How much does SNAP Matter? SNAP's Effects on Food Security

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Abstract

Supplemental Nutrition Assistance Program (SNAP) aims to improve food security of low-income households in the U.S. A new, continuous food security measure called the Probability of Food Security (PFS), which proxies for the official food security measure but is implementable on longer periods, enables the study of SNAP's effects on the intensive margin. Using variations in state-level SNAP administrative policies as an instrument for individual SNAP participation, I find that SNAP participation increases the PFS by 18% within the low-income eligible population, with stronger effects on those with lower food security status.

1 INTRODUCTION

Food security is defined as access by all people at all times to enough food for an active, healthy life (World Food Summit 1996). Food security is a fundamental human right and is associated with a range of well-being outcomes, including child nutrition, mental health and cognitive problems (Gundersen and Ziliak 2015). 12.8% of households in the U.S. were food insecure in December 2022, and more than one out of ten households have been food insecure every year since 1995, the year the United States Department of Agriculture (USDA) first estimated food security (Rabbitt et al. 2023). More surprisingly, food insecurity is often recurrent (chronic) rather transitory; among households that were food insecure at any point in 2022, 25% of them were food insecure in almost every month, and among households "very low food security" (the worst food insecurity status), 75% suffered that status in 3 or more months, and 25% of them in almost every month. (Rabbitt et al. 2023)

The Supplemental Nutrition Assistance Program (SNAP), formerly known as the Food Stamp Program, is a federal safety net program designed to reduce poverty and food insecurity among the low income population. SNAP provides benefits to purchase healthy foods at participating food retail outlets. SNAP eligibility and benefit amount are mainly determined by household income. One out of 8 people in the U.S. (approximately 41 million) received SNAP benefits in 2022, $230 on average (USDA 2023). Many low-income households' food spending relies heavily on SNAP benefits, implying that the loss of eligibility or a decrease in benefit could have a negative consequence on food security as well as other well-beings, both in the short-term and the long-term. For instance, the gradual state-level phase-out of the SNAP emergency allotment that provided additional benefits in response to the COVID-19 pandemic and ended in March 2023 in the last participating states, is widely perceived to have put SNAP participating households at greater risk of food insecurity, financial insecurity and housing instability (Propel 2023). Monthly surveys of a random sample of SNAP households suggest that the share of households that skipped meals in April 2023 increased by 42% (to nearly 50%) in a month, and over 30% relied at least partially on food pantries for food consumption, the highest ratio since Jan 2021 (Propel 2023).

SNAP has been politically controversial since it first became a permanent safety net program in 1964 (Bosso 2023). From one perspective, SNAP is essential to protect low-income residents from hunger and poverty, while from another perspective SNAP discourages work among the able-bodied by providing income. These conflicting perspectives have caused SNAP program rules - eligibility and benefits - to undergo considerable changes over the decades, both at state-level and national-level. For instance, the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996 eliminated SNAP eligibility from most legal immigrants (later restored in 2002), and imposed work requirements and three-month maximum SNAP benefit periods limit on the able-bodied adults without dependents (ABAWDs), a person aged 18 through 49 who does not have a child under age 18 in their SNAP household and who is fit for work. The 2023 debt ceiling deal as included people aged 50 in the ABAWDs, and will gradually include those aged 51-54 in the next couple of years.

Researchers exhibit mixed findings on the effects of SNAP on food security, from positive effects on reducing food insecurity or negative effects of the loss of eligibility (Borjas 2004; Yen et al. 2008; Mykerezi and Mills 2010; Ratcliffe, McKernan, and Zhang 2011; Shaefer and Gutierrez 2013) to null effects (Gundersen and Oliveira 2001; Gibson-Davis and Foster 2006; Chojnacki et al. 2021).[1] However, existing studies focus mostly on extensive margin (i.e. whether households are food secure or not) rather on intensive margin (i.e. how severe household food security is). Two existing studies of SNAP's intensive marginal effects found that SNAP decreases food insecurity by 7% (Yen et al. 2008) and 30-40% (Mykerezi and Mills 2010). This limited number of SNAP's intensive marginal effects is due to the nature of the existing food security measure (Food Security Scale Score, FSSS). FSSS, an official food security measure designed by the USDA. FSSS is a discrete, ordinal measure categorizing food security status as "food secure", "marginally food secure", "low food secure (or food insecure)" or "very low food secure (or very food insecure)", depending on the number of questions respondents affirmatively answered to the Household Food Security Survey Module (HFSSM). The USDA estimates the official food insecurity prevalence rate based on the HFSSM administered in the Current Population Survey (CPS) every December. FSSS's discrete nature has limited researchers from studying the SNAP's intensive margin of SNAP effects on food insecurity. Furthermore, due to the lack of sufficiently long-term panel data, there is little studies analyzed effects of SNAP on food insecurity from chronic food insecurity perspective; Does SNAP have long-lasting effects on food insecurity? How does SNAP differently affect those chronically food insecure, compared to those who are transiently food insecure?

In this paper, I investigate the effects of the SNAP on food security over 17 years, using longitudinal individual-level data from the Panel Study of Income Dynamics (PSID) over 9 rounds from 1997 to 2015. I assess household-level food security using the Probability of Food Security

1. Schanzenbach (2023) summarizes the broader SNAP literature, including the effects on other well-being indicators.

(PFS), a food insecurity measure defined as the estimated probability that a household's predicted food expenditures equal or exceed the minimum cost of a healthful diet, reflected in the USDA's Thrifty Food Plan (TFP) which anchors SNAP benefits (Lee, Barrett, and Hoddinott 2023, LBH hereafter). The LBH established that the PFS serves as a good proxy for the USDA's official food security measure, Food Security Scale Score (FSSS), but unlike the FSSS, the PFS can be implemented in longer panel data sets, like Panel Study of Income Dynamics (PSID), that have food expenditure and household demographic and socioeconomic data. Furthermore, the PFS is a continuous measure which can be used to estimate SNAP's effects on not only food insecurity incidence (i.e. extensive margin) but also on food insecurity severity (i.e. intensive margin) which have not been done in the literature. Furthermore, the PFS can be constructed from the existing panel data to observe household- or individual-level food insecurity over a larger period that has been feasible to date (LBH).

I use variation in state-level SNAP administrative policies for causal identification, as others have successfully used in the literature (Yen et al. 2008; Meyerhoefer and Pylypchuk 2008; Ratcliffe, McKernan, and Zhang 2011; Kreider et al. 2012; Gregory and Deb 2015; Swann 2017; Heflin and Ziliak 2024). Legislative changes since 1990, including the 1996 welfare reform and the 2002 Farm Bill, states could implement their own SNAP administrative rules determining eligibility, enrollment and re-enrollment process, such as exempting vehicles from eligibility test and requiring fingerprint in application. States have adopted different rules at different times, generating considerable state-level variations over the years. I use the USDA's SNAP Policy Index, which assess the generosity of SNAP policies, as an instrument to control for endogenous individual SNAP participation (Stacy, Tiehen, and Marquardt 2018). This identification strategy is based on the hypotheses that SNAP administrative policies are strongly relevant to SNAP participation, and that they affect estimated food security only through SNAP participation.

I find that SNAP increases the PFS by 12 percentage point (18%) among the low-income population, defined as whose family income was ever below 130% of the federal poverty guideline which determines SNAP eligibility. SNAP does not have significant effects on the entire population. Indeed, quantile regression results show that SNAP's positive effects are stronger on low-PFS households except extremely food insecure individuals, implying SNAP has greater effects on food insecure individuals but not as much as on the neediest residents who possibly face non-financial constraints cannot be remedied by SNAP. On average, SNAP does not have significant effects on food insecurity incidence (i.e. at the extensive margin). In terms of long-term effects, SNAP has positive effects on food security in the long run, mostly through earlier SNAP redemption.

This paper contributes to the literature in two ways. First, I investigate SNAP's effects not only on food security incidence but also on its severity, allowing us to assess whether SNAP reduces the severity of SNAP recipients' food insecurity even if they nonetheless remain food insecure. Second, I examine dynamic causal effects of SNAP on food insecurity over years. This contribution stems from the use of the PFS measures that can be constructed from household demographic and food expenditure data in far more survey data sets than the FSSS which requires a separate survey module (Household Food Security Supplement Module, HFSSM).

2 DATA

2.1 Panel Study of Income Dynamics (PSID)

PSID is a nationally representative panel survey of U.S. families. Starting with 18,000 individuals from 4,800 households in 1968, the PSID has surveyed 82,000 individuals from about 9,000 households over 42 waves as of 2021, annually until 1997 and biennially since then. Since its initial survey in 1968, the PSID has followed those surveyed in 1968 as well as those who are genealogically related to them (i.e. children and grandchildren). The PSID sample has remained nationally representative by regularly adjusting survey weights to capture attrition and new immigration, as validated by using various economics indicators, against similar estimates from other nationally representative surveys (Andreski et al. 2014; Li et al. 2010; Gouskova, Andreski, and Schoeni 2010; Tiehen, Vaughn, and Ziliak 2020). The PSID collects the individual-level information (e.g., household role, demographics, socioeconomic status) as well as household-level information (e.g., expenditures, SNAP participation).[2]

I construct individual-level panel data of 83,267 observations from 11,933 individuals over 9 waves (1997-2013). Although food-related outcomes are household-level, we use the individual-level data due to the nature of the PSID data and to ensure consistency with the way the outcome measure is constructed. The PSID assigns a unique ID per individual, but does not assign a unique ID per household over time. If a person has lived in the same household over time, the PSID assigns different household IDs to that person's household in every survey period, even if there has been no change in the household at all. Second, the PFS is a function of conditioning variables, period and panel data construction methods, implying that different construction methods could yield different PFS estimates. Instead of constructing household-level PFS only for this study, I use the PFS constructed from the individual-level panel data of 40-year period (1979-2019) introduced in Lee et al. (2024). I do not include Hawaii and Alaska, which do not have the PFS measure due to the absence of monthly TFP cost, and do not include New Hampshire and a subset of New Jersey, South Dakota, Maine and Rhode Island due to the absence of the Cost of Living Index (COLI) (Council for Community and Economic Research 2023) which I use to adjust for spatial variation in the food prices.[3] I use the PSID's longitudinal individual survey weights for weighted estimates, as the unit of analyses is individual-level. I use weighted estimates as my primary results, and replicate key results without weights in Section 5.1.

Table 1 presents weighted summary statistics of the sample.[4] The left panel is the entire study sample, the right panel is the subsample whose household income was below 130% of the federal poverty line, the income threshold for SNAP eligibility, at least once over the study period. 23% of household units have a female reference person (RP, the official term that replaced "household head" in the PSID since 2017), 81% of RPs are White and 66% are married. 7% used SNAP

2. Strictly speaking, the PSID collects information on a "family", which differs from "household" in the survey. Household is a location-based definition which can include more than one family residing in a single housing unit. However, as of the latest PSID survey wave in 2021, more than 92% of households consist of a single family. Therefore, I use the term "household" synonymously with "family," as is common in the literature.

3. The following state-years are excluded due to the absence of the COLI data: Maine (2007, 2009, 2011, 2013), New Jersey (all but 1999), Rhode Island (2005 to 2013), South Dakota (all but 2009)

4. Table B1 in the Appendix provides unweighted summary statistics.

with average benefit of $330. 78% of the sample is likely to spend no less than the TFP cost, and 11% of the observations have the PFS below a certain cut-off, the threshold I use to define individuals as being food insecure.

Table 1: Summary Statistics

	(Full sample)			(Low income population)		
	N	mean	sd	N	mean	sd
Reference Person						
Female (=1)	83,234	0.23	0.42	39,867	0.38	0.49
Age (years)	83,234	49.30	16.48	39,867	47.01	17.92
White (=1)	83,234	0.81	0.39	39,867	0.69	0.46
Married (=1)	83,234	0.66	0.47	39,867	0.48	0.50
Employed (=1)	83,234	0.71	0.45	39,867	0.61	0.49
Disabled (=1)	83,234	0.19	0.39	39,867	0.25	0.43
Highest educational degree						
Less than high school (=1)	83,234	0.12	0.33	39,867	0.24	0.43
High school (=1)	83,234	0.35	0.48	39,867	0.42	0.49
College w/o degree (=1)	83,234	0.19	0.39	39,867	0.17	0.37
College degree (=1)	83,234	0.33	0.47	39,867	0.18	0.38
Household						
Household size	83,234	2.81	1.49	39,867	2.93	1.72
% children in household	83,234	0.20	0.25	39,867	0.25	0.27
Monthly income per capita (thousands)	83,234	3.12	2.68	39,867	1.73	1.82
Food exp (with FS benefit)	83,234	315.68	188.25	39,867	264.99	172.32
Received SNAP (=1)	83,234	0.07	0.25	39,867	0.17	0.38
SNAP benefit amount	10,501	330.37	231.69	9,950	334.48	235.22
SNAP Policy Index (unweighted)	83,234	5.99	2.02	39,867	5.98	1.99
SNAP Policy Index (weighted)	83,234	7.39	1.79	39,867	7.37	1.78
PFS	83,234	0.78	0.23	39,867	0.67	0.25
Food Insecure (=1 if PFS below cut-off)	83,234	0.11	0.31	39,867	0.20	0.40

* Including SNAP benefit amount
** Non-SNAP households are excluded.
Monetary values are converted to Jan 2019 dollars using Jan 2019 Consumer Price Index. Top 1% values of monetary variables are winsorized. Estimates are weighted using longitudinal individual weight in the PSID.

2.2 SNAP Policy Index

SNAP is a federally funded program for which the federal government determines income eligibility and maximum benefit amounts that are uniform across states which administer the program for their residents. The program used to have little state-level variation initially, but legislative changes since 1990, including the 1996 welfare reform and the 2002 Farm Bill, granted states some autonomy to set their own SNAP administration rules (Stacy, Tiehen, and Marquardt 2018). For instance, states can decide to waive certain requirements or make SNAP applications easier to file, each of which could increase SNAP participation, or states can apply stricter eligibility requirements, each of which could discourage SNAP participation by increasing the cost of participation (Currie et al. 2001), disproportionately affecting the needier groups whom the program mainly targets (Finkelstein and Notowidigdo 2019). States adopted different administrative rules at different times, and these changes have significantly affected SNAP participation (Ganong and Liebman 2018; Dickert-Conlin et al. 2021; Heflin, Fannin, and Lopoo 2023). One thing to note is that these state policies do not affect the SNAP benefit amount; the benefit amount is still determined at the federal level.

Therefore, I use the SNAP Policy Index (SPI), an index capturing the generosity of state administrative rules towards the eligible population developed by Stacy, Tiehen, and Marquardt (2018). The SPI provides a source of exogenous variation in SNAP participation to identify the causal effects of individual-level SNAP participation. The SPI runs 1996 to 2014, constructed from 10 policy variables under four different channels that affect program participation. The first channel is through eligibility; exemption of all (or some) vehicle from the SNAP asset test, 'broad-based categorical eligibility (BBCE)', and an eligibility restriction for adult non-citizens. The second channel is through transaction costs; proportion of working households with short re-certification periods (1 to 3 months), simplified reporting, and online application availability. The third channel is through stigma; proportion of state benefits through electronic benefit transfer (EBT) and a fingerprinting requirement. The last channel is through outreach; federally funded ratio or TV advertisement of the program. The index assigns positive (negative) value to the policies that are expected to increase (decrease) the SNAP participation, so a higher index value implies more generous state administrative rules which should be and is positively correlated with the SNAP participation.

Stacy, Tiehen, and Marquardt (2018) provides SPI in two different versions: unweighted and weighted. The unweighted index is constructed by applying equal weight to all policies in index construction, while the weighted index is constructed by policy-specific weights based upon how much each policy is associated with SNAP participation. Table 2 provides the list of state administrative policies, their contribution to the SPI, and the weights used to construct the weighted SPI. Generous (restrictive) policies associated with greater (lesser) SNAP participation are marked as plus (minus) sign in the "Contribution to the Index" column. The unweighted index is constructed by summing up the number of generous policies adopted minus the number of restrictive policies adopted. If a state adopts all generous policies but none of the restrictive policies, the unweighted SPI would be six (The first two policies affecting eligibility are mutually exclusive). If a state adopts all restrictive policies but none of the restrictive policies, the unweighted SPI would be -3. Then the final unweighted index is scaled to vary from 1 to 10 by adding 4. The weight is the estimated contribution of each policy on SNAP participation, and is used to construct the weighted SPI which is also scaled to vary from 1 to 10.[5] The weighted and unweighted SPIs are very strongly correlated with a Pearson correlation of 0.95 per Stacy, Tiehen, and Marquardt (2018)). I use the weighted index as a source of exogenous variation to capture relative importance of each policy.

Figure 1 shows annual trends of the SPI and two macroeconomic outcomes - official nationwide food insecurity rate and unemployment rate from the study period 1997 to 2014. We find that the SPI is low in 1997, immediately after the 1996 welfare reform which restricted SNAP participation, but gradually increased until 2014. As of 2014, 14 states (Alabama and 13 others) have the highest SPI (8.8), and Alaska (6.5), Wyoming (6.6) and Indiana (6.8) are the states with the lowest SPI. In terms of within-state change over time, the SPI increased the most in California (3.7 to 8.6) and New York (2.3 to 8.6) (Stacy, Tiehen, and Marquardt 2018). These intertemporal variations within states capture greater variations compared to the interstate variations (st.dev 1.63 vs st.dev 1.05). While the U.S. recorded high unemployment rate and food insecurity rate during the Great Recession, there was no major change in the SPI's trend. Figure 2 shows that the change in the SPI is uncorrelated with the change in state macroeconomic status reflected in unemployment rate

5. Stacy, Tiehen, and Marquardt (2018) provides the full detail of the imputation of weights and the construction of the weighted SPI.

Table 2: SNAP policy variables and their contributions to the SNAP Policy Index

	Contribution to the Index	Weight
Policies affecting eligibility		
Exempts at least one but not all vehicles from SNAP asset test	+	1.624
Exempts all vehicles from SNAP asset text	+	1.552
Broad-based categorical eligibility (BBCE)	+	1.828
Eligibility restrictions for adult non-citizens	-	4.800
Policies affecting transaction costs		
Proportion of working households with short re-certification periods (1-3 months)	-	3.180
Simplified reporting	+	1.132
Online application availability	+	0.456
Policies affecting stigma		
Mean proportion of State benefits issued via electronic benefits transfer (EBT)	+	0.276
Fingerprinting required during application	-	1.864
Policies affecting outreach		
Federally funded radio or TV ad	+	0.148

Source: Stacy, Tiehen, and Marquardt (2018), Table 1

from 1996 to 2014. These findings show that the states did not adjust their administrative policies in response to macroeconomic status, implying the exogeneity of state SNAP policies.

3 EMPIRICAL STRATEGY

3.1 The Probability of Food Security

I estimate households' food security status using the PFS measure introduced by the LBH. The PFS is the estimated probability that an individual i' will have food expenditure greater than or equal to $\underline{W_{it}}$, the TFP cost of the household the individual h lives in year t, conditional upon the set of covariates Θ.

I construct the Probability of Food Security (PFS) in the same way I did in Lee, Barrett, and Hoddinott (2023) (LBH hereafter), following three steps introduced in Cissé and Barrett (2018), with a couple of changes. First, I regress (per capita) monthly food expenditure of individual i in

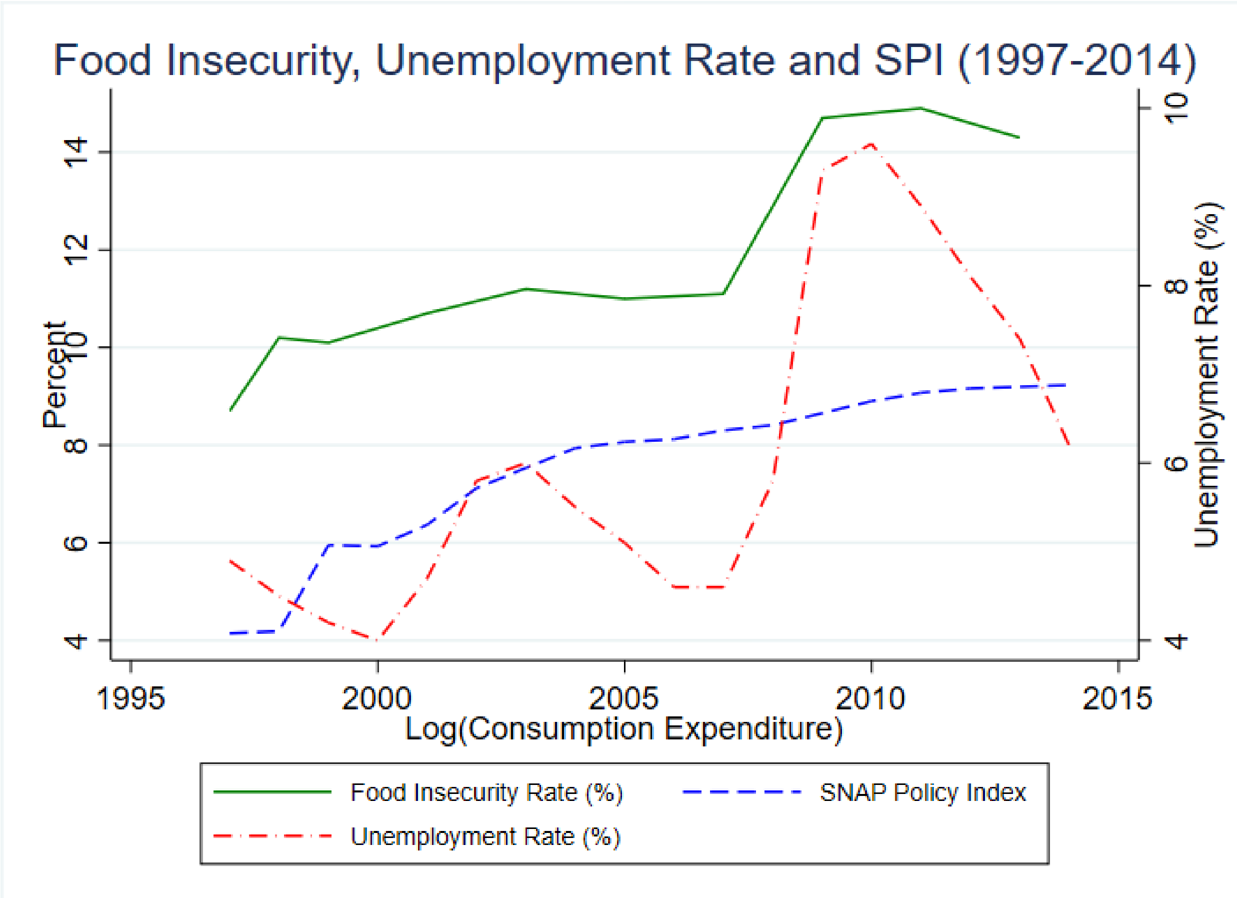

Figure 1: The SPI and Macroeconomic Indicators, 1996-2014

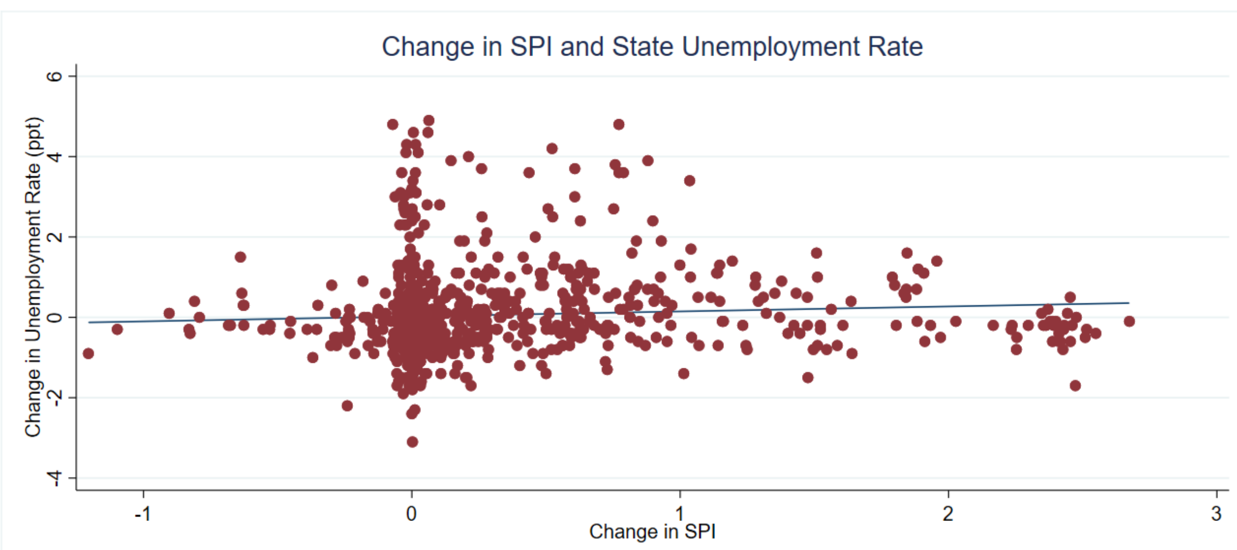

Figure 2: Change in the SPI and state unemployment rates, 1996-2014

state s in year t on a polynomial of its prior period value - thereby allowing for nonlinear dynamics - as in equation (1).

(1) $$W_{ist} = \sum_{\gamma=1}^{2} \pi_{\gamma} W_{is,t-2}^{\gamma} + \Lambda X_{ist} + \Omega_s + \omega_t + \theta_i + u_{ist}$$

where X_{ist} is a household-level characteristics and state-, year- and individual-fixed effects. To comply with the biennial structure of the PSID since 1997, I include the food expenditure of two years ago (not of the previous year) as the lagged status. The predicted value of W_{ihst},$\hat{W}_{ihst}$, is the estimated conditional mean of W_{ist}.

Once the conditional mean of food expenditure is estimated from the equation (1), the second step to construct the $F_{W_{it}}$ is to estimate the conditional variance of $W_{ist}, V[W_{ist}]$. Given a mean zero error term $E[u_{ist}] = 0$, we can estimate it by regressing the squared residual from the equation (1) on the same set of covariates as equation (2) below. The absolute value of the predicted $\hat{u}^2$, $|\hat{\sigma}^2|$, is the conditional variance of monthly household food expenditure per capita ($V[W_{ist}] = E[|\hat{u}_{ist}^2|] = |\hat{\sigma}_{ist}^2|$).

(2) $$W_{ist} = \sum_{\gamma=1}^{2} \Pi_{\gamma} W_{is,t-2}^{\gamma} + \lambda X_{ist} + \Delta_s + \delta_t + \Theta_i + \eta_{ist}$$

The third and the last step is to impose an assumption that W_{ist} follows a specific probability distribution and construct the distribution parameters using the method of moments. As I did in the LBH, I assume W_{ist} follows Gamma distribution as a benchmark distribution since it is non-negative, then I can calibrate Gamma distribution parameters as $\left(\alpha = \frac{\hat{W}_{it}^2}{|\hat{\sigma}_{it}^2|}, \beta = \frac{|\hat{\sigma}_{it}^2|}{\hat{W}_{it}}\right)$. Then the PFS is defined as one minus the conditional cumulative distribution function (CDF) in equation (3)

(3) $$PFS_{it} = Pr(W_{it} \geq \underline{W_{it}}|\Theta) = 1 - F_{W_{it}}(\underline{W_t}|\Theta) \in [0, 1]$$

There are three differences in constructing the PFS between the LBH and this paper. First, while the LBH did not adjust for spatial variation in food prices, I adjusted the TFP cost $\underline{W_{it}}$ to account for spatial variation in food prices. The TFP cost does not consider spatial variation in food prices that is strongly associated with regional variations in food security and SNAP purchasing power (Gregory and Coleman-Jensen 2013; Christensen and Bronchetti 2020; Davis, You, and Yang 2020). The PFS could under- or over-estimate food security depending on relative food prices without spatial food price variation adjustments. I adjusted the TFP cost based on the Cost of Living Index (COLI) developed by the Council for Community and Economic Research (Council for Community and Economic Research 2023). COLI is a quarterly, metropolitan statistical area (MSA)-level index capturing the relative prices in different categories such as groceries and housing. COLI is constructed in a way that the U.S. national average index equals 100, and the higher the index, the higher the relative prices. I constructed the state-year-level COLI (grocery) index by imputing the state-year-level average. COLI varies from 88 to 166 over the study period. I adjusted the TFP cost by multiplying the TFP cost by COLI divided by 100. Second, while the LBH used a generalized linear model (GLM) logit link regression under Gamma distributional assumption in equation (1) and (2), I use Poisson quasi-MLE which is consistent for any non-negative response variables (Wooldridge 1999). Third, the LBH BH included state- and year- fixed effects, I include state-, year- and individual fixed effects.

Table 3 shows the associations between estimated PFS and household-level characteristics. The average PFS in the sample is 0.72 (unweighted) / 0.78 (weighted). The PFS is associated - positively with education, employment, income, and negatively with RP being female, having a physical disability, household size - are intuitive and consistent with the literature. The negative associations between SNAP status and the PFS across all specifications imply self-selection into SNAP participation. Figure 3 shows kernel density plots of the PFS by different subgroups, where vulnerable groups (women, non-White, less-educated) are more concentrated in lower PFS.

To determine whether an individual is food secure or not measured by the PFS, I need a threshold probability such that an individual is categorized as food insecure if the PFS is below

Table 3: PFS and Household Characteristics

	Full sample		Low income population	
	(1)	(2)	(3)	(4)
	PFS	PFS	PFS	PFS
Individual				
Female (=1)	-0.009***	0.000	-0.001	0.000
	(0.00)	(.)	(0.00)	(.)
Age (years)	-0.001***	-0.004***	-0.001***	-0.006***
	(0.00)	(0.00)	(0.00)	(0.00)
College degree (=1)	0.007***	-0.002	0.009*	-0.009**
	(0.00)	(0.00)	(0.01)	(0.00)
Reference Person				
Female (=1)	-0.027***	-0.046***	-0.038***	-0.047***
	(0.00)	(0.00)	(0.00)	(0.00)
Age (years)	0.000**	0.001***	0.000	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
White (=1)	0.080***	0.012***	0.043***	0.019***
	(0.00)	(0.00)	(0.00)	(0.00)
Married (=1)	0.036***	0.007***	0.003	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)
Employed (=1)	0.041***	0.051***	0.040***	0.056***
	(0.00)	(0.00)	(0.00)	(0.00)
Disabled (=1)	-0.031***	-0.018***	-0.023***	-0.015***
	(0.00)	(0.00)	(0.00)	(0.00)
College degree (=1)	0.034***	0.017***	0.019***	0.019***
	(0.00)	(0.00)	(0.00)	(0.00)
Household				
Household size	-0.067***	-0.071***	-0.065***	-0.073***
	(0.00)	(0.00)	(0.00)	(0.00)
% children in household	0.034***	-0.001	0.046***	0.002
	(0.00)	(0.00)	(0.01)	(0.00)
Monthly income per capita (thousands)	0.024***	0.010***	0.037***	0.023***
	(0.00)	(0.00)	(0.00)	(0.00)
Received SNAP (=1)	-0.095***	-0.091***	-0.087***	-0.087***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.799***	1.010***	0.806***	1.012***
	(0.00)	(0.04)	(0.01)	(0.06)
N	82,617	82,222	39,622	39,459
R^2	0.42	0.93	0.37	0.91
Mean PFS	0.72	0.72	0.62	0.62
Individual FE	N	Y	N	Y

Note: State and Year FE are included. Base category is a male/White/single/male/no college degree/not employed/not disabled.

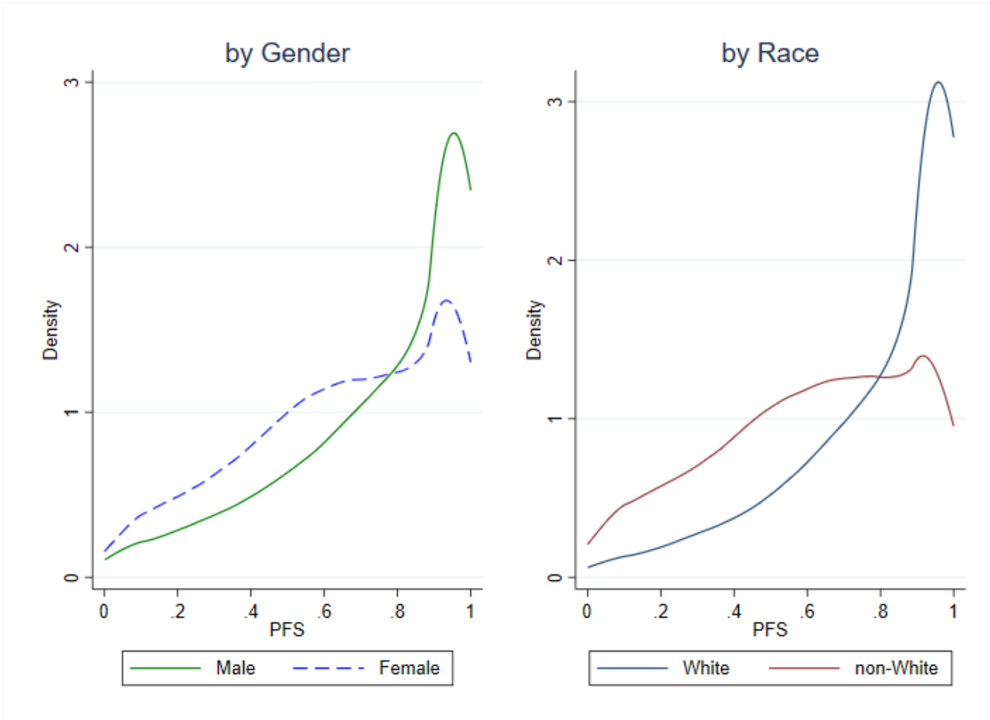

Figure 3: Kernel Density Plots of the PFS

the threshold. I set year-specific threshold probability in a way that the share of food insecure individuals in the study sample matches the annual individual food insecurity prevalence rate the USDA has reported. Cut-off probabilities vary from 0.38 to 0.57 with the average value of 0.49, as shown in Figure 4.

3.2 Identification Strategy

I regress food security outcomes, including the PFS and binary food insecurity status (=1 if PFS is below cut-off probability), on SNAP status as in the equation (4).

$$Y_{ist} = \beta_1 SNAP_{ist} + \beta_2 X_{ist} + \varphi_t + c_i + \zeta_{ist} \tag{4}$$

$$Y_{ist} = \beta_1 SNAP_{ist} + \beta_2 X_{ist} + \varphi_t + \beta_3 \overline{X}_i + \overline{\varphi_i} + \zeta_{ist} \tag{5}$$

where Y_{ist} is an outcome of interest of an individual i in state s, in year t, regressed on a vector of

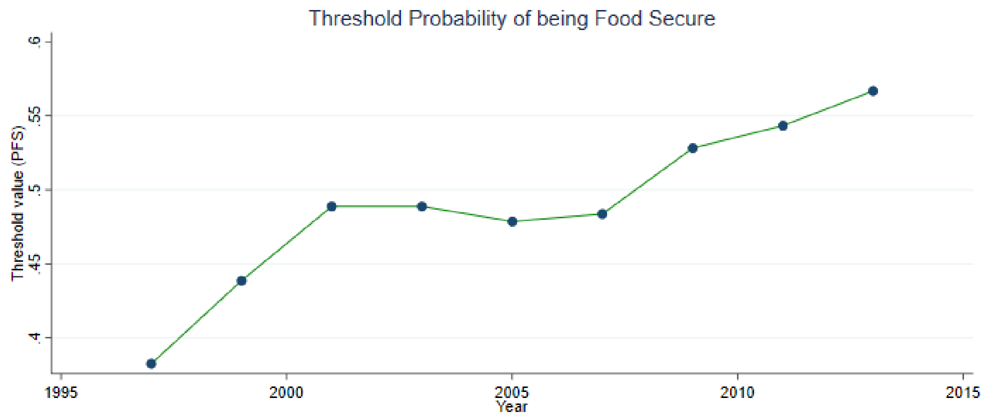

Figure 4: Threshold Probabilities of being Food Secure, 1997-2013

covariates X, year fixed-effect φ_t, and individual-level unobservable fixed effect c_i. The parameter of interest is β_1, the effect of binary SNAP participation status on the estimated food security outcome. Since the state SNAP policies do not affect the SNAP benefit amounts, which are federally determined, I do not study the effect of the SNAP benefit amounts on Y_{ist}. I use a correlated random effect estimator (CRE, Mundlak 1978), $\beta_{1,CRE}$, in which I replace c_i with a linear function of time averages of the individual-level covariates and year dummies $(\overline{X_i}, \overline{\varphi_i})$ in equation (5).[6] Wooldridge (2019) showed that the CRE estimator on β_1 is equivalent to the fixed effect estimator even in unbalanced panel data, which makes it attractive parameters (Wooldridge 2019; Yang 2022; Arkhangelsky and Imbens 2023).

I control for selection into SNAP participation using the 2SLS estimator of β_1, instruments using exogenous variation in SNAP administrative policies as reflected in the SPI. A conventional way to do this is to directly use SPI as an instrument, often denoted as Z, to predict SNAP status in the first stage from the first stage equation (6), and estimate β_1 in equation (4) using $\widehat{SNAP}_{ist}$ estimated from the first stage, both using OLS. However, since the endogenous SNAP participation status is binary while SPI is continuous, the predicted $\widehat{SNAP}_{ist}$ could be above 1 or below zero when the first stage is estimated through the linear probability model using OLS. An alternative way to estimate an 2SLS estimator is to use non-linearly predicted SNAP status, $\widehat{SNAP}_{ist}$, as an

6. Wooldridge (2019) argued that while we would not include the time-average of year dummies, $\overline{\varphi_i}$, in a balanced panel since it is just a vector of constants, we should include $\overline{\varphi_i}$ in an unbalanced panel since it varies across units.

instrument Z in equation (6) (Angrist and Pischke 2009). Under this approach, I predict SNAP status on SPI using a non-linear logit model in equation (7), and use the predicted $\widehat{SNAP}_{ist}$ as an instrument Z in equation (6), and then follow the conventional 2SLS procedure. I use the latter approach in this study since more than 5% of observations have negative predicted probability under the former approach.[7]

$$SNAP_{ist} = \alpha_1 Z_{ist} + \alpha_2 X_{hst} + \phi_t + \alpha_3 \overline{X}_i + \overline{\phi_i} + \theta_{ist} \tag{6}$$

$$SNAP_{ist} = \gamma_1 SPI_{st} + \gamma_2 X_{hst} + \phi_t + \gamma_3 \overline{X}_i + \overline{\phi_i} + \theta_{ist} \tag{7}$$

Non-stationarity is a possible concern in panel data, although N is large and T is small in this study (Baltagi 2021). I conducted a Harris-Tzavalis unit-root test (Harris and Tzavalis 1999), and confirmed that the PFS and household-level covariates are stationary (except the RP's age-squared which is trend-stationary).[8] Year-fixed effects ϕ_t should address non-stationarity in trend-stationary variables.

Table 4 presents the survey-weighted estimation results from equation (6) and (7). Panel (a) shows the marginal effects of the SNAP policy index (SPI) on the binary SNAP status from the logit regression of equation (7). SNAP participation is positively associated with administrative policies; one-unit increase in the index is associated with 11% (0.008/0.07) to 14% (0.01/0.07) increase in SNAP participation on the full sample (column (1) to (3)), and 12% (0.021/0.17) to 16% (0.027/0.17) increase in SNAP participation on the low-income population (column (4) to (6)).

Panel (b) shows the results from the equation (6), the first-stage estimates where $Z_{ist} = \widehat{SNAP}_{ist}$ is predicted binary SNAP status from the logit regression of the equation (7). All estimates are substantially relevant and robust across specifications. These strong associations between

7. Figure B1 shows the distributions of predicted SNAP participation under OLS and MLE model.

8. I used a subset of the study sample (44,928 observations from strongly balanced 4,992 individuals over 9 periods), since the test requires the data to be strongly balanced.

SNAP participation and the SPI imply that SNAP administrative policies are relevant to SNAP participation, consistent with the literature suggested positive (negative) associations between generous (restrictive) SNAP state policies and SNAP participation (Yen et al. 2008; Meyerhoefer and Pylypchuk 2008; Ratcliffe, McKernan, and Zhang 2011; Gregory and Deb 2015; Swann 2017).

Table 4: Weak IV Test

	Full sample			Low-income population		
	(1)	(2)	(3)	(4)	(5)	(6)
	SNAP (=1)	SNAP (=1)	SNAP (=1)	SNAP (=1)	SNAP (=1)	SNAP (=1)
SNAP Policy Index	0.009***	0.008***	0.010***	0.021***	0.024***	0.027***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	82850	82850	82850	82850	82850	82850
Mean SNAP	0.07	0.07	0.07	0.07	0.07	0.07
Controls	N	Y	Y	N	Y	Y
Year FE	N	Y	Y	N	Y	Y
Mundlak	N	N	Y	N	N	Y

Panel A: SNAP Policy Index

	Full sample			Low-income population		
	(1)	(2)	(3)	(4)	(5)	(6)
	SNAP (=1)	SNAP (=1)	SNAP (=1)	SNAP (=1)	SNAP (=1)	SNAP (=1)
	b/se	b/se	b/se	b/se	b/se	b/se
Predicted SNAP	1.056***	0.847***	0.854***	1.058***	0.859***	0.848***
	(0.08)	(0.04)	(0.04)	(0.08)	(0.06)	(0.06)
N	39710	39710	39710	39710	39710	39710
Mean SNAP	0.17	0.17	0.17	0.17	0.17	0.17
Controls	N	Y	Y	N	Y	Y
Year FE	N	Y	Y	N	Y	Y
Mundlak	N	N	Y	N	N	Y
F-stat(KP)	167.46	494.66	436.77	158.71	212.29	181.40

Panel B: Non-linearly Predicted SNAP Participation Status

Note: Controls include RP's characteristics (gender, age, age squared race, marital status, disability, and college degree). Mundlak includes time-average of controls and year fixed effects. Estimates are adjusted with longitudinal individual survey weight provided in the PSID. Standard errors are clustered at individual-level.

In addition to contemporaneous effects, I estimate the dynamic effects of SNAP on food security over years using an autoregressive distributed lag model as the equation (8) below.

$$Y_{it} = \delta_0 Y_{i,t-2} + \alpha_h \widehat{SNAP_{i,t-h}} + \Phi X_{t-h} + \zeta_{it} \quad (8)$$

where δ_0 estimates the persistent effect of previous food security status on contemporary food security, and α_h captures the effect of SNAP participation in h years ago on contemporaneous food security net of persistence in food security status. If $Y_{i,t-2}$ is omitted, then α_h estimates the total effect of earlier SNAP on current food security, including both direct effect and indirect effects through earlier food security status. I estimate both the total effect (without $Y_{i,t-2}$) and the direct effect (with $Y_{i,t-2}$) of earlier SNAP on contemporary food security. I cluster standard errors at individual-level which corrects for both serial correlation and heteroscedasticity.

4 RESULTS

4.1 SNAP Effects on the PFS

Table 5 shows the second-stage estimates, equation (5) where $SNAP$ is replaced with the predicted $\widehat{SNAP}$ from equation (6). Outcome variable is PFS in Panel (A) and binary indicator for food insecurity in panel (B). In Panel A, OLS coefficients are negative on both full sample (column (1)) and low-income population (column (3)), reflecting self-selection into SNAP which causes estimates to suffer from downward bias. Column (2) and (4) show that participating into SNAP decreases the PFS by 3% (0.026/0.78) in the full sample and increases the PFS by 17% (0.115/0.67) in low-income population, while I cannot reject the null hypothesis of no effects in the former and can reject the null in the latter. However, when I use binary food insecurity status as an outcome in Panel (B), SNAP effects are neither precisely estimated on both full and low-income sample. These results imply that SNAP has positive effects on improving food security status on the low-income population, but not sufficiently large enough to make them food secure.

To investigate how SNAP effects vary across PFS distribution, I generate quantile estimates

Table 5: Food Security on SNAP participation

	Full sample		Low-income population	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
SNAP (=1)	-0.186***	-0.026	-0.157***	0.115*
	(0.01)	(0.04)	(0.01)	(0.06)
N	82850	82850	39710	39710
R^2	0.23	0.20	0.18	0.04
Mean PFS	0.78	0.78	0.67	0.67

Panel A: PFS

	Full sample		Low-income population	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
SNAP (=1)	0.241***	0.081	0.223***	-0.064
	(0.01)	(0.05)	(0.01)	(0.09)
N	82850	82850	39710	39710
R^2	0.11	0.09	0.10	0.03
Mean PFS	0.11	0.11	0.20	0.20

Panel B: Food Insecurity (=1 if PFS below cut-off)

Note: All models include control variables, year fixed effects and Mundlak controls. Controls include RP's characteristics (gender, age, age squared race, marital status, disability, and college degree). Estimates are adjusted with longitudinal individual survey weight provided in the PSID. Standard errors are clustered at individual-level.

of SNAP's effects on PFS. Figure 5 shows SNAP effects on the PFS over the distribution from 5th percentile (leftmost coefficient) to 90th percentile (rightmost coefficient). 99% of food insecure households have a PFS below the 20th percentile. This plot implies the following. First, SNAP's effects on increasing food security are stronger on the lower distribution - those with lower food security status. Second, for those extremely food insecure (below 5th percentile), SNAP effect is not as strong as those moderately food insecure, implying that extremely food insecure individuals may suffer from non-income issues (i.e. mental health or homelessness) that cannot be effectively remediable by SNAP benefits. Third, in terms of food insecure households located in the bottom 4 percentiles of the distribution (5th to 20th percentiles), the effects are not largely different from their average post-SNAP PFS (0.1, 0.22, 0.34, 0.42), compared to the threshold PFS on the bottom two percentiles (5th, 10th) which could be the reason for the insignificant SNAP effects on food insecurity incidence.

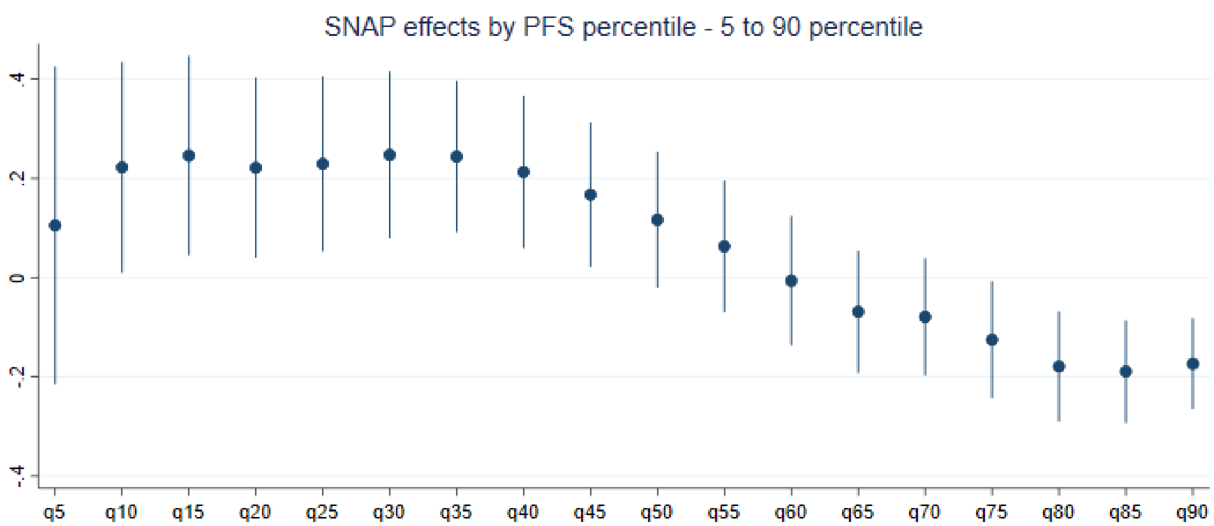

Figure 5: SNAP Effects on PFS over Distribution - low-income population

Heterogeneous effects by persistence of food insecurity to be added.

4.2 SNAP Effects on Food Security Dynamics

Note: These results are preliminary. Table 6 shows the SNAP's dynamic effects on the food insecurity. Distributed lags model without lagged outcome in column (1) to (3) show that SNAP's positive effects last at least over 6 years. These effects include both direct effect of earlier SNAP participation on current food security and indirect effect of earlier SNAP through earlier food security status. Autoregressive distributed lag models in Column (4) to (6) show that the total SNAP effects are indirect through past SNAP redemption; once food security status in earlier stage is controlled, there are no direct SNAP effects on food security.

Table 6: Dynamics Effects of SNAP on Food Security

	(1) PFS	(2) PFS	(3) PFS	(4) PFS	(5) PFS	(6) PFS
PFS (2 years ago)				0.879***	0.875***	0.871***
				(0.01)	(0.01)	(0.01)
SNAP 2 years ago	0.142**			0.018		
	(0.06)			(0.01)		
SNAP 4 years ago		0.142**			0.007	
		(0.07)			(0.01)	
SNAP 6 years ago			0.117*			0.013
			(0.07)			(0.02)
N	32561	26560	21865	32561	26171	20865
R^2	0.02	0.03	0.05	0.80	0.80	0.80
Mean PFS	0.67	0.67	0.67	0.67	0.67	0.67
F-stat(Kleibergen-Paap)	157.33	119.99	110.83	184.06	135.25	114.34

5 ROBUSTNESS CHECK

5.1 Weighted vs Unweighted Estimates

I have reported estimates using the survey weights, which would be more of policy-relevant as it better represents the population. Furthermore, Solon, Haider, and Wooldridge (2015) argued that weighted estimates are preferred over unweighted estimates because (i) more precise estimates by correcting for heteroscedasticity; (ii) consistent estimates after correcting for endogenous sampling; and (iii) identification of average partial effects in the case of heterogeneous effects. However, Solon, Haider, and Wooldridge (2015) also argued that large disparities between unweighted and weighted estimates could imply mis-specification of the model. They therefore recommended reporting both weighted and unweighted estimates. Therefore, I replicate the main estimates in earlier sections without survey weights. Since the PSID oversamples low-income population, I hypothesize that the (unweighted) SNAP effects on food insecurity would be greater.

Table 7 replicates Table 5 estimating SNAP effects on food security (PFS) and food insecurity incidence. The sign and magnitude of the estimates are consistent with the weighted estimates in Table 5, with greater effect sizes as hypothesized. Column (4) in panel A shows that SNAP increases the PFS by 30% (0.182/0.62) compared to 17% increase in weighted estimates. Panel B shows that the estimated SNAP effects on food insecurity incidence is nearly as twice as great as the weighted estimates, but they are both imprecisely estimated. Figure 6 replicates Figure 5 estimating SNAP effects over the distribution of the PFS. The effects are larger on lower distribution and gradually fades out, consistent with the weighted estimates.

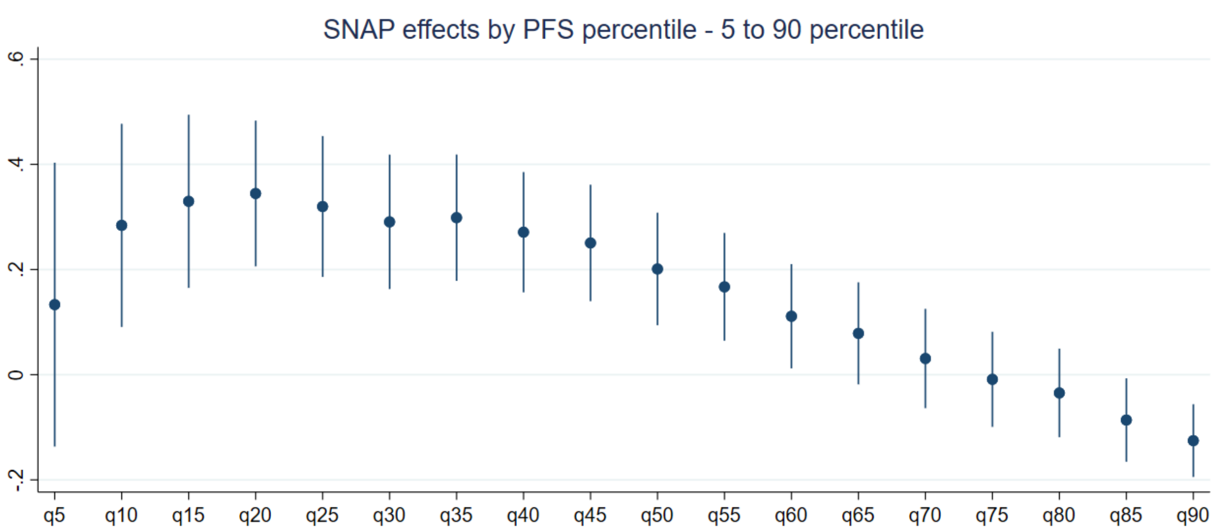

Figure 6: (Unweighted) SNAP Effects on PFS over Distribution - low-income population

Table 8 replicates Table 6 estimating dynamics effects of SNAP on food security. The sign and magnitude of effects are similar between weighted and unweighted estimates. In terms of dynamic causal effects, the direct effect of SNAP participation 2 years ago on current SNAP is

Table 7: Food Security on SNAP participation - Unweighted

	Full sample		Low-income population	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
SNAP (=1)	-0.165***	0.083***	-0.146***	0.182***
	(0.00)	(0.03)	(0.00)	(0.05)
N	82850	82850	39710	39710
R^2	0.26	0.18	0.18	-0.08
Mean PFS	0.72	0.72	0.62	0.62

Panel A: PFS

	Full sample		Low-income population	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
SNAP (=1)	0.242***	0.020	0.224***	-0.122
	(0.01)	(0.04)	(0.01)	(0.07)
N	82850	82850	39710	39710
R^2	0.13	0.10	0.10	0.00
Mean Outcome	0.16	0.16	0.26	0.26

Panel B: Food Insecurity (=1 if below cut-off)

Note: All models include controls, year fixed effects and Mundlak controls. Controls include RP's characteristics (gender, age, age squared race, marital status, disability, and college degree). Mundlak includes time-average of controls and year fixed effects. Standard errors are clustered at individual-level.

now precisely estimated.

Table 8: Dynamics Effects of SNAP on Food Security - Unweighted

	(1) PFS	(2) PFS	(3) PFS	(4) PFS	(5) PFS	(6) PFS
PFS (2 years ago)				0.872***	0.867***	0.861***
				(0.01)	(0.01)	(0.01)
SNAP 2 years ago	0.207***			0.026**		
	(0.05)			(0.01)		
SNAP 4 years ago		0.194***			0.006	
		(0.06)			(0.01)	
SNAP 6 years ago			0.164***			0.006
			(0.06)			(0.01)
N	32561	26560	21865	32561	26171	20865
R^2	-0.09	-0.06	-0.02	0.78	0.78	0.78
Mean PFS	0.62	0.62	0.62	0.62	0.62	0.62
F-stat(Kleibergen-Paap)	265.19	216.70	190.34	326.63	257.67	213.62

6 CONCLUSION

This study investigates the effect of SNAP participation on food security over a 17-year period. The study of SNAP's causal effects on food security dynamics on intensive margin as well as dynamic effects have been limited due to the nature of the official food security measure that are discrete and available only in the short-term panel. I use a new food security measure based on food expenditure and individual- and household demographic and socioeconomic data, which allows me to study SNAP's effects on the level of food security as well as dynamic effects over longer periods. Using the variations in SNAP administrative policies as an instrument, I found that SNAP improves food security of the SNAP-eligible low-income population by 12% with stronger effects on those who need, but does not have significant effects on reducing the level of food insecurity. Further, SNAP has long-lasting effects over the years.

This study has important limitations, which can be investigated in follow-on research. First, I do not consider the possible misreporting of SNAP participation, which has been increasing (Meyer, Mok, and Sullivan 2015). The measurement errors could be both classical due to different recall periods in food expenditure and SNAP status, or non-classical due to stigma. Possible approaches to overcome this limitation would include using SNAP administrative data, partially identifying the effect (Gundersen, Kreider, and Pepper 2017) or post-startifying survey weights (Jolliffe et al. 2023). Second, my study does not capture the change in SNAP status between 2-year period. Considering many families lose stamp benefits in the middle of the year due to failure to comply with the benefit requirements, my study could mis-measure the duration of SNAP benefits even when SNAP participation is correctly measured.

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Appendices

A ADDITIONAL TABLES AND FIGURES

Table B1: Summary Statistics - unweighted

	(Full sample)			(Low income population)		
	N	mean	sd	N	mean	sd
Reference Person						
Female (=1)	83,234	0.30	0.46	39,867	0.45	0.50
Age (years)	83,234	45.83	15.76	39,867	43.57	16.20
White (=1)	83,234	0.59	0.49	39,867	0.41	0.49
Married (=1)	83,234	0.59	0.49	39,867	0.43	0.49
Employed (=1)	83,234	0.72	0.45	39,867	0.62	0.48
Disabled (=1)	83,234	0.17	0.38	39,867	0.21	0.41
Less than high school (=1)	83,234	0.16	0.36	39,867	0.26	0.44
High school (=1)	83,234	0.37	0.48	39,867	0.43	0.49
College w/o degree (=1)	83,234	0.20	0.40	39,867	0.18	0.39
College degree (=1)	83,234	0.27	0.44	39,867	0.14	0.34
Household size	83,234	3.11	1.63	39,867	3.31	1.82
% children in household	83,234	0.26	0.27	39,867	0.32	0.28
Monthly income per capita (thousands)	83,234	2.53	2.39	39,867	1.41	1.52
Monthly food exp per capia	83,234	282.02	178.00	39,867	239.22	160.42
Received SNAP (=1)	83,234	0.13	0.33	39,867	0.25	0.43
SNAP benefit amount	10,501	365.36	251.42	9,950	369.82	254.27
SNAP Policy Index (unweighted)	83,234	5.97	2.00	39,867	6.00	1.98
SNAP Policy Index (weighted)	83,234	7.37	1.81	39,867	7.40	1.80
PFS	83,234	0.72	0.25	39,867	0.62	0.26
FI (=1)	83,234	0.16	0.37	39,867	0.26	0.44
Outcomes						
PFS	83,234	0.78	0.24	39,867	0.67	0.26
PFS < 0.5 (=1)	83,234	0.15	0.35	39,867	0.26	0.44

* Including SNAP benefit amount
** Non-SNAP households are excluded.
Monetary values are converted to Jan 2019 dollars using Jan 2019 Consumer Price Index. Top 1% values of monetary variables are winsorized.

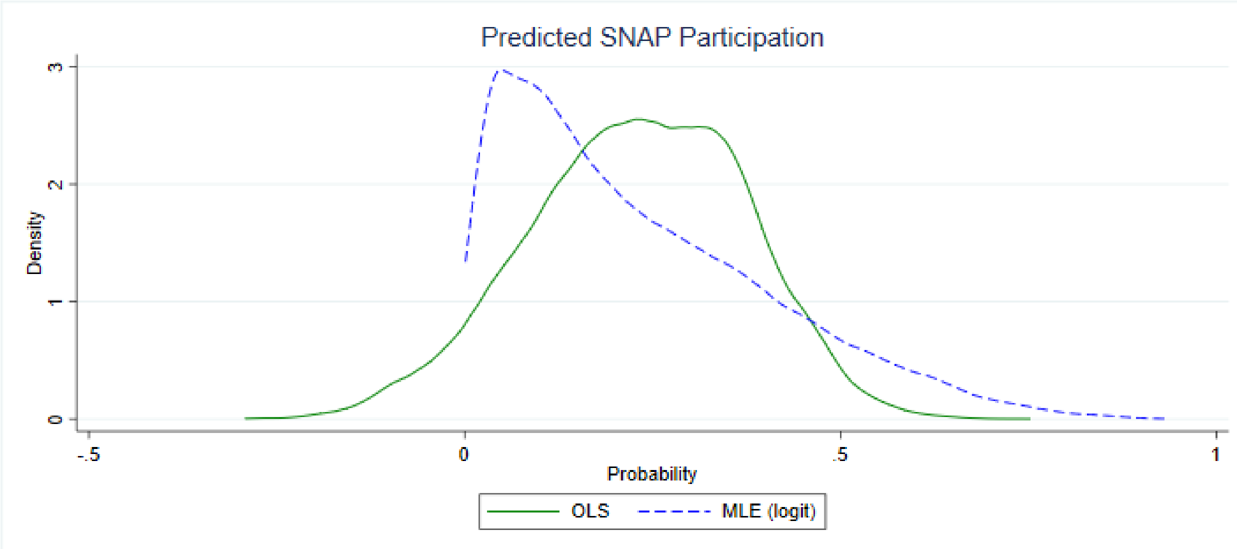

Figure B1: Predicted SNAP Probability