Food Insecurity Amongst Older Adults: Cohort Analysis and Alternative Measurement

A Thesis Presented for the
Master of Science
Degree
The University of Tennessee, Knoxville

Arfanul Ibna Mustafa Sakib
August 2025

ABSTRACT

The prevalence of food insecurity among older adults (individuals aged 60 or older) increased steadily from 2001 to 2011, peaking in 2012, before gradually declining but not returning to pre-Great Recession levels. Research indicates this increase was primarily driven by younger older adults (those below age 80), suggesting potential cohort effects linked to the adverse economic impacts of experiencing the Dot-Com Bubble Recession, the Great Recession, and the Covid-19 Recession during their prime working years. While food insecurity is often assessed using binary measures, such approaches may overlook nuances in the severity of food hardships. Using data from the Current Population Survey (CPS)-FSS (Food Security Supplement) and the Annual Social and Economic Supplement (ASEC) from 2004 to 2023, we investigate generational changes in food insecurity amongst older adults using an age-period-cohort (APC) analysis. Additionally, the research uses a traditional binary indicator along with three additional measures, including a binary variable for needing more money and two continuous variables that capture the amount of additional money required to meet basic needs and the extent of the food insecurity gap. The findings reveal a generational shift, with later birth cohorts experiencing higher rates of food insecurity and requiring greater financial resources to meet basic needs, especially the Baby Boomer generation (born between 1946 to 1964). The study also suggests that the latest Baby Boomer generation (born between 1960-1964) spends more money on food, indicating a change in their food behavior, which may be attributed to their need for more money to meet their basic food needs.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

The United States (U.S.) is in the midst of a substantial demographic shift as the number of older adults, those above the age of 60, comprises an increasingly large portion of the population. Between 2000 and 2020, the percentage of the U.S. population above 50 years old increased from 27.4 to 35.7 percent, and those above 60 years old increased from 16.4 to 23.3 percent (United States Census Bureau, 2023). During this same period, which includes the Great Recession, the prevalence of food insecurity increased from approximately 6 percent in 2001 until it reached a peak in 2015 at around 9 percent (Ziliak et al., 2023). By 2018, rates had returned to their pre-Great Recession levels for many age groups, but not for older adults (source Ziliak and Gundersen, 2021; Ziliak et al., 2022).

Given that the number of older adults will continue to rise, due primarily to the aging of the Baby Boomer generation (born between 1946 to 1964), it is important to have a better understanding of the determinants of food insecurity amongst older adults (Vespa et al., 2020). Of particular concern are the findings that newer generations or cohorts of older adults may be at greater risk for food insecurity than older cohorts, even after controlling for socioeconomic status (Mudrazija and Butrica, 2023). Thus, food insecurity rates may rise, or at least fail to fall, due to the types of individuals entering older adulthood, in addition to the conditions they experience as older adults.

Brucker et al. (2022) found that midlife experiences between the ages of 40 and 54 play a significant role in shaping the risk of food insecurity during later years, particularly between the ages of 60 and 69. For Baby Boomers, these ages overlapped with three recessions: the Dot-Com Bubble Recession that began in 2001, the Great Recession that began in 2007, and the COVID-19 Recession that began in 2020 (National Bureau of Economic Research [NBER], n.d.; Rich, 2022).

Thus, it is possible that the experience of living through multiple recessions during their prime working years made Baby Boomers more at risk for food insecurity in older age.

These differences are known as cohort effects, seen among people who share a common life event, like birth, during the same period (Yang and Land, 2013; Barrera and Shively, 2022). Age-period-cohort (APC) models provide a framework in which to study and better isolate the influence of cohort effects by differentiating between three key influences, age, period, and cohort, that shape individual outcomes over time (Yang and Land, 2013). *Age effects* capture how individuals change as they grow older, *Period effects* reflect time-specific events or conditions that impact all age groups simultaneously, and *Cohort effects* represent the lasting impact of formative experiences shared by people born around the same time, such as attitudes shaped by growing up during a financial boom or crisis.

While Mudrazija and Butrica (2023) provided some initial evidence for the influence of cohort effects on food insecurity amongst older adults, their study has several limitations. First, they use data from the Health and Retirement Survey (HRS), which includes a limited set of food-related questions and a 2-year recall window to assess food insecurity. Secondly, although they highlight that while poverty remains a strong predictor of food insecurity, it fails to explain the full complexity of the phenomenon, suggesting that age, cohort, and period effects may reveal deeper insight into food insecurity. Thus, their model includes indicators for cohorts; however, the cohort groupings are inconsistently defined (e.g., some cohorts have seven birth years, some have eleven birth years), and they do not control for age or time period effects, which may bias the estimated cohort impacts.

Therefore, the purpose of this study is to use an APC framework to investigate the influence of cohort effects on food insecurity amongst older adults (i.e., those equal to or above the age of 60). We used data from the Current Population Survey (CPS) from 2004 through 2023. The CPS includes a full 18-item survey used to determine annual rates of food insecurity in the United States (Blumberg et al., 1999; Ohls, 1999; Radimer, 2002).

Our analysis provides several contributions to the literature. First, using the formal APC framework, we will be able to control for the age and period effects while analyzing the cohort effect. Additionally, we control for socio-economic and demographic variables in our analysis, which allows us to better understand the cohort effect. Second, we include several measures of food hardship and food expenditures to better investigate variations in food needs across generations.

We include both the traditional binary measure (*Binary_FI*) of food insecurity constructed from responses to the 18-item survey from the CPS and the food insecurity gap (*FGap*), which adds information on the amount of additional expenditures required to meet food needs to the traditional binary measure (Gundersen, 2023). While the *Binary_FI* identifies whether a household is food insecure, it fails to capture the severity or depth of that insecurity. This lack of differentiation can obscure the true extent of need and may lead to incomplete or misleading conclusions in research, policy design, and intervention strategies (Gunderson, 2023).

Furthermore, to address the potential stigma associated with answering food insecurity questions, particularly among older generations, we include a binary indicator for self-reporting the need for more money to meet basic food needs (Needs_More) and a continuous measure of the amount of additional money required (*Amount_More*) (Ashbrook, 2023). The *Amount_More* information is also utilized in constructing the *FGap* measure. Finally, we include a measure of typical food expenditure (*FExp*). Comparing results across these multiple outcomes will allow us to investigate if the cohort effects reflect changes in the experiences of the food insecure or if they speak to broader intergenerational changes in living standards.

CHAPTER TWO

LITERATURE REVIEW

We have categorized the previous findings into three categories. First, we discuss how food insecurity has been measured and how we are going to do it differently. Second, we summarize findings related to food insecurity among older adults. Third, we highlight the application of the age–period–cohort (APC) framework in relevant studies.

Measuring Food Insecurity

Food-insecure houses are those that experience uncertainty about having enough food or are unable to obtain enough food to meet the needs of household members due to a lack of funds or other resources (USDA, 2023). The Food Security Supplement (FSS), administered in the Current Population Survey (CPS), is used in the United States to determine household food security based on respondents' answers to 18 questions about specific food behaviors over the last 12 months. Food security is generally measured using a binary indicator based on responses to the Food Security Supplement (FSS) that assumes food insecurity, which is defined as inadequate access to food due to limited financial resources, can be measured using responses to questions about certain food behaviors ranging from worrying about running out of money to reducing meal sizes. All respondents are asked 10 survey questions, and households with children respond to an additional 8 questions[1]. Based on the responses, households are categorized into four categories: food secure, marginal food secure, low food secure, and very low food secure. Households without children are categorized as low food secure when they report 3 to 5 food insecurity questions, and as very low food secure when they report 6 or more. Similarly, households with children are classified as low food secure if they report between 3 and 7 questions, and as very low food secure if they report 8 or more (Rabbitt et al., 2024). Together, low food secure and very low food secure households are termed

[1] The questions include items such as: "In the last 12 months, did you or other adults in the household ever cut the size of your meals or skip meals because there wasn't enough money for food?" See Rabbitt et al. (2024) for more details.

food insecure. The full categorization criteria are presented in **Table 1** (All tables and figures are in the APPENDIX).

The results from the FSS are used to create a binary indicator of food insecurity: either the household is food insecure, or it is not. However, this simple measure can overlook important nuances. Treating all food-insecure households as identical disregards the varying degrees of their struggles, failing to capture the depth of food insecurity they experience and potentially leading to incomplete or misleading conclusions in studies and interventions (Gunderson, 2023). For instance, one food-insecure household might report needing a small amount of additional money to achieve food security, while another food-secure household might require a significantly larger amount. To address the limitations associated with the binary indicator, Gunderson (2023) introduces an alternative measurement known as the food insecurity gap (*FGap*), which includes additional information on the amount of additional money needed to meet basic food needs.

In the FSS, all households are asked whether they would need less, the same, or more money to meet their basic food needs. If the response indicates a need for more money (*Needs_More*), the household is then asked to specify how much additional money per week would be required to meet its basic food needs (*Amount_More*). The *FGap* measure combines the *Binary_FI* measure with the *Amount_More* measure. This allows researchers to consider both the incidence and depth of food insecurity. Otherwise, when the *Binary_FI* measure is used, households indicating a need for $10 per week to achieve food security are categorized identically to households of similar size reporting a need for $20 per week (Gunderson, 2023).

Using data from 2010 to 2021 CPS, Gunderson (2023) found that, while measuring food insecurity using the traditional binary method, there was a 30.21 percent decrease in food insecurity among younger adults (age 18 to 64), while among older adults (age 65 and above) it decreased by only 4.86 percent. In comparison, when measured by the food insecurity gap, there was a 21.88 percent decrease in food insecurity among younger adults, but there was an increase of 89.45 percent in food insecurity among older adults. The observed variation in findings across different measures of food insecurity among older adults underscores the necessity for researchers to utilize both *Binary_FI* and *FGap* measures when examining food insecurity.

Apart from the *Binary_FI* and the *FGap* Measures, we utilize *Needs_More* and *Amount_More* as measures of food insecurity in our analysis. Using these two measures can help assess if the cohort effect is related to stigma associated with answering the traditional food insecurity questions. Older cohorts, for example, may be less comfortable responding to multiple behavior-based items due to stigma or social norms and may find a single, need-based question more acceptable or easier to answer (Ashbrook, 2023). The *Needs_More* question is asked to all households regardless of their food security status; thus, it can be useful in capturing the food hardship among households who are considered food secure under the *Binary_FI* measure but still say they require more money to meet their basic food needs. Likewise, the *Amount_More* variable provides further insight by capturing the degree of hardship. It reflects how much additional money respondents believe they would need to meet basic food needs. The difference between the *FGap* and *Amount_More* measure is that the *FGap* measures the depth of food hardship among the households that are termed as food insecure under the traditional binary measure, whereas the *Amount_More* measure captures the depth of food hardship for all households.

These two measurements highlight important measurement gaps, suggesting that although these individuals are not classified as food insecure by standard definitions, they may still face food-related hardship. If that weren't the case, both *Binary_FI* and *Needs_More*, as well as both *FGap* and *Amount_More* measures, would yield the same results. The need to include these measures becomes even clearer when we look at the hypothetical example in **Table 2**. Where it shows that there can be discrepancies between *Binary_FI* and *Needs_More*, as well as between *Amount_More* and *FGap*, suggesting that each measure captures distinct aspects of food insecurity, further validating the need for using all measures.

The *Amount_More* and *FGap* measures present a challenge because they are based on self-reported financial needs, which may be influenced by two underlying factors. First, generational differences in wealth may lead to newer cohorts requiring more needs due to lower economic endowments. Second, rising food expenses or a change in food behavior may push individuals to report higher financial needs to meet the same basic food consumption. To better interpret the results, we also investigate how food expenditures have changed across cohorts. An increase in food expenses among newer cohorts might indicate that they are spending more on food than earlier cohorts, possibly because they prefer more expensive options. This could weaken the observed cohort effect, as the higher need for money may be driven by spending preferences rather than actual hardship.

Food Insecurity Amongst Older Adults

There is a limited, but growing, number of studies that examine determinants of food insecurity unique to older adults. Past research shows that living arrangements, particularly living with children and grandchildren, or being unmarried, can increase food insecurity (Gunderson and Ziliak, 2015; Ziliak and Gunderson, 2016; Butcher et al., 2023; Ziliak et al, 2023). Similar to younger adults, older adults who are Black or Hispanic, or are in poorer health, are also at greater risk for food insecurity (Levy, 2022; Leung et al., 2024; Mudrazija and Butrica, 2023). Further, amongst older adults, the likelihood of food insecurity declines with age (Ziliak, 2008; Berning et al, 2023).

Since older adults are more likely to be retired and not working, the resources they have available to acquire food are also slightly different. Similar to younger adults, older adults with lower household incomes are at greater risk for food insecurity (Leung et al., 2024; Ziliak et al., 2023). However, the relationship between food insecurity and poverty is imperfect. Not only does the discrepancy between poverty and food insecurity tend to be larger in older adults, but it may be even larger for younger cohorts of older individuals, which suggests that the relationship between poverty and food insecurity may be changing for older adults (Mudrazija and Butrica, 2023).

Further, Loibl et al. (2022) found that an important source of household wealth, homeownership, can also contribute to food security amongst older adults. Specifically, each $10,000 increase in mortgage borrowing was associated with a decline in food insufficiency by 2.2 percentage points (Loibl et al., 2022; Ziliak et al., 2022). Additionally, when people retire, food expenditures decline, but consumption does not, in part because households are able to increase the time they spend on meal preparation (Aguiar and Hurst, 2005). Although this increase in time use also has a positive influence on food security, the impact is not as great as other factors such as age and employment status (Berning et al., 2023).

For older adults, experiences during midlife (ages 40–54) may also influence food insecurity due to their impact on wealth accumulation. Brucker et al. (2022) found that stable employment, higher income, and consistent health insurance during midlife significantly reduce the risk of food insecurity. However, economic insecurity in midlife was the strongest predictor of food insecurity in older adulthood.

Research also suggests that food insecurity is increasing amongst older adults. Leung et al. (2024) found that, between 1999–2003 and 2015–2019, food insecurity among U.S. families with older adults rose significantly, from 12.5% to 23.1%. The proportion experiencing recurring food insecurity more than doubled (from 5.6% to 12.6%), while chronic food insecurity more than tripled (from 2.0% to 6.3%). Mudrazija and Butrica (2023) found that the increased prevalence was driven by older adults under the age of 80.

Given that this time period coincided with the Great Recession, and that prior research suggests experiencing economic insecurity in midlife increases the risk of food insecurity in older age, we explore the potential influence of cohort effects on food insecurity amongst older adults. These cohort effects could arise if Baby Boomers, who have more recently entered older adulthood after experiencing the Dot-Com Bubble Recession, the Great Recession, and the COVID-19 Recession during their primary working age, are at greater risk for food insecurity even after controlling for age.

APC Framework

For decades, age–period–cohort (APC) analysis has been employed in quantitative research by social scientists studying individuals across different time periods. The APC model aims to separate three temporal effects: age effects (changes associated with aging), period effects (influences affecting all age groups at a particular time), and cohort effects (impacts unique to individuals born in the same period) (Bell, 2021).

Apart from the social sciences, the APC framework has been used extensively in the field of economics. Grigoli et al. (2021), using cohort data from 17 advanced economies between 1985 and 2016, observed that women's labor force participation has risen across successive generations, resulting in higher participation rates throughout various stages of life. Barrera and Shively (2022) employ an age, sex, and cohort-specific framework to analyze data from 156 countries over the past century, revealing that excess calorie availability is linked to higher adult BMI for both men and women, and to early-life influences on adult BMI in males. Freedman (2024) tracks generational income trends across eight countries and finds that younger cohorts, especially those born after 1980, entered the labor market with comparatively lower earning opportunities.

There have also been several studies that analyze the age and cohort effects of food insecurity. For example, Miller et al. (2020), using 2014 National Health Interview Survey (NHIS) data, found that the early (ages 35–49) and late midlife (ages 50-64) experience more food hardship than the younger or older adults. Mudrazija and Butrica (2023) found that the likelihood of experiencing food insecurity is rising among younger generations, independent of their personal characteristics. Even though their model includes indicators for cohorts, the cohort groupings are inconsistently defined (e.g., some cohorts have seven birth years, some have eleven birth years), and they do not control for age or time period effects, which may bias the estimated cohort impacts.

In the context of food insecurity, the prior literature suggests that the age effect should be negative, as being old decreases the prevalence of food insecurity even amongst older adults (people above age 60). Specifically, senior older adults (aged 80 and above) tend to be more food secure than younger older adults (those under 80) (Mudrazija and

Butrica, 2023). Period effects are important to capture the influence of significant economic events, such as the Great Recession or the COVID-19 pandemic, on the likelihood of food insecurity for all ages (Kim-Mozeleski et al., 2023; Coleman-Jensen and Gregory, 2014). Finally, we hypothesize that cohort effects will be present in food insecurity because the age at which individuals experience significant economic events, such as the Great Recession, has an impact on their food insecurity in older age.

CHAPTER THREE
DATA AND METHODS

Data

In this study, we used data from the 2004 to 2023 Current Population Survey (CPS), accessed from the Integrated Public Use Microdata Series (IPUMS) (Flood et al., 2024). We combined data from the December Food Security Supplement (FSS) and the March Annual Social and Economic Supplement (ASEC). The FSS provides comprehensive data on food security and other food-related outcomes, while ASEC provides an indicator for home ownership. Only households with observations in both datasets were included in the analysis.

One challenge with merging FSS and ASEC data is that the CPS collects the data using a 4-8-4 rotation pattern (Rivera Drew et. al., 2014). In this pattern, households are interviewed for 4 consecutive months, excluded for 8 months, and finally, reenter the survey for 4 months. This rotation pattern results in the possibility that households will have either a two-month gap, in the case that they take the FSS first and then ASEC, or an eight-month gap, in the case that they take the ASEC first and then the FSS. Since it is possible that households could have a change in their housing situation (i.e., move, purchase a home) in the larger time gap, we drop the observations with an eight-month gap between their FSS and ASEC interviews.

The unit of observation in the CPS is the individual, so each household will have multiple observations. However, food insecurity, the outcome variable of primary interest, is measured at the household level. Therefore, we aggregate responses so that each observation represents a household. For variables that are measured at the household level, including food security status and homeownership, we keep only responses from the heads of households. For variables that must be constructed from individual responses, including the number of children, we aggregate by summing over the responses for individual household members.

Finally, we limit the sample to older adults, defined as respondents who are at least 60 years old and no older than 84. We also dropped observations without complete responses to the variables used in the analysis. This yields a sample size of 49,813 observations.

Of primary interest to this study is the influence of birth year cohort. Cohorts are generated using the year of birth because they move through different life stages together and are thus affected by the same historical events at the same age (Yang and Land, 2013; Barrera and Shively, 2022). To create birth cohort indicator variables, we first calculated the birth year from the given age for each household head in the CPS dataset. Then, we created a birth cohort group with 5-year increments with the 1920-1924 birth cohort as the reference category, and the other remaining categories are 1925-1929, 1930-1934, 1935-1939, 1940-1944, 1945-1949, 1950-1954, 1955-1959, and 1960-1964. We also created similar 5-year indicator variables for age groups (60-64, 65-69, 70-74, 75-79, and 80-84) and period groups (2004-2008, 2009-2013, 2014-2018, 2019-2023).

We included four outcome variables: the traditional binary method of measuring food insecurity (*Binary_FI*), a binary indicator for needing more money (*Needs_More*), the amount of additional money needed (*Amount_More*), and a modified version of Gunderson's (2023) food insecurity gap (*FGap*).

The traditional binary indicator comes from responses to the food security instrument listed in CPS-FSS. To assess the traditional food insecurity, households are asked whether they faced certain conditions in the past 12 months that indicate trouble affording food due to financial constraints. Those without children answer 10 questions, while those with children answer 18 questions. If a household answers "yes" to three or more of these items, it is classified as food insecure (Rabbitt et al., 2024).

For the alternative measurement of food insecurity, we first created a binary indicator variable, *Needs_More*, for affirmative responses to the FSS question "Would you need to spend more money than you currently do, or could you spend less, to buy enough food to meet (your needs/ your household's needs)?"

For households that respond affirmatively, they are then asked, “How much additional money would you need to meet the basic needs of you (or your household)?” Responses to this question were recorded on an interval scale (i.e., \$20 - \$40 per week), which we converted to a continuous measure by using the midpoint of the interval. This continuous measure became our outcome variable: *Amount_More*. For households that reported not needing additional money, their *Amount_More* was set to zero.

Finally, we created a food insecurity gap similar to Gunderson (2023) by using the following formula:

$$FGap_i = Binary\_FI_i * Amount\_More_i$$

Where $FGap_i$ indicates the food insecurity gap for household i. Where the $Binary\_FI_i$ and $Amount\_More_i$ are the binary and continuous outcome variables, respectively, as described previously. In this way, the *FGap* measures the depth of food insecurity, which is the amount of additional money needed amongst those identified as food insecure by the traditional binary method. Comparing results when using the *FGap* or *Amount_More* as outcome variables allows us to investigate if the perceived need for additional money is unique to the food-insecure older adults or is experienced by older adults more generally.

The Food Expenditure (*FExp*) measure is important to help provide context for the *Amount_More* results. Households could report needing more money either because they are spending less money on food or because they perceive a need to spend more, perhaps due to changes in living standards. In the CPS, food expenditure data are reported in ranges (e.g., \$325–\$334 per week). We used the midpoint of each range (e.g., \$330 per week) to estimate weekly household food expenditures. For top-coded categories, expenditures were recorded at the threshold values: \$565 for 2011, \$495 for 2012, \$445 for 2020, and \$600 for all other years.

We also created several additional variables to control for the influence of household demographics and socioeconomic status on food insecurity. We included a binary indicator for household income below 130% federal poverty line (FPL) and named *FPL ≤ 130%* in our analysis. We used the 130% threshold because it is often used to identify 'poor' households (Alaimo et al., 2001) and is an income eligibility threshold for both the Supplemental Nutrition Assistance Program (SNAP) and the National School Lunch Program (NSLP). The income to FPL ratio is calculated using the following formula:

$$\text{Income to the FPL ratio} = \frac{household\ income}{federal\ poverty\ treshold\ income} * 100$$

We used family income as a proxy for *household income* to calculate the income to the FPL ratio. In CPS, household income is reported in ranges (i.e., \$2000 - \$2500 annually), rather than continuous values; we used the midpoint (i.e., \$2250 annually) of those ranges as the household income. For households that report an income of \$150,000 or more, their incomes are recorded as \$150,000. The FPL in the denominator comes from the poverty guidelines published by the Office of the Assistant Secretary for Planning and Evaluation (ASPE) (https://aspe.hhs.gov/topics/poverty-economic-mobility/poverty-guidelines). Poverty guidelines are determined annually and vary by household size and geographic location (FPL for Hawaii and Alaska are reported separately).

Several additional variables were included to capture a household's demographic and socioeconomic status. The summary statistics of the variables in shown in **Table 3**. We categorized the educational qualifications of household heads into four groups: *High School or Less Degree*, *Some College or Associated Degree* (which includes individuals who started but did not complete a bachelor's degree, or completed an associated degree), *College Degree* (for those who completed a bachelor's degree), and *Advanced Degree* (which includes individuals with a master's, professional, or doctoral degree).

The marital status of the head of the household was categorized using three indicators: those who are married, regardless of whether their spouse is present or absent, are classified as *Married*; those who are separated, divorced, or widowed are classified as *Separated*; and those who have never been married are classified as *Single*.

Similarly, three category variables were used to capture the current employment status of the head of household: *Employed* (which includes both full-time and part-time employment), *Other Employment Status* (which includes those who are not currently employed, perform unpaid household work, or engage in any kind of unpaid work such as charitable activities), and *Retired*.

Ethnicity and racial status of individuals were categorized into four groups: *Non-Hispanic Black*, *Non-Hispanic White*, *Non-Hispanic Other/Multiracial* (which includes individuals who are Asian, of other races, or of multiple racial backgrounds), and *Hispanic*.

Then we created variables to capture household composition. Using data collected from each individual of their age, we created an indicator for the presence of children (defined as a person less than 18 years old) or adults (aged more than 18 years old). Then, we determined the total number of children and adults, and the household size (i.e., number of adults plus children). Binary variables for gender (*Male* and *Female*) were also created.

The household's housing status was assessed using data from the ASEC. A binary variable *Own a House/Apt.* indicates that households self-reported owning the home or apartment they currently live in, even if they are still paying the mortgage. Those who rented the house or apartment either paid through cash or not are termed as *Rent a House/Apt.*

Since we have been using data for over a decade, it is important to adjust any variable measures in dollar terms to address the effect of inflation. Specifically, we inflation-adjusted the *Amount_More* variable, which represents the additional money required to meet basic food needs, and the Food Expenditure variable (*FExp*). To do that, we first adjusted continuous dollar variables to the year 1999 as a base, then adjusted those amounts to the year 2023 using the inflation adjustor from the IPUMS-CPS (https://cps.ipums.org/cps/cpi99.shtml).

Methods

Our analysis will proceed in three stages. In the first, graphical methods will be used to provide a descriptive analysis. We will use two-dimensional plots of tabulated age-cohort-specific food insecurity prevalence rates to examine trends in food security by age and across cohorts (Yang and Land, 2013). Prior research suggests all cohorts should experience a downward trend in food insecurity by age, however, if there are cohort effects present, the cohort contour lines will be separated by a parallel shift. We hypothesize that there will be an upward shift in the cohort contour lines for younger cohorts, suggesting that the life experiences of newer old adults (i.e. younger cohorts) have left them more vulnerable to food insecurity in old age.

However, there are some limitations in the graphical method. In many cases, the data does not show patterns that can be clearly linked to just one of these factors (Fannon, 2020). Also, it is not possible in a 2D figure to capture all three variables in the data. Thus, it is also necessary to utilize regression models to control for all three effects (Thijs et al., 2020; Bell, 2021). In the second step of the analysis will use model-fitting statistics to provide evidence of the existence of any cohort effects.

In the original statistical APC framework, researchers were interested in identifying the linear relationship between age, period, cohort, and an outcome variable, which in this study is food insecurity, as in Equation 1.

$$Binary\_FI = \alpha + \beta\ (age) + \gamma\ (period) + \mu\ (birth\ cohort) + \varepsilon \qquad (1)$$

Where *Binary_FI* is the traditional binary food insecurity measure, α is the intercept; age, period, and birth cohort are measured in years; β, γ, and μ are the slopes for age, period, and cohort, respectively; and ε is random error.

However, this is challenging because the three variables of interest, age, period, and cohort, are all related as demonstrated in Equation 2. Thus, given values for any two variables, it is possible to perfectly predict the value of the third.

$$Birth\ cohort = period - age \qquad (2)$$

Since age, period, and cohort are perfectly linearly associated (birth cohort = period − age), individuals who are the same age at the same time also share the same birth year (Keyes, 2022). This means there is no variation in the cohort when age and period are fixed, making it impossible to separately identify or estimate the linear effect of the cohort (Fosse et. al., 2020; Bell, 2021).

Much of the literature related to APC models has been focused on addressing these dual challenges of identification and multicollinearity (Bell, 2021). An important finding from this literature is that identification issues primarily pertain to the linear effects of age, period, and cohort. Thus, it is possible to identify and estimate nonlinear effects. One common way of estimating the nonlinear effects is with the classical APC (C-APC) model, also known as the multiple classification model (Mason et al. 1973) or accounting model (Mason and Fienberg 1985), which is shown in Equation 3 (Mason and Fienberg 1985; Yang and Land, 2013).

$$\text{C-APC model: } Binary\_FI_{ijk} = \alpha^{1} + \beta^{1}{}_{i} + \gamma^{1}{}_{j} + \mu^{1}{}_{k} + \varepsilon^{1}{}_{ijk} \qquad (3)$$

Where, $i = 1,\ldots\ldots, I$ represent the age group, $j = 1,\ldots\ldots, J$ the period group, and $k = 1,\ldots\ldots, K$ the birth cohort with $k = j - i + 1$ and $K = I + J - 1$. $Binary\_FI_{ijk}$ represents the traditional binary food insecurity rate for an individual belonging to the i^{th} age cohort, the j^{th} period cohort, and the k^{th} birth cohort; α^{1} is the intercept; $\beta^{1}{}_{i}$ represents the i^{th} age effect; $\gamma^{1}{}_{j}$ represents the j^{th} period effect; $\mu^{1}{}_{k}$ represents the k^{th} birth cohort effect; and $\varepsilon^{1}{}_{ijk}$ is the error term. Thus, this analysis will utilize the C-APC model estimated using a linear regression to investigate potential cohort effects in food insecurity amongst older adults.

The full C-APC model (Equation 3) contains age, period, and cohort effects. We can then create more restrictive models by excluding all period effects, known as an Age-Cohort (AC) model (Equation 4); excluding all cohort effects, known as an Age-Period (AP) model (Equation 5); excluding all age effects, known as a Period-Cohort (PC) model (Equation 6); and excluding both age and period effects, known as a cohort (C) model

(Equation 7). Each of these models will be estimated using ordinary least squares (OLS) regression with the *Binary_FI* outcome variable. If the models without any cohort effects better fit the data, it provides some evidence against the presence of any cohort effect.

An ideal model is one that appropriately trades off model complexity for a good fit to the data. Minton (2020) stated that "A good model is one that effectively balances model fit against model complexity" and recommended using AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) values to guide model selection. Similarly, Fosse (2020) employed log-likelihood values, p-values derived from the Wald chi-square test, along with AIC and BIC values, to see if the full APC model is better than AC, AP, PC, and C models. The Wald Chi-square test (χ^2) evaluates whether one or more parameters in a statistical model are significantly different from zero (or some other null value) (Andrews, 1988; Gudicha et al., 2017). A significant p-value ($p < 0.05$) indicates that the reduced model fits significantly worse than the full model, suggesting that the excluded parameters (e.g., non-linear effects) contribute meaningfully to model fit (Hayashi et al., 2011; Pavlov et al., 2020).

$$\text{AC Model: } Binary\_FI_{ijk} = \alpha^1 + \beta^1{}_i + \mu^1{}_k + \varepsilon^1{}_{ijk} \quad (4)$$

$$\text{AP } Model\text{: } Binary\_FI_{ijk} = \alpha^1 + \beta^1{}_i + \gamma^1{}_j + \varepsilon^1{}_{ijk} \quad (5)$$

$$\text{PC } Model\text{: } Binary\_FI_{ijk} = \alpha^1 + \gamma^1{}_j + \mu^1{}_k + \varepsilon^1{}_{ijk} \quad (6)$$

$$\text{C } Model\text{: } Binary\_FI_{ijk} = \alpha^1 + \mu^1{}_k + \varepsilon^1{}_{ijk} \quad (7)$$

Finally, after selecting the appropriate model, in the third step of our analysis, we estimate the full C-APC model for each outcome variable, Y_{ijk}, of interest: *Binary_FI*, *Needs_More*, *Amount_More*, *FGap,* and *FExp*. Each model is estimated using OLS, and we adjusted the standard errors using clustering at the state level because we assume that observations within the same state are not independent of one another, as they might be affected by the same factors (i.e., same economic policies).

$$Y_{ijk} = \alpha + \beta_i + \gamma_j + \mu_k + \varepsilon_{ijk} \quad (8)$$

$$Y_{ijk} = \alpha + \beta_i + \gamma_j + \mu_k + \delta \boldsymbol{D}_{ijk} + \varepsilon_{ijk} \tag{9}$$

In the first model, captured in Equation 8, we include only age, period, and cohort covariates. In the second model, captured in Equation 9, we also control for demographic and socioeconomic variables that can influence food insecurity. The vector ***D*** contains these additional covariates discussed in *Data* subsection in Chapter 3, which includes *FPL ≤ 130%, presence of children, household size,* educational attainment *(High School or Less, Some College or Associate Degree, College Degree, Advanced Degree),* marital status *(Married, Separated, Single),* employment status *(Employed, Retired, Other Employment Status),* housing status *(Own a House/Apt., Rent a House/Apt.),* race/ethnicity *(Non-Hispanic White, Non-Hispanic Black, Non-Hispanic Other/Multiracial, Hispanic),* gender *(Male, Female).*

CHAPTER FOUR
RESULTS AND DISCUSSION

Graphical Analysis

In this section, we discuss the graphical analysis of food insecurity among older adults from the period 2004 to 2023. The researchers use two approaches in the graphical analysis of the age-period-cohort (Yang and Land, 2013). One is the outcome followed over the periods, which is depicted in **Figure 1**. And another is the two-dimensional plots of tabulated rates, such as age-period or age-cohort-specific rate tables, which are depicted in **Figures 2, 3, and 4**.

Figure 1 illustrates the food insecurity rate among older adults aged 60 to 84 from 2004 to 2023 in the United States. The graph reveals an increase in food insecurity during the Great Recession, with a peak observed in 2012, followed by a subsequent decline. The rate reached its lowest point in 2020, before rising again during the COVID-19 recession.

Although **Figure 1** shows that there is an increase in the food insecurity rate around the Great Recession and the COVID-19 Recession period, it doesn’t tell us which cohorts are most affected by it, nor does it account for the age effect.

This weakness in **Figure 1** is addressed in **Figures 2, 3, and 4**. First, **Figure 2** shows food insecurity rates (%) by survey year (2004–2023) for birth cohorts born between 1920 and 1964. Each line represents a five-year birth cohort and tracks the share of respondents reporting food insecurity in each survey period.

It can be observed from **Figure 2** that the contour lines for more recent (younger) birth cohorts generally lie above those of older cohorts, indicating that individuals from newer generations have tended to experience higher rates of food insecurity in any given year. For instance, those born between 1955–1959 and 1960–1964 consistently show higher levels of food insecurity compared to earlier cohorts, such as those born in 1935–1939 or 1940–1944. This upward shift across successive cohorts points to a potential cohort effect, suggesting that newer generations may be more vulnerable to food insecurity, possibly due to differences in life-course experiences.

However, this pattern should be interpreted with caution. The graph does not account for age effects. Older cohorts, simply by being older during survey years, may exhibit lower food insecurity rates regardless of cohort-specific factors as indicated by Mudrazija and Butrica (2023).

Figure 3 presents food insecurity rates (%) by age for successive birth cohorts from 1920 to 1964. Each colored line represents a single cohort, tracking changes in food insecurity as its members age. While some cohorts begin with higher rates than others, these differences often diminish or reverse over time. The lines intersect frequently, and no cohort consistently remains above or below the others across all ages.

Even though the graph doesn't tell us much about the cohort effect, one noticeable point is that younger cohorts (1950-1964) started with a higher food insecurity rate than the older cohorts (born before 1950) in their 60s.

Figure 4 presents food insecurity rates among older adults by birth year across different age groups. There is an upward trend in food insecurity among the 60–64 age group who were born between 1950 to 1954. But between these periods, the food insecurity rate declined for the age group of 65 to 69. In contrast, the oldest age group (80–84) tends to have consistently lower rates of food insecurity across birth years, suggesting that both age and cohort factors may influence these patterns.

While these methods offer some initial insight, they often fall short of capturing the more complex relationships between age, period, and cohort effects. In many cases, the data does not show patterns that can be clearly linked to just one of these factors (Fannon, 2020). Also, the three-dimensional effect of age-period-cohort cannot be explained in the 2D graphs. Researchers working with cohort data often treat graphs as a useful starting point, but not a substitute for more rigorous analysis. For instance, Almond (2006) builds on his graphical findings by modeling deviations from a linear cohort trend. Following this logic, we now turn to the regression model described in the *Methods* subsection in Chapter 3 to further investigate these effects.

Model Selection

Before estimating the regression model, it is essential to select the appropriate model specification. **Table 4** presents the results from model fit statistics and tests, which are used to investigate the presence of any cohort effects in the traditional binary food insecurity outcome. Each row in the table refers to a different model, which corresponds to Equations 3-7. The results show that the full APC model has the highest likelihood (-5827.59) and lowest AIC among all models (11689.19), meaning it fits the data best relative to its complexity. However, the AP model has the lowest BIC (11772.94), substantially below APC's BIC (11839.06).

We compare each simpler (AC, AP, PC, and C) model to the full APC using Wald χ^2 tests. A significant p-value ($p<0.05$) means the reduced model fits significantly worse (Hayashi et al., 2011; Pavlov et al., 2020). These results indicate that omitting any one of age, period, or cohort leads to a statistically significant loss in fit. In other words, each term contributes meaningfully, and the simpler models cannot replicate the full model's fit. Thus, we use the full-APC model in our analysis.

Regression Analysis

The results for the C-APC model without covariates are included in **Table 5**. The regression results without covariates indicate that all cohorts are insignificant for the *Binary_FI* measure, meaning there are no cohort effects for the traditional binary food insecurity measure. Regarding the *Needs_More* measure, the newest cohort shows a higher likelihood of needing more money. However, for both *Amount_More* and *FGap* measures, the late silent generation (born between 1935 and 1944) demonstrates a significant need for a positive amount of money to meet basic food needs, and this amount increases substantially for each newer cohort, including the Baby Boomer generation (born between 1945 and 1964). The *FExp* measure shows a positive increase for the newer cohorts even after accounting for inflation, indicating a change in food behavior among the newer generations.

The effect of APC can be more validify after controlling for socio-economic and demographic variables. **Table 6** contains the results from the C-APC model with covariates. In each table, the columns contain the results for a different outcome variable (binary food insecurity (*Binary_FI)*, the need for more money (*Needs_More*), the amount of more money needed (*Amount_More*), the food gap (*FGap*), and Food Expenditure (*FExp*).

First, comparing the results for the age groups across the multiple outcome variables, **Table 6** shows that, except for the 80–84 age group, other age groups do not have a statistically significant effect on the *Binary_FI* measure. The results suggest that the 80–84 age group appears less food insecure than the 60–64 reference group in the *Binary_FI*. There is no significant effect of the age group on the *Needs_More* measure, suggesting that the likelihood of reporting a need for more money does not differ between the reference age group and other age groups. The Amount_More measure is statistically insignificant for most age groups, except for the 70–74 and 75–79 age group. Specifically, the 70–74 age group requires an additional $1.69 ($p < 0.001$), and the 75–79 age group requires $1.88 ($p < 0.05$), compared to the reference group. These results indicate that older age groups, particularly those aged 70-74 and 75-79, require significantly more money to meet their food needs compared to the reference group. Similar to the *Needs_More* measure, there is no age group effect for the *FGap* measure.

The birth cohort variables, ranging from 1920-1924 to 1960-1964, reveal a clear and consistent pattern of increasing food hardship among later-born cohorts in all measures. For the *Binary_FI*, individuals born in the 1950s and 1960s show a significantly higher likelihood of being food insecure. This indicates that individuals born in the 1950s and 1960s are between 4.3% to 5.3% more likely to experience food insecurity compared to the reference cohort (1925-1929) indicated by the *Binary_FI*. The *Needs_More* measure shows a similar trend, with significant positive coefficients for cohorts born between 1945 to 1964, and the rate is between 5.5% to 8.2%. This result suggests that the later cohorts who have been more likely to be exposed to the Great Recession and COVID-19 recession during their prime working years show a higher likelihood of needing more money to meet basic food needs.

This pattern is also present in the alternative measures. For *Amount_More*, the coefficients increase substantially for later cohorts: 1935-1939 (\$2.68, $p < 0.05$), 1940-1944 (\$3.78, $p < 0.001$), 1945-1949 (\$5.20, $p < 0.001$), 1950-1954 (\$6.82, $p < 0.001$), 1955-1959 (\$7.85, $p < 0.001$), and 1960-1964 (\$10.95, $p < 0.001$). This indicates that individuals born in the 1960-1964 cohort require around \$11 more than those born in 1920-1924 to meet their food needs. This suggests a growing financial burden among more recent generations, regardless of food security status, even after controlling for inflation.

Similarly, for *FGap*, the coefficients show a significant increase for later cohorts, 1935-1939 (2.03, $p < 0.001$), 1940-1944 (2.92, $p < 0.001$), 1945-1949 (3.89, $p < 0.001$), 1950-1954 (5.10, $p < 0.001$), 1955-1959 (5.40, $p < 0.001$), and 1960-1964 (6.78, $p < 0.001$). The food gap for the 1960-1964 cohort is \$6.78 larger than that of the reference cohort, further showing the depth of hardship among food insecure household experienced by later generations.

The period groups (2004–2008 to 2019–2023) capture time-related impacts on food insecurity. The period effect is insignificant for most measures, except for the *FGap* measure in the 2019–2023 cohort (\$-1.53, $p < 0.001$), indicating that individuals who are food insecure in this period needed less money to be food secure compared to the 2004–2008 period. Overall, the period effects are generally small and less consistent than the birth cohort effects, further emphasizing the importance of generational differences.

The result of household food expenditure is captured in the *FExp* column in **Table 6**. The results show that older age groups tend to spend less on food. Specifically, individuals aged 75–79 spend \$10.33 less ($p < 0.01$), and those aged 80–84 spend \$15.31 less ($p < 0.001$) compared to the reference group (ages 60–64). Regarding the period effect, households spent significantly less on food during all observed periods compared to the reference period (2004–2008): \$15.37 less in 2009–2013 ($p < 0.001$), \$15.29 less in 2014–2018 ($p < 0.001$), and \$11.25 less in 2019–2023 ($p < 0.01$). This trend suggests that households reduced their food spending during these years, possibly due to economic constraints. Only the 1960–1964 cohort spent more on food (\$26.09 more, $p < 0.05$) than the reference group born in 1920–1924. This may account for their higher reported food needs in the *Amount_More* and *FGap* outcomes. But for the other cohorts, food expenditure is no different than the reference cohort (1920-1924).

The estimated results for the demographic and socio-economic variables follow the expected patterns. For example, being below 130% of the FPL significantly increases the likelihood of being food insecure (indicated in *Binary_FI*) and the amount needed to meet food needs (indicated in *Amount_More)*, consistent with the findings of Levy (2022) and Mudrazija and Butrica (2023). Similarly, having children in the household, having less than some college or an associated degree, and being non-Hispanic Black are associated with higher food insecurity across different measures. In contrast, being employed, retired, non-Hispanic White, or owning a house/apt is associated with lower food insecurity across all measures.

Diagnostics

Since we are concerned with the multicollinearity problem among age, period, and cohort, it is essential to check the presence of multicollinearity in this APC framework. To do that, we calculated the Generalized Variance Inflation Factor (GVIF) adjusted by degrees of freedom ($\text{GVIF}^{(\frac{1}{2}*df)}$) test to check for the multicollinearity among these variables, which was introduced by Fox and Monette (1992). **Table 7** shows the estimated GVIF value adjusted by degrees of freedom for age-period-cohort variables. Since all models produce the same results, we have shown results for only the *Binary_FI* model.

Although there is no threshold to decide on multicollinearity, a $\text{GVIF}^{(\frac{1}{2}*df)}$ value less than 2.2 is considered no multicollinearity (Fox and Monette, 1992; Fox, 2015). As we can see, the estimated $\text{GVIF}^{(\frac{1}{2}*df)}$ values for the APC variables are less than 2.2, which indicates no multicollinearity among age, period, and cohort.

CHAPTER FIVE
CONCLUSIONS AND RECOMMENDATIONS

Between 2001 and 2011, individuals aged 60 and over experienced a steady rise in food insecurity, which peaked in 2012, followed by a slow decline that still hasn't returned to pre-Great Recession levels. The purpose of the study is to investigate the potential influence of cohort effects on food insecurity amongst older adults in the United States.

We estimated a C-APC model using data from the Current Population Survey (CPS)-Food Security Supplement (FSS) and the Annual Social and Economic Supplement (ASEC) from 2004 to 2023. In addition to the traditional binary method (*Binary_FI*), which classifies a household as food-insecure if it responds affirmatively to three or more food security questions, we used multiple alternative measures, including *Needs_More*, which examines if a household reports needing more money to meet basic needs, and *Amount_More*, which indicates how much more money households need to meet basic food needs regardless of their food security status. This helps to understand the depth of food hardship among both food-secure and food-insecure individuals.

We also used the Food Insecurity Gap (*FGap*) measure introduced by Gundersen (2023), which captures the depth of food hardship among food-insecure people only. Since the *Amount_More* and *FGap* measures include self-reported amounts of additional money needed, the results could reflect increases in household food expenditures (*FExp*). To fully analyze the issue, we also examined the effects of age, period, and cohort on household food expenditures over time.

The analysis reveals that later birth cohorts, especially those born in the 1950s and 1960s, experience a significantly higher likelihood of food insecurity compared to earlier cohorts born in the 1920s and 1930s across all measures. The newer cohorts also exhibit greater depth of hardship in both the *Amount_More* and *FGap* measures, indicating increases in both food insecurity and the depth of food hardship among the Baby Boomer generations. However, food expenditures across all cohorts show that the latest Baby Boomer generation (1960–1964 cohort) has notably higher food expenses, suggesting they may be consuming more expensive food or have different food habits compared to earlier cohorts. This could contribute to their greater need for additional money to meet basic needs. For other baby boomer cohorts, food expenses did not differ significantly from those of the earliest cohorts, indicating that the generational effect is most evident among Baby Boomers, many of whom were in the workforce during the Great Recession and the COVID-19 Recession.

The findings support the hypothesis that birth cohort effects play a role in shaping food insecurity among older adults. The study also underscores the need for alternative measures like *Needs_More*, *Amount_More*, and *FGap*, as traditional binary methods fail to capture both the existence and the depth of food hardship.

While this paper presents a comprehensive analysis of the generational effects on persistent food insecurity among older adults using multiple measures, it is not without limitations; thus, there are some areas the research could explore to gain further insight to mitigate food insecurity among older adults. The main limitation is that it uses CPS data, which are repeated cross-sectional rather than longitudinal. As a result, we cannot follow the same individuals over time. However, the data still provides valuable insight into generational patterns and trends in food insecurity, sufficient for the study, but longitudinal data might have helped to better understand food insecurity. Future research should explore longitudinal data to further understand the cohort effects and see how economic experiences during midlife shape food security in later years.

Notwithstanding any limitations, our findings have important policy implications. The increased vulnerability of younger older adults, especially baby boomers, highlights the need for targeted interventions, such as enhanced SNAP benefits, workforce reintegration programs, or financial assistance directed to those most affected. Additionally, the use of alternative measures, such as the food insecurity gap, enables a better understanding of the depth of need and helps with direct support where it is needed most.

REFERENCES

Aguiar, M., & Hurst, E. (2005). Consumption versus expenditure. *Journal of Political Economy*, *113*(5), 919-948.

Alaimo, K., Olson, C. M., Frongillo Jr, E. A., & Briefel, R. R. (2001). Food insufficiency, family income, and health in US preschool and school-aged children. *American journal of public health*, *91*(5), 781.

Andrews, D. W. (1988). Chi-square diagnostic tests for econometric models: theory. *Econometrica: Journal of the Econometric Society*, 1419-1453.

Ashbrook, A. (2023, May 19). *Food insecurity among older adults is often invisible*. Food Research & Action Center. https://frac.org/blog/food-insecurity-among-older-adults-is-often-invisible

Barrera, E. L., & Shively, G. (2022). Excess calorie availability and adult BMI: a cohort analysis of patterns and trends for 156 countries from 1890 to 2015. *Food Policy*, *109*, 102271.

Bell, A. (2021). *Age Period and Cohort Effects*. Routledge.

Berning, J., Cleary, R., & Bonanno, A. (2023). Food insecurity and time use in elderly vs. non-elderly: An exploratory analysis. *Applied Economic Perspectives and Policy*, *45*(1), 280-299.

Blumberg, S. J., Bialostosky, K., Hamilton, W. L., & Briefel, R. R. (1999). The effectiveness of a short form of the Household Food Security Scale. *American journal of public health*, *89*(8), 1231-1234.

Brucker, D., Jajtner, K., & MItra, S. (2022, Dec.). Understanding food-related hardships among older Americans: Evidence from the Panel Study of Income Dynamics. University of Kentucky Center for Poverty Research Discussion Paper Series, DP2022-05, Retrieved [Date] from *http://ukcpr.org/research*.

Butcher, K. F., Schmidt, L., Shore-Sheppard, L., & Watson, T. (2023). Living with children and food insecurity in seniors. *Applied Economic Perspectives and Policy*, *45*(1), 234-261.

Coleman-Jensen, A., & Gregory, C. (2014). Inflation and Higher Food Prices Kept Food Insecurity Rates Relatively High After the 2007-09 Recession. *Amber Waves: The Economics of Food, Farming, Natural Resources, and Rural America*, (11).

Fannon, Z. (2020). *Age-period-cohort models for individual-level data: An acceleration-based regression framework* (Doctoral dissertation, University of Oxford).

Fosse, E., Winship, C., & Daoud, A. (2020). Learning from age–period–cohort data: Bounds, mechanisms, and 2D-APC graphs. In *Age, Period and Cohort Effects* (pp. 84-116). Routledge.

Fox, J., & Monette, G. (1992). Generalized collinearity diagnostics. *Journal of the American Statistical Association*, *87*(417), 178-183.

Fox, J. (2015). *Applied regression analysis and generalized linear models*. Sage publications.

Freedman, M. (2024). Earnings, Cohort Effects, and Inter-Generational Inequality: Evidence From the Luxembourg Income Study. *Review of Income and Wealth*, *70*(2), 278-290.

Grigoli, F., Koczan, Z., & Topalova, P. (2021). A cohort-based analysis of labor force participation for advanced economies. *Oxford Economic Papers*, *73*(2), 623-643.

Gudicha, D. W., Schmittmann, V. D., & Vermunt, J. K. (2017). Statistical power of likelihood ratio and Wald tests in latent class models with covariates. *Behavior research methods*, *49*, 1824-1837.

Gundersen, C., & Ziliak, J. P. (2015). Food insecurity and health outcomes. *Health affairs*, *34*(11), 1830-1839.

Gundersen, C. (2023). A reconsideration of food insecurity trends in the United States. *Applied Economic Perspectives and Policy*.

Hayashi, K., Bentler, P. M., & Yuan, K. H. (2011). *Structural equation modeling. Essential Statistical Methods for Medical Statistics, 202–234*.

Keyes, K. M., Rutherford, C., & Smith, G. S. (2022). Alcohol-induced death in the USA from 1999 to 2020: a comparison of age–period–cohort methods. *Current Epidemiology Reports*, *9*(3), 161-174.

Kim-Mozeleski, J. E., Moore, S. N. P., Trapl, E. S., Perzynski, A. T., Tsoh, J. Y., & Gunzler, D. D. (2023). Food insecurity trajectories in the US during the first year of the COVID-19 pandemic. *Preventing Chronic Disease*, *20*, E03.

Leung, C. W., Insolera, N. E., & Wolfson, J. A. (2024, March). Trends in recurring and chronic food insecurity among US families with older adults. In *JAMA Health Forum* (Vol. 5, No. 3, pp. e235463-e235463). American Medical Association.

Levy, H. (2022). The long-run prevalence of food insufficiency among older Americans. *Applied economic perspectives and policy*, *44*(2), 575-590.

Loibl, C., Rhodes, A. P., Moulton, S., Haurin, D., & Edmunds, C. (2022). Food insecurity among older adults in the US: The role of mortgage borrowing. *Applied Economic Perspectives and Policy*, *44*(2), 549-574.

Mason, K. O., Mason, W. M., Winsborough, H. H., & Poole, W. K. (1973). Some methodological issues in cohort analysis of archival data. *American sociological review*, 242-258.

Mason, W. M., & Fienberg, S. E. (1985). Introduction: Beyond the identification problem. In *Cohort analysis in social research: beyond the identification problem* (pp. 1-8). New York, NY: Springer New York.

Miller, L. M. S., Tancredi, D. J., Kaiser, L. L., & Tseng, J. T. (2020). Midlife vulnerability and food insecurity: Findings from low-income adults in the US National Health Interview Survey. *PLoS one*, *15*(7), e0233029.

Minton, J. (2020). The Lexis surface: a tool and workflow for better reasoning about population data. In *Age, Period and Cohort Effects* (pp. 41-69). Routledge.

Mudrazija, S., & Butrica, B. A. (2023). The dynamic nature of poverty and food insecurity among older adults: Evidence from the Health and Retirement Study. *Applied Economic Perspectives and Policy*, *45*(1), 262-279.

National Bureau of Economic Research [NBER] (n.d.). *Business Cycle Dating. https://www.nber.org/research/business-cycle-dating*

Ohls, J. C. (1999). Testing the robustness of the Food Security Scale with more recent CPS data. In *2nd Food Security Measurement and Research Conference. Alexandria, VA: US Department of Agriculture*.

Pavlov, G., Shi, D., & Maydeu-Olivares, A. (2020). Chi-square difference tests for comparing nested models: An evaluation with non-normal data. *Structural Equation Modeling: A Multidisciplinary Journal*, *27*(6), 908-917.

Rabbitt, M.P., Hales, L.J., Burke, M.P., & Coleman-Jensen, A. (2023). *Household food security in the United States in 2022* (Report No. ERR-325). U.S. Department of Agriculture, Economic Research Service. *https://doi.org/10.32747/2023.8134351.ers*

Radimer, K. L. (2002). Measurement of household food security in the USA and other industrialised countries. *Public health nutrition*, *5*(6a), 859-864.

Rich, M. (2022). From dot. com to pandemic: Reflections on how universities respond. *Advances in Online Education: A Peer-Reviewed Journal*, *1*(1), 16-25.

Rivera Drew, J. A., Flood, S., & Warren, J. R. (2014). Making full use of the longitudinal design of the Current Population Survey: Methods for linking records across 16 months\m {1}. *Journal of economic and social measurement*, *39*(3), 121-144.

Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, Daniel Backman, Annie Chen, Grace Cooper, Stephanie Richards, Megan Schouweiler, and Michael Westberry. IPUMS CPS: Version 12.0 [dataset]. Minneapolis, MN: IPUMS, 2024. *https://doi.org/10.18128/D030.V12.0*

Thijs, P., Te Grotenhuis, M., & Scheepers, P. (2020). The pros and cons of constraining variables. In *Age, period and cohort effects* (pp. 9-22). Routledge.

United States Census Bureau (May 25, 2023). *How Has Our Nation's Population Changed?*. *https://www.census.gov/library/visualizations/interactive/how-has-our-nations-population-changed.html*

USDA (2023). "Food Security in the U.S." *https://www.ers.usda.gov/topics/food-nutrition-assistance/food-security-in-the-u-s/*

Vespa, J., Medina, L., & Armstrong, D. M. (2020). *Demographic turning points for the United States: Population projections for 2020 to 2060. Population estimates and projections (P25-1144)*. U.S. Census Bureau. *https://www.census.gov/content/dam/Census/library/publications/2020/demo/p25-1144.pdf*

Yang, Y., & Land, K. C. (2013). *Age-period-cohort analysis: New models, methods, and empirical applications*. Taylor & Francis.

Ziliak, J. P., Haist, M., & Gundersen, C. (2008). *The causes, consequences, and future of senior hunger in America* (pp. 1-88). Alexandria, VA: National Foundation to End Senior Hunger.

Ziliak, J. P., & Gundersen, C. (2016). Multigenerational families and food insecurity. *Southern Economic Journal*, *82*(4), 1147-1166.

Ziliak, J., and C. Gundersen (2021). The Health Consequences of Senior Hunger in the United States: Evidence from the 1999-2016 NHANES. Report submitted to Feeding America.

Ziliak, J. P., Gundersen, C., & Ismail, M. (2022). Introduction to senior hunger special issue. *Applied Economic Perspectives and Policy*, *44*(2), 534-548.

Ziliak, J. P., Gundersen, C., & Vaudin, A. (2023). Introduction to senior hunger special issue. *Applied Economic Perspectives and Policy*, *45*(1), 221-233.

APPENDIX

Table 1: Categorization of Different Food Security Status.

Food Security Status	Household without Children	Household with Children
Food Secure	Less than 3 questions or income greater than 185% of FPL.	Less than 3 questions or income greater than 185% of FPL.
Low Food Secure	3 to 5 questions.	3 to 7 questions.
Very Low Food Secure	6 questions or more.	8 questions or more.

Note: FPL stands for Federal Poverty Line. The Food Secure category consists of both food-secure and marginal food-secure households.

Table 2: Hypothetical Example for Alternative Measure of Food Insecurity.

Household ID	*Binary_FI* (a)	*Needs_More*	*Amount_More* (b)	*FGap* (a*b)
A	1	1	5	5
B	1	0	0	0
C	0	1	0	0
D	1	1	10	10
E	0	1	10	0
Average			5	3

Note: *Binary_FI* is a binary indicator, where 1 indicates food insecurity and 0 indicates otherwise. Similarly, for the *Needs_More* measure, a value of 1 indicates that the household needs additional money, while a value of 0 indicates otherwise.

Table 3: Summary Statistics.

Variables	Mean	Standard Deviation
Age Group (60–64) (%)	0.29	0.45
Age Group (65–69) (%)	0.25	0.43
Age Group (70–74) (%)	0.20	0.40

Table 3 Continues...

Age Group (75–79) (%)	0.15	0.36
Age Group (80–84) (%)	0.11	0.31
Birth Cohort (1920-1924) (%)	0.01	0.07
Birth Cohort (1925-1929) (%)	0.05	0.21
Birth Cohort (1930-1934) (%)	0.09	0.28
Birth Cohort (1935-1939) (%)	0.14	0.34
Birth Cohort (1940-1944) (%)	0.21	0.41
Birth Cohort (1945-1949) (%)	0.22	0.41
Birth Cohort (1950-1954) (%)	0.18	0.38
Birth Cohort (1955-1959) (%)	0.10	0.30
Birth Cohort (1960-1964) (%)	0.02	0.15
Period Group (2004–2008) (%)	0.21	0.41
Period Group (2009–2013) (%)	0.26	0.44
Period Group (2014–2018) (%)	0.27	0.44
Period Group (2019–2023) (%)	0.25	0.43
FPL<130% (%)	0.24	0.43
Presence of Child (%)	0.14	0.35
Number of Household Members	2.64	1.67
High School or Less Degree (%)	0.42	0.49
Some college or Associated College Degree (%)	0.27	0.45
College Degree (%)	0.17	0.38
Advanced Degree (%)	0.13	0.34
Married (%)	0.51	0.50

Table 3 Continues...

Separated (%)	0.42	0.49
Single (%)	0.07	0.26
Employed (%)	0.30	0.46
Unemployed (%)	0.01	0.12
Retired (%)	0.58	0.49
Other Employment Status (%)	0.10	0.30
Hispanic (%)	0.05	0.22
Non-Hispanic White (%)	0.82	0.38
Non-Hispanic Black (%)	0.08	0.27
Non-Hispanic Other/Multiracial (%)	0.04	0.21
Male (%)	0.50	0.50
Female (%)	0.50	0.50
Own a House/Apt. (%)	0.82	0.38
Rent a House/Apt. (%)	0.18	0.38
Binary_FI (%)	0.08	0.27
Needs_More (%)	0.11	0.31
Amount_More ($/week)	7.61	28.39
FGap ($/week)	3.45	19.82
FExp ($/week)	161.00	128.49

Table 4: Fit Statistics for Various APC Models.

	Log-likelihood	AIC	BIC	Chi-square	P-value
APC model	**-5827.59**	**11689.19**	11839.06	NA	NA
AC model	-5840.07	11708.13	11831.56	24.94	0.0000

Table 4 Continues...

AP model	**-5837.80**	**11693.60**	**11772.94**	**20.41**	**0.0089**
PC model	-5834.76	11695.51	11810.12	14.32	0.0063
C model	-5866.53	11753.07	11841.23	77.92	0.0000

Note: Chi-square (χ^2) statistics and p-values based on Wald tests comparing the full APC model with the specified candidate model.

Table 5: Ordinary Regression Analysis with APC Model (Without Covariates).

Variables	*Binary_FI*	*Needs_More*	*Amount_More*	*FGap*	*FExp*
(Intercept)	0.078***	0.091***	2.937*	0.615	159.073***
	(0.016)	(0.022)	(1.401)	(0.764)	(10.580)
Age Group (65-69)	-0.013***	-0.001	0.305	-0.155	-5.316***
	(0.004)	(0.005)	(0.461)	(0.310)	(1.912)
Age Group (70-74)	-0.016*	0.002	0.949•	0.261	-11.351***
	(0.007)	(0.007)	(0.559)	(0.421)	(2.900)
Age Group (75-79)	-0.015	0.008	1.098	0.628	-22.700***
	(0.010)	(0.010)	(0.896)	(0.687)	(4.495)
Age Group (80-84)	-0.028*	0.006	0.875	0.201	-33.470***
	(0.011)	(0.011)	(0.975)	(0.670)	(5.216)
Birth Cohort (1925-1929)	-0.013	-0.011	0.762	0.412	-5.812
	(0.013)	(0.020)	(1.133)	(0.439)	(8.043)
Birth Cohort (1930-1934)	-0.007	-0.012	1.253	0.852	14.133 •
	(0.015)	(0.020)	(1.087)	(0.575)	(7.633)
Birth Cohort (1935-1939)	0.003	0.000	2.630*	1.788***	18.435*
	(0.014)	(0.021)	(1.261)	(0.653)	(8.112)
Birth Cohort (1940-1944)	0.006	0.007	3.198*	2.357***	25.553***
	(0.015)	(0.022)	(1.338)	(0.757)	(8.627)
Birth Cohort (1945-1949)	0.011	0.017	4.464***	3.214***	35.467***
	(0.017)	(0.023)	(1.537)	(0.890)	(9.627)
Birth Cohort (1950-1954)	0.028	0.039	6.547***	4.701***	34.636***
	(0.019)	(0.026)	(1.773)	(1.139)	(10.438)

Table 5 Continues...

Birth Cohort (1955-1959)	0.036•	0.051•	8.313***	5.416***	43.343***
	(0.021)	(0.027)	(1.998)	(1.271)	(11.000)
Birth Cohort (1960-1964)	0.045•	0.073*	11.806***	6.897***	59.308***
	(0.025)	(0.030)	(2.657)	(1.678)	(12.372)
Period Group (2009-2013)	0.012***	0.013*	0.743•	0.531*	-20.006***
	(0.004)	(0.005)	(0.432)	(0.261)	(3.233)
Period Group (2014-2018)	0.005	-0.003	-0.396	-0.456	-21.946***
	(0.008)	(0.008)	(0.523)	(0.449)	(4.179)
Period Group (2019-2023)	-0.008	-0.008	-1.305•	-1.445*	-17.809***
	(0.009)	(0.010)	(0.751)	(0.571)	(4.801)
Num.Obs.	49813	49813	49813	49813	49813
R2	0.006	0.003	0.004	0.004	0.026
R2 Adj.	0.005	0.003	0.004	0.003	0.026

Note: ***, **, *, and • indicate the estimated coefficient is significantly different from zero at 0.01%, 1%, 5%, and 10% test levels. Clustered standard errors by state were used. The Birth Cohort 1920–1924, Age Group 60–64, and Period Group 2004–2008 were used as reference categories.

Table 6: Ordinary Regression Analysis with APC Model (With Covariates).

Variables	*Binary_FI*	*Needs_More*	*Amount_More*	*FGap*	*FExp*
(Intercept)	0.256***	0.237***	14.592***	9.275***	132.787***
	(0.021)	(0.025)	(1.923)	(1.415)	(11.411)
Age Group (65-69)	-0.007•	0.003	0.777•	0.118	-0.252
	(0.004)	(0.004)	(0.424)	(0.297)	(1.757)
Age Group (70-74)	-0.008	0.008	1.694***	0.703•	-3.546
	(0.007)	(0.006)	(0.496)	(0.392)	(2.659)

Table 6 continues...

Age Group (75-79)	-0.008	0.012	1.878*	1.045	-10.335***
	(0.009)	(0.009)	(0.795)	(0.642)	(3.999)
Age Group (80-84)	-0.027***	0.005	1.429	0.428	-15.315***
	(0.011)	(0.010)	(0.905)	(0.652)	(4.575)
Birth Cohort (1925-1929)	-0.014	-0.012	0.532	0.298	-7.800
	(0.014)	(0.019)	(1.122)	(0.497)	(6.891)
(Birth Cohort (1930-1934)	-0.002	-0.007	1.208	0.974	4.627
	(0.015)	(0.019)	(1.110)	(0.666)	(6.896)
Birth Cohort (1935-1939)	0.012	0.009	2.680*	2.025***	3.270
	(0.015)	(0.021)	(1.293)	(0.725)	(7.439)
Birth Cohort (1940-1944)	0.023	0.024	3.773***	2.923***	4.984
	(0.015)	(0.022)	(1.352)	(0.795)	(7.789)
Birth Cohort (1945-1949)	0.031•	0.039•	5.195***	3.885***	10.126
	(0.017)	(0.022)	(1.523)	(0.913)	(8.716)
Birth Cohort (1950-1954)	0.043*	0.055*	6.820***	5.096***	9.221
	(0.018)	(0.024)	(1.702)	(1.126)	(9.534)
Birth Cohort (1955-1959)	0.043*	0.060*	7.850***	5.397***	17.690•
	(0.019)	(0.025)	(1.903)	(1.225)	(9.636)
Birth Cohort (1960-1964)	0.053*	0.082***	10.951***	6.784***	26.091*
	(0.023)	(0.027)	(2.475)	(1.615)	(11.316)
Period Group (2009-2013)	0.000	0.002	-0.045	-0.022	-15.365***
	(0.004)	(0.005)	(0.425)	(0.259)	(2.828)
Period Group (2014-2018)	-0.004	-0.011•	-0.869•	-0.826•	-15.289***
	(0.007)	(0.006)	(0.468)	(0.431)	(3.261)
Period Group (2019-2023)	-0.011	-0.011	-1.332•	-1.534***	-11.253***
	(0.008)	(0.009)	(0.713)	(0.551)	(3.970)
FPL ≤130%	0.113***	0.113***	7.045***	5.382***	-35.604***
	(0.006)	(0.006)	(0.452)	(0.365)	(1.547)
	0.038***	0.047***	6.051***	2.491***	44.921***

Table 6 continues...

Presence of Children	(0.004)	(0.006)	(0.560)	(0.347)	(2.309)
Number of Household Members	-0.004***	-0.005***	0.193	0.020	9.544***
	(0.001)	(0.001)	(0.137)	(0.063)	(0.540)
High School or Less Degree	0.029***	0.046***	2.781***	0.986***	-49.911***
	(0.003)	(0.004)	(0.392)	(0.240)	(2.591)
Some College or Associated Degree	0.019***	0.034***	1.818***	0.677***	-33.067***
	(0.003)	(0.004)	(0.394)	(0.216)	(2.461)
College Degree	0.005	0.009*	0.442	0.103	-16.154***
	(0.003)	(0.004)	(0.368)	(0.226)	(2.681)
Married	-0.025***	-0.010	-0.313	-0.687	55.556***
	(0.006)	(0.008)	(0.641)	(0.513)	(2.783)
Separated	0.006	0.009	0.356	0.232	5.678*
	(0.008)	(0.008)	(0.689)	(0.604)	(2.599)
Employed	-0.127***	-0.102***	-8.149***	-6.373***	12.831***
	(0.009)	(0.009)	(0.775)	(0.715)	(2.053)
Unemployed	-0.028*	-0.025•	-2.310	-1.567	-1.440
	(0.012)	(0.013)	(1.435)	(1.305)	(5.526)
Retired	-0.118***	-0.090***	-7.327***	-5.735***	2.610
	(0.009)	(0.009)	(0.697)	(0.699)	(1.983)
Non-Hispanic Black	0.027***	0.049***	3.964***	2.374***	-19.326***
	(0.010)	(0.011)	(1.096)	(0.720)	(4.196)
Non-Hispanic Other/multiracial	-0.027•	-0.056***	-4.182*	-1.895•	12.029
	(0.014)	(0.016)	(1.728)	(0.983)	(8.752)
Non-Hispanic White	-0.052***	-0.079***	-7.989***	-3.610***	-2.170
	(0.006)	(0.009)	(0.957)	(0.493)	(3.575)
Male	-0.004•	-0.012***	-0.335	0.085	6.761***

Table 6 continues...

	(0.002)	(0.003)	(0.304)	(0.193)	(1.362)
Own a House/Apt.	-0.082***	-0.065***	-4.157***	-3.582***	10.563***
	(0.006)	(0.006)	(0.659)	(0.418)	(1.781)
Num.Obs.	49813	49813	49813	49813	49813
R2	0.142	0.107	0.077	0.066	0.207
R2 Adj.	0.142	0.106	0.076	0.066	0.206

Note: ***, **, *, and • indicate the estimated coefficient is significantly different from zero at 0.01%, 1%, 5%, and 10% test levels. Clustered standard errors by state were used. The birth cohort of 1920-1924, Age Group 60-64, Period Group 2004-2008, Advanced Degree, Single, Other Employment, Hispanic, Female, Rent a House/Apt., were used as the reference.

Table 7: Multicollinearity Test among Age, Period, and Cohort.

Variables	GVIF	df	$\mathbf{GVIF}^{(\frac{1}{2}*df)}$
Age Group	9.73	4	1.33
Period Group	18.67	8	1.39
Birth Cohort	7.24	3	1.20

Note: Result for only *Binary_FI* shown here since all models produce the same outcome.

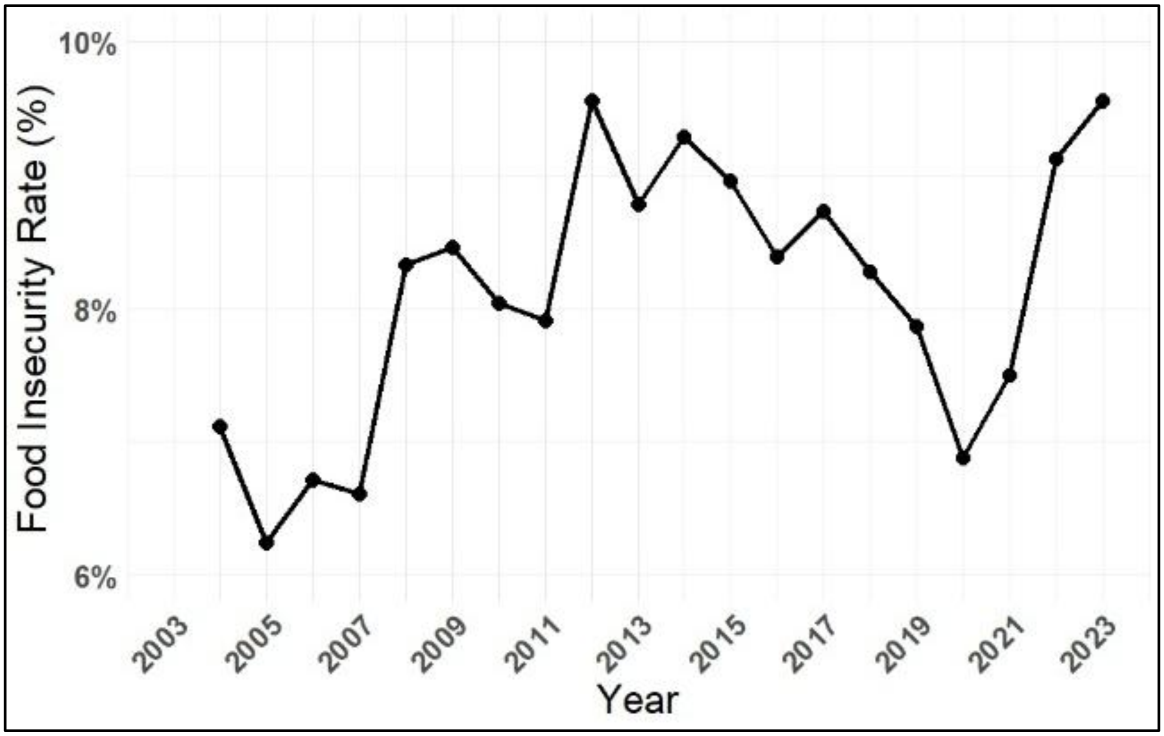

Figure 1: Food Insecurity Rate among Older Adults by Year.

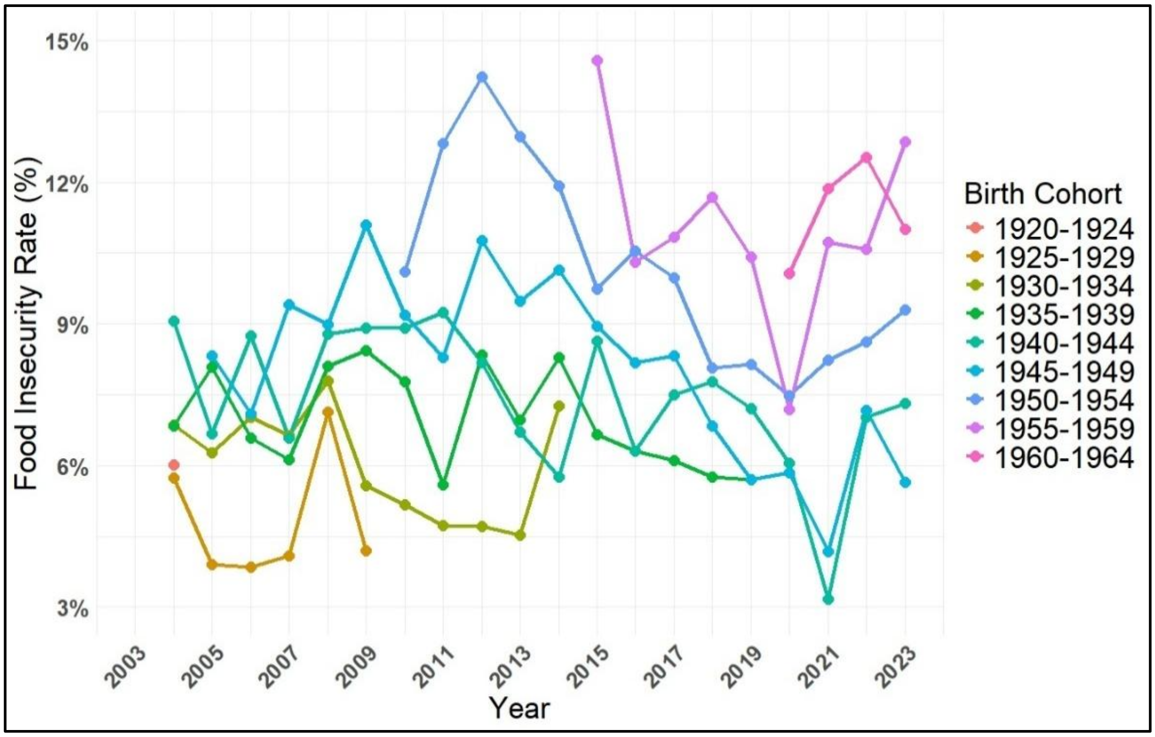

Figure 2: Food Insecurity Rate among Older Adults by Year and Birth Cohort.

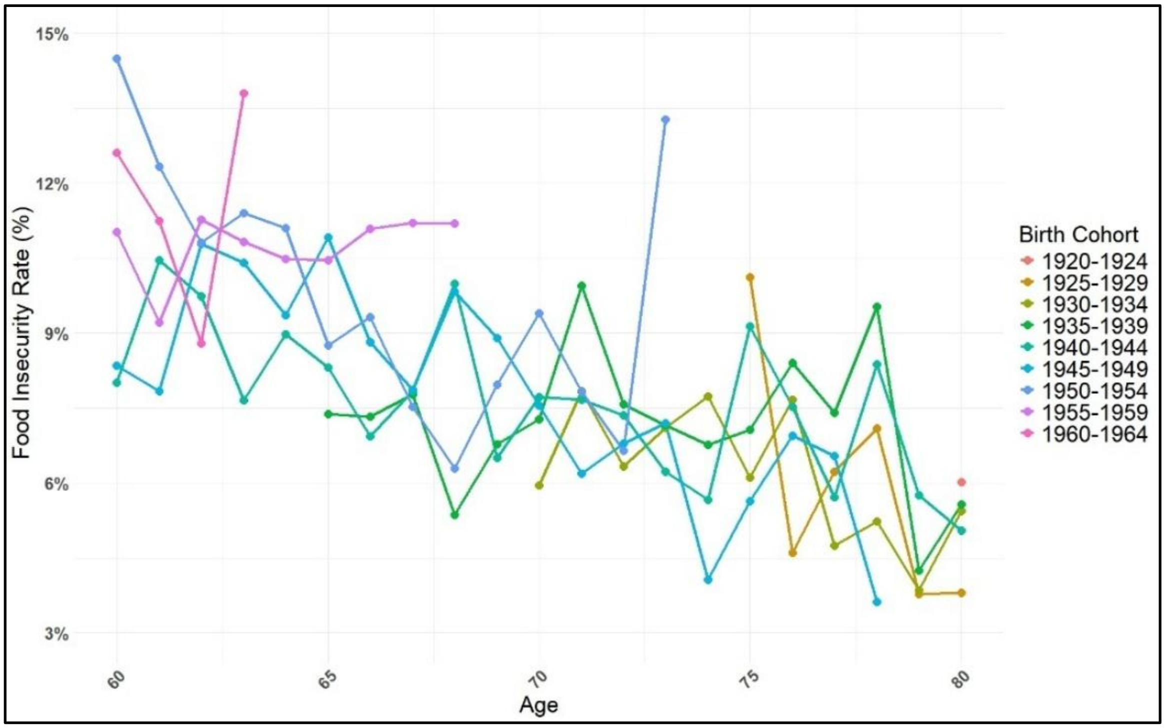

Figure 3: Food Insecurity Rates for Different Ages by Birth Cohort.

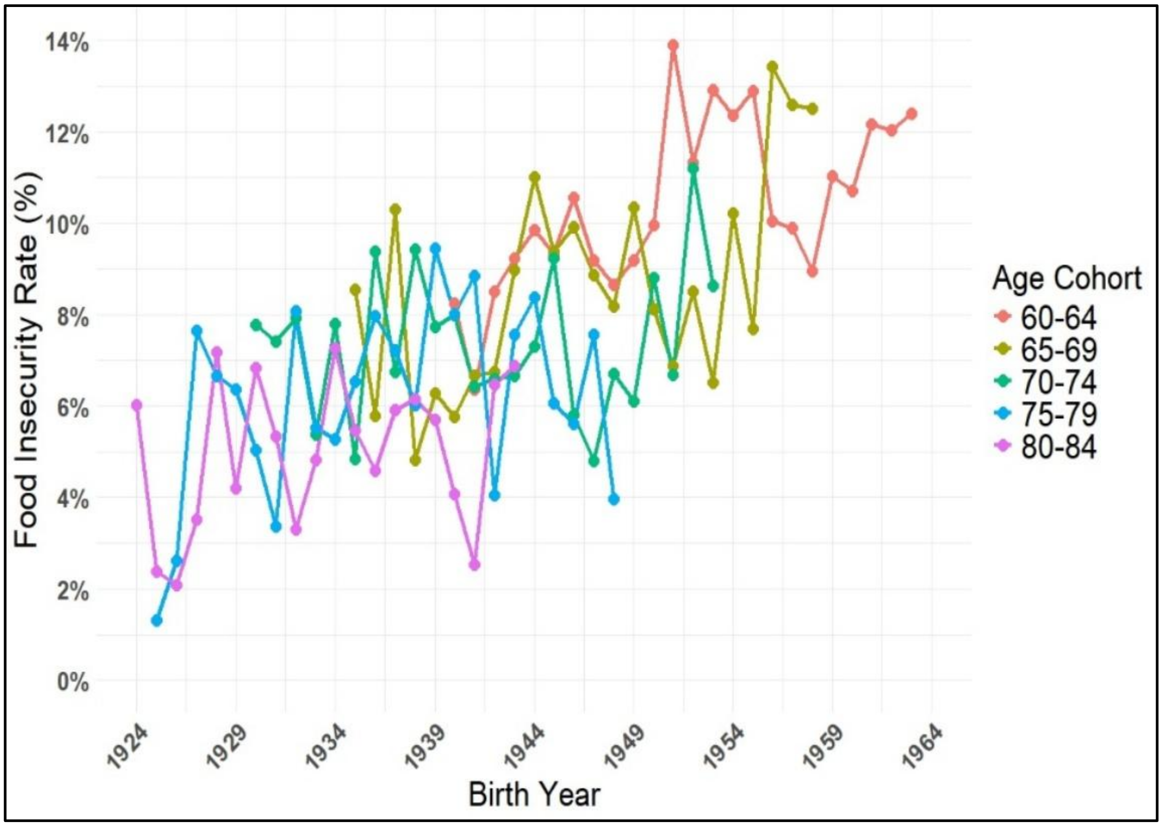

Figure 4: Food Insecurity Rates by Birth Year and Age Cohort.

VITA

Arfanul Ibna Mustafa Sakib is a second-year master's student at the University of Tennessee, Knoxville, pursuing a degree in Agricultural Economics with a minor in Statistics. Originally from Bangladesh, he completed his undergraduate studies at the University of Chittagong. As a first-generation college graduate, Sakib is deeply committed to using economic research to address food insecurity and poverty.

His research focuses on food security in the United States, particularly the impact of online grocery shopping and SNAP benefits for older adults. He presented his work at the 2025 Southern Agricultural Economic Association Conference and currently serves as a Graduate Research Assistant under Dr. Jacqueline Yenerall.

Beyond academics, Sakib works as a social media liaison at UTK, promoting cultural diversity on campus. With plans to pursue a Ph.D. in Agricultural and Applied Economics, Sakib is determined to contribute to research that improves food access and economic stability for vulnerable populations.