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Food insecurity among seniors: The role of social insurance

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CONTENTS

Abstract: The goals of this program of research are to estimate (1) the sociodemographic predictors of food insufficiency among seniors ages 60 and older and (2) the causal impacts of Social Security, Medicare, and Medicaid on food insecurity and/or insufficiency among seniors. I use data from the Health and Retirement Study (HRS), Current Population Survey (CPS), National Health Interview Survey (NHIS) and American Community Survey (ACS). Analyses using HRS data show that, consistent with earlier studies, age, income, work status, disability, education, and race/ethnicity are all significant determinants of food insufficiency; neuroticism is also a significant predictor of food insufficiency. Exploiting the Social Security "notch" in benefits that resulted in lower payments to individuals born just after January 1, 1917 compared with those born just before, I find using HRS data from 1995 that lower income is associated with higher food insufficiency and SNAP use, but these results are imprecisely estimated. Next, using NHIS and HRS data from multiple years, I find no evidence that becoming age-eligible for Medicare at age 65 reduces food insecurity. Finally, a difference-in-difference analysis of the Affordable Care Act's Medicaid expansion using ACS and CPS data shows that despite significant increases in Medicaid among seniors in states that implemented expansion compared with those that did not, food insecurity among seniors did not decline. These results suggest that public health insurance does not reduce food insecurity among seniors, perhaps because this benefit is not fungible.

Executive Summary

The overarching goal of this project is to estimate the impacts of these three programs – Social Security, Medicare, and Medicaid – on food insecurity and/or insufficiency among Americans ages 60 and older, using well-established identification strategies to isolate causal effects.

Aim 1 estimates the economic, demographic, health-related, and psychosocial predictors of food insufficiency among seniors in both cross-sectional and longitudinal analyses using data from the Health and Retirement Study for 1998 through 2016. I find that younger age, lower levels of education, non-employment, lower levels of income and wealth, and poor physical health or functional status are significant predictors of food insufficiency in both cross-sectional and longitudinal analyses. These findings are consistent with patterns of food insecurity in the more widely used data from the Current Population Survey, which supports the validity of using Health and Retirement Study data for Aims 2 and 3. I also find in Aim 1 that neuroticism – a personality trait that reflects the extent to which an individual is moody, worrying, nervous, and/or not calm - is significantly correlated with food insufficiency.

Aim 2 uses the Social Security "notch", a discontinuous drop in the generosity of benefits for individuals born just after January 1, 1917 compared with those born just before that date to estimate whether Social Security income reduces food insufficiency among seniors. Using a regression discontinuity design and data from the 1995 Health and Retirement Study, I find suggestive but very imprecisely estimated evidence that lower income at the notch may have increased food insufficiency among seniors.

Aim 3 uses a regression discontinuity design to estimate how near-universal Medicare eligibility at age 65 affects the likelihood of food insecurity. I find no significant discontinuity in food insecurity or insufficiency at age 65, using data from both the Health and Retirement Study and National Health Interview Survey, suggesting that at least in the short run, Medicare does not affect food insecurity.

Aim 4 uses a difference-in-differences design to estimate the impact of Medicaid expansion on insurance coverage and food insecurity on individuals ages 50 through 64. The analysis uses data from the 2008 through 2018 American Community Survey for insurance outcomes and the 2008 through 2018 December Current Population Survey for food security outcomes. I find significant increases in insurance coverage as a result of Medicaid expansion but no corresponding reductions in food insecurity.

Taken as a whole, the results in this report suggest that public health insurance programs do little to reduce food insecurity among seniors. This may be because these benefits are not fungible.

1. Introduction

Older Americans have access to a safety net that younger individuals do not. In particular, Social Security and Medicare are social insurance programs with eligibility determined largely by age, rather than means-tested transfer programs, and so are nearly universal for older Americans. Social Security and Medicare have been shown to reduce other types of material hardship among seniors. Medicaid, too, significantly reduces financial strain in the years prior to Medicare eligibility at age 65. To what extent do these programs also reduce food insecurity? The overarching goal of this project is to estimate the impacts of these three programs – Social Security, Medicare, and Medicaid – on food insecurity and/or food insufficiency among Americans ages 60 and older, using well-established identification strategies to isolate causal effects. This Year 2 Report presents the results of this research.

I begin in **Aim 1** by estimating the economic, demographic, health-related, and psychosocial predictors of food insufficiency among seniors in both cross-sectional and longitudinal analyses using data from the Health and Retirement Study (HRS). I find that younger age, lower levels of education, non-employment, lower levels of income and wealth, and poor physical health or functional status are significant predictors of food insufficiency in both cross-sectional and longitudinal analyses. These findings are consistent with patterns of food insecurity in the more widely-used data from the Current Population Survey (CPS), which supports the validity of using HRS data for Aims 2 and 3. I also find in Aim 1 that neuroticism is significantly correlated with food insufficiency.

Aim 2 uses the Social Security "notch" – a discontinuity in the generosity of benefits for individuals born before/after January 1, 1917 – to estimate how much Social Security income reduces food insufficiency among seniors. The Social Security notch refers to the fact that between the years of 1972 and 1977, higher-than-usual benefits were paid to Social Security beneficiaries born between 1910 and 1916. As a result, Social Security recipients born in the years 1910 through 1916 received more generous benefits than those born later, creating a "notch" at birth dates before versus after January 1917. Regression discontinuity is a well-established empirical approach (Lee and Lemieux 2010) that has been used to identify the effects additional Social Security income on a range of outcomes related to the well-being of the elderly including retirement behavior (Krueger and Pischke 1992), mortality (Snyder and Evans 2006), poverty (Engelhardt and Gruber 2006), living arrangements (Engelhardt et al. 2005), prescription drug use (Moran and Simon 2006), and use of long-term care services (Goda et al. 2011).[1] I find suggestive but very imprecisely-estimated evidence that the notch may have increased food insufficiency among seniors.

The goal of **Aim 3** is to understand how becoming age-eligible for Medicare at age 65 affects the likelihood of food insecurity. Near-universal eligibility for Medicare at age 65 has been shown to improve access to care and health outcomes (Card et al. 2008; Card et al. 2009) and to relieve financial strain (Barcellos and Jacobson 2015; Caswell and Goddeeris 2020; Finkelstein 2007; Finkelstein and McKnight 2008; Goldsmith-Pinkham et al. 2021). In spite of this, I find no significant discontinuity in food insecurity or insufficiency at age 65, using data from both the HRS and National Health Interview Survey (NHIS)

To analyze the impact of Medicaid on food insecurity among older Americans in **Aim 4**, I compare trends in outcomes in states that have implemented Medicaid expansion under the Affordable Care Act compared with those that have not. This difference-in-differences strategy has been used in many papers in the literature to estimate the impact of Medicaid expansion; for

[1] This identification strategy has also been used to find precisely estimated zero effects of Social Security income on body mass index (Cawley et al. 2010).

example, studies using this approach have found that Medicaid expansion leads to gains in coverage without significant effects on employment (Leung and Mas 2018); improvements in access to care and diagnosis of chronic conditions (Wherry and Miller 2016; Miller and Wherry 2017), and declines in mortality (Miller et al. 2021). Nonetheless, I find no significant impact of Medicaid expansion on food insecurity in data from the CPS. I do find significant increases in SNAP participation, consistent with earlier work (Baicker et al. 2014).

2. Research methods

The research in this report relies on the analysis of publicly available microdata from household surveys. The specific analytic methods are tailored to each research aim; an overarching theme is the focus on empirical methods that support causal inference, allowing me to disentangle the causal impact of a particular program – Medicare, Social Security, or Medicaid – on food insecurity from the other factors that may lead individuals to be food insecure. Here, I provide a brief description of the methods used for each of the study's aims.

2.1. Methods, Aim 1 (predictors of food insecurity): The goal of Aim 1 is to provide a descriptive analysis of the economic, demographic, and personality determinants of food insecurity at a point in time and also over time. I use panel data from the Health and Retirement Study for this analysis, described in more data below. The use of panel data allows me to estimate both cross-sectional and individual fixed-effects regression models with food insecurity as the dependent variable. Cross-sectional multivariable models allow me to identify factors that differ systematically for individuals who do and do not experience food insecurity, although these estimates do not rule out the possibility that other, unobserved individual characteristics explain differences in food insecurity across individuals. Individual fixed-effect models rely on changes over time for a given individual to identify the relationship between their characteristics and the likelihood of food insecurity; for example, does a change in health status predict an increase in food insecurity? One limitation of this approach is that it does not estimate the contribution of characteristics such as race and gender that do not change over time. Also, the possibility remains that significant predictors of food insecurity in a fixed-effects analysis are correlated with other time-varying characteristics that are not observed in the data. For example, both retirement and an increase in food insecurity might be prompted by a decline in physical capacity that is not adequately measured by time-varying health characteristics included in the model. But multivariable fixed-effect models are nonetheless a powerful tool for isolating descriptive predictors of food insecurity in a way that controls unobservable, individual-specific factors that do not change over time.

In Aim 1, I first estimate OLS regression models (that is, linear probability models) of the form:

$$Pr(Y_{it} = 1) = \beta_0 + \beta_1 \cdot X1_i + \beta_2 \cdot X2_{it} + \varepsilon_{it} \tag{1}$$

Where $X1_i$ is a vector of time-invariant characteristics (for example, sex; or, in this population, educational attainment) and $X2_{it}$ is a vector of characteristics that may vary over time such as income, cognitive ability, or marital status.

I also estimate individual-fixed effects models of the form:

$$\Pr(Y_{it} = 1) = \alpha_i + \alpha_1 \cdot X1_i + \alpha_2 \cdot X2_{it} + \upsilon_{it} \tag{2}$$

Note that the fixed-effects model will not provide estimates of α_1 since $X1_i$ does not vary over time.

Both the cross-sectional and fixed-effects models have a dependent variable equal to one if the individual is in a household with low food security, and include a rich set of covariates, described in more detail below. I also use data on transitions – that is, pairs of observations in consecutive HRS waves – to estimate models of entry into and exit from food insecurity:

$$Pr(Y_{i,t+1} = 1) = \beta_0 + \beta_1 \cdot X_{1i} + \beta_2 \cdot X_{2it} + \varepsilon_{it} \text{ if } Y_{i,t} = 0 \qquad \text{[entry model]} \quad (3)$$

$$Pr(Y_{i,t+1} = 0) = \beta_0 + \beta_1 \cdot X_{1i} + \beta_2 \cdot X_{2it} + \varepsilon_{it} \text{ if } Y_{i,t} = 1 \qquad \text{[exit model]} \quad (4)$$

Taken together, the models in Aim 1 present a comprehensive picture of the predictors of food security both at a point in time and over time.

2.2 Methods, Aim 2 (Social Security):

Aim 2 use a regression discontinuity approach that exploits the Social Security "notch" in benefits affecting the cohort born just after January 1917 to estimate the effect of income on food insufficiency. The running variable in this analysis, also sometimes called the assignment or forcing variable (Lee and Lemieux 2010), is the individual's age in months relative to January 1917. Using data from the 1995 wave of the Health and Retirement Study for individuals born in 1912 through 1921, I test for discontinuities in income and food insufficiency for those born just before versus after January 1917. More specifically, these models have the form:

$$Y_i = b_0 + b_1 \cdot POST + b_2 \cdot AGE + b_3 \cdot POST \cdot AGE + \varepsilon_i \qquad (6)$$

In this analysis, *AGE* is the individual's age in months relative to January 1917 (so December 1916 = -1, January 1917 = 0, February 1917=1, etc.) and *POST* is equal to one if the individual is born in January 1917 or later and zero otherwise. (The analysis in Aim 3, which exploits a different discontinuity to estimate the impact of Medicare on food insecurity, will operationalize these variables differently.) The outcome variables are an indicator equal to one if the individual lives in a household that reports low food sufficiency and zero otherwise, as well as measures of household income and SNAP use. In effect, these models estimate a linear relationship between birth month/year and the outcome variable, and the intercept and slope of the line are allowed to vary before versus after January 1917. Any discontinuity in the outcome is reflected by the coefficient on *POST*. I also estimate a quadratic version of the regression discontinuity model that estimates a nonlinear relationship between birth month/year and the outcome, where the shape of the curves are allowed to vary before and after the cutoff:

$$Y_i = b_0 + b_1 \cdot POST + b_2 \cdot AGE + b_3 \cdot AGE^2 + b_4 \cdot POST \cdot AGE + b_5 \cdot POST \cdot AGE^2 + \varepsilon_i \quad (7)$$

In the nonlinear model, as in the linear model, the coefficient b_1 on the dummy *POST* reflects the presence or absence of a discontinuity for those born in January 1917 and later.

These regression models provide information needed for hypothesis testing. At the same time, the intuition underlying the regression discontinuity lends itself well to graphical representation. I present multiple figures in which one-month averages for the outcome of interest are used to construct a scatterplot and then lines or curves based on equations (6) or (7) are overlaid on the scatterplot.

I also estimate models with measures of household income as the dependent variable since this is, in theory, the intermediate variable through which differences in Social Security benefits on either side of the notch would lead to differences in food insecurity. (This is sometimes colloquially referred to as the "first stage" outcome, as an analogy to instrumental variables estimation; the notch affects income (first stage) and therefore, because of its effect on income, the notch also affects food inufficiency.) The use of SNAP is a potential mediating variable in these analyses, in the sense that lower income might lead to higher SNAP use, which would potentially reduce food insecurity. In order to test for this possibility, I estimate models with SNAP receipt as the dependent variable.

The validity of the regression discontinuity design is predicated on the assumption that characteristics other than income that might affect food insecurity do *not* change discontinuously at the critical threshold. Therefore, I also report the results of estimating equations (6) and (7) with other characteristics such as years of education or fraction female as dependent variables in order to make sure that they exhibit no discontinuity, supporting the validity of the RD design.

2.3 Methods, Aim 3 (Medicare):

The methods for Aim 3, as for Aim 2, rely on regression discontinuity. In Aim 3, the running variable, *AGE*, is age in months at the time of the interview relative to age 65, and *POST* is a dummy indicating whether the individual is above or below age 65. For example, an individual who turned 65 in May 2000 who was interviewed in July 2000 would have *AGE*=2 and *POST*=1.

$$Y_i = b_0 + b_1 \cdot POST + b_2 \cdot AGE + b_3 \cdot POST \cdot AGE + \varepsilon_i \qquad (8)$$

As in Aim 2, I also estimate a version using a quadratic specification:

$$Y_i = b_0 + b_1 \cdot POST + b_2 \cdot AGE + b_3 \cdot AGE^2 + b_4 \cdot POST \cdot AGE + b_5 \cdot POST \cdot AGE^2 + \varepsilon_i \qquad (9)$$

I estimate models based on equations (8) and (9) with food insecurity as the outcome and also with Medicare and uninsurance as outcomes, since changes in these types of coverage at exactly age 65 are the reason why there might be a discontinuity in food insecurity. As in Aim 2, I also estimate models with SNAP use as the dependent variable, and models estimated with other characteristics as dependent variables in order to test the assumption that there is no discontinuity in these other characteristics.

2.4 Methods, Aim 4 (Medicaid):

The methods for Aim 4 are different from those used in Aims 2 and 3. Instead of a regression discontinuity approach, the empirical work relies on comparing outcomes over time in states that implemented Medicaid expansion under the Affordable Care Act compared with those that have not. This analyses uses data on individuals ages 50 through 64. Those ages 65 and older were not eligible for Medicaid expansion under the ACA. Restricting the sample to only those ages 60 through 64 yields too small a sample in the December CPS for meaningful analysis.

The estimation strategy for this aim includes two sets of regression analyses. The first set relies on a differences-in-differences (DD) specification of the following form:

$$Y_{ist} = \beta_0 + \beta_1 \cdot treatment_{st} + \alpha_s + \gamma_t + X'_{ist}\theta + e_{st} \tag{10}$$

The model is estimated separately for health insurance outcomes (Medicaid coverage, private non-group coverage, employer coverage, and uninsured) and low or very low food security over either a 12-month or a 30-day recall period. The variable $treatment_{st}$ is 1 for any observation in a state/year in which Medicaid expansion is in effect and is 0 otherwise. (This is analogous to the variable *post x treatment* in a standard difference-in-differences framework, but accounts for the fact that expansion occurred at different times in different states.) The coefficient β therefore measures the marginal effect of Medicaid expansion on the outcome. The model also includes a full set of state and year dummies (α_s and γ_t, respectively); these can be thought of as disaggregated versions of the *treatment* and *post* dummies in a simple DD model, allowing the underlying path of the outcomes to vary flexibly. The vector X_{ist} consists of individual-level controls: age, education, race/ethnicity, sex, and marital status. The model is estimated as a linear probability model weighted by the ACS survey weights. Robust standard errors are clustered by state.

A key advantage of this specification is that the coefficient β provides a concise estimate of the effect of the Medicaid expansions. This basic DD model has two limitations, however. First, it does not provide a clear test of the critical parallel trends assumption. Second, it imposes the assumption that the full impact of Medicaid expansion is realized immediately and is the same over the post-implementation period; in fact, the effect may grow over time, as consumer understanding of their insurance options grows. Therefore, I also estimate a second, more flexible event history specification. In this model, the dummy $treatment_{st}$ is replaced with a vector of dummies D_{st}^{k} indicating time relative to the year in which Medicaid expansion occurs:

$$Y_{ist} = \sum_{k=-7}^{4} \delta_k D_{st}^{k} + \gamma_t + \alpha_s + X_{ist}'\theta + u_{ist} \tag{11}$$

The dummy D^0 – which for most expansion states is equal to one in 2013 – is omitted, so that all effects are being measured compared to the size of the expansion/non-expansion gap in the year just before the expansion took effect. The coefficients δ_k on the event-time dummies, and their associated standard errors, are presented graphically; coefficients on other variables in the model (all except the vectors of state, year, and age dummies) are reported in appendix tables.

3. Data

This section describes in detail the data used in the analysis. As an overview, the following table very briefly summarizes the data used for each research aim:

Data Table Which data sources are used for each aim?				
	Aim 1 Demographics	Aim 2 Social Security	Aim 3 Medicare	Aim 4 Medicaid
Data	HRS 1998 - 2016	HRS 1995	NHIS 2011-2014 HRS 1998-2016	CPS 2008 – 2018 ACS 2008 - 2018
Measures of food insecurity	Food insufficiency	Food insufficiency; Very low food sufficiency	NHIS: low/very low food security HRS: low/very food sufficiency	CPS: low/very low food security
Other key outcomes	None	Household income; SNAP	NHIS and HRS: Medicare; uninsurance; SNAP	ACS: Medicaid; uninsurance CPS: SNAP

Current Population Survey (CPS), Food Security Supplements, 1996 through 2019

CPS food security supplements have been conducted each year since 1995. Since 2000, this supplement has been administered in December; before that, it was administered in other months (September 1996, April 1997, August 1998, and April 1999). The December 2008 through December 2018 data are used for Aim 4 (Medicaid) to analyze the impact of Medicaid expansion under the Affordable Care Act on food insecurity among seniors. Because expanded eligibility for Medicaid was only for adults under age 65, I use observations on individuals between the ages of 50 and 64 in Aim 4. The result is a dataset with approximately 20,000 observations in each year.

CPS outcome measures: The CPS measures of food security are comprehensive, relying on an 18-question sequence known as the Core Food Security Module (CFSM), which supports the calculation of different indices measuring food insecurity with a 12-month recall period (Gundersen and Kreider 2008). Additional CPS questions ask about food insecurity over a 30-day recall period. Appendix Table A1 lists the questions used to calculate food insecurity in the CPS. The outcome for the CPS analyses in this report is a dichotomized version of the CPS summary food security status variable with 12-Month Recall (HRFS12M1), the main variable used in the USDA's series of annual food security reports (USDA, 2020). Based on this, I code respondents as either food insecure or not. The category of "food insecure" includes both those with low and very low food security, as coded in the CPS variable HRFS12M1. For some analyses, I also use very low food security as an outcome. An additional outcome is whether anyone in the household has received SNAP benefits in the past 12 months.

Other CPS variables: For CPS analyses involving multivariable regression, I use basic controls collected in the monthly CPS questionnaire for education, age, gender, marital status, race, and ethnicity. In addition, some analyses use only respondents with low income, defined as family income less than 185% of the federal poverty threshold.

All CPS analyses are conducted at the individual level and use person-level survey weights provided on the public use file (pwsupwgt).

Health and Retirement Study (HRS), 1995 through 2016 (HRS Longitudinal File 2018 V1, 2019). HRS data are used for Aim 1 (demographics), Aim 2 (Social Security), and Aim 3 (Medicare). The HRS is a biannual, longitudinal study of older Americans that has been conducted since 1992 (Sonnega et al. 2014). HRS began as a study of two cohorts: those born in 1931 through 1941, who were first interviewed in 1992, and those born in 1923 and earlier, who were first interviewed in 1993. Each of these cohorts was interviewed again two years after their first wave of interviews. In 1998, additional cohorts were added to the study, so that the combined sample became representative of the US population born in 1947 and earlier. These cohorts have been interviewed every two years since, with new, younger cohorts added to the sample in 2004, 2010, and 2016.[2] Most of the analyses in Aim 1 include data on all HRS respondents ages 60 and older, with a sample size of approximately 13,000 observations in each year. Aim 2 analyses use data on individuals born from 1910 to 1923 who were interviewed in 1995: about 5,000 respondents.

The key HRS variables used in this report are the following:

HRS outcome measures: The HRS measures used in this report are based on two yes/no questions asked in the context of other questions about income and wealth: "In the last two years,

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[2] Much more information on the design of the HRS, as well as a very helpful schematic diagram illustrating the cohort structure over time, is available at https://hrs.isr.umich.edu/documentation/survey-design.

have you always had enough money to buy the food you need?" If the answer is "yes," there is a follow-up question: "Did you ever eat less than you felt you should because there wasn't enough money to buy food?" These questions are listed in Table A2. This is, of course, less comprehensive than the 30-item set of questions developed by the USDA for the purpose of assessing food insecurity. The HRS questions appear to measure what the USDA might term food *insufficiency*.[3] A key difference is that the food insufficiency questions that are included in the CPS do not have a definite reference period, while those in the HRS have a two-year recall.[4] Nonetheless, I use the term "food insufficiency" (or "low food sufficiency") in this report to describe the HRS measure, and code those who respond "yes" to the first question as having low food sufficiency. I code those who respond "yes" to the second question as having very low food sufficiency. These questions were first asked in the 1995 wave of the HRS. In 1995 through 2006, the reference period for the second question was two years (or "since the last interview" for repeat respondents). Beginning in 2008, the second question was asked with a twelve-month recall period: "In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money to buy food?"

Other HRS variables: The HRS includes detailed information on respondent demographics, including age, race, ethnicity, gender, and marital status, educational attainment, and Census region. Years of education is top-coded at 17 to reflect those who have some education beyond college. I use HRS measures of health insurance coverage to construct indicators for coverage by Medicaid, Medicare, private non-group coverage, and no coverage at

[3] More information on the distinction between food insecurity and food insufficiency as measured by the USDA is available at https://www.ers.usda.gov/topics/food-nutrition-assistance/food-security-in-the-us/measurement.aspx#insufficiency.
[4] More recently, the Household Pulse Survey conducted by the US Census Bureau included a food sufficiency question with a seven-day recall period.

the time of the survey. The HRS also collects information on SNAP use in the past two years, including whether the household is receiving benefits at the time of the survey, which I use to construct a measure of current SNAP use. For many additional characteristics, I rely on the RAND longitudinal HRS file.[5] The RAND file provides measures of socioeconomic status including employment, household income, and wealth; income measures are inflated to real 2010 value using the CPI-U.[6] I also use variables from the RAND file measuring health status and disability, including self-reported heath status and limitations on Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs); and a measure of cognitive ability, word recall, described in detail in McCammon et al. (2019). Word recall is not assessed for respondents who rely on a proxy to assist them with their interview (about 7% of the sample). In multivariate regressions that include cognitive ability as a control, I include a vector of categorical dummies, with "cognitive data missing due to proxy status" as one of the categories, in order not to lose data from this group in the regressions.

HRS personality measures: In a subset of analyses in Aim 1, I include explanatory variables based on standard measures of personality collected in the HRS Psycho-Social Questionnaire, a paper-and-pencil survey that is given to alternating half-samples of the HRS sample in each wave. Following Smith et al. (2017), I use these data to calculate the "Big Five" personality traits: openness, conscientiousness, extraversion, agreeability, and neuroticism. I then standardize these measures so they have mean equal to zero and standard deviation equal to one. The half-sample design means that pooling multiple years of data yields a dataset with

[5] The RAND HRS Longitudinal File is an easy-to-use dataset based on the HRS core data. This file was developed at RAND with funding from the National Institute on Aging and the Social Security Administration.
[6] Specifically, I use BLS Series CUUR0000SA0. Wealth measures are included in my analyses as vectors of dummies indicating wealth<0, wealth==0, and deciles of wealth if positive, which are calculated to be specific to each year, and so this variable is independent of inflation.

personality measures for most HRS respondents. In this report, I use data from 2010 through 2016 for analyses that include personality measures.

All HRS analyses are conducted at the person level and use person-level survey weights provided on the public use file.

National Health Interview Survey (NHIS), 2011 – 2014

National Health Interview Survey data are used for Aim 3 (Medicare). My identification strategy for Aim 3 requires knowing the exact month in which the individual was born, which is a publicly available data item in NHIS between 2011 and 2014; therefore, these are the years used in my analysis. The sample for Aim 3 is individuals who are within five years (either before or after) of their 65th birthday; this is about 9,000 respondents in each year.

NHIS outcome measures: Since 2011, the NHIS has asked a set of ten questions modeled on a subset of the CPS CFSM questions using a 30-day recall period. These questions are listed in Appendix Table A3. Respondents who say "yes" to three or more of these questions are coded as having low food security; those who say "yes" to six or more are coded as having very low food security. Additional outcomes in the NHIS are whether the respondent has Medicare and whether the respondent has no health insurance coverage of any kind (i.e. the respondent is uninsured). The NHIS also measures whether the household received any SNAP benefits in the prior calendar year.

NHIS key explanatory variables: Key variables for my identification strategy include month and year of the respondent's birth and the month and year of the interview.

NHIS other covariates. The analyses in Aim 3 (Medicare) using NHIS also examine a number of other characteristics to assess the validity of that Aim's regression discontinuity design, by testing whether they are smooth through the January 1917 birth month. Characteristics analyzed in this way include whether the respondent was working at the time of the survey; years of education (re-coded to more closely match HRS codes, which are somewhat less detailed); gender and race/ethnicity; and self-rated health on a scale of excellent (1), very good (2), good (3), fair (4), or poor (5).

All NHIS analyses are conducted at the individual level and use person-level survey weights provided on the public use file.

American Community Survey (ACS), 2008 – 2018

The ACS data are used in Aim 4 (Medicaid) to confirm that Medicaid expansion increased overall health insurance coverage rates in expansion relative to non-expansion states. The ACS is conducted annually and includes about 3 million individuals each year. Restricting the sample to adults ages 50 through 64, as I do for the analysis in Aim 4, yields a sample of approximately 600,000 observations per year. Since 2008, the ACS has asked a single question about health insurance: "Is this person CURRENTLY covered by any of the following types of health insurance or health coverage plans?" This question is followed by an 8-item checklist and respondents choose all types of coverage that apply.[7] I examine four insurance-related outcomes of interest: uninsured, which is defined as having none of the sources of coverage listed; Medicaid or other public coverage; employer-sponsored private coverage (which would include both COBRA coverage through a former employer and coverage as a dependent on a spouse's policy); and non-group private coverage. These outcomes are not mutually exclusive. In addition, I use ACS measures of education (less than high school, high school, some college, college or more), sex and marital status, and race/ethnicity as controls in regression models. All

[7] The options are: (a) employer-sponsored insurance; (b) insurance purchased directly from an insurance company; (c) Medicare; (d) Medicaid or other public insurance; (e) TRICARE/military health care; (f) Veteran's Administration; (g) Indian Health Service; and (h) any other type of health plan. Respondents are coded as uninsured if they answer no to all of these options.

ACS analyses are conducted at the individual level and use the person-level survey weights provided on the public use file.

Benchmarking food security measures across datasets

Before presenting results for each of the study aims, this section benchmarks estimated rates of food insufficiency/insecurity in the HRS and the NHIS to the CPS, which is the main source of government estimates. As noted above, the three surveys use different measures of food insufficiency/insecurity. Because of this, it is not surprising that they yield different estimates at any point in time. Figure 0.1 presents trends in food insufficiency in the HRS and food insecurity in the NHIS and CPS for the full sample of individuals ages 60 and older over time, covering the period 1996 - 2019. Both the HRS and the NHIS track the corresponding measures in the CPS fairly well over time. There are persistent differences in the levels, which is not surprising given the differences in measurement described above. For example, the prevalence of food insufficiency using a two-year recall in the HRS is consistently about a percentage point lower than the twelve-month rate of food insecurity in the CPS. The prevalence of low food security using a 30-day recall in NHIS is about one to two percentage points higher than the 30-day recall measure in the CPS. Figure 0.2 shows a similar benchmarking exercise for measures of very low food sufficiency/security.

In addition to the fact that movements up and down over time in food insufficiency/insecurity are generally the same across HRS and CPS or NHIS and CPS, the determinants are largely the same. Appendix Table A4 shows linear regressions with a covariate vector consisting of age, sex, marital status, education and race/ethnicity; the dependent variables are either 30-day low food security or 30-day very low food security, and results are presented in parallel for NHIS and CPS. Similarly, Appendix Table A5 presents regressions for HRS versus

CPS. In this case, the comparison is between the HRS measure of food insufficiency with a two-year recall period versus the CPS measure of food security with a 12-month recall. Data are for the period in which all three surveys have data for the outcomes being examined: 2011 through 2016 (for HRS, data are only available in even years). While the coefficients are certainly not identical, the general patterns are the same and the results are statistically significant across all three datsets and both recall periods: food insecurity/insufficiency declines with age; is higher for single men or women than married men or women; declines with education; and is higher for respondents who are nonwhite or Hispanic. Therefore, I proceed to use the HRS and NHIS with some confidence that they benchmark well to the CPS in terms of how food insecurity/insufficiency varies over time and with respondent characteristics.

4. Results

Results, Aim 1: Predictors of food insecurity

Aim 1 uses a dataset consisting of HRS respondents ages 60 and older who live in the community rather than a nursing home and who completed at least one interview in any survey wave from 1998 to 2016. This dataset includes 133,495 observations on 27,028 individuals; it is an unbalanced panel, with respondents contributing between one and 10 observations to the data depending on when they entered the sample and how many interview waves they completed. I also construct a dataset that keeps only observations for which I have data from the same individual in the next survey way, so that I can analyze wave-to-wave transitions in food sufficiency status. This means dropping all observations from 2016, as well as approximately 15% of observations in 1998 through 2014 year for which the respondent is not observed in the following wave. This smaller dataset of transitions contains 78% of the observations in the original one. Respondents dropped from the transitions sample are significantly different from those who remain on in many ways; in particular, they are about 1 percentage point more likely to be food insecure, and are in significantly worse health. But since they make up only one-fifth of the total, the characteristics of the full sample and the transitions sample are quite similar (Table 1.1).

I begin by documenting some basic facts about how food insufficiency varies with income. Figure 1.1 shows the cumulative distribution of all seniors ages 60 and older, and the cumulative distribution of food insufficient seniors, by household income relative to poverty using pooled HRS data for the years 2002 through 2016.[8] Approximately nine percent of all seniors live below the poverty level, and many of those – more than one in five - experience food insufficiency. The probability of food insufficiency declines with income, but remains surprisingly high even at higher levels of income. Approximately ten percent of seniors are food insufficient just above the gross income level at which SNAP phases out for younger households (130% of FPL); even at much higher levels of income, up to about 400% of poverty, at least three percent of seniors are food insufficient. As a result, most food insufficient seniors are not poor. Thirty-one percent of food insufficient seniors live below the poverty level, and another 10 percent live in households with income above poverty but below 130% of FPL. The remaining 59% of food insecure seniors have incomes high enough that it is very unlikely that they would qualify for SNAP benefits.[9] However, they nearly all receive both Medicare and Social Security, which are not means-tested. This is the rationale for analyzing the impact of these programs on food insufficiency.

[8] Although most of the data in this part of the analysis are for 1998 through 2016, data for Figure 1.1 begin in 2002 since this is the year when the RAND HRS file begins including income relative to poverty thresholds as a variable.
[9] Non-elderly SNAP recipients face a gross income limit of 130% of FPL and a net income limit of 100% of FPL. Elderly recipients do not face the gross income limit; however, since my data include gross, but not net, income, I compare reported gross income to the 130% income limit in order to get a sense of roughly how many seniors are likely to be above the level at which they would not qualify for SNAP benefits.

Figure 1.2 shows how trends in food insufficiency vary with selected respondent characteristics. Panel A shows results over time for different subgroups defined by age. The "youngest old" – in this analysis, the group ages 60 through 64 – have the highest rates of food insufficiency at any point in time. Moreover, they experience the largest increase at the time of the Great Recession, probably since they are more likely than older groups to rely on earned income. Panel B in Figure 1.2 shows trend by education level. Not surprisingly, less education means more food insufficiency. Those with less than a high school education have markedly higher rates throughout this period, but particularly after 2008. Panel C of Figure 1.2 shows trends by sex and marital status. Unmarried women were at the highest risk of food insufficiency throughout this period, and – as with disparities by age and education – this gap widened after 2008. Thus, already-disadvantaged subgroups became even more so, in both relative and absolute terms, following the Great Recession.

Next, I consider multivariate determinants of food insufficiency. These results are reported in Table 1.2, which shows results from four different models. The models reported in columns 1 through 3 of Table 1.2 are all simple OLS models, corresponding to equation (1) in the Methods section above, but they have slightly different covariates and years included in the model. Column (1) is the base model, a pooled cross-sectional model estimated using OLS with data from 1998 through 2016, with a rich set of covariates discussed in more detail below. Column (2) estimates the same model using only data from 2010 through 2016 that has non-missing personality measures, for comparison with the model in column (3). The model in column (3) is identical to the one in column (2), but augments the covariate vector with measures of personality that became available starting in 2010. The sample and covariates for the model in column (4) are the same as the base model in column (1), but the model is estimated using an individual fixed effect, corresponding to equation (2) in the Methods section above.

All three of the OLS models – that is, the results in columns 1, 2, and 3 of Table 1.2 – are very similar. Comparing columns (1) and (2), it is evident that dropping data from 1998 through 2008, as well as the random half-sample in each year from 2010 through 2016 without personality measures, increases the standard errors as one would expect due to the smaller sample size. The coefficients, though, do not change very much, suggesting considerable stability in the relationships between individual characteristics and food insufficiency. This is consistent with the basic intuition from Figure 1.2. Although gradients over time my change somewhat, the fundamental relationship between, for example, education and food insufficiency does not change; less education always means a higher risk of food insufficiency.

Comparing the models in columns (2) and (3) shows that the addition of personality traits as explanatory variables changes the coefficients very little. Neuroticism is significantly positively correlated with food insufficiency. This is generally consistent with research using other measures of personality that find that some traits are correlated with food insufficiency (Laraia et al. 2006; Nikolaus et al. 2019). In this analysis, however, none of the personality measures other than neuroticism has a significant effect. In a naïve model (not reported here), regressing food insufficiency on personality traits without other controls suggests a larger effect for neuroticism, a significant role for conscientiousness in reducing food insufficiency, and a marginally significant effect of agreeableness in increasing food insufficiency. The addition of a relatively short vector of covariates (age, sex/marital status, education, race/ethnicity, Census region, and year) to the model does not substantially alter these patterns. However, the addition of economic covariates – work status, income, and wealth – to the model reduces the coefficients on these personality traits to the point where they are not significantly different from zero. Neuroticism remains highly significant, as reported in column (3) of Table 1.2, even with the addition of controls for health, ADL/IADLs, and cognition. Thus, it would appear there may be a potential role for neuroticism in explaining food insufficiency; but for other personality traits, studies attempting to estimate a correlation with food insufficiency should carefully consider the mediating role of economic characteristics such as employment and income (as do both of the studies cited above).

Returning to the results in column (1) and focusing on the effect of the covariates other than personality traits, demographic characteristics predict food insufficiency in largely expected ways, based on earlier work (Ziliak, Gundersen and Haist 2008; Ziliak and Gundersen 2011; Ziliak and Gundersen 2016; Ziliak and Gundersen 2017; Ziliak and Gundersen 2020). Older age and more education each reduces the probability of food insufficiency; being an unmarried woman or a racial/ethnic minority increases it. All nonworkers are at higher risk of food insufficiency than workers, with particularly large effects (6.5 to 6.7 percentage points) for the unemployed and disabled; this represents a doubling of the baseline rate of 6%. Not surprisingly, income and wealth each significantly reduces food insufficiency. The effects of cognitive ability are complex and interact with the measurement of cognition in the HRS. Word recall tests are not administered to proxy respondents, so I treat them as having missing cognition data, which is the omitted category of cognition relative to a vector reflecting quartiles of the distribution of word recall scores. Food insufficiency is significantly *lower* by two to three percentage points for proxy respondents than any group of those with complete data on word recall. Among those with non-missing word recall data, higher scores mean less food insufficiency, but only by about a percentage point.[10]

Next, I compare the pooled cross-sectional model in column (1) to the individual fixed-effect model in column (4).[11] The general pattern of effects is the same, but some explanatory variables have larger coefficients in the fixed-effect model than OLS, while others have smaller effects. The effect of age is markedly larger in the fixed-effect models: seven-tenths of a percentage point rather than three-tenths. The effect of unemployment is much smaller – about two percentage points compared with more than six in the OLS model – suggesting that some of the cross-sectional correlation between unemployment and food insufficiency is driven by unobserved, individual-level factors that increase the risk of both. A similar argument applies to reported disability (as a labor market status), which is no longer significant in the fixed-effect model. Self-rated health and functional status remain significant in the fixed-effect model, but with smaller coefficients than in model (1). Marital status matters in the cross section for women, with married women having lower rates of food insecurity than unmarried women, but changes in marital status do not affect food insecurity for either men or women in the fixed-effect models.

The final component of the analysis for Aim 1 uses the transitions sample described above to analyze movements into and out of food insufficiency over time, following the work of Ziliak and Gundersen (2016) who conducted a similar analysis of food insecurity among adults ages 40 and older using year-to-year transitions in the CPS. Table 1.3 shows a simple Markov

[10] A Breusch-Pagan test strongly indicates considerable heterogeneity in the error term associated with the model in column (1) (χ^2 = 73234, p = 0.0000). However, the OLS coefficient estimates remain unbiased in the presence of heteroskedastic errors. Moreover, given the high level of significance of most of the covariates in the model, a more efficient estimation approach would be very unlikely to change the significance of the results even if it considerably increased the standard errors.

[11] As a specification check, I also estimated a similar model using random effects. A Hausman test strongly rejects the hypothesis that the two sets of coefficients do not differ systematically ($\chi2$=1174; p = 0.0000), so the fixed effect model reported in the paper is the preferred specification.

matrix with transition probabilities from one wave to the next. Individuals who are food sufficient at the outset are likely to remain in that state; only 3.3% of individuals who are food sufficient in one wave are food insufficient the next. Food *in*sufficiency is less persistent; 39 percent of those who are food insufficient at a point in time are not food insufficient in the following wave. Thus, for all individuals and all years in the sample, the overall rate of entry into food insufficiency is 3%, and the rate of exit from food insufficiency is 39%. These rates of entry and exit vary with time and with individual characteristics. For example, the fraction of the sample that is food insufficient in a given year evolves as rates of entry and exit change over time. Figure 1.3 illustrates this dynamic; the fraction of seniors who are food insufficient increased with the Great Recession (as shown earlier in Figure 0.1), and this was largely because of declining rates of exit from food insufficiency. In other words, food insufficiency went up for seniors in the latter part of this period (2004 and later) because those who were food insufficient were less likely to get out of that state.

Figure 1.4 shows analogous results for age rather than year. The gradually declining rate of food insufficiency with age is driven by both a decline in the already-quite-low rate of entry into food insufficiency and by a striking increase in the likelihood of exit. Food insufficient individuals in their sixties have about a 50 to 60% chance of escaping food insufficiency in the next wave, while this fraction is closer to 70% for those ages 75 and older.

For a multivariate analysis of the determinants of entry and exit, Table 1.4 shows multivariate models of entry and exit (based on equations 3 and 4 in the methods section above). The effects of individual characteristics on entry and exit probabilities generally mirror each other, but not always. Consistent with what was illustrated in figure 1.4, even after controlling for other characteristics, age reduces risk of entry and increase the probability of exit, and the probability of exit increases more steeply with age – by about one percentage point per year of age - than the probability of entry declines (by about one tenth of a percentage point per year of age). Unsurprisingly, disability increases entry, but – surprisingly - does not appear to reduce exit. Hispanics are more likely to both enter and exit (perhaps reflecting income volatility, which may be an important topic for future research).

Ultimately, the results in Aim 1 lead to two conclusions. The first is that the use of a novel dataset yields some novel findings, such as the correlation between neuroticism and food insufficiency and the analysis of the determinants of entry into and exit from food insufficiency for an older population. The second, though, is that my findings on what predicts food *insufficiency* in HRS are very similar to those reported in the existing literature using other data on what predicts food *insecurity* among seniors. This is reassuring, since Aims 2 and 3 in this report use HRS data on food insufficiency as an outcome. The results in Aim 1 provide reason to believe that those findings may generalize to the outcome of food insecurity as well.

Results, Aim 2: Social Security.

Aim 2 (Social Security) uses HRS data from 1995. The relevant cohort for this analysis is individuals born from 1910 to 1923, spanning the January 1917 birth date that is associated with a notch in Social Security benefits. Food insufficiency questions were first asked in the 1995 wave of the HRS, when members of this cohort were in their late seventies.

As described above, the analysis of how Social Security income affects food insufficiency uses data from the 1995 wave of the HRS on individuals born between 1910 and 1923, on either side of the "notch" in Social Security benefits affecting those born in January1917 and later. Table 2.1 shows the average characteristics in 1995 of this sample of 5,288 individuals, overall and also broken into those born before and after the January 1917 cutoff. Overall, about 7% of these individuals – who were in their late seventies and early eighties at the time of the interview - were food insufficient, with 1.3 percent experiencing very low food sufficiency.

Figure 2.1 shows scatterplots of the data on food insufficiency, with each circle representing the average rate of food insufficiency for individuals born in a one-month period.[12] These "bins" are defined by the number of months before or after January 1917 the person was born. Overlaid on the left-hand plot are the two lines that are estimated by the linear RD approach (see equation [6] above) and on the right-hand plot are the two curves that are estimated by the quadratic RD approach (see equation [7] above). The point where they meet (or not) on the graph at X = 0 is the potential discontinuity at the notch. For both low food sufficiency (Figure 2.1) and very low food sufficiency (Figure 2.2), both the linear and the quadratic models show an increase at the notch, consistent with the fact that the post-1917 birth cohorts received lower Social Security benefits than those born slightly earlier. Income, both in levels and in logs, is also lower for the post-1917 birth cohorts in both linear and quadratic models (Figures 2.3 and 2.4). Consistent with these results, SNAP receipt is higher for the post-1917 birth cohorts in both linear and quadratic models (Figure 2.5).

These figures tell a fairly consistent story: for the post-1917 birth cohort, the Social Security notch resulted in lower income and higher rates of food insufficiency, even though they also had higher SNAP use. But these effects turn out to be very imprecisely estimated. Table 2.2 contains estimates of equations (6) and (7) for the outcomes low food sufficiency, very low food

[12] Recall that the sample consists of about 5,000 people born in a window from 84 months before January 1917 to 83 months after. This means that each birth month has about 30 people in it (for example, the sample has 36 people born in February 1917, 34 born in March 1917, 29 born in April 1917, and so on). Given the low rates of very low food sufficiency, many months have no one reporting this outcome; this is reflected in the circles along the horizontal axis in these figures

sufficiency, household income in the previous calendar year, the natural log of household income, and any use of SNAP in the past two years. The effect of the notch (that is, the coefficient on the POST dummy) is insignificant in the food sufficiency and income models in columns 1 through 8 of Table 2.2. Thus, there is no compelling evidence of an increase in food sufficiency as a result of the notch, but it is hard to say this with much certainty given the wide confidence intervals implied by the estimates. There is suggestive evidence of an increase in SNAP use at the notch; both linear and quadratic models have about a 2.5 percentage point increase, but this is significant only in the linear model. Table 2.3 estimates equations (6) and (7) for models with dependent variables that are individual characteristics which one would expect to be smooth through the discontinuity: work status, years of education, sex, race/ethnicity, and self-reported health. Although none of these variables is significant, some of the estimated coefficients are quite large. Based on this, and the results in Table 2.2, the bottom line is that future work using this method requires a larger sample. While it is not possible to rule out an effect of Social Security and, presumably, income more generally on food insufficiency at older ages, more data are necessary to confirm the validity of the approach and to estimate models that are precise enough to pin down whether the effect of Social Security income on food insufficiency is significant. I am not aware of other data that include both measures of food insecurity or insufficiency and exact month of birth for individuals born just before and after 1917 that would support such an analysis.

Results, Aim 3: Medicare. The identification strategy for estimating the effect of Medicare on food insecurity/insufficiency relies on the discontinuity in Medicare coverage at age 65. The figures and regressions are therefore very similar to those just discussed for Aim 2 (Social Security), but the running variable is months of age relative to age 65 rather than months born before/after January 2017. Because the discontinuity at age 65 is not only for a specific birth cohort, as was the case in Aim 2, I can pool multiple years' worth of data for a larger sample from each survey. For this analysis, I use HRS data from the 1998 through 2016 survey waves, keeping only observations gathered from respondents who were five years before or after the month of their 65th birthday at the time of the interview in order to observe the window around near-universal Medicare eligibility at age 65, and a similarly defined sample of individuals in the NHIS in 2011 through 2014, the years for which exact month of birth is available on the public use file and food insecurity measures were included. I treat the NHIS estimates as preferred because the food security measure in NHIS, which uses a 30-day recall period rather than the two-year recall in the HRS, is better suited to the identification strategy.

Table 3.1 shows average characteristics for both the NHIS and HRS samples, overall and broken into age groups based on whether they are before or after the month of their 65th birthday (labelled 60 to 64 and 65 to 69 in the table). Comparing HRS to NHIS, the samples are quite similar, with about 7 or 8% reporting low food security/sufficiency and 3.5 to 4% reporting very low food security/sufficiency, despite numerous differences in the measures. Demographic characteristics – age, work status, education, sex/marital status, and race/ethnicity – are quite similar across the two samples. The pattern of outcomes for younger versus older subgroups are also quite similar across the two datasets. In both HRS and NHIS, the over-65 group has lower food insecurity/insufficiency than the under-65 group. At age 65, Medicare increases dramatically and uninsurance drops almost to zero in both samples.

Figure 3.1 and Figure 3.2 show the discontinuity plots for low food security and low food sufficiency using data from NHIS and HRS, respectively. These show generally similar patterns, with little to no discontinuity evident at age 65. The same is true for the outcome very low food security/sufficiency (Figures 3.3 and 3.4). Figures 3.5 and 3.6 confirm that in both samples, Medicare increase sharply at age 65, while Figures 3.7 and 3.8 confirm a sharp reduction at uninsurance. Results for SNAP are ambiguous, with linear models in both samples suggesting a small drop in SNAP use at age 65 but quadratic models suggesting a very small increase (Figures 3.9 and 3.10).

Regression results based on equations (6) and (7) are reported in Table 3.2 for NHIS and Table 3.3 for HRS. These confirm the intuition from the figures, with significant discontinuities at age 65 for the insurance-related outcomes (Medicare and uninsured), and no significant changes at age 65 in any measure of food security/sufficiency or in SNAP use. Models estimated with other characteristics as dependent variables, such work status and gender, are presented in Tables 3.4 and 3.5, and these generally confirm the smoothness of these variables through the age 65 discontinuity.

Taken as a whole, these results suggests that the regression discontinuity approach at age 65 is valid, but that the large increase in insurance coverage due to Medicare does not translate into increased food security/sufficiency. Moreover, this result is fairly precisely estimated. Looking at the confidence intervals implied by the coefficients and standard errors reported in Tables 3.2 and 3.3, the largest reduction in food insecurity/insufficiency that cannot be ruled out with 95% confidence is a 1.7 percentage point reduction in low food sufficiency (HRS, quadratic model) or a 1.2 percentage point reduction in very low food sufficiency (HRS, quadratic model). In the NHIS, the lower bounds of the 95% confidence intervals are close to zero in all models: at most a 1.3 percentage point reduction in low food security cannot be ruled out with 95% confidence. These reductions might still be considered large relative to the baseline rates of food insecurity of about 7 to 8% but are small compared with, for example, the increase in food insecurity that occurred as a result of the Great Recession.

Results, Aim 4: Medicaid. My analysis of the impact of Medicaid on food insecurity among seniors relies on the expansion of Medicaid under the Affordable Care Act beginning in 2010. Extending Medicaid eligibility to all adults with family incomes below 138% FPL was originally intended as an integral part of the ACA's coverage expansion. A Supreme Court ruling in 2012, however, meant that states had a choice about whether or not to change their Medicaid eligibility rules in this way. To date, 39 states and the District of Columbia have expanded Medicaid, while the remaining 12 states have not. In a typical state that chose to expand coverage, the income eligibility limit for able-bodied adults without dependents went from zero – in other words, this group had no access to Medicaid - to 138% of the federal poverty threshold. Table 4.1 shows which states expanded Medicaid and when.

Table 4.2 provides an overview of the data used in this analysis, showing mean values for key outcomes and covariates in both datasets before the expansion of Medicaid (2008 through 2013). Results are presented for subsamples defined by whether or not the observation comes from a state that will subsequently implement Medicaid expansion. There are differences in outcomes across the two types of states; both uninsurance and food insecurity are more prevalent in non-expansion states, and rates of SNAP use are higher. However, as long as these differences are not changing over time in ways that do not depend on Medicaid expansion, the DD approach is valid. Below, I confirm that trends in key outcomes are parallel across the two types of states prior to Medicaid expansion.

I begin by using ACS data to document that Medicaid expansion resulted in increases in Medicaid coverage and reductions in uninsurance in both expansion and non-expansion states, and that both of these changes were larger in expansion than non-expansion states. Figure 4.1 presents simple trends using ACS data in four insurance coverage outcomes – Medicaid, private non-group coverage, employer-sponsored coverage, and uninsured - for 2008 through 2018 for individuals ages 50 through 64 in two groups: those who lived in states that expanded Medicaid in January 2014 and those who lived in states that had not expanded Medicaid as of the end of 2018. Note that for this figure, I drop data from the seven states that expanded Medicaid after January 2014 (the middle column in Table 4.1), although data from these states will be incorporated into regression analyses below. These figures show dramatic gains in Medicaid coverage for adults ages 50 through 64 in expansion states. Both expansion and non-expansion states experienced gains in non-group coverage, and there was a moderate slowdown in the long-standing decline in employer-sponsored coverage in both. The net impact of these changes is that the fraction uninsured declined in both expansion and non-expansion states, with larger declines in the expansion states, as I document more precisely below. Moreover, the fact that coverage gains in expansion states were tilted toward Medicaid, which has very little cost sharing for enrollees, rather than private non-group coverage, which can be quite expensive even with government subsidies, has the potential to reduce household out-of-pocket spending on both medical care and health insurance (Blavin et al. 2018; Selden et al. 2017). Similar analyses for three subgroups of Americans ages 60 through 64 who were most likely to benefit from Medicaid expansion show similar patterns (although I have not included those figures in this report): those with low levels of education (high school graduate or less), low incomes (family income ≤ 185% of poverty), or those who are not working (mostly retirees, but also the unemployed). Trends for these subgroups are similar although levels of employer coverage are lower and levels of uninsurance are higher than for the full sample prior to 2014; gains in

Medicaid in 2014 and later are larger for these groups than for the full sample, as one would expect.

Table 4.3 reports the estimates of β from equation (1) for all four insurance outcomes for the full sample of individuals ages 50 through 64 and the three subgroups listed above. Note that the table contains only estimates of β, the differences-in-differences estimate of the impact of Medicaid expansion; additional results from these models, which include controls for age, education, sex and marital status and their interaction, and race/ethnicity are presented in Appendix Table A6. Overall, Medicaid expansion resulted in a 4.3 percentage point increase in Medicaid among this age group, as well a decline in non-group coverage of about 1.8 percentage points and a very small and non-significant decline in employer coverage. The net effect of Medicaid expansion on this group, therefore, is a significant decline in uninsurance of 1.8 percentage points. For subgroups most likely to have benefited from Medicaid expansion (columns 2 through 4 of Table 4.3) – those with low education levels or low income, and non-workers - gains in Medicaid and declines in uninsurance were larger than for the full sample.

In also estimate "event study" models of insurance coverage (see equation 11 above). These models test whether there are differences across expansion and non-expansion states prior to 2014 that would suggest the differences-in-differences approach is not valid; they also allow the impact of Medicaid expansion to vary over time after implementation. Key results, which are the coefficients δ_k on the event time dummies in equation 11, are presented graphically in Figure 4.2. (Additional results from these models, which include controls for age, education, sex and marital status and their interaction, and race/ethnicity are presented in Appendix Table A6.) Figure 4.2 confirms two things. First, there were no differential trends in insurance coverage outcomes in expansion states relative to non-expansion states that would render the differences-in-differences approach invalid. Second, as suggested by the simple trends and the differences-in-differences analysis, there was a significant increase in Medicaid coverage, a relative decline in non-group coverage (that is, a smaller increase in expansion than in non-expansion states), and small but significant relative decline in the fraction uninsured following expansion. The coverage impact is evidence immediately after implementation and continues to grow for another two or three years.

This analysis of ACS data establishes that Medicaid expansion had a significant effect on coverage of those ages 50 through 64 and therefore might reasonably have an impact on food insecurity. In order to test this hypothesis, I repeat the analysis just presented, but instead of using ACS data on insurance coverage as the outcome I use December CPS data for 2008 through 2018 with low food security or very low food security as the outcome. These results are presented graphically in Figures 4.3 and 4.4, with the coefficients on the “treatment” dummy from the difference-in-differences analysis (Equation 1 above) presented in Table 4.4. (Additional results for the differences-in-differences and event study models with food insecurity as the outcome are reported in Appendix Tables A6 and A7.)

Surprisingly, these analyses show no effect of Medicaid expansion on food insecurity among 60 through 64 year olds, either in the full sample or in the three vulnerable subgroups. This is true whether I use low food security or very low food security as the outcome, measured over a 12-month or 30-day recall period. This is particularly surprising in light of earlier studies showing impacts of Medicaid expansion on food insecurity among working-age adults (Himmelstein 2019; Moellman 2020).[13]

[13] I am able to exactly replicate the result in Himmelstein (2019) using the specification in the paper; however, when estimating a more flexible specification that includes both year and state dummies (as opposed to single “post” and “treatment” dummies), and estimating the model only for those ages 50 through 64, the effect is not significant.

In terms of SNAP receipt, in the ACS I find evidence of a significant increase in use as a result of Medicaid expansion, ranging from 0.8 percentage points in the full sample to 2.4 percentage points in the low-income sample (Table 4.3). This is consistent with the results of Baicker et al. (2014) based on the Oregon Health Insurance Experiment. Estimates of the impact of Medicaid expansion on SNAP using CPS data are smaller (0.3 to 0.8 percentage points) and not significantly different from zero, as shown in Table 4.4.

Discussion

On the face of it, the results for Medicare and Medicaid are very puzzling. How can it be the case that massive transfers in the form of heavily-subsidized public insurance programs – free, in the case of Medicaid – do not reduce food-related hardship, even though they have been shown to reduce other forms of financial hardship, such as debts referred for collection? One possibility is that the consumption value of these programs for recipients may be very limited; Finkelstein, Hendren, and Luttmer (2019) explore this possibility for Medicaid. In the case of Medicaid, most of the households who become eligible were spending very little on medical care before gaining coverage (Levy, Buchmueller, and Nikpay 2018), so there is little scope for Medicaid expansion to ease household budgets enough for an unemployed family member to extend his or her job search as result. If households without insurance either go without medical care when they need it – or in the event of a true emergency, visit the hospital and accumulate debt – then expanding coverage will reduce foregone care and improve the debt burden of these households (and the hospitals that serve them), but will not translate into less hardship in other domains, such as food insecurity. Another way to put this is that if very low-income households already prioritized food spending above paying off medical debt, expanding public coverage will increase what providers are paid but not improve food security for those households.

Conclusion

The central question for this program of research is how social insurance and transfer programs other than SNAP affect food insecurity among seniors. Estimates of the impact of Social Security on these outcomes suggest that it helps to reduce them, but these estimates are very imprecise. As for Medicare and Medicaid, the results in this report suggest that neither program significantly reduces food insecurity/insufficiency among older Americans.

For older adults, perhaps even more than younger ones, the ability to translate resources into food security may depend not just on material resources but also on individual capabilities - physical, cognitive, and socio-emotional – that may themselves be deteriorating with age. This dynamic may help explain why for older Americans, food insecurity occurs at surprisingly high levels of income, and why limitations in the ability to perform activities of daily living (IADLs) are consistently associated with higher rates of food insecurity, holding income and other characteristics such as education constant. If this is the case, then simply giving seniors more resources will be less effective at reducing food insecurity than providing other kinds of supports such as prepared meals, congregate meal programs, and other home and community-based supportive services.

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List of Tables and Figures

Tables

Appendix Tables

Figures

Table 1.1 Sample Characteristics, Ages 60+
Data: HRS, 1998-2016

	Full Sample	Transitions sample
Food insufficiency	0.059	0.056
Age	71.1	70.5
Female	0.556	0.559
Married	0.619	0.634
Education < high school	0.332	0.337
White non-Hispanic	0.814	0.820
Black non-Hispanic	0.090	0.087
Other non-Hispanic	0.024	0.023
Hispanic	0.072	0.070
Worker	0.192	0.200
Unemployed	0.012	0.012
Retired	0.779	0.773
Disabled	0.017	0.016
Median real income	$35,880	$36,421
Wealth ≤ 0	0.065	0.060
Health is fair or poor	0.280	0.256
Number of ADLs	0.335	0.265
Number of IADLs	0.142	0.102
Word recall score (out of 20)*	9.7	9.8
Sample size	133,495	104,319

*Word recall score is missing for respondents who relied on a proxy to complete the interview, or 7% of the sample. Sample sizes for word recall are 126,168 in the full sample and 98,012 in the transitions sample.

Table 1.2: Regression models
Dependent variable = 1 if food insufficient
Data: Health and Retirement Study

Years	1998 - 2016	2010-2016	2010-2016	1998 - 2016
Estimation method	OLS	OLS	OLS	Fixed effects
Personality variables?	No	No	Yes	No
	(1)	(2)	(3)	(4)
Age	-0.003***	-0.004***	-0.004***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.002)
Married men	[Omitted]	[Omitted]	[Omitted]	-
Single men	-0.015***	-0.017**	-0.017**	-
	(0.002)	(0.006)	(0.006)	
Married women	-0.005***	-0.006	-0.010*	-
	(0.002)	(0.004)	(0.004)	
Single women	0.011***	0.014**	0.012**	-
	(0.002)	(0.004)	(0.005)	
Married	-	-	-	0.003
				(0.003)
Years of Education	-0.002***	-0.001	-0.001	[Omitted]
	(0.000)	(0.001)	(0.001)	
White non-Hispanic	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Black non-Hispanic	0.038***	0.019**	0.022***	[Omitted]
	(0.002)	(0.006)	(0.006)	
Other non-Hispanic	0.026***	0.034***	0.035***	[Omitted]
	(0.004)	(0.010)	(0.010)	
Hispanic	0.016***	-0.010	-0.009	[Omitted]
	(0.003)	(0.007)	(0.007)	

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Table 1.2 (continued)

	(1)	(2)	(3)	(4)
Worker	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Unemployed	0.065***	0.045***	0.042**	0.022***
	(0.006)	(0.013)	(0.013)	(0.006)
Retired	0.014***	0.009*	0.009*	0.010***
	(0.002)	(0.004)	(0.004)	(0.002)
Disabled	0.067***	0.107***	0.106***	0.005
	(0.005)	(0.018)	(0.018)	(0.006)
Ln (real income)	-0.013***	-0.020***	-0.020***	-0.005***
	(0.001)	(0.002)	(0.002)	(0.001)
Wealth<0	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Wealth=0	-0.085***	-0.092***	-0.090***	-0.045***
	(0.005)	(0.013)	(0.013)	(0.006)
Wealth>0: quintile 1	-0.118***	-0.120***	-0.120***	-0.051***
	(0.004)	(0.009)	(0.009)	(0.004)
Wealth>0: quintile 2	-0.155***	-0.154***	-0.153***	-0.054***
	(0.004)	(0.008)	(0.008)	(0.004)
Wealth>0: quintile 3	-0.186***	-0.196***	-0.195***	-0.066***
	(0.004)	(0.008)	(0.008)	(0.004)
Wealth>0: quintile 4	-0.192***	-0.200***	-0.199***	-0.071***
	(0.004)	(0.008)	(0.008)	(0.005)
Wealth>0: quintile 5	-0.186***	-0.192***	-0.191***	-0.075***
	(0.004)	(0.008)	(0.008)	(0.005)

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Table 1.2 (continued)

	(1)	(2)	(3)	(4)
Health is fair or poor	0.027***	0.020***	0.018***	0.005*
	(0.002)	(0.004)	(0.004)	(0.002)
Number of ADLs	0.016***	0.019***	0.018***	0.002
	(0.001)	(0.002)	(0.002)	(0.001)
Number of IADLs	0.010***	0.029***	0.028***	0.009***
	(0.001)	(0.004)	(0.004)	(0.002)
Word recall:				
Proxy/no cognition	[Omitted]	[Omitted]	[Omitted]	[Omitted]
0-6 words (worst)	0.033***	0.057***	0.057***	0.016***
	(0.003)	(0.012)	(0.012)	(0.004)
7-9 words	0.027***	0.054***	0.053***	0.013***
	(0.003)	(0.012)	(0.012)	(0.004)
10-11 words	0.024***	0.044***	0.044***	0.014***
	(0.003)	(0.012)	(0.012)	(0.004)
12+ words (best)	0.022***	0.034**	0.034**	0.013**
	(0.003)	(0.012)	(0.012)	(0.004)
Region=Northeast	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Region=Midwest	-0.012***	-0.016***	-0.016**	-0.039***
	(0.002)	(0.005)	(0.005)	(0.011)
Region=South	0.001	-0.008	-0.008	-0.031***
	(0.002)	(0.005)	(0.005)	(0.008)
Region=West	-0.002	0.010	0.011*	-0.051***
	(0.002)	(0.005)	(0.005)	(0.011)
Region=Other	-0.001	0.054	0.057	-0.060*
	(0.016)	(0.054)	(0.054)	(0.030)

Table continues on next page

Table 1.2 (continued)

	(1)	(2)	(3)	(4)
Neuroticism			0.010***	
			(0.002)	
Extraversion			0.003	
			(0.002)	
Openness			0.003	
			(0.002)	
Agreeableness			0.000	
			(0.002)	
Conscientiousness			0.001	
			(0.002)	
Constant	0.554***	0.644***	0.635***	0.624***
	(0.010)	(0.028)	(0.028)	(0.104)
Observations	133,495	20,121	20,121	133,495

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Note: All models also include year dummies that are not reported in the table.

Table 1.3
Wave-to-wave transition probabilities in food insufficiency
Data: Health and Retirement Study, 1998 through 2016

	Status at wave 2:		
Status at wave 1:	Food sufficient	Food insufficient	Total
Food sufficient (n=97,587)	0.967	0.033	1.000
Food insufficient (n=6,316)	0.608	0.392	1.000

Table 1.4
Determinants of Entry into and Exit from Food Insufficiency
Health and Retirement Study, 1998 – 2016

	Entry	Exit
	(1)	(2)
Age	-0.001***	0.007***
	(0.000)	(0.001)
Married men	[Omitted]	[Omitted]
Single men	-0.006**	0.098***
	(0.002)	(0.021)
Married women	-0.002	0.024
	(0.001)	(0.017)
Single women	0.003*	-0.057***
	(0.002)	(0.016)
Years of Education	-0.002***	0.005*
	(0.000)	(0.002)
White non-Hispanic	[Omitted]	[Omitted]
Black non-Hispanic	0.025***	-0.025
	(0.002)	(0.015)
Other non-Hispanic	0.015***	-0.032
	(0.004)	(0.030)
Hispanic	0.011***	0.163***
	(0.003)	(0.019)
Worker	[Omitted]	[Omitted]
Unemployed	0.022***	0.061
	(0.006)	(0.038)

Table continues on next page

Table 1.4 (continued)

	Entry	Exit
	(1)	(2)
Retired	0.005**	-0.032
	(0.002)	(0.017)
Disabled	0.036***	-0.068*
	(0.005)	(0.028)
Ln_real_income	-0.007***	0.022***
	(0.001)	(0.004)
Wealth<0	[Omitted]	[Omitted]
Wealth=0	0.009	0.124***
	(0.005)	(0.024)
Wealth>0: quintile 1	-0.023***	0.094***
	(0.004)	(0.018)
Wealth>0: quintile 2	-0.044***	0.139***
	(0.004)	(0.020)
Wealth>0: quintile 3	-0.059***	0.208***
	(0.004)	(0.023)
Wealth>0: quintile 4	-0.065***	0.338***
	(0.004)	(0.028)
Wealth>0: quintile 5	-0.061***	0.417***
	(0.004)	(0.031)
Health is fair or poor	0.016***	-0.052***
	(0.001)	(0.013)
Number of ADLs	0.009***	-0.021***
	(0.001)	(0.005)
Number of IADLs	0.002	-0.022*
	(0.002)	(0.010)

Table continues on next page

Table 1.4 (continued)

	Entry	Exit
	(1)	(2)
Word recall:		
Proxy/no cognition	[Omitted]	[Omitted]
0-6 words (worst)		
	0.011***	-0.072*
	(0.003)	(0.028)
7-9 words		
	0.006*	-0.084**
	(0.003)	(0.028)
10-11 words		
	0.007*	-0.104***
	(0.003)	(0.030)
12+ words (best)		
Word recall:	0.004	-0.127***
	(0.003)	(0.030)
Region=NE	[Omitted]	[Omitted]
Region=Midwest	-0.008***	0.039*
	(0.002)	(0.019)
Region=South	0.004*	0.013
	(0.002)	(0.016)
Region=West	-0.001	0.003
	(0.002)	(0.019)
Region=Other	0.004	-0.047
	(0.016)	(0.106)
	(0.003)	(0.030)
Constant	0.245***	-0.007
	(0.010)	(0.082)
Observations	97,587	6,316

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Table 2.1
Mean characteristics in 1995 of 1910-1916 and 1917 - 1923 birth cohorts
Health and Retirement Study, 1995

	Born 1910 - 1916	Born 1917 - 1923	Total
Low food sufficiency	0.065	0.072	0.069
Very low food sufficiency	0.012	0.014	0.013
Household income	26,762	33,285	30,930
Ln(household income)	9.7	10.0	9.9
Receiving SNAP	0.048	0.045	0.046
Age	81.6	74.8	77.2
Working	0.016	0.050	0.038
Years of education	10.9	11.5	11.3
Female	0.602	0.542	0.564
White non-Hispanic	0.880	0.872	0.875
Black non-Hispanic	0.076	0.073	0.074
Hispanic	0.033	0.040	0.037
Self-rated health (1 = EX, 5 = POOR)	3.1	2.9	3.0
Sample size	1,986	3,302	5,288

Table 2.2
Regression discontinuity models: Does the Social Security notch affect outcomes?
Health and Retirement Study, 1995

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Low food sufficiency		Very low food sufficiency		Real household income		Ln(real household income)		SNAP	
post	0.018	-0.004	0.004	-0.002	-1,562	-4,448	-0.034	-0.099	0.025*	0.024
	(0.015)	(0.022)	(0.006)	(0.009)	(2,576)	(3,677)	(0.061)	(0.089)	(0.011)	(0.017)
AGE	-0.000	0.001	0.000	0.000	58	198	0.004**	0.007	-0.001**	-0.001
	(0.000)	(0.001)	(0.000)	(0.000)	(44)	(163)	(0.001)	(0.005)	(0.000)	(0.001)
post_AGE	0.000	-0.001	-0.000	0.000	74	5	-0.000	-0.002	0.000	0.001
	(0.000)	(0.001)	(0.000)	(0.000)	(60)	(224)	(0.001)	(0.006)	(0.000)	(0.001)
AGEsq		0.000		0.000		2		0.000		-0.000
		(0.000)		(0.000)		(2)		(0.000)		(0.000)
post_AGEsq		-0.000		-0.000		-3		-0.000		-0.000
		(0.000)		(0.000)		(3)		(0.000)		(0.000)
Constant	0.057***	0.075***	0.012**	0.013*	28939***	30763***	9.878***	9.922***	0.026***	0.026*
	(0.011)	(0.015)	(0.005)	(0.006)	(1,857)	(2854)	(0.050)	(0.072)	(0.008)	(0.010)
Observations	5,122	5,122	5,122	5,122	5,122	5,122	5,122	5,122	5,122	5,122
R-squared	0.000	0.001	0.000	0.000	0.008	0.008	0.019	0.019	0.002	0.002

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Table 2.3
Regression discontinuity models: Are there discontinuities in other variables at the Social Security notch?
Health and Retirement Study, 1995

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Working		Years of education		Female		Nonwhite		Self-rated health	
post	-0.006	0.008	-0.000	-0.500	0.048	0.079	0.000	0.020	-0.064	-0.181
	(0.010)	(0.014)	(0.207)	(0.312)	(0.032)	(0.049)	(0.015)	(0.023)	(0.072)	(0.109)
AGE	0.000	-0.000	0.009*	0.021	-0.001**	-0.003	-0.000	-0.001	-0.002	0.006
	(0.000)	(0.000)	(0.004)	(0.014)	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	(0.005)
post_AGE	0.001**	0.000	-0.003	0.010	0.000	0.002	0.000	-0.000	-0.001	-0.008
	(0.000)	(0.001)	(0.005)	(0.018)	(0.001)	(0.003)	(0.000)	(0.001)	(0.002)	(0.006)
AGEsq		-0.000		0.000		-0.000		-0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
post_AGEsq		0.000		-0.000*		0.000		0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	0.022***	0.018*	11.26***	11.40***	0.550***	0.523***	0.086***	0.078***	3.07***	3.17***
	(0.006)	(0.009)	(0.158)	(0.234)	(0.025)	(0.037)	(0.011)	(0.017)	(0.055)	(0.083)
Observations	5,122	5,122	5,122	5,122	5,122	5,122	5,122	5,122	5,122	5,122
R-squared	0.012	0.013	0.011	0.012	0.007	0.007	0.000	0.000	0.013	0.014

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Table 3.1
Food insecurity/insufficiency and other characteristics at ages 60-64 vs. 65-69

	Health and Retirement Study 1996 - 2016			National Health Interview Survey 2011-2014		
	Age 60-64	Age 65-69	Total	Age 60-64	Age 65-69	Total
Low food security/sufficiency*	0.079	0.062	0.072	0.092	0.074	0.084
Very low food security/ sufficiency*	0.044	0.032	0.039	0.040	0.028	0.035
Medicare	0.121	0.925	0.468	0.109	0.901	0.456
Uninsured	0.103	0.010	0.063	0.115	0.014	0.071
SNAP receipt	0.056	0.047	0.052	0.096	0.084	0.091
Working	0.440	0.197	0.335	0.510	0.288	0.413
Years of education	13.1	12.9	13.0	13.4	13.2	13.3
Female	0.526	0.535	0.530	0.522	0.529	0.525
White non-Hispanic	0.784	0.805	0.793	0.761	0.785	0.772
Black non-Hispanic	0.102	0.094	0.098	0.106	0.091	0.099
Hispanic	0.083	0.076	0.080	0.084	0.080	0.082
Self-reported health (1 = excellent, 5 = poor)	2.7	2.8	2.7	2.6	2.6	2.6
Sample size	33,954	29,586	63,540	21,321	16,544	37,865

*The HRS measure is food sufficiency; the NHIS measure is food security

Table 3.2
Regression discontinuity: Are there discontinuities in outcomes at age 65?
National Health Interview Survey, 2011-2014

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Low food security		Very low food security		Medicare		Uninsured		SNAP	
post	0.002	0.005	0.000	0.007	0.706***	0.674***	-0.089***	-0.083***	-0.002	0.008
	(0.006)	(0.009)	(0.004)	(0.006)	(0.008)	(0.013)	(0.006)	(0.009)	(0.006)	(0.009)
dage	-0.000***	-0.001	-0.000**	-0.001	0.001***	0.002**	-0.000	-0.000	-0.000**	-0.001
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
post_dage	0.000	0.001	0.000	0.000	0.001***	0.002**	-0.000*	-0.001	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
dagesq		-0.000		-0.000		0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
post_dagesq		0.000		0.000		-0.000***		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	0.079***	0.075***	0.032***	0.028***	0.138***	0.148***	0.114***	0.113***	0.086***	0.081***
	(0.004)	(0.006)	(0.003)	(0.004)	(0.005)	(0.008)	(0.005)	(0.008)	(0.004)	(0.006)
Observations	37837	37837	37837	37837	37837	37837	37837	37837	37837	37837
R-squared	0.001	0.001	0.002	0.002	0.626	0.626	0.038	0.038	0.001	0.001

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Table 3.3
Regression discontinuity models: Are there discontinuities in outcomes at age 65?
Health and Retirement Study, 1998 – 2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Low food sufficiency		Very low food sufficiency		Medicare		Uninsured		SNAP	
post	-0.002	-0.002	-0.002	0.000	0.726***	0.697***	-0.092***	-0.096***	-0.008	0.001
	(0.005)	(0.008)	(0.004)	(0.006)	(0.007)	(0.011)	(0.004)	(0.007)	(0.005)	(0.007)
dage	-0.000*	-0.000	-0.000*	-0.000	0.001***	0.002***	0.000	0.001	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
post_dage	-0.000	-0.000	0.000	0.000	0.000*	0.001	-0.000	-0.001	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
dagesq		-0.000		-0.000		0.000		0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
post_dagesq		-0.000		0.000		-0.000***		-0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	0.071***	0.071***	0.038***	0.037***	0.155***	0.165***	0.106***	0.110***	0.055***	0.050***
	(0.004)	(0.006)	(0.003)	(0.005)	(0.005)	(0.008)	(0.004)	(0.007)	(0.003)	(0.005)
Observations	62530	62530	62530	62530	62530	62530	62530	62530	62530	62530
R-squared	0.001	0.001	0.001	0.001	0.640	0.640	0.036	0.036	0.000	0.000

* p<0.05; ** p<0.01; *** p<0.001

Table 3.4
Are covariates smooth through the potential discontinuity at age 65?
National Health Interview Survey, 2011-2014

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(11)
	Worker		Years of Education		Female		Nonwhite		Self-rated Health	
post	-0.014	-0.000	0.132*	0.061	0.023*	-0.002	-0.007	-0.008	-0.027	0.038
	(0.011)	(0.018)	(0.066)	(0.100)	(0.012)	(0.018)	(0.006)	(0.010)	(0.026)	(0.040)
dage	-0.004***	-0.005***	-0.004**	0.001	-0.000	0.001	-0.000	0.000	0.000	-0.006**
	(0.000)	(0.001)	(0.001)	(0.005)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)
post_dage	0.002***	0.003*	-0.003	-0.005	-0.000	0.001	0.000	-0.000	-0.000	0.006*
	(0.000)	(0.001)	(0.002)	(0.008)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.003)
dagesq		-0.000		0.000		0.000		0.000		-0.000**
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
post_dagesq		0.000		-0.000		-0.000		-0.000		0.000*
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	0.374***	0.363***	13.301***	13.350***	0.516***	0.524***	0.107***	0.110***	2.586***	2.520***
	(0.008)	(0.012)	(0.044)	(0.067)	(0.008)	(0.013)	(0.004)	(0.007)	(0.018)	(0.027)
Observations	37837	37837	37837	37837	37837	37837	37837	37837	37837	37837
R-squared	0.067	0.067	0.002	0.002	0.000	0.000	0.001	0.001	0.000	0.000

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Table 3.5
Are covariates smooth through the potential discontinuity at age 65?
Health and Retirement Study, 1998 through 2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Worker		Years of Education		Female		Nonwhite		Self-rated Health	
post	0.004	0.001	0.048	0.059	-0.005	0.005	-0.005	-0.001	-0.043	-0.052
	(0.009)	(0.014)	(0.062)	(0.094)	(0.010)	(0.016)	(0.006)	(0.009)	(0.022)	(0.033)
dage	-0.005***	-0.004***	-0.005***	-0.011*	0.000	-0.000	-0.000	-0.001	0.001**	0.003
	(0.000)	(0.001)	(0.001)	(0.005)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)
post_dage	0.003***	0.001	-0.002	0.011	0.000	0.000	-0.000	0.001	0.001	-0.001
	(0.000)	(0.001)	(0.002)	(0.007)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.003)
dagesq		0.000		-0.000		-0.000		-0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
post_dagesq		-0.000		0.000		0.000		0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	0.273***	0.285***	12.994***	12.924***	0.530***	0.524***	0.128***	0.122***	2.760***	2.775***
	(0.007)	(0.010)	(0.042)	(0.065)	(0.007)	(0.011)	(0.004)	(0.006)	(0.015)	(0.023)
Observations	62530	62530	62530	62530	62530	62530	62530	62530	62490	62490
R-squared	0.091	0.091	0.003	0.003	0.000	0.000	0.000	0.000	0.001	0.001

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Table 4.1

Summary of State Medicaid Expansion Decisions as of 12/31/2018

Expansion States		**Non-Expansion States (19)**
By January 2014 (25)	**After January 2014 (7)**	
Arizona	4/14: Michigan	No expansion as of 5/2021
Arkansas	8/14: New Hampshire	Alabama
California	1/15: Pennsylvania	Florida
Colorado	2/15: Indiana	Georgia
Connecticut	9/15: Alaska	Kansas
Delaware	1/16: Montana	Mississippi
District of Columbia	7/16: Louisiana	North Carolina
Hawaii		South Carolina
Illinois		South Dakota
Iowa		Tennessee
Kentucky		Texas
Maryland		Wisconsin
Massachusetts		Wyoming
Minnesota		
Nevada		Subsequent expansion:
New Jersey		1/19: Virginia
New Mexico		1/19: Maine
New York		1/20: Idaho
North Dakota		1/20: Utah
Ohio		10/20: Nebraska
Oregon		7/21: Oklahoma
Rhode Island		Pending: Missouri
Vermont		
Washington		
West Virginia		

Note: Six states listed here as non-expansion – Virginia, Maine, Idaho, Utah, Nebraska, and Oklahoma– have implemented or enacted expansion after 2018, the most recent year in my data, and so they are treated as non-expansion states in this analysis.

Source: Kaiser Family Foundation, Status of State Action on the Medicaid Expansion Decision, consulted on May 18, 2021

Table 4.2
Summary statistics in Medicaid expansion vs. non-expansion states before expansion
Individuals ages 50 through 64
American Community Survey and Current Population Survey, 2008 through 2013

	American Community Survey			Current Population Survey		
	Non-Expansion	Expansion	Total	Non-Expansion	Expansion	Total
Uninsured	0.161	0.125	0.138	-	-	-
Medicaid	0.079	0.096	0.090	-	-	-
Private non-group coverage	0.123	0.122	0.122	-	-	-
Employer-sponsored coverage	0.646	0.676	0.665	-	-	-
Food insecure (12 month recall)	-	-	-	0.134	0.116	0.123
Food insecure (30 day recall)	-	-	-	0.079	0.070	0.074
Very low food security (12 month recall)	-	-	-	0.057	0.051	0.053
Very low food security (30 day recall)	-	-	-	0.034	0.030	0.032
SNAP receipt	0.108	0.094	0.099	0.079	0.069	0.072
Working	0.650	0.664	0.659	0.653	0.664	0.660
Education less than high school graduate	0.127	0.115	0.119	0.112	0.101	0.105
Female	0.520	0.516	0.517	0.516	0.516	0.516
White non-Hispanic	0.722	0.738	0.732	0.718	0.739	0.731
Black non-Hispanic	0.141	0.089	0.108	0.143	0.089	0.109
Hispanic	0.098	0.098	0.098	0.101	0.099	0.100
Sample size	1,458,250	2,423,600	3,881,850	46,978	86,208	133,186

Table 4.3
Difference-in-differences analyses of insurance by Medicaid expansion/non-expansion status, American Community Survey, 2008 - 2018

	Sample includes individuals ages 50 through 64 who are:			
	(1)	(2)	(3)	(4)
	All	Education: HS or less	Income <185% FPL	Non-worker
Dependent variable:	Coefficient on *treatment* dummy (see Equation 10 in text):			
Medicaid	0.043***	0.063***	0.123***	0.069***
	(0.005)	(0.009)	(0.012)	(0.007)
Uninsured	-0.018*	-0.032*	-0.062***	-0.040***
	(0.009)	(0.014)	(0.015)	(0.011)
Non-Group coverage	-0.018**	-0.022**	-0.041***	-0.020***
	(0.006)	(0.007)	(0.008)	(0.004)
Employer coverage	-0.005	-0.007	-0.015**	-0.008
	(0.005)	(0.007)	(0.004)	(0.007)
SNAP	0.008*	0.014**	0.024**	0.016***
	(0.003)	(0.005)	(0.008)	(0.004)
Observations	7,266,271	2,890,293	1,481,812	2,434,386

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Note: All models also include controls for age, education, sex and marital status and their interaction, race/ethnicity, and full sets of state and year dummies.

Table 4.4
Difference-in-differences analyses of food insecurity,
By Medicaid expansion/non-expansion status,
Current Population Survey, 2008 - 2018

	Sample includes individuals ages 50 through 64 who are:			
	(1)	(2)	(3)	(4)
	All	Education: HS or less	Income <185% FPL	Non-worker
Dependent variable:	Coefficient on *treatment* dummy (see Equation 10 in text):			
Food insecure	0.001	0.004	-0.004	0.005
in last 12 months	(0.006)	(0.011)	(0.015)	(0.009)
Food insecure	-0.002	-0.002	-0.010	-0.007
In last 30 days	(0.004)	(0.008)	(0.011)	(0.007)
Very low food security	-0.002	-0.004	-0.012	-0.008
in last 12 months	(0.005)	(0.008)	(0.012)	(0.008)
Very low food security	-0.001	0.000	-0.005	-0.004
in last 30 days	(0.003)	(0.006)	(0.009)	(0.006)
SNAP receipt	0.003	0.004	0.004	0.008
	(0.003)	(0.006)	(0.014)	(0.007)
Unweighted n	232,004	92,397	51,013	74,886

Standard errors in parentheses
* $p<0.05$; ** $p<0.01$; *** $p<0.001$

Note: All models also include controls for age, education, sex and marital status and their interaction, race/ethnicity, and full sets of state and year dummies.

Appendix Table A1
Food Insecurity Questions in the December CPS Food Security Supplement

The Core Food Security Module consisting of the following 18 questions has been asked in every December CPS since 2001 (adapted from Table 1 in Gundersen and Kreider 2008):

1. ‘‘We worried whether our food would run out before we got money to buy more.’’ Was that often, sometimes, or never true for you in the last 12 months?

2. ‘‘The food that we bought just didn’t last and we didn’t have money to get more.’’ Was that often, sometimes, or never true for you in the last 12 months?

3. ‘‘We couldn’t afford to eat balanced meals.’’ Was that often, sometimes, or never true for you in the last 12 months?

4. ‘‘We relied on only a few kinds of low-cost food to feed our children because we were running out of money to buy food.’’ Was that often, sometimes, or never true for you in the last 12 months?

5. 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? (Yes/No)

6. ‘‘We couldn’t feed our children a balanced meal, because we couldn’t afford that.’’ Was that often, sometimes, or never true for you in the last 12 months?

7. In the last 12 months, did you ever eat less than you felt you should because there wasn’t enough money for food? (Yes/No)

8. (If yes to Question 5) How often did this happen—almost every month, some months but not every month, or in only
1 or 2 months?

9. ‘‘The children were not eating enough because we just couldn’t afford enough food.’’ Was that often, sometimes, or never true for you in the last 12 months?

10. In the last 12 months, were you ever hungry, but didn’t eat, because you couldn’t afford enough food? (Yes/No)

11. In the last 12 months, did you lose weight because you didn’t have enough money for food? (Yes/No)

12. In the last 12months, did you ever cut the size of any of the children’s meals because there wasn’t enough money for food? (Yes/No)

13. In the last 12 months did you or other adults in your household ever not eat for a whole day because there wasn’t enough money for food? (Yes/No)

14. In the last 12 months, were the children ever hungry but you just couldn’t afford more food? (Yes/No)

15. (If yes to Question 13) How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?

(Table continues on next page)

Table A1, cont'd: Food Insecurity Questions in the December CPS Food Security Supplement

16. In the last 12 months, did any of the children ever skip a meal because there wasn't enough money for food? (Yes/No)
17. (If yes to Question 16) How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?
18. In the last 12 months did any of the children ever not eat for a whole day because there wasn't enough money for food? (Yes/No)

Appendix Table A2
Food Insufficiency Questions in the Health and Retirement Study

The following question has been asked in the HRS core survey in every year since 1995:

HRS1. In the last two years, have you always had enough money to buy the food you need?

In addition, one of the following two questions has been asked in the HRS core survey in every year since 1995:

[IN 1995 THROUGH 2006] HRS2A. At any time in the last two years have you skipped meals or eaten less than you felt you should because there was not enough food in the house?

[IN 2008 AND LATER] HRS2B. In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money to buy food?

Appendix Table A3:
Food Insecurity Questions in the NHIS

Since 2011, the NHHIS has asked the following 10 questions that are used to construct a measure of 30-day food security:

FSRUNOUT: “[I/we] worried whether [my/our] food would run out before [I/we] got money to buy more." Was that often true, sometimes true, or never true for [you/your family] in the last 30 days?

FSLAST: “The food that [I/we] bought just didn't last, and [I/we] didn't have money to get more." Was that often true, sometimes true, or never true for [you/your family] in the last 30 days?

FSBALANC: "[I/We] couldn't afford to eat balanced meals." Was that often true, sometimes true, or never true for [you/your family] in the last 30 days?

FSSKIP: In the last 30 days, did [you/you or other adults in your family] ever cut the size of your meals or skip meals because there wasn't enough money for food?

FSSKDAYS: In the last 30 days, how many days did this happen?

FSLESS: In the last 30 days, did you ever eat less than you felt you should because there wasn't enough money for food?

FSHUNGRY. In the last 30 days, were you ever hungry but didn't eat because there wasn't enough money for food?

FSWEIGHT. In the last 30 days, did you lose weight because there wasn't enough money for food?

FSNOTEAT. In the last 30 days, did [you/you or other adults in your family] ever not eat for a whole day because there wasn't enough money for food?

FSNEDAYS. In the last 30 days, how many days did this happen?

Appendix Table A4
Benchmarking NHIS to CPS, 2011 - 2016
30-day Measures of Low and Very Low Food Security

	(1)	(2)	(3)	(4)
	Low food security		Very low food security	
	NHIS	CPS	NHIS	CPS
Age 60-64	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Age 65-69	-0.018***	-0.012***	-0.011***	-0.006***
	(0.002)	(0.002)	(0.001)	(0.001)
Age 70-74	-0.031***	-0.024***	-0.018***	-0.013***
	(0.002)	(0.002)	(0.001)	(0.001)
Age 75-79	-0.048***	-0.035***	-0.026***	-0.017***
	(0.002)	(0.002)	(0.001)	(0.001)
Age 80+	-0.074***	-0.057***	-0.038***	-0.026***
	(0.002)	(0.002)	(0.001)	(0.001)
Married men	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Single men	0.044***	0.047***	0.025***	0.021***
	(0.002)	(0.002)	(0.001)	(0.001)
Married women	-0.007***	0.006***	-0.003**	0.003***
	(0.002)	(0.001)	(0.001)	(0.001)
Single women	0.054***	0.040***	0.025***	0.021***
	(0.002)	(0.002)	(0.001)	(0.001)
Less than HS	[Omitted]	[Omitted]	[Omitted]	[Omitted]
=HS	-0.067***	-0.047***	-0.025***	-0.020***
	(0.002)	(0.002)	(0.001)	(0.001)

Table continues on next page

Table A4, continued

Some college	-0.074***	-0.051***	-0.025***	-0.021***
	(0.002)	(0.002)	(0.001)	(0.001)
College+	-0.103***	-0.074***	-0.038***	-0.031***
	(0.002)	(0.002)	(0.001)	(0.001)
White non-Hispanic	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Black non-Hispanic	0.082***	0.046***	0.031***	0.016***
	(0.002)	(0.002)	(0.002)	(0.001)
Other non-Hispanic	0.020***	0.007**	0.003	-0.000
	(0.003)	(0.002)	(0.002)	(0.002)
Hispanic	0.062***	0.041***	0.018***	0.006***
	(0.003)	(0.002)	(0.002)	(0.001)
Constant	0.128***	0.088***	0.051***	0.038***
	(0.002)	(0.002)	(0.002)	(0.001)
Observations	121,198	138,060	121,198	138,060

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Appendix Table A5
Benchmarking HRS to CPS, 2011 - 2016
Food sufficiency with two-year recall in HRS vs. food security with 12-month recall in CPS

	(1)	(2)	(3)	(4)
	Low food security/sufficiency		Very low food security/sufficiency	
	HRS	CPS	HRS	CPS
Age 60-64	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Age 65-69	-0.024***	-0.018***	-0.018***	-0.010***
	(0.003)	(0.002)	(0.003)	(0.001)
Age 70-74	-0.044***	-0.037***	-0.036***	-0.019***
	(0.004)	(0.002)	(0.003)	(0.001)
Age 75-79	-0.066***	-0.055***	-0.054***	-0.025***
	(0.004)	(0.002)	(0.003)	(0.002)
Age 80+	-0.090***	-0.087***	-0.073***	-0.042***
	(0.004)	(0.002)	(0.003)	(0.001)
Married men	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Single men	0.023***	0.077***	0.018***	0.036***
	(0.004)	(0.002)	(0.003)	(0.001)
Married women	-0.012***	0.009***	-0.009***	0.004***
	(0.003)	(0.002)	(0.002)	(0.001)
Single women	0.065***	0.067***	0.050***	0.036***
	(0.003)	(0.002)	(0.003)	(0.002)
Less than HS	[Omitted]	[Omitted]	[Omitted]	[Omitted]
=HS	-0.058***	-0.083***	-0.031***	-0.033***
	(0.004)	(0.002)	(0.003)	(0.002)

Table continues on next page

Table A5, continued

Some college	-0.077***	-0.094***	-0.045***	-0.034***
	(0.004)	(0.002)	(0.003)	(0.002)
College+	-0.096***	-0.134***	-0.061***	-0.051***
	(0.004)	(0.002)	(0.003)	(0.002)
White non-Hispanic	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Black non-Hispanic	0.077***	0.089***	0.037***	0.029***
	(0.004)	(0.003)	(0.003)	(0.002)
Other non-Hispanic	0.077***	0.015***	0.036***	0.002
	(0.007)	(0.003)	(0.006)	(0.002)
Hispanic	0.059***	0.067***	0.018***	0.013***
	(0.005)	(0.003)	(0.004)	(0.002)
Constant	0.140***	0.157***	0.089***	0.062***
	(0.005)	(0.003)	(0.004)	(0.002)
Observations	38,810	138,062	3,8810	138,062

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Table A6/Aim 4
Additional regression coefficients from difference-in-differences and event study models estimating changes in insurance coverage
American Community Survey, 2008 – 2018

	(1) Medicaid	(2) Medicaid	(3) Uninsured	(4) Uninsured	(5) Non-Group	(6) Non-Group	(7) Employer	(8) Employer	(9) SNAP	(10) SNAP
Treatment	0.043***		-0.018*		-0.018**		-0.005		0.008*	
	(0.005)		(0.009)		(0.006)		(0.005)		(0.003)	
t-6		-0.002		-0.008		0.005		0.007		0.014
		(0.006)		(0.008)		(0.003)		(0.006)		(0.008)
t-5		-0.006		0.001		0.003		0.002		0.003
		(0.003)		(0.004)		(0.002)		(0.005)		(0.007)
t-4		-0.005*		0.002		0.004*		-0.001		0.003
		(0.003)		(0.004)		(0.002)		(0.003)		(0.005)
t-3		-0.002		0.001		0.003		0.001		0.000
		(0.002)		(0.002)		(0.002)		(0.003)		(0.003)
t-2		-0.002		-0.001		0.002		0.002		-0.004
		(0.001)		(0.002)		(0.001)		(0.002)		(0.002)
t-1		-0.002		-0.002		0.002		0.004*		-0.005**
		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)
t+1		0.024***		-0.010*		-0.011**		-0.001		0.005**
		(0.003)		(0.005)		(0.003)		(0.003)		(0.002)

t+2		0.042***		-0.017		-0.018**		-0.004		0.008***
		(0.005)		(0.009)		(0.006)		(0.004)		(0.002)
t+3		0.047***		-0.020*		-0.019**		-0.004		0.008**
		(0.006)		(0.009)		(0.006)		(0.004)		(0.003)
t+4		0.048***		-0.023*		-0.017*		-0.004		0.010**
		(0.006)		(0.010)		(0.007)		(0.004)		(0.003)
t+5		0.048***		-0.027*		-0.014		-0.004		0.007
		(0.006)		(0.012)		(0.008)		(0.005)		(0.004)
Education<HS	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Education=HS	-0.138***	-0.138***	-0.081***	-0.081***	0.021***	0.021***	0.210***	0.210***	-0.116***	-0.116***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.001)	(0.001)	(0.005)	(0.005)	(0.011)	(0.011)
Education=Some_college	-0.178***	-0.178***	-0.121***	-0.121***	0.028***	0.028***	0.293***	0.293***	-0.150***	-0.150***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.002)	(0.002)	(0.005)	(0.005)	(0.011)	(0.011)
Education=College_degree	-0.217***	-0.217***	-0.148***	-0.148***	0.043***	0.043***	0.355***	0.355***	-0.189***	-0.189***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.003)	(0.003)	(0.006)	(0.006)	(0.013)	(0.013)
Education=Post-college	-0.233***	-0.233***	-0.166***	-0.166***	0.039***	0.039***	0.401***	0.401***	-0.201***	-0.201***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.004)	(0.004)	(0.006)	(0.006)	(0.013)	(0.013)
Female	0.024***	0.024***	-0.034***	-0.034***	-0.000	-0.000	0.042***	0.042***	0.032***	0.032***

	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Married	-0.106***	-0.106***	-0.097***	-0.097***	-0.004	-0.004	0.253***	0.253***	-0.095***	-0.095***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.007)	(0.007)
Female_x_Married	-0.023***	-0.023***	0.037***	0.037***	0.014***	0.014***	-0.052***	-0.052***	-0.034***	-0.034***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
White non-Hispanic	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Black non-Hispanic	0.073***	0.073***	0.014***	0.014***	-0.033***	-0.033***	-0.045***	-0.045***	0.113***	0.113***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
Asian non-Hispanic	0.037**	0.037**	0.066***	0.066***	0.021***	0.021***	-0.113***	-0.113***	0.017***	0.017***
	(0.013)	(0.013)	(0.007)	(0.007)	(0.005)	(0.005)	(0.016)	(0.016)	(0.004)	(0.004)
Other non-Hispanic	0.066***	0.066***	0.057***	0.057***	-0.029***	-0.029***	-0.097***	-0.097***	0.082***	0.082***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.004)	(0.004)	(0.010)	(0.010)	(0.008)	(0.008)
Hispanic (any race)	0.015	0.015	0.111***	0.111***	-0.039***	-0.039***	-0.084***	-0.084***	0.049***	0.049***
	(0.012)	(0.012)	(0.008)	(0.008)	(0.007)	(0.007)	(0.014)	(0.014)	(0.013)	(0.013)
Constant	0.302***	0.301***	0.302***	0.302***	0.088***	0.089***	0.259***	0.260***	0.296***	0.296***
	(0.010)	(0.009)	(0.011)	(0.011)	(0.005)	(0.005)	(0.006)	(0.005)	(0.013)	(0.013)
N	7266271	7266271	7266271	7266271	7266271	7266271	7266271	7266271	7266271	7266271

R2	0.116	0.116	0.082	0.082	0.011	0.011	0.147	0.147	0.112	0.112

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Note: Each regression also includes controls for age and a full set of state and year dummies that are not reported here.

Table A7/Aim 4
Additional regression coefficients from difference-in-differences and event study models estimating changes in food insecurity
Current Population Survey, 2008 – 2018

	(1) LFS12M	(2) LFS12M	(3) LFS30D	(4) LFS30D	(5) VLFSYR	(6) VLFSYR	(7) VLFSMO	(8) VLFSMO	(9) SNAP	(10) SNAP
Treatment	0.001		-0.002		-0.002		-0.001		0.003	
	(0.006)		(0.004)		(0.005)		(0.003)		(0.003)	
t_6		-0.033**		-0.023**		-0.015		-0.009*		-0.007
		(0.011)		(0.007)		(0.008)		(0.004)		(0.010)
t_5		-0.003		-0.003		-0.004		-0.001		-0.002
		(0.008)		(0.007)		(0.005)		(0.004)		(0.006)
t_4		0.004		0.004		-0.001		0.000		0.002
		(0.007)		(0.006)		(0.005)		(0.004)		(0.006)
t_3		-0.013		-0.006		-0.007		-0.004		0.007
		(0.009)		(0.006)		(0.005)		(0.003)		(0.006)
t_2		-0.009		-0.002		-0.003		-0.000		-0.002
		(0.008)		(0.006)		(0.005)		(0.004)		(0.006)
t_1		-0.012		-0.006		0.002		0.001		0.010*
		(0.007)		(0.006)		(0.005)		(0.003)		(0.004)
t1		-0.003		-0.009*		-0.008*		-0.006*		0.005
		(0.008)		(0.004)		(0.004)		(0.003)		(0.006)
t2		-0.004		-0.002		-0.007		-0.005		0.004
		(0.008)		(0.006)		(0.006)		(0.004)		(0.006)
t3		-0.010		-0.003		-0.002		0.003		0.003
		(0.008)		(0.006)		(0.005)		(0.004)		(0.007)

t4		0.002 (0.009)		0.003 (0.006)		0.004 (0.006)		0.003 (0.004)		0.004 (0.008)
t5		-0.011 (0.009)		-0.005 (0.006)		-0.004 (0.006)		0.002 (0.003)		0.013 (0.007)
1.Education	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]
2.Education	-0.109*** (0.008)	-0.109*** (0.008)	-0.065*** (0.005)	-0.065*** (0.005)	-0.047*** (0.006)	-0.047*** (0.006)	-0.031*** (0.004)	-0.031*** (0.004)	-0.119*** (0.012)	-0.119*** (0.012)
3.Education	-0.130*** (0.008)	-0.130*** (0.008)	-0.077*** (0.005)	-0.077*** (0.005)	-0.054*** (0.006)	-0.054*** (0.006)	-0.035*** (0.004)	-0.035*** (0.004)	-0.144*** (0.012)	-0.144*** (0.012)
4.Education	-0.193*** (0.009)	-0.193*** (0.009)	-0.115*** (0.006)	-0.115*** (0.006)	-0.084*** (0.006)	-0.084*** (0.006)	-0.054*** (0.004)	-0.054*** (0.004)	-0.181*** (0.013)	-0.181*** (0.013)
Female	0.042*** (0.005)	0.042*** (0.005)	0.030*** (0.003)	0.030*** (0.003)	0.019*** (0.003)	0.019*** (0.003)	0.013*** (0.003)	0.013*** (0.003)	0.035*** (0.004)	0.035*** (0.004)
Married	-0.076*** (0.003)	-0.076*** (0.003)	-0.048*** (0.002)	-0.048*** (0.002)	-0.048*** (0.002)	-0.048*** (0.002)	-0.029*** (0.001)	-0.029*** (0.001)	-0.073*** (0.005)	-0.073*** (0.005)
Female_x_Married	-0.048*** (0.005)	-0.048*** (0.005)	-0.033*** (0.003)	-0.033*** (0.003)	-0.021*** (0.003)	-0.021*** (0.003)	-0.014*** (0.003)	-0.014*** (0.003)	-0.037*** (0.004)	-0.037*** (0.004)
1.Race_Ethnicity	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]	[Omitted]
2.Race_Ethnicity	0.080***	0.080***	0.042***	0.042***	0.028***	0.028***	0.016***	0.016***	0.082***	0.082***

	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
3.Race_Ethnicity	0.021*	0.021*	0.011*	0.011*	0.003	0.003	0.003	0.003	0.018**	0.018**
	(0.009)	(0.009)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.006)	(0.006)
4.Race_Ethnicity	0.048***	0.048***	0.030***	0.030***	0.001	0.001	0.001	0.001	0.016	0.016
	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.010)	(0.010)
_cons	0.310***	0.308***	0.187***	0.186***	0.150***	0.149***	0.093***	0.092***	0.254***	0.255***
	(0.009)	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.013)	(0.014)
N	231852	231852	231849	231849	231852	231852	231849	231849	231315	231315
adj. R-sq	0.081	0.081	0.050	0.050	0.039	0.040	0.025	0.025	0.099	0.099

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Note: Each regression also includes controls for age and a full set of state and year dummies that are not reported here.

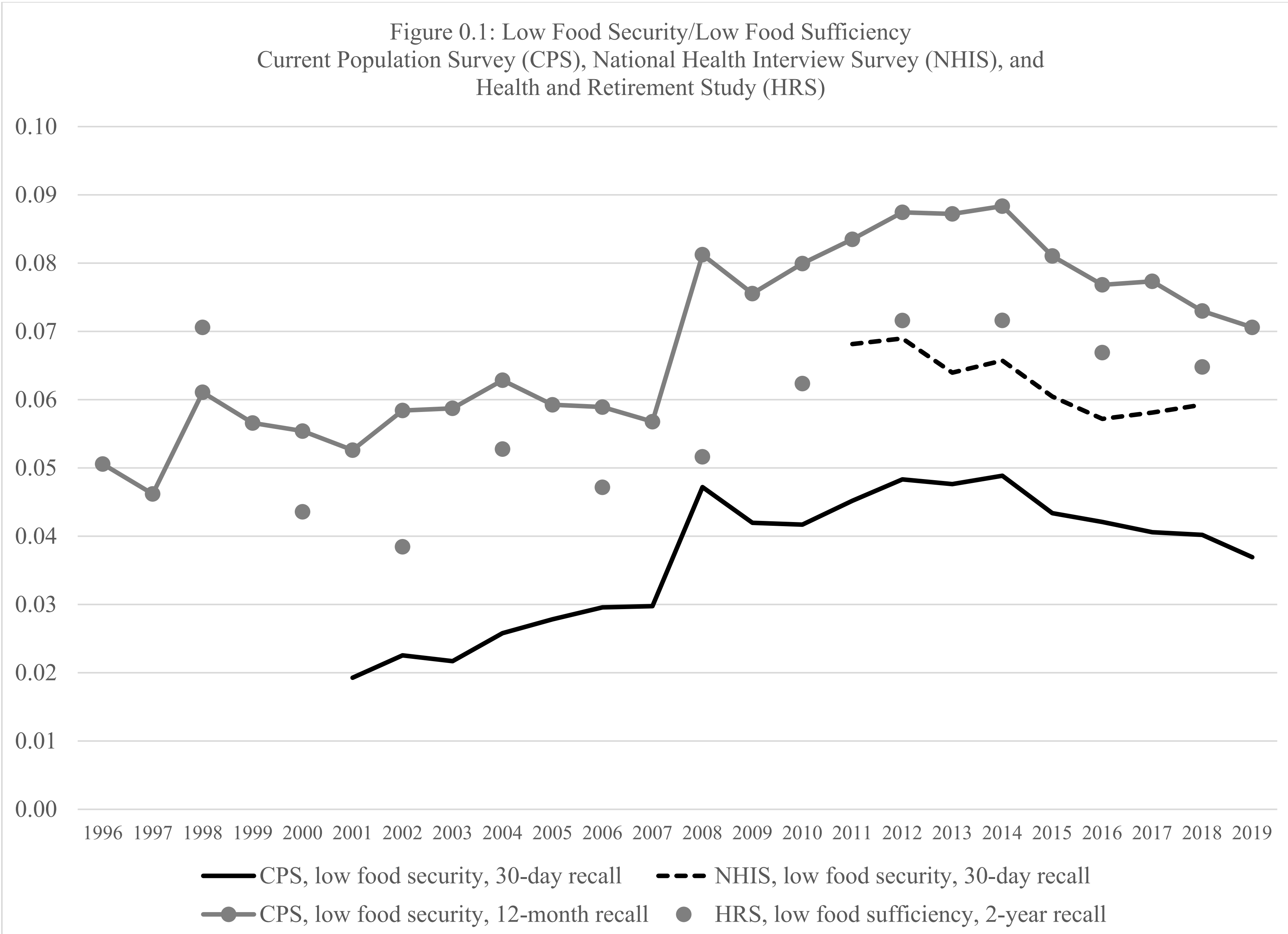


Figure 0.1: Low Food Security/Low Food Sufficiency
Current Population Survey (CPS), National Health Interview Survey (NHIS), and
Health and Retirement Study (HRS)
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019
CPS, low food security, 30-day recall
NHIS, low food security, 30-day recall
CPS, low food security, 12-month recall
HRS, low food sufficiency, 2-year recall

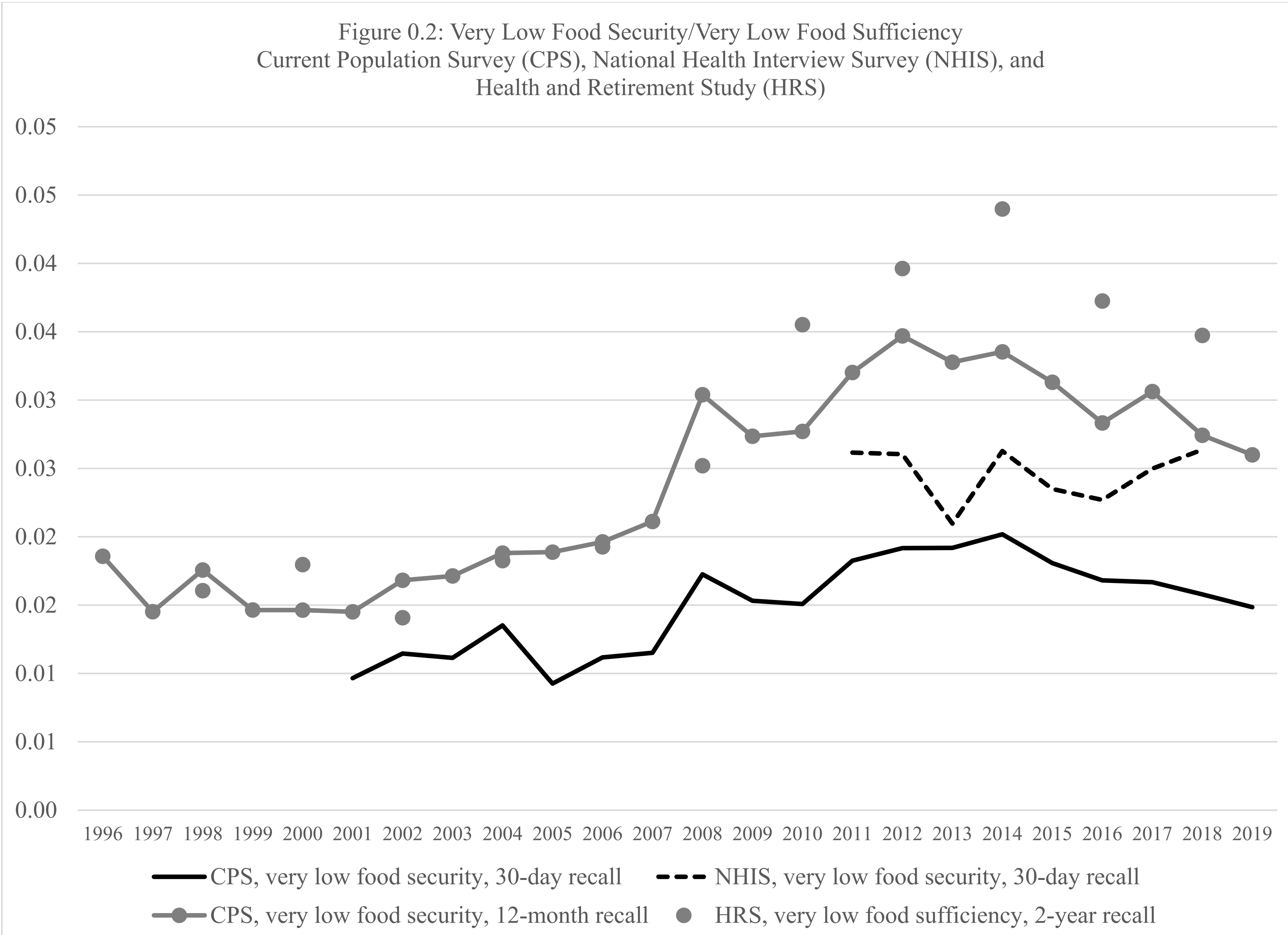


Figure 0.2: Very Low Food Security/Very Low Food Sufficiency
Current Population Survey (CPS), National Health Interview Survey (NHIS), and
Health and Retirement Study (HRS)
0.05
0.05
0.04
0.04
0.03
0.03
0.02
0.02
0.01
0.01
0.00
1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019
CPS, very low food security, 30-day recall
NHIS, very low food security, 30-day recall
CPS, very low food security, 12-month recall
HRS, very low food sufficiency, 2-year recall

Figure 1.1

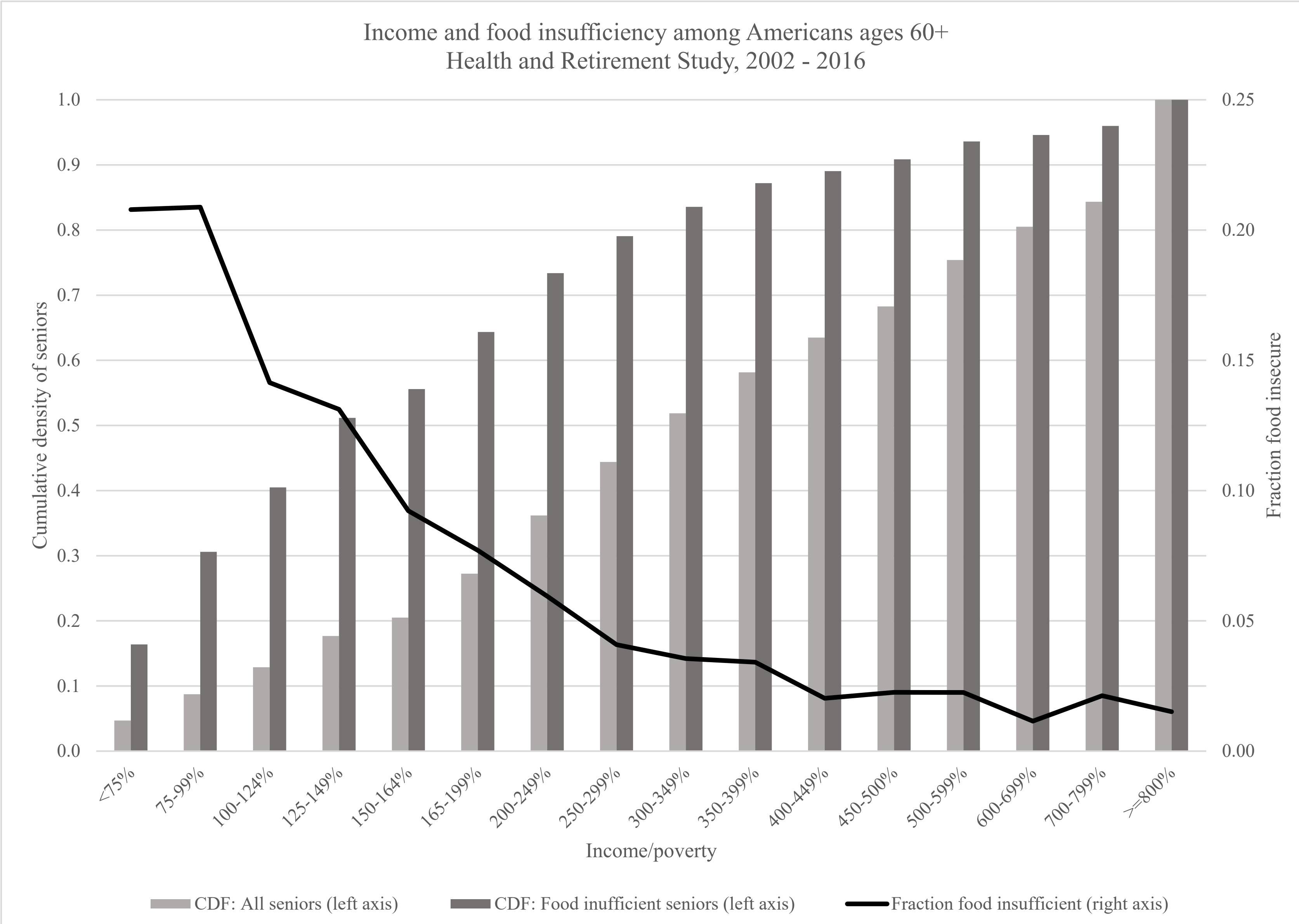
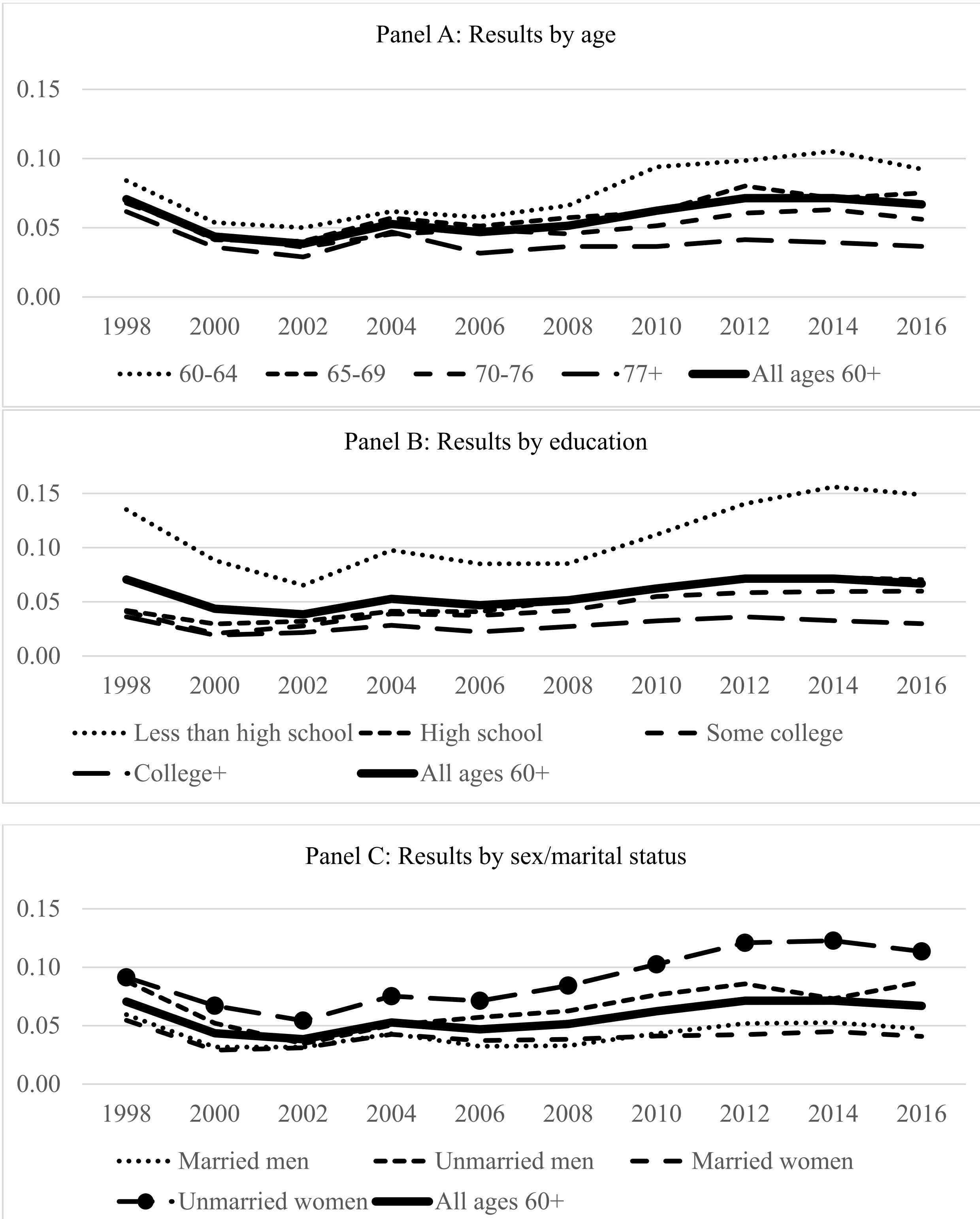

Income and food insufficiency among Americans ages 60+
Health and Retirement Study, 2002 - 2016
Cumulative density of seniors
Fraction food insecure
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0.25
0.20
0.15
0.10
0.05
0.00
<75%
75-99%
100-124%
125-149%
150-164%
165-199%
200-249%
250-299%
300-349%
350-399%
400-449%
450-500%
500-599%
600-699%
700-799%
>=800%
Income/poverty
CDF: All seniors (left axis)
CDF: Food inufficient seniors (left axis)
Fraction food insufficient (right axis)

Figure 1.2: Trends in Food Insufficiency by Respondent Characteristics, Ages 60+
Health and Retirement Study, 1998 - 2016



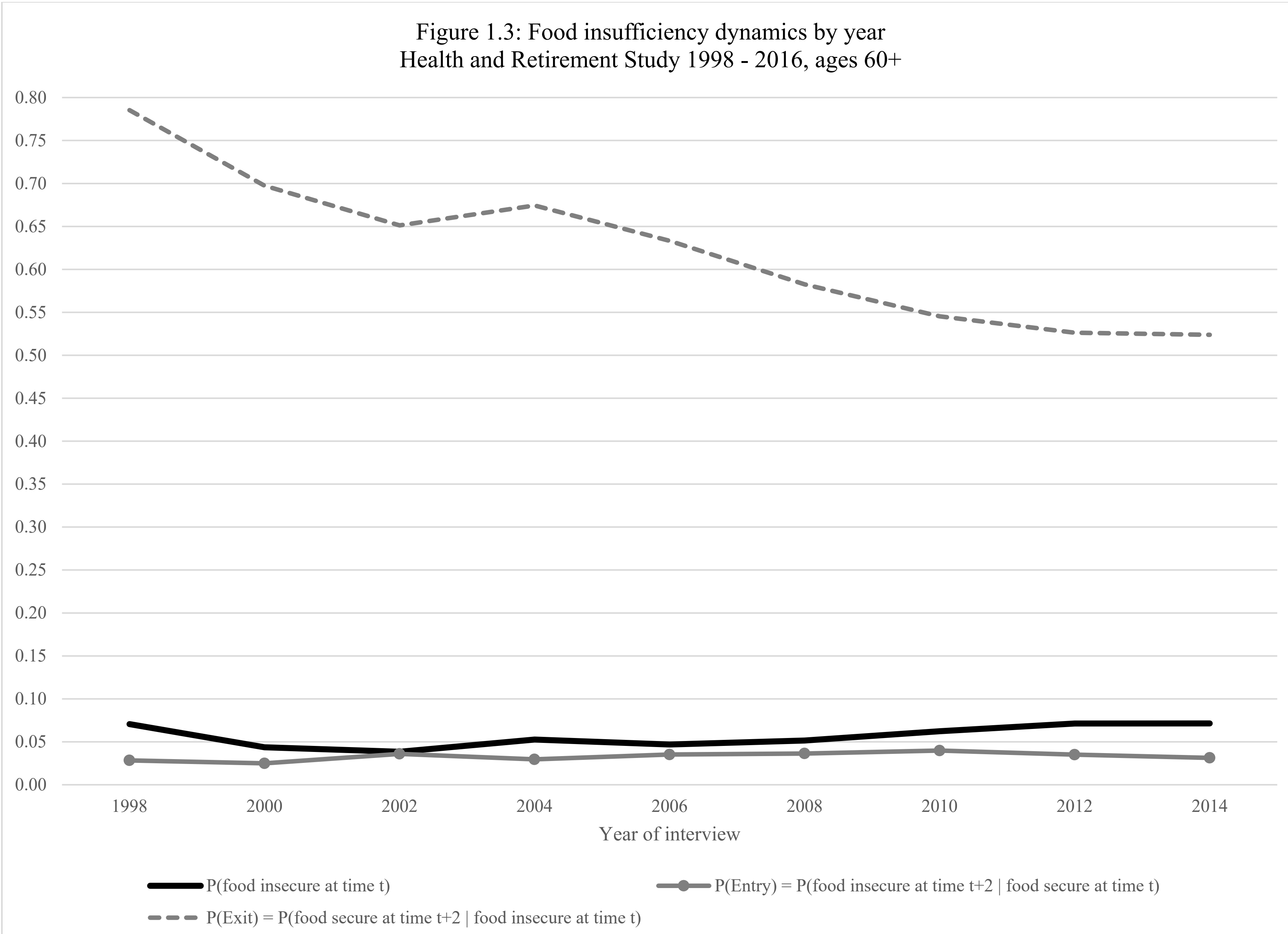


Figure 1.3: Food insufficiency dynamics by year
Health and Retirement Study 1998 - 2016, ages 60+
0.80
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
1998
2000
2002
2004
2006
2008
2010
2012
2014
Year of interview
P(food insecure at time t)
P(Entry) = P(food insecure at time t+2 | food secure at time t)
P(Exit) = P(food secure at time t+2 | food insecure at time t)

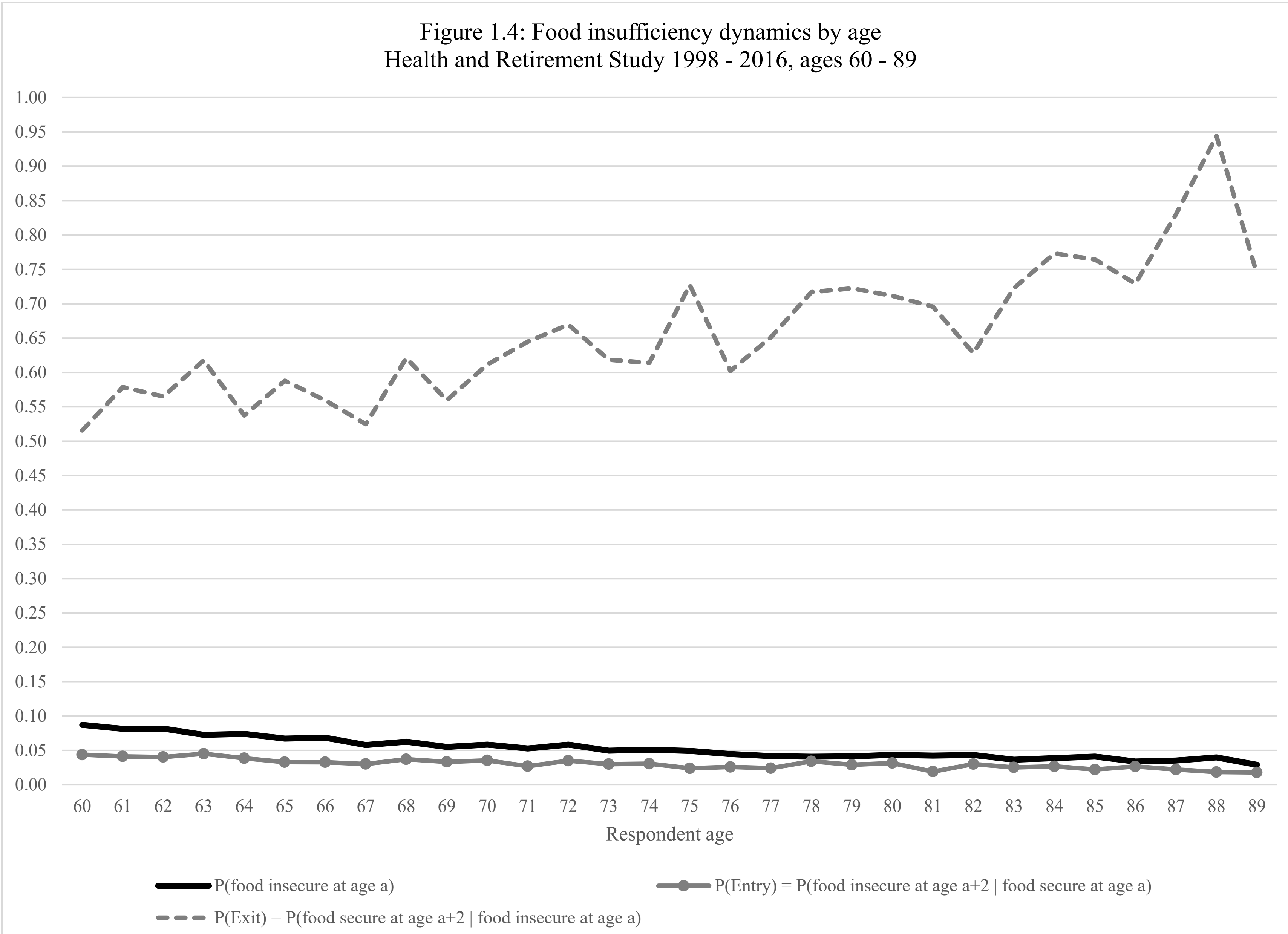


Figure 1.4: Food insufficiency dynamics by age
Health and Retirement Study 1998 - 2016, ages 60 - 89
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89
Respondent age
P(food insecure at age a)
P(Entry) = P(food insecure at age a+2 | food secure at age a)
P(Exit) = P(food secure at age a+2 | food insecure at age a)

Figure 2.1

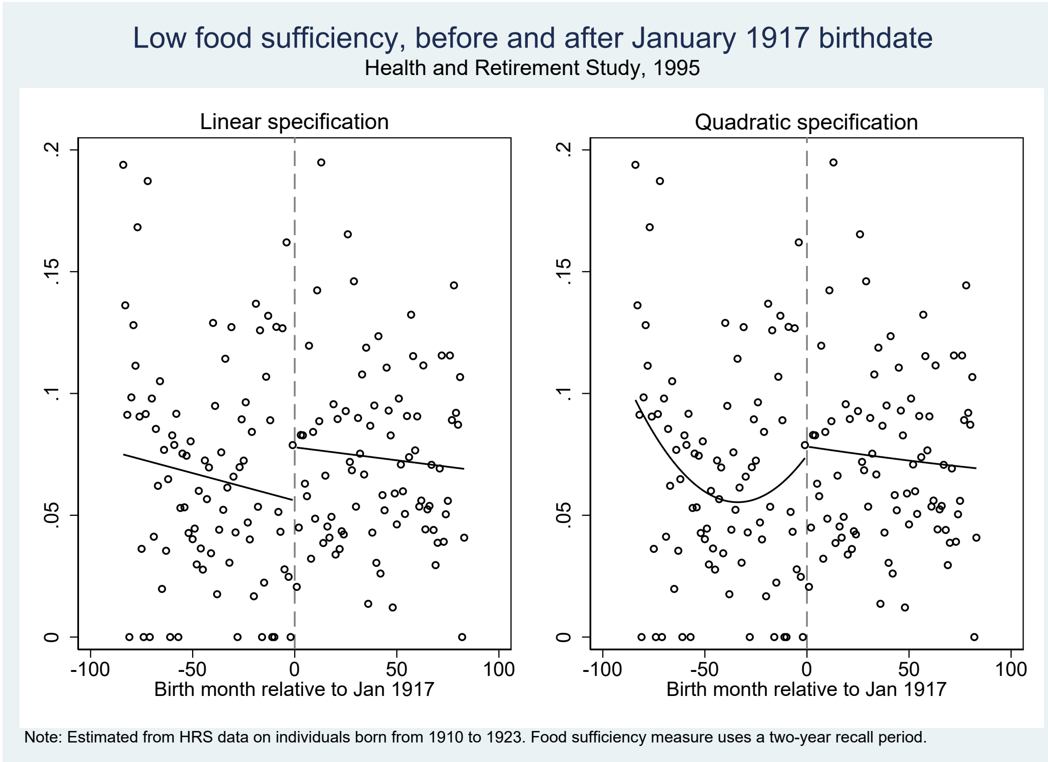


Figure 2.2

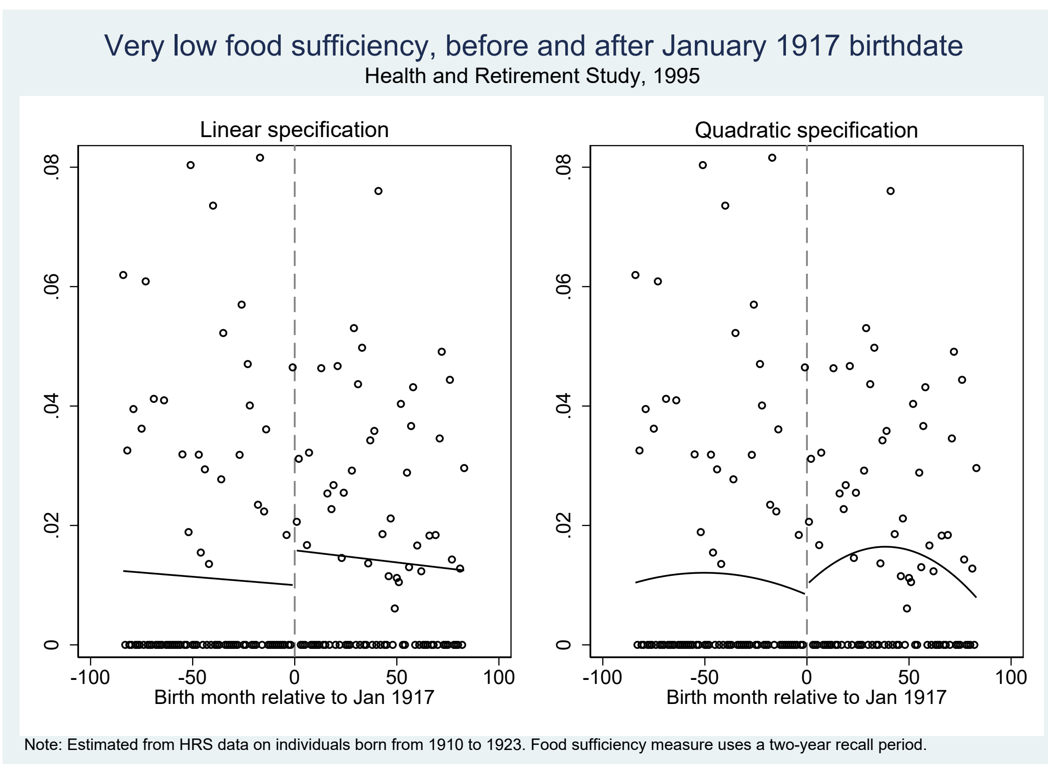


Figure 2.3

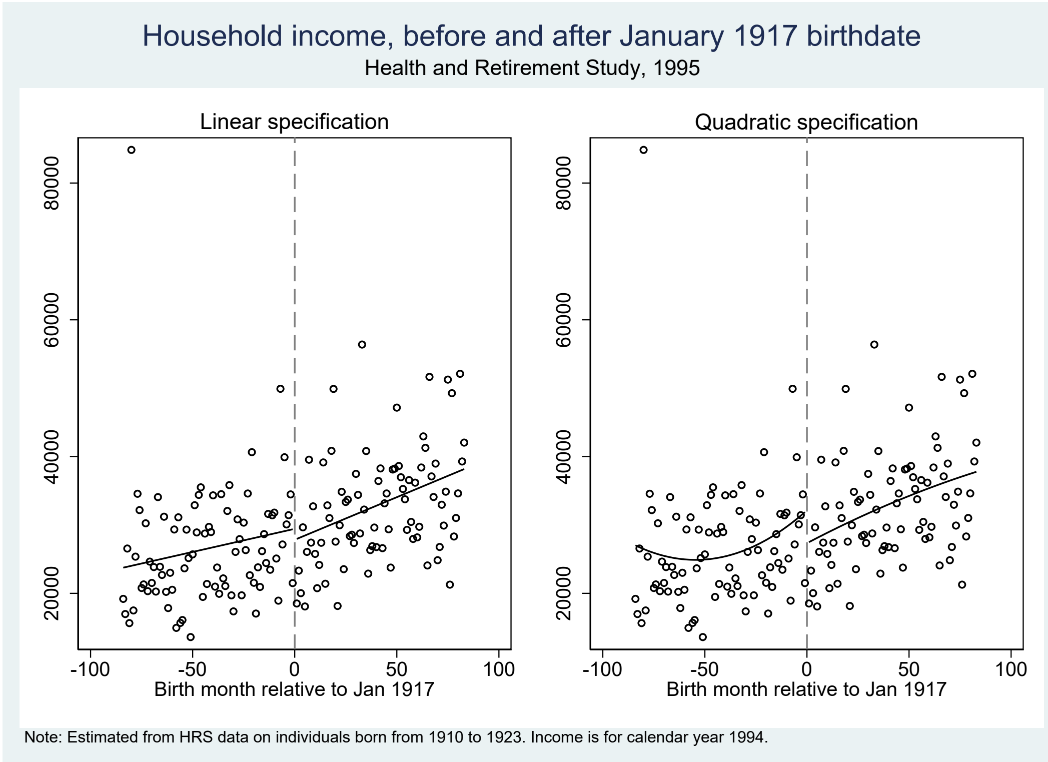


Figure 2.4

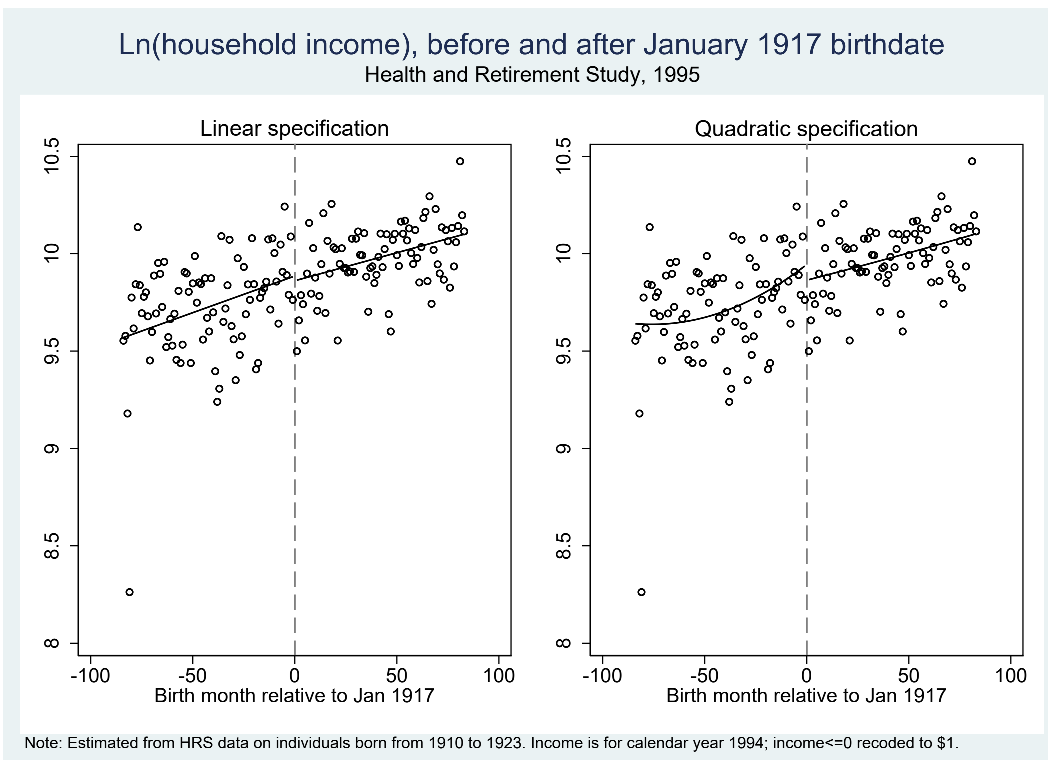


Figure 2.5

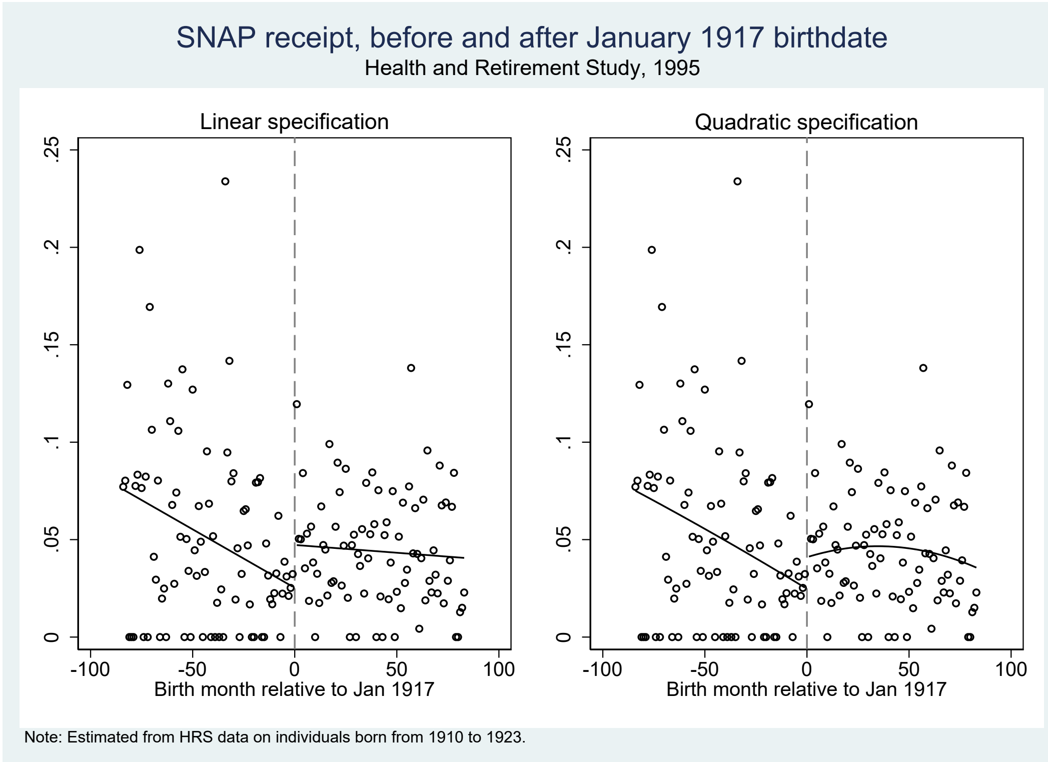

SNAP receipt, before and after January 1917 birthdate
Health and Retirement Study, 1995
Linear specification
Quadratic specification
0
.05
.1
.15
.2
.25
-100
-50
0
50
100
Birth month relative to Jan 1917
Note: Estimated from HRS data on individuals born from 1910 to 1923.

Figure 3.1

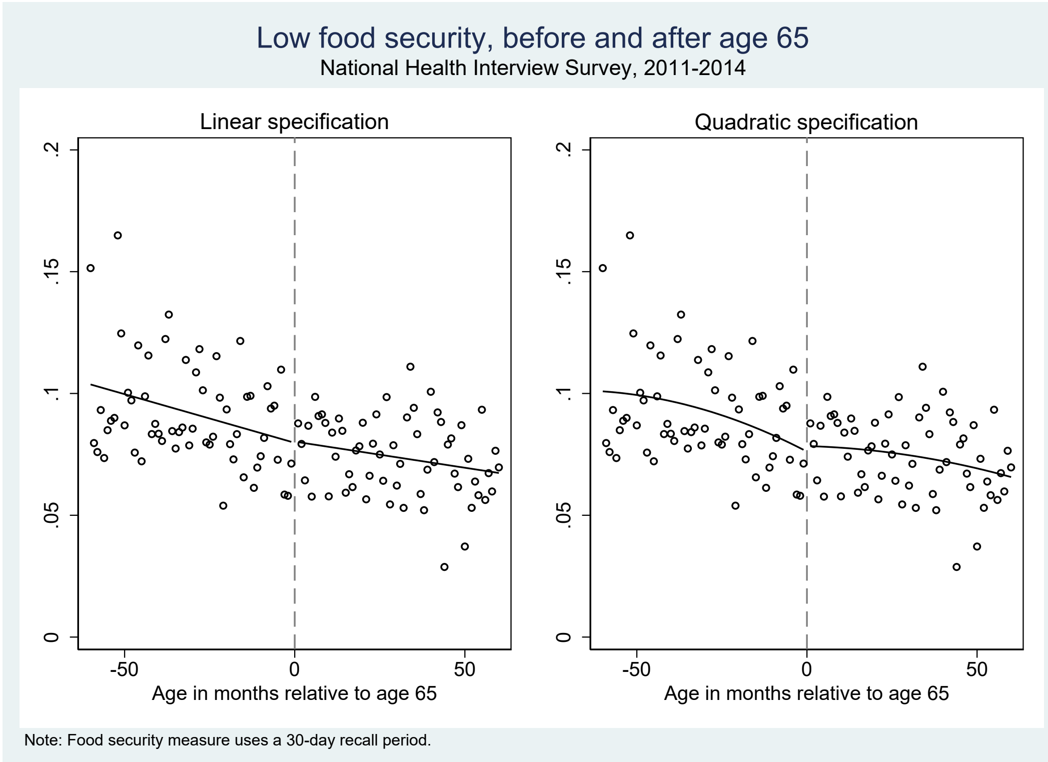


Figure 3.2

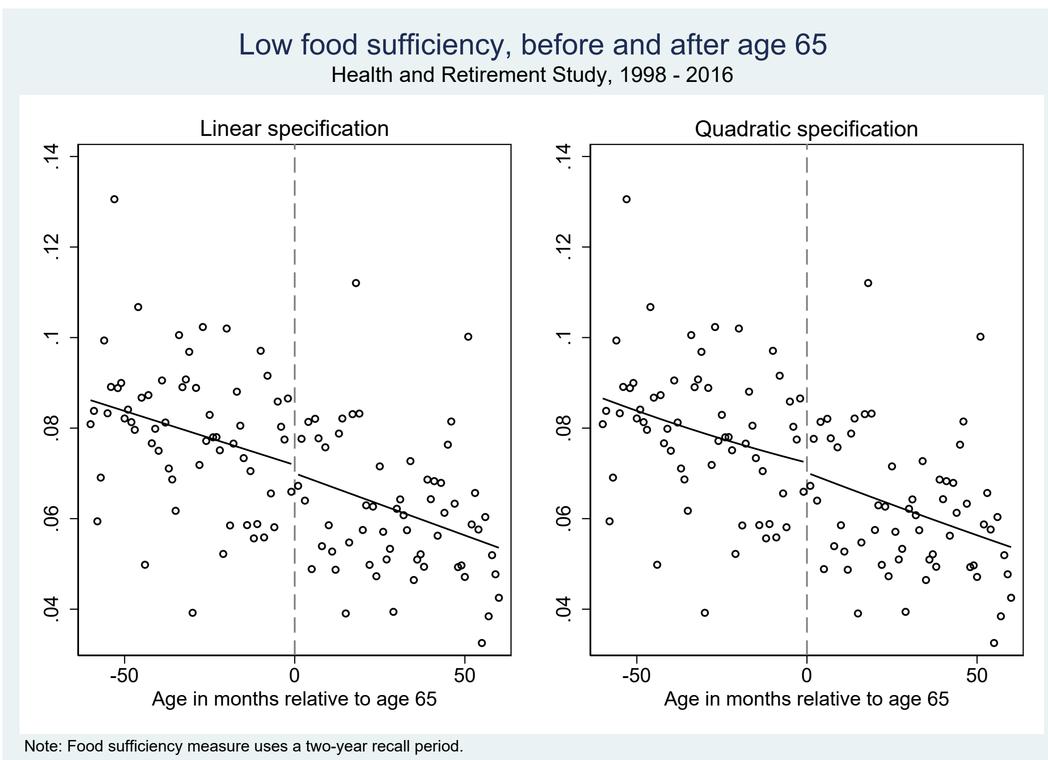


Figure 3.3

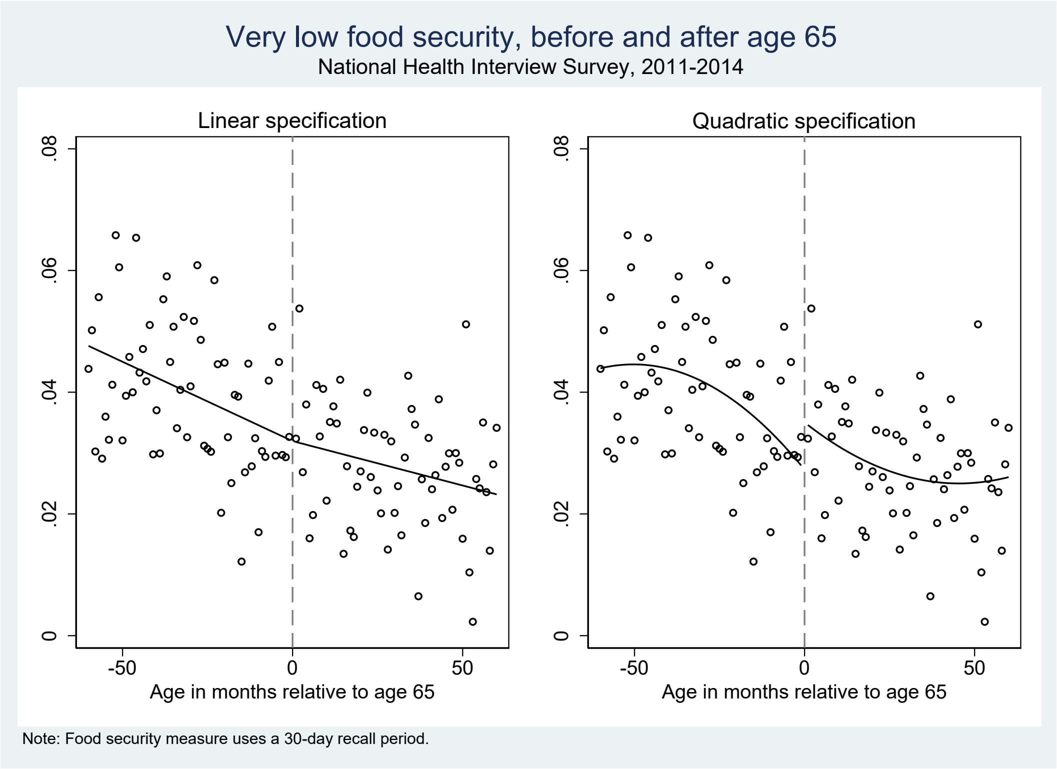


Figure 3.4

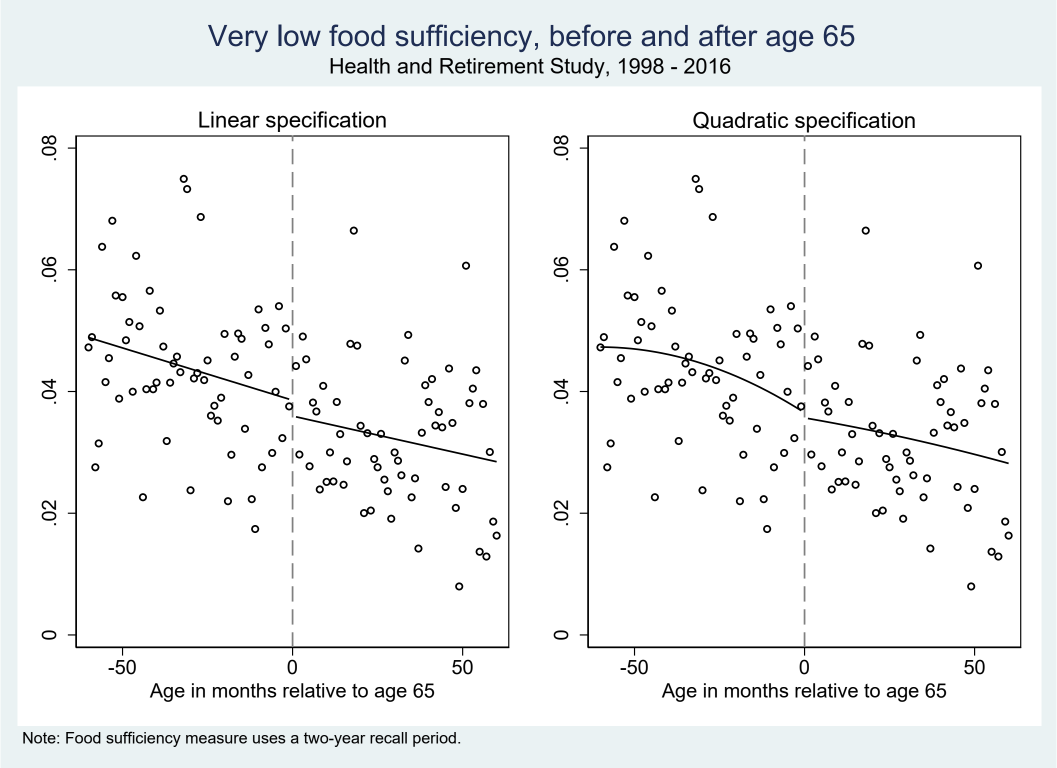
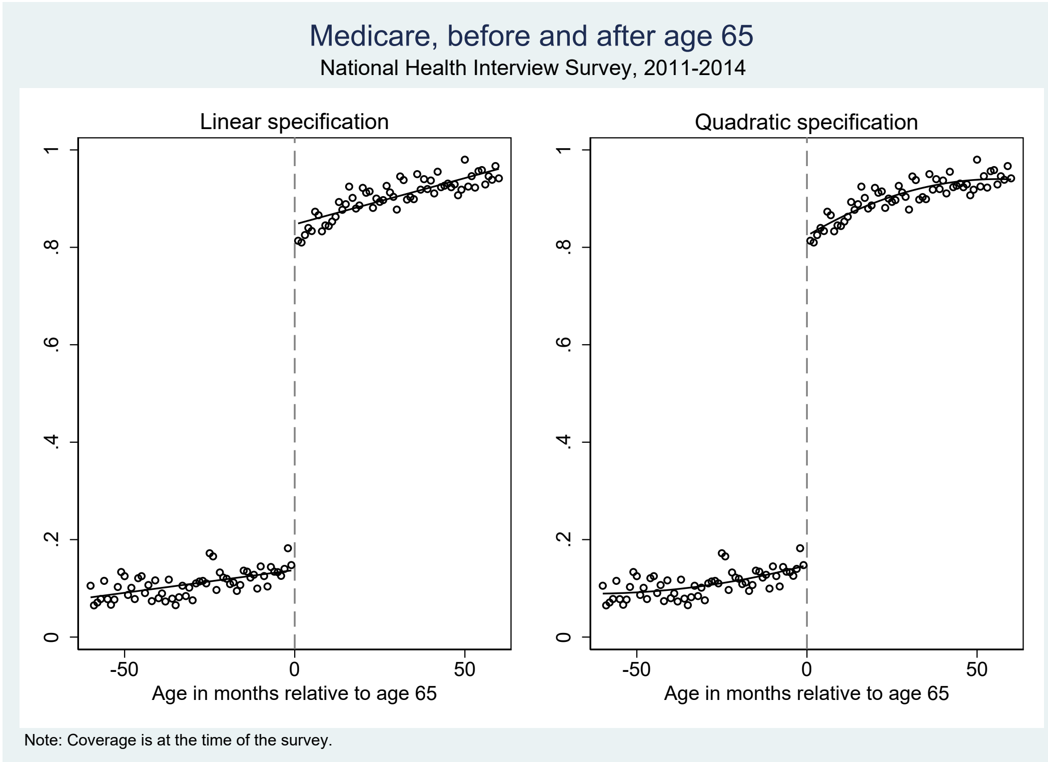


Figure 3.5



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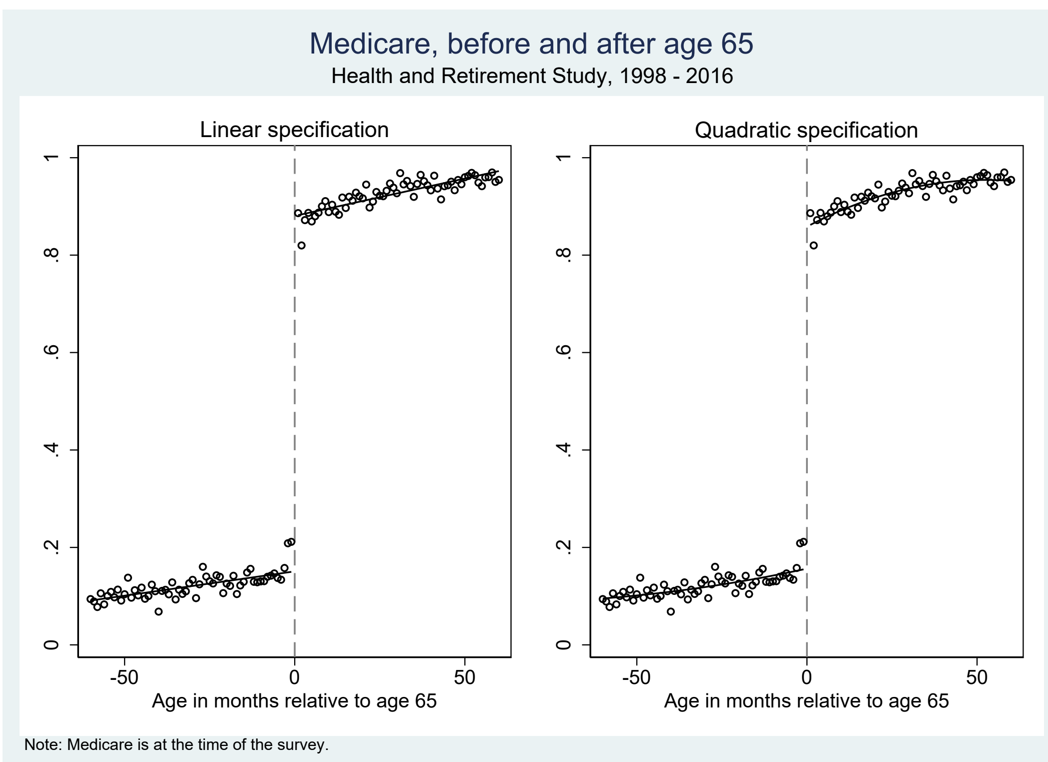


Figure 3.7

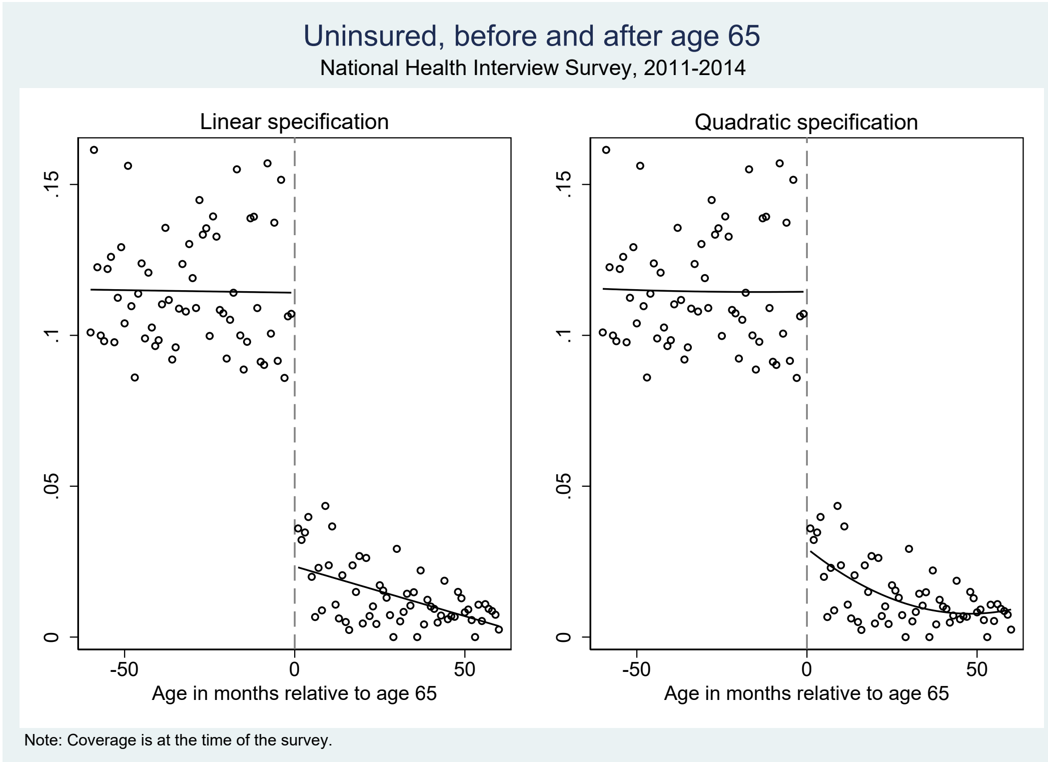


Figure 3.8

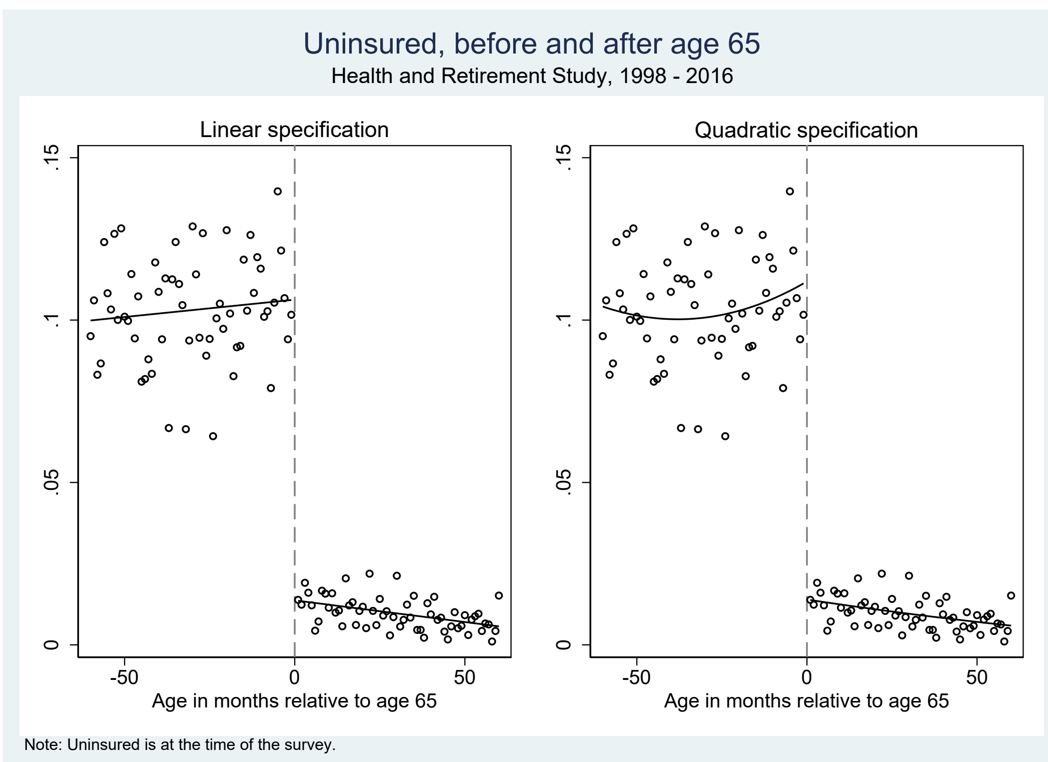


Figure 3.9

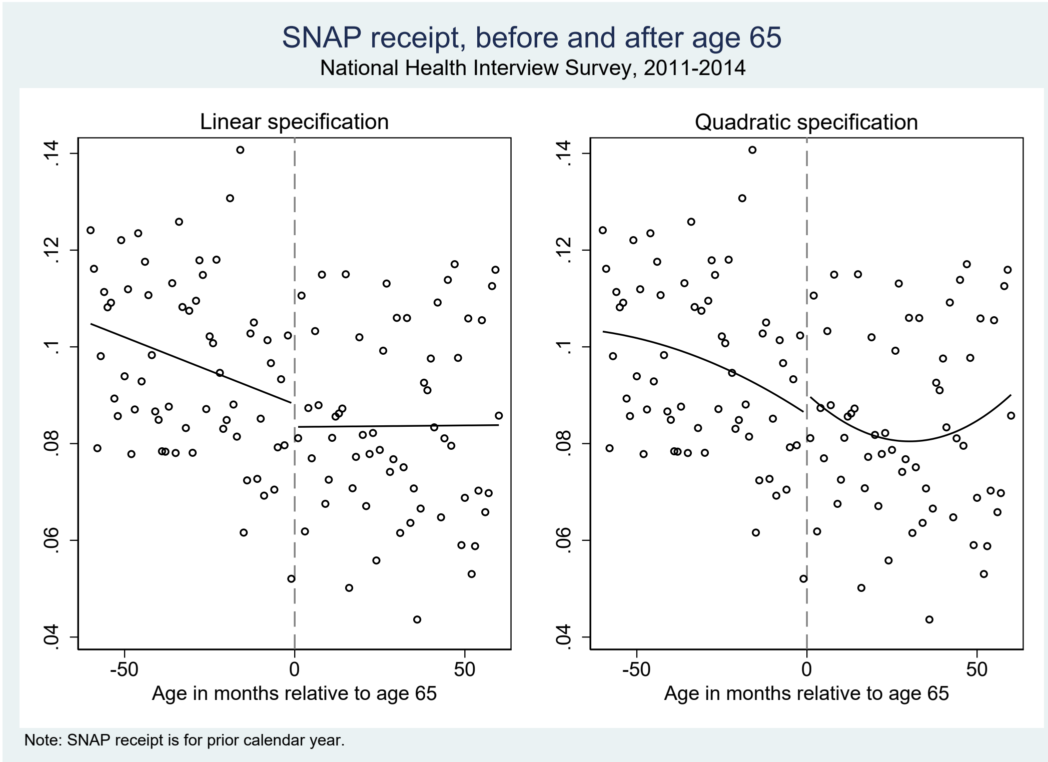


Figure 3.10

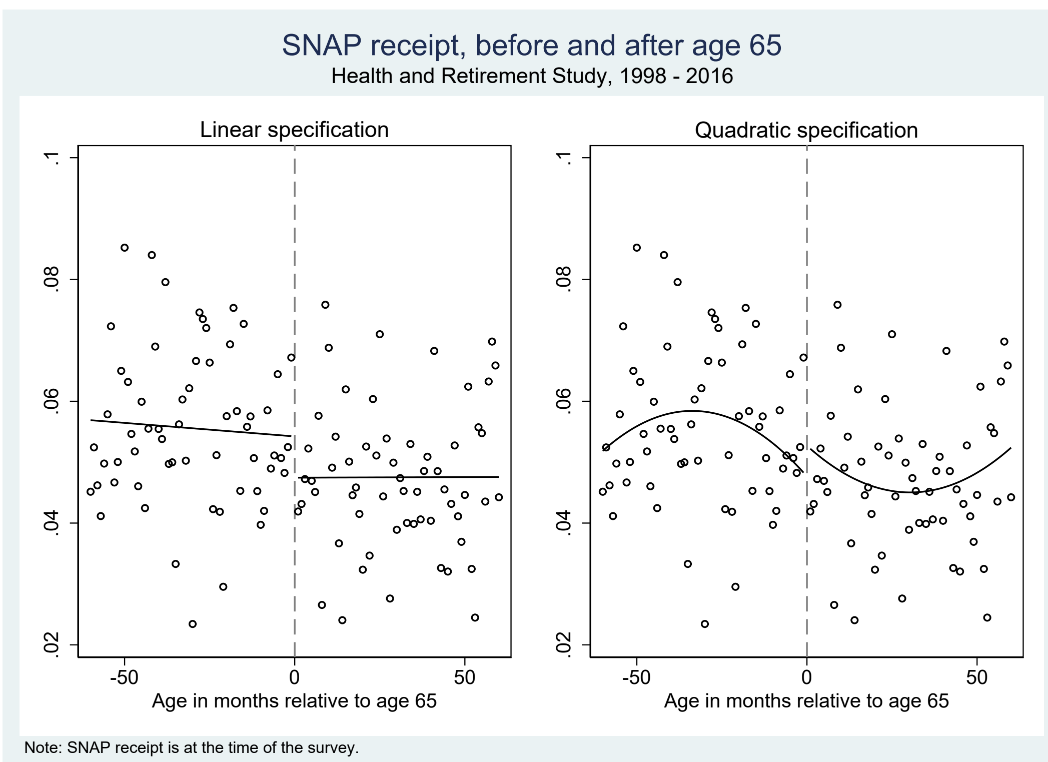


Figure 4.1

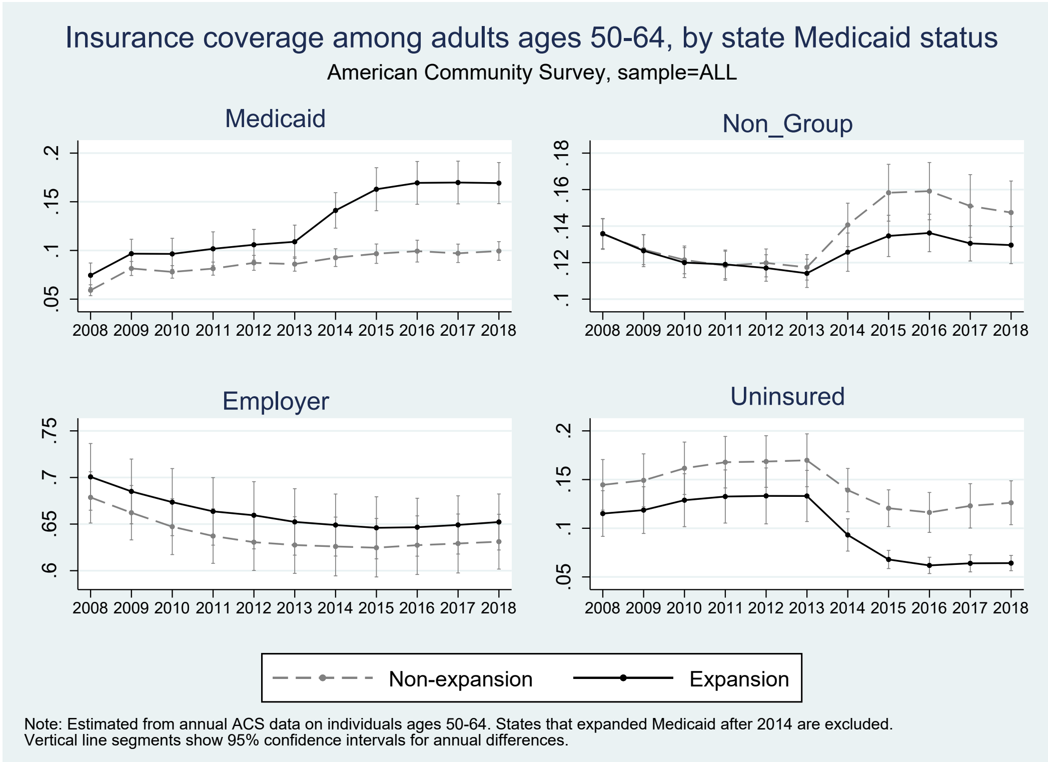


Figure 4.2

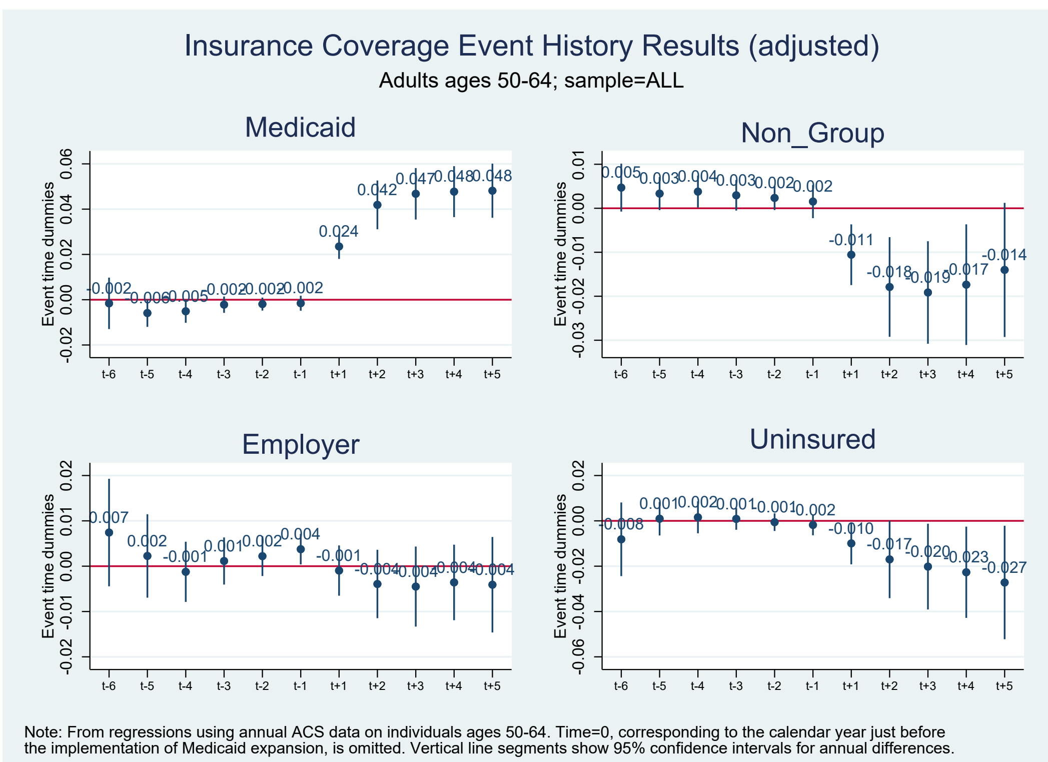
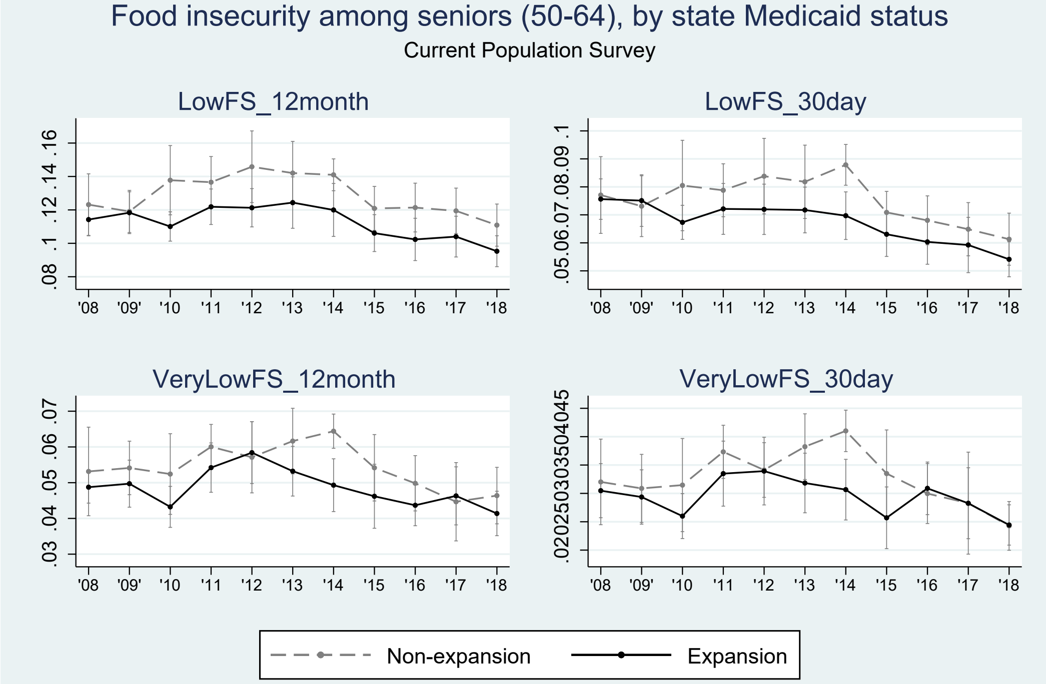
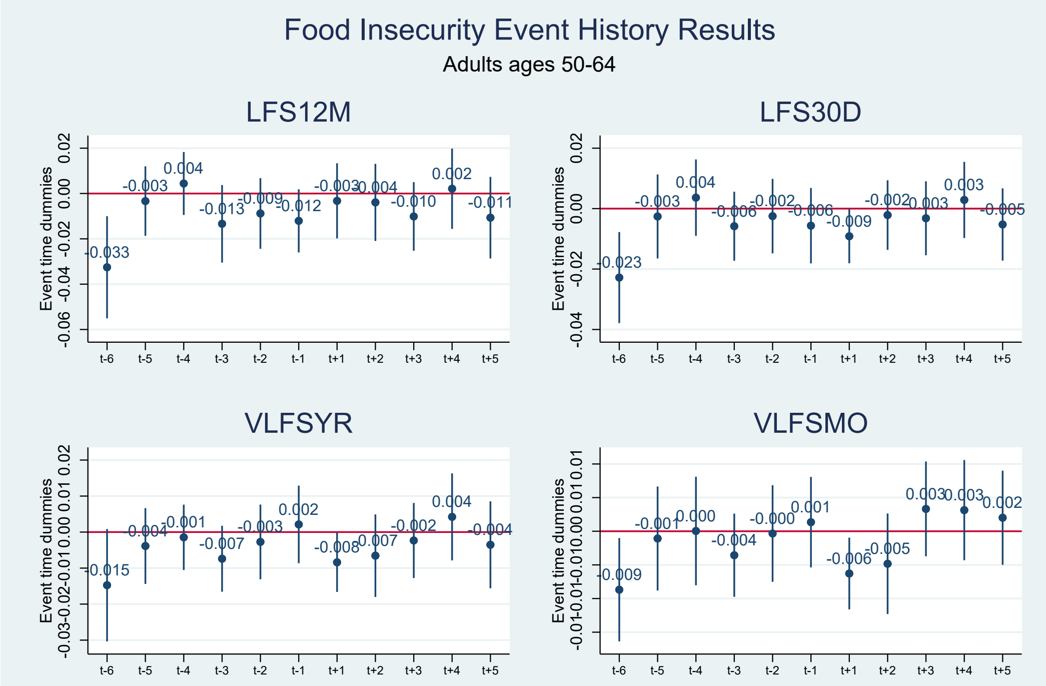


Figure 4.3



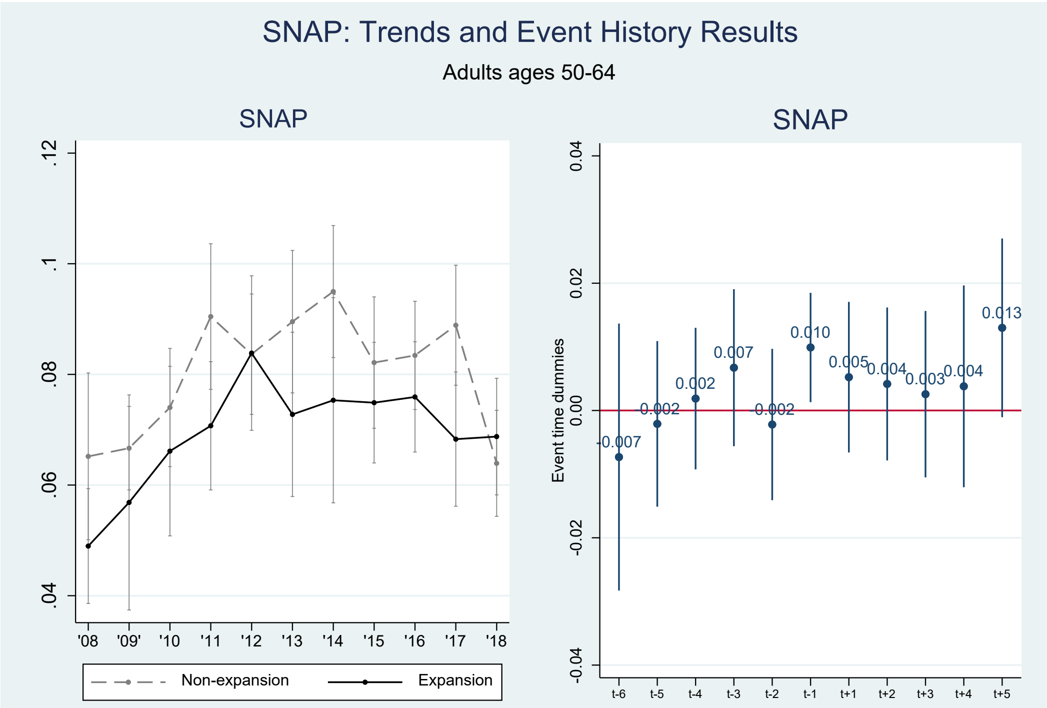
Note: Estimated from annual CPS data on individuals ages 50-64. States that expanded Medicaid after 2014 are excluded.
Vertical line segments show 95% confidence intervals for annual differences.

Figure 4.4



Note: From regressions using annual CPS data on individuals ages 50-64. Time=0, corresponding to the calendar year just before
the implementation of Medicaid expansion, is omitted. Vertical line segments show 95% confidence intervals for annual differences.

Figure 4.5



Note: Estimated from annual CPS data on individuals ages 50-64.