# Food Security Dynamics in the United States, 2001-2017*

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**Abstract**

This paper studies household food security dynamics in the United States from 2001 to 2017. We introduce a new measure, the probability of food security (PFS), the estimated probability that a household's food expenditures equal or exceed the minimum cost of a healthful diet. We use PFS to analyze household-level as well as subpopulation-scale dynamics by investigating both the conditional distribution of food insecurity spells and the chronic and transient components of food insecurity over an extended period. More than half of newly food insecure households resume food security within two years. Households headed by female, non-White, or less educated individuals disproportionately suffer persistent, chronic food insecurity.

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# 1 Introduction

Food security – defined as access by all people at all times to enough food for an active, healthy life (Coleman-Jensen et al. 2021) – is of both intrinsic and instrumental value. It is intrinsically valuable because food is needed to sustain life and directly generates pleasure. It is instrumentally valuable because food insecurity has myriad adverse consequences on health and other welfare outcomes. A large literature, summarized by Gundersen and Ziliak (2015), finds that in the United States (U.S.) household food insecurity is associated with poorer child nutrition (anemia, lower nutrient intakes), mental health (increased aggression and anxiety; behavioral problems; depression; and suicide ideation), cognitive problems and poorer health, both specific conditions (asthma, oral health) and general status.

At least one out of ten U.S. households has been food insecure in any given year since the United State Department of Agriculture (USDA) first began reporting the current official food security measure in 1995. The most recent, 2020 nationwide prevalence for the U.S., estimated from the December supplement to the Current Poulation Survey (CPS), was 10.5% (Coleman-Jensen et al. 2021). The COVID-19 pandemic shock initially drove this sharply higher (Gundersen et al. 2021). According to the Census Bureau's Household Pulse Survey (HPS) data, the prevalence of food insufficiency increased from 9.5% in April 2020 to 13.4% in December 2020 before decreasing to 8.0% in April 2021 (Coleman-Jensen et al. 2021). Although the HPS-based food insufficiency and the CPS-based food insecurity measures differ, such that they are not directly comparable, the dynamics of the higher frequency HPS measure seem informative about the trajectory of food security at population scale. Unfortunately, we lack a similar understanding of such dynamics at household scale.

Given food insecurity's adverse effects on a host of economic, health and social outcomes, and those outcomes' feedback on household incomes, dietary behaviors, and subsequent food security status, a sound understanding of food security dynamics can help with effective policy design and evaluation. For example, if one expects the millions of households unexpectedly driven into food insecurity by the 2020 COVID-19 shock to reattain food secure quickly, then temporary private and public food assistance financed by one-off appropriations or charitable donations may suffice to avert longer-term consequences. But if instead one should reasonably expect a large share of those made suddenly food insecure to persist in that new (to them) state, then longer-lasting interventions and funding arrangements may be necessary. And if identifiable subpopulations predictably experience different food security dynamics, then different programs might usefully target distinct, identifiable groups.

Unfortunately, there do not exist good long-term estimates of food security dynamics in the United States. This stems directly from measurement and data collection issues that are global, not specific to the U.S. (Barrett 2010). U.S. food security studies rely mainly on the official Household Food Security Measure (HFSM) developed by USDA based on a survey instrument first introduced in the Household Food Security Survey Module (HFSSM) supplement to the CPS in 1995. Households answer up to 18 HFSSM questions (10 questions for households without children) listed in Table A1. Household food security status is then assessed based on the number of questions households affirm, standardized into 29 discrete values in the [0.0,9.3] interval that are grouped into three ordinal categories (food security, low food security, and very low food security) to enable comparison among households with and without children (Table A2). The CPS has a rotating panel design that tracks the same household no more than 8 times over a 16-month period, including a maximum of two observations from the annual HFSSM. So CPS does not enable the study of household food security dynamics beyond a one year interval.

Other longitudinal household surveys have fielded the HFSSM among the same households for longer intervals, but even those data sharply limit the study of food security dynamics. The Panel Study of Income Dynamics (PSID) has implemented HFSSM only for six waves (1999, 2001, 2003, 2015, 2017, 2019), within which there exists a significant gap from 2003-2015. The Early Childhood Longitudinal Survey (ECLS) collected food security data over different survey periods (1999-2007, 2010-2016). But ECLS surveys span less than 10 years, do not include the full HFSSM in most waves, and their samples are restricted to households with young children, thus they are not nationally representative.

The discrete, ordinal nature of the HFSM also limits our capacity to understand change in food security status over time as one might with a continuous measure. For example, for households with children who affirm every question in consecutive periods, the measure provides no additional information regarding prospective change in the severity of their food insecurity (Bickel et al. 2000). The official categories are also quite broad and invariant with respect to the specific manifestation of compromised food access. Each household with children that affirms any eight (of 18) questions is similarly classified as suffering very low food security. Consequently, not only do we have limited information on food security dynamics, we also know relatively little about the dynamics of the severity of food insecurity.

These data limitations have significantly limited research on food security dynamics in the U.S. (Hofferth 2004; Kennedy et al. 2013; Ryu and Bartfeld 2012; Wilde, Nord, and Zager 2010; Ziliak and Gundersen 2016). No prior study has more than five observations per household, making analysis of dynamics somewhat vulnerable to both measurement error and real, but transitory shocks to food security status (Baulch and Hoddinott 2000; Dercon and Shapiro 2007; Naschold and Barrett 2011). Studies analyzing transitions and persistence using discrete categorical status necessarily suppress within-category variation over time in the severity of the food insecurity households experience. Gundersen (2008) constructed indices of food security using the discrete Rasch scale values, adapting the workhorse Foster-Greer-Thorbecke (FGT) poverty measures (Foster, Greer, and Thorbecke 1984). That analysis relies on categorical data, however, thus still does not fully capture within-category variation and covers a rather limited period. Further, these prior studies are now dated; none investigates food security dynamics post-2010.

We develop a new method for measuring household food security that overcomes the main limitations of existing data. The probability of food security (PFS) is the estimated probability that a household's observed food expenditures equal or exceed the minimal cost of a healthful diet, as reflected by the USDA's Thrifty Food Plan (TFP) cost that provides the basis for maximum Supplemental Nutrition Assistance Program (SNAP) benefits. Adapting an econometric method used to study food security in low-and-midle-income countries (Cissé and Barrett 2018; Knippenberg, Jensen, and Constas 2019; Phadera et al. 2019; Vaitla et al. 2020), we estimate PFS by computing the conditional density of household food expenditures and estimating, for each household and survey period, the inverse cumulative density beyond the TFP threshold specific to that household composition and survey date.

The PFS tracks the official HFSM well and is implementable in longer panels, such as PSID, that include continuous measures of food expenditures. The PFS measure enables the study of food security dynamics in longer panels than has been previously feasible because food expenditures data are more commonly available in each survey wave in longitudinal household surveys than are HFSSM-based measures. PFS tracks the official HFSM better than do realized food expenditures - an alternate measure that the HFSM was developed in part to replace - and generates qualitatively identical results to those produce by using the simpler alternative of the ratio of a household's food expenditures to its TFP cost. Because PFS is a continuous, decomposable measure in the FGT tradition, it also enables the study of distribution-sensitive, continuous measures of food security severity, including at sub-group level. PFS thus offers the opportunity to obviate data constraints that have previously limited the study of food security dynamics in the U.S..

We apply the PFS measure to investigate household-level food security dynamics in the U.S. between 2001 and 2017 using two different approaches: a spells approach to study transitions in food security status between survey waves, and decomposition into chronic and transitory food insecurity based on 17-year, household-specific histories. We estimate these measures nationally but also by subgroups based on household characteristics such as the gender, race, and educational attainment of the household head.

We find that roughly half of American households that newly become food insecure each year become food secure within two years. The persistence of food insecurity is positively correlated with the duration of the household's prior food insecurity experience. On average, from half to two-thirds of households that are food insecure in any given year will remain food insecure two years later. The duration of a household's expected food insecurity is negatively correlated with the strength of the macroeconomy. During the Great Recession, for example, recovery from new food insecurity episodes slowed markedly relative to before the macroeconomic slowdown, or as compared to later in the 2010s.

Food security dynamics vary considerably by demographic characteristics and, especially, household income, and relatively less by geography, creating a mosaic with distinct patterns. Headcount prevalence rates of chronic food insecurity differ by a factor of up to 15 - and severity measures by a factor of up to 33 - among sub-groups defined by race, gender and educational attainment. Non-White and female-headed households with low educational attainment disproportionately suffer persistent, chronic food insecurity. Households headed by White men with a college education hardly ever suffer food insecurity. Most intertemporal fluctuation in food security status occurs among White-headed households without a college degree. The latter group accounted for 86% of the surge in food insecurity from 2007 to 2009, for example.

# 2 Empirical Framework

## 2.1 Data

We use the PSID, the leading nationally representative panel survey of U.S. households. PSID has tracked a nationally representative sample of U.S. households annually from 1968-1997 and biennially since 1997, enabling a study of long-term dynamics in a way no other data set does. PSID has regularly adjusted its survey weights to account for differential attrition rates and family composition change, and added a new, nationally representative immigrant population subsample to maintain its representativeness. As a result, economic indicators estimated from PSID align closely with those derived from other representative surveys such as the CPS or the Consumer Expenditure Survey (Andreski et al. 2014; Li et al. 2010; Gouskova, Andreski, and Schoeni 2010; Tiehen, Vaughn, and Ziliak 2020). Additionally, PSID included the HFSSM in the 1999-2003 and 2015-2017 waves, enabling us to calibrate and validate the PFS measure against the official food security measure that USDA estimates from CPS data each year. Tiehen, Vaughn, and Ziliak (2020) assessed the difference in food security prevalence estimates generated from PSID and CPS data, concluding that their findings "lend credence to the use of the PSID for food insecurity research" (p.20).

PSID has three sub-samples: the original, Survey Research Center (SRC) nationally representative household sample, the Survey of Economic Opportunities (SEO), which over-sampled low-income households to permit the study of that sub-population, and Immigrant Refreshers added in 1997, 1999 and 2017 to represent immigrant populations. We use the SRC and SEO subsamples, which account for 93% of the PSID sample. We omit the immigrant sub-sample because, unlike the SRC and SEO sub-samples, its representativeness with respect to food security status has not yet been validated (Tiehen, Vaughn, and Ziliak 2020). We restrict our sample to households where the identity of the household head remained unchanged over time, yielding a balanced sample of approximately 23,000 observations from 2,700 households observed over 9 waves between 2001 and 2017.[1]

Because PSID incorporates complex survey design features (e.g., stratification, clustering, weighting), estimation must take this structure into account or else point estimates and standard errors will be biased (Heeringa, Berglund, and Khan 2011). Unless otherwise noted, all parameter estimates and standard errors we report are robust and design-adjusted based on the primary sampling unit through the procedure suggested by Heeringa, West, and Berglund (2010).[2]

Table 1 reports summary statistics for both our full sample and the SRC and SEO sub-samples. Table A3 describes the variables used in this paper. As one would expect from the over-sampling design of the SEO sub-sample, SRC households have higher per capita income and food expenditures, are more educated and less likely to receive food stamp assistance in the previous year relative to SEO households. Note that income includes transfer and social security income.

Further description of the food expenditures data is helpful. Starting in 1999,

1. We omit attritted and split-off units (i.e., those that disappear from the sample or newly created households from existing households), for multiple reasons. First, they necessarily offer shorter sequences of observations, which can improve precision in understanding shorter-term dynamics but much less so on the longer-term dynamics that motivate this paper. Second, PSID survey weights update regularly to adjust for panel attrition due to non-response (Chang et al. 2019). Third, split-off households may still depend heavily on their origin households, leading to complex correlation structures in the data that could bias inferences.

2. Our estimates are not clustered at household-level. The example from Heeringa, West, and Berglund (2010) shows that the preferred, design-adjusted estimates without household-level clustering yield "very similar inferences" to those generated by a mixed model with clustering.

households reported three forms of food expenditures, the value of food consumed at home; expenditures on food purchased and consumed outside the home; and expenditures on food delivered to the home. We added the value of SNAP benefits/food stamps to the aggregate of these three types of reported food expenditures.[3] Respondents could choose the recall period over which that they report these expenditures, from daily to yearly. If these vary across survey rounds (for example, households report weekly expenditures in one round and yearly expenditures in the subsequent round), it becomes difficult to determine if differences in food expenditures across rounds reflect real differences or simply differences in reporting periods. Among households with non-missing PFS over our study period, 57% of households reported weekly expenditures in all survey rounds and a further 31% used only two different recall periods. Across all rounds, 90% of households used weekly expenditures and a further 5% used a monthly recall period. This consistency in recall period across households and over time suggests that measurement errors from differential recall periods should not be a major concern.

The method we employ compares each household's expenditures to a normative food expenditures threshold. A natural candidate for such a threshold is the cost of the USDA's Thrifty Food Plan (TFP) diet, which "serves as a national standard for a nutritious, minimal-cost diet" (Coleman-Jensen et al. 2021). USDA reports TFP monthly in its *Cost of Food Reports*.[4] The report provides individual costs by gender and age group as well as multipliers for different household sizes. We generate household-year-specific TFP diet costs by matching individual household member's age, gender and surveyed month with the monthly costs reported, summing up the individual costs within household and applying the appropriate multiplier corresponding to the household size, and then dividing by the number of household members to express this in per capita terms.[5]

3. In 2017, the latest year in our study sample, the average household redeemed 96% of the SNAP benefit they received before the next issuance (USDA 2020), so the value received is nearly equivalent to the value redeemed.

4. The Cost of Food Reports present weekly and monthly costs corresponding to four USDA-designed food plans: Thrifty, Low-cost, Medium-cost, and Liberal. TFP is the cheapest of these. It is used to determine a household's maximum SNAP benefit (Ziliak 2016).

5. For households in Alaska and Hawaii where costs are only reported semi-annually, we use the first half-year costs for households surveyed from January to June, and the second half-year costs

Table 1: Summary Statistics

| | Total | | SRC | | SEO | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | mean | sd |
| Household Head | | | | | | |
| Age | 56.04 | 13.69 | 56.26 | 12.24 | 53.06 | 24.03 |
| Race | | | | | | |
| White | 0.86 | 0.35 | 0.92 | 0.24 | 0.01 | 0.21 |
| Non-White | 0.14 | 0.35 | 0.08 | 0.24 | 0.99 | 0.21 |
| Married | 0.62 | 0.48 | 0.64 | 0.42 | 0.31 | 0.91 |
| Female | 0.22 | 0.41 | 0.20 | 0.35 | 0.50 | 0.98 |
| Highest educational degree | | | | | | |
| Less than high school | 0.08 | 0.26 | 0.07 | 0.22 | 0.20 | 0.78 |
| High school | 0.31 | 0.46 | 0.30 | 0.41 | 0.39 | 0.96 |
| Some college | 0.25 | 0.43 | 0.25 | 0.38 | 0.27 | 0.87 |
| College | 0.37 | 0.48 | 0.38 | 0.43 | 0.14 | 0.68 |
| Employed | 0.66 | 0.47 | 0.66 | 0.42 | 0.58 | 0.97 |
| Disabled | 0.19 | 0.39 | 0.18 | 0.34 | 0.23 | 0.83 |
| Mental problem | 0.08 | 0.26 | 0.08 | 0.23 | 0.07 | 0.50 |
| Household | | | | | | |
| Income per capita | 39.58 | 30.47 | 40.87 | 27.36 | 21.47 | 35.40 |
| Food expenditure per capita | 3.65 | 2.07 | 3.72 | 1.85 | 2.71 | 3.36 |
| Family size | 2.30 | 1.27 | 2.30 | 1.12 | 2.31 | 2.82 |
| % of children | 0.11 | 0.20 | 0.11 | 0.18 | 0.16 | 0.48 |
| Food Assistance | | | | | | |
| SNAP/food stamp | 0.05 | 0.22 | 0.04 | 0.18 | 0.22 | 0.82 |
| Child meal | 0.05 | 0.21 | 0.03 | 0.16 | 0.19 | 0.77 |
| Change in status | | | | | | |
| No longer employed | 0.08 | 0.26 | 0.08 | 0.23 | 0.10 | 0.58 |
| No longer married | 0.01 | 0.11 | 0.01 | 0.10 | 0.01 | 0.19 |
| No longer owns house | 0.03 | 0.16 | 0.03 | 0.14 | 0.03 | 0.33 |
| Became disabled | 0.07 | 0.25 | 0.07 | 0.23 | 0.07 | 0.51 |
| N | 23,403 | | 17,268 | | 6,135 | |

Note: The sample consists of the households from the SRC and the SEO sample surveyed from 2001 to 2017. Top 1% values of income and expenditure values are winsorized.

## 2.2 Methods

### 2.2.1 PFS Construction

We construct the PFS following the method introduced by Cissé and Barrett (2018) and first employed in international food security analysis by Upton, Cissé, and Barrett (2016). First, we estimate the conditional mean of annual household per capita food expenditures by regressing it on a polynomial of its prior period value - thereby allowing for nonlinear dynamics - and other covariates,

$$W_{ijt} = \sum_{\gamma=1}^{3} \pi_\gamma W_{ijt-1}^{\gamma} + \Lambda X_{it} + \omega_t + \theta_j + u_{ijt} \tag{1}$$

where $W_{ijt}$ is annual per capita food expenditures for household *i* in state *j* and year *t*. We construct this dependent variable by dividing the annual food expenditure by the number of members of the household. Food expenditures have long been used in food security analysis internationally not only because they direct capture household food consumption but also because they are strongly associated with other food security indicators, such as dietary diversity, food consumption scores, coping strategy indices, etc. (Hoddinott and Yohannes 2002).

$X_{i,t}$is a vector of household-level covariates that previous studies have found to be associated with food security, including demographics (age, gender, race, and educational attainment of the household head), income/expenditure, and changes since the prior survey round in employment, marriage, housing and disability status. The $\omega_t$ and $\theta_j$ parameters are year- and region- fixed effects, respectively. To account for possible nonlinear dynamics, we include the lagged dependent variable as a third order polynomial in $W_{ijt}$.[6]

The predicted value of the outcome variable, $\hat{W}_{ijt}$, is the conditional mean

for those surveyed from July to December. Also, those two states do not report the costs for some age groups (1-5, 12-19, 51+ years), so we use the costs reported for 6-8 for the first missing group and the costs reported for 20-50 for the other two missing groups.

6. Table A4 shows that the coefficient estimates on higher order polynomial terms are statistically insignificant in model with a fourth order polynomial, and the linear term is no longer significant in the model with a fifth order polynomial. The principle of parsimony thus favors a third order polynomial specification. That decision is supported by Akaike Information Criterion (AIC) statistics that remain nearly unchanged across different polynomial specifications beyond the first order.

of the household per capita food expenditure. We assume $W_{ijt}$ follows a Gamma distribution since it is continuous and non-negative.[7] We therefore estimate a generalized linear model (GLM) logit link regression for equation (1). As an alternative, we also estimated the more general relationship in equation (1) using two different machine learning algorithms: LASSO and Random Forest. Neither model significantly improved prediction over the GLM. We therefore use GLM as it is easier to interpret.[8]

Given a mean zero error term, $E[u_{ijt}] = 0$, the expected value of the squared residuals equals the conditional variance of annual per capita food expenditures for household *i* in state *j* and year *t*, $V[W_{ijt}] = E[\hat{u}^2_{ijt}] = \hat{\sigma}^2_{ijt}$. Regressing the squared residuals from the conditional mean equation on covariates therefore yields a regression equation for the conditional variance of per capita food expenditures, using the same basic specification as in equation (1).

$$\hat{u}^2_{ijt} = \sum_{\gamma=1}^{3} \rho_\gamma W^\gamma_{ijt-1} + \Omega X_{it} + \delta_t + \phi_j + \eta_{ijt} \tag{2}$$

The final step uses the household-and-period-specific conditional mean and variance estimates to construct a household-and-period-specific cumulative density function (CDF). Assuming $W_{ijt} \sim Gamma\,(\alpha, \beta)$, we calibrate the parameters using the method of moments such that $\left(\alpha = \frac{\hat{W}^2_{ijt}}{\hat{\sigma}^2_{ijt}}, \beta = \frac{\hat{\sigma}^2_{ijt}}{\hat{W}_{ijt}}\right)$.

We then estimate the probability of food security (PFS) as the inverse CDF, i.e., the conditional cumulative density above the household-specific TFP diet cost that serves as the normative threshold for a minimal cost, nutritionally adequate diet for that household:

$$\hat{\rho}_{ijt} = 1 - F\left(X_{ijt}, W_{ijt-1} | \underline{W_{ijt}}\right) \in [0, 1]\,. \tag{3}$$

7. The mean of the outcome differs significantly from its variance in our sample, so we do not use a Poisson distribution, which requires the mean equals the variance.

8. We assessed model performances through out-of-sample prediction accuracy; we trained the model using the sample from 2001 to 2015, and used 2017 sample as out-of-sample. We used "cvlasso","lasso2", and "rforest" commands in Stata to run ML models (Ahrens, Hansen, and Schaffer 2020; Schonlau and Zou 2020) Root mean square prediction error (RMSPE) of LASSO (1.78) and Random Forest (1.82) were not significantly better than that of GLM (1.83).

We categorize households as food secure in year $t$ if $\hat{\rho}_{it} \geq \underline{P_t}$, where $\underline{P_t}$ is the externally determined cut-off probability such that the proportion of food secure households in year $t$ exactly matches the annual USDA population prevalence estimate based on the HFSM data from CPS. For example, if the USDA reported 10.0% of households as food insecure in year $t$, then we sort households in year $t$ by the PFS and assign the PFS of the household at the 10th percentile in the weighted sample as $\underline{P_t}$.[9] The estimated prevalence of food insecure households is thus mechanically equal to the official USDA estimate.

As reported below, we validate the PFS as a food security measure as follows. First, we assess how strongly PFS correlates with the HFSM both by estimating rank correlations and by regressing the HFSM on the PFS measure. Second, we regress both the official USDA and the PFS measures on household characteristics and examine whether the two different measures exhibit similar associations with covariates.

Lastly, we replicate our main analyses using an alternative food security measure based solely on realized food expenditures. More precisely, we calculated the ratio of household food expenditures to the TFP cost for that household (denote this ratio as E hereafter), and categorized households as food insecure in the same way as we did with the PFS, mechanically generating the same national prevalence of food insecurity as HFSM. The patterns we find using PFS are mostly identical to those based on E. But PFS tracks HFSM better than E does, most likely because HFSM was expressly designed to incorporate respondents' worry whether "food would run out before we got money to buy more" (Q1, see Appendix Table A1), not just expenditures realizations, and PFS offers an expressly probablistic measure of food expenditures.

9. An alternative approach would be using a fixed cut-off probability $\underline{P}$ over the period. We use varying cut-off probabilities to ensure our analysis corresponds directly with the official HFSM. Figure A1 depicts the resulting interannual variation in $\underline{P_t}$, which varies modestly across years, in the interval (0.55, 0.60).

### 2.2.2 Household-level Dynamics

We adopt two different approaches to study food insecurity dynamics, borrowing from the poverty dynamics literature (Baulch and Hoddinott 2000; Jalan and Ravallion 2000; McKay and Lawson 2003). The first, the spells approach, characterizes the duration of households' continuous experience of food insecurity, as reflected by households' PFS in successive survey waves. We categorize observations into four categories: (1) Food insecure in two successive waves, (2) Food insecure in the preceding wave but food secure subsequently, (3) Food secure in the preceding wave but food insecure subsequently, and (4) Food secure in both waves. Figure 1 depicts this categorization.

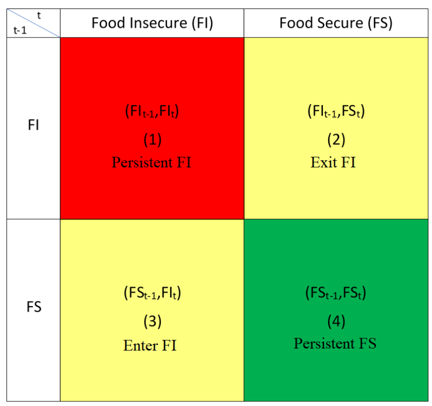



Figure 1: Food Security Transition Matrix

The joint distribution of these four categories yields estimates of persistence and entry rates. The persistence rate is the conditional probability that a food insecure household remains food insecure as observed in the next survey wave. One minus the persistence rate is the exit rate. The entry rate is the conditional probability a household becomes food insecure in the following wave conditional on being food secure initially. We classify food insecurity as recurrent if it persists for two or more consecutive waves and transient if it is not observed in consecutive survey waves. We compute persistence, entry and exit rates for the full sample and for distinct subpopulations to investigate inter-group heterogeneity in food security dynamics. We also measure the distribution of spell lengths - i.e., of duration of consecutive observations of food insecurity - as well as spell lengths and exit rates conditional on a household newly entering the ranks of the food insecure. These estimates help us understand whether food security exhibits path dependence, unconditionally or for distinct sub-populations. Such estimates are especially germane at the present moment, following a large increase in food insecurity during the COVID-19 pandemic (Center on Budget and Policy Priorities 2021; Gundersen et al. 2021).

Our second approach to studying food security dynamics identifies chronic food insecurity (CFI) by mean intertemporal PFS, and transient food insecurity (TFI) by deviations from the household-specific intertemporal mean. Following Jalan and Ravallion (2000), denote $TFI_i$ as the observed sequence of PFS measures for household *i* and $CFI_i$ as its chronic component. The difference, $TFI_i - CFI_i$, represents the transient component:

$$TFI_i(\alpha, PFS_{i1}, ..., PFS_{it}) = \frac{1}{T}\sum_{t=1}^{T}\left(1 - \frac{min(PFS_{it}, \underline{P_t})}{\underline{P_t}}\right)^{\alpha} \tag{4}$$

$$CFI_i(\alpha, PFS_{i1}, ..., PFS_{it}) = \left(1 - min\left[1, \frac{\sum_{t=1}^{T} PFS_{it}}{\sum_{t=1}^{T} \underline{P_t}}\right]\right)^{\alpha} \tag{5}$$

A household with $CFI_i > 0$ is considered chronically food insecure, i.e., it is food insecure in expectation in any given period over the full time series. TFI and CFI are FGT-style measures with the important modification that they aggregate over time within households. Parameter $\alpha$ is a measure of food insecurity aversion, which reflects sensitivity to the severity of PFS shortfalls relative to $\underline{P_t}$. For $\alpha = 0, 1, 2$, $CFI_i$ reflects the period-mean PFS shortfall, the average severity of such shortfalls, which we label the food insecurity gap (FIG), and a more loss averse, squared food insecurity gap (SFIG), respectively. TFI is additively decomposable into sub-periods; the TFI over any period is simply the weighted sum of TFI over the component sub-periods. TFI satisfies Sen (1976)'s monotonicity and transfer axioms between time periods. The monotonicity axiom means that TFI falls weakly monotonically with an increase in PFS, while the transfer axiom means that TFI falls as a household transfers food expenditure from a higher PFS period to a lower one. CFI, however, satisfies the monotonicity axiom but neither satisfies the transfer axiom nor is it additively decomposable into sub-periods because it takes as an argument the intertemporal mean PFS, which cannot be decomposed into sub-periods, as Calvo and Dercon (2009) explain. In order to reduce measurement and sampling error, we compute TFI and CFI only for the 99% of sample households with five or more years of non-missing PFS.

Under the chronic method, we again categorize households into four categories. The first category is persistently food insecure households, i.e., $CFI_i > 0$ and $PFS_{it} < \underline{P_t}; \forall t$. The second category encompasses households that are chronically but not persistently food insecure, i.e., $CFI_i > 0$ and $\exists t$ such that $PFS_{it} \geq \underline{P_t}$. The third category represents transiently food insecure households, i.e., $CFI_i = 0$ and $\exists t$ such that $PFS_{it} < \underline{P_t}$. Finally, there are persistently food secure households, i.e., $CFI_i = TFI_i = 0$.

Each method has strengths and weaknesses. The permanent approach is less vulnerable to measurement error and data truncation - i.e., data unavailable prior to the start year and after the final year of the study period can censor spell length observations - but also to long survey intervals, because one cannot observe possible breaks in a spell during multi-year, inter-wave intervals (McKay and Lawson 2003). The permanent approach, however, assumes a stationary process - i.e., it ignores trends or permanent shocks that lead to a structural change in a household's food security status over time - and requires more rounds of data collected over a longer period to estimate the intertemporal mean without small sample bias.

#### 2.2.3 Groupwise decomposition

We decompose population-level PFS to generate group-specific estimates and track how those change over time. Following Gundersen (2008), we construct three different FGT-style national indices for each time period t based on the same food insecurity aversion parameter, $\alpha$, introduced in equations (4) and (5) and each household's PFS estimate: the prevalence or headcount ratio (HCR), the food insecurity gap (FIG) and the squared food insecurity gap (SFIG):

$$FGT_t(\alpha, PFS_{1t}, ..., PFS_{Nt}) = \frac{1}{N}\sum_{i=1}^{N}\left(1 - \frac{min(PFS_{it}, \underline{P_t})}{\underline{P_t}}\right)^{\alpha} \quad (6)$$

where $N$ is the number of households in the population and $\underline{P_t}$ is the threshold probability of food security earlier. HCR, FIG and SFIG take $\alpha = 0, 1, 2$, respectively. HCR represents the proportion of food insecure households in the population, i.e., the prevalence. The two measures with $\alpha$=1 or 2, by contrast, provide new, continuous measures of the severity of food insecurity. The FIG, analogous to the poverty gap measure in the poverty literature (Foster, Greer, and Thorbecke 1984), describes the depth of food insecurity and can be interpreted as the average PFS shortfall of the population. For instance, if FIG is *x%*, then household average PFS in the food insecure population is lower than the threshold PFS by *x%*. The SFIG, analogous to the squared poverty gap index in the poverty literature, describes the severity of food insecurity where the (normalized) gap between the PFS and its cut-off value is weighted by itself.

These measures complement each other. HCR is simple and intuitive. The official USDA-reported food security prevalence measure is an HCR. HCR satisfies neither Sen (1976)'s monotonicity nor transfer axioms. FIG and the SFIG are less intuitive, but FIG satisfies the monotonicity axiom (but not the transfer axiom), while SFIG satisfies both axioms. We focus on the more distribution-sensitive SFIG measure when describing the severity of food insecurity, as it satisfies all the desirable properties of well-being measures per Sen (1976).

We report HCR, FIG and SFIG measures overall over the study period, 2001-2017. Since all three measures are additively decomposable, we decompose these measures and their intertemporal patterns into groupwise aggregates based on the race, gender, and educational attainment of the household head. This allows us to unpack whether different groups experience chronic and transitory food insecurity, or food insecurity prevalence and severity, differently.

# 3 Results

## 3.1 Validating the PFS measure

Before describing estimated food security dynamics in the U.S., we first assess the validity of the PFS measure by comparing it to USDA's official HFSM.[10] We begin by constructing two simple measures of rank correlation: a Spearman rank correlation coefficient and Kendall's $\tau$. This produces values of 0.31 and 0.25 respectively, and we reject the null hypothesis that both measures are independent at p-values less than 0.00 in both cases. This imperfect correspondence between the two measures arises in part because HFSM is a modeled numeric variable constructed from counts of categorical variables fit to a Rasch model, while PFS is an inherently continuous probability measure generated from the modeling approach described above.

Next, we regress the USDA scale on the PFS. As shown in Table 2, PFS is positively associated with the HFSM using either a linear or quadratic specification and when we control for locational (state) and time (survey wave) fixed effects, despite both measures' strong positive skewness.[11]

In terms of targeting accuracy, type I (food secure by PFS but food insecure by HFSM) and type II errors (food insecure by PFS but food secure by HFSM) are 3.2% and 9.9%, respectively.

Table 3 shows how household characteristics associate with the USDA scale and the PFS. In column (1) and (2), correlates that are statistically significantly associated with both HFSM and the PFS, and that exhibit the same sign, include income per capita, disability status, the percentage of household members who are children, high school completion and participation in food assistance programs. Most covariates have the same sign estimates, even if the magnitudes and precision of

10. To make these comparisons easier to understand, we rescale the HFSM so that it ranges in value from zero to one, with a higher value implying greater food security. Specifically, we calculate $HFSM_{rescale} = \frac{9.3 - HFSM_{it}}{9.3}$ for each household $i$ in year $t$ in the data.

11. By the nature of its construction, the PFS distribution is relatively smooth compared to the HFSM, resulting in an association that is stronger over the lower range of the PFS, that is, among the food insecure, where we most want the measures to correspond. Among the PSID sample households, 90% have an HFSM value of 1, indicating food security, while the median estimated PFS is 0.9 and the 90th percentile equals 0.995. Figure A2 displays these distributions.

Table 2: Regression of the HFSM on the PFS

| | (1) HFSM | (2) HFSM | (3) HFSM | (4) HFSM |
|---|---|---|---|---|
| PFS | 0.158 | 0.265 | 0.162 | 0.236 |
| | (0.02) | (0.09) | (0.02) | (0.09) |
| PFS$^2$ | | -0.075 | | -0.052 |
| | | (0.06) | | (0.06) |
| Fixed Effects | N | N | Y | Y |
| N | 10,378 | 10,378 | 10,378 | 10,378 |
| $R^2$ | 0.062 | 0.062 | 0.081 | 0.082 |

Note: Sample include households surveyed in 2001, 2003, 2015 and 2017 with both the HFSM and the PFS available. Fixed effects include both state and year.

the estimated coefficients differ. The PFS' correlations with these variables generally conform with the existing literature (e.g., Hofferth 2004; Tiehen, Vaughn, and Ziliak 2020). However, age is associated convexly with the HFSM but concavely with the PFS. To us, the PFS relation appears more sensible, reflecting life cycle effects indicating that food security peaks around retirement age, when household income typically peaks.[12] Appendix Table A5 reports the conditional mean and variance regression coefficient estimates from equations (1) and (2). Conditional mean is significantly nonlinear in lagged per capita food expenditures and in the age of household head. The basic patterns of associations are intuitive: food expenditures are positively correlated with income, educational attainment, and employment status, and negatively correlated with family size, a female household head, and food assistance program participation. These associations suggest PFS relates to household attributes in a sensible way.

We further replicate the main analyses of this paper using the E as an alternative outcome. PFS shows stronger rank correlation with HFSM than E does, 0.31 (PFS) vs 0.23 (E) by the Spearman coefficient, and 0.25 (PFS) vs 0.18 (E) using Kendall's $\tau$), indicating that PFS better preserves the ordering of food insecure households. In addition, the patterns we find with the PFS measure, as described in

12. Figure A3 depicts the predicted PFS as a function of age of household head. The age at which PFS peaks, along with retirement age, shifted very slightly downward until the Great Recession of 2007-9, after which both shifted upward

Table 3: Food Security Indicators and Their Correlates

| | (1) HFSM† | (2) PFS | (3) HFSM | (4) PFS |
|---|---|---|---|---|
| Age | -0.001 (0.00) | 0.008 (0.00) | -0.001 (0.00) | 0.006 (0.00) |
| $Age^2/1000$ | 0.019 (0.01) | -0.069 (0.01) | 0.018 (0.01) | -0.053 (0.02) |
| Non-White | -0.006 (0.01) | -0.055 (0.01) | -0.005 (0.01) | -0.064 (0.01) |
| Married | 0.008 (0.01) | 0.043 (0.01) | 0.008 (0.01) | 0.087 (0.01) |
| Female | -0.008 (0.01) | -0.061 (0.01) | -0.009 (0.01) | -0.087 (0.01) |
| ln(income per capita) | 0.024 (0.01) | 0.094 (0.00) | 0.025 (0.01) | 0.102 (0.01) |
| Disabled | -0.039 (0.01) | -0.029 (0.01) | -0.038 (0.01) | -0.018 (0.02) |
| Mental problem | -0.040 (0.01) | 0.001 (0.01) | -0.041 (0.01) | 0.022 (0.02) |
| Employed | 0.007 (0.01) | -0.006 (0.01) | 0.007 (0.01) | 0.015 (0.01) |
| Family size | 0.003 (0.00) | -0.047 (0.00) | 0.003 (0.00) | -0.071 (0.01) |
| % of children | 0.043 (0.01) | 0.105 (0.01) | 0.043 (0.01) | 0.194 (0.03) |
| Less than high school | -0.023 (0.01) | -0.024 (0.01) | -0.022 (0.01) | -0.036 (0.02) |
| Some college | 0.002 (0.01) | 0.035 (0.01) | 0.002 (0.01) | 0.047 (0.01) |
| College | -0.001 (0.01) | 0.040 (0.01) | 0.000 (0.01) | 0.025 (0.01) |
| Food stamp/SNAP | -0.103 (0.02) | -0.059 (0.01) | -0.100 (0.02) | -0.176 (0.03) |
| Child meal | -0.028 (0.01) | -0.022 (0.01) | -0.027 (0.01) | -0.126 (0.03) |
| No longer employed | -0.009 (0.01) | -0.031 (0.01) | -0.008 (0.01) | -0.026 (0.02) |
| No longer married | -0.013 (0.01) | -0.026 (0.01) | -0.014 (0.01) | 0.016 (0.02) |
| No longer owns house | 0.000 (0.01) | 0.006 (0.01) | 0.001 (0.01) | 0.047 (0.02) |
| Became disabled | 0.023 (0.01) | -0.007 (0.01) | 0.022 (0.01) | -0.034 (0.02) |
| Wave FE | Y | Y | Y | Y |
| Region FE | N | N | Y | Y |
| N | 10,378 | 10,378 | 10,378 | 10,378 |
| $R^2$ | 0.211 | 0.516 | 0.219 | 0.302 |

† HFSM is not continuous, but discrete

Note: Base household is as follows: Household head is white/single/male/completed high school/not employed/not disabled.

Section 3, are mostly identical to those we observe using E as an alternative measure, and where the two differ, the PFS results appear more reasonable.[13]

The strong positive correlation of the PFS measure with the USDA scale, combined with the broad consistency of associational patterns the two measures exhibit with household attributes and near identical patterns in findings when we use food expenditures instead, suggest that PFS provides a useful complement to the USDA food security measure in the U.S.

13. The entire replication using E is presented in Appendix B.

### 3.2 Household-level Dynamics: Spells Approach

Table 4 presents the distribution of food insecurity spell lengths, along with the estimated conditional persistence, i.e., the probability a household remains food insecure conditional on the spell length of its current food insecurity episode. Because PSID data are biennial, a household could become food insecure immediately after one PSID survey round and remain food insecure through the next survey wave until just prior to the third wave, implying that a one wave spell could have a duration of as much as nearly four years. Conversely, the survey could have captured a household just after it entered food insecurity and it exited soon thereafter, implying a spell length of less than a year. Hence the broad intervals for the duration in years estimates in the left column of Table 4.

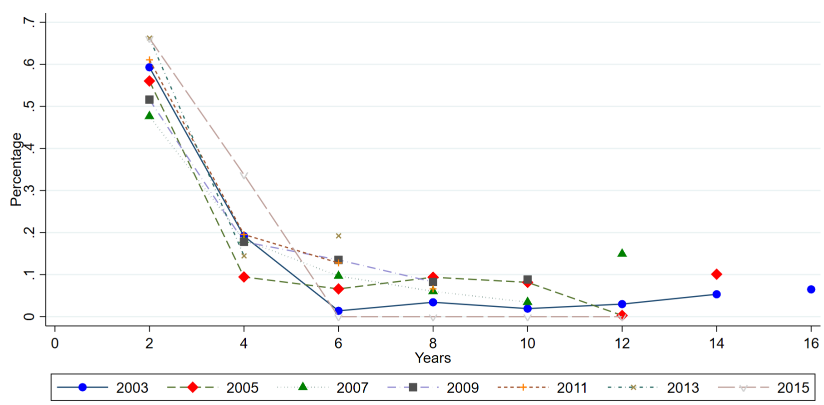
Table 4: Spell Length Distribution and Conditional Persistence Estimates

| Survey waves (Years duration) | Proportion | Conditional Persistence (Std.Error) |
|---|---|---|
| 1 (1-4) | 0.57 | 0.45 (0.02) |
| 2 (3-6) | 0.17 | 0.64 (0.03) |
| 3 (5-8) | 0.09 | 0.67 (0.04) |
| 4 (7-10) | 0.05 | 0.75 (0.05) |
| 5 (9-12) | 0.03 | 0.77 (0.04) |
| 6 (11-14) | 0.03 | 0.83 (0.05) |
| 7 (13-16) | 0.02 | 0.84 (0.05) |
| 8 (15-18) | 0.02 | 0.78 (0.05) |
| 9 (17+) | 0.03 | . |

Note: Sample consists of the balanced panel of households with PFS estimates from 2001 to 2017. Duration reflects the number of consecutive (biennial) survey waves and years households experienced food insecurity. As data are right censored, there is no upper limit on the range for the spell length of 9 survey waves, the entire study period. Other spell lengths can likewise be right-censored if the household was food insecure in 2017.

More than half (57%) of household food insecurity spells last just a single survey wave. That indicates that U.S. food insecurity spells are roughly equally likely to be transitory or persistent. Conditional persistence measures are both large and statistically weakly increasing with spell length, indicating that the longer a household remains food insecure, the less likely it is to exit food insecurity. Once a household has been food insecure for four consecutive waves, it faces a probability of at least 0.75 that it remains food insecure until at least the next PSID wave.

Food insecurity spells have a long tail. Figure 2 shows the distribution of spell length conditional on the start year of the food insecurity spell. The unconnected dots at the right-end of each distribution indicate the share of households who remained food insecure through the 2017 PSID survey wave, implying that their spell length is right-censored; they might remain food insecure for a longer, unobserved spell.[14] The share of single wave ($\sim$2 year) spell lengths varies from under 50% to nearly 70% over time, peaking in 2013 when macroeconomic conditions were relatively robust, and with a noticeable increase in overall spell length in 2007, as the Great Recession began. Just as the prevalence and severity of food insecurity increased in the immediate run-up to and throughout the Great Recession from December 2007 to June 2009,[15] so did food insecurity spell lengths increase during that period. In these data, they appear to be pronounced business cycle effect on food insecurity in the U.S.




Note: Sample includes households with PFS observations from 2001 to 2017. The unconnected rightmost dots reflect the right-censored share.

Figure 2: Spell Length of Food Insecurity (2003-2015)

Table 5 shows food security status transitions and persistence/entry rates per the spells approach, disaggregated by years and groups. Note that Table 5 reports the unconditional persistence rate unlike the conditional (on spell length) persistence

14. Figure A4 depicts the distribution of spell length in 2001, for which spell lengths are also left-censored.

15. Recession dating per the *U.S. Business Cycle Expansions and Contractions* report of the National Bureau of Economic Research.

rates shown in Table 4. Transition shares necessarily sum to one (up to rounding error) across the four columns describing the joint distribution.

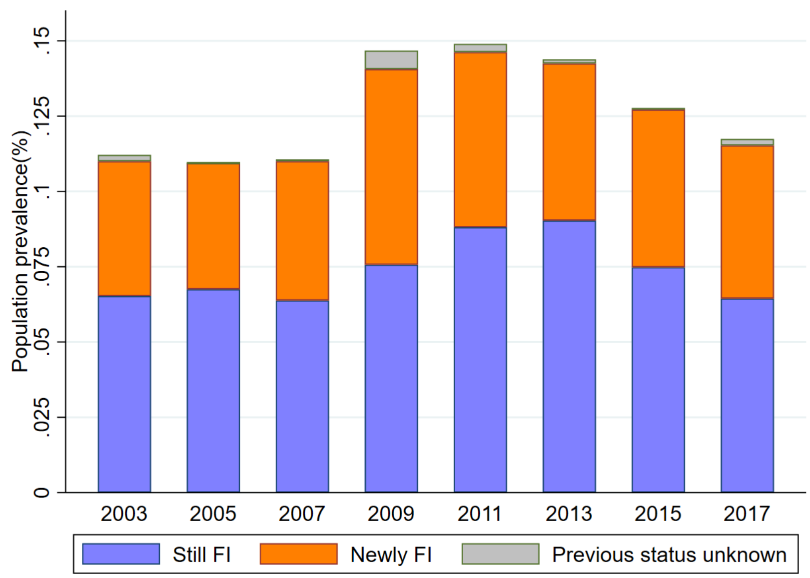
Table 5: Transition in Food Security Status

| | N | $(FI_{t-1},FI_t)$ | $(FI_{t-1},FS_t)$ | $(FS_{t-1},FI_t)$ | $(FS_{t-1},FS_t)$ | Persistence* | Entry* |
|---|---|---|---|---|---|---|---|
| Year | | | | | | | |
| 2003 | 2,522 | 0.07 | 0.04 | 0.05 | 0.85 | 0.61 | 0.05 |
| 2005 | 2,548 | 0.07 | 0.05 | 0.04 | 0.84 | 0.60 | 0.05 |
| 2007 | 2,548 | 0.06 | 0.05 | 0.05 | 0.84 | 0.59 | 0.05 |
| 2009 | 2,527 | 0.08 | 0.03 | 0.07 | 0.82 | 0.72 | 0.08 |
| 2011 | 2,628 | 0.09 | 0.06 | 0.06 | 0.80 | 0.60 | 0.07 |
| 2013 | 2,615 | 0.09 | 0.06 | 0.05 | 0.80 | 0.61 | 0.06 |
| 2015 | 2,607 | 0.08 | 0.07 | 0.05 | 0.81 | 0.53 | 0.06 |
| 2017 | 2,602 | 0.06 | 0.06 | 0.05 | 0.82 | 0.51 | 0.06 |
| Gender | | | | | | | |
| Male | 16,100 | 0.05 | 0.04 | 0.04 | 0.87 | 0.53 | 0.04 |
| Female | 4,497 | 0.17 | 0.09 | 0.09 | 0.64 | 0.65 | 0.13 |
| Race | | | | | | | |
| White | 13,896 | 0.05 | 0.04 | 0.04 | 0.86 | 0.55 | 0.05 |
| Non-White | 6,701 | 0.20 | 0.10 | 0.10 | 0.60 | 0.67 | 0.14 |
| Region | | | | | | | |
| Northeast | 1,401 | 0.02 | 0.02 | 0.02 | 0.94 | 0.44 | 0.02 |
| Mid-Atlantic | 2,825 | 0.08 | 0.04 | 0.05 | 0.83 | 0.65 | 0.05 |
| South | 7,178 | 0.08 | 0.05 | 0.05 | 0.82 | 0.60 | 0.06 |
| Midwest | 5,122 | 0.09 | 0.06 | 0.06 | 0.79 | 0.59 | 0.07 |
| West | 3,972 | 0.08 | 0.06 | 0.06 | 0.81 | 0.57 | 0.06 |
| Highest Degree | | | | | | | |
| Less than high school | 1,927 | 0.25 | 0.12 | 0.11 | 0.52 | 0.67 | 0.18 |
| High school | 7,181 | 0.10 | 0.07 | 0.08 | 0.75 | 0.60 | 0.09 |
| Some college | 5,167 | 0.06 | 0.05 | 0.04 | 0.85 | 0.54 | 0.05 |
| College | 6,322 | 0.03 | 0.03 | 0.02 | 0.92 | 0.52 | 0.03 |
| Disability | | | | | | | |
| Not disabled | 17,097 | 0.06 | 0.05 | 0.04 | 0.85 | 0.57 | 0.05 |
| Disabled | 3,500 | 0.13 | 0.08 | 0.09 | 0.70 | 0.62 | 0.12 |
| SNAP/Food stamp recipient | | | | | | | |
| Not SNAP/food stamp recipient | 18,730 | 0.05 | 0.05 | 0.05 | 0.85 | 0.54 | 0.05 |
| SNAP/food stamp recipient | 1,867 | 0.41 | 0.14 | 0.16 | 0.29 | 0.75 | 0.36 |
| Change in status | | | | | | | |
| No longer employed | 1,601 | 0.08 | 0.03 | 0.08 | 0.81 | 0.74 | 0.09 |
| No longer married | 299 | 0.03 | 0.14 | 0.01 | 0.82 | 0.16 | 0.01 |
| Became disabled | 1,343 | 0.11 | 0.04 | 0.10 | 0.75 | 0.71 | 0.12 |
| Newly received food stamp/SNAP | 536 | 0.26 | 0.20 | 0.16 | 0.39 | 0.57 | 0.28 |

Note: $FS_t(FI_t)$ is a dummy variable whether household is food secure(insecure) in time $t$. $(FI_{t-1},FI_t)$, $(FI_{t-1},FS_t)$, $(FS_{t-1},FI_t)$ and $(FS_{t-1},FS_t)$ are the four transition categories. Entries in each column report the proportion of households in that category.

These results show two important facts. First, among households that are food insecure in any given period, the persistence rate varies from 51-72% across survey rounds, peaking during the Great Recession. While many, even most, food insecurity spells are transitory, lasting just one survey wave, most food insecure households in any one survey wave remain food insecure in the subsequent survey, indicating considerable persistence. Second, persistence and entry rates are both higher during the Great Recession and are lower in periods when the economy was relatively strong, reinforcing our earlier finding of business cycle effects on food insecurity status.

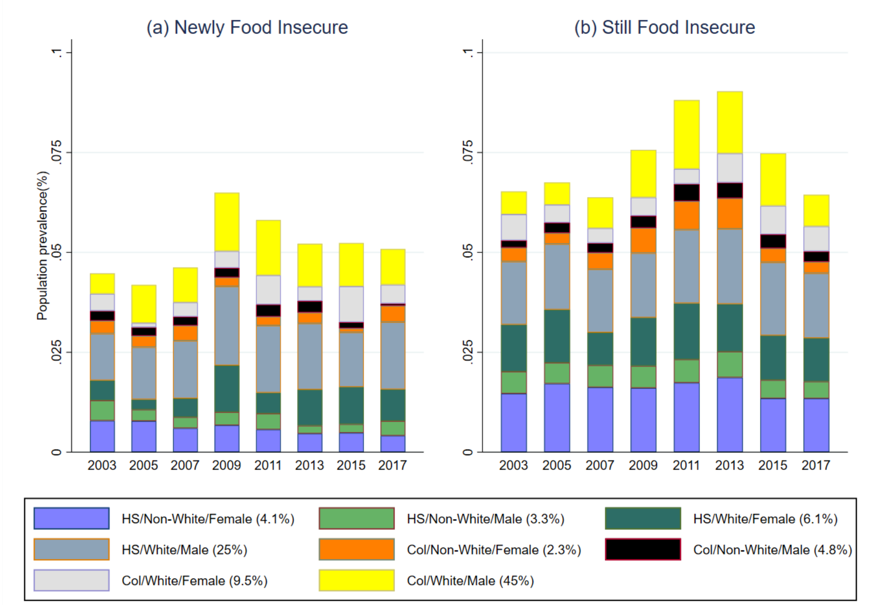
Figure 3 depicts these trends. We see that food security prevalence, as reported by USDA and replicated in the PFS, was quite steady around 11% from 2003-2007, then jumped to just under 15% in 2009 and 2011 before slowly but incompletely recovering by 2017. Unpacking the patterns by household heads' race, gender and educational attainment, we see in Table 5 and Figure 4 that both the prevalence and persistence of food insecurity are markedly higher among households headed by non-Whites, women, those without a high school degree, the physically disabled, and SNAP/food stamp recipients. In terms of change in status, households whose head lost his/her job or became disabled have especially high food insecurity persistence rates. By contrast, households whose head became unmarried through separation, divorce or death have especially low rates of food insecurity persistence.




Note: Sample includes households from 2003 to 2017. "Still FI" and "Newly FI" refer to households that were or were not food insecure in the preceding survey wave, respectively. "Previous status unknown" refers to households whose PFS in the preceding wave is missing. The prevalence reported at the top of each bar matches the official HFSM by construction

Figure 3: Change in Food Security Status

Figure 4 depicts the dynamics of food insecurity prevalence, distinguishing between those who newly became food insecure in a PSID survey year (top panel, a) and those who remained food insecure, having been so in the prior survey wave (bottom panel, b). These graphics reflect the combination of sub-group population sizes as well as the group-specific transitions reflected in Table 5.




Note: Sample includes households with non-missing PFS from 2003 to 2017. "Still food insecure" and "Newly food insecure" refer to food insecure households that were and were not food insecure in the preceding survey wave, respectively. "HS" indicates the head has no education beyond high school. "Col" indicates that the head has at least some college education. "Non-white" indicates the head's race is not White. Percentages in parentheses report each category's share of the total population.

Figure 4: Change in Food Security Status by Group

Both panels clearly show vulnerable subgroups' disproportionately high rates of entry and persistence. For example, over this period, female-headed households accounted for 22% of the population but 38% of the newly food insecure and 48% of persistently food insecure households, on average. Around the period of the Great Recession, they account for 37% of the households that newly became food insecure between 2007-2009 and 26% of still food insecure households immediately after the Great Recession (2009-2011). Households headed by White females without a college education account for only 6.1% of the population but they represented the largest share of newly food insecure households during the Great Recession (37%) and the third-largest share of still food insecure immediately after the recession (16%). That same sub-group shows the greatest reduction in newly food insecure households (12% to 5%) in the post-Great Recession recovery (2009-2011). By contrast, the most vulnerable sub-group - households headed by non-White women with no high school degree - exhibited a relatively stable entry rate before and after the recession and by far the highest persistence rate.

## 3.3 Household-level Dynamics: Permanent Approach

Table 6 columns (1) to (4) report the estimated chronic component (CFI) of total food insecurity (TFI) measures from the headcount ratio (HCR) with $\alpha = 0$. Columns (5) to (8) show the distribution of households among those who are chronically and persistently food insecure (column 5), chronically food insecure but transiently food secure some periods (column 6), those who are occasionally food insecure but on average food secure (column 7), and those never food insecure (column 8).[16]

Overall, two-thirds of households (67%) never experienced food insecurity over the 17 years we study, implying persistent food security is the dominant state in the U.S. population. This persistence ratio is smaller than the analog measure that uses the HFSM(86%), perhaps because the former covers nine waves from 2003 to 2017, including the Great Recession, the latter includes just five waves (1999, 2001, 2003, 2015, 2017), none of them during the Great Recession. Among the one-third who experience food insecurity, 73% of the food insecurity that households experience is chronic.

Sub-group analyses again show that households whose head is female, non-White, or did not complete high school have far higher rates of TFI than those with male, White, or college-educated heads, three or more times as much. Perhaps most

16. We tested for nonstationarity in the PFS series using a Fisher-type panel data unit-root test and an augmented Dickey–Fuller test for each household (Choi 2001). Assuming no trend in the data generating process, we reject the null hypothesis that all the panels have unit roots, implying that at least one panel is stationary. This is a weak test but provides some assurance that the analysis based on the permanent approach is not excessively compromised by nonstationarity in the PFS series.

Table 6: Chronic Food Insecurity Status from the Permanent Approach

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| | N | TFI | CFI | TFI-CFI | (CFI/TFI) | Chronic | | Transient | Never food insecure |
| | | | | | | Persistent | Not persistent | | |
| Total | 23,301 | 0.126 | 0.091 | 0.035 | 0.726 | 0.014 | 0.077 | 0.244 | 0.665 |
| Gender | | | | | | | | | |
| Male | 18,176 | 0.086 | 0.049 | 0.037 | 0.574 | 0.006 | 0.044 | 0.228 | 0.723 |
| Female | 5,125 | 0.266 | 0.240 | 0.027 | 0.900 | 0.044 | 0.196 | 0.299 | 0.461 |
| Race | | | | | | | | | |
| White | 15,692 | 0.095 | 0.058 | 0.037 | 0.609 | 0.008 | 0.050 | 0.231 | 0.711 |
| Non-White | 7,609 | 0.307 | 0.288 | 0.018 | 0.940 | 0.053 | 0.236 | 0.318 | 0.394 |
| Region | | | | | | | | | |
| Northeast | 1,587 | 0.042 | 0.020 | 0.022 | 0.471 | 0.000 | 0.020 | 0.125 | 0.856 |
| Mid-Atlantic | 3,177 | 0.123 | 0.084 | 0.039 | 0.683 | 0.015 | 0.069 | 0.225 | 0.691 |
| South | 8,130 | 0.133 | 0.106 | 0.027 | 0.796 | 0.018 | 0.088 | 0.233 | 0.661 |
| Midwest | 5,797 | 0.148 | 0.112 | 0.036 | 0.757 | 0.016 | 0.096 | 0.284 | 0.604 |
| West | 4,491 | 0.128 | 0.085 | 0.043 | 0.662 | 0.014 | 0.071 | 0.268 | 0.647 |
| Metropolitan area | | | | | | | | | |
| Metropolitan | 16,125 | 0.113 | 0.080 | 0.033 | 0.707 | 0.015 | 0.064 | 0.224 | 0.697 |
| Non-metropolitan | 7,102 | 0.156 | 0.118 | 0.038 | 0.756 | 0.012 | 0.106 | 0.290 | 0.592 |
| Education | | | | | | | | | |
| Less than HS | 2,687 | 0.363 | 0.322 | 0.041 | 0.888 | 0.088 | 0.234 | 0.403 | 0.275 |
| High school | 8,430 | 0.161 | 0.115 | 0.046 | 0.713 | 0.011 | 0.103 | 0.318 | 0.567 |
| Some college | 5,680 | 0.091 | 0.062 | 0.029 | 0.684 | 0.007 | 0.055 | 0.217 | 0.721 |
| College | 6,504 | 0.055 | 0.029 | 0.026 | 0.525 | 0.003 | 0.026 | 0.150 | 0.821 |

Note: Sample include households with non-missing PFS for 5 or more years from 2001 to 2017. The food insecurity measure is the headcount ratio (HCR) using the PFS following the method from Jalan and Ravallion (2000). Metropolitan area include the counties in metropolitan area with 250,000 or more population. States excluding Alaska and Hawaii belong to one of the five regions as described in Table A3. AK, HA and other U.S. territories are excluded in regional categories. The last four columns describe the distribution of households status which add up to one.

strikingly, the CFI/TFI ratio ranges from 89-94% for households within each of those three groups. Not only are households in disadvantaged demographic groups more likely to be food insecure, but their food insecurity is much more likely chronic than is the food insecurity experience of other groups.

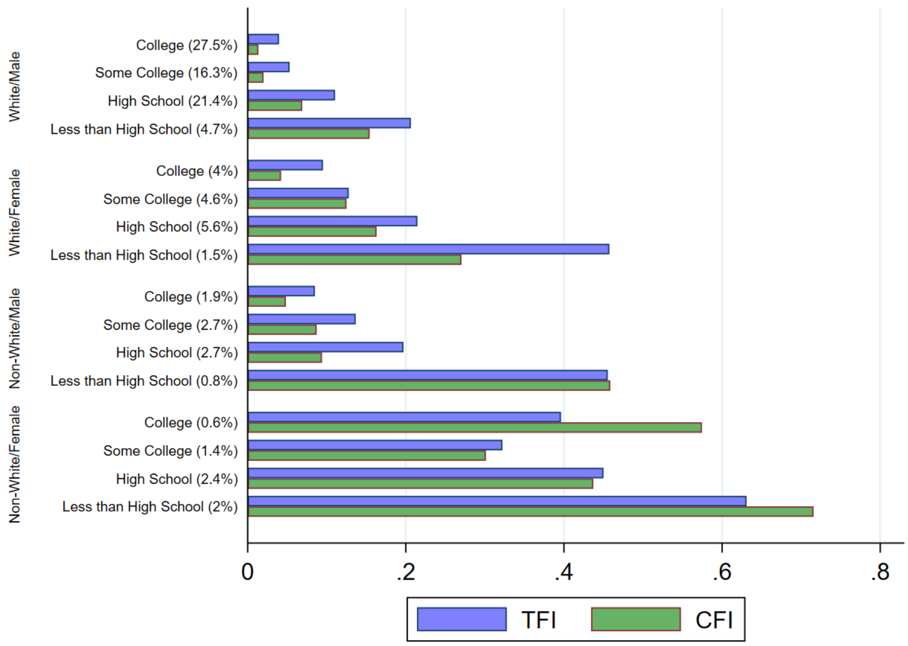
Figure 5 shows these patterns across different subgroups; completing high-school or college significantly reduces both the TFI and the CFI across all four subgroups. The prominent role of educational attainment is similar to the finding from poverty dynamics literature that households with higher human capital have lower chronic poverty rates (Neilson et al. 2008). This pattern is consistent with our findings from the spells approach, so does not appear an artifact of how one estimates the dynamics.[17]

A key policy-relevant question is whether food insecurity is more a feature of people or of places. Figure 6 displays the spatial variation we observe in CFI and TFI, as represented by the regional fixed effects estimates of the regression of TFI or CFI on the same set of covariates found in Table 3.[18] There exists some spatial variation in TFI, especially in Midwestern and some Southern states. The spatial variation in CFI is generally smaller than that in TFI, and most CFI regional fixed effects estimates are not statistically significantly different from zero. This suggests that short-term shocks (e.g., business cycle effects) may affect regions differently, but the core patterns of chronic food insecurity are more strongly associated with household characteristics than with their location.

Table 7 supplements the finding in Figure 6 by reporting the Shapley decomposition of the explained component of variation in CFI and TFI. The vector of region fixed effects cumulatively accounts for only 5-6% of the variation in food security status. By contrast, household income and food assistance program participation capture roughly half of the explained variation in both TFI and CFI. In the U.S., household-level budget constraints are the best predictors of food insecurity status. Spatial variance in food security manifests itself largely from transitory food insecurity.

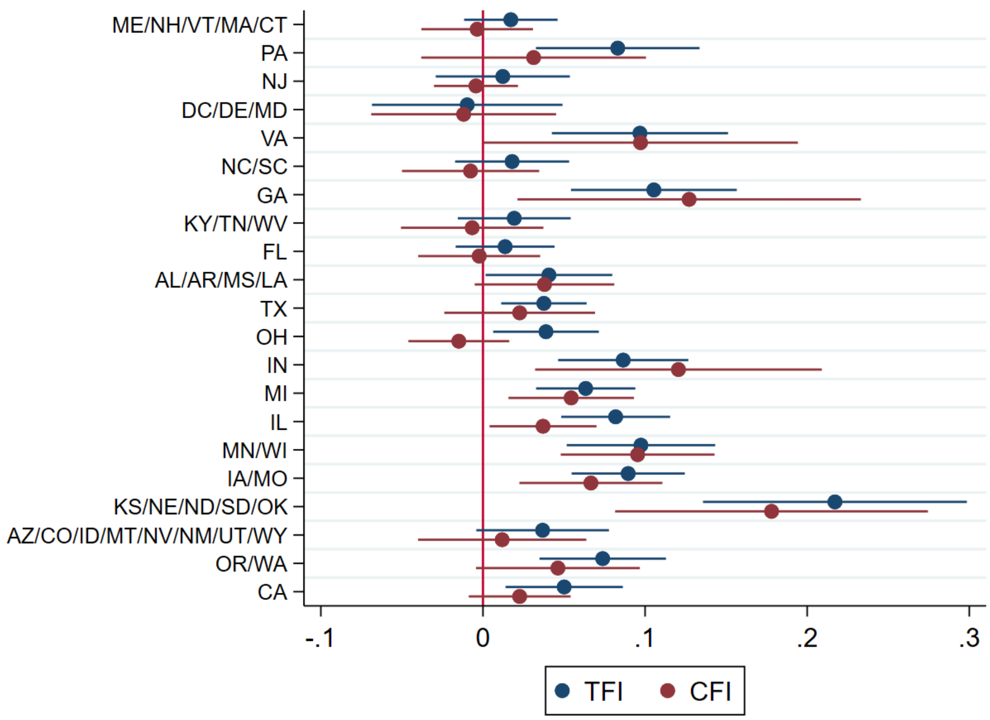
17. We further estimated more distributionally sensitive TFI and CFI using $\alpha = 2$ (i.e., for SFIG), in Table A7. The patterns are very similar to those in Table 6.

18. Table A6 presents the full regression results. Note that we aggregate a number of smaller, geographically adjacent states with small PSID sample sizes into a larger unit.




Note: The vertical axis shows the categories to which household heads belong. The percentage in parentheses indicates that category's population share. "Some college" indicates the household head at least attended college. "College" indicates the household head earned at least a bachelor's degree. Because PSID does not report educational status for every individual in every round, we base the head's educational status on the earliest available status recorded for that individual in the 2001-17 period.

Figure 5: Chronic Food Insecurity by Group




Note: Reference region is NY. AK, HA and other U.S. territories are excluded

Figure 6: Spatial Variation of TFI/CFI

Table 7: Shapley Decomposition of the TFI and the CFI

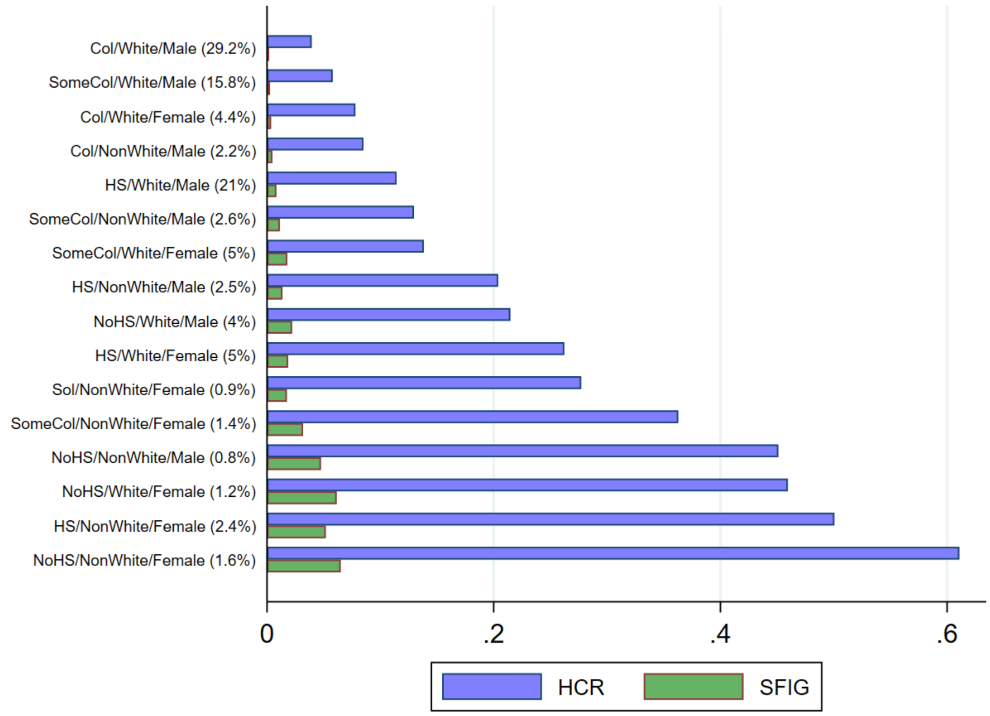
| | TFI | | CFI | |
|---|---|---|---|---|
| | $R^2$ | % | $R^2$ | % |
| Region | 0.032 | 0.058 | 0.022 | 0.052 |
| Education | 0.055 | 0.098 | 0.038 | 0.090 |
| Age | 0.005 | 0.010 | 0.003 | 0.008 |
| Gender | 0.052 | 0.092 | 0.048 | 0.114 |
| Race | 0.083 | 0.147 | 0.049 | 0.115 |
| Marital status | 0.029 | 0.052 | 0.023 | 0.054 |
| ln(income per capita) | 0.143 | 0.255 | 0.101 | 0.238 |
| Food Assistance (SNAP, WIC, etc.) | 0.096 | 0.171 | 0.090 | 0.212 |
| Others | 0.063 | 0.112 | 0.049 | 0.115 |
| Total | 0.559 | 0.996 | 0.424 | 0.996 |

Note: This decomposition is from the unadjusted (unweighted, no panel data adjustment) regression. Sample include households with non-missing PFS for 5 or more years from 2001 to 2017. "Others" include family size, % of children, employment, disability and change in status. Variation from time FE (less than 0.04) is omitted from this table..

## 3.4 Groupwise Decomposition

We saw earlier that there exist pronounced, identifiable differences among distinct sub-populations in food security dynamics under the spell lengths approach. By using the permanent approach and varying $\alpha$, we can study inter-group differences in the severity of food insecurity under the permanent approach as well.

Figure 7 shows how the prevalence (HCR) and severity (SFIG) of PFS vary across households defined again by household head race, gender and education characteristics. The results are, frankly, distressingly jarring. The HCR (61.0%) of the most food insecure group (households headed by a non-White woman with no more than a high school education) is 15 times greater than that (3.9%) of the most food secure group (households headed by white, men with college education). All three dimensions matter. A household headed by a non-White college graduate woman is more likely to experience food insecurity as one headed by a white man who never graduate from high school (28.0% versus 21.5%), but it is less than half as likely to be food insecure as if that non-White woman never completed high school. Within every race-education pair, female-headed households are between 35% and 226% more likely to be food insecure than an otherwise-comparable male-headed household.




Note: "HCR" and "SFIG" represent the headcount ratio and the squared food insecurity gap, respectively, of TFI. The vertical axis reflects categories to which household heads belong. The percentages in parentheses are population shares. "NoHS" means no completion of high school, "HS" indicates an earned high school degree but did not attend any college, "SomeCol" indicates some college attendance, and "Col" indicates completion of at least a bachelor's degree.

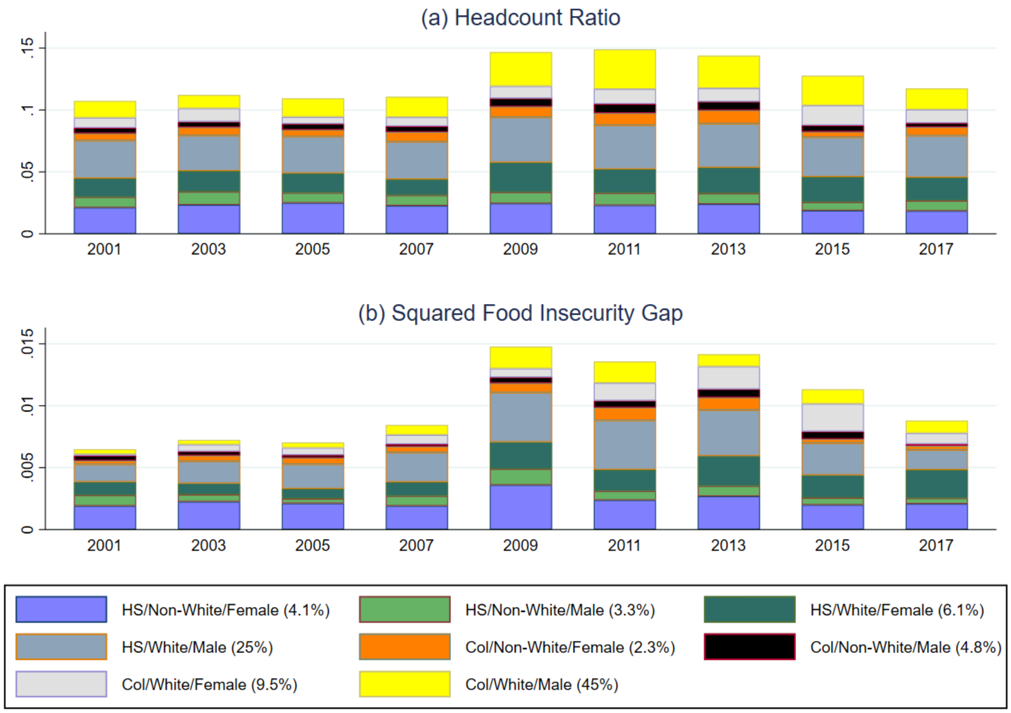
Figure 7: Food Insecurity Prevalence and Severity by Group

The same patterns exist, and are even starker, in terms of the severity of a household's food insecurity. The SFIG measure is 33 times greater for the most food insecure group (households headed by a non-White woman with no more than a high school education) as compared to that of the most food secure group (households headed by White men with a college education). Despite strong and positive correlation between prevalence and severity, higher prevalence does not necessarily imply higher severity, consistent with earlier findings based on HFSM data from the CPS (Flores-Lagunes et al. 2018). For example, among the female-headed households, those with a non-White head with high school education are more likely to be food insecure than those headed by a White woman without a high school degree, but its SFIG is lower. The broader message from these groupwise prevalence and severity decompositions, however, is that there exist large differences among demographic groups that vary in multiple race, gender or educational attainment dimensions, and that the known differences in groupwise prevalence of food insecurity masks even greater differences between groups in the severity of their food insecurity.

Figure 8 shows the change in HCR (top panel, a) and SFIG (bottom panel, b) over the period, decomposed by group.[19] Similar to our prevalence findings using the spells approach, HCR was stable prior to the Great Recession, rapidly increased from 2007 to 2009 as the recession struck, then slowly but incompletely recovered in the years thereafter. The surge in HCR between 2007 and 2009 was mostly driven by White-headed households, which accounted for 86% of the increase. Meanwhile, among non-White households without a college education, prevalence remained relatively stable.

Table 8 compares group-level HCR in three different years: pre-Recession (2003), right after the Recession (2011) and post-recession (2017). While the prevalence in 2003 (11.2%) is similar to that in 2017 (11.9%), we observe significant changes in group-level prevalence of food insecurity. The most food insecure groups in 2003 - those with non-White, female heads with no more than a high school education - became less food insecure in 2017 relative to 2003 (with HCR falling from 0.54 to 0.49), but the most food secure in 2003 - those with White, male heads with at least some college education - became less food secure (HCR rose from 0.02 to 0.04). Households with higher educational attainment were more likely to become food insecure during the Great Recession but also quickly recovered compared to those with low educational attainment. For instance, the increase among female, non-White-headed households was 4 percentage points for low attainment compared to 10 percentage point increase for households headed by female, non-White college graduates. Similarly, food insecurity prevalence among male, White-headed households increased by 36% (11% to 15%) among those with no more than a high school degree and has scarcely recovered since then (only to 14%), but for college graduates the increase was by 350% (from 2% to 7%) but they largely recovered

19. Appendix Figure A5 panel B displays an analogous plot of the FIG estimates.




Note: Household categories same as in Figure 4

Figure 8: Food Security Status By Group and Year

in 2017 (4%). Partly this reflects the patterns of chronic food insecurity, as those who are already food insecure cannot become food insecure during a business cycle downturn. But it also may reflect greater labor market volatility among jobs requiring at least some college education. The exception to this pattern are households headed by White females who attended college, among whom food insecurity prevalence fell even during the Great Recession.

The bottom panel of Figure 8 shows how food insecurity severity has changed over time. While the general pattern is similar to that of HCR, the proportional increase in severity, as reflected in SFIG, was much greater than in prevalence, reflecting worsening food insecurity among those already food insecure at the onset of the Great Recession. The 2013-2017 recovery in SFIG was also proportionately more rapid than in HCR. The most food insecure group (households headed by non-White women who never attended college) makes up merely 4% of our study sample but

Table 8: Pre- and Post- Food Insecurity Prevalence by Group

| | 2003 | 2011 | 2017 |
|---|---|---|---|
| High School or below, Non-White, Female | 0.54 | 0.58 | 0.49 |
| High School or below, Non-White, Male | 0.29 | 0.30 | 0.28 |
| High School or below, White, Female | 0.25 | 0.33 | 0.33 |
| High School or below, White, Male | 0.11 | 0.15 | 0.14 |
| College, Non-White, Female | 0.32 | 0.42 | 0.28 |
| College, Non-White, Male | 0.10 | 0.15 | 0.07 |
| College, White, Female | 0.13 | 0.12 | 0.11 |
| College, White, Male | 0.02 | 0.07 | 0.04 |
| Total | 0.11 | 0.15 | 0.12 |

Note: "College" is households where household head has at least one year of college education, Total prevalence is equal to that in the official USDA report

accounts for a plurality of the increase in severity during the Great Recession (27%) and 11% of the recovery between 2013 to 2017. Those changes are unobservable with conventional prevalence measures. White, male-headed households, which comprise a quarter of the study sample, accounts for the second largest increase in severity during the Great Recession (25%), and for the largest recovery (39%) from 2013 to 2017. The food insecurity severity indicators that the PFS measures enable thus add important insights to the official food security prevalence estimates, even of the ordinal HFSM groupings that USDA reports. Unpacking the causal mechanisms behind these group-differentiated food insecurity dynamics at both the extensive and intensive margins is an important direction of future research.

# 4 Conclusions

The study of long-term food security dynamics among U.S. households has been limited by constraints arising from HFSSM data availability. This paper introduced a new food security measure, PFS, the estimated probability that a household's food expenditures equals or exceeds the minimum cost of a nutritious diet. PFS is calibrated to, and strongly correlated with the official USDA food insecurity prevalence measure. One key advantage of PFS is that it can be generated over longer periods for which food expenditures data are available but HFSSM data are not. A second key advantage is that PFS offers a continuous measure that lends itself more readily to measuring the severity of food insecurity than do the categorical measures derived from HFSSM data.

We estimate PFS in 2001-2017 PSID data and study food security dynamics using both spells and permanent approaches. We found that just over half of food insecurity episodes are of short duration, just a single survey wave. The persistence of a food insecurity episode is positively correlated with its current spell length and negatively correlated with the strength of the macroeconomy. Although roughly two-thirds of households never experience food insecurity, more than half of all food insecurity experienced is chronic because of conditional persistence.

Sharp differences exist among groups categorized based on just the educational attainment, gender and race of household heads. A household's income is, unsurprisingly, the single best predictor of its food security status. The correlation of income with racial, gender and educational differences results in dramatic differences in households' propensity to suffer food insecurity, and especially in the severity of the food insecurity they experience. By contrast, geographic variation, conditional on household attributes, is rather modest, especially in chronic food insecurity.

Our study suffers important limitations that merit attention in follow-on research. For data reasons, we have limited information on recent immigrant populations. We excluded households whose heads changed, although the reasons for such changes - e.g., divorce, death - may be correlated with household food security. And we did not track new households that split from original households. Those issues will be especially salient if one extends the analysis over even longer periods than we study, as the population share represented by such households grows steadily over time. In addition, food security dynamics could be decomposed by other criteria, such as whether households include any children and/or senior citizens. One might also try to disentangle structural changes to households' expected food security status, following similar advances in the poverty dynamics literature (Carter and Barrett 2006). Our analysis also raises a host of questions about underlying mechanisms, especially about the causal effects of food assistance programs on food security status, severity, and persistence. These represent a rich research agenda for the future.

Reliably distinguishing chronic from transient food security is essential to inform policy design. Perhaps especially in the wake of massive unemployment shocks due to the COVID-19 pandemic and its economic disruptions, there seems considerable value to more precisely identifying how long one might expect households suddenly thrust into food insecurity to persist in that state, at least absent interventions to ameliorate their situation. Does job loss lead to similar near- or long-term food insecurity as does a lasting physical or mental disability caused by the disease, or sudden homelessness following an eviction or foreclosure after one cannot keep up with housing payments? If some identifiable subpopulations are much more likely to suffer persistent food insecurity than others, it may be feasible to target such people for assistance programs intended to remedy a longer-term challenge while encouraging shorter-term safety net protections for those expected to escape food insecurity reasonably quickly. The longer household panels we can build with PFS, as compared to the official measure based on HFSSM data, permit more careful study of food security dynamics that might usefully inform policy design and evaluation.

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For Online Publication

# Appendices

## A Additional Tables and Figures

Table A1: Household Food Security Survey Module

| Household Food Security Survey Module | |
|---|---|
| No. | Question |
| Q1 | "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? |
| Q2 | "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? |
| Q3 | "We couldn't afford to eat balanced meals." Was that often, sometimes, or never true for you in the last 12 months? |
| Q4 | 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) |
| Q5 | (If yes to question 4) How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months? |
| Q6 | 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) |
| Q7 | In the last 12 months, were you ever hungry, but didn't eat, because there wasn't enough money for food? (Yes/No) |
| Q8 | In the last 12 months, did you lose weight because there wasn't enough money for food? (Yes/No) |
| Q9 | 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) |
| Q10 | (If yes to question 9) How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months? |
| Questions 11-18 were asked only if the household included children age 0-17 | |
| Q11 | 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? |
| Q12 | "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? |
| Q13 | "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? |
| Q14 | In the last 12 months, did you ever cut the size of any of the children's meals because there wasn't enough money for food? (Yes/No) |
| Q15 | In the last 12 months, were the children ever hungry but you just couldn't afford more food? (Yes/No) |
| Q16 | In the last 12 months, did any of the children ever skip a meal because there wasn't enough money for food? (Yes/No) |
| Q17 | (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? |
| Q18 | 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) |

Source: Coleman-Jensen et al. (2021)

Table A2: Food Security Scale Values and Status Levels

| Number of Affirmative Responses | | FS Scale | FS Status Level* |
|---|---|---|---|
| (Out of 18) Households with children | (Out of 10) Households without children | | |
| 0 | 0 | 0.0 | Food security |
| 1 | | 1.0 | |
| | 1 | 1.2 | |
| 2 | | 1.8 | |
| | 2 | 2.2 | |
| 3 | | 2.4 | Low food security |
| 4 | | 3.0 | |
| | 3 | 3.0 | |
| 5 | | 3.4 | |
| | 4 | 3.7 | |
| 6 | | 3.9 | |
| 7 | | 4.3 | |
| | 5 | 4.4 | |
| 8 | | 4.7 | Very low food security |
| | 6 | 5.0 | |
| 9 | | 5.1 | |
| 10 | | 5.5 | |
| | 7 | 5.7 | |
| 11 | | 5.9 | |
| 12 | | 6.3 | |
| | 8 | 6.4 | |
| 13 | | 6.6 | |
| 14 | | 7.0 | |
| | 9 | 7.2 | |
| 15 | | 7.4 | |
| | 10 | 7.9 | |
| 16 | | 8.0 | |
| 17 | | 8.7 | |
| 18 | | 9.3 | |

Source: Bickel et al. (2000)

*Originally, the food security status level was categorized as "Food secure", "Food insecure without hunger", and "Food insecure with hunger." The USDA renamed these categories in 2005.

## Table A3: Description of Variables

| Variable | Description |
|---|---|
| Age | Age of household head |
| Female | Binary, =1 if household head is female |
| Non-White | Binary, =1 if household head is not White (African-American, American Indian, etc.)* |
| Married | Binary, =1 if household head is married |
| Income per capita | Total annual household income per capita (thousand dollars) |
| Food expenditure per capita | Total annual food expenditure per capita (thousand dollars) |
| Employed | Binary, =1 if household head is employed |
| Disabled | Binary, =1 if household head self-report as disabled |
| Mental problem | Binary, =1 if household head ever had any emotional, nervous, or psychiatric problems |
| Family size | Total number of people in household |
| % of children | Ratio of the number of children (0-17) to total number of family members |
| Less than high school | Binary, =1 if household head neither completed high school (attended school less than 12 years) nor achieved GED |
| High school | Binary, =1 if household head completed high school but did not attend college (attended school 12 years) |
| Some college | Binary, =1 if household head attended college but did not hold the bachelor's degree (attended school between 13 to 15 years) |
| College | Binary, =1 if household head completed the bachelor's degree (attended school 16 years or longer) |
| Food stamp/SNAP | Binary, =1 if household received food stamp/SNAP any time this year |
| Child meal | Binary, =1 if any child received free or reduced meal (breakfast or lunch) at school last year |
| No longer employed | Binary, =1 if household was employed in previous wave (2 years ago) but not employed (looking for work, retired, disabled, etc.) in current wave |
| No longer married | Binary, =1 if household was married in previous wave (2 years ago) but is not married (widowed, divorced, separated) in current wave |
| No longer owns house | Binary, =1 if household owned house in previous wave (2 years ago) but do not own house (rent or else) in current wave |
| Became disabled | Binary, =1 if household was not disabled in previous wave (2 years ago) but is disabled in current wave |
| (Group of) states | 23 Binary variables, states are grouped into 23 groups based on their location and sample size, and =1 if household resides in the corresponding group: Northeast (ME/NH/VT/MA/CT/RI, NY), Mid-Atlantic (PA, NJ, DC/DE/MD, VA), South (NC/SC, GA, KY/TN/WV, FL, AL/AR/MS/LA, TX), Mid-west (OH, IN, MI, IL, MN/WI, IA/MO), West (KS/NE/ND/SD/OK, AZ/CO/ID/MT/NV/NM/UT/WY, OR/WA, CA) and AK/HA/Don't know/Not Applicable |

*Races neither White nor African-American account for less than 3% of our study sample, so we do not further decompose non-White category.

Table A4: Estimates of Annual per capita Food Expenditure

| Variables | (1) $W_{ijt}$ | (2) $W_{ijt}$ | (3) $W_{ijt}$ | (4) $W_{ijt}$ | (5) $W_{ijt}$ |
|---|---|---|---|---|---|
| $W_{ijt-1}$ | 131.840 | 246.735 | 278.289 | 247.960 | 75.816 |
| | (3.29) | (9.73) | (23.21) | (50.69) | (90.31) |
| $W_{ijt-1}^2$ | | -11.926 | -19.278 | -7.347 | 93.034 |
| | | (0.81) | (4.41) | (16.35) | (42.37) |
| $W_{ijt-1}^3$ | | | 0.469 | -1.250 | -25.292 |
| | | | (0.26) | (2.11) | (8.92) |
| $W_{ijt-1}^4$ | | | | 0.080 | 2.560 |
| | | | | (0.09) | (0.85) |
| $W_{ijt-1}^5$ | | | | | -0.091 |
| | | | | | (0.03) |
| Controls | Y | Y | Y | Y | Y |
| Fixed Effects | Y | Y | Y | Y | Y |
| AIC | 99.83 | 99.74 | 99.74 | 99.74 | 99.73 |

Note: Independent variables are re-scaled by dividing them into 1,000 to properly display parameter estimates

Table A5: Regression of Food Expenditure and its Conditional Variance

| | Food exp per capita<br>(1) | Variance (food exp)<br>(2) |
|---|---|---|
| (Lagged) food exp per capita | 0.278 (0.02) | 0.012 (0.07) |
| (Lagged) food exp per capita$^2$ | -0.019 (0.00) | 0.046 (0.01) |
| (Lagged) food exp per capita$^3$/1,000 | 0.469 (0.26) | -3.290 (0.86) |
| Age | 0.005 (0.00) | -0.025 (0.01) |
| Age$^2$/1,000 | -0.054 (0.02) | 0.182 (0.08) |
| Non-White | -0.029 (0.01) | 0.175 (0.07) |
| Married | -0.015 (0.01) | -0.276 (0.06) |
| Female | -0.080 (0.01) | -0.093 (0.07) |
| ln(income per capita) | 0.105 (0.01) | 0.133 (0.03) |
| Employed | 0.012 (0.01) | 0.027 (0.06) |
| Disabled | -0.008 (0.01) | 0.123 (0.07) |
| Mental problem | 0.008 (0.02) | 0.033 (0.08) |
| Family size | -0.079 (0.01) | -0.136 (0.03) |
| % of children | -0.030 (0.03) | -0.611 (0.15) |
| Less than high school | 0.015 (0.02) | 0.170 (0.09) |
| Some college | 0.035 (0.01) | 0.069 (0.06) |
| College | 0.048 (0.01) | 0.105 (0.06) |
| Food stamp/SNAP | -0.043 (0.03) | -0.054 (0.16) |
| Child meal | 0.012 (0.02) | -0.195 (0.11) |
| No longer employed | -0.045 (0.02) | 0.075 (0.08) |
| No longer married | 0.208 (0.04) | 0.563 (0.08) |
| No longer owns house | 0.038 (0.02) | 0.287 (0.10) |
| Became disabled | 0.003 (0.02) | 0.060 (0.10) |
| N | 23,403 | 23,403 |
| Fixed Effects | Y | Y |

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Note: Sample includes household responses from 2001 to 2017. The generalized linear model (GLM) with log link function is used in the first column, assuming Gamma distribution. Base household is as follows: Household head is white/single/male/has high school diploma/not employed/not disabled/lives without spouse or partner or cohabitor. Fixed effects include wave(year) fixed effect and region(group of states) fixed effect.

Table A6: Regression of TFI and CFI on Characteristics

| | TFI (1) | CFI (2) |
|---|---|---|
| Age | -0.004 (0.00) | -0.002 (0.00) |
| $Age^2/1000$ | 0.039 (0.02) | 0.015 (0.03) |
| Non-White | 0.105 (0.01) | 0.113 (0.02) |
| Married | -0.053 (0.01) | -0.032 (0.02) |
| Female | 0.101 (0.02) | 0.122 (0.02) |
| ln(income per capita) | -0.077 (0.01) | -0.067 (0.01) |
| Employed | -0.006 (0.01) | -0.016 (0.01) |
| Disabled | 0.034 (0.01) | 0.037 (0.02) |
| Mental problem | -0.023 (0.01) | -0.049 (0.01) |
| Family size | 0.047 (0.01) | 0.045 (0.01) |
| % of children | -0.125 (0.02) | -0.136 (0.03) |
| Less than high school | 0.079 (0.02) | 0.081 (0.03) |
| Some college | -0.048 (0.01) | -0.036 (0.01) |
| College | -0.030 (0.01) | -0.014 (0.01) |
| Food stamp/SNAP | 0.131 (0.02) | 0.182 (0.03) |
| Child meal | 0.137 (0.02) | 0.190 (0.03) |
| No longer employed | 0.004 (0.01) | 0.006 (0.01) |
| No longer married | 0.038 (0.01) | 0.034 (0.02) |
| No longer owns house | -0.015 (0.01) | -0.020 (0.01) |
| Became disabled | -0.015 (0.01) | -0.016 (0.01) |
| N | 23,301 | 23,301 |
| $R^2$ | 0.470 | 0.339 |
| Fixed Effects | Y | Y |

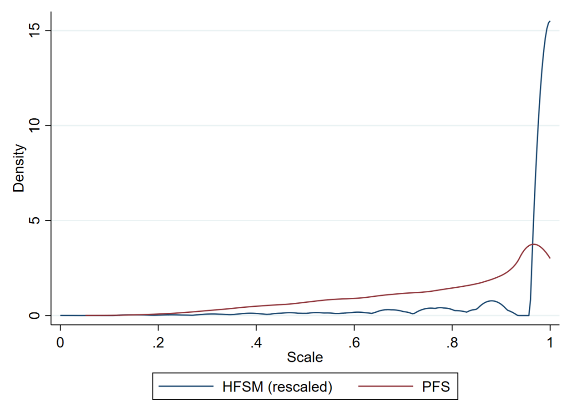
Note: Sample include households with non-missing PFS for 5 or more years from 2001 to 2017. Base household is as follows: Household head is white/single/male/has high school diploma/not employed/not disabled/lives without spouse or partner or cohabitor. Fixed effects include wave(year) fixed effect and region(group of states) fixed effect.

Table A7: Chronic Food Insecurity Status from the Permanent Approach - SFIG

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| | N | TFI | CFI | TFI-CFI | (CFI/TFI) | Chronic | | Transient | Never food insecure |
| | | | | | | Persistent | Not persistent | | |
| Total | 23,301 | 0.010 | 0.004 | 0.006 | 0.382 | 0.014 | 0.077 | 0.244 | 0.665 |
| Gender | | | | | | | | | |
| Male | 18,176 | 0.006 | 0.002 | 0.004 | 0.297 | 0.006 | 0.044 | 0.228 | 0.723 |
| Female | 5,125 | 0.025 | 0.011 | 0.014 | 0.454 | 0.044 | 0.196 | 0.299 | 0.461 |
| Race | | | | | | | | | |
| White | 15,692 | 0.007 | 0.003 | 0.005 | 0.354 | 0.008 | 0.050 | 0.231 | 0.711 |
| Non-White | 7,609 | 0.028 | 0.012 | 0.016 | 0.424 | 0.053 | 0.236 | 0.318 | 0.394 |
| Region | | | | | | | | | |
| Northeast | 1,587 | 0.002 | 0.000 | 0.002 | 0.105 | 0.000 | 0.020 | 0.125 | 0.856 |
| Mid-Atlantic | 3,177 | 0.008 | 0.003 | 0.005 | 0.331 | 0.015 | 0.069 | 0.225 | 0.691 |
| South | 8,130 | 0.012 | 0.005 | 0.008 | 0.385 | 0.018 | 0.088 | 0.233 | 0.661 |
| Midwest | 5,797 | 0.012 | 0.004 | 0.008 | 0.367 | 0.016 | 0.096 | 0.284 | 0.604 |
| West | 4,491 | 0.010 | 0.005 | 0.006 | 0.447 | 0.014 | 0.071 | 0.268 | 0.647 |
| Metropolitan area | | | | | | | | | |
| Metropolitan | 16,125 | 0.009 | 0.004 | 0.006 | 0.393 | 0.015 | 0.064 | 0.224 | 0.697 |
| Non-metropolitan | 7,102 | 0.012 | 0.005 | 0.008 | 0.363 | 0.012 | 0.106 | 0.290 | 0.592 |
| Education | | | | | | | | | |
| Less than HS | 2,687 | 0.038 | 0.018 | 0.020 | 0.479 | 0.088 | 0.234 | 0.403 | 0.275 |
| High school | 8,430 | 0.013 | 0.004 | 0.009 | 0.329 | 0.011 | 0.103 | 0.318 | 0.567 |
| Some college | 5,680 | 0.007 | 0.003 | 0.005 | 0.366 | 0.007 | 0.055 | 0.217 | 0.721 |
| College | 0.003 | 0.001 | 0.002 | 0.292 | 0.003 | 0.026 | 0.150 | 0.821 | |

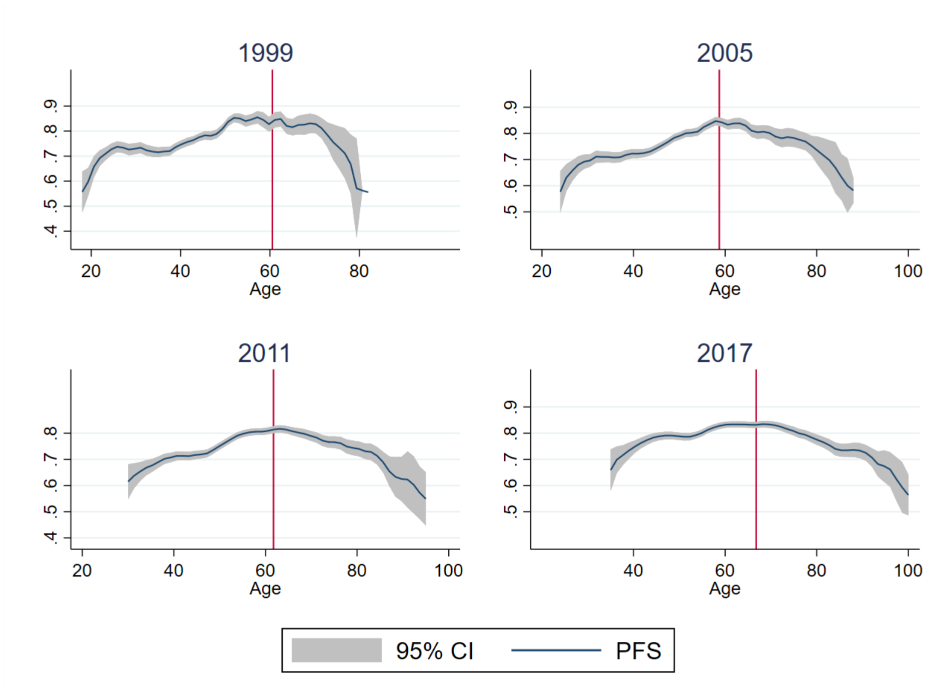
Note: Sample include households with non-missing PFS for 5 or more years from 2001 to 2017. The food insecurity measure is the squared food insecurity gap (SFIG) using the PFS following the method from Jalan and Ravallion (2000). Metropolitan area include the counties in metropolitan area with 250,000 or more population. States excluding Alaska and Hawaii belong to one of the five regions as described in Table A3. AK, HA and other U.S. territories are excluded in regional categories. The last four columns describe the distribution of households status which add up to one.


Figure A1: Probability Thresholds for being Food Secure



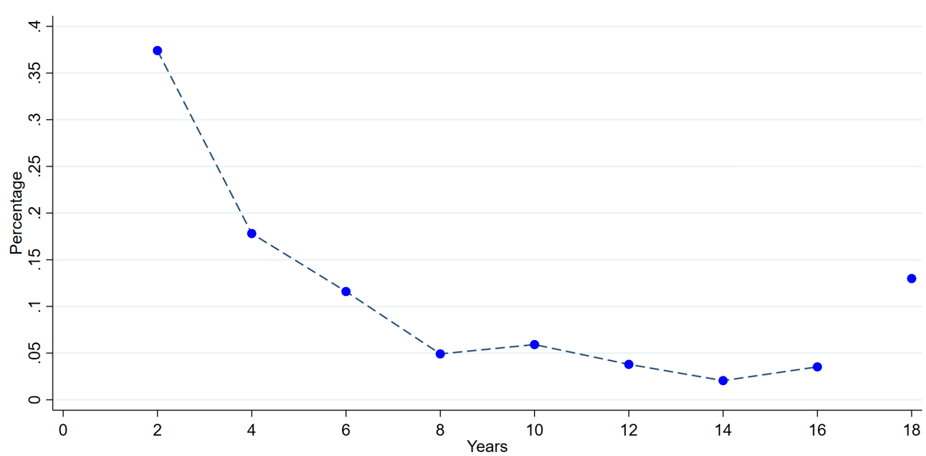

Note: The sample includes the waves where both measures are available (2001,2003,2015,2017), Mean/SD: 0.97/0.11(HFSM), 0.83/0.18(PFS))

Figure A2: Density Estimates of Food Security Indicators




Note: Vertical lines are the average retirement ages of the households in the sample

Figure A3: Predicted PFS over ages




Note: Sample includes households with the balanced PFS from 2001 to 2017. Note that the highest value includes potentially right-censored observations; it should be understood as the minimum spell length for those households.

Figure A4: Spell Length of Food Insecurity (2001)

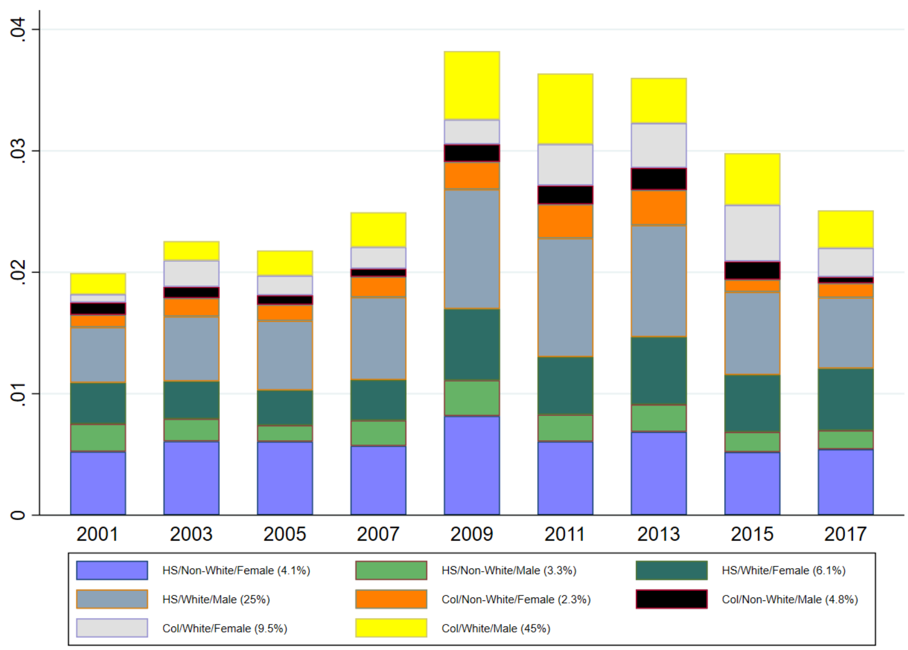



Figure A5: Food Insecurity Status (FIG) by Group and Year

# B Replication using Realized Food Expenditures Only

Table B1 replicates Table 3, showing how household characteristics are associated with different outcome indicators, including HFSM, PFS (both of which are identical to columns (3) and (4) in Table 3) and E, the ratio of household food expenditures to TFP cost. Nearly all the characteristics that are significantly associated with E are also significantly associated with the PFS in same direction, and those associated in the opposite direction are insignificant. The only exception is child meal status which is significantly associated in the opposite direction.

Table B1: Food Security Indicators and Their Correlates - with E

| | (1)<br>HFSM | (2)<br>PFS | (3)<br>E |
|---|---|---|---|
| Age | -0.001 (0.00) | 0.006 (0.00) | 0.015 (0.01) |
| $Age^2/1000$ | 0.018 (0.01) | -0.053 (0.02) | -0.157 (0.06) |
| Non-White | -0.005 (0.01) | -0.064 (0.01) | -0.210 (0.06) |
| Married | 0.008 (0.01) | 0.087 (0.01) | -0.052 (0.04) |
| Female | -0.009 (0.01) | -0.087 (0.01) | -0.206 (0.05) |
| ln(income per capita) | 0.025 (0.01) | 0.102 (0.01) | 0.373 (0.04) |
| Disabled | -0.038 (0.01) | -0.018 (0.02) | -0.062 (0.04) |
| Mental problem | -0.041 (0.01) | 0.022 (0.02) | -0.093 (0.07) |
| Employed | 0.007 (0.01) | 0.015 (0.01) | -0.015 (0.04) |
| Family size | 0.003 (0.00) | -0.071 (0.01) | -0.146 (0.02) |
| % of children | 0.043 (0.01) | 0.194 (0.03) | 0.024 (0.08) |
| Less than high school | -0.022 (0.01) | -0.036 (0.02) | 0.048 (0.04) |
| Some college | 0.002 (0.01) | 0.047 (0.01) | 0.131 (0.04) |
| College | 0.000 (0.01) | 0.025 (0.01) | 0.263 (0.05) |
| Food Stamp/SNAP | -0.100 (0.02) | -0.176 (0.03) | -0.020 (0.05) |
| Child meal | -0.027 (0.01) | -0.126 (0.03) | 0.173 (0.05) |
| No longer employed | -0.008 (0.01) | -0.026 (0.02) | -0.045 (0.05) |
| No longer married | -0.014 (0.01) | 0.016 (0.02) | 0.041 (0.12) |
| No longer owns house | 0.001 (0.01) | 0.047 (0.02) | 0.128 (0.08) |
| Became disabled | 0.022 (0.01) | -0.034 (0.02) | -0.003 (0.05) |
| FE | Y | Y | Y |
| N | 10,377 | 10,377 | 10,377 |
| $R^2$ | 0.219 | 0.302 | 0.250 |

Note: Base household is as follows: Household head is white/single/male/completed high school/not employed/not disabled.

Figure B1 replicates Figure 2 using E. This shows the distribution of food insecurity spells, defined by E, over years. This figure shows business cycle effects of food insecurity very similar to those generated using the PFS measure; households suffer longer food insecurity when they become food insecure when macroeconomic conditions are weak.

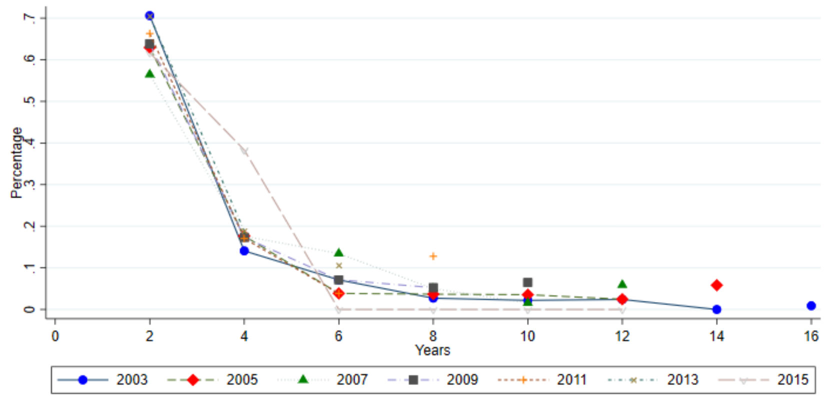



Figure B1: Spell Length of Food Insecurity (E) (2003-2015)

Table B2 replicates Table 5 with E, showing food security status transitions. We again see greater persistence and entry during the Great Recession and among more vulnerable groups. However, we find a higher ratio of those whose status changed - (FI, FS) and (FS, FI) - and a correspondingly lower ratio of those whose status remained unchanged - (FI, FI) and (FS, FS), reflecting slightly lower persistence and higher entry when we use the E measure that include period-specific stochastic realizations.

Figures B2 and B3 replicate Figures 3 and 4 with E. We observe a somewhat greater share of newly food insecure households with E compared to that we find with the PFS, again reflecting the year-on-year stochastic variation in E that PFS avoids. We also observe a greater food insecure share among groups that are less likely to be food insecure (e.g., households headed by a White male with college degree), also reflecting short-lived stochastically low draws from their food expenditures distribution when they are food secure in expectation.

We replicate Table 6 with E in Table B3. The overall ratio of "always food secure" is lower than that under the PFS, because more households could have temporarily have lower food expenditure and experience short-term food insecurity. The ratio of CFI to TFI is much lower (0.444) than that under the PFS measure (0.726). The differences in the CFI/TFI ratio across groups are not only much

Table B2: Transition in Food Security Status - with E

| | N | $(FI_{t-1},FI_t)$ | $(FI_{t-1},FS_t)$ | $(FS_{t-1},FI_t)$ | $(FS_{t-1},FS_t)$ | Persistence* | Entry* |
|---|---|---|---|---|---|---|---|
| Year | | | | | | | |
| 2003 | 2,681 | 0.05 | 0.06 | 0.06 | 0.83 | 0.44 | 0.07 |
| 2005 | 2,682 | 0.05 | 0.07 | 0.06 | 0.82 | 0.41 | 0.07 |
| 2007 | 2,682 | 0.05 | 0.06 | 0.06 | 0.83 | 0.48 | 0.06 |
| 2009 | 2,682 | 0.06 | 0.05 | 0.09 | 0.80 | 0.52 | 0.10 |
| 2011 | 2,682 | 0.07 | 0.08 | 0.08 | 0.78 | 0.49 | 0.09 |
| 2013 | 2,682 | 0.07 | 0.08 | 0.07 | 0.78 | 0.46 | 0.09 |
| 2015 | 2,682 | 0.06 | 0.08 | 0.07 | 0.79 | 0.43 | 0.08 |
| 2017 | 2,682 | 0.06 | 0.07 | 0.06 | 0.81 | 0.48 | 0.06 |
| Gender | | | | | | | |
| Male | 16,671 | 0.04 | 0.06 | 0.06 | 0.84 | 0.43 | 0.06 |
| Female | 4,784 | 0.11 | 0.10 | 0.10 | 0.68 | 0.53 | 0.13 |
| Race | | | | | | | |
| White | 14,292 | 0.05 | 0.06 | 0.06 | 0.83 | 0.46 | 0.07 |
| Non-white | 7,092 | 0.12 | 0.12 | 0.12 | 0.64 | 0.48 | 0.16 |
| Region | | | | | | | |
| Northeast | 1,451 | 0.02 | 0.04 | 0.04 | 0.90 | 0.28 | 0.04 |
| Mid-Atlantic | 2,938 | 0.06 | 0.07 | 0.06 | 0.80 | 0.49 | 0.07 |
| South | 7,504 | 0.06 | 0.07 | 0.08 | 0.80 | 0.44 | 0.09 |
| Midwest | 5,312 | 0.06 | 0.08 | 0.08 | 0.78 | 0.44 | 0.09 |
| West | 4,129 | 0.07 | 0.06 | 0.06 | 0.80 | 0.53 | 0.07 |
| Highest Degree | | | | | | | |
| Less than high school | 2,433 | 0.12 | 0.11 | 0.13 | 0.64 | 0.51 | 0.16 |
| High school | 7,791 | 0.08 | 0.08 | 0.08 | 0.76 | 0.48 | 0.10 |
| Some college | 5,673 | 0.05 | 0.07 | 0.06 | 0.82 | 0.44 | 0.07 |
| College | 6,824 | 0.04 | 0.05 | 0.05 | 0.87 | 0.43 | 0.05 |
| Disability | | | | | | | |
| Not disabled | 17,787 | 0.05 | 0.06 | 0.06 | 0.82 | 0.45 | 0.07 |
| Disabled | 3,668 | 0.09 | 0.09 | 0.09 | 0.72 | 0.50 | 0.12 |
| SNAP/Food stamp recipient | | | | | | | |
| Not SNAP/food stamp recipient | 19,424 | 0.05 | 0.06 | 0.06 | 0.82 | 0.46 | 0.07 |
| SNAP/food stamp recipient | 2,031 | 0.15 | 0.17 | 0.18 | 0.49 | 0.47 | 0.27 |
| Change in status | | | | | | | |
| No longer employed | 1,675 | 0.06 | 0.06 | 0.10 | 0.78 | 0.50 | 0.11 |
| No longer married | 312 | 0.05 | 0.12 | 0.10 | 0.73 | 0.28 | 0.12 |
| Became disabled | 1,413 | 0.08 | 0.08 | 0.09 | 0.74 | 0.50 | 0.11 |
| Newly received food stamp/SNAP | 584 | 0.12 | 0.21 | 0.11 | 0.55 | 0.37 | 0.17 |

Note: $FS_t(FI_t)$ is a dummy variable whether household is food secure(insecure) in time $t$. $(FI_{t-1},FI_t)$, $(FI_{t-1},FS_t)$, $(FS_{t-1},FI_t)$ and $(FS_{t-1},FS_t)$ are the four transition categories. Entries in each column report the proportion of households in that category.

smaller when measured under E, but also sometimes counter-intuitive. For instance, the ratio is higher for White-headed households compared to non-White-headed, and does not decrease monotonically as educational attainment increases. These results suggest that PFS better captures food security than does the simpler E measure.

Figure B4 shows TFI and CFI across different groups. Compared to the finding with the PFS in Figure 5, we observe significantly lower CFI for those more vulnerable to food insecurity, implying a greater share of households whose food expenditures fall above the threshold E. One reason is that vulnerable households are more likely to receive SNAP benefits, raising their total food expenditures (which include the SNAP benefit).

Table B3: Chronic Food Insecurity Status from the Permanent Approach -E

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| | N | TFI | CFI | TFI-CFI | (CFI/TFI) | Chronic | | Transient | Never food insecure |
| | | | | | | Persistent | Not persistent | | |
| Total | 24,136 | 0.126 | 0.056 | 0.070 | 0.444 | 0.006 | 0.050 | 0.362 | 0.582 |
| Gender | | | | | | | | | |
| Male | 18,754 | 0.102 | 0.041 | 0.060 | 0.406 | 0.006 | 0.035 | 0.333 | 0.625 |
| Female | 5,382 | 0.214 | 0.108 | 0.105 | 0.507 | 0.008 | 0.101 | 0.462 | 0.429 |
| Race | | | | | | | | | |
| White | 16,072 | 0.107 | 0.048 | 0.059 | 0.449 | 0.007 | 0.041 | 0.327 | 0.625 |
| Non-White | 7,964 | 0.238 | 0.103 | 0.135 | 0.434 | 0.003 | 0.100 | 0.563 | 0.334 |
| Region | | | | | | | | | |
| Northeast | 1,645 | 0.063 | 0.011 | 0.052 | 0.174 | 0.002 | 0.009 | 0.266 | 0.723 |
| Mid-Atlantic | 3,300 | 0.130 | 0.059 | 0.070 | 0.458 | 0.006 | 0.054 | 0.350 | 0.591 |
| South | 8,422 | 0.130 | 0.052 | 0.078 | 0.402 | 0.002 | 0.050 | 0.378 | 0.569 |
| Midwest | 5,980 | 0.140 | 0.062 | 0.078 | 0.444 | 0.006 | 0.056 | 0.408 | 0.531 |
| West | 4,648 | 0.131 | 0.071 | 0.060 | 0.540 | 0.015 | 0.056 | 0.335 | 0.594 |
| Metropolitan area | | | | | | | | | |
| Metropolitan | 16,740 | 0.112 | 0.045 | 0.067 | 0.403 | 0.003 | 0.042 | 0.343 | 0.612 |
| Non-metropolitan | 7,301 | 0.159 | 0.081 | 0.078 | 0.510 | 0.014 | 0.068 | 0.405 | 0.514 |
| Education | | | | | | | | | |
| Less than HS | 2,781 | 0.257 | 0.114 | 0.143 | 0.445 | 0.009 | 0.105 | 0.613 | 0.273 |
| High school | 8,243 | 0.149 | 0.064 | 0.085 | 0.426 | 0.007 | 0.057 | 0.421 | 0.516 |
| Some college | 5,714 | 0.111 | 0.049 | 0.062 | 0.443 | 0.003 | 0.046 | 0.343 | 0.608 |
| College | 6,498 | 0.080 | 0.033 | 0.047 | 0.410 | 0.008 | 0.025 | 0.262 | 0.705 |

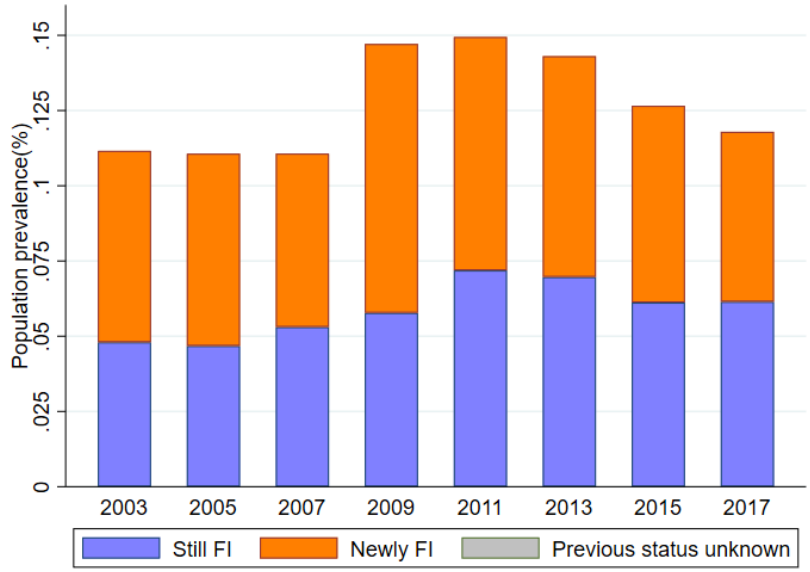



Figure B2: Change in Food Security Status - E

Figure B5 and Table B4 replicate Figure 6 and Table 7, respectively, using E. We find greater regional fixed effects and greater variation explained by regional differences in both TFI and CFI. This difference likely arises because spatial variation in cost of living has greater transitory impacts on realized food expenditures than on the PFS.

Figures B6 and B7 show group-wise decompositions of HCR and SFIG constructed from E. The E-based measures suggest smaller inter-group differences than do those based on the PFS measure. The HCR and SFIG of the most food insecure groups are 5-7 times greater than those of the most food secure groups, compared to the 15-33 times differences with PFS. This smaller gap largely reflects greater stochasticity among those groups who are typically food secure. The food insecure are structurally, and commonly chronically, food insecure, a feature that PFS picks up more clearly. Note, too, that the scales of the measures differ for the mechanical reason that E can exceed 1 while PFS cannot.

Table B5 replicates Table 8 using E. The patterns are again very similar.

Table B4: Shapley Decomposition of the TFI and the CFI - E

| | TFI | | CFI | |
|---|---|---|---|---|
| | $R^2$ | % | $R^2$ | % |
| Region | 0.023 | 0.086 | 0.014 | 0.137 |
| Education | 0.030 | 0.112 | 0.009 | 0.092 |
| Age | 0.002 | 0.008 | 0.001 | 0.012 |
| Gender | 0.016 | 0.059 | 0.006 | 0.055 |
| Race | 0.061 | 0.225 | 0.014 | 0.140 |
| Marital status | 0.012 | 0.044 | 0.005 | 0.051 |
| ln(income per capita) | 0.075 | 0.277 | 0.025 | 0.249 |
| Food Assistance (SNAP, WIC, etc.) | 0.027 | 0.101 | 0.010 | 0.096 |
| Others | 0.025 | 0.094 | 0.019 | 0.192 |
| Total | 0.271 | 1.004 | 0.104 | 1.025 |

Table B5: Pre- and Post- Food Insecurity Prevalence by Group - E

| | 2003 | 2011 | 2017 |
|---|---|---|---|
| High School or below, Non-White, Female | 0.29 | 0.43 | 0.35 |
| High School or below, Non-White, Male | 0.20 | 0.25 | 0.22 |
| High School or below, White, Female | 0.20 | 0.30 | 0.34 |
| High School or below, White, Male | 0.11 | 0.15 | 0.13 |
| College, Non-White, Female | 0.13 | 0.34 | 0.21 |
| College, Non-White, Male | 0.10 | 0.17 | 0.08 |
| College, White, Female | 0.12 | 0.15 | 0.11 |
| College, White, Male | 0.07 | 0.09 | 0.06 |
| Total | 0.11 | 0.15 | 0.12 |

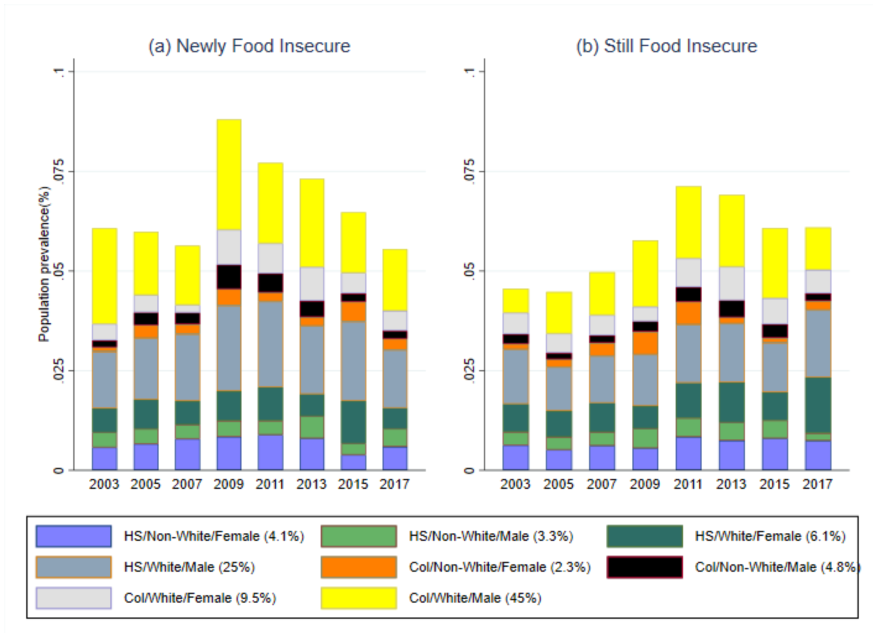



Figure B3: Change in Food Security Status by Group - E

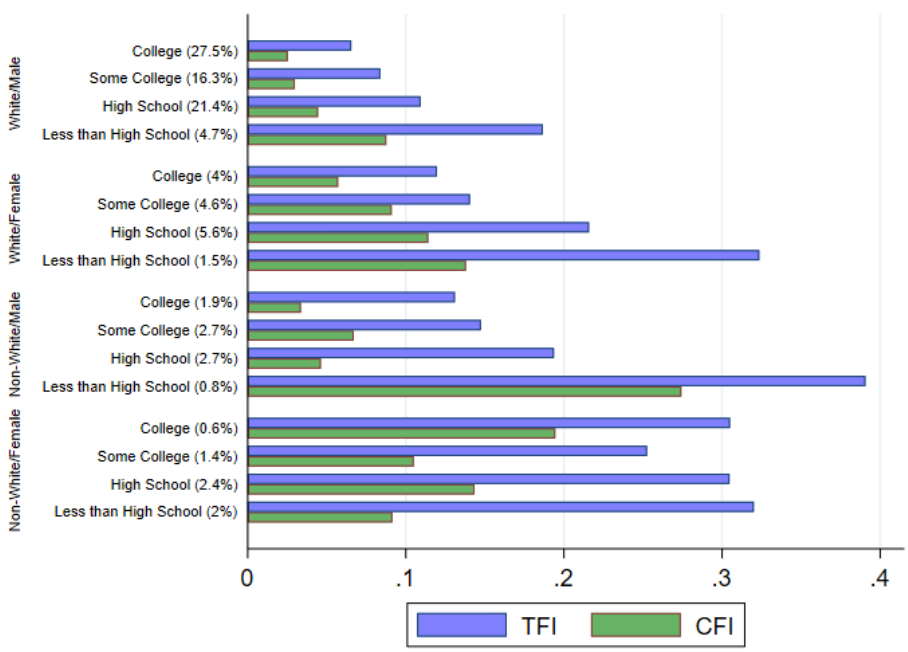
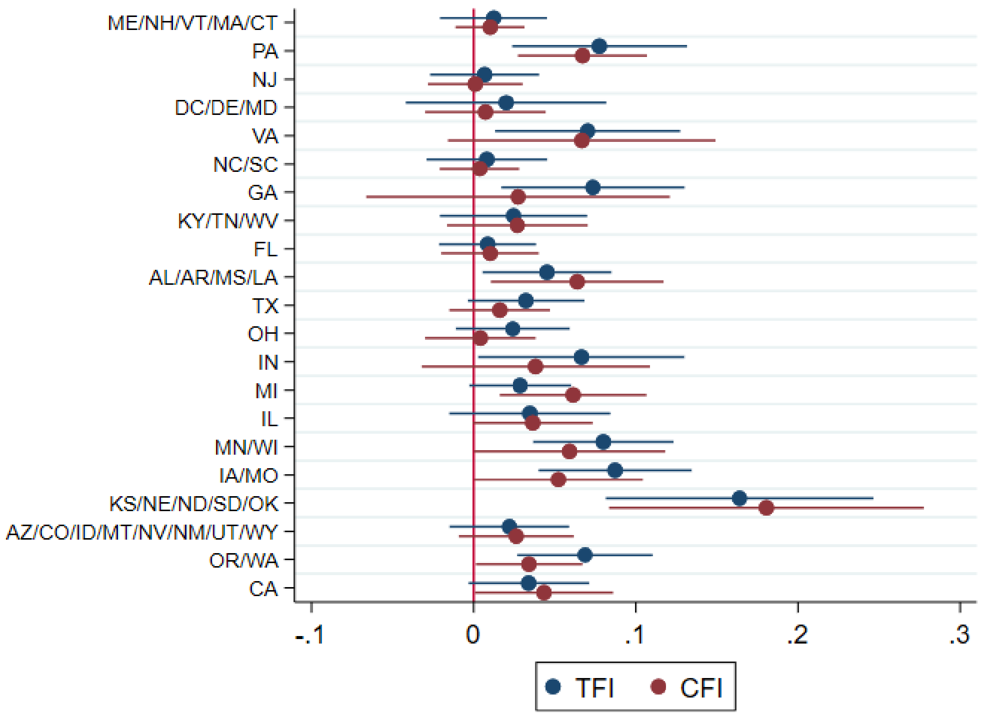



Figure B4: Chronic Food Insecurity by Group - E




Note: Reference region is NY. AK, HA and other U.S. territories are excluded

Figure B5: Spatial Variation of TFI/CFI - E

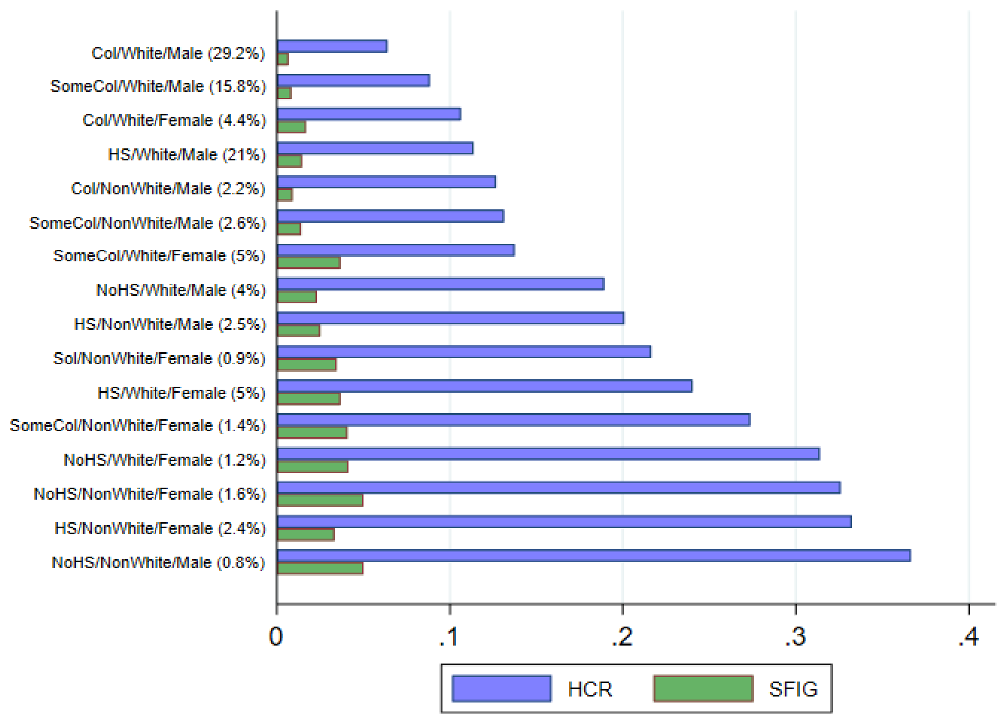



Figure B6: Food Insecurity Prevalence and Severity by Group - E

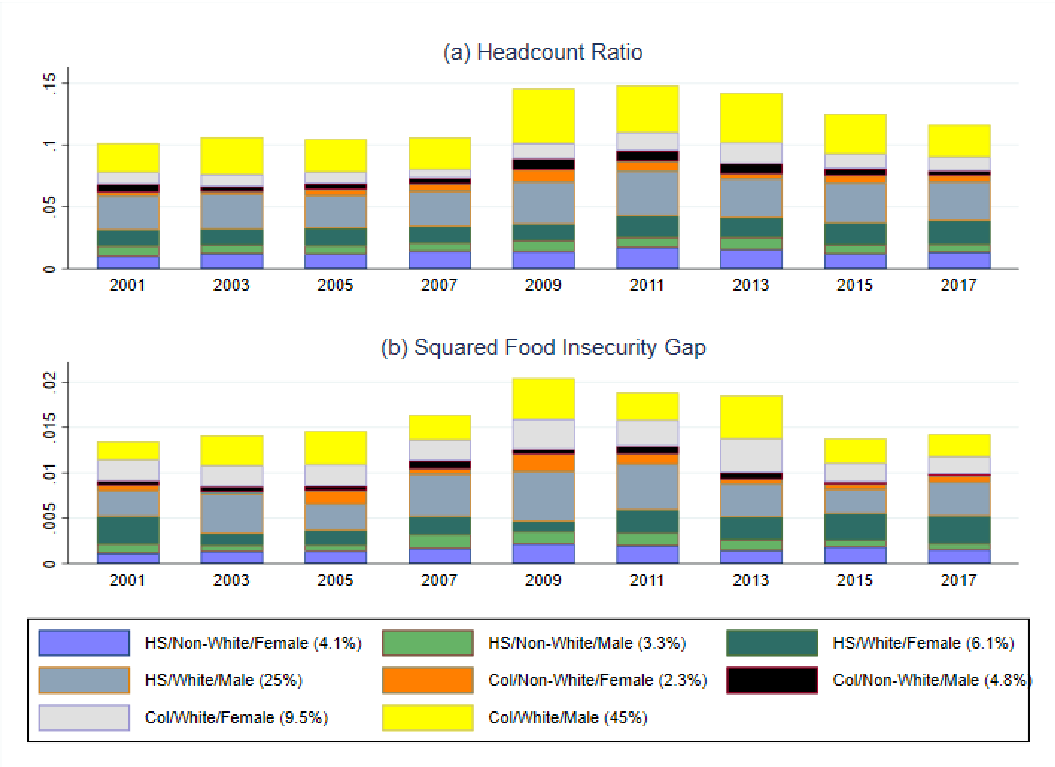



Figure B7: Food Security Status By Group and Year - E