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

Seungmin Lee† Christopher B. Barrett† John F. Hoddinott†

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Abstract

We study household food security dynamics in the United States from 2001 to 2017 using 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 and subpopulation-scale dynamics by investigating the conditional distribution of estimated food insecurity spells and the chronic and transient components of estimated food insecurity. We find that two-thirds of households experienced no estimated food insecurity during the 2001-17 period and more than half of newly food insecure households regain food security within two years. Households headed by female, non-White, or less educated individuals disproportionately suffer persistent, chronic and/or severe food insecurity. (JEL Q18, I3, D60) (Keywords: food security, dynamics, well-being, welfare)

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†Seungmin Lee - Ph.D. candidate, Christopher B. Barrett - Stephen B. and Janice G. Ashley Professor of Applied Economics and Management, John F. Hoddinott - H.E. Babcock Professor of Food & Nutrition Economics and Policy. The authors are all affiliated with the Charles H. Dyson School of Applied Economics and Management, Cornell University. Correspondence: Seungmin Lee, Charles H. Dyson School of Applied Economics and Management, Cornell University, 137 Reservoir Ave, Ithaca, NY 14850, United States, Email: sl3235@cornell.edu

1 INTRODUCTION

At least one out of ten U.S. households has been food insecure in any given year since the United States Department of Agriculture (USDA) first began reporting its current official food security measure in 1995. In 2021 nationwide prevalence for the U.S., estimated from the annual December Food Security Supplement to the Current Population Survey (CPS-FSS), was 10.2% (Coleman-Jensen et al. 2022). This is of concern as food security – defined as access by all people at all times to enough food for an active, healthy life (Coleman-Jensen et al. 2022) – is intrinsically valuable. It is also instrumentally valuable because food insecurity has myriad adverse consequences on health and other welfare outcomes. 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 (Gundersen and Ziliak 2015).

Those disturbingly high prevalence estimates only capture a snapshot at a point in time, however. 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 household-scale 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 security 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. In this paper, we develop a method to quantify food security dynamics and find considerable intergroup variation in households' dynamic experience of food insecurity, in ways that should matter for policy design and evaluation.

Unfortunately, there do not exist good long-term estimates of household-scale food security dynamics in the United States (or elsewhere). This stems directly from measurement and data collection issues that are global, not specific to the U.S. (Barrett 2002, 2010; Maxwell, Vaitla, and Coates 2014). Official U.S. food security studies rely mainly on the Food Security Scale Score (FSSS) developed by USDA based on a survey instrument first introduced in the CPS-FSS in 1995. Households answer up to 18 CPS-FSS questions (10 questions for households without children) listed in the online supplementary appendix, Table D1. Household food security status is then assessed as a count measure based on the number of questions households affirm, and then standardized into 29 discrete, scalar-valued values in the [0.0,9.3] interval based on a Rasch hodel. Thse Rasch scores are then sometimes 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 D2 in the online supplementary appendix). The monthly CPS survey 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 CPS-FSS. So CPS-FSS data do not enable the study of household food security dynamics beyond a one-year interval.

Other longitudinal household surveys have fielded a household food security survey module (HFSSM) akin to that in CPS-FSS 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.

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). Further, these prior studies are now dated; none investigates food security dynamics post-2010.

Another challenge of analyzing food security dynamics using the FSSS arises from its discrete, ordinal nature. That limits our capacity to understand change in food security status over time as one might with a truly continuous measure. For example, for a household that has no demographic change and affirms the same number of questions (and therefore has the same FSSS) in consecutive periods, the measure assumes no change in the severity of the household's food insecurity, even if some adverse conditions became worse over that period (Bickel et al. 2000). The FSSS is likewise invariant in cross-section with respect to the specific manifestation of compromised food access. For example, each household with children that affirms any eight (of 18) questions is similarly classified as suffering very low food security, although they may have substantively different experiences that reflect differing severity of food insecurity within the coarse categories used in the official, FSSS-based measure. Consequently, we know relatively little about cross-sectional, and perhaps especially intertemporal, variation in food insecurity severity.[1] A truly continuous measure would relax the strong assumptions necessitated by the categorical nature of the original HFSSM data, enabling more nuanced study of food security dynamics.

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.

To characterize longer-run, household-scale food security dynamics in the United States, we need a method that overcomes the limitations of existing data and measures. Doing so is the first contribution of this paper. We construct a new measure, the probability of food security (*PFS*). This 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-middle-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. *PFS* is intended as a complement to the FSSS to enable the study of food security dynamics. As explained below, we anchor the *PFS* measure directly to USDA ERS' official, FSSS-based prevalence estimates.

The *PFS* is based on household food expenditure data. Food expenditures are correlated with latent food security status, but imperfectly so. Mindful of this, we construct the *PFS* using the estimated association between food expenditure and household characteristics that are strongly associated with food security, and we calibrate the *PFS* in a way that the food insecurity prevalence estimated by the *PFS* exactly equals the official FSSS-based prevalence estimates. Thus, while the *PFS* is not identical to food insecurity as currently measured in the United States, it tracks the official measure in a way that allows us to uncover food insecurity dynamics that cannot presently be studied using the official measure. To help distinguish *PFS*-based estimates from the official, FSSS-based measures, in discussing our results we refer to the former as 'estimated' or 'probabilistic' food security measures.

We also show that the *PFS* tracks the official FSSS measure well, but is implementable in longer panels, such as PSID, that include continuous measures of food expenditures. *PFS* tracks the official FSSS better than do realized food expenditures - an alternate measure that the FSSS 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.

Our second and main contribution is applying the *PFS* measure to investigate household-level food security dynamics in the U.S. between 2001 and 2017. We use two 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 two-thirds of American households' estimated *PFS* classify them as continuously food secure throughout the entire 2001-17 period. Roughly half of American households whose estimated *PFS* declined to make them newly probabilistically food insecure experience an increase in *PFS* within two years such that they return to probabilistic food security. The persistence of households' probabilistic food insecurity is positively correlated with the duration of the household's prior probabilistic food insecurity experience. On average, from half to two-thirds of households that are in the probabilistic food insecure category in any given year remain probabilistically food insecure two years later. The longer-run series broadly confirm that when U.S. household experience food insecurity, it is usually recurrent not constant (Coleman-Jensen et al. 2022). The duration of a household's probabilistic 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.

We estimate that household probabilistic food security dynamics vary considerably by demographic characteristics and income, and relatively less by geography, creating a mosaic with distinct patterns. Probabilistic 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 subgroups defined by household head race, gender, and educational attainment. Non-White and female-headed households with low educational attainment disproportionately suffer persistent, chronic, and/or severe probabilistic food insecurity. Households headed by White men with a college education rarely suffer probabilistic food insecurity. Most intertemporal fluctuation in probabilistic food security status occurs among White-headed households. 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. A strength of the PSID is that it 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-FSS 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 subpopulation, 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.[2] Table D3 in the online supplementary appendix reports sample summary statistics and descriptions of the variables used in this paper.

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).[3]

Further description of the food expenditures data is helpful. Starting in 1999, 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. In addition, as part of the PSID, respondents are asked whether their household received SNAP benefits, and then asks either the amount of benefit received and extra amount spent on food beyond the benefit (if they received SNAP), or the amount spent on food (if they did not receive SNAP).[4] To harmonize food expenditure across SNAP recipients and non-recipients, we add the value of SNAP benefits/food stamps to the aggregate of these three types of reported food expenditures, which makes the measure consistent with the food expenditures variable in the CPS-FSS.

Respondents could choose the recall period over which 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. While self-reported food expenditures are subject to measurement error (even weekly food expenditure recall is a cognitively challenging task), 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. 2022). USDA reports TFP monthly in its *Cost of Food Reports* (USDA 2020b).[5] 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). 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 an individual household member's age, gender and surveyed month with the monthly costs reported, summing up the individual costs within the 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.[6]

2.2 Methods

2.2.1 PFS construction

We construct the *PFS* following the method introduced by Cissé and Barrett (2018) and 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,

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

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. $\mathbf{X_{it}}$ 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 ω_t and θ_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}.[7]

The predicted value of the outcome variable, $\hat{W}_{ijt}$, is the conditional mean of the household per capita food expenditure. We assume W_{ijt} follows a Gamma distribution since it is continuous and non-negative.[8] 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.[9]

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).

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

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:

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

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 CPS-FSS data. 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 $\underline{P_t}$.[10] 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 FSSS both by estimating rank correlations and by regressing the FSSS 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 (Appendix A in the online supplementary appendix). Because the PSID does not contain HFSSM data over the full study period, we cannot validate dynamics. Instead, we focus on static comparisons.

Lastly, we replicate our main analyses using the ratio of realized food expenditure to the cost of the TFP, the alternative measure the USDA reports every year (we denote this ratio as the Normalized Money Expenditure (*NME*), following Yang, Davis, and You (2019)), categorizing households as food insecure in the same way as we did with the *PFS*, mechanically generating the same national prevalence of food insecurity as FSSS. The patterns we find using *PFS* are largely identical to those based on *NME*. But *PFS* tracks FSSS statistically significantly better than *NME* does, as we show in section B in the online supplementary appendix. The superior correlation with the official measure may arise because FSSS was expressly designed to incorporate respondents' worry whether "food would run out before we got money to buy more" (Q1, see online supplementary appendix Table D1), not just expenditures realizations, and *PFS* offers an expressly probabilistic measure of food expenditures that corresponds with the internationally agreed definition of food security (Barrett 2002; Upton, Cissé, and Barrett 2016). *NME* necessarily adds noise arising from households' stochastic realizations of food spending. Both conceptually and statistically, we therefore favor *PFS* over *NME* as a measure to use for estimating household-level food security dynamics.

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.

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 sub-populations 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 subpopulations.

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:

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

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

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 α 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 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 spells approach is more 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. Truncation can generate an underestimate of the "true" spell length of household food insecurity. For instance, households that are food insecure in the first two periods in our study could have already been food insecure prior to our study period which we do not observe (left-censoring). Similarly, households experiencing food insecurity in the last study period could remain food insecure beyond the study period (right-censoring). In addition, our approach ignores unobserved changes in food security status that occur between survey rounds (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, α, 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*):

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

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 households categorized as food insecure by the *PFS* in the population, i.e., the prevalence. The two measures with α=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 for 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.

Table 1: 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.

3 RESULTS

3.1 Household-level dynamics: spells approach

Table 1 presents the distribution of probabalistic 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. We stress that these results are based on the *PFS*, not the FSSS. Our findings on food security status (spell length, level, severity) are based on estimated probabilistic food security status unless stated otherwise. 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 in principle 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 1.[11]

More than half (57%) of the estimated 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 probabilistically 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.

The estimated food insecurity spells have a long tail. Figure 1 shows the distribution of spell length (number of years a household is food insecure) conditional on the start year of the food insecurity spell (as shown by different colored symbols and lines). 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. 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, (the period based upon the U.S. Business Cycle Expansions and Contractions (National Bureau of Economic Research 2020)) 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.

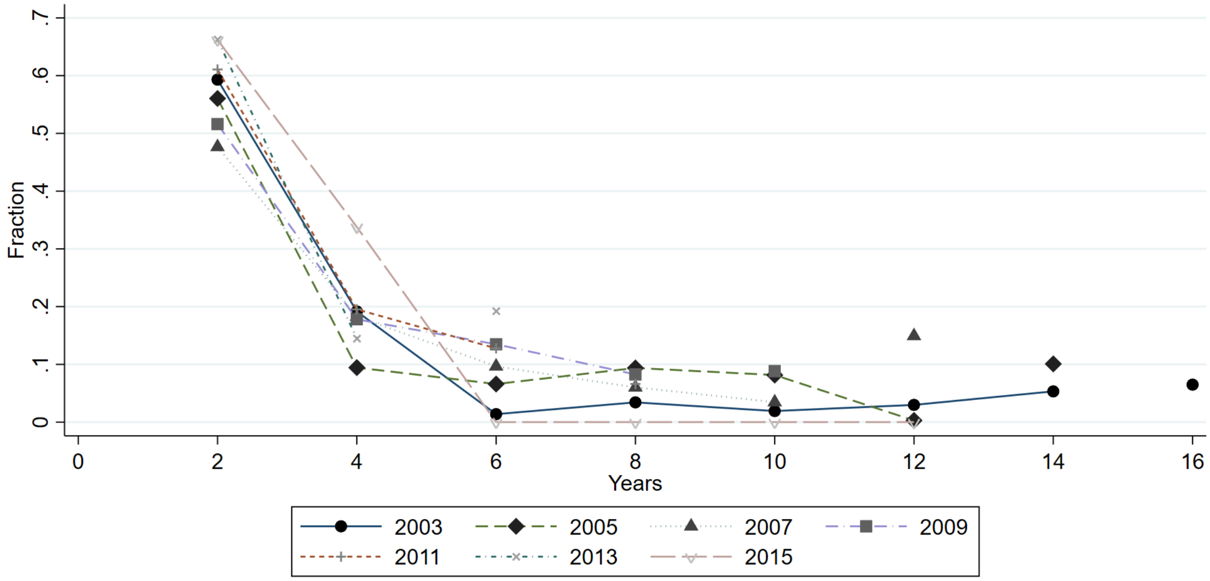
Table 2 shows the estimated food security status transitions and persistence/entry rates per the spells approach, disaggregated by years and groups. Note that the four columns describing the joint distribution in Table 2 reports the unconditional persistence rate, unlike the conditional (on spell length) persistence rates shown in Table 1. Transition shares sum to one (up to rounding error) across the four columns describing the joint distribution.

Table 2 shows that among households that are estimated 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

Table 2: Transitions in Estimated Food Security Status

Category	N	Transition shares (food insecurity over two rounds)				Persistence and Entry	
		Insecure in both rounds	Insecure in 1st round only	Insecure in 2nd round only	Secure in both rounds	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
Food stamp/SNAP recipient							
Not recipient	18,730	0.05	0.05	0.05	0.85	0.54	0.05
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: Entries in each column report the proportion of households in that category. "Persistence" is the share of households probabilistically food insecure in both rounds among households estimated food insecure in the first round, and "Entry" is the share of households food insecure in both rounds among households food secure in the first round per PFS estimates.



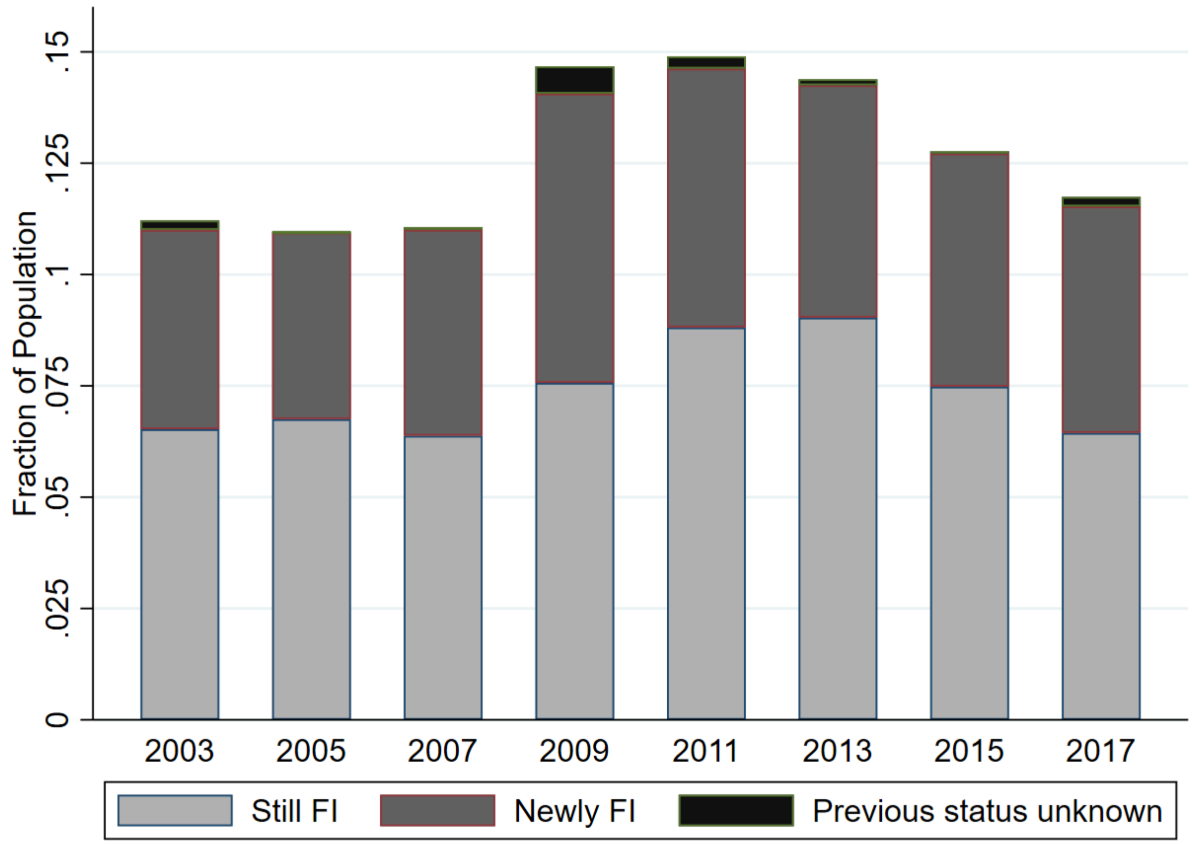
Note: Sample includes households with *PFS* observations from 2001 to 2017. The unconnected rightmost dots reflect the right-censored share.

Figure 1: Spell Length of Estimated Food Insecurity (2003-2015)

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 2 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 2 and Figure 3 that both the estimated prevalence and persistence of food insecurity are markedly higher among households headed by non-Whites, women, those without a high school diploma, 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 lower rates of estimated food insecurity persistence.

Figure 3 depicts the dynamics of estimated food insecurity prevalence, distinguishing between those who newly became food insecure in a PSID survey year (left panel, a) and those who

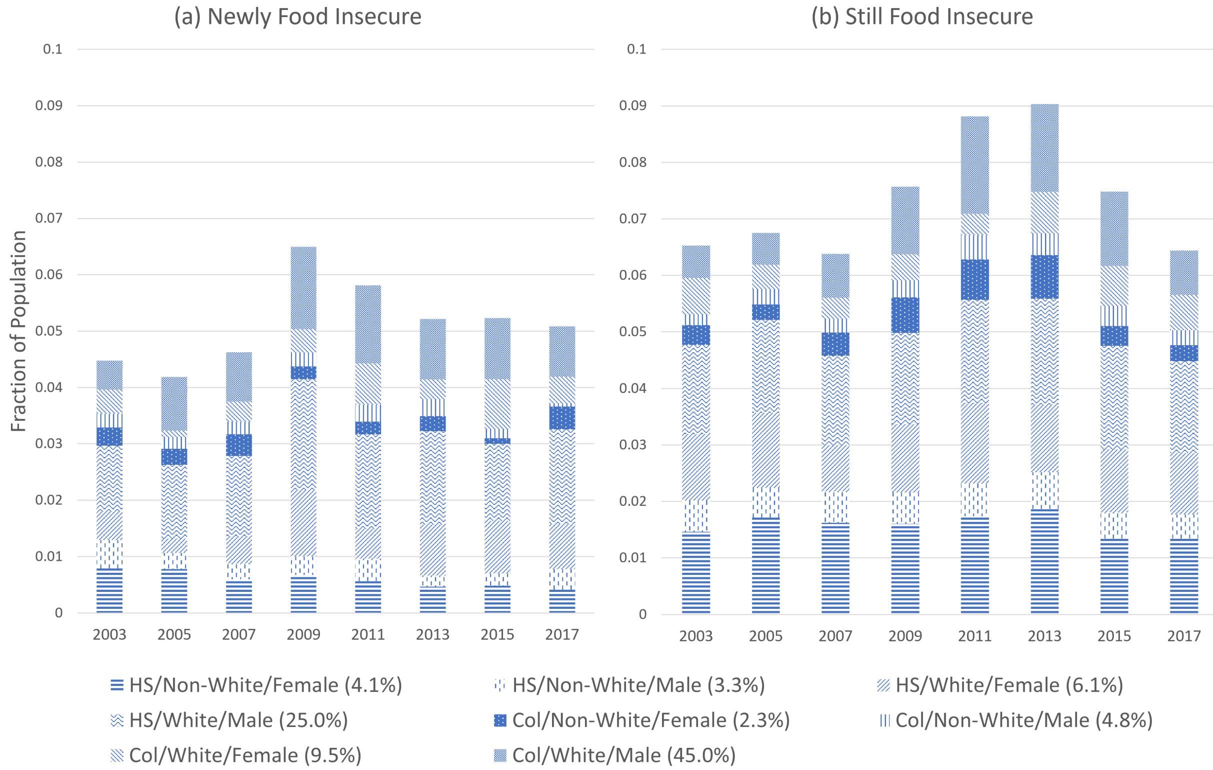


Note: Sample includes households from 2003 to 2017. "Still FI" and "Newly FI" refer to households that were or were not estimated to be food insecure under the *PFS* (Section 2.2.1 has the detailed explanation of how we categorize food insecurity status with the *PFS*) in the preceding survey wave, respectively. "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 FSSS by construction

Figure 2: Change in Estimated Food Security Status

remained food insecure, having been so in the prior survey wave (bottom right, b). These graphics reflect the combination of subgroup population sizes as well as the group-specific transitions reflected in Table 2.

Both panels clearly show vulnerable subgroups' disproportionately high rates of entry and persistence. Over this period, female-headed households accounted for 22% of the population but 40% of the newly food insecure and 51% of persistently food insecure households, on average. Around the period of the Great Recession, they account for 38% of the households that newly became food insecure between 2007-2009 and 48% of still food insecure households immediately



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 estimated food insecure under the 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 3: Change in Estimated Food Security Status by Group

after the Great Recession (2009-2011). Households headed by White males without a college education account for 25% of the population, but they represented the largest shares of both newly food insecure households during the Great Recession (30%) and still food insecure immediately after the recession (21%). Meanwhile, households headed by White females without a college education shows the greatest reduction in newly food insecure households (20% to 9%) in the post-Great Recession recovery (2009-2011). By contrast, the most vulnerable subgroup - households headed by non-White women with no high school diploma - exhibited a relatively stable entry rate before and after the recession and by far the highest persistence rate (34-47%, peaking immediately after the recession (2009-2011).

3.2 Household-level dynamics: permanent approach

Table 3 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 estimated to be 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).[12]

Using our *PFS* measure, we estimate that two-thirds of households (67%) never experienced food insecurity over the 17 years we study from the first row of column (8), 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 FSSS (86%), partly 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.

Subgroup 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 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.

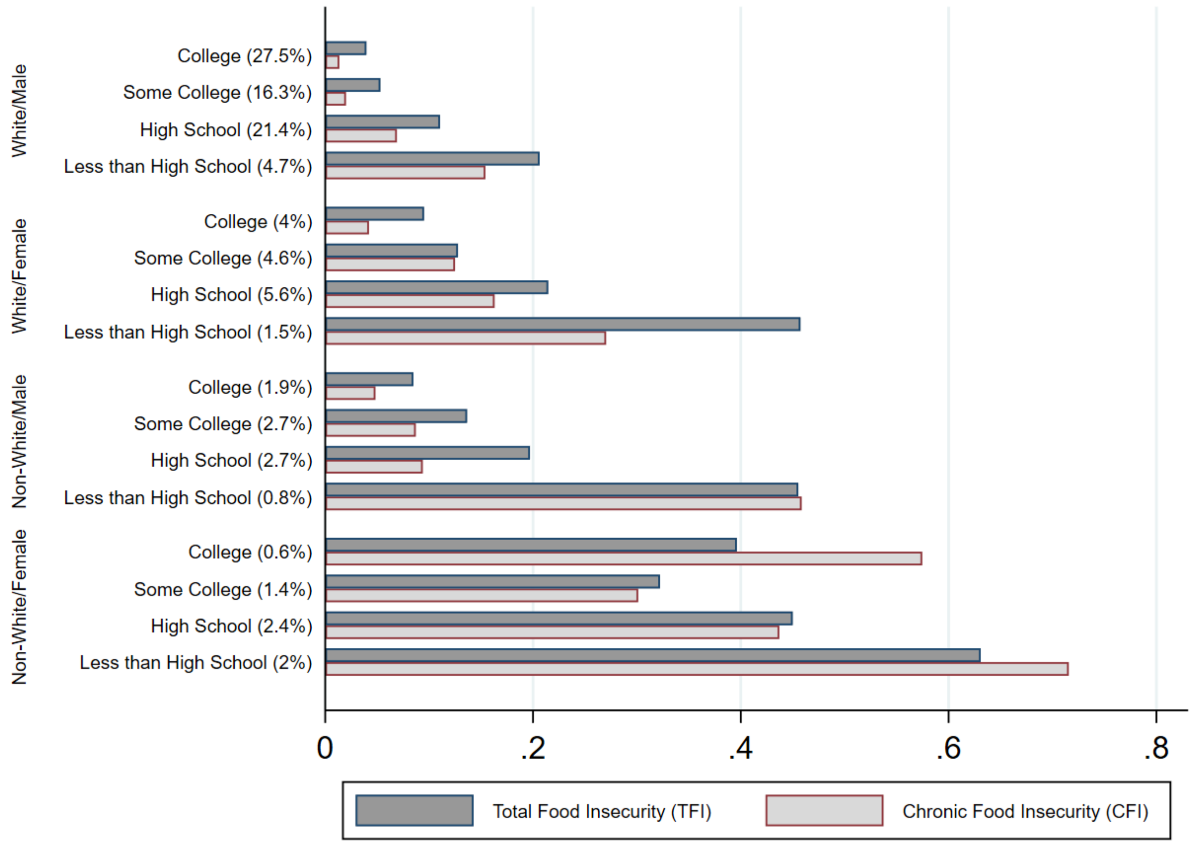
Figure 4 shows these patterns across different subgroups; completing high-school or college significantly reduces both the *TFI* and the *CFI* across all four subgroups. The prominent role of educational attainment is similar to the finding from poverty dynamics literature that households with higher 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.[13]

To this point, we have focused on correlates of household characteristics and food inse-

Table 3: Estimated Chronic Food Insecurity Status from the Permanent Approach

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Category	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

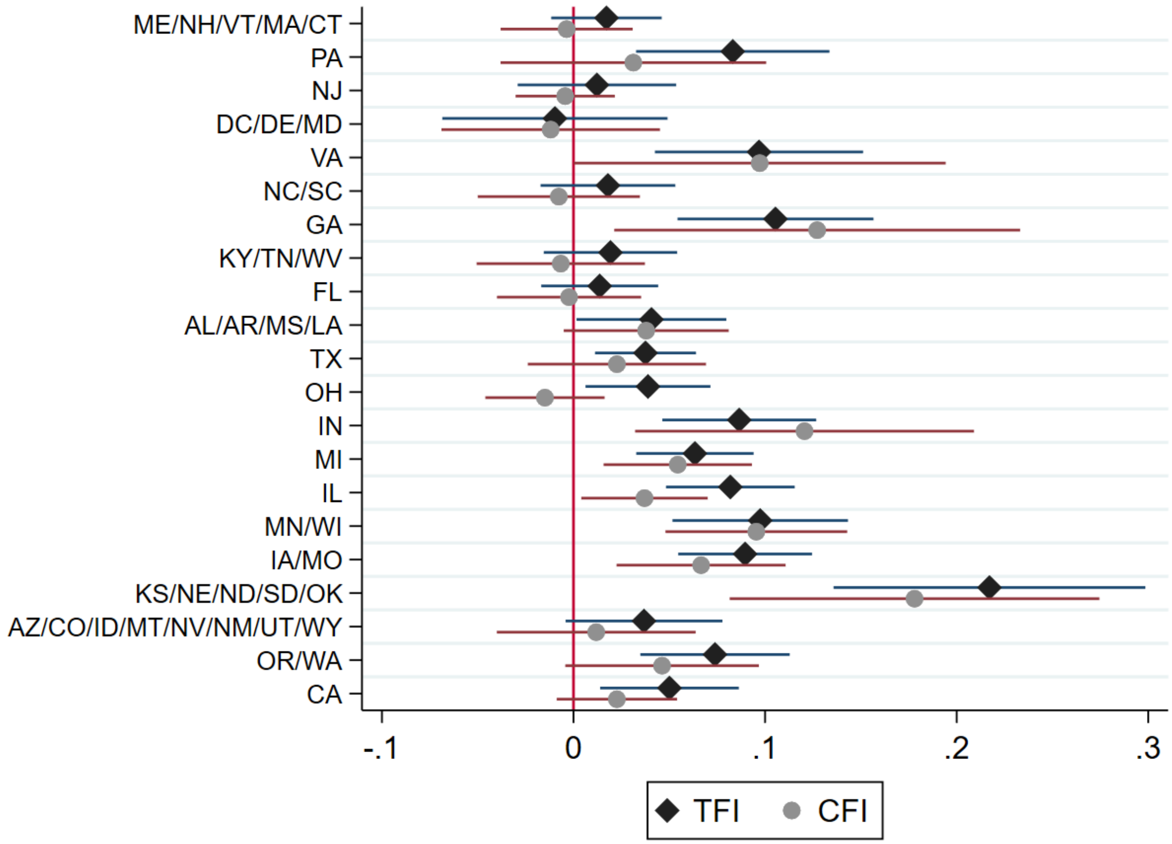
Note: Sample include households with non-missing PFS for 5 or more years from 2001 to 2017. The food insecurity measure is the headcount ratio (HCR) using the PFS following the method from Jalan and Ravallion (2000). Metropolitan area include the counties in metropolitan area with 250,000 or more population. States excluding Alaska and Hawaii belong to one of the five regions, as described in Table D3 in the online supplementary appendix. AK, HI 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.



Note: Sample include households with non-missing PFS for 5 or more years from 2001 to 2017. 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 4: Estimated Chronic Food Insecurity by Group

curity dynamics. However, a key policy-relevant question is whether our measures are more a feature of people or of places. We address this issue by regressing the set of covariates found in Table A2 in the online supplementary appendix (characteristics of the household head (age, sex, race, education employment status), income, household size, inclusion in SNAP or school meals) on *CFI* and *TFI*. We add to this specification state/regional effects. The omitted state is New York state. In cases where the number of observations in a state is small, we aggregate contiguous states with similar economic profiles into a region (so for example, we combine Delaware, Maryland and Washington DC into one region). Figure 5 displays the coefficient estimates for these state/regional



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

Figure 5: Spatial Variation of *TFI*/*CFI*

effects along with their confidence intervals. (We report the full regression results in the online supplementary appendix, Table D6 in the online supplementary appendix presents the full regression results.) 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. Correction for interstate and metro versus non-metro price differences only reduces the spatial variation further (Online supplementary appendix, section C), signaling that some of the variation observed arises from geographic price differences alone.

Table 4: Shapley Decomposition of the *TFI* and the *CFI*

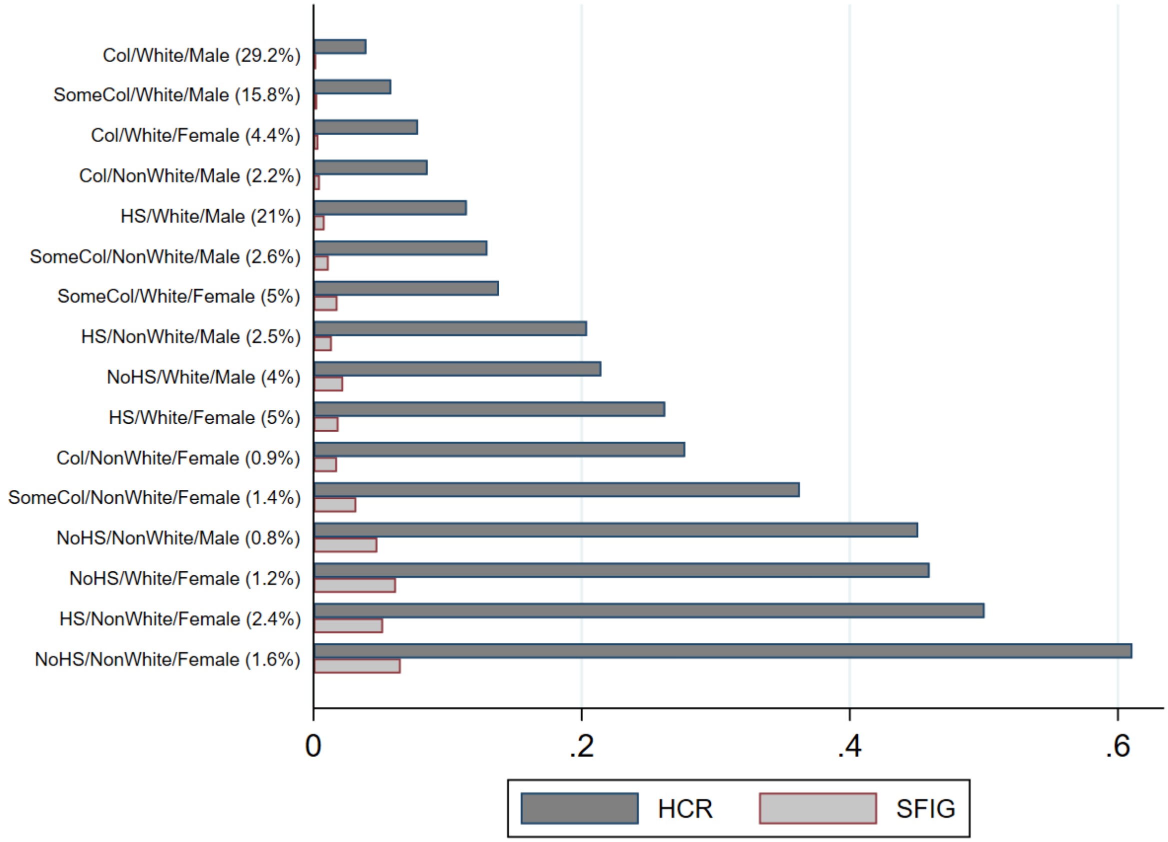
	TFI		*CFI*	
Component	R^2	share	R^2	share
Region	0.032	0.058	0.022	0.052
Education	0.055	0.098	0.038	0.090
Age	0.005	0.010	0.003	0.008
Gender	0.052	0.092	0.048	0.114
Race	0.083	0.147	0.049	0.115
Marital status	0.029	0.052	0.023	0.054
ln(income per capita)	0.143	0.255	0.101	0.238
Food Assistance (SNAP, 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.

We complement the results reported in Figure 5 by constructing a Shapley decomposition of the explained component of variation in *CFI* and *TFI* in Table 4. The vector of region fixed effects cumulatively accounts for only 5-6% of the variation in these measures. By contrast, household income and food assistance program participation capture roughly half of the explained variation in both *TFI* and *CFI*.

3.3 Groupwise decomposition

Figure 6 shows how the prevalence (*HCR*) and severity (*SFIG*) of *PFS* vary across households defined by household head race, gender and education characteristics. The results are jarring. The *HCR* (61.0%) of the most food insecure group, as defined by the *PFS* (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 (27.7% 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 house-



Note: Sample include households with non-missing PFS for 5 or more years from 2001 to 2017. "*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 diploma but did not attend any college, "SomeCol" indicates some college attendance, and "Col" indicates completion of at least a bachelor's degree.

Figure 6: Estimated Food Insecurity Prevalence and Severity by Group

holds are between 35% and 226% more likely to be food insecure than an otherwise-comparable male-headed household.

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 as defined by the *PFS* (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

Note: See Figure 3 for definition of household categories

Figure 7: Estimated Food Security Status By Group and Year

FSSS data from the CPS (Flores-Lagunes et al. 2018). Among 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 diploma, 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 7 shows the change in *HCR* (top panel, a) and *SFIG* (bottom panel, b) over the period, decomposed by group.[14] 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 5 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. Based on our *PFS* measure, 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 diploma 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 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 were households headed by White females who attended college, among whom food insecurity prevalence fell even during the Great Recession.

The bottom panel of Figure 7 shows how estimated food insecurity severity has changed over time. While the general pattern is similar to that of *HCR*, the proportional increase in severity,

Table 5: Estimated Pre- and Post- Food Insecurity Prevalence (*HCR*) by Group

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

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 accounts for a plurality of the increase in severity during the Great Recession (27%) and 11% of the recovery between 2013 and 2017. White, male-headed households without a college degree, which comprise a quarter of the study sample, account for both the second-largest increase in severity during the Great Recession (25%), and for the largest recovery (39%) from 2013 to 2017.

4 CONCLUSIONS

In this paper, we construct a new measure of food security measure in the United States, the *PFS*. This is the estimated probability that a household's food expenditures equal or exceed the minimum cost of a nutritious diet. *PFS* complements USDA's official, FSSS-based estimates of food insecurity. The *PFS* is calibrated to, and highly correlated with, the official USDA food insecurity prevalence measure. A strength of the *PFS* is that it can be estimated for a long longitudinal sample of households, thus allowing us to unpack the dynamics of food insecurity in the United

States in ways infeasible with the official, FSSS measure. Because it is a continuous measure, it also lends itself more readily to measuring the severity of food insecurity than do the categorical measures derived from HFSSM data.

We estimate *PFS* using PSID data from 2001-2017. We estimate that two-thirds of households in this representative sample never experienced food insecurity over that period. Among the one-third of U.S. households whom we estimated as suffering probabilistic food insecurity, 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 probabilistic food insecurity, more than half of all food insecurity experienced is chronic because of conditional persistence.

Sharp differences exist in the prevalence, conditional persistence and severity of estimated food insecurity 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 in both chronic and transitory food insecurity, conditional on household attributes, is modest.

Our approach has 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, for example about the causal effects of food assistance programs or life experiences (e.g., military service, job loss) on food security status, severity, and persistence. These represent a rich research agenda for future study.

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 a health shock, 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 FSSS measure based on HFSSM data, permit more careful study of food security dynamics that might usefully inform policy design and evaluation.

NOTES

1. Flores-Lagunes et al. (2018) study the dynamics of group-level food insecurity incidence and severity using FSSS measures from 2003 to 2011. Note that these are not individual-level dynamics and can only use the FSSS ordinal categories.

2. 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. We note that this sample restriction criteria may underestimate periods of food insecurity if food insecurity is associated with households splitting or attritting.

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

4. 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 2020a), so the value received is nearly equivalent to the value redeemed.

5. TFP does not account for spatial variation in food costs, which can be considerable (Davis, You, and Yang 2020; Christensen and Bronchetti 2020). As a robustness check, we replicate our analyses adjusting the national TFP cost by Regional Price Parities (RPP), an index that measures the differences in price levels across states and metro/non-metro area for a given year, expressed as a percentage of the overall national price level. (Further intra-state decomposition into specific metropolitan areas or rural vs. urban is not feasible in the publicly available PSID data.) RPP is available only from 2008 onwards, so we can only compare our *PFS* results to RPP-adjusted *PFS* for the 2009 to 2017 period. Because our findings are reasonably robust to state-level price differences we focus on the longer time series here. Online supplementary appendix section C reports the replication with the RPP adjustments.

6. 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 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.

7. Table D4 in the online supplementary appendix shows that the coefficient estimates on higher order polynomial terms are statistically insignificant in the 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.

8. 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.

9. 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 (1.83) were not significantly better than that of GLM (1.83).

10. 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 FSSS. Figure D1 in the online supplementary appendix depicts the resulting interannual variation in $\underline{P_t}$, which varies modestly across years, in the interval (0.55, 0.60).

11. In the data, however, 92% of the intervals between survey rounds fall between 21 and 27 months. We also find no difference in the survey interval distribution between households that are food insecure in just one wave versus all households. Nor is a household's food security status statistically significantly associated with the survey interval, conditional on being food insecure in the prior survey round. Although PSID's biennial surveys are coarse for studying dynamics, that seems unlikely to significantly distort *PFS*-based estimates of transient or transitory food insecurity.

12. 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.

13. Estimates using the more distributionally sensitive *TFI* and *CFI* using $\alpha = 2$ (i.e., for *SFIG*), in Table D7 in the online supplementary appendix. The patterns are very similar to those in Table 3.

14. Figure D5 in the online supplementary appendix displays an analogous plot of the *FIG* estimates.

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