Food Security Dynamics in the United States: Insights using a New Measure*

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February 2021

Abstract

This paper introduces a new measure, the probability of food security (PFS), to study food security dynamics in the United States. PFS represents the estimated probability that a household's food expenditures equal or exceed the minimum cost of a healthful diet, as reflected in the United States Department of Agriculture's Thrifty Food Plan monthly cost estimates. PFS matches the official food security prevalence measure in a given period, but enables richer study of the dynamics and severity of food insecurity. Applied to 2001-17 data from the Panel Study of Income Dynamics, we find that roughly half of households that become newly food insecure resume food security within two years. But the positive association of persistence with prior food insecurity means that half to two-thirds of food insecure households at any given time remain food insecure at least two years later. PFS varies dramatically with income and demographic characteristics, such that inter-group prevalence and severity measures differ by one or two orders of magnitude. Households headed by non-White women with low educational attainment disproportionately suffer persistent, chronic food insecurity, while White-headed households without a college degree account for most of the business cycle-associated variation in national food insecurity.

*We thank Liz Bageant, Anne Byrne, Will Davis, Matt Rabbitt and seminar participants at Cornell, Mississippi State and USDA ERS for helpful discussions and comments on earlier drafts. We are grateful to the US Department of Agriculture Economic Research Service (USDA ERS) and the University of Kentucky Research Foundation for financial support through cooperative agreement 58-4000-6-0059 subaward 3200000900-20-212. The views expressed in this paper are the authors' sole responsibility and do not represent those of USDA or ERS.

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1 Introduction

Food security means that people have access at all times to sufficient and nutritious foods to enjoy an active and healthy life (FAO 2020; Coleman-Jensen et al. 2020). Food insecurity has well-established, long-term, negative implications for health and educational outcomes, social skills, and adult economic productivity (Jyoti, Frongillo, and Jones 2005; Alderman, Hoddinott, and Kinsey 2006; Hoddinott et al. 2008; Gundersen and Ziliak 2015; Gundersen and Kreider 2009; Hoddinott et al. 2013) and therefore has been an important policy objective globally.

In the United States (US), at least one out of ten 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, 2019 nationwide prevalence for the US was 10.5% (Coleman-Jensen et al. 2020). But the Coronavirus Disease (COVID) pandemic shock has driven this sharply higher (Schanzenbach and Pitts 2020). According to the Census Bureau's Household Pulse Survey for Nov. 25 - Dec. 7, 2020, roughly 13 % of adults reported their households did not have enough to eat in the prior week, nearly four times the rate rate that USDA had reported for the whole of calendar year 2019 (Center on Budget and Policy Priorities 2021).

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 descriptive 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 shock to quickly become food secure again, temporary private and public food assistance financed by one-off appropriations or charitable donations may suffice to avert longer-term consequences. If instead one should reasonably expect a large share of the suddenly food insecure to persist in that new (to them) state, longer-lasting interventions and funding arrangements may be necessary. And if identifiable subpopulations predictably experience different food security dynamics, that should inform program targeting. Unfortunately, the empirical literature on food security dynamics in the US is quite thin, arguably insufficient to provide a firm empirical foundation to inform policy.

The dearth of food security dynamics evidence stems directly from measurement and data collection issues that are global, not specific to the US (Barrett 2010). US food security studies rely mainly on the Household Food Security Measure (HFSM), the official measure developed by USDA based on a survey instrument first introduced in the Household Food Security Survey Module (HFSSM) supplement to the Current Population Survey (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 and three ordinal categories (food security, low food security, and very low food insecurity) 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 five waves (1999, 2001, 2003, 2015, 2017), within which there exists a significant gap from 2003-15. The Early Childhood Longitudinal Survey (ECLS) collected food security data over different survey periods (1999-2007, 2010-2016). But both 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. But just as policymakers now routinely rely on poverty measures in the Foster–Greer–Thorbecke

(FGT, Foster, Greer, and Thorbecke 1984) tradition that can report more than just headcount prevalence, enabling study of distribution-sensitive severity of deprivation, so too would it be nice to study fluctuations in food insecurity severity over time.

These data limitations have significantly limited research on food security dynamics in the US. A few nice studies investigate household-level dynamics over time (Hofferth 2004, Kennedy et al. 2013, Ryu and Bartfeld 2012, Wilde, Nord, and Zager 2010). But none 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). Prior studies can also only study transitions and persistence using discrete categorical status, necessarily suppressing within-category variation over time in the severity of the food insecurity households experience. Further, these prior studies all predate Great Recession, raising questions as to past findings' current relevance.

To overcome these limitations, we introduce a new measure that is directly linked to the official HFSM and is implementable in longer panels, such as PSID, that include continuous measures of food expenditures. 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) allotments. 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. PFS adapts an econometric method (Cissé and Barrett 2018) that has been applied to study food security in the low-income world (Upton, Cissé, and Barrett 2016; Phadera et al. 2019; Vaitla et al. 2020; Knippenberg, Jensen, and Constas 2019).

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. Because PFS is a continuous, decomposable measure in the FGT tradition, it also enables the study of distribution-sensitive measures of food security severity, including at sub-group level. PFS thus offers the opportunity to obviate the data constraints that have previously limited the study of food security dynamics.

We apply the new PFS measure to investigate household-level food security dynamics in the US over 17 years using PSID data. We use approximately 23,000 survey responses from 2,700 nationally representative households surveyed biennially from 2001 to 2017, nine times each in total. We employ two different approaches to study food security dynamics reflected in PFS: 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.

The descriptive insights afforded by this new measure are striking. We find that roughly half of households that newly become food insecure in a given 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. As a result of these two facts, on average from half to two-thirds of households that are food insecure in any given year will still be food insecure two years later. The duration households remain food insecure 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. At sub-group level, the persistence of food insecurity is strongly associated with household characteristics. Food security status varies largely by demographic characteristics and, especially, household income, and relatively less by geography. Headcount prevalence rates differing by a factor of up to 28 - and severity measures by a factor of up to 112 - among sub-groups defined by race, gender and educational attainment.

The result is a mosaic of distinct patterns of food security dynamics in the US. Black and female-headed households with low educational attainment disproportionately suffer persistent, chronic food insecurity, while household headed by White men with a college education hardly ever suffer food insecurity, and a majority of the intertemporal fluctuation in food security status occurs among White-headed households without a college degree. The latter group accounted for 81% of the surge in food insecurity from 2007 to 2009, for example. This new descriptive evidence opens up many deeper questions about underlying mechanisms, the causal impacts of food assistance and other interventions, etc. The PFS measure offers a useful tool with which the research and policy communities can begin to explore these issues.

2 Empirical Framework

2.1 Data

This study uses the PSID, the leading nationally representative panel survey of US households, for two reasons. First, the PSID included the HFSSM in the 1999-2003 and 2015-2017 waves,[1] enabling us to calibrate and validate the PFS measure against the official food security measure that USDA estimates from CPS data each year. Second,the PSID's intensive tracking of a nationally representative sample of US households annually from 1968-1997 and biennially since 1997, enables study of long-term dynamics in a way no other data set does.[2].

We study a balanced sample of approximately 23,000 observations from 2,700 households where household heads remain the same over the 9 waves from 2001 to 2017. [3] The PSID has three sub-samples; Survey Research Center (SRC), which is

1. There are minor differences in the food security module between the PSID and the CPS. For example, while the CPS includes household income level as a screening criterion for whether households answer the HFSSM, the PSID does not have any screening criteria and all households answer the HFSSM instead. Tiehen, Vaughn, and Ziliak (2019) explains the differences in detail, concluding that their findings "lend credence to the use of the PSID for food insecurity research" (p.20).

2. The 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 the PSID either align fairly closely with, or at least exhibit similar trends as, 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 2019)

3. We omit attrited and split-off units (i.e., those that disappear from the sample or newly created households from existing households), for the following 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 descriptive statistics.

the original nationally representative household sample, Survey of Economic Opportunities (SEO), which is an over-sampling of low-income households so as to permit the study of that subpopulation, and Immigrant Refreshers added in 1997, 1999 and 2017 to represent immigrant population. We use the SRC and SEO subsamples, which account for 93% of the entire PSID population. We omit the immigrant subsample because its representativeness with respect to food security status has not yet been validated, unlike the other two sub-samples (Tiehen, Vaughn, and Ziliak 2019). Table 1 reports summary statistics of the sample households and each sub-sample[4]. 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, as compared to the SEO households. Note that the income variable does not include the value of food stamps or other public benefits (e.g., free or reduced price school meals).

The probability of food security (PFS) measure provides an estimate of the likelihood that a household's food expenditures equal or exceed some normative threshold value. Households report three different food expenditure categories - at home, delivered and eaten out - with their choice of period from daily to yearly. During our study period majority of households reported weekly expenditure.[5] PSID has provided the annual food expenditure by imputing and aggregating the three food expenditures since 1999. A natural candidate 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. 2020). USDA reports TFP monthly in its *Cost of Food Reports*.[6] The report provides individual costs per 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 and gender with the

4. Unless expressly indicated, all parameter estimates and standard errors we report are adjusted to account for panel survey data structure based on the survey weights, stratum and cluster codes the PSID includes in its raw data. We constructed a new survey weight and a new cluster to take into account serial correlation within household, as suggested by Heeringa, West, and Berglund (2010).

5. In the entire 1999 wave 83% of households reported weekly at-home food expenditure

6. 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).

Table 1: Summary Statistics

	Total		SRC		SEO	
	mean	sd	mean	sd	mean	sd
Household Head						
Age	56.35	13.62	56.58	12.17	53.19	23.84
Race						
White	0.85	0.35	0.91	0.24	0.01	0.20
Non-white	0.15	0.35	0.09	0.24	0.99	0.20
Married	0.61	0.48	0.63	0.42	0.30	0.90
Female	0.22	0.41	0.20	0.35	0.50	0.98
Highest educational degree						
Less than high school	0.11	0.31	0.10	0.26	0.24	0.84
High school	0.27	0.44	0.27	0.39	0.35	0.93
Some college	0.25	0.43	0.25	0.38	0.27	0.87
College	0.37	0.48	0.39	0.43	0.14	0.68
Employed	0.65	0.47	0.66	0.42	0.58	0.97
Disabled	0.19	0.39	0.19	0.34	0.23	0.83
Household						
Income per capita	40.26	30.43	41.60	27.30	21.71	35.24
Food expenditure per capita	3.65	2.11	3.73	1.87	2.51	3.55
Family size	2.22	1.16	2.22	1.02	2.26	2.67
% of children	0.10	0.19	0.10	0.17	0.16	0.47
Food Assistance						
Food stamp	0.05	0.22	0.04	0.18	0.22	0.81
Child meal	0.04	0.19	0.03	0.15	0.18	0.75
WIC	0.01	0.11	0.01	0.08	0.05	0.42
Elderly meal	0.01	0.07	0.00	0.06	0.02	0.24
Change in status						
No longer employed	0.08	0.27	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	0.26	0.07	0.23	0.07	0.51
N	22,556		16,602		5,954	

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.

monthly costs reported in June of each year, 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 in order to express everything in per capita terms.[7]

2.2 Empirical Strategy

2.2.1 Construction of the PFS

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

$$W_{ijt} = \sum_{\gamma=1}^{3} \beta_{M_\gamma} W_{ijt-1}^{\gamma} + \delta_M X_{ijt} + \omega_{Mt} + \theta_{Mj} + u_{Mijt} \tag{1}$$

In equation 1, 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. Note that food expenditures does not include the value of government transfers such as food stamps received. 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 the existing literature has found associated with food security, including demographics (age, gender, race, and educational attainment of the household head), income (which does not include the value of government transfers, such as SNAP), and changes since the prior survey round in employment, marriage, housing and disability status. The ω_t and θ_j parameters are year- and region- fixed effects and the M subscript indicates parameters

7. For households in Alaska and Hawaii where costs are only reported semi-annually, we use the costs reported in the first half of the year. 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.

related to the (conditional) mean. We include the lagged dependent variable up to a third order polynomial in W_{ijt}.[8] The predicted value of the outcome variable, $\hat{W}_{ijt}$, is the conditional mean of the household per capita food expenditure distribution. We assume W_{ijt} follows a Gamma distribution since it is continuous and non-negative.[9] We therefore estimate a generalized linear model (GLM) logit link regression for equation 1.

Given a mean zero error term, $E[u_{Mijt}] = 0$, the expected value of the squared residuals, $E[\hat{u}^2_{Mit}]$, equals the conditional variance. So regressing the squared residuals from the conditional mean equation on covariates yields a regression equation for the conditional variance of per capita food expenditures, using the same basic specification as in equation 1:

$$(\hat{u}_{Mit} - E[\hat{u}_{Mit}])^2 = \hat{u}^2_{Mit} = \sum_{\gamma=1}^{3} \beta_{V_\gamma} W^{\gamma}_{ijt-1} + \delta_V X_{ijt} + \omega_{Vt} + \theta_{Vj} + u_{Vijt} \tag{2}$$

where the V subscript stands for (conditional) variance and the other notation is as in equation 1. We estimate the conditional variance equation 2 by ordinary least squares because GLM would not reliably converge.

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 $\left(\alpha = \frac{\hat{W}^2_{ijt}}{\hat{\sigma}^2_{ijt}}, \beta = \frac{\hat{\sigma}^2_{ijt}}{\underline{W_{ijt}}}\right)$ where $\underline{W_{ijt}}$ is the per capita cost of the TFP diet calculated as described in Section 2.1.[10]

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,

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

8. Table A4 shows that the coefficient estimates on higher order polynomial terms are statistically insignificant thus the principle of parsimony favors a third order polynomial. That decision is supported by Akaike Information Criterion (AIC) statistics that remain nearly unchanged across different polynomial specifications.

9. 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.

10. For 847 observations (3.7% of the sample) the conditional mean and/or variance estimates were negative, thus their inverse CDF could not be constructed.We drop those outliers from the subsequent analysis.

We then 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 matches the annual USDA population prevalence estimate. For example, if the USDA reported 10% 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 10th percentile in the weighted sample as $\underline{P_t}$.[11] The estimated prevalence of food insecure households is thus mechanically equal to the official USDA estimate.

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.

2.2.2 Household-level Dynamics

Reliably distinguishing chronic from transient food security is essential to inform policy design. Perhaps especially now, in the wake of 2020's massive unemployment shocks due to the COVID pandemic and its economic disruptions, there is considerable value in having a clear sense as to 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 homeless 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 programs intended to remedy a longer-term challenge while encouraging shorter-term safety net protections for those expected to escape food insecurity almost as quickly as they entered. The longer panels we can build with PFS, as compared to the official measure based on HFSSM data, permits more careful study of food security dynamics that might usefully inform policy design and evaluation.

11. An alternative approach would be using a fixed cut-off probability $\underline{P}$ over the period as Cissé and Barrett (2018) originally did. We use varying cut-off probabilities so as to ensure our analysis corresponds directly with the official HFSM. Figure A1 depicts the resulting interannual variation in $\underline{P_t}$, which varies between (0.48, 0.59).

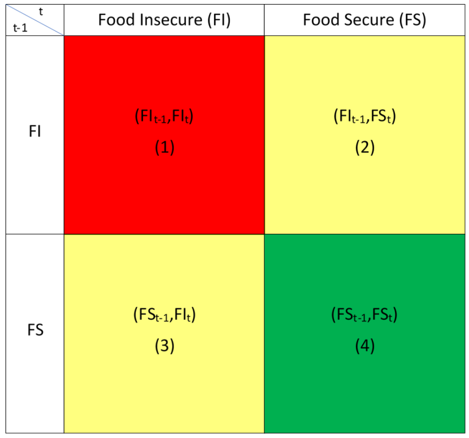


Figure 1: Food Security Transition Matrix

We adopt two different approaches to study food insecurity dynamics, borrowing from the poverty dynamics literature. The spells approach studies 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.

This joint distribution naturally yields estimates of persistence and entry rates. The persistence rate is the conditional probability that a food insecure household remains food insecure the next survey wave. One minus the persistence rate is often called 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. Under the spells approach, 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 can compute persistence and entry or exit rates for distinct sub-populations in order to investigate inter-group heterogeneity in food security dynamics. We can also investigate 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.

The second, permanent approach to studying food security dynamics identifies chronic food insecurity by mean intertemporal PFS and transient food insecurity 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, thus 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 chronically food insecure under the permanent approach, i.e., in expectation it is food insecure in any given period. TFI and the CFI are FGT-style measures, with important modification that they aggregate over time within households while FGT indices aggregate over households within a specific time period. The aversion parameter α reflects sensitivity to the severity of PFS shortfalls relative to $\underline{P_t}$. For $\alpha = 0, 1, 2$, CFI_i reflects the frequency of food insecurity, average severity of such shortfalls, which we lable 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.[12] 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.

We again categorize households into four categories, but now based on the permanent approach's CFI_i and TFI_i measures rather the spells approach. The first

12. As a FGT-style measure, TFI satisfies Sen (1976)'s monotonocity 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 expenditures from a higher PFS period to a lower one. See Foster, Greer, and Thorbecke (1984) or Cissé and Barrett (2018) for more in depth discussion and proofs. 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 (2007) explain.

category are 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 are 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., $CFI_i = TFI_i = 0$.

The two methods overlap imperfectly. The recurrently food insecure under the spells approach include the persistently food insecure under the permanent approach as a proper subset. The former could include some households that the permanent approach classifies as chronically but not persistently food insecure because those identified as chronically food secure by the spells approach can experience transient food security in a given year. Conversely, the persistently food secure under the permanent approach include as a proper subset the recurrently food secure under the spells approach, i.e., those who never experience consecutive periods of food insecurity but could experience nonconsecutive periods of food insecurity.

Each method has both strengths and weaknesses. Lawson and McKay (2002) favors the permanent approach not only because it 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 when survey intervals are more than a year in length, because one cannot observe possible breaks in a spell during multi-year, inter-wave intervals. The permanent approach, however, assumes a stationary process - i.e., it ignores trends or permanent shocks that lead to a structural change over time - and requires longer periods of panel data in order to estimate the intertemporal mean without small sample bias.

2.2.3 Groupwise aggregation

One can aggregate PFS over households - or, equivalently, decompose population-level PFS - to generate group-specific estimates and track how those change over time. We construct three different FGT-style national indices for each time period t based on the same α aversion parameter 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 α is the aversion parameter, N is the number of households in the population and $\underline{P_t}$ is the threshold probability of food security from Section 2.2.1. HCR, FIG and SFIG take $\alpha = 0, 1, 2$, respectively, and are thus also referred as P_0, P_1 and P_2 measure. The HCR represents the proportion of food insecure households in the population. The FIG, analogous to the poverty gap measure in poverty literature, 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 population is lower than the threshold PFS by $x\%$. The SFIG, analogous to the squared poverty gap index in 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, each having both strengths and weaknesses. On one hand, the HCR is the simplest and the most intuitive among the three measures. The official USDA-reported food security prevalence measure is an HCR. On the other hand, the HCR satisfies neither of Sen (1976)'s two basic axioms of well-being measures: the Monotonicity Axiom, which requires a measure increase as the food security of any person declines, and the Transfer Axiom, which requires the measure increase if there is a transfer from someone who is food insecure to someone whose is less (or not) food insecure. On the other hand, the FIG and the SFIG are less intuitive, but the FIG satisfies the Monotonicity Axiom (but not the Transfer Axiom), while the SFIG satisfies both axioms. For that reason, we favor the more distribution-sensitive SFIG measure in reporting on severity of food insecurity.

We report HCR, FIG and SFIG measures overall over the study period, 2001-17. Since all three measures are additively decomposable, we decompose these measures and their intertemporal patterns into groupwise aggregates based on key, easily targetable attributes of a household head: race, gender and education. 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

We begin by confirming the correspondence of the PFS measure with the official USDA Household Food Security Measure (HFSM). We re-scaled the HFSM such that it varies from zero to 1 and higher scale implies higher food security[13], so we can compare it with the PFS. The conditional mean and variance regression coefficient estimates from equations (1) and (2) are reported in Table A5. Both conditional moments are 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 among SNAP and WIC recipients. These associations suggest PFS relates to household attributes in a sensible way.

The PFS measure is strongly, positively correlated with the USDA scale. The Spearman rank correlation coefficient and Kendall's τ between the two measures are 0.31 and 0.25, respectively, significantly different from zero. The regression of the USDA scale on the PFS – reported in Table 2 – shows a strongly significant positive relationship despite the fractional nature of the HFSM and both measures' strong positive skewness.[14] By the nature of its construction, the PFS distribution is relatively smooth as 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.

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 the USDA scale and the PFS, and with the same sign, include income per capita, % of household members who are children, receipt of food stamps, lack of a high school diploma, and disability status, where the first two are positively and the other three are negatively associated. Most covariates have the same sign es-

13. $HFSM_{rescale} = \frac{9.3-HFSM}{9.3}$

14. Among the PSID sample households, 89% have a USDA scale value of 1, indicating food security, while the median estimated PFS is 0.9 and the 90th percentile equals 0.996). Figure A2 displays these distributions.

Table 2: Regression of the USDA scale on the PFS

	(1)	(2)	(3)	(4)
	HFSM	HFSM	HFSM	HFSM
PFS	0.180***	0.465***	0.182***	0.442***
	(0.02)	(0.08)	(0.02)	(0.08)
PFS^2		-0.217***		-0.199***
		(0.05)		(0.05)
Fixed Effects	N	N	Y	Y
N	11,798	11,798	11,798	11,798
R^2	0.117	0.127	0.137	0.146

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Sample include households surveyed in 2001, 2003, 2015 and 2017 with both the USDA scale and the PFS available. Fixed effects include region (state) and time (wave) fixed effects.

timates, even if the magnitudes and precision of the estimated coefficients differ. The PFS' correlations with these variables generally conform with the existing literature (e.g., Hofferth 2004, Tiehen, Vaughn, and Ziliak 2019). There exist a few correlates, however, that significantly correlate with both the USDA scale and the PFS, but in opposite directions. For example, age is associated convexly with the HFSM but concavely with the PFS. To us, the PFS relation appears more sensible, reflecting life cycle effects that food security peaks around retirement age,[15] as does the positive and significant effect of college attendance or completion, as well as the negative and significant correlation of PFS with the household head being female or non-White.

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, suggest to us that the PFS provides a useful complement to the USDA food security measure in the US.[16]

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

16. We also constructed the PFS using two different machine learning algorithms - LASSO and Random Forest - but the results were not significantly different from the PFS constructed using GLM, so in the interests of accessibility, we omit them here.

Table 3: Food Security Indicators and Their Correlates

	Continuous		Binary	
	(1)	(2)	(3)	(4)
	HFSM**	PFS	HFSM	PFS
	b/se	b/se	b/se	b/se
Age	-0.001 (0.00)	0.009*** (0.00)	-0.002 (0.00)	0.005*** (0.00)
$\text{Age}^2/1000$	0.020*** (0.01)	-0.077*** (0.01)	0.035*** (0.01)	-0.041** (0.02)
Female	-0.013 (0.01)	-0.065*** (0.01)	-0.019 (0.01)	-0.067*** (0.02)
Non-White	-0.003 (0.01)	-0.064*** (0.01)	-0.001 (0.01)	-0.060*** (0.01)
Married	0.009 (0.01)	0.038*** (0.01)	0.020* (0.01)	0.052*** (0.01)
ln(income per capita)	0.025*** (0.01)	0.103*** (0.01)	0.038*** (0.01)	0.093*** (0.01)
Family size	0.004 (0.00)	-0.035*** (0.00)	0.004 (0.01)	-0.032*** (0.01)
% of children	0.045*** (0.01)	0.114*** (0.02)	0.070*** (0.02)	0.125*** (0.03)
Less than high school	-0.014* (0.01)	-0.018* (0.01)	-0.021 (0.02)	-0.031 (0.02)
Some college	0.002 (0.01)	0.027*** (0.01)	0.002 (0.01)	0.025** (0.01)
College	-0.001 (0.01)	0.027*** (0.01)	-0.001 (0.01)	0.009 (0.01)
Employed	0.010* (0.01)	-0.002 (0.01)	0.021** (0.01)	0.007 (0.01)
Disabled	-0.041*** (0.01)	-0.038*** (0.01)	-0.065*** (0.01)	-0.032** (0.01)
Food stamp	-0.112*** (0.02)	-0.319*** (0.01)	-0.189*** (0.03)	-0.546*** (0.03)
Child meal	-0.016 (0.02)	-0.083*** (0.01)	-0.040 (0.03)	-0.184*** (0.03)
WIC	0.004 (0.02)	-0.034* (0.02)	-0.007 (0.04)	-0.157*** (0.05)
Elderly meal	0.013 (0.03)	-0.007 (0.03)	0.035 (0.05)	-0.039 (0.06)
No longer employed	-0.005 (0.01)	-0.034*** (0.01)	0.004 (0.01)	-0.026 (0.02)
No longer married	-0.018 (0.01)	-0.033*** (0.01)	-0.038 (0.02)	0.003 (0.02)
No longer owns house	-0.002 (0.01)	0.002 (0.01)	0.007 (0.02)	0.022 (0.02)
Became disabled	0.023** (0.01)	-0.008 (0.01)	0.030 (0.02)	-0.027 (0.02)
Fixed Effects	Y	Y	Y	Y
N	9842	9842	9842	9842
R^2	0.217	0.667	0.168	0.471

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

** HFSM is not continous, but discrete

Note: In column (1) and (2) dependent variables are continuous varying from 0 to 1, and in column (3) and (4) dependent variables are binary indicators whether household is food secure. Base household is as follows: Household head is white/single/male/completed high school/not employed/not disabled.Fixed Effects including wave (year) fixed effects and region (group of states) fixed effects.

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. Note that because PSID data are biennial, in theory, a household could have become food secure immediately after one PSID survey round and remained food insecure through the next survey wave until just prior to the third wave, implying that a one wave spell could have a duration as long 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, given that nearly three quarters of the households reported weekly food expenditure. Hence the broad intervals for the duration in years estimates in Table 4.

Table 4: Spell Length Distribution and Conditional Persistence Estimates

Spell Length Survey waves (Years duration)	Proportion	Conditional Persistence (Std.Error)
1 (1-4)	0.53	0.48 (0.03)
2 (3-6)	0.19	0.64 (0.03)
3 (5-8)	0.07	0.77 (0.04)
4 (7-10)	0.05	0.77 (0.05)
5 (9-12)	0.04	0.83 (0.04)
6 (11-14)	0.02	0.85 (0.04)
7 (13-16)	0.02	0.87 (0.05)
8 (15-18)	0.01	0.88 (0.03)
9 (17+)	0.06	.

Note: Includes 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. Since the data are right-censored, there is no upper limit of the range for the spell length of 9, the entire study period. Other spell lengths can likewise be right-censored if the household was food insecure in 2017.

Just over half (53%) of household food insecurity spells last just a single survey wave. That indicates that most US food insecurity spells are transitory, recovering immediately in the next wave. Yet, the longer households remain food insecure, the less likely they are to exit, as reflected in conditional persistence measures that are both large and increase steadily with spell length. Once a household has been food insecure for three consecutive waves or more, it faces a probability of at least 0.77 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 into the future.[17] Note the striking variation in the share of single wave (2 year) spell lengths, which range from 43-45% for those who were first food insecure in the 2005 or 2007 rounds just prior to the Great Recession, to 67-69% for those who were first food insecure during more robust macroeconomic conditions in 2003 and 2013. 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[18] (see below), so did food insecurity spell lengths increase. Not surprisingly, there seems a pronounced business cycle effect on food insecurity in the US.

Table 5 shows food security status transitions and persistence/entry rates, disaggregated by years and groups. Note that Table 5 reports the unconditional persistence rate, in contrast to the conditional (on spell length) persistence rate in Table 4. Transition shares necessarily sum to one (up to rounding error) across the four columns.

These results show two important facts. First, among households that are food insecure in any given period, whether or not they were previously food insecure, the persistence rate nationwide varies from 59-75% across years, peaking during the Great Recession. While food insecurity spells are predominantly transitory, lasting just one survey wave, most food insecure households in 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

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

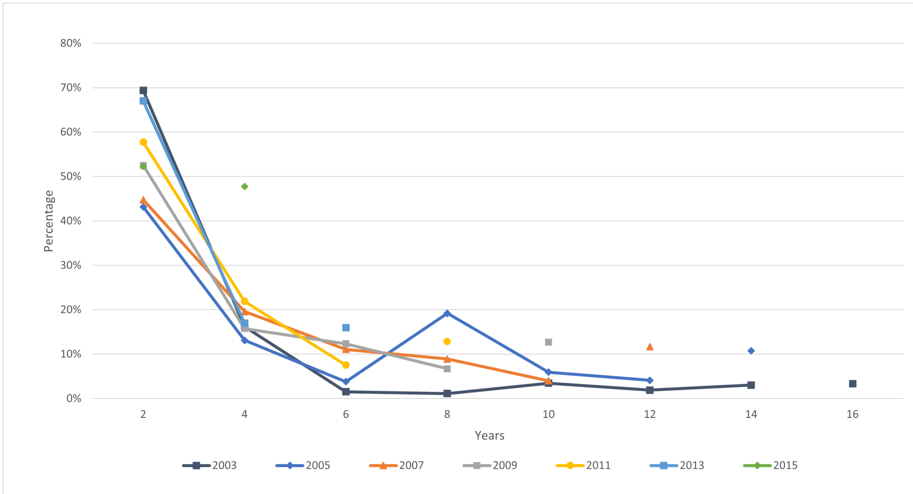
18. Recession dating per the *US Business Cycle Expansions and Contractions* report of the National Bureau of Economic Research.

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	2,164	0.06	0.04	0.04	0.85	0.61	0.05
2005	2,338	0.07	0.04	0.03	0.85	0.64	0.04
2007	2,431	0.07	0.03	0.04	0.86	0.69	0.04
2009	2,411	0.08	0.03	0.06	0.83	0.75	0.07
2011	2,540	0.09	0.05	0.04	0.81	0.63	0.05
2013	2,570	0.09	0.05	0.05	0.81	0.65	0.06
2015	2,569	0.08	0.06	0.04	0.82	0.59	0.05
2017	2,590	0.08	0.05	0.03	0.84	0.61	0.04
Gender							
Male	15,215	0.04	0.04	0.03	0.89	0.54	0.04
Female	4,398	0.21	0.08	0.08	0.63	0.72	0.11
Race							
White	13,150	0.05	0.04	0.04	0.88	0.56	0.04
Non-White	6,463	0.26	0.08	0.08	0.58	0.76	0.12
Region							
Northeast	1,337	0.03	0.02	0.01	0.94	0.65	0.01
Mid-Atlantic	2,675	0.06	0.05	0.05	0.84	0.57	0.05
South	6,968	0.10	0.05	0.04	0.81	0.67	0.05
Midwest	4,733	0.10	0.05	0.05	0.80	0.67	0.06
West	3,801	0.07	0.05	0.04	0.84	0.60	0.05
Highest Degree							
Less than high school	2,561	0.26	0.08	0.08	0.57	0.75	0.13
High school	5,998	0.10	0.06	0.06	0.77	0.61	0.07
Some college	4,967	0.07	0.04	0.04	0.85	0.64	0.04
College	6,087	0.02	0.02	0.02	0.93	0.47	0.02
Disability							
Not disabled	16,218	0.06	0.04	0.03	0.87	0.59	0.04
Disabled	3,395	0.17	0.06	0.08	0.69	0.73	0.10
SNAP/Food stamp recipient							
Not SNAP recipient	17,861	0.04	0.05	0.03	0.88	0.48	0.04
SNAP recipient	1,752	0.71	0.02	0.20	0.06	0.97	0.76
Change in status							
No longer employed	1,548	0.08	0.03	0.09	0.80	0.74	0.10
No longer married	284	0.04	0.13	0.03	0.81	0.23	0.03
Became disabled	1,273	0.11	0.03	0.10	0.75	0.76	0.12
Newly received SNAP	510	0.49	0.40	0.04	0.07	0.55	0.39

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. Temporary employment leave is classified as employed. "No longer married" includes divorced, widowed, separated, etc. Regions are as follows: Northeast (ME, NH, VT, MA, CT, NY, RI), Mid-Atlantic (PA, NJ, VA, DC, DE, MD), South (NC, SC, GA, KT, TN, WV, FL, AL, AR, MS, LA, TX), Midwest (OH, MI, IN, IL, MN, WI, IA, MO) and West (KS, NE, ND, SD, OK, AZ, CO, ID, MT, NV, NM, OR, WA, CA, UT, WY). AK, HA and other U.S. territories are excluded in regional categories (99 observations).

*Persistence = $Pr(FI_t|FI_{t-1})$, Entry = $Pr(FI_t|FS_{t-1})$



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

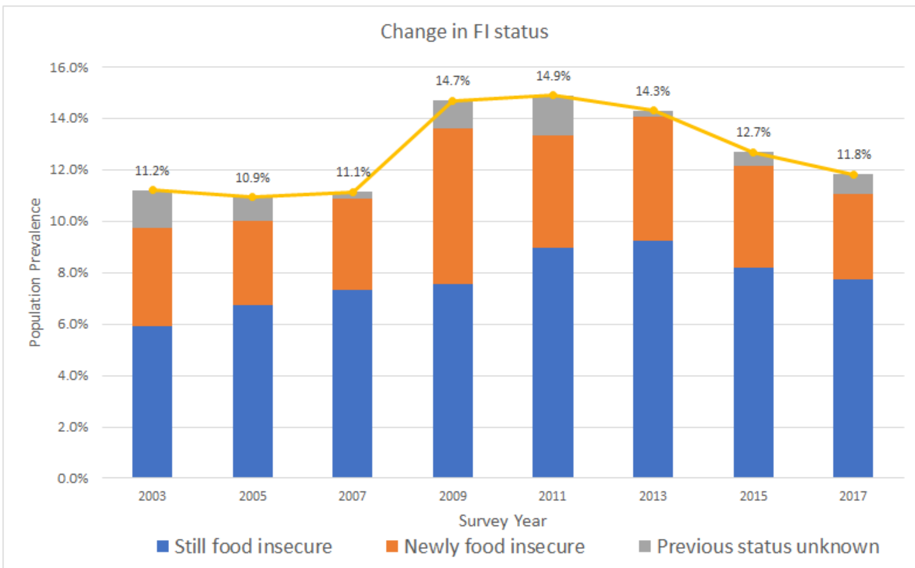
Figure 2: Spell Length of Food Insecurity (2003-2015)

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 2003-7, then suddenly jumped to just under 15% in 2009 and 2011 before slowly but incompletely recovering by 2017.

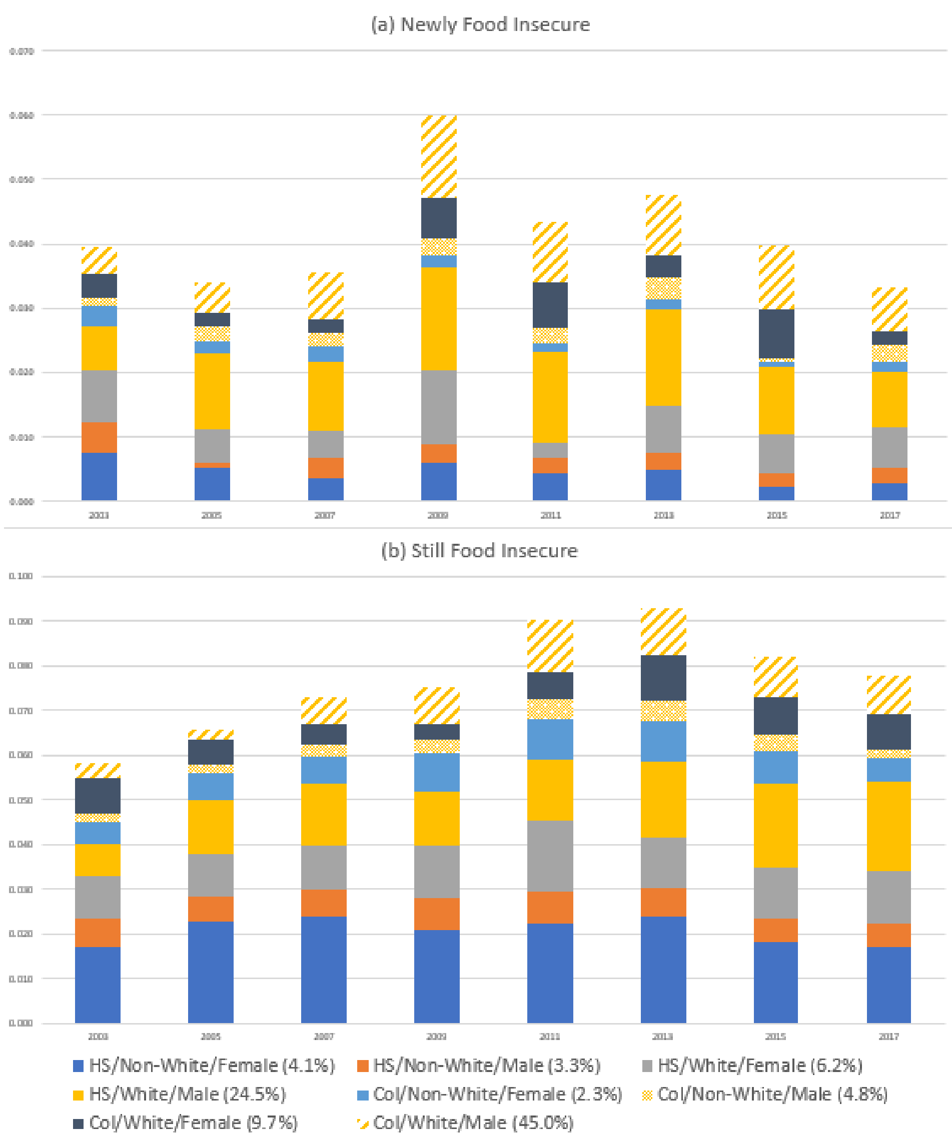
Unpacking the patterns in Figure 3 by household heads' race, gender and educational attainment, we see in Table 5 and Figure 4 that both the prevalence and persistence of food insecurity are markedly higher among households headed by women, those without a high school degree, the physically disabled, and SNAP recipients. Households whose head lost his or her job have especially high food insecurity persistence rates. Households whose head became unmarried through separation, divorce or death have especially low food insecurity persistence rates.

Figure 4 depicts the groupwise dynamics of food insecurity prevalence, divided among 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 as well (bottom panel, b). These graphics reflect the combination of sub-group population sizes as well as the group-specific transitions reflected in Table 5. Both panels clearly show vulnerable subgroups' disproportionately high rates of entry and persistence.



Note: Sample includes households with non-missing PFS from 2003 to 2017. "Still food insecure" and "Newly food insecure" 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



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. “Color” indicates the head is a person of color. Percentages in parentheses report each category’s share of the total population.

Figure 4: Change in Food Security Status by Group

For example, over this period, female-headed households accounted for 22.4% of the population but 40% of the newly food insecure and 60% of persistently food insecure households. The ratio of newly food insecure households increased by 70% during the Great Recession between 2007 to 2009 (3.6% to 6.1%) where 30% of the increase consisted of households whose head is female without a college education. That same sub-group accounted for 54% of the reduction in newly food insecure households in the post-Great Recession recovery. 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. Households headed by white women with no more than a high school degree accounted for the largest share (27%) of still food insecure households immediately after the Great Recession (2009-2011).

3.3 Household-level Dynamics: Permanent Approach

Turning to the permanent approach to the study of food insecurity dynamics, Table 6 columns (1) to (4) report the estimated chronic component (CFI) of total food insecurity (TFI) measures from the headcount ratio (HCR), following equation (4) and (5) with $\alpha = 0$. Columns (5) to (8) then 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)[19].

Overall, nearly 70% of households never experienced food insecurity over the 17 years we study. Persistent food security is thus the dominant state in the population. But among the 30% who are food insecure, 74% of the food insecurity households experience is chronic, meaning expected in every period. Sub-group analyses again show households whose head is female or non-White or have not completed high school have sharply higher rates of TFI. Perhaps most strikingly, CFI falls in the

19. We test for nonstationarity in the PFS series using the Fisher-type panel data unit-root test and an augmented Dickey–Fuller (ADF) 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 a weak test but provides some assurance that the permanent approach is not 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	22,324	0.124	0.092	0.032	0.744	0.026	0.066	0.210	0.698
Gender									
Male	17,291	0.076	0.044	0.032	0.577	0.010	0.034	0.191	0.765
Female	5,033	0.288	0.259	0.030	0.896	0.083	0.176	0.276	0.466
Race									
White	14,937	0.086	0.052	0.034	0.605	0.011	0.041	0.198	0.750
Non-White	7,387	0.345	0.327	0.018	0.947	0.113	0.213	0.283	0.390
Region									
Northeast	1,525	0.046	0.034	0.013	0.727	0.004	0.029	0.090	0.876
Mid-Atlantic	3,022	0.110	0.079	0.031	0.722	0.014	0.066	0.205	0.716
South	7,942	0.147	0.120	0.027	0.819	0.042	0.078	0.203	0.677
Midwest	5,401	0.146	0.104	0.042	0.709	0.036	0.068	0.248	0.649
West	4,316	0.115	0.082	0.033	0.711	0.015	0.067	0.226	0.693
Metropolitan area									
Metropolitan	15,532	0.115	0.084	0.031	0.727	0.026	0.058	0.197	0.719
Non-metropolitan	6,719	0.145	0.112	0.033	0.774	0.028	0.085	0.242	0.646
Education									
Less than HS	3,307	0.355	0.318	0.036	0.898	0.114	0.205	0.338	0.344
High school	7,259	0.148	0.105	0.043	0.708	0.023	0.082	0.282	0.613
Some college	5,472	0.098	0.065	0.033	0.666	0.020	0.045	0.199	0.736
College	6,286	0.042	0.023	0.020	0.535	0.003	0.019	0.114	0.864

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.

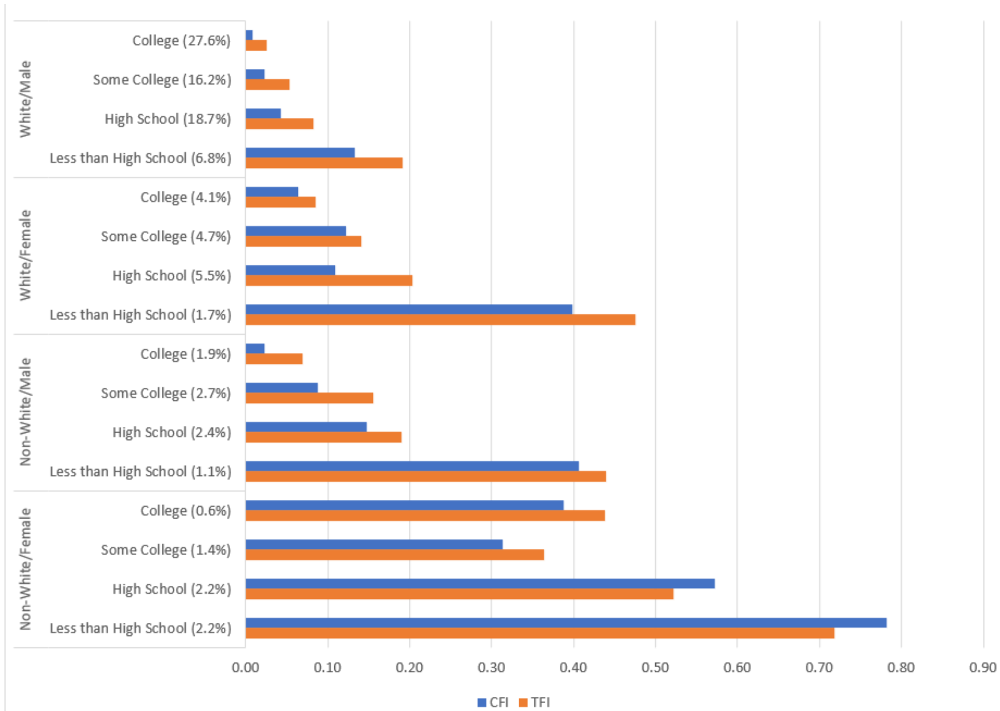
90-95% range for households within each of those three groups. Although most food insecure households within those sub-groups experience periods of food security - as reflected in the comparison of columns 5 and 6 - in expectation they are highly likely to be food insecure in any one period. Figure 5 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.[20]

A key policy-relevant question is whether food insecurity is more a feature of people or of places. If there exists considerable spatial variation independent of individual characteristics, then a stronger case can be made for geographic targeting of food assistance. Conversely, if individual characteristics drive most of the variation in food security status and severity, then indicator targeting or proxy means testing typically work better to direct scarce food assistance resources to those who most need it (Barrett 2002). 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.[21] One one hand, there exists certain level of spatial variation in TFI, especially in Midwestern states. On the other hand, there exists little spatial variation in CFI; there magnitudes are smaller than that of TFI, and most of them are not statistically significant. This difference in variation implies that short-term shocks (e.g. business cycle) affect regions differently; some regions are largely affected while some other regions are less affected.

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 merely 4% of the variation in food security status. By contrast, household income and food assistance program participation capture roughly a half of the explained variation in both TFI and CFI. In the US, household-level budget constraints are the best predictors of food insecurity status.

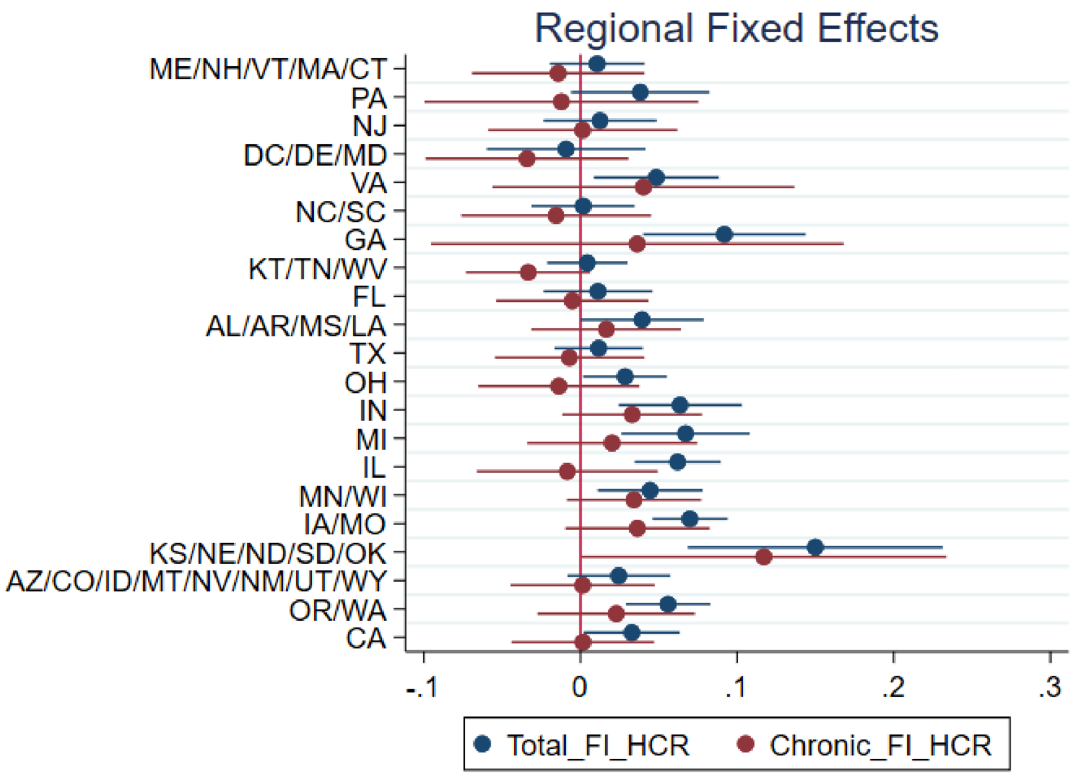
20. We further estimated more distributionally sensitive TFI and CFI using the aversion parameter $\alpha = 2$ (i.e., for SFIG), in Table A7. The patterns are very similar to those in Table 6.

21. Table A6 presents the full regression results.



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

Spatial variance in food security mostly comes from transitory food insecurity.

Table 7: Shapley Decomposition of the TFI and the CFI

	TFI		CFI	
	R^2	%	R^2	%
Region	0.027	0.042	0.019	0.036
Highest degree achieved	0.052	0.079	0.037	0.072
Age	0.008	0.012	0.004	0.008
Gender	0.063	0.096	0.060	0.116
Race	0.093	0.141	0.064	0.124
Marital status	0.043	0.066	0.029	0.056
ln(income per capita)	0.152	0.232	0.112	0.217
Food Assistance (SNAP, WIC, etc.)	0.166	0.253	0.148	0.287
Others	0.051	0.078	0.043	0.084
Total	0.655	0.998	0.517	0.999

Note: This decomposition is from the *unadjusted* 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 0.001) is omitted from this table.

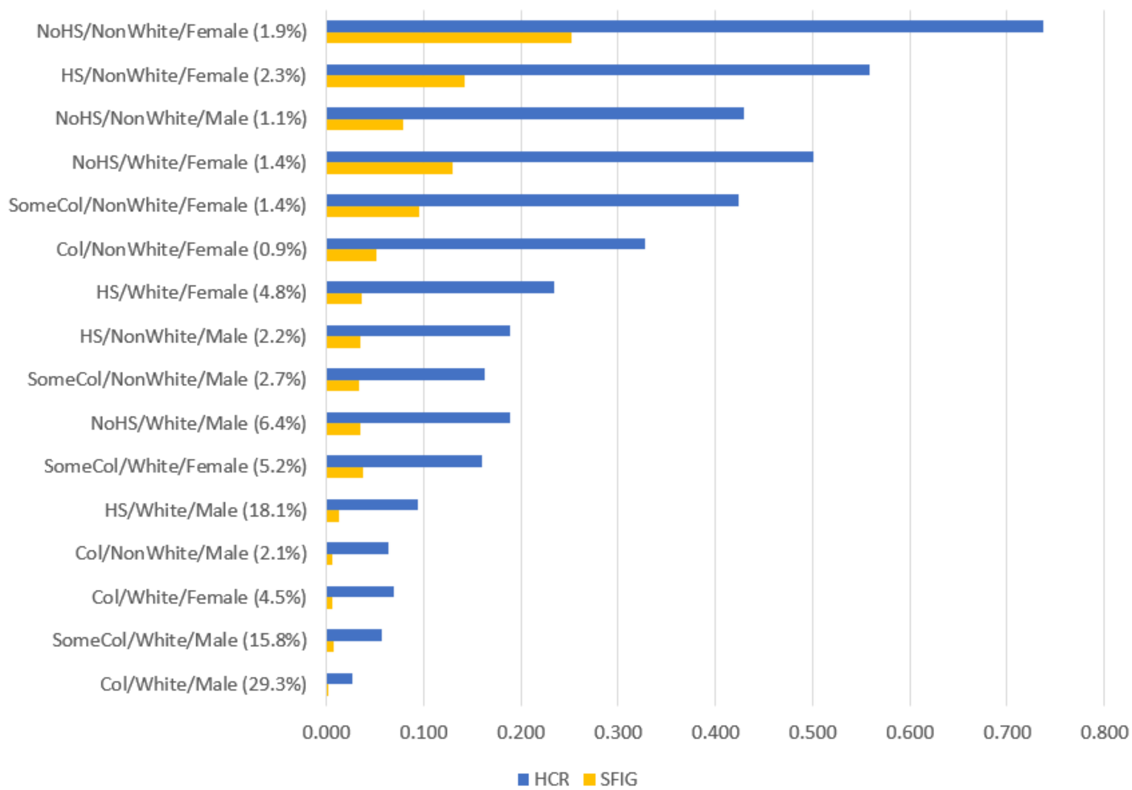
We saw earlier that there exist pronounced, identifiable differences among distinct sub-populations in food security dynamics under the spell lengths approach. By using the permanent approach and varying the aversion parameter, α, we can study inter-group differences in the severity of food insecurity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

Figure 7 shows how the prevalence (HCR) and severity (SFIG) of TFI vary across households defined again by household head race, gender and education characteristics. The results are, frankly, distressingly jarring. The HCR (73.7%)of the most food insecure group (households headed by a non-White woman with no more than a high school education) is 28 times greater than that (2.7%) of the most food secure group (households headed by white, men with college education). All three dimensions matter. A household headed by a college graduate who is a non-White woman is nearly twice as likely to experience food insecurity as one headed by a white man who never graduate from high school (32.8% versus 18.8%), 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 72 and 414% more likely to be food insecure than an otherwise-comparable male-headed household.

The same patterns exist, are indeed even starker, in terms of the severity of a household's food insecurity. The SFIG measure is 112 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 college education). Despite strong, positive correlation between prevalence and severity, higher prevalence does not necessarily imply higher severity. For example, households headed by non-White men who did not complete high school are more likely to be food insecure than those headed by non-White women who attended some college NoHS/non-White/male has higher HCR than SomeCol/non-White/female, but its SFIG is lower.

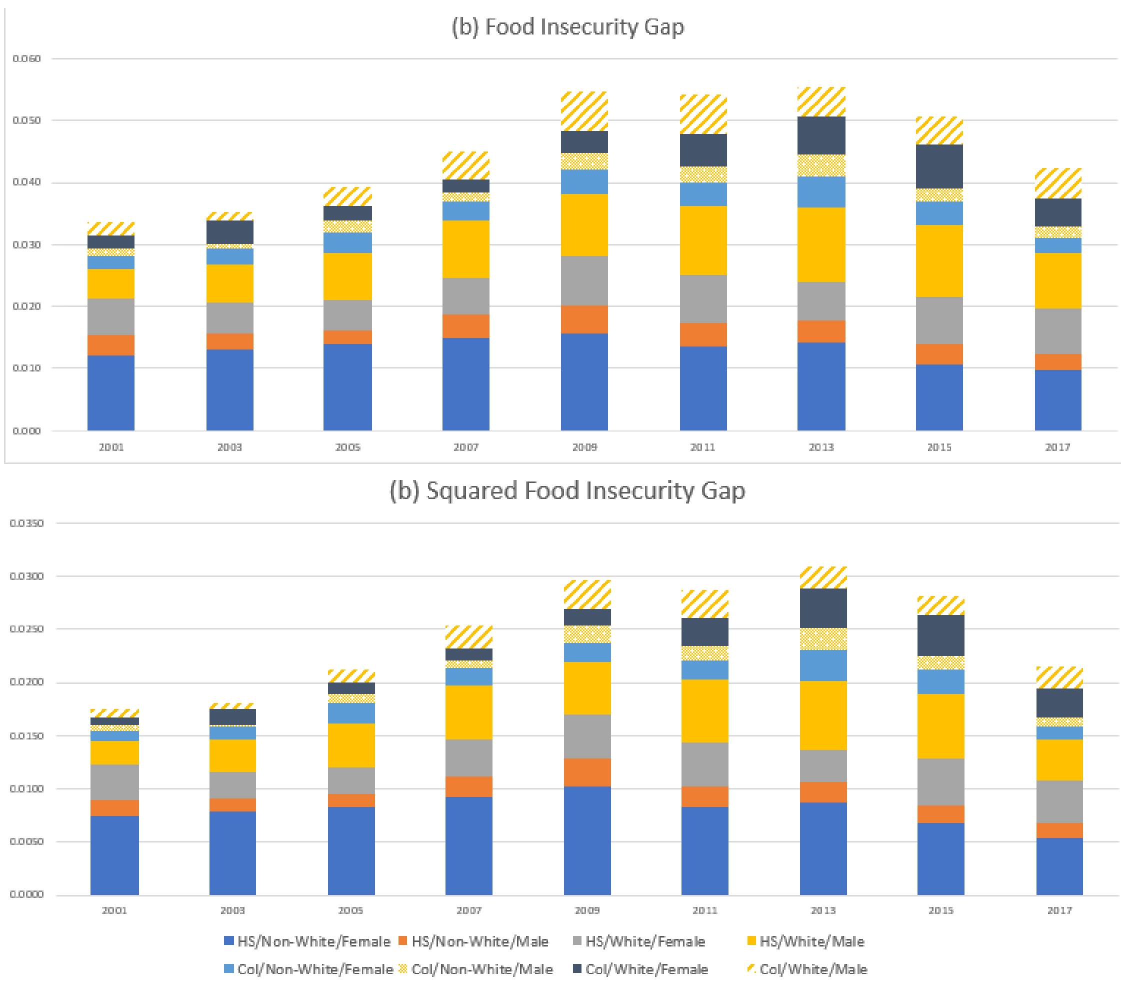
Figure 8 shows the change in HCR (top panel, a) and SFIG (bottom panel, b) over the period, decomposed by group[22]. Quite similar to our prevalence findings using the spells approach, HCR was stable prior to the Great Recession, rapidly increased from 2007 to 2009 as the Recession struck, then slowly 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 81% of the increase. Meanwhile, among non-white households without 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 (11.8%), we observe significant changes in group-level prevalence of food insecurity. The most food insecure groups in 2003 - those with non-White, female heads - became less food insecure in 2017 relative to 2003, but the most food secure in 2003 - those with White, male heads - became less food secure. The biggest rise in food insecurity prevalence from 2003-2011 occurred among households with non-White, female heads with at least some college education. That same group also enjoyed, by far, the greatest improvement in food security status from 2011-17. Households headed by non-White, males with no college education were the only subgroup not to experience an increase in food insecurity prevalence during the Great Recession, and have seen modest, steady

22. Figure A5 adds FIG



Note: "HCR" and "SFIG" represent the headcount ratio and the squared food insecurity gap, respectively, of TFI. The vertical axis reflect 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



Note: Household categories same as in Figure 4

Figure 8: Food Security Status By Group and Year

decline in the years since, although the prevalence of food insecurity in this group remains more than double the national average.

The bottom panel, however, shows that food insecurity severity was increasing steadily from 2001 through 2009. The severity of food insecure household's situation worsened even as their numbers remained largely unchanged. Conversely, the food insecurity severity measure improved relatively more rapidly from 2013-17 than did the HCR. 55% of the increased food insecurity severity prior to the Great Recession was among white, male-headed households, the most food secure sub-population. Most of the post-recession reduction in food insecurity severity occurred among the most food insecure sub-population, households headed by non-White women who never attended college. Unpacking the mechanisms behind these group-differentiated food security dynamics at the extensive and intensive margins is an important direction of future research.

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

	2003	2011	2017
High School or below, Non-White, Female	0.64	0.66	0.58
High School or below, Non-White, Male	0.30	0.29	0.26
High School or below, White, Female	0.26	0.33	0.33
High School or below, White, Male	0.09	0.14	0.13
College, Non-White, Female	0.37	0.46	0.28
College, Non-White, Male	0.11	0.16	0.11
College, White, Female	0.13	0.14	0.10
College, White, Male	0.02	0.06	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.

4 Conclusions

The study of long-term food security dynamics among US households has long been limited by constraints arising from HFSSM data availability. This paper introduced a new food security measure, the estimated probability that a household's food expenditures equals or exceeds the minimum cost 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 is a continuous measure that lends itself more readily to measuring the severity of food insecurity than do the categorical measures arising from HFSSM data.

We estimate PFS in 2001-17 PSID data and study food security dynamics using both spells and permanent approaches. We found that roughly 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 70% of households never experience food insecurity, more than half of all food insecurity experienced is chronic.

Sharp differences exist among groups categorized based on just the educational attainment, gender and race of household heads. Observed geograhic variation independent of household attributes are small, mostly short-term based. 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. This descriptive evidence raises a host of follow-on questions about underlying mechanisms, about the causal effects of food assistance programs on food security status, severity, and persistence, and related policy-relevant questions.

As a first application of the PFS measure, moreover, further refinements merit attention. 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 those two categories of households grows steadily over time. One might also, in the permanent approach to studying food insecurity dynamics, try to disentangle structural changes to households' expected food security status, following similar progression in the poverty dynamics literature (Carter and Barrett 2006).

Today we regularly see vivid images of suddenly-food-insecure households waiting in long food pantry lines. As we contemplate how best to respond, a crucial question is how we expect households' food security conditions to change over time in the absence of intervention. Our findings that food security spells typically last longer when initiated during an economic downturn, that most of the food insecure at any moment in time will remain food insecure for at least two years, and that food insecurity dynamics, prevalence, and severity differ dramatically across sub-populations targetable by easily-identified characteristics, carry policy relevant implications. Policy debates are building around the next five-year Farm Bill, which authorizes SNAP and other public food assistance programs in the US. PFS as another useful food security measure, and these empirical findings, offer entry points for further policy research to help inform food assistance program design and evaluation. If the Great Recession provides a guide, the current surge in food insecure households will persist for some time, necessitating sustained efforts to address unnecessary human suffering.

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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 (2019)

Table A2: Food Security Scale Values and Status Levels

Number of Affirmative Responses (Out of 18) Households with children	Number of Affirmative Responses (Out of 10) Households without children	FS Scale	FS Status Level*
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 were 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 variable, =1 if household head is female
Non-White	Binary variable, =1 if household head is not White
Married	Binary variable, =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 variable, =1 if household head is employed
Disabled	Binary variable, =1 if household head self-report as disabled
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 variable, =1 if household head did not complete high school (attended school less than 12 years)
High school	Binary variable, =1 if household head completed high school but did not attend college (attended school 12 years)
Some college	Binary variable, =1 if household head attended college but did not hold the Bachelor's degree (attended school between 13 to 15 years)
College	Binary variable, =1 if household head completed the Bachelor's degree (attended school 16 years or longer)
Food stamp	Binary variable, =1 if household received food stamp last year
Child meal	Binary variable, =1 if any child received free or reduced meal (breakfast or lunch) at school last year
WIC	Binary variable, =1 if household received foods from the WIC (Women, Infants, and Children) program last year
Elderly meal	Binary variable, =1 if household received free or reduced-cost meals for the elderly last year
No longer employed	Binary variable, =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 variable, =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 variable, =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 variable, =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, KT/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

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}	0.131***	0.250***	0.298***	0.323***	0.274**
	(0.00)	(0.01)	(0.03)	(0.07)	(0.12)
W_{ijt-1}^2		-0.0126***	-0.0241***	-0.0349	-0.00300
		(0.00)	(0.01)	(0.02)	(0.06)
W_{ijt-1}^3			0.000754**	0.00237	-0.00569
			(0.00)	(0.00)	(0.01)
W_{ijt-1}^4				-0.0000771	0.000782
				(0.00)	(0.00)
W_{ijt-1}^5					-0.0000323
					(0.00)
Controls	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y
AIC	98.36	98.25	98.24	98.24	98.24

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Regression of Food Expenditure and its Conditional Variance

	Food expenditure per capita (thousands)	Variance(food exp)
	(1)	(2)
	b/se	b/se
Lagged food expenditure per capita	0.298^{***} (0.03)	-0.288 (0.17)
Lagged food expenditure per capita^2	-0.0241^{***} (0.01)	0.134^{***} (0.04)
Lagged food expenditure per capita^3	0.000754^{**} (0.00)	-0.00641^{**} (0.00)
Age	0.00377^{*} (0.00)	-0.0778^{***} (0.02)
Age^2	-0.0000402^{**} (0.00)	0.000625^{***} (0.00)
Color	-0.0202 (0.02)	0.344^{**} (0.14)
Married	-0.0232 (0.01)	-0.575^{***} (0.16)
Female	-0.100^{***} (0.02)	-0.262 (0.18)
ln(income per capita)	0.135^{***} (0.01)	0.145^{*} (0.08)
Employed	0.0302^{**} (0.01)	0.284^{*} (0.15)
Disabled	-0.0000862 (0.02)	0.341^{**} (0.16)
Family size	-0.0766^{***} (0.01)	-0.176^{***} (0.04)
% of children	-0.0244 (0.03)	-0.834^{***} (0.25)
Less than high school	0.0206 (0.02)	0.224 (0.17)
Some college	0.0298^{**} (0.01)	0.131 (0.14)
College	0.0362^{***} (0.01)	0.194 (0.15)
Food stamp	-0.371^{***} (0.04)	0.207 (0.32)
Child meal	-0.0336 (0.03)	-0.318^{*} (0.18)
WIC	-0.106^{*} (0.05)	0.266 (0.48)
Elderly meal	0.0472 (0.04)	-0.362 (0.53)
No longer employed	-0.0358^{*} (0.02)	0.368 (0.23)
No longer married	0.199^{***} (0.04)	1.915^{***} (0.45)
No longer owns house	0.0525^{**} (0.02)	0.708^{**} (0.28)
Became disabled	0.00125 (0.03)	0.180 (0.26)
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, and the ordinary least square (OLS) is used in the second column. 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 state) fixed effect.

Table A6: Regression of TFI and CFI on Characteristics

	TFI	CFI
	(1)	(2)
	b/se	b/se
Age	0.000502 (0.00)	0.000604* (0.00)
Age^2	-0.00000990*** (0.00)	-0.00000850*** (0.00)
Female	0.0237*** (0.00)	0.0194*** (0.00)
Color	0.0206*** (0.00)	0.0115*** (0.00)
Married	-0.00642* (0.00)	-0.000518 (0.00)
ln(income per capita)	-0.0178*** (0.00)	-0.00923*** (0.00)
Employed	-0.0134*** (0.00)	-0.0119*** (0.00)
Disabled	0.00813** (0.00)	0.00359 (0.00)
Family size	0.00485** (0.00)	0.00296 (0.00)
% of children	-0.0237** (0.01)	-0.00754 (0.01)
Less than high school	0.0174*** (0.00)	0.00965* (0.01)
Some college	-0.00109 (0.00)	0.00113 (0.00)
College	0.00260 (0.00)	0.00429** (0.00)
Food stamp	0.145*** (0.01)	0.119*** (0.02)
Child meal	0.0748*** (0.01)	0.0652*** (0.01)
WIC	0.0479*** (0.01)	0.0413** (0.02)
Elderly meal	-0.00101 (0.01)	-0.00174 (0.01)
No longer employed	-0.00749*** (0.00)	-0.00936*** (0.00)
No longer married	0.00579 (0.00)	0.00260 (0.00)
No longer owns house	-0.00494* (0.00)	-0.00718*** (0.00)
Became disabled	-0.00318 (0.00)	-0.00195 (0.00)
N	22,324	22,324
R^2	0.574	0.445
Fixed Effects	Y	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

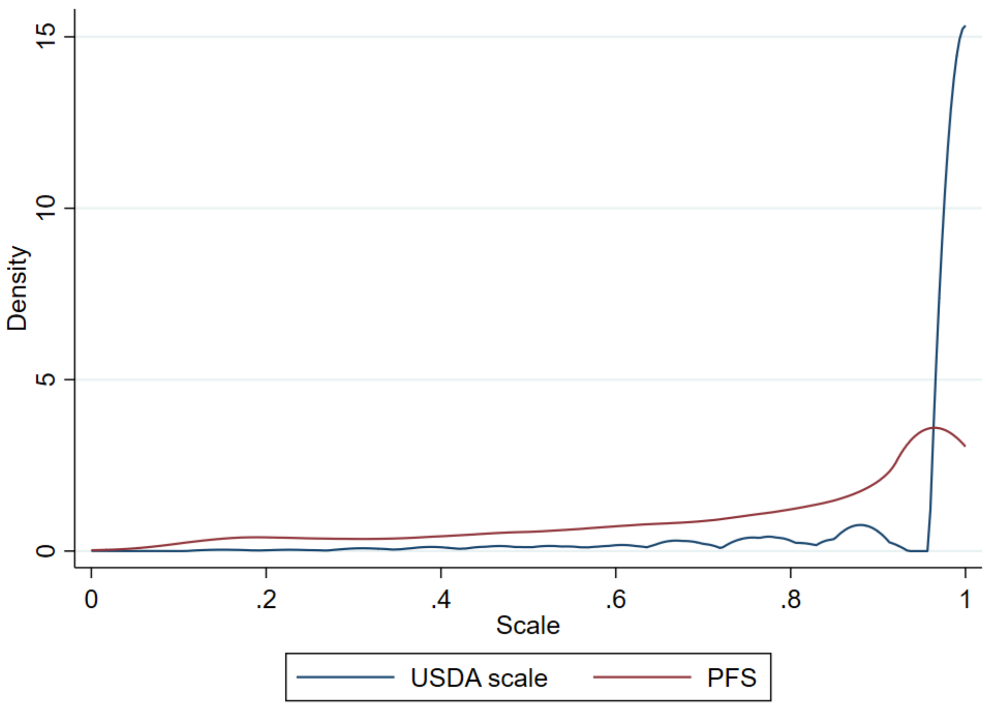
Note: Sample includes household responses from 2001 to 2017. Base household is as follows: Household head is white/single/male/has high school diploma/not employed/not disabled/lives without spouse or partner or cohabitor. Fixed effects include wave(year) fixed effect and region(group of states) fixed 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	22,324	0.024	0.013	0.011	0.540	0.026	0.066	0.210	0.698
Gender									
Male	17,291	0.012	0.004	0.008	0.367	0.010	0.034	0.191	0.765
Female	5,033	0.068	0.044	0.024	0.646	0.083	0.176	0.276	0.466
Race									
White	14,937	0.014	0.006	0.008	0.427	0.011	0.041	0.198	0.750
Non-White	7,387	0.086	0.056	0.030	0.647	0.113	0.213	0.283	0.390
Region									
Northeast	1,525	0.007	0.003	0.005	0.364	0.004	0.029	0.090	0.876
Mid-Atlantic	3,022	0.018	0.009	0.010	0.477	0.014	0.066	0.205	0.716
South	7,942	0.034	0.020	0.014	0.591	0.042	0.078	0.203	0.677
Midwest	5,401	0.033	0.020	0.013	0.603	0.036	0.068	0.248	0.649
West	4,316	0.016	0.006	0.010	0.358	0.015	0.067	0.226	0.693
Metropolitan area									
Metropolitan	15,532	0.023	0.013	0.010	0.562	0.026	0.058	0.197	0.719
Non-metropolitan	6,719	0.027	0.014	0.014	0.500	0.028	0.085	0.242	0.646
Education									
Less than HS	3,307	0.090	0.057	0.033	0.634	0.114	0.205	0.338	0.344
High school	7,259	0.027	0.013	0.014	0.480	0.023	0.082	0.282	0.613
Some college	5,472	0.019	0.010	0.009	0.518	0.020	0.045	0.199	0.736
College	6,286	0.004	0.001	0.003	0.234	0.003	0.019	0.114	0.864

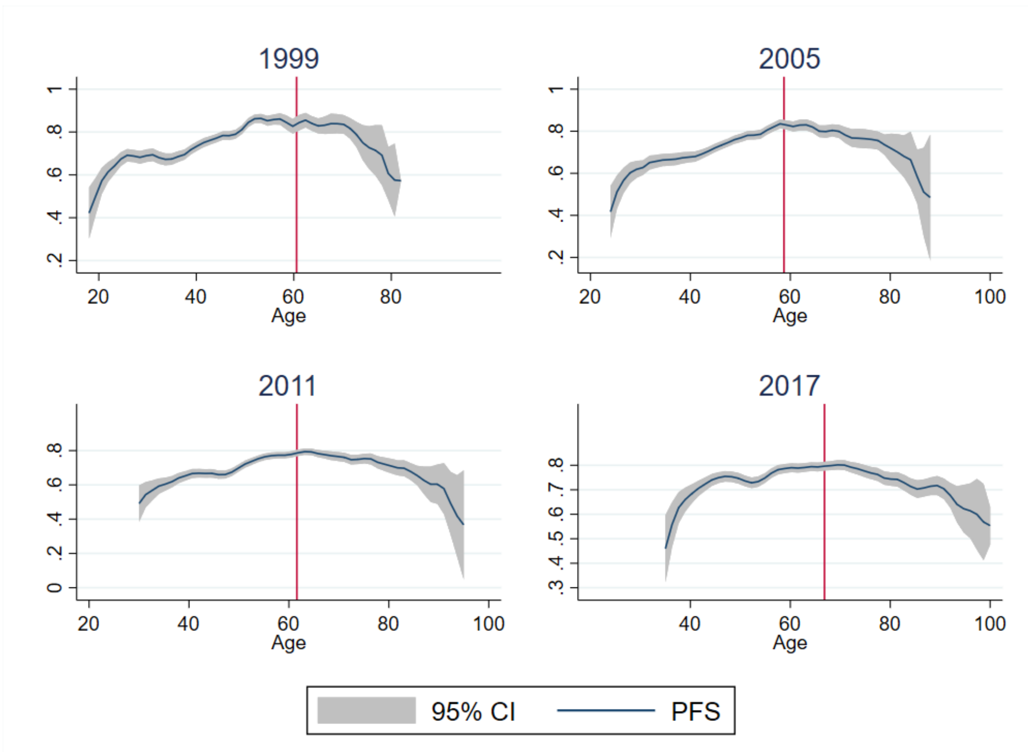
Note: Sample include households with non-missing PFS for 5 or more years from 2001 to 2017. The food insecurity measure is the squared food insecurity gap (SFIG) using the PFS following the method from Jalan and Ravallion (2000). Metropolitan area include the counties in metropolitan area with 250,000 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



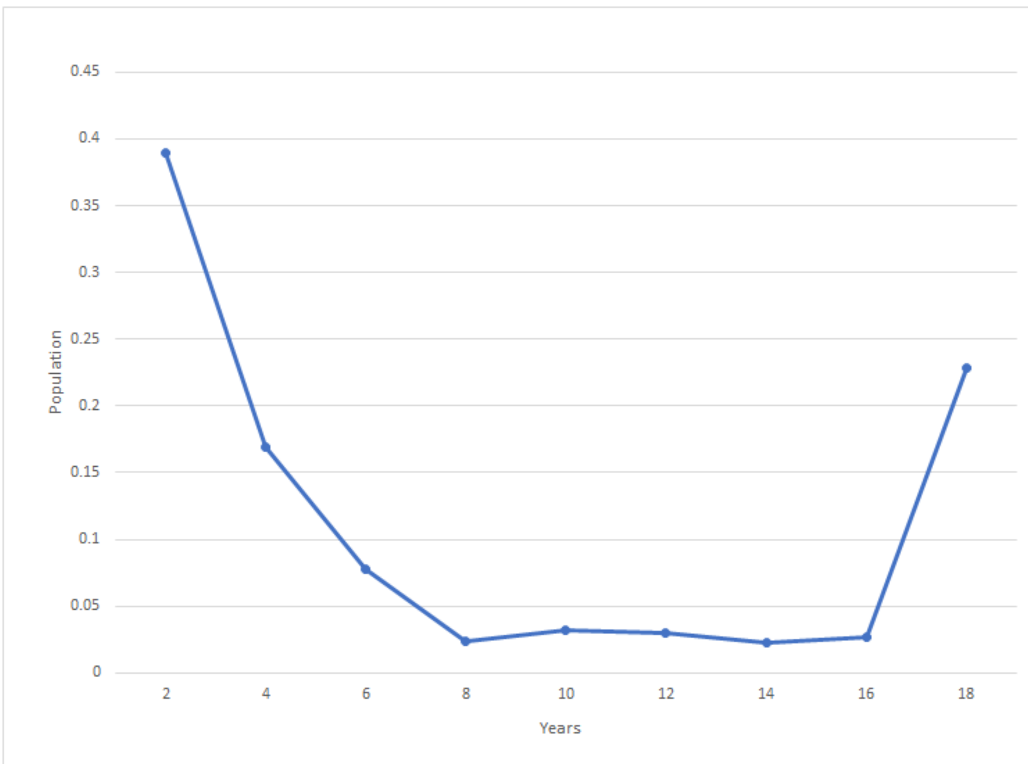
Note: The sample includes the waves where both measures are available ('01,'03,'15,'17))",
Mean/SD: 0.97/0.11(USDA), 0.82/0.22(PFS)")

Figure A2: Density Estimates of Food Security Indicators



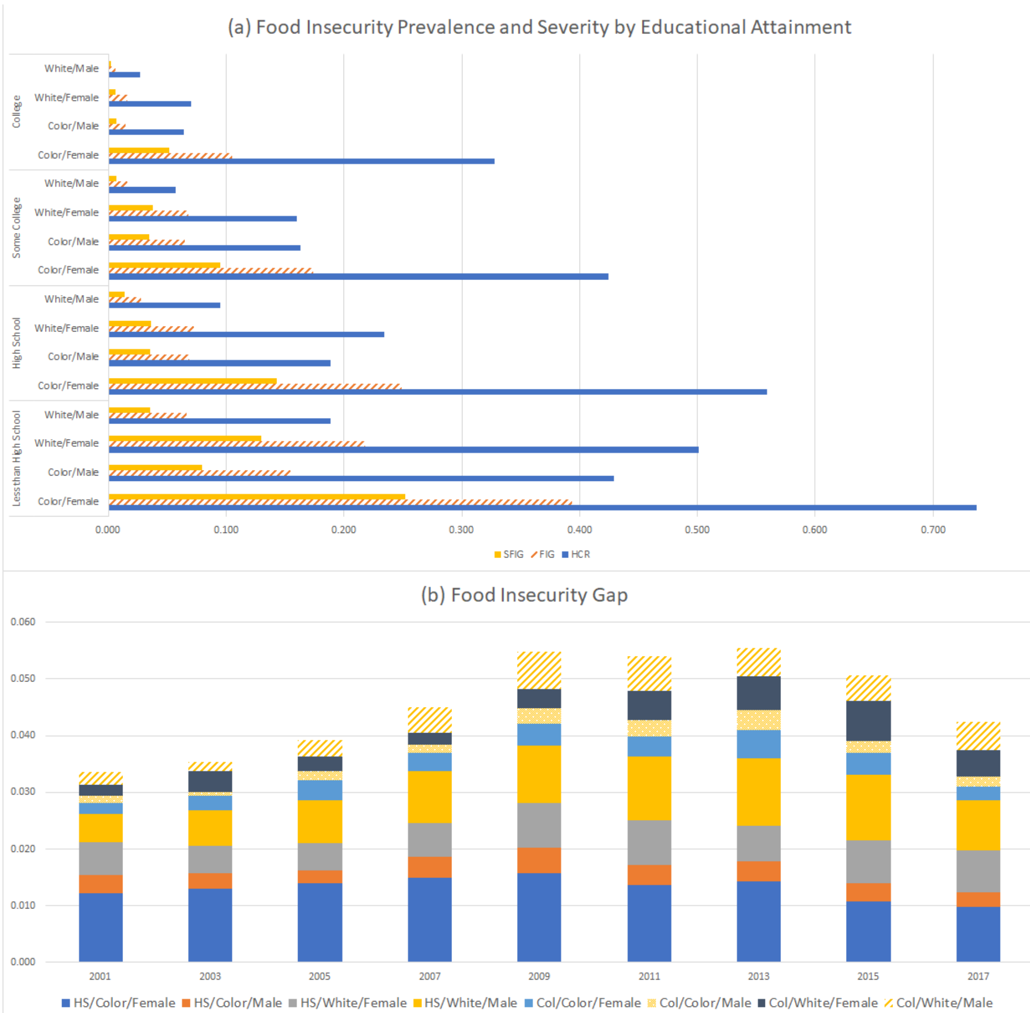
Note: Vertical lines are the average retirement ages of the households in the sample

Figure A3: Predicted PFS over ages



Note: Sample includes households with the balanced PFS from 2001 to 2017. Each dot in each distribution imply ”longer than or equal to”

Figure A4: Spell Length of Food Insecurity (2001)



Note: "HCR", "FIG" and "SFIG" are the headcount ratio, food security gap and the squared food insecurity gap. The vertical axis shows the categories household heads belong to. "NoHS" is household head does not have high school diploma, "HS" is household has high school diploma, "SomeCol" is household head has some college experience, and "Col" is household head has Bachelor's degree. Education status is based on the earliest available achievement.

Figure A5: Food Insecurity Prevalence and Severity by Group - FIG