS data instead of our preferred sample, such that the bins are representative of the U.S. distribution overall. Each dot represents approximately 2.5% of the unrestricted civilian sample, sorted relative to the FPL. The sample includes those below the 50th percentile. Civilian pay is assigned by randomly assigning a value within the individual's CPS pay bin, then converting to a percent of the poverty line based on their household size.

Figure 1. Fraction food insecure by federal poverty level in civilians (CPS data)

Takeaway 4: The FY2023 NDAA's method of eligibility for the BNA will not significantly reduce military food insecurity.

2. Budget-Based Method

For the budget-based method, we use the federal supplemental poverty measure (SPM) to identify the relevant poverty line for each civilian and service member's observed calendar year, family size, and metropolitan area. SPM approach allows for geographical differences in the cost of living and makes other improvements on the poverty-line approach described above. Appendix B provides additional details. Only 4.2% of service members earn less than 150% of their relevant supplemental poverty level in 2021. Like FPL, SPM is also not a strong indicator of food insecurity risk; a figure similar to Figure 1 that instead uses SPM has a slope similar to (see Figure 17 in Appendix A). Given these patterns in the civilian data, a sharp SPM cutoff for assistance in the military setting (e.g., 150% SPM) would not address those who are food insecure at higher income levels.

3. Machine Learning Prediction

The final method of identifying risk of food insecurity expands beyond family size and local cost of living to include more potentially relevant variables. To obtain a better prediction of food insecurity that is applicable to the entire military sample, we use the detailed CPS data to identify risk factors for and protective factors against food insecurity among civilians, using the detailed CPS data. This method can add additional important factors such as age or marital status into the model. Specifically, we use a Least Absolute Squares Selection Operator (LASSO) model to identify which of potentially hundreds of variables and variable interactions best predict food insecurity in the civilian setting.

We implement the LASSO model in increasingly complicated models, with Model (4) being the most comprehensive and our preferred model. See Appendix A for further discussion. For Model (4), we generate interactions between being from a military family, gender, age, race/ethnicity, education, marital status, number of children in the household, having a child under age five, local meal cost, local housing costs, local childcare cost, income bins, count of employed adults, and the continuous family income variable, as well as quadratics for non-dichotomous variables. This allows, for instance, the effect of each variable to differ across married and unmarried individuals. We also include fixed effects for year, state, number of children, and being in a non-metropolitan area. With so many interactions and fixed effects, any individual coefficient is very difficult to interpret, but in combination the model should predict the outcome with the greatest precision. The appendix contains more details on this model.

We have equivalent data points on the risk factors for and protective factors against food insecurity for service members based on the DMDC data. We apply the prediction algorithm generated from the LASSO model to the same characteristics among military families to calculate a risk score for each service member. If a factor increases food insecurity for civilians, the machine learning method assumes the same pattern occurs in the military sample. In this measure, the outcome will be a predicted probability for each service member's family, from 0% (there is *no* chance the family is food insecure) to 100% (this family is certainly food insecure) and the full range in between, thus allowing for more nuance than the previously shown dichotomous values. As we will see in the following section, the overall predicted rate of food insecurity for service members in 2021 was 6.9% under this method.

4. Summary of Methods

This research question is about how the Navy/Marine Corps should define the risk of food insecurity. Using a particular percent of the poverty line is easy and straightforward, but it is inaccurate. The budget-based method and machine learning strategies incorporate more factors but are also more difficult for the Navy to estimate. All three of these methods, however, are based on observable characteristics, which allow us to "war game" what would happen if we changed characteristics (e.g., increased income by a certain amount).

For ease and consistency with DOD and federal policy, the Navy and Marine Corps will likely continue to use the FPL definition to identify the risk of food insecurity. However, this measure is very rough and will understate the extent of food insecurity in the military. Supplementing that raw measure with survey data to get a more accurate picture of what service members and military families are experiencing will remain important. The LASSO model used in the remainder of this paper is likely outside the scope of day-to-day operations for the Navy.

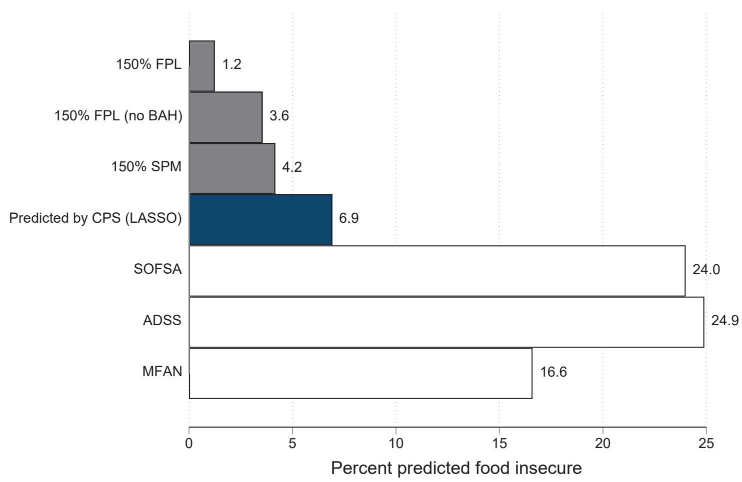
The final chapter of this report discusses some additional options not studied here.

C. Q3: HOW WIDESPREAD IS THE RISK OF FOOD INSECURITY, AND WHO IS MOST AT RISK OF FOOD INSECURITY?

We applied the predictions from the CPS data to the parallel DOD data (including estimated civilian spouse income). For instance, because families with more children are predicted to have a greater risk of food insecurity, larger military families receive a higher risk of food insecurity. Each individual in the DOD data is given a risk score of being food insecure from 0 to 100% based on their particular characteristics.

1. How Widespread is the Risk of Food Insecurity?

Figure 2 displays a summary of the predicted food insecurity risk by each of the methods in this paper, plus three additional, survey-based estimates of food insecurity from SOFSA, ADSS, and MFAN. In 2021, 1.2% of service members made less than 150% FPL, and only 3.6% made less than 150% FPL when we exclude BAH. Even with the SPM, which takes into account local costs, only 4.2% of service members made less than 150% SPM. As described above, we believe the FPL-based measures understate the risk of food insecurity. Using our preferred LASSO model approach, we estimate that 6.9% of the military was likely to be food insecure in 2021.[3]



Notes: Dark blue indicates our preferred LASSO model; gray indicates our other estimates; white indicates survey-based measures from others.

Figure 2. Predicted percent food insecure by different methodologies

Takeaway 5: We estimate that 6.9% of the military is at risk of food insecurity.

[3] We get similar estimates for LASSO Models (2) and (3), with predicted rates of 4.1% and 3.9%, respectively, in 2021 (see Appendix). The LASSO rate is 7.5% over the full period (2013-2021). The predicted rate is 16.8% if we include those who are marginally food insecure.

These numbers are lower than those identified using survey methods (L'Esperance et al., 2022).There are several potential reasons for the divergence between our preferred LASSO-based estimate and the survey estimates. First, survey-based estimates can be biased if the people who respond to the surveys are not representative of the larger population. The sample of active duty and spouses who are willing to respond to a survey may differ from the average service member. Someone experiencing food hardship may be more likely to respond to a survey asking about their experiences with being able to afford food, and to the extent that this occurs the surveys will overstate the prevalence of food insecurity in the DOD. Junior enlisted may be more likely to respond to surveys, and because they earn less, they are more likely to be food insecure. However, it is possible to re-weight surveys to account for differences in response rates across factors like rank. With this in mind, when we limit the CPS LASSO predictions to include only junior enlisted (E1-4), our estimate is 10.9%, but this rate is still lower than the survey estimates (see Appendix A). However, surveys cannot be adjusted to account for, say, if a certain *type* of junior enlisted is more likely to respond, unless there is additional information on differences among junior enlisted respondents/non-respondents.

Another factor is the CPS civilian data come from live interviews, which generally report lower rates of food insecurity reported than computer or paper surveys not administered by a person (Karpman et al., 2018).

Finally, there may be differences between civilians and military individuals that we did not capture in our methods. Imagine a civilian and a service member with the same income, demographic, geographic, and all other characteristics included in the model. If the civilian has more outside support available than the service member, and we did not capture those unobserved protective factors in our model, we would systematically underestimate the risk to the service member. However, we know of no civilian programs that are also not available to service members in the income range we study, so this seems unlikely to drive the patterns. Moreover, if service members are more disciplined in their money management than civilians with the same characteristics, or if there are more opportunities for support for service members, then our LASSO estimates will overstate the risk of food insecurity.

2. Who Is Most at Risk of Food Insecurity in the DOD?

The topline numbers mask heterogeneity by a variety of characteristics: whether it's a location that receives COLA, local cost of living, grade, branch of service, family size, and marital status. DoD provides COLA if the non-housing cost of living for a given area is at or above 108% of the CONUS average. Service members assigned to a zip code that received COLA in September 2021 are designated as receiving COLA; the rest are not. Separately, we use the regional price parity index to identify low, middle, and high cost of living locations. Locations at or below 92% of the national price average are defined as low-cost areas; those at or above 108% are defined as high-cost areas.

Figure 3 displays the predicted percent risk of food insecurity using the status quo definitions available under the FY2023 NDAA (150% FPL and, with SECDEF approval, 150% FPL excluding BAH) and the LASSO-based model. Non-COLA locations are more at risk of food insecurity across all measures, though very few are under 150% FPL. Rates generally do not differ by cost of living based on the regional price parity measure.

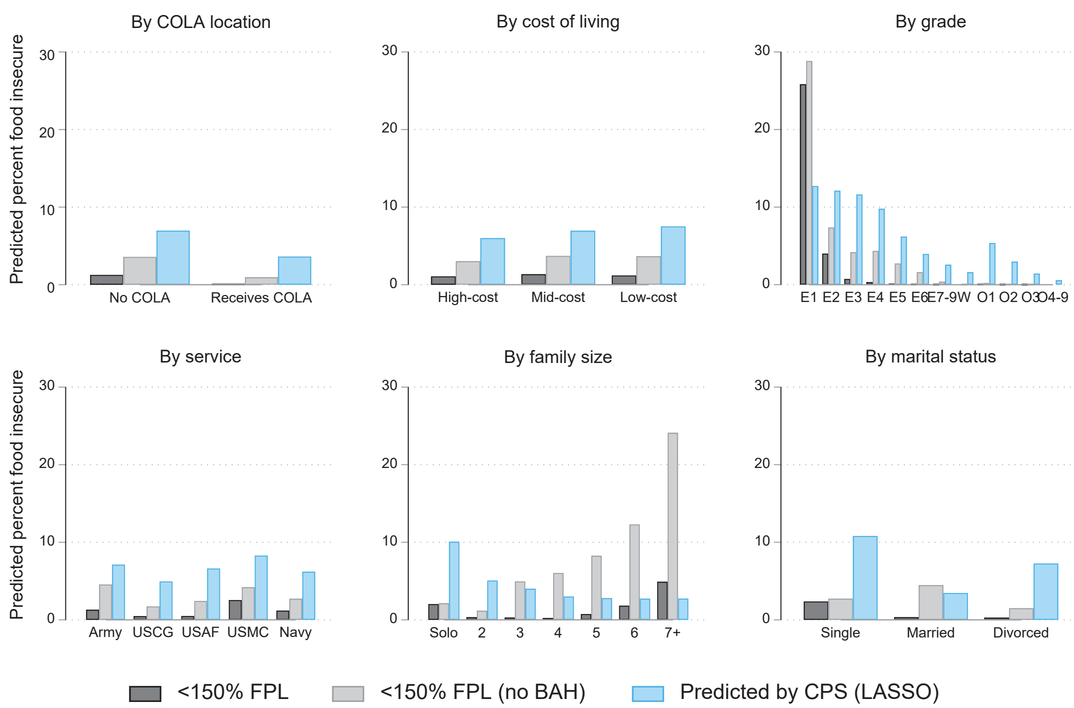


Figure 3. Percent of service members at risk of food insecurity by various characteristics

Rates are highest among junior enlisted, with around 25% of E1s having an annualized wage that is below 150% FPL. Moving up the ranks, the percentage drops quickly across the FPL-based measures, while the more nuanced LASSO model predicted rates around 10.9% among junior enlisted. Marines have the highest predicted probability across services. Family size presents a slightly different picture. Because the federal poverty line automatically goes up with family size, but income does not, very large families are most likely to be below 150% FPL. Thus, under the FY2023 NDAA, it is very large families who are most likely to qualify for the BNA. If BAH was removed from the BNA qualification calculation, in 2021, around 24% of families with seven or more members would have qualified at 150% FPL, while the LASSO model only predicts about a 2.7% rate of food insecurity for these large families. Finally, divorced individuals are predicted to be more at risk of food insecurity than those married in the LASSO model; the FPL-based measures reverse this because they are based on family size and don't consider the additional differences between married and divorced individuals.

Of course, there are very few families with seven or more members, and most families are not divorced. Appendix A includes a figure with the count of individuals predicted to be food insecure across categories. The highest count of individuals at risk of food insecurity are single service members because there are many more of them than there are service members with 7+ family members. Similarly, the Army has more people at risk of food insecurity simply because it is the largest branch, and E3 and E4 are the most common grade for food insecurity risk because there are many E3s and E4s.

Appendix A explores these patterns for the Navy. Predicted risk of food insecurity is higher in certain locations. Appendix A includes the top 10 DoD and Navy counties.

D. Q4: WHAT POLICIES MOST EFFECTIVELY MITIGATE THE RISK OF FOOD INSECURITY?

Many potential policy solutions could reduce the predicted risk of food insecurity for military families. We conduct a simulation exercise to examine potential policy solutions: the BNA approved in the NDAA, a change in the BNA to exclude BAH, an increase in the COLA adjustment, a COLA-based BNA, a per-child Dependent Allowance, an increase in spouse employment, an increase in enlisted pay, and expanded SNAP eligibility. We chose these policies because they are straightforward and relatively easy to implement with data already on hand. We simulate what the predicted risk of food insecurity would have been in 2021 if a given policy had been in place. We choose 2021 because it is the most recent year that is available. This simulation allows us to compare the cost of a policy against how much it changes the predicted risk of food insecurity. The most cost-effective policy would target those most at risk of food insecurity. An ineffective policy would either not provide enough support or provide supplements to families unlikely to face food insecurity. We review the potential policies below.

1. Adding the Basic Needs Allowance

We first simulate increasing pay to 150% FPL for those who had fallen below that threshold. For simplicity, we assign everyone below the given level this additional BNA, though this is perhaps an overestimate of the true take-up, since the real policy requires applications and paperwork. These bureaucratic hurdles may limit take-up, so we consider this an upper bound for the per-person benefits and potential reduction in risk of food insecurity. We run the simulations with and without BAH. Excluding BAH from the income calculation would provide more money to more service members, but it would also cost more. Appendix A includes models in which we change the FPL threshold used, allow single service members to receive BNA, or use the SPM instead.

2. Adding a Dependent Allowance

The next set of simulations replaces the BNA with a dependent allowance for enlisted families. For the first dependent allowance, we provide a fixed additional benefit per household child under the age of 18. We use a policy of $2,000 per dependent. Appendix A explores a range of potential benefits, though we keep the benefits standard per child for simplicity. Implementation could instead limit the number of beneficiaries or decrease the benefit per child for each additional child (e.g., 100% of the benefit for child 1, 80% for child 2, and so on). We model a second dependent allowance on the civilian WIC program, providing a bonus for each child under age five, as well as for female spouses or enlisted individuals who have added a dependent in the last year. We do not provide a bonus for pregnant women, mainly because we do not observe pregnancy. For both allowance types, we limit eligibility to enlisted only, and dual military families only receive one bonus per child.

3. Increasing COLA

For a COLA simulation, we use regional price parity (RPP) as an alternative measure of local cost of living. RPP indicates how local costs relate to the national average, with a range in our data from 80.9% of the national average in the lowest-cost location to 119.8% in the highest-cost location. In theory, the DoD could use RPP to identify a wider range of high-cost locations. We simulate this alternative COLA adjustment in two ways. First, we adjust all basic pay by the RPP, and basic pay would decrease in low-cost areas, so that someone living in the lowest-cost place would make 80.9% of their years-of-service/rank's basic pay and someone in the highest-cost places would make 119.8% of their basic pay. We implement a second COLA simulation that only makes the basic pay adjustment for those above the national average RPP (that is, no basic pay would decrease but it would increase in locations with RPP > 100%).

4. Increasing Spouse Employment

Next, we implement a simulation that increases civilian spouse employment and labor force participation rates to the levels observed among prime-age adult civilians in August 2023, applied separately for men and women civilian spouses. In other words, we simulate based on the assumption that spouses married to service members have the same employment probabilities as same-gendered civilians in the general population.

5. Increasing Enlisted Basic Pay

We next implement a simulation that increases enlisted pay based on a new pay scale proposed by a United States House subcommittee in June 2023 for the FY2024 NDAA (National Defense Authorization Act for Fiscal Year 2024, 2023). The draft bill changed the E1-6 wage scale, with junior enlisted basic pay increasing over 30% (Kheel, 2023). The proposal is not in the current FY2024 NDAA draft. To implement the simulation, we take the proposed changes to the FY2023 pay scales listed in the proposal, assign them to each individual based on their grade and time in service in a given month, remove the 2.7% and 4.6% pay increases in 2022 and 2023, respectively (Bushatz, 2022), and then sum up the prior twelve months' pay to get the estimated pay for September 2021. In other words, this simulation approximates what wages would have been in 2021, if the proposed wage scale had always been in place. We use the same estimated civilian spouse wages as the main simulations but make the proposed adjustments for military basic pay.

6. Expanding SNAP

Finally, we implement a simulation where everyone receives SNAP benefits according to the SNAP benefit formula, ignoring the maximum (gross) income test where it applies. We do not include BAH in the calculation of wages. We then add any projected SNAP benefits as additional income.

7. Comparing Across Policies

Figure 4 displays the simulated effects of the various policies overall (Panel A) and for junior enlisted (Panel B), as well as the projected cost of the policy (Panel C) in 2021. For reference, it includes the LASSO prediction with no policy changes in blue. The BNA will have no effect on predicted risk of food insecurity, both because few people qualify and because those that do will receive little money relative to their current pay. A $2000/dependent allowance, whether for all children or modeled after WIC, is predicted to slightly reduce the risk of food insecurity at a cost of over $1 billion per year. Changing COLA across all levels of RPP (i.e., moving basic wage up or down depending on location) would not substantially change the net risk of food insecurity, though it would save over $0.5 billion in basic pay due to lower pay costs in low-cost locations. Having a COLA policy for places above the average regional price parity levels would decrease predicted food insecurity levels from 6.9% to 6.8% (10.9% to 10.8% for junior enlisted) at a cost of around $1.5 billion per year. Increasing spouse employment to general civilian levels would not cost the DoD anything in direct dollars, though DoD may need to spend additional money on programs to increase spouse employment. The simulation predicts that such an increase in spouse employment would have resulted in a 6.5% rate of food insecurity across the DoD in 2021 (10.4% for junior enlisted). The enlisted pay proposal does not change predicted food insecurity rates, but it does cost $2 billion. Finally, imputing universal receipt of SNAP to all service members under the income calculation will have little effect on food insecurity at a cost of $64 million to the USDA.

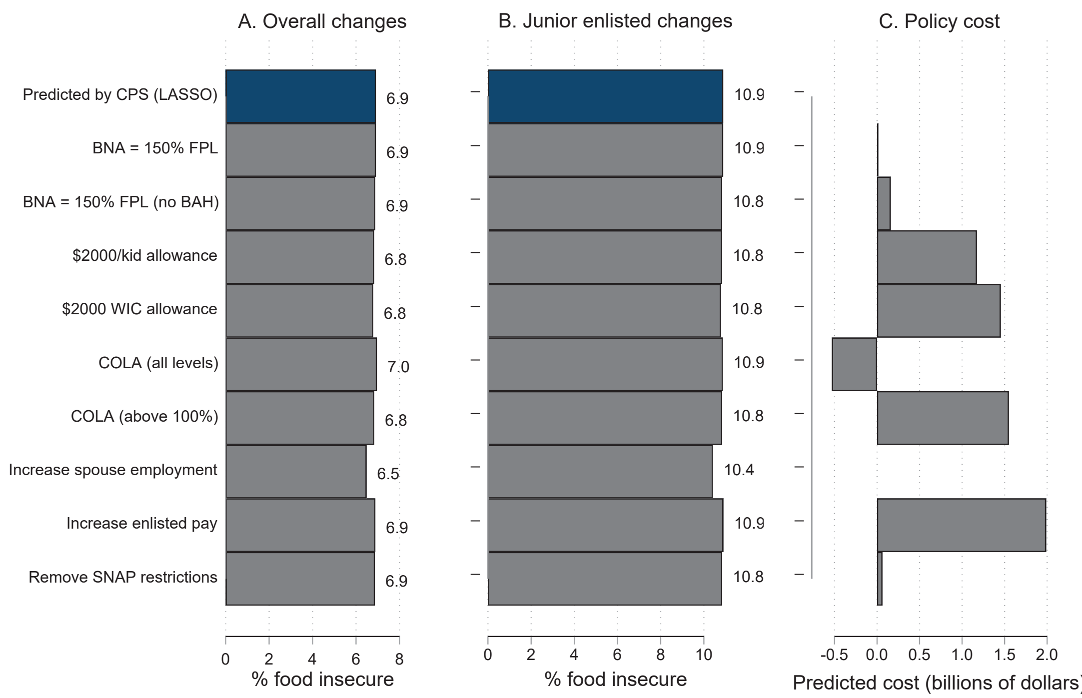


Figure 4. Projected effects of various policies (LASSO simulation).

Food insecurity rates persist even well above the poverty level in civilian settings. The wargaming conducted here projects that food insecurity is also likely to persist, even with generous increases in military benefits. By way of comparison, some policies are less money-focused. Imagine everyone in the military had a BA and was at least 22 years old, for instance (and nothing else changed, which is an unlikely assumption). Then, predicted rates would drop to 4.2% (6.5% among junior enlisted). Requiring a BA to serve is infeasible for a variety of reasons but highlights that money alone may not solve food insecurity in the military.

Takeaway 6: Moderate increases in benefits or income will not eliminate food insecurity.

V. CONCLUSIONS

We use civilian data to identify factors associated with food insecurity in the civilian setting, use a machine learning model to predict rates of food insecurity using the same characteristics in the DOD data, and then wargame various policies to evaluate how they would be expected to change the risk of food insecurity. There are six major takeaways from this research:

- Takeaway 1: Having a larger family size and if the head of house is a woman, divorced, Black, or Hispanic are associated with a higher probability of being food insecure (risk factors).
- Takeaway 2: Being from a military family, being married, having more education, and more income are associated with a lower probability of being food insecure (protective factors).
- Takeaway 3: Few service members have income levels at or below BNA eligibility criteria.
- Takeaway 4: The FY2023 NDAA's method of eligibility for the BNA will not significantly reduce military food insecurity.
- Takeaway 5: We estimate that 6.9% of the military is at risk of food insecurity.
- Takeaway 6: Moderate increases in benefits or income will not eliminate food insecurity.

This work should not be interpreted as a reason to give up hope of eliminating food insecurity in the military. Instead, the results indicate that food insecurity is a multi-faceted issue that will not be solved with money alone.

Though current BNA policy is unlikely to meaningfully reduce food insecurity in the military, the DOD could pursue a variety of tactics. First, it remains unclear what unique military factors are driving rates of food insecurity. For instance, Asche et al. (2023) found that service members were often supporting extended family members back home. More research—including directly interviewing service members at risk of food insecurity—is necessary. Research should examine whether military respondents, with their unique lifestyles, interpret the six-item USDA food security survey used by the SOFSA and ADSS differently than civilian respondents, and whether the peculiarities of military life may inflate positive responses on that survey. For instance, if an individual has access to a dining facility, how do they interpret questions about having enough money to buy more food?

Dining facilities may be an area of intervention. During this research, a variety of individuals mentioned difficulty for people in barracks to use the dining facilities, either due to the hours of the facility (compared to the hours of work) or the location of the facility (far from work or barracks). Dining facilities should be open at hours and locations that are convenient to service members' schedules.

Another option is creating a risk score index for service members as they arrive at a new command. In the Navy, this could be managed by Fleet & Family Support Centers. Developing, implementing, and assessing such a risk score could be a useful exercise for a future study. The USDA already has its short-form food questionnaire, which could be adapted at intake. Alternatively, the Navy could develop a risk index that, say, gives each service member a score based on their observed characteristics (e.g., age, marital status, number of dependents) and provides more directed support to those deemed as most at-risk. Such a measure would need to be validated and tested in future work.

Military members—and their families—should not face food insecurity. The current BNA will not change much about current rates of food insecurity. Indeed, small tweaks to pay are unlikely to have a meaningful effect on rates of food insecurity. Instead, a more comprehensive approach to food insecurity is needed.

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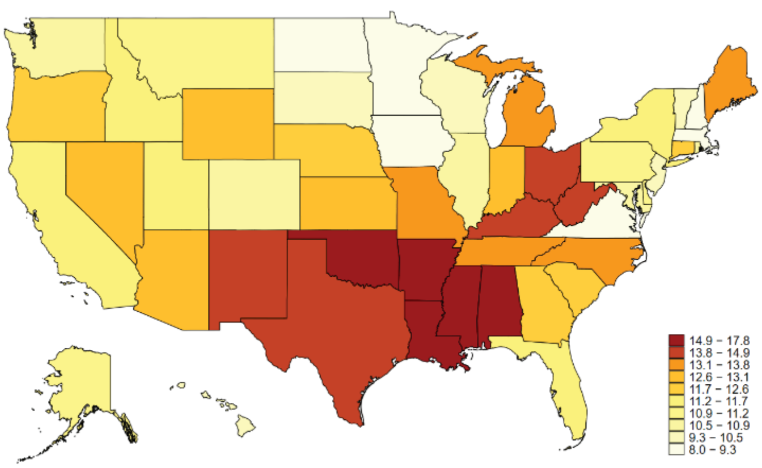
APPENDIX A. ADDITIONAL BACKGROUND, DATA, METHODS, AND RESULTS

A. GEOGRAPHIC DISTRIBUTION OF CIVILIAN FOOD INSECURITY RATES AND COST OF LIVING

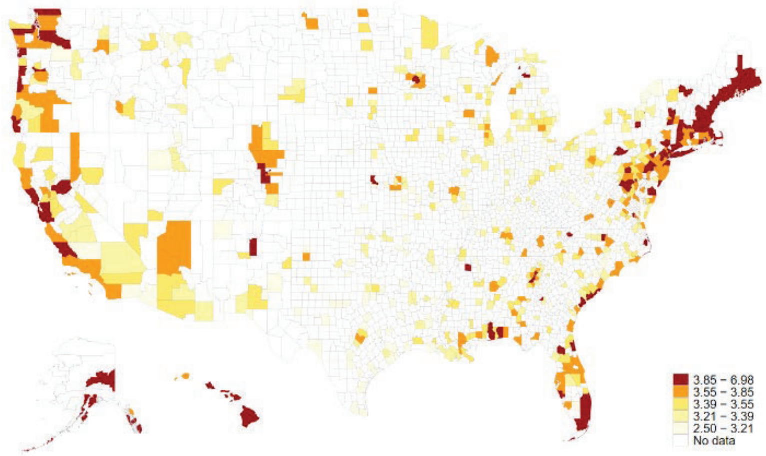
Figure 5 displays the distribution of food insecurity calculated from 2010-2021 based on the CPS data. We will use factors that predict food insecurity among civilians to predict food insecurity in the military. For instance, there are higher rates of food insecurity in the south and southwest regions of the country (Bonanno & Li, 2015; Coleman-Jensen et al., 2022; Gundersen et al., 2021). Large cities and rural areas also have higher rates of food insecurity than the national average (Bonanno & Li, 2015; Coleman-Jensen et al., 2022). Higher food prices and housing costs are associated with higher food insecurity (Gregory & Coleman-Jensen, 2013), which may explain some of the geographic variation.



Source: Calculated by author from primary CPS data.

Figure 5. Average food insecurity by state in 2010-2021.

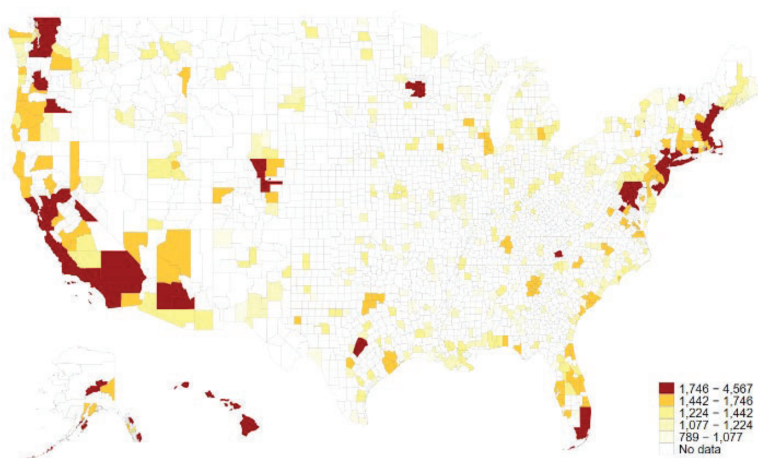
One important factor in predicting food insecurity is an individual's local cost of living. A variety of expenses differ by geography, and troops are often stationed in high-cost areas. The following figures display the distribution of various costs of necessities among counties with at least five active-duty service members in September 2021. Figure 6 displays the average cost of a meal by county (Feeding America, 2022). Several patterns stand out. First, there are many counties without service members in 2021; these are displayed in white. Second, the highest meal costs are along the western, northeastern, and Florida coastline, as well as a few sporadic inland areas in the mountain west.



Source: Calculated by author from Feeding America (2022) data.

Figure 6. Average meal cost by county in 2021.

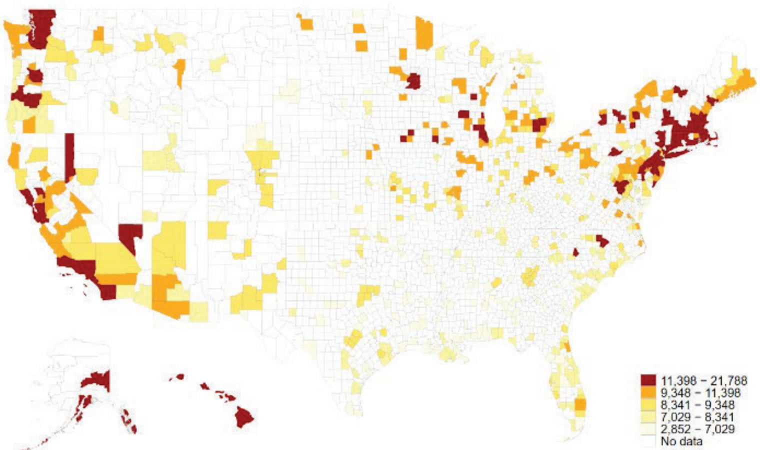
Figure 7 displays the average fair market rental cost of a 3-bedroom house. The fair market rental price is defined as the 40th percentile of rental costs; HUD defines these for 0-, 1-, 2-, 3-, and 4-bedroom homes by metropolitan area each year. Housing rental costs are highest along the western, northeastern, and Florida coastlines, as well as a few sporadic inland areas in Texas, the upper Midwest, and the West.



Source: Calculated by author from the Office of Policy Development and Research at the Department of Housing and Urban Development (2023) data.

Figure 7. Average monthly fair market rental cost of a 3-bedroom house by county in 2018

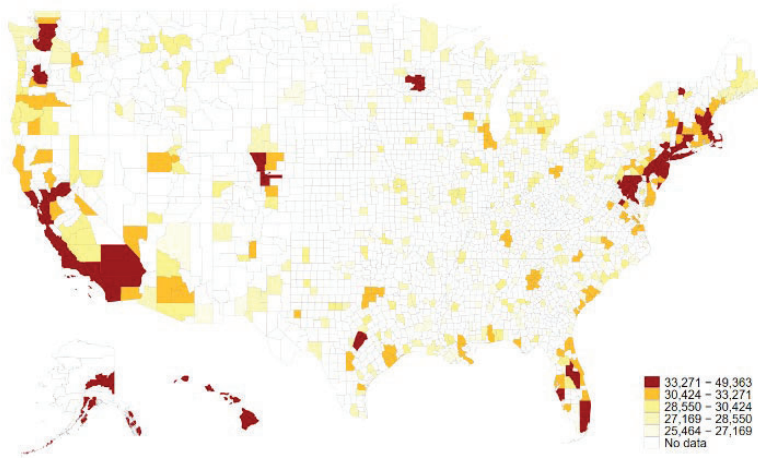
Figure 8 displays the cost of childcare for toddlers in 2018, which is the most recent data available (Women's Bureau, Department of Labor, 2020). Colorado, Indiana, New Mexico, and some counties in other states did not provide data. For any county missing data, the chart uses the state's average cost (weighted by DOD population); for states missing data, we uses the national average. Childcare costs are highest along the western coastline, the urban northeast, and a few sporadic inland areas in the upper Midwest.



Source: Calculated by author from the Women's Bureau at the Department of Labor (2020) data.

Figure 8. Average annual cost of toddler care by county in 2018

Finally, Figure 9 displays the annual poverty threshold level calculated for the Census Bureau's Supplemental Poverty Measure (SPM) for households with two adults and two children (Creamer et al., 2022; Fox & Burns, 2021; U.S. Census Bureau, 2021). Unlike the official poverty measure, which does not vary within the 48 contiguous states, the SPM accounts for local differences in cost of living and reflects that the level of income to be out of poverty differs in high- and low-cost areas. The SPM threshold is highest along the western, northeastern, and Florida coastlines, as well as a few sporadic inland areas in Texas, the upper Midwest, and the West.



Source: Calculated by author from U.S. Census Bureau (2021) data.

Figure 9. Supplementary poverty threshold for a 2-adult, 2-child household by county in 2018

In sum, the maps indicate that costs for a variety of household necessities vary by geography. If geographic variation in military pay does not adequately account for differences in cost of living, we would expect to find higher rates of food insecurity in high-cost areas.

B. PROGRAM ELIGIBILITY REQUIREMENTS

A variety of civilian and military-specific programs seek to reduce households' and individuals' rates of food insecurity. A recent RAND report provides a broad background in eligibility rules for several food assistance programs (Asch et al., 2023), which it turn, were derived from several civilian sources (Food and Nutrition Service, USDA, 2021; GAO, 2016; Golfin et al., 2020; Hoynes & Schanzenbach, 2016). The Supplementary Nutrition Assistance Program (SNAP) and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) are the two largest programs targeting food insecurity in the United States. SNAP generally provides additional resources for food to households with total incomes below 130% of the federal poverty line (130% FPL) and net incomes (e.g., after deductions for certain expenses) below 100% FPL for their net income.[4] This calculation does not count in-kind housing as part of income, but it does count the military's Basic Allowance for Housing (BAH). This

[4] SNAP also limits the amount of financial resources a household can have available and includes work requirements. Some states have raised the FPL threshold levels, meaning that by states the eligibility level is between 130% and 185% FPL. For further information on these programs or information about the National School Lunch Program or the School Breakfast Program, see the RAND report.

distinction means that many military families receiving BAH are ineligible for SNAP (Asch et al., 2023; London & Heflin, 2015). WIC, on the other hand, has a higher income limit at 185% FPL and does not count BAH as income, but is limited to expectant and postpartum mothers and children ages zero through four (Asch et al., 2023; Hodges & Todd, 2023). The higher income threshold and exclusion of BAH from the income calculation allows more military families to access WIC than SNAP. About a third of DoD and Coast Guard families with children five and under report ever using WIC (Asch et al., 2023).

The DoD's Family Supplemental Subsistence Allowance (FSSA) program provides supplementary income to lower-income service members. The program was substantially curtailed in 2016, after a report found that it was poorly advertised, required application through the chain of command, removed people from SNAP eligibility, and included BAH in its eligibility (Bushatz, 2022; Military Compensation and Retirement Modernization Commission, 2015). Today, FSSA is limited to families serving abroad. The eligibility threshold is 130% FPL, and it includes both BAH and the cash equivalent of in-kind housing as income. Further, the service member must have at least one dependent. In practice, only 92 members received FSSA in FYs 2015-19 (Asch et al., 2023).

The newest DOD-run assistance program is the Basic Needs Allowance (BNA), which was created in the FY2022 NDAA. The DOD originally used a gross income of 130% FPL as the BNA eligibility threshold, but the FY2023 NDAA increased the threshold to 150% FPL as of July 2023 (National Defense Authorization Act, 2022; Defense Finance and Accounting Service, 2023). The allowance allocates additional monthly pay to bring the service members' gross household income up to the threshold FPL for service members with at least one dependent. Service members without dependents are ineligible. Like SNAP and FSSA, BNA includes BAH as part of the income calculation, although the statute allows the Secretary of Defense to exclude any portion of the BAH from a household's income for service members who reside in areas with a high cost of living (37 USC § 402b, 2022). If eligible, the monthly BNA payment is the difference between the current year's BNA eligibility threshold and the preceding year's gross household income, divided by twelve.[5]

In practice, very few military families qualify for the BNA: under the 130% FPL guideline, the Navy, Marine Corps, Air Force and Space Force combined identified 85 service members who may have been eligible (Jowers, 2023). Military family advocates argue that the BNA should exclude BAH to increase access to the benefit (Bushatz, 2022). Table 2 summarizes SNAP, WIC, FSSA, and BNA eligibility.

Table 3. Food Assistance Program Eligibility Criteria

PROGRAM	INCOME LIMIT	FAMILY REQUIREMENTS	TREATMENT OF HOUSING ALLOWANCE
SNAP*	130% FPL (gross); 100% FPL (net)	Household unit is determined by the number of people who live and prepare food together	BAH is treated as income; in-kind housing is not counted as income
WIC	185% FPL	Pregnant or postpartum women, infants, and children under age 5 are eligible	BAH is not counted as income
FSSA	130% FPL	Military personnel must have at least one dependent and live overseas	BAH and cash equivalent of in-kind housing are counted as income
BNA**	150% FPL	Military personnel must have at least one dependent	BAH is counted as income

*Notes: *Federal guidelines for SNAP. States can make the program more generous. **Based on FY2023 NDAA. Sources: Table 2.2 from Asch et al. (2023); FY2023 NDAA.*

C. DATA

1. Federal Data

As an additional measure of the local cost of living, we use the Regional Price Parity (RPP) level from the Bureau of Economic Analysis (BEA). This measure provides an estimate of the price differences across metropolitan regions (U.S. Bureau of Economic Analysis, 2022). For non-metropolitan areas, we use the state RPP.

The Department of Housing and Urban Development (HUD) provides housing cost estimates by number of bedrooms, county, and year (Office of Policy Development and Research, Department of Housing and Urban Development, 2023). Specifically, the fair market rental (FMR) rate is the estimate of the 40th percentile rent for a standard unit within the metropolitan region. For any region missing data, we apply the state average.

[5] For instance, if the relevant 150% FPL level for the current year is $45,000, and the gross household income was $39,000 last year and $41,000 this year, the service member would receive a BNA of ($45,000-$39,000)/12=$500 per month. See https://www.dfas.mil/MilitaryMembers/payentitlements/bna/ for details.

For all families, we assume those without children will have a one-bedroom rental, those with one child will have a two-bedroom, those with two children will have a three-bedroom rental, and those with more than three children will have a four-bedroom rental. We do not differentiate the number of bedrooms or quality by officer status. We give a housing cost of zero to service members for whom the DOD has provided housing.

The Women's Bureau at the Department of Labor (2020) provides average childcare prices by county. For any counties missing data (many of which are in Missouri, Alaska, and Hawaii), we apply the state average. For states missing data (Colorado, New Mexico, and Indiana), we apply the national average. We use the 2018 data for all years. Notably, this is the civilian cost data, which is likely substantially higher than the DOD-subsidized childcare available at DOD-run Child Development Centers (CDCs) or through various childcare support programs.

2. Map the Gap

Map the Gap estimates the cost of food for each county in the United States by applying local tax rates to Neilson market basket prices for the county (Feeding America, 2022). This produces an estimated cost per meal (from a grocery store).

3. Military Earnings

We have direct data on all sources of DoD payments to active-duty individuals from 2012-2021. We include basic pay, bonus pay (e.g., language bonuses), and allowances such as the basic allowance for housing (BAH) and the basic allowance for subsistence (BAS).[6] Active-duty individuals who are in the United States and are not provided government housing (e.g., barracks) are provided BAH; the amount of BAH provided is based on rank, whether the member has dependents, and the zip code of their permanent duty station. BAS is meant to cover the meal costs of service members but not their dependents. BAS is adjusted annually based on the USDA food cost index, and it is higher for enlisted than officers. In 2018, for instance, officers received \$254.39 per month, while enlisted received \$369.39 per month. Service members do not get BAS while the government provides them with meals on deployment or during field-training exercises.

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[6] See: https://militarypay.defense.gov/Pay/ for more information on basic pay, special and incentive pays, and allowances.

Because monthly pay can be somewhat idiosyncratic and because the BNA is based on a year's income, we sum the prior months' annual income (October-September) to obtain annualized income. If a person has been in service for less than 12 months, we take the available data and annualize; for instance, we would sum all available pay data for a service member with four months of service and multiply by three to annualize the pay. This method will be less noisy than multiplying every month by 12, but it also allows for more data than requiring that we sum data for 12 consecutive months. In particular, most service members promote from E1 by 12 months, so requiring at least 12 months of data would prohibit us from looking at E1 earnings.

4. Predicting Civilian Spouse Earnings

We do not have income data for the *family members* of military service members. For unmarried individuals, we assume the only income comes from the service member's military pay. For dual military families, we link spouses' total income and assume the only family income comes from their combined military pay. We keep both individuals in the data so that the data is at the service member level, not the family level. For service members married to a civilian, we take several steps:

1. Assume the civilian spouse has the same level of education as the military member (high school, some college, or college).
2. Assume that 64% of civilian spouses are in the labor force, which has been a relatively consistent rate over recent years (OPA, 2022a). Impute civilian spouses' employment status by randomly assigning employment to 64% of civilian spouses.
3. Among civilian spouses randomly assigned to be in the labor force, randomly assign a subset to be unemployed, based on ADSS estimates by year and grade (OPA, 2022a).[7]
4. If randomly assigned to be working, assume that the spouse makes the median civilian weekly full-time earnings from the third quarter of the given year, based on the education level of the service member.[8]
5. Annualize the civilian spouse pay by multiplying by 52.

[7] We 2015 estimates for 2015 and earlier, 2017 for 2016-2017, 2019 for 2018-2019, and 2021 for 2020 and later. We use O4-6 numbers for officers above O6. In 2021, 31% of E1-4, 20% of E5-9, 18% of O1-3, and 15% of O4-6 were unemployed (OPA, 2022a).

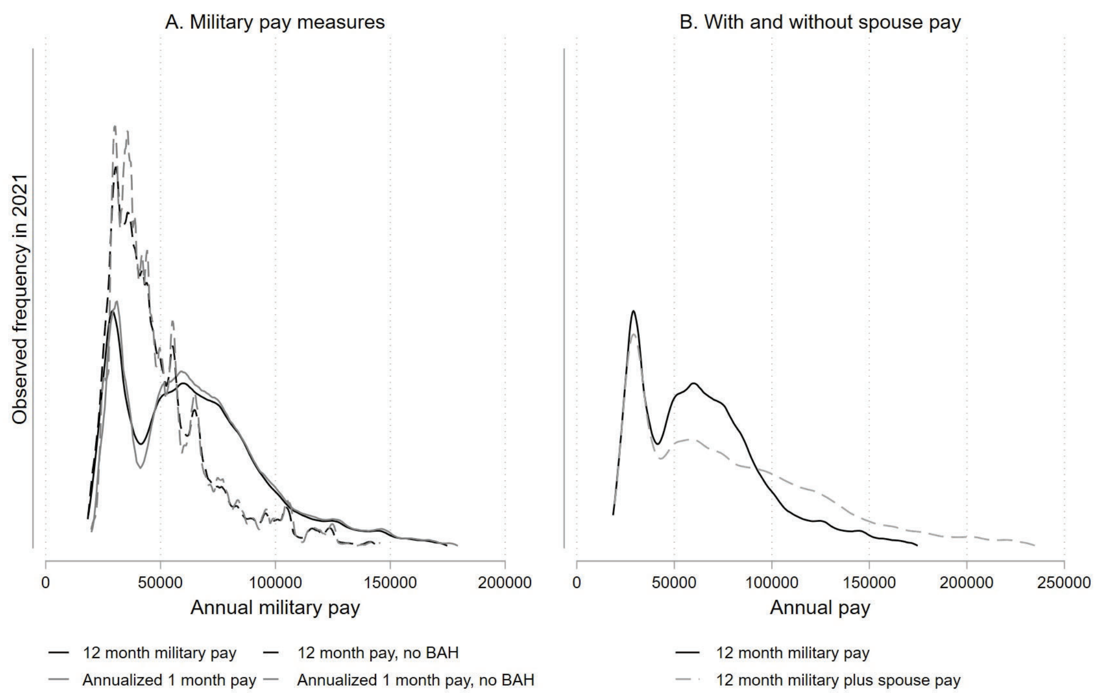
[8] See usual weekly earnings over time by education at https://www.bls.gov/charts/usual-weekly-earnings/usual-weekly-earnings-over-time-by-education.htm.

6. Combine the service member pay (based on twelve months of annualized pay) and civilian spouse pay to get total annual family pay.
7. If not assigned to have a working spouse, assume the only income comes from the service member's military pay.

Note that this method will certainly have errors, does not allow for underemployment or differences in employment probability by education level, and does not allow for nuance in, say, probability of employment by whether a family has recently had a permanent change of station (PCS). We are likely to be incorrect in the estimate for any given individual family, but on net these individual-level errors will even out as we estimate a population-level risk of food insecurity. Despite drawbacks, incorporating spouse pay provides a more realistic assessment of the resources available to provide food for a family than only including military pay.

Panel A of Figure 10 displays the range of predicted annualized military 2021 pay using various measures, limited, for readability, to the range from the first to the 99th percentile for each measure. The one-month method multiples the income in September by 12, while the 12-month method uses the actual, observed prior months of data. The one-month and 12-month methods produce very similar results, with somewhat less noise from the 12-month version. Panel B displays the range of predicted 2021 pay using our preferred 12-month method with and without including the estimated civilian spouse pay. The solid black lines are the same in Panels A and B. Mean (median) estimated family pay is \$80,702 (\$71,760), with a fifth percentile of \$24,496 and a 95th percentile of \$183,039. Moving forward, we exclude any military families who have an annualized family income less than \$15,000 (about 0.7% of the data) and top-code high earners to the 99th percentile.[9]

[9] Very low or even negative values can appear as fixes to accounting errors (e.g., a large one-time negative pay period if a service member had been overpaid) or if a service member has been court martialed with docked pay (Department of Defense, 2001). We winsorize the data to set the top 1% of earners at the 99th percentile.



Notes: Excludes minimum and maximum 1%.

Figure 10. Distribution of various pay estimates for 2021

Figure 11 displays the military pay of service members by various characteristics. The dark gray segment of the bar is the average annual service member pay excluding BAH, the light gray segment is the average annual BAH, and the light blue adds the estimated spouse pay, such that the total bar height is the estimated total household income. Notably, service members in locations that receive COLA generally earn more for their military pay, their BAH, and their estimated total family income. High-cost areas (defined by the BEA's RPP measure) also receive higher pay and BAH than low-cost areas. As expected, given the formulaic pay structure in the DOD, wages increase with grade. The Coast Guard and Navy are the highest paid, while the Marines are the lowest-paid branch. Generally, pay increases with family size, both because BAH increases with the first dependent and also because marriage and birth tend to happen as individuals move up the ranks. Similarly, married and divorced individuals receive higher pay, on average, than single members.

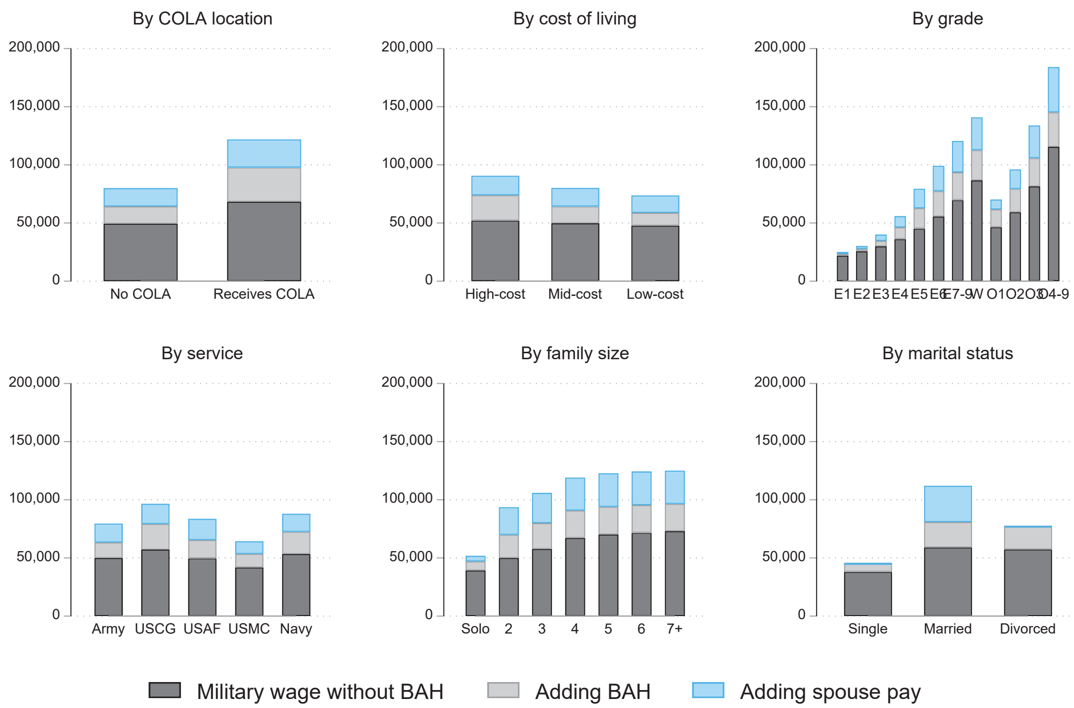


Figure 11. Mean service member pay without BAH, with BAH, and with spouse pay by various characteristics.

We convert the family wages to the family income bins used by CPS to create equivalent variables across the military and civilian datasets. The most common bin was \$60,000-\$74,999 for military pay and \$75,000-\$99,999 when including predicted family income.

Table 4. Military-only and predicted total family income by CPS income bins.

	Military Pay	Total Predicted Family Pay
<\$20,000	2%	2%
\$20,000-24,999	7%	7%
\$25,000-\$29,999	10%	10%
\$30,000-\$34,999	6%	6%
\$35,000-\$39,999	5%	4%
\$40,000-\$49,999	13%	9%
\$50,000-\$59,999	14%	9%
\$60,000-\$74,999	18%	12%
\$75,000-\$99,999	15%	17%
\$100,000-\$149,999	9%	17%
>\$150,000	1%	7%

Notes: Displays proportion of wage type falling into each CPS income bin in 2021 for the military sample.

5. Summary Statistics

Table 5 displays the mean characteristics of observations in our primary civilian and military samples. To make the civilian data as comparable as possible to the military data, we limit the sample to those ages 18-50 who are not living in group quarters, with at least a high school diploma, where at least one adult in the family is working, and with incomes greater than $15,000 per year (because the extremely low-income civilians are not representative of the military population). In the CPS survey, 9.8% of the subsample were food insecure (low or very low food security); 90.2% were food secure (high or marginal food security).

Table 5. Descriptive characteristics of primary civilian and DOD samples

	Civilian (CPS)	**DOD**
N	476,535,172 (97.8%)	10,620,605 (2.2%)
Food security status		
High food security	393,518,649 (82.6%)	NA
Marginal food security	36,129,907 (7.6%)	NA
Low food security	32,192,160 (6.8%)	NA
Very low food security	14,694,455 (3.1%)	NA
Family type		
Civilian	468,723,638 (98.4%)	0 (0.0%)
Military	7,811,534 (1.6%)	10,620,605 (100.0%)
Gender		
Male	248,323,419 (52.1%)	8,942,200 (84.2%)
Female	228,211,753 (47.9%)	1,678,405 (15.8%)
Race/ethnicity category		
White	304,646,385 (63.9%)	6,363,498 (59.9%)
Black	57,846,450 (12.1%)	1,671,771 (15.7%)
Hispanic	69,812,718 (14.7%)	1,532,021 (14.4%)
Other	44,229,619 (9.3%)	1,053,315 (9.9%)
Education level		
High school	167,277,315 (35.1%)	7,154,132 (67.4%)
Some college	88,436,305 (18.6%)	1,330,087 (12.5%)
Bachelor's+	220,821,552 (46.3%)	2,136,386 (20.1%)
Marital status		
Single	156,193,921 (32.8%)	4,383,954 (41.3%)
Married	259,306,541 (54.4%)	5,730,992 (54.0%)
Divorced	61,034,711 (12.8%)	505,659 (4.8%)
# of children	1.08 (1.22)	0.82 (1.20)
Age	36.64 (8.18)	28.37 (7.43)
Regional Price Parity (RPP)	99.66 (8.39)	98.85 (8.27)
Avg. meal cost ($ per meal)	3.10 (0.44)	3.11 (0.37)
Avg. housing costs ($ per month)	1103.50 (490.44)	848.85 (683.70)
Childcare cost: Toddlers ($ per month)	863.34 (254.70)	779.52 (260.76)

Notes: Data from 2013-2021 CPS Food Insecurity Supplement and DOD administrative files for primary sample (not living in civilian group quarters, aged 18-50, at least a high school degree, at least one employed adult, and a family income of at least $15,000). Parentheses indicate percent distribution for categorical variables and standard deviations for continuous variables. Data excludes civilians living in group housing. The civilian data are weighted using the food insecurity household weights. Each DOD service member has a weight of one.

Among the civilian sample, about 1.6% of the families have an adult in the military. While the genders are fairly evenly mixed among civilians, males are over-represented in the DOD data. There is also a smaller proportion of white individuals in the DOD than the civilian sample. Household size is somewhat smaller in the civilian than the DOD households, with more single individuals and fewer children, perhaps because the DOD sample is younger, on average. Moving to the cost data, the annual national average of the RPP is normalized to 100. Both the civilian and DOD samples we use here live in places slightly below that level, indicating that purchasing costs are 99.7% and 98.9% of the national average, respectively. The average individual meal in this timeframe costs about $3.10. Housing costs are lower for the DOD sample, partly because service members living in barracks have no housing costs. Among service members with housing costs, the average is $1,154 per month, which is slightly higher than civilian costs. The DOD population generally lives in areas with lower childcare costs than civilians do.

Figure 12 displays the count of DOD observations in 2021 by six factors: by whether the service member receives a cost-of-living adjustment (COLA), by general cost of living in the area, grade, branch of service, family size, and marital status. The DOD provides a COLA if the non-housing cost of living for a given area is at or above 108% of the CONUS average.[10] Military members assigned to a zip code that received COLA in September 2021 are designated as receiving COLA; the rest are not. Separately, we use the regional price parity (RPP) index to identify generally low, middle, and high cost of living locations. Locations at or below 92% of the national price average are defined as low-cost areas; those at or above 108% are defined as high-cost areas. We group higher grades and number of dependents together to simplify the display.

[10] For more information, including COLA adjustments by year, location, and grade, see: https://www.travel.dod.mil/Allowances/CONUS-Cost-of-Living-Allowance.

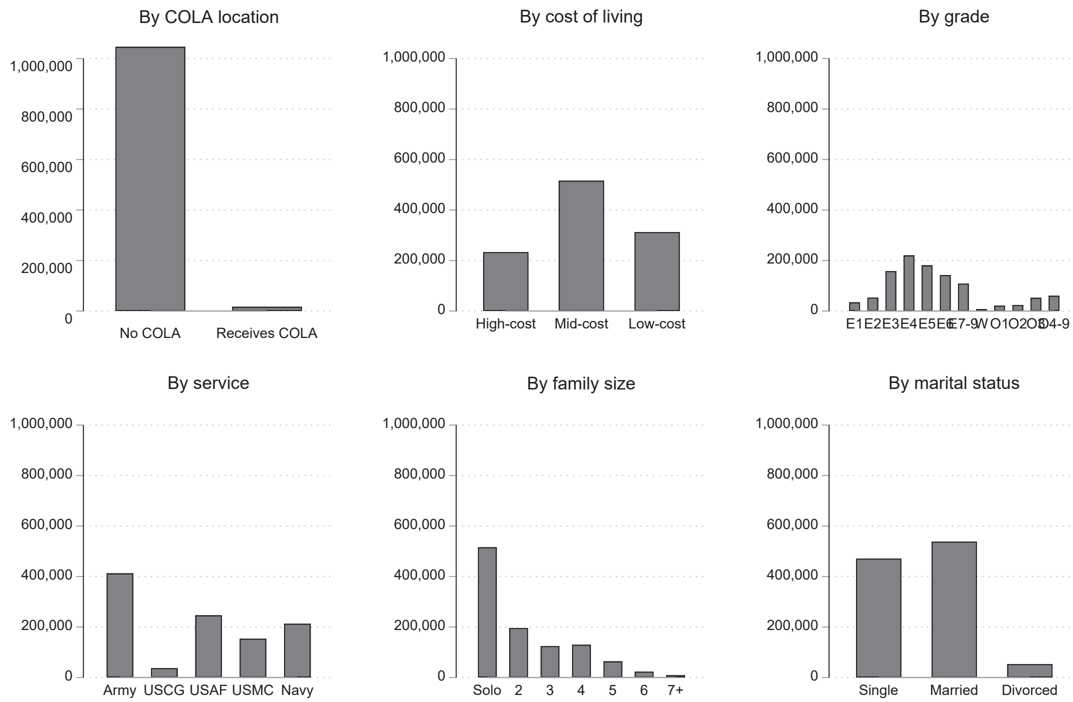
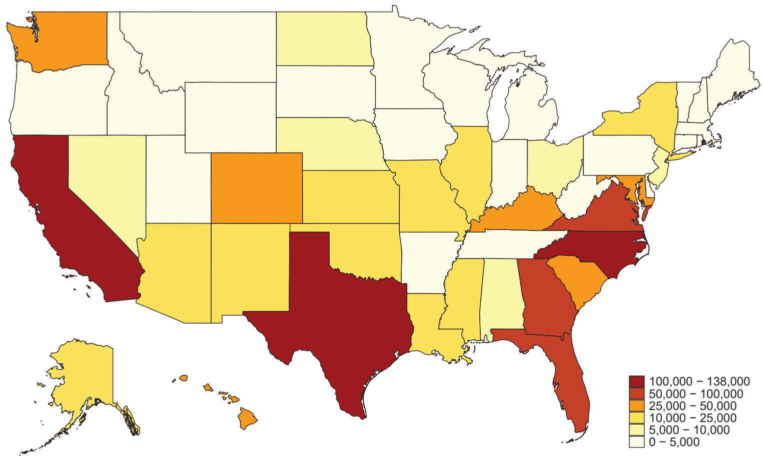


Figure 12. Count of service members by various characteristics

About 99% of service members live in locations without COLA; even in places with high prices (with a regional price parity greater than 108%), only 3% of service members receive COLA. Still, more service members live in low-cost (RPP < 92%) or mid-cost places (RPP between 92% and 108%). Most are enlisted members, with E4 being the largest single grade. The Army is the largest branch of service, with similar numbers of Air Force and Navy individuals. The most common family size is one, indicating the service member has no dependents. The average family size is 2.2, and 97% of families have five or fewer members.

Figure 13 displays the geographic distribution of service members in 2021. The largest within-county location is San Diego County, and there are several other large bases across the country. There are also many service members spread throughout the country.



Note: Count rounded to the nearest 1000.

Figure 13. Distribution of service members by state (2021)

D. RESEARCH QUESTION 1

The table below displays the results from research question 1.

Table 6. Associations between various characteristics and food insecurity

	(1) All	(2) Only age 18-55	(3) + Only HS grads	(4) + income & employment controls	(5) + income >$15,000 & >1 employed
Military family	-0.0516***	-0.0481***	-0.0491***	-0.0498***	-0.0538***
	(0.0053)	(0.0055)	(0.0055)	(0.0054)	(0.0051)
Female	0.0296***	0.0458***	0.0436***	0.0297***	0.0267***
	(0.0012)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Age	0.0045***	0.0040***	0.0040***	0.0121***	0.0053***
	(0.0003)	(0.0011)	(0.0011)	(0.0011)	(0.0012)
Age-squared	-0.0001***	-0.0001***	-0.0001***	-0.0002***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Black	0.0867***	0.0801***	0.0805***	0.0482***	0.0480***
	(0.0026)	(0.0038)	(0.0039)	(0.0038)	(0.0041)
Hispanic	0.0429***	0.0288***	0.0353***	0.0143***	0.0133***
	(0.0024)	(0.0031)	(0.0032)	(0.0031)	(0.0032)
Other race/ethnicity	0.0261***	0.0195***	0.0207***	0.0027	0.0073*
	(0.0024)	(0.0031)	(0.0031)	(0.0031)	(0.0030)
No HS degree	0.0965***	0.1009***			
	(0.0030)	(0.0052)			
Some college	-0.0056**	-0.0093**	-0.0088**	0.0002	0.0044
	(0.0019)	(0.0031)	(0.0031)	(0.0030)	(0.0032)
College degree	-0.0858***	-0.1127***	-0.1117***	-0.0564***	-0.0450***
	(0.0014)	(0.0022)	(0.0022)	(0.0023)	(0.0023)
Married	-0.0694***	-0.0828***	-0.0824***	-0.0230***	-0.0181***
	(0.0016)	(0.0026)	(0.0027)	(0.0030)	(0.0030)
Divorced	0.0348***	0.0273***	0.0268***	0.0281***	0.0205***
	(0.0022)	(0.0038)	(0.0039)	(0.0037)	(0.0038)
# children in household	0.0231***	0.0259***	0.0287***	0.0267***	0.0275***
	(0.0010)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Any child < 5	0.0074**	0.0057*	0.0048	-0.0005	-0.0061*
	(0.0026)	(0.0029)	(0.0029)	(0.0028)	(0.0028)
Avg. meal cost	-0.0227***	-0.0208***	-0.0227***	-0.0160***	-0.0115***
	(0.0026)	(0.0036)	(0.0036)	(0.0035)	(0.0034)

Housing costs	-0.0227***	-0.0208***	-0.0227***	-0.0160***	-0.0115***
($1,000s/month)	(0.0026)	(0.0036)	(0.0036)	(0.0035)	(0.0034)
Toddler childcare cost	-0.0053	0.0057	0.0050	0.0216***	0.0167***
($1,000s/month)	(0.0032)	(0.0050)	(0.0050)	(0.0049)	(0.0047)
Non-metropolitan	0.0121***	0.0138***	0.0143***	-0.0000	-0.0041
	(0.0015)	(0.0026)	(0.0026)	(0.0026)	(0.0025)
Under $5,000				Reference	
$5,000 - 7,499				0.0443**	
				(0.0140)	
$7,500 - 9,999				0.1078***	
				(0.0140)	
$10,000 - 12,499				0.0546***	
				(0.0125)	
$12,500 - 14,999				0.0359**	
				(0.0127)	
$15,000 - 19,999				0.0373***	Reference
				(0.0110)	
$20,000 - 24,999				0.0185	-0.0105
				(0.0102)	(0.0110)
$25,000 - 29,999				-0.0139	-0.0428***
				(0.0100)	(0.0106)
$30,000 - 34,999				-0.0436***	-0.0716***
				(0.0096)	(0.0101)
$35,000 - 39,999				-0.0628***	-0.0925***
				(0.0096)	(0.0101)
$40,000 - 49,999				-0.0980***	-0.1310***
				(0.0089)	(0.0093)
$50,000 - 59,999				-0.1265***	-0.1593***
				(0.0088)	(0.0092)
$60,000 - 74,999				-0.1523***	-0.1863***
				(0.0086)	(0.0089)
$75,000 - 99,999				-0.1720***	-0.2057***
				(0.0085)	(0.0089)
$100,000 - 149,999				-0.1868***	-0.2222***
				(0.0085)	(0.0088)
$150,000 and over				-0.1874***	-0.2243***
				(0.0085)	(0.0089)
# employed adults=0				Reference	
# employed adults=1				-0.0700***	Reference
				(0.0049)	
# employed adults=2				-0.0778***	-0.0066**
				(0.0051)	(0.0025)
Constant	0.1008***	0.1461***	0.1413***	0.0906***	0.1751***
	(0.0085)	(0.0211)	(0.0212)	(0.0217)	(0.0234)
Observations	383164	174527	161876	161876	138391
Adjusted R^2	0.086	0.089	0.079	0.133	0.102

*Notes: * p<0.05; ** p<0.01, *** p<0.001. Table displays coefficients from a logit model predicting the risk of food insecurity on the CPS data. Models increasingly restrict the sample to be more like the military. Heteroskedasticity robust standard errors included in parentheses. All models weighted using the food security supplement statistical weights. All models include year fixed effects.*

E. RESEARCH QUESTION 2

1. Further Discussion of 150% FPL

The designation of whether someone is above or below 150% FPL is dichotomous for each service member's family, meaning that people below the cutoff have a value of 1, while those at or above this level have a value of 0. (Recall that two service members with identical incomes will have different FPL percentages if they have different household sizes). There is no gray area allowed. A benefit of this FPL cutoff approach is that it is simple to measure and explain. A drawback, though, is that empirically there are many households with incomes greater than 150% FPL that are food insecure, and the majority of households with incomes less than 150% FPL are food secure. In our main civilian sample, 24.1% of those below 150% FPL and 6.8% of those above FPL were food insecure in 2021. A more sophisticated model will improve the estimate of food insecurity in the military. Nonetheless, below we describe how many military families fall below a 150% FPL cutoff.

Figure 13 displays the average military income value by grade for enlisted families (E1 through E7) in 2021; the figure does not include any predicted civilian spouse pay. The horizonal lines display the federal poverty line for various family sizes for the continental United States (CONUS). As expected, few E1s receive BAH, but even without BAH, the average single E1 makes more than 150% FPL (that is, the bar is about the “single” line). However, E1s with dependents earn less than 150% FPL, on average (that is, the bar is below the other lines). At higher grades, only those with many dependents fall below 150% FPL when BAH is included. For E4, the most common grade, those with three dependents (a total household size of four) make more than 150% FPL, on average, when including BAH. When BAH is excluded, however, the average military pay for E4s is below 150% FPL for those with at least three dependents.

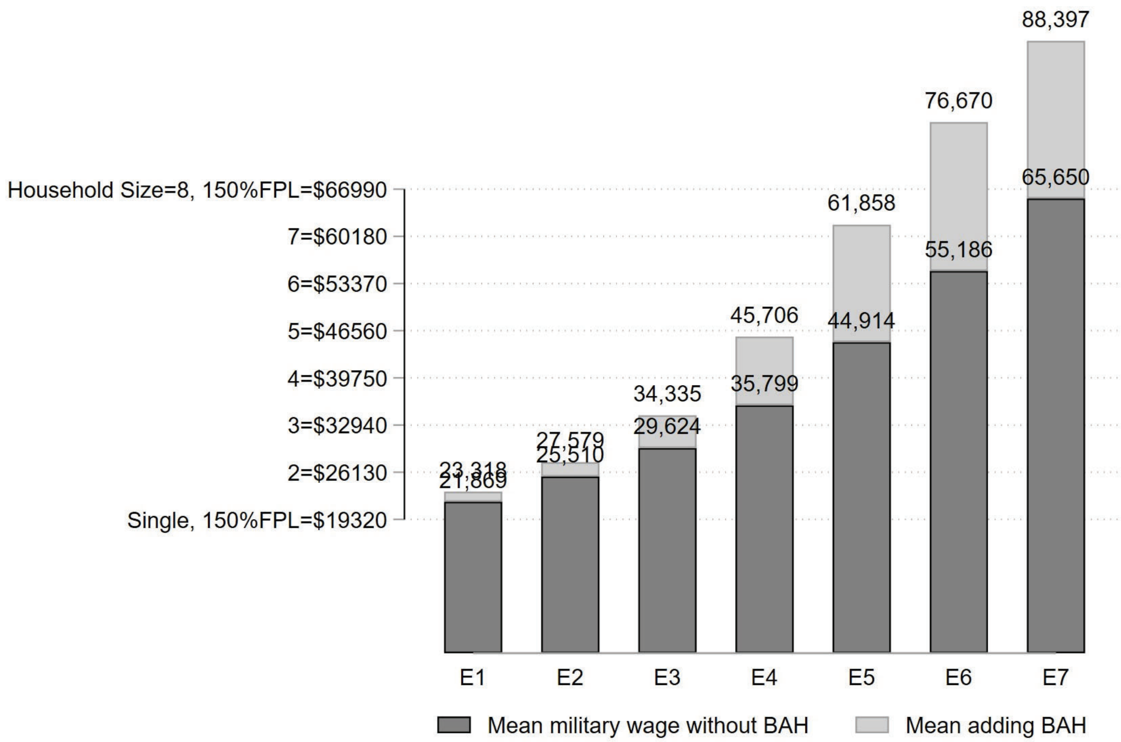


Figure 14. Average military income by grade with and without BAH and 150% FPL by number of family members in 2021 (contiguous United States)

Individuals below 150% FPL are geographically concentrated. Table 7 displays the percent of all individuals with incomes less than 150% FPL for the DoD and Navy, respectively. After estimating spouse income, the only counties predicted to have more than 2,000 service members below 150% FPL in 2021 were Lake County in Illinois (home of many E1s, due to the Naval Station Great Lakes) and San Diego County in California (home to the Marine Corps Recruit Depot San Diego and Naval Base San Diego). Each had about 16% of the total number of service members making less than 150% FPL in 2021. Restricting to the Navy, 82% of Sailors below 150% FPL were at Great Lakes Naval Station.

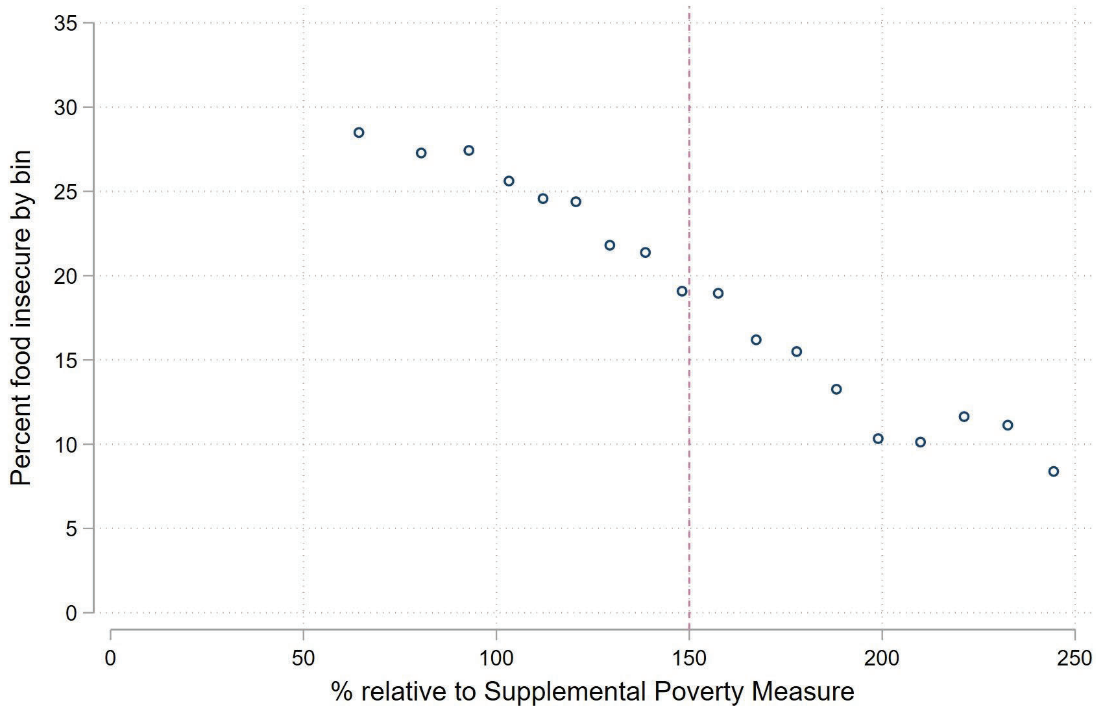
Table 7. Top 10 counties with service members below 150% FPL in 2021 (DOD and Navy)

DOD County	%	Navy County	%
San Diego County, CA	15.9	Lake County, IL	82.4
Lake County, IL	15.8	Escambia County, FL	7.2
Muscogee County, GA	9.4	Bexar County, TX	2.0
Beaufort County, SC	9.2	San Diego County, CA	2.0
Bexar County, TX	6.4		
Richland County, SC	5.7		
Pulaski County, MO	4.2		
Comanche County, OK	3.4		
Onslow County, NC	2.7		
Prince George County, VA	2.4		
Everywhere else	24.9	Everywhere else	6.4

Notes: Percent adds to 100% of those below 150% FPL for the given group. Excludes places with less than 50 service members under 150% FPL.

2. Further Discussion of the Budget-based Method

For the budget-based method, we use the federal government's supplemental poverty measure (SPM) to identify the relevant poverty line for each civilian and service member's observed calendar year, family size, and metropolitan area. Recall that the SPM approach allows for geographical differences in the cost of living and makes other improvements on the poverty-line approach described above. The data needed for the SPM analysis is available for a subset of our CPS data that also participated in the Annual Social and Economic Supplement (ASEC) of the CPS. We observe the outcome of interest (food insecurity) in the civilian CPS data and use this to calculate the probability that civilians in each SPM bin are food insecure. We display the estimates in Figure 15. The figure illustrates that SPM is also not a strong indicator of food insecurity risk. The first three bins, each representing about 2.5% of civilians, are below the supplemental poverty level, and about 27% of these households are food insecure. As income increases relative to the SPM, the likelihood of food insecurity declines but remains high among civilians: at 200% SPM, about 10% of households report food insecurity. Given these patterns in the civilian data, a sharp SPM cutoff for assistance in the military setting (e.g., 150% SPM) would not address those who are food insecure at higher income levels. Moreover, only 4.2% of service members made less than 150% of their relevant supplemental poverty level in 2021.



Notes: Each dot represents approximately 2.5% of the unrestricted civilian sample, sorted relative to the SPM. The sample includes those between the 5th and 50th percentiles. We exclude the bottom two bins due to inconsistencies related to the self-employed.

Figure 15. Percent food insecure by supplemental poverty line in civilians (CPS data, ASEC-Food Security Supplement overlap sample)

3. Further Discussion of the Machine Learning Prediction

The LASSO model can identify which factors predict food insecurity (or a lack thereof) in the CPS data. We implement this in increasingly complicated models. Model (1) recreates the final model from the Q1 analysis, though here it is run as a logit model. The logit model makes the coefficients somewhat more difficult to interpret but may be more accurate for predicting an uncommon event like food insecurity. Model (2) is the same as Model (1), but run as a LASSO, which will remove variables that do not add to the prediction. For example, the variable for number of children in the household is still entered linearly, but if number of children does not matter for risk of food insecurity, the prediction will drop the variable from the model. With few variables, there is not a large benefit to the LASSO model. These first two models are very similar to each other and fairly straightforward to interpret.

Model (3) adds additional variables and illustrates the benefits of the LASSO model: it performs repeated tests to determine which of many potential variables best predict the outcome. The LASSO process will determine which variables are most useful for predicting the outcomes, include variables that improve the fit, and remove variables that do not. Compared to Model (2), Model (3) adds an interaction between marital status and meal cost, an interaction between number of children in the household and meal cost, an interaction between number of children under five and childcare costs, fixed effects for each state, and a more detailed income variable. The interactions allow effects to differ by family type, while the state fixed effects capture any state-specific influences on food security probability not captured by the other variables. Further, most of the CPS data only has income categories, which are rough buckets of family income. However, the ASEC data includes the dollar value of family income for a subsample of the data. If the continuous dollar value adds information for the prediction above that the income bins provide, the continuous variable will be selected by the LASSO estimate.[11] Ultimately, this continuous variable may help with identifying small-dollar changes in income, when we wargame different policies in the next section.

Finally, Model (4) pushes the model even further. We generate interactions between being from a military family, gender, age, race/ethnicity, education, marital status, number of children in the household, having a child under age five, local meal cost, local housing costs, local childcare cost, income bins, count of employed adults, and the continuous family income variable, as well quadratics for non-dichotomous variables. This allows, for instance, the effect of each variable to differ across married and unmarried individuals. We also include fixed effects for year, state, number of children, and being in a non-metropolitan area. With so many interactions and fixed effects, any individual coefficient is very difficult to interpret, but in combination, the model should predict the outcome with the greatest precision.

Table 8 displays a summary of the results; full results are available in Appendix B. Our goal is to train the LASSO model on CPS data. To measure goodness-of-fit, the bottom row of the table includes a measure recommended by Bellemare (2012), which

[11] This model also includes an indicator variable for having the total family income and gives the mean income to those non-ASEC participants.

sums the fraction of zeros (here, food secure) correctly predicted and the fraction of ones (here, food insecure) correctly predicted (McIntosh & Dorfman, 1992). Values over 1 are considered a good fit, with higher numbers better than lower numbers, a minimum value of zero (i.e., the model predicted nothing correctly), and a maximum value of two (i.e., the model predicted everything correctly).

Table 8. Predicting rates of food insecurity using the LASSO model (CPS data)

	Basic model	Basic LASSO	Some Interactions	Final Model
Military family	–	–	–	
Female	+	+	+	X
Age	+	+	+	X
Age-squared	–	–	–	X
Race/ethnicity category				
White	Ref.	–	–	X
Black	+	+	+	X
Hispanic	+	+	+	X
Other	+	Ref.	Ref.	X
Education level				
High school	Ref.	Ref.	Ref.	X
Some college	+	+	+	X
Bachelor's+	–	–	–	X
Marital status				
Single	Ref.	Ref.	Ref.	X
Married	–	–	–	X
Divorced	+	+	+	X
# of children	+	+	+	X
Child under 5 (0/1)	–	–	X	X
Avg. meal cost ($ per meal)	–	–	–	X
Avg. housing costs ($ per month)	–	X	+	X
Childcare cost ($ per month)	+	+	–	X
Childcare cost missing	+	+	X	X
Non-metropolitan	–	–	–	–
Income category				
$15,000 – 19,999	Ref.	+	+	Ref.
$20,000 – 24,999	–	+	+	Ref.
$25,000 – 29,999	–	+	+	Ref.
$30,000 – 34,999	–	+	+	Ref.
$35,000 – 39,999	–	+	+	+
$40,000 – 49,999	–	+	+	Ref.
$50,000 – 59,999	–	Ref.	Ref.	Ref.
$60,000 – 74,999	–	–	–	Ref.
$75,000 – 99,999	–	–	–	Ref.
$100,000 – 149,999	–	–	–	Ref.
$150,000 and over	–	–	–	–
# employed adults=2	–	–	–	X
HH wage	O	O	–	X
HH wage missing	O	O	–	X
Interactions				
# of children × Meal cost	O	O	–	X
Child under 5=1 × Childcare cost	O	O	–	X
Military family=0 × Black	O	O	O	+
Military family=0 × # of children	O	O	O	+
Military family=0 × $15,000 – 19,999	O	O	O	+
Military family=0 × $20,000 – 24,999	O	O	O	+
Military family=0 × $25,000 – 29,999				+
Military family=0 × $30,000 – 34,999	O	O	O	+

Military family=1 × $40,000 – 49,999	O	O	O	+
Bachelor's + × HH wage	O	O	O	–
Married × HH wage	O	O	O	–
HH wage × Meal cost	O	O	O	–
Male × White				–
Female × # of children	O	O	O	+
Female × # employed adults=1	O	O	O	+
$15,000 – 19,999 × Age	O	O	O	+
$30,000 – 34,999 × Age	O	O	O	+
$150,000 and over × Age	O	O	O	–
White × Bachelor's+	O	O	O	–
Black × Child under 5=0	O	O	O	+
White × $25,000 – 29,999	O	O	O	+
White × $75,000 – 99,999	O	O	O	–
White × $100,000 – 149,999	O	O	O	–
Bachelor's+ × Meal cost	O	O	O	–
Bachelor's+ × Year	O	O	O	–
Single × # children in HH	O	O	O	+
Divorced × # children in HH	O	O	O	+
$30,000 – 34,999 × # children in HH	O	O	O	+
$40,000 – 49,999 × # children in HH	O	O	O	+
# employed adults=1 × # children in HH	O	O	O	+
$30,000 – 34,999 × # employed adults=2	O	O	O	+
$60,000 – 74,999 × Meal cost	O	O	O	+
$35,000 – 39,999 × Childcare cost	O	O	O	+
$75,000 – 99,999 × Year	O	O	O	–
$100,000 – 149,999 × Year	O	O	O	–
N	138,391	138,391	138,391	138,391
Positive state fixed effect coefficients	O	O	AR, CO, CT, HI, KS, ME, MD, MI, MN, MO, NE, NV, OH, OK, OR, PA, UT, WA	X
Negative state fixed effect coefficients	O	O	AZ, CA, FL, GA, ID, IL, IA, KY, LA, MS, NJ, NC, SC, TN	X
Max covariates	49	49	109	656
Covariate selected	49	33	66	34
Bellemare (2012) goodness-of-fit	1.0178	1.0172	1.0199	1.0169
Actual civilian risk in 2021 (in-sample)	8.1%	8.1%	8.1%	8.1%
Predicted military risk in 2021 (out of sample)	4.1%	4.1%	3.9%	6.9%

Notes: Model 1 run as a logit model; Models 2—4 run as adaptive LASSO logit models with 5-fold cross validation. Ref.=Reference group. O=Not entered into the model. +=positive association with food insecurity. –=negative association with food insecurity. X=not selected by LASSO. All models also include year fixed effects.

Model (2) finds the same broad pattern as Model (1), though age, housing costs, missing childcare data, and being from a non-metropolitan area do not add enough to the prediction and so are removed from the model. Models (1) and (2) provide some correlational evidence of the risk and protective factors for predicting food insecurity; these largely align with findings in military surveys.

Model (3) adds more nuance and interaction terms, some of which are not predictive and so are removed from the model. For instance, each additional child decreases a household's probability of being food insecure less in places with higher food costs (somewhat counterintuitively). The interpretation of any individual coefficient is more complicated as additional variables are added. The preferred Model (4) adds interactions among all variables.

It is very difficult to interpret individual coefficients in Model (4); for instance, to understand the relationship between having a bachelor's degree and risk of food insecurity requires also looking at all of the interactions that include having a bachelor's degree. However, the purpose of this model is not to examine individual coefficients but instead to calculate an overall risk.

All four models have a Bellemare (2012) goodness-of-fit statistic above 1, and all predict military food insecurity rates around 4%. The final model, though it has the most available variables to include, selects fewer variables than Model (3). None of the state fixed effects are included once the interactions are available for selection.

4. Summary of Methods

For quick reference, Table 9 presents a summary of the methods used in this paper. Using a particular percent of the poverty line is easy and straightforward, but it is inaccurate. The budget-based method and machine learning strategies incorporate more factors but are also more difficult for the Navy to estimate. All three of these methods, however, are based on observable characteristics, which allow us to "war game" what would happen if we changed characteristics (e.g., increased income by a certain amount).

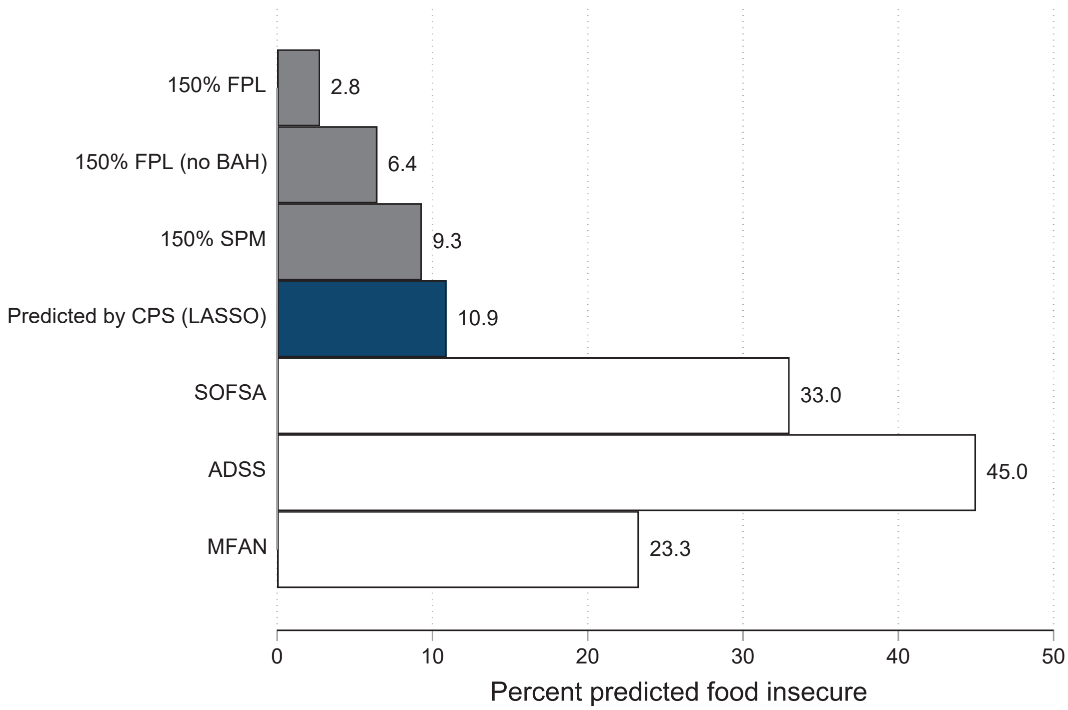
Table 9. Summary of potential measures of the risk of food insecurity

	150% FPL	**Budget-Based Method (Below 150% SPM)**	**Machine Learning Prediction**
Source	DHHS definition (federal poverty line)	DHHS definition (supplemental poverty measure)	Prediction from comparable civilians (comprehensive model)
Outcome range	0/1	0/1	Predicted probability (0-100%)
Key assumption	Cost of living does not change risk; stark cutoff captures risk	Family size and local cost of living accurately measured; stark cutoff captures risk	Comparable civilians are a good representation of military probability
Calculation ease	Easy	Moderate (requires some data)	Difficult (requires statistical software and detailed data)
Accuracy of risk prediction	Low (see above)	Low (see above)	Moderate (see below)

Ability to wargame	High	High	High
Predicted food insecurity rate	1.2%	4.2%	6.9%

F. RESEARCH QUESTION 3

1. Additional Graphs and Tables



Notes: Dark blue indicates our preferred LASSO model; gray indicates our other estimates; white indicates survey-based measures from others.

Figure 16. Predicted percent food insecure by different methodologies for junior enlisted

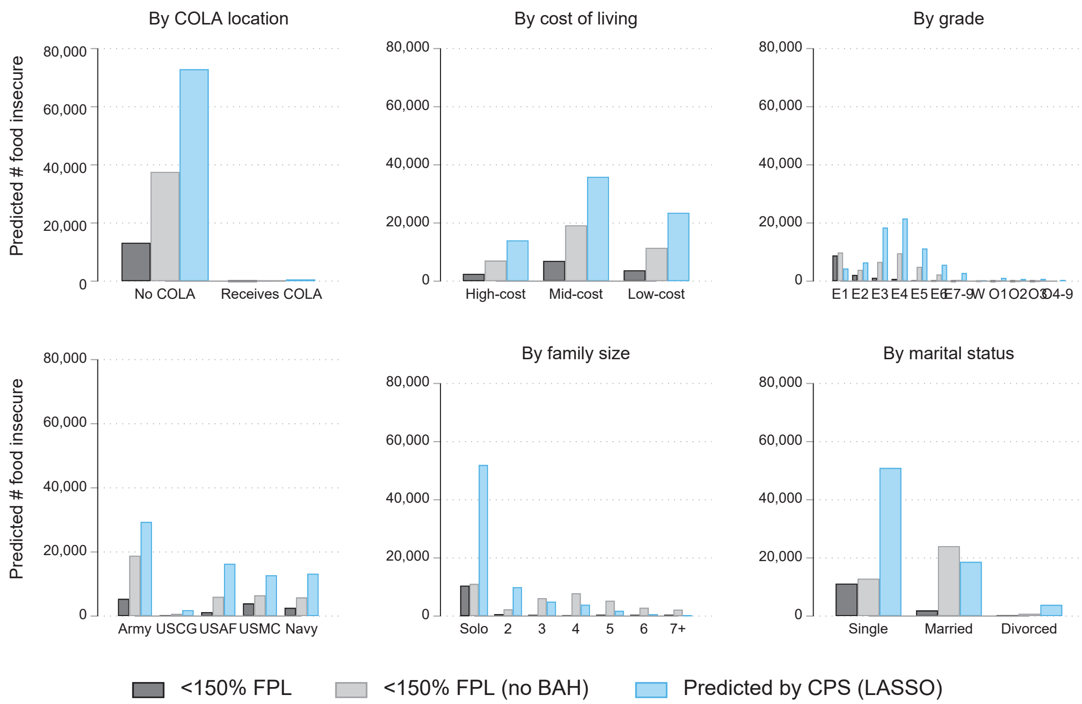


Figure 17. Count of service members at risk for food insecurity by various characteristics in 2021

Table 10. Top 10 counties at risk for food insecurity (LASSO estimate, DOD)

A. Percent		**B. Count**	
County	**%**	**County**	**#**
Lake County, IL	10.9%	San Diego County, CA	6,056
Benton County, MO	10.4%	Onslow County, NC	3,685
Bates County, MO	10.1%	Cumberland County, NC	3,196
Beaufort County, SC	9.6%	Bell County, TX	3,005
Tom Green County, TX	9.4%	Honolulu County, HI	2,158
Wichita County, TX	9.3%	Bexar County, TX	2,197
San Bernardino County, CA	9.2%	Christian County, KY	2,158
Eastland County, TX	9.1%	El Paso County, CO	2,086
Iberia Parish, LA	9.0%	El Paso County, TX	2,063
Comanche County, OK	9.0%	Pierce County, WA	2,002

Notes: Top 10 counties in terms of percent and count of service members predicted to be at risk of food insecurity in 2021. Excludes places with less than 50 service members predicted for percent column.

2. Who is Most at Risk of Food Insecurity in the Navy?

Broad patterns within the DOD may not represent the patterns in the Navy, particularly given geographic concentration and high cost of living in the Navy. This section explores patterns within the Navy only. Results are broadly similar. Almost no one in the Navy earns less than 150% FPL, with or without including BAH. Figure 18 displays the observed distribution of income relative to the FPL in 2021. This graph only includes the Sailor's income and does not include predicted income of a civilian spouse.

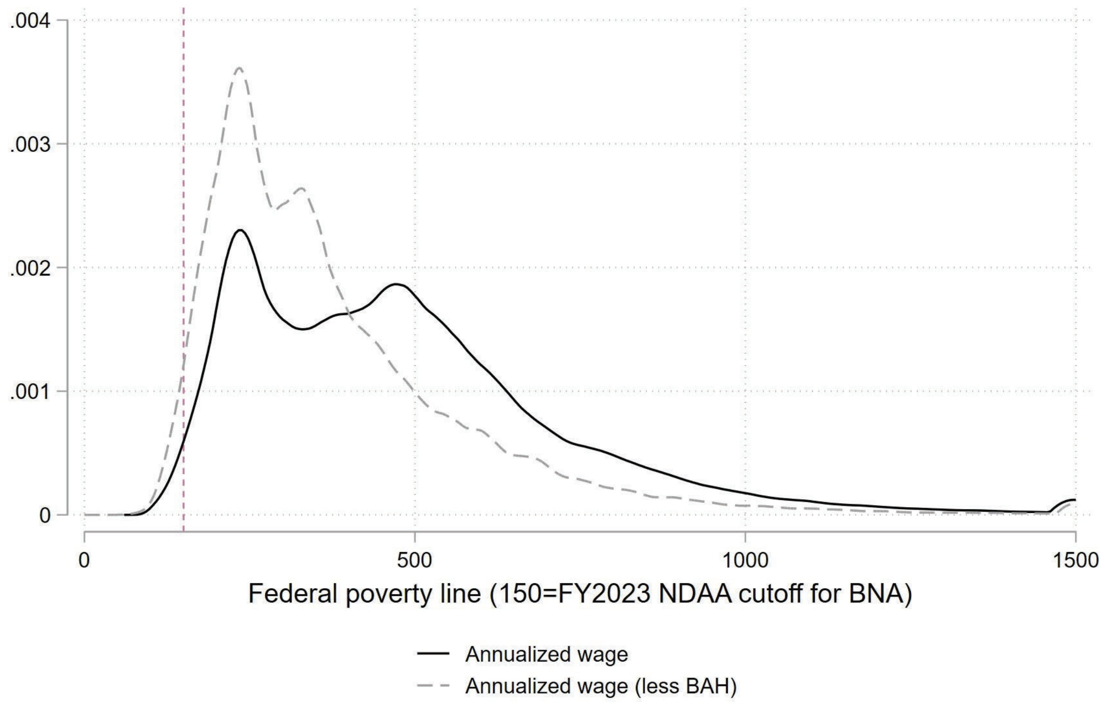
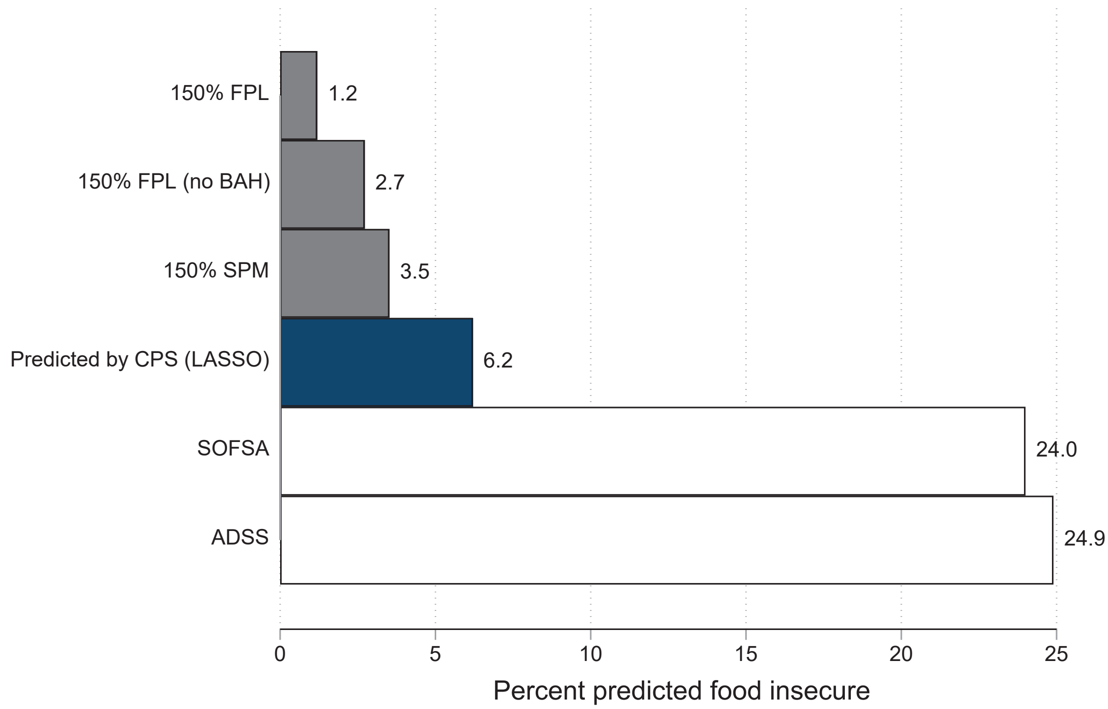


Figure 18. Distribution of income relative to the federal poverty line with and without including BAH in 2021 (Navy only)

Figure 19 displays a summary of all the methods in this paper, plus two additional survey-based estimates of food insecurity from SOFSA and ADSS, for the Navy only. We find an overall rate of 3.5% using the SPM-based method and 6.2% using the LASSO model. Again, for the reasons discussed above, these numbers are lower than those identified using survey methods among those surveys with specific Navy information.



Notes: Dark blue indicates our preferred LASSO model; gray indicates our other estimates; white indicates survey-based measures from others.

Figure 19. Predicted percent food insecure by different methodologies for the Navy

As in the overall DOD analysis, the topline numbers mask heterogeneity by a variety of characteristics. Figure 20 displays the predicted risk of food insecurity by six factors: whether the Sailor receives COLA, local cost of living, grade, race/ethnicity, family size, and marital status. COLA pushes Sailors above the FPL, so only those who do not receive COLA are below 150% FPL. Similarly, those receiving COLA are predicted to be at lower risk of food insecurity in the LASSO model. Based on the overall cost of living, the middle-cost states have higher rates. Rates are highest among junior enlisted, and Black individuals are predicted to have higher rates than other groups. If BAH was removed from the BNA qualification calculation, 22.6% of families with seven or more members are predicted to qualify, though the LASSO model only predicts a 2.4% rate of food insecurity for these large Navy families. Married individuals are the least likely to be food insecure, partly because married civilians may also bring income into the family.

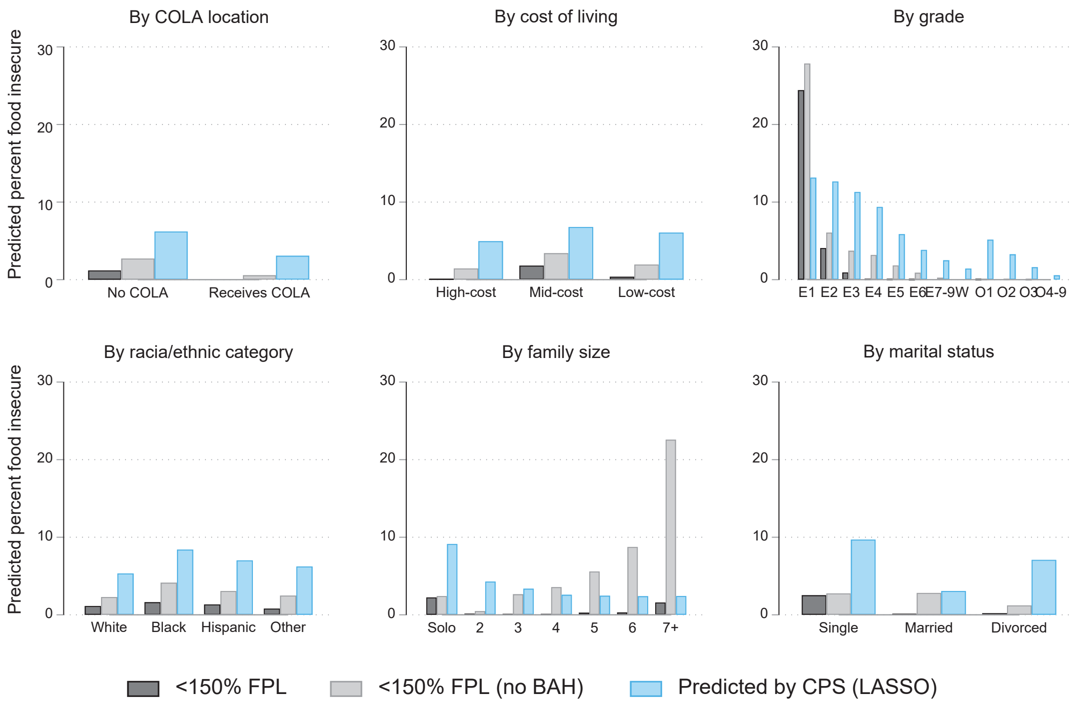


Figure 20. Percent of Navy Sailors at risk for food insecurity by various characteristics in 2021

Figure 21 displays the predicted count of Sailors by various characteristics in 2021. Patterns are similar to the overall DOD patterns, with, for instance, many more single Sailors are predicted to be food insecure because the highest count of sailors are single. Again, very few Navy families have more than four children. There are basically no Sailors receiving COLA at risk of food insecurity both because those receiving COLA are at lower risk of food insecurity (see Figure 20) and because relatively few Sailors receive COLA.

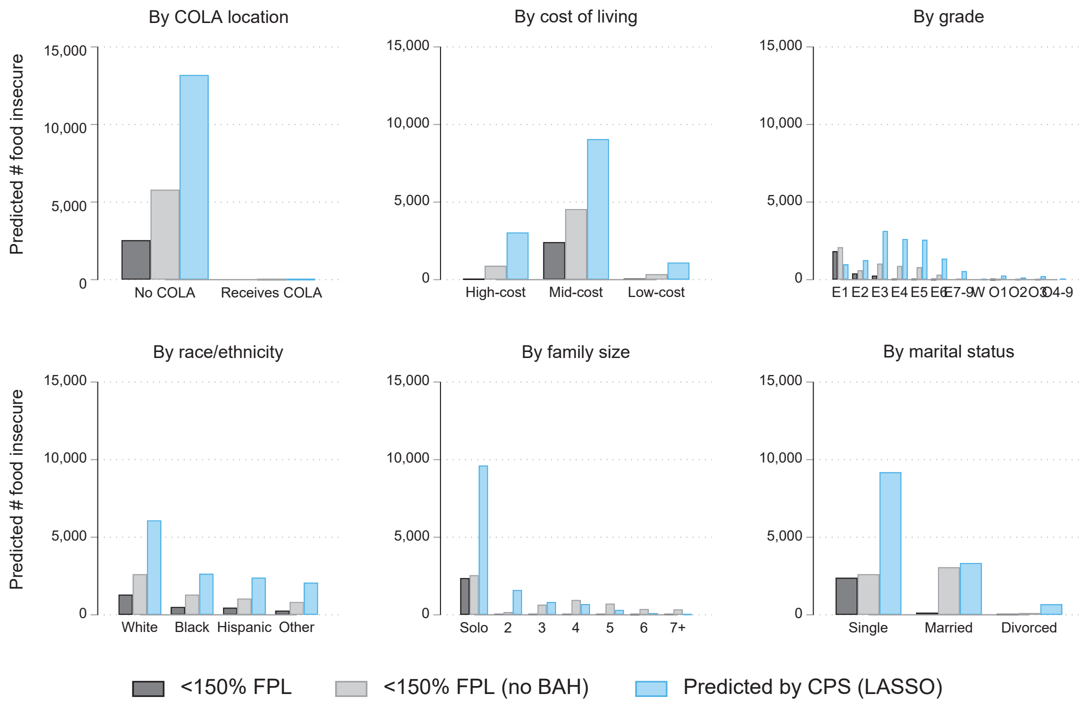


Figure 21. Count of Navy Sailors at risk for food insecurity by various characteristics in 2021

Next, we display the top counties for percent and count predicted to be food insecure among Sailors in Table 11. While 11.5% of Sailors are predicted to be food insecure in Prince George's County, it is a relatively small location. Almost 2,000 Sailors are predicted to be food insecure in San Diego, though the San Diego rate of food insecurity is not in the top 10.

Table 11. Top 10 counties at risk for food insecurity (LASSO estimate, Navy)

Percent County	%	Count County	#
Prince George's County, VA	11.8%	San Diego County, CA	1,983
Lake County, IL	11.0%	Lake County, IL	1,540
Bexar County, TX	9.1%	Norfolk City, VA	1,014
Escambia County, FL	9.0%	Virginia Beach City, VA	954
Lauderdale County, MS	8.9%	Escambia County, FL	779
Tippah County, MS	8.7%	Duval County, FL	767
Plaquemines Parish, LA	8.1%	Berkeley County, SC	585
Tom Green County, TX	8.1%	Kings County, CA	523
Imperial County, CA	8.0%	Island County, WA	472
Berkeley County, SC	7.8%	Bexar County, TX	322

Notes: Top 10 counties in terms of percent and count of Sailors predicted to be at risk of food insecurity in 2021. Excludes places with less than 50 Sailors predicted for percent column.

G. RESEARCH QUESTION 4

This section explores additional policies in more detail.

1. Basic Needs Allowance

We first simulate increasing pay to various percent levels of the federal poverty line for those who had fallen below the given level. For simplicity, we assign everyone below the given level this additional BNA, though this is perhaps an overestimate of the true take-up, since the real policy requires applications and paperwork. These bureaucratic hurdles may limit take-up, so we consider this an upper bound for the per-person benefits and potential reduction in risk of food insecurity. We run the simulations with and without BAH. Excluding BAH from the income calculation would provide more money to more service members, but it would also cost more.

Figure 22 displays the simulated effect of the BNA across a range of generosity rates, from 100% (less generous than the status quo) to 300% (twice the current threshold). The left-hand Y-axis is the predicted risk of food insecurity for the given policy. The right-hand Y-axis is the predicted cost of a given level (ignoring any administrative costs of administering the program). The predicted food insecurity rates barely change across policies. Both policies (including or excluding BAH) start at a predicted rate of 6.9% at 100% FPL. The predicted rates initially do not change because very few service members make that little and so do not qualify. As a result, the program costs very little with low threshold generosity. Increasing the FPL cutoff initially has little change, especially when BAH is included in the wage calculation, as most service members also make more than 150% FPL. However, increasing the cut point to 250% FPL would cost nearly $1 billion if BAH was included in wages and nearly $3 billion if BAH was excluded. Ultimately, however, these substantially more generous policies do not substantially reduce the predicted risk of food insecurity. For instance, if the BNA excluded BAH and brought all service members up to at least 250% FPL, food insecurity rates are predicted to go from 6.9% to 6.6%.

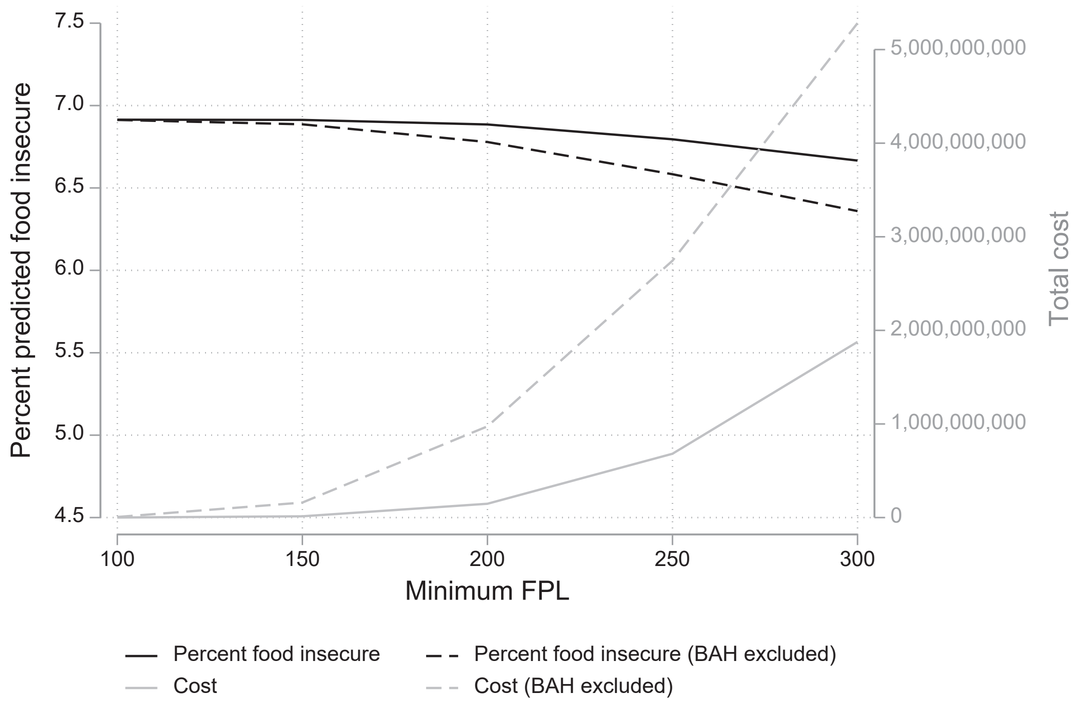


Figure 22. Projected effects of changing the minimum % FPL for BNA (LASSO simulation), with and without including BAH as income

Changing the policy to allow service members without dependents to receive BNA does not change the predicted risk of food insecurity at 150% FPL. At 250% FPL, such a policy is predicted to decrease the risk to 6.7%—at a cost of about $2 billion.

2. SPM-based BNA

Unlike the FPL, the SPM adjusts by local cost of living. As an alternative potential policy, we define the cut point for receiving BNA based on the SPM. For this simulation, we ensure that every service member earns at least the given percent level of their locally adjusted SPM for their number of dependents.

Figure 22 displays the effect of a range of SPM adjustments (100–300% SPM). The left-hand Y-axis is the predicted risk of food insecurity for the given policy. The X-axis ranges from 100 to 300% of the SPM. The right-hand Y-axis is the predicted cost of a given level (ignoring any administrative costs of administering the program). The predicted level starts at 6.9%. Increasing the SPM cutoff initially has little change, as most service members already make more than 150% SPM. If the BNA brought all service members up to at least 250% SPM, food insecurity rates are predicted to be 6.0%—at a cost of $17 billion.

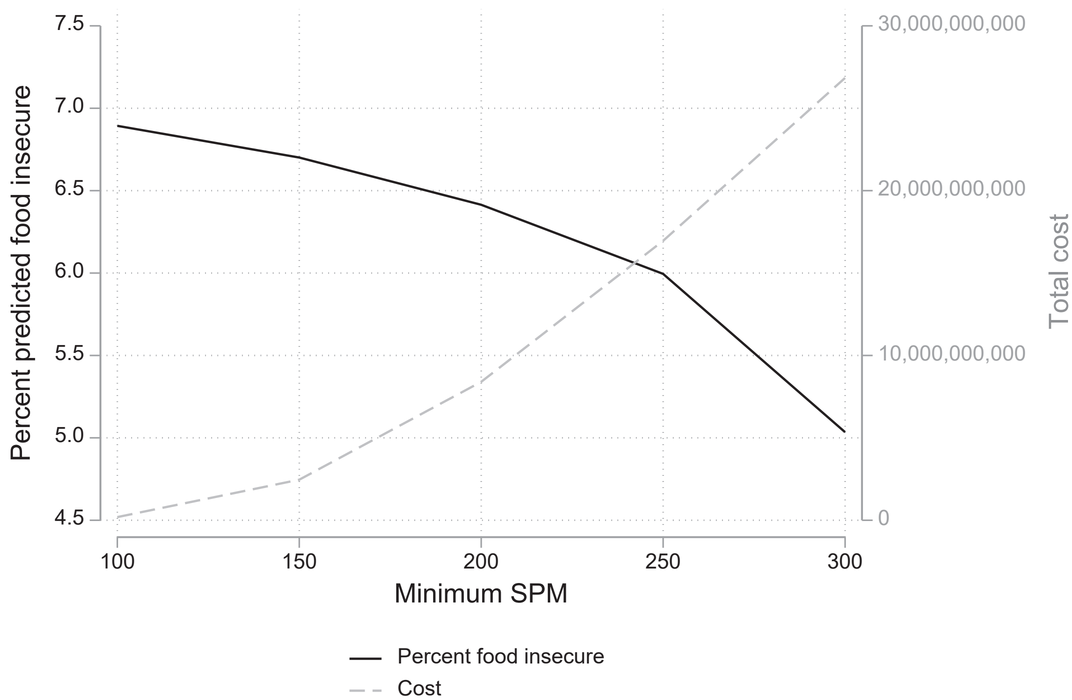
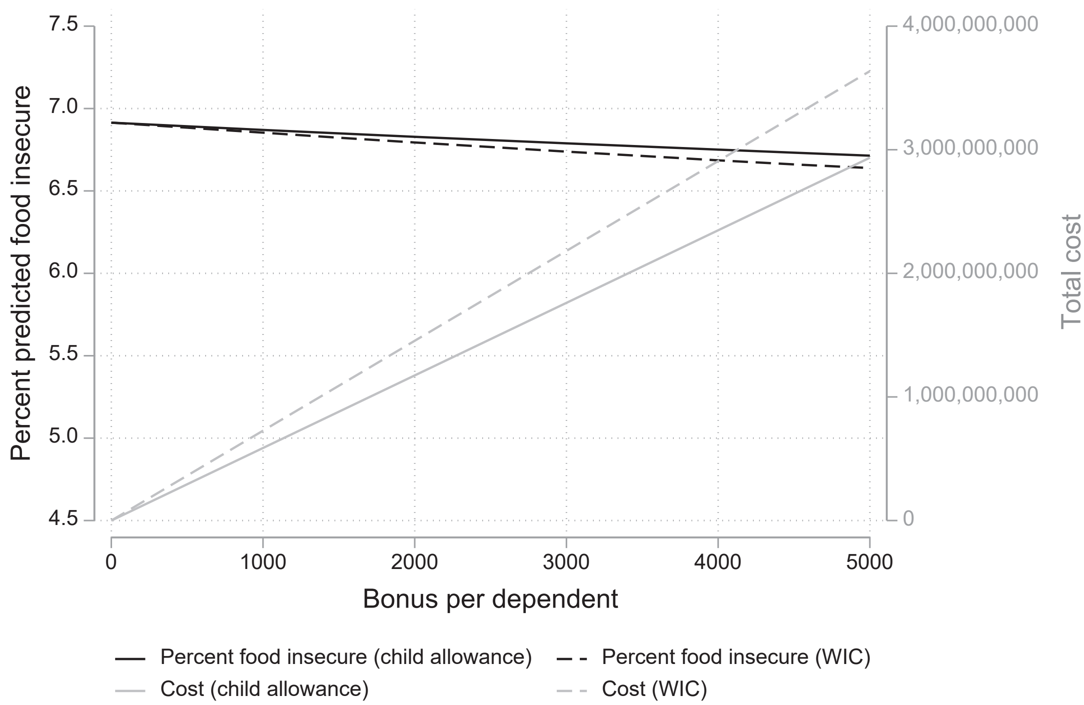


Figure 23. Projected effects of changing the minimum % SPM for BNA (LASSO simulation)

3. Dependent Allowance

The next set of simulations replaces the BNA with a dependent allowance for enlisted families. For the first dependent allowance, we provide a fixed additional benefit per household child under the age of 18. We explore a range of potential benefits, though we keep the benefits standard per child for simplicity. We note that implementation could instead limit the number of beneficiaries or decrease the benefit per child for each additional child (e.g., 100% of the benefit for child 1, 80% for child 2, and so on). We model the second dependent allowance on the civilian WIC program, providing a bonus for each child under age five, as well as for female spouses or enlisted individuals who have added a dependent in the last year. We do not provide a bonus for pregnant women, mainly because we do not observe pregnancy. For both allowance types, we limit eligibility to enlisted only, and dual military families only receive one bonus per child.

Figure 23 displays the effect of a range of monthly dependent allowances. The left-hand Y-axis is the predicted risk of food insecurity for the given policy. The X-axis begins with the status quo ($0 per child), then increasing benefits up to $5000 per dependent per year. The right-hand Y-axis is the predicted total cost (ignoring any fixed administrative costs of administering the program). These programs are predicted to make very little change to the risk of food insecurity. A $5,000 per child annual bonus would cost $3 billion but is only projected to bring the risk from 6.9% to 6.7%.



Notes: Displays projected effects of providing allowances for all children (solid lines) or young children and pregnant/postpartum mothers (dashed lines).

Figure 24. Projected effects of providing allowances (LASSO simulation)

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APPENDIX B. FULL LASSO RESULTS

Table 12: Full LASSO results

	(1) Basic	(2) LASSO	(3) All	(4) All interactions
main				
Military family=0	0.0000	0.8004	0.7866	
	(.)			
Military family=1	-0.8080***			
	(0.0017)			
Male	0.0000	-0.3076	-0.3062	
	(.)			
Female	0.3088***			
	(0.0003)			
Age	0.0275***	0.0190	0.0139	
	(0.0002)			
Age # Age	-0.0004***	-0.0003	-0.0002	
	(0.0000)			
White	0.0000	-0.0469	-0.0601	
	(.)			
Black	0.4218***	0.3708	0.3840	
	(0.0005)			
Hispanic	0.1276***	0.0693	0.0757	
	(0.0005)			
Other	0.0534***			
	(0.0007)			
HS	0.0000			
	(.)			
Some college	0.0495***	0.0403	0.0381	
	(0.0004)			
Bachelor's+	-0.6282***	-0.6287	-0.6199	
	(0.0004)			
Single	0.0000			
	(.)			
Married	-0.1803***	-0.1835	-0.1609	
	(0.0005)			
Divorced	0.1639***	0.1614	0.1625	
	(0.0005)			
# children in household	0.2659***	0.2601	0.5274	
	(0.0002)			
No children<5	0.0000	0.0751		

	(.)			
Children<5	-0.0822***			
	(0.0005)			
Avg. meal cost	-0.2044***	-0.2165	-0.0817	
	(0.0007)			
Toddler childcare cost	-0.0299***		0.1221	
	(0.0006)			
Toddler childcare cost	0.1395***	0.1114	-0.1607	
	(0.0009)			
Childcare cost: Missing=0	0.0000	-0.0145		
	(.)			
Childcare cost: Missing=1	0.0491***			
	(0.0007)			
Non-metropolitan=0	0.0000	0.0175	0.0343	
	(.)			
Non-metropolitan=1	-0.0348***			
	(0.0004)			
$15,000 - 19,999	0.0000	1.0034	0.9886	
	(.)			
$20,000 - 24,999	-0.0375***	0.9658	0.9529	
	(0.0008)			
$25,000 - 29,999	-0.2002***	0.8037	0.7940	
	(0.0008)			
$30,000 - 34,999	-0.3594***	0.6441	0.6396	
	(0.0008)			
$35,000 - 39,999	-0.4777***	0.5260	0.5229	0.4406
	(0.0008)			
$40,000 - 49,999	-0.7498***	0.2536	0.2499	
	(0.0008)			
$50,000 - 59,999	-1.0086***			
	(0.0008)			
$60,000 - 74,999	-1.3512***	-0.3443	-0.3368	
	(0.0008)			
$75,000 - 99,999	-1.7270***	-0.7208	-0.7034	
	(0.0009)			
$100,000 - 149,999	-2.3533***	-1.3480	-1.3129	
	(0.0010)			
$150,000 and over	-2.8428***	-1.8385	-1.7754	-1.5416
	(0.0013)			
# employed adults=1	0.0000	0.0766	0.0794	
	(.)			

# employed adults=2	-0.0797***		
	(0.0004)		
year=2012	0.0000	0.0144	0.0503
	(.)		
year=2013	-0.0075***	0.0026	0.0406
	(0.0007)		
year=2014	0.0405***	0.0648	0.0918
	(0.0007)		
year=2015	-0.0803***	-0.0265	
	(0.0007)		
year=2016	-0.0474***		
	(0.0007)		
year=2017	-0.0481***		
	(0.0007)		
year=2018	-0.0412***		
	(0.0008)		
year=2019	-0.0503***		
	(0.0008)		
year=2020	-0.0257***		
	(0.0008)		
year=2021	0.0069***	0.0196	
	(0.0008)		
Household wage			-0.0000
Has detailed income/wage data=0			0.1376
# children in household # Avg. meal cost			-0.0969
Children<5 # Toddler childcare cost			-0.0909
Assigned unit FIPS state=4			-0.0543
Assigned unit FIPS state=5			0.0470
Assigned unit FIPS state=6			-0.1029
Assigned unit FIPS state=8			0.1412
Assigned unit FIPS state=9			0.3896
Assigned unit FIPS state=12			-0.1826

Assigned unit FIPS state=13	-0.2773
Assigned unit FIPS state=15	0.0827
Assigned unit FIPS state=16	-0.0410
Assigned unit FIPS state=17	-0.0968
Assigned unit FIPS state=19	-0.2040
Assigned unit FIPS state=20	0.0424
Assigned unit FIPS state=21	-0.1761
Assigned unit FIPS state=22	-0.0517
Assigned unit FIPS state=23	0.3536
Assigned unit FIPS state=24	0.1901
Assigned unit FIPS state=26	0.2240
Assigned unit FIPS state=27	0.0898
Assigned unit FIPS state=28	-0.0838
Assigned unit FIPS state=29	0.2086
Assigned unit FIPS state=31	0.1010
Assigned unit FIPS state=32	0.0862
Assigned unit FIPS state=34	-0.0028
Assigned unit FIPS state=37	-0.0520
Assigned unit FIPS state=39	0.1589
Assigned unit FIPS state=40	0.0516
Assigned unit FIPS state=41	0.2557

Assigned unit FIPS state=42	0.1901	
Assigned unit FIPS state=45	-0.4764	
Assigned unit FIPS state=47	-0.1369	
Assigned unit FIPS state=49	0.0660	
Assigned unit FIPS state=53	0.1714	
Military family=0 # Black		0.1605
Military family=0 # # children in household		0.2216
Military family=0 # $15,000 - 19,999		0.5409
Military family=0 # $20,000 - 24,999		0.9259
Military family=0 # $25,000 - 29,999		0.6170
Military family=0 # $30,000 - 34,999		0.4470
Military family=0 # $40,000 - 49,999		0.1486
Bachelor's+ # Household wage		-0.0000
Married # Household wage		-0.0000
Household wage # Avg. meal cost		-0.0000
Male # White		-0.1957
Female # # children in household		0.0318
Female # # employed adults=1		0.2461
$15,000 - 19,999 # Age		0.0125
$30,000 - 34,999 # Age		0.0022

$150,000 and over # Age				-0.0046
White # Bachelor's+				-0.3450
Black # No children<5				0.1318
White # $25,000 - 29,999				0.2966
White # $75,000 - 99,999				-0.1690
Bachelor's+ # Avg. meal cost				-0.0375
Bachelor's+ # year				-0.0002
Single # # children in household				0.0019
Divorced # # children in household				0.0371
$30,000 - 34,999 # # children in household				0.0195
$40,000 - 49,999 # # children in household				0.0587
# employed adults=1 # # children in household				0.0182
$30,000 - 34,999 # # employed adults=2				0.1966
$60,000 - 74,999 # Avg. meal cost				-0.1046
$35,000 - 39,999 # Toddler childcare cost				0.0493
$75,000 - 99,999 # year				-0.0003
$100,000 - 149,999 # year				-0.0006
Constant	-1.2670*** (0.0036)	-2.7213	-2.6136	-1.9029
Observations	138391	138391	138391	138391

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