Food Security in a Snap: How does the Combined Application Project Increase Elderly SNAP Participation Rates and Food Security?

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Abstract

In 2015, only 42% of eligible seniors participated in the Supplemental Nutrition Assistance Program (SNAP) while approximately 5.1 million seniors (7%) faced some level of food insecurity (National Council of Aging). To improve SNAP take-up rates among the elderly, eighteen states have implemented the Combined Application Project (CAP), a policy through which elderly Supplemental Security Income (SSI) recipients from single-households receive a simplified SNAP application process. This makes it easier to apply and qualify for SNAP. This research determines to what extent the CAP Policy increased the number of elderly low-income individuals participate in SNAP. Additionally, this research looks at how, through SNAP take up, this policy affected levels of food security for the elderly. Estimating a two-stage regression model with data from the Current Population Survey and Department of Agriculture, I find CAP increases the SNAP participation rate by 26% for SSI recipients. I also find SNAP in turn results in a 30% increase in the chance a low-income elderly individual in a single household is food secure, although with negligible statistical significance.

Acknowledgements

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Section 1: Introduction

The Supplemental Nutrition Assistance Program (SNAP) is one of the largest U.S. social safety net programs serving 37.5 million individuals in the country. However, large portions of eligible households do not participate in SNAP, especially among the elderly. Specifically, only 42% of the elderly (65 years+) population that is eligible for SNAP participate compared to 82% of the total eligible population (Food Research Action Center, 2019; USDA, 2020). While the literature has looked at non-participation in social safety net programs in general, there is little work on SNAP participation amongst the elderly in particular. In this paper, I address questions on both SNAP participation rates and the impact of SNAP on food security levels for the elderly.

Nutrition assistance programs like SNAP, formerly the Food Stamps Program (FSP) were established to ensure minimum nutrient intakes for low-income population. The literature on SNAP focuses very broadly on 'health outcomes' using measures of hospital visits (very vague) or nutrient intake (more specific) to make generalizable claims on health measures. However, similar to the work on SNAP participation, there is not much work in understanding how the goal of nutrition intake is fulfilled for the elderly population in particular.

Existing work on the relation of SNAP and health levels offers three arguments as to how SNAP purchasing power may impact health levels (largely for children, however they are applicable generally). SNAP can provide 1) a direct nutrition effect where SNAP increases the quality or quantity of food received by the individual 2) indirect impact on health where households spend less non-SNAP income on food and can use income to consume other goods that can improve health (like healthcare) and 3) SNAP as a source of income support can just reduce levels of stress and improve mental health (Bronchetti, Christensen, & Hoynes, 2019).

The USDA identifies low-income seniors as having some of the highest risks for food insecurity (Coleman-Jensen et al., 2022). As a vulnerable group with comparatively low participation rates, recent SNAP policy reforms have focused on incentivizing SNAP participation amongst the elderly. One such policy implemented at the state level is the Combined Application Program (CAP). States enacting CAP automatically apply elderly (above the age of 65) recipients of the Supplemental Security Income for SNAP if they meet the income (and other) eligibility criteria without going through a separate application process. Supplemental Security Income (SSI) is a federal social safety net program through the SSA that provides cash assistance to disabled individuals and low-income elderly over the age of 65 years. SSI benefits are in the form of monthly payments to those that qualify. CAP has been implemented by eighteen states as of 2016 to increase SNAP participation among SSI recipients.

This research contributes to the literature by answering two questions: 1) To what extent does the implementation of CAP change SNAP participation rates for SSI recipients and 2) How does this change in SNAP affect food security levels for the elderly low-income population? Two models are used to evaluate the effect of CAP on SNAP participation rates for SSI recipients. The results from a linear model suggest a 17% increase in SNAP participation in states with CAP for SSI recipients although low statistical significance. The results from a logit-model imply a statistically significant marginal effect of CAP on SSI recipients and participation in SNAP of around 26%. This paper also presents a two-stage regression analysis to determine the effect on food security levels through instrumenting SNAP using CAP as an instrumental variable. I find SNAP increases food security by 30%, but these results are not statistically significant. These results are robust and consistent with variations in the model accounting for year fixed effects and clustering standard errors at the state level.

I use data from the Current Population Survey, U.S. Department of Agriculture and Bureau of Labor Statistics and Office of the Assistant Secretary for Planning and Evaluation Poverty Guidelines[1]. Due to limitations in reported data in the CPS, as well as limitations in the years for which state effects are accurately provided in the SNAP policy database by the USDA, I restrict my analysis to the years 1996-2016.

The results presented in this paper suggest that policies like CAP which simplify the application process for nutritional assistance programs show a strong, statistically significant, positive effect in the program participation. Additionally, the evidence suggests that through this increase in take up, nutrition outcomes measured through food security levels may increase in response.

This paper has the following structure: Section 2 presents the background literature, Section 3 presents a conceptual model of the theory, Section 4 describes the data, Section 5

[1] This paper differs from the main literature in that most papers utilize longitudinal data like the Panel Study of Income Dynamics (Vartanian and Houser, 2012) and Survey of Income and Program Participation (Ratcliffe and McKernan, 2010) or administrative data to determine the impact of SNAP on food security. However, the share of elderly single-household low-income individuals is much smaller and less represented in such datasets and thus this paper uses CPS data.

discusses the empirical methodology, Section 6 and Section 7 present the empirical results for the SNAP participation model and food security models respectively, and Section 8 provides a discussion of the findings along with some limitations.

Section 2: Background and Literature Review

2.1 Policy Background

SNAP functions as a voucher program where recipients can purchase foods from grocery store locations. If eligible and approved for SNAP, recipients receive an Electronic Benefit Transfer card which functions similarly to a debit card. Funds are loaded on to the card monthly by the state and the card can be used at select grocery stores across the state. Specific eligibility criteria vary across states. Generally, a household is SNAP eligible if their gross monthly income is below 130% of the federal poverty line. In 2023, the poverty line for a single household is $14,580. By 2016, 26 states had taken steps to increase the income threshold for SNAP eligibility in some cases going as high as 200% of the federal poverty line.

SNAP is one of the most prominent benefit programs in the social safety net. In 2016, SNAP provided $66.5 billion in benefits (Center for Poverty and Inequality, 2018). The national average for SNAP benefits in a household was $239 in 2018 (USDA, 2018). While SNAP is a key part of the social safety net, researchers have struggled to determine the effect of SNAP in part because the program is fairly homogeneous across the country in terms of implementation and eligibility for SNAP as compared to other welfare programs like Temporary Assistance for Needy Families or the Women, Infants, Children program. Studies have highlighted the difficulty in examining SNAP effects due to this homogeneity and lack of quasi-experimental variation (Bronchetti, Christensen & Hoynes 2019). However, more recently policies have been adopted at the state level to expand SNAP. Many states have expanded their income requirement to 200% of the federal poverty level, thus increasing the number of people eligible for SNAP, and several states have also implemented policies which make the SNAP application process itself more accessible to low-income individuals. Such policies include removing in person requirements to be certified as SNAP eligible, implementing online applications, removing biometric requirements, etc. These policies aimed at increasing accessibility or reducing the SNAP application process have resulted in an overall increase in the rates of SNAP enrollment wherever implemented (Yen et al., 2008; Mykerezi and Mills, 2010; Shaefer and Gutierrez, 2013; Ratcliffe et al., 2011). At the administrative level, SNAP outreach workers have also identified improved applications and application processing infrastructure as a necessity for increasing SNAP participation alongside reducing negative social perceptions regarding food stamps[2] (Fricke et al. 2015).

Some states have adopted broad-based categorical eligibility (BBCE) which expands income requirements for SNAP eligibility by removing assets from eligibility consideration or increasing the income threshold limit. This has reduced overall time required in determining eligibility, reduced required interactions during the application process and allowed state offices to use already known information on income requirements if the household is a recipient of another social safety net program. Mabli and Ferrerosa find a 6.2% increase in SNAP take up in states that implement BBCE through reducing the burden or cost to apply to SNAP.

In this paper, I evaluate the impact of CAP on SNAP take-up. The Social Security Administration (SSA) offices have been required by Federal Law to allow SSI recipients to apply for SNAP at the SSA office when applying for SSI since 1997 (FNS). However, enrollment in a welfare program other than SNAP is associated with lower participation rates in SNAP, despite eligibility (Pinard et al., 2019; Wu, 2009). Additionally, participation is known to be affected by other policy reforms as seen with the Personal Responsibility and Work Opportunity Reconciliation Act which resulted in fewer SNAP applications[3]. The CAP is targeted towards this population of single household elderly that already receive SSI and effectively reduce or even remove the administrative burden to apply for SNAP. Under the CAP policy, SSI recipients are automatically provided a simplified application to receive SNAP benefits.

2.2 SNAP Participation

Senior participation rates are comparatively low across all social safety nets as seen in a 2019 report by the Office of the Assistant Secretary for Planning and Evaluation (ASPE). Most

[2]For the purpose of this study, we might assume that the social perceptions do not play a significant role in changes in observed SNAP participation with CAP since we are interested in individuals who already receive SSI and participate in a welfare program.

[3]The Personal Responsibility and Work Opportunity Reconciliation Act passed in 1996 essentially kept SNAP as a federally funded program but with stricter eligibility requirements and higher accountability for the states. This resulted in longer processing periods for applications, certification requiring interacting with applicants' employers, landlords, in person interviews, etc. (USDA). Additionally, for the years immediately after this act, large shares of SNAP recipients were required to go through recertification, i.e., the application process all over again at frequencies as high as every 3 months. This caused a drop in SNAP caseloads.

notably, SNAP participation for the elderly population, at 42%, is 40-percentage points lower than the national rate.

Despite the low participation rates, there is very little research on SNAP participation among the elderly. Wu (2009) finds that about 1/3 of the difference in take up between elderly and non-elderly SNAP eligible groups can be explained by a relatively lower expected benefit level for the elderly compared to non-elderly. Additionally, 60% of elderly eligible were unaware of their eligibility status. This share increases as you move towards the upper quartile of elderly age distribution. I hypothesize that CAP as a means through which SSI applicants are made aware of SNAP eligibility can address some of this effect.

One reason for low participation rates among those eligible that is commonly seen in research is a lack of perceived need for SNAP (Hill, 1990; Daponte et al., 1999 and Wu, 2009). The findings corroborate results in Nord and Golla (2009) where only the severely food insecure or those with perceived need participation SNAP.

2.3 SNAP and Food Security

The empirical literature finds fairly consistent positive effects of SNAP on health and food security levels. Pak and Kim (2020) conduct a longitudinal analysis of elderly Americans finding that SNAP resulted in a decrease of poor health outcomes through an increase in food security levels. Gregory and Deb (2015) run a multivariate regression utilizing data from the medical expenditure panel survey and determine an improvement in self assessed health for nonelderly Americans from SNAP participation. There is a related literature comparing the impact SNAP has on food expenditures with that of lumpsum cash amounts. The USDA, in summarizing this literature, concludes that a dollar provision of SNAP resulted in a 20-45 cent increase in food consumption compared to only a 5-10 cent increase if there was a $1 increase in cash income (Fraker, 1990).

Assessing the effect of SNAP on food security levels is difficult. SNAP participation as a determinant of food security or health outcomes has been identified as endogenous in a large portion of the literature. Hoynes (2008) discusses the shortcomings of a simple comparison of health outcomes of participants with non-participants. She highlights the upward bias in this approach by not accounting for inherent differences in the control and treatment group. Likewise, Nord and Golla (2009) determine self-selection effect into SNAP and identify households select into SNAP when they are more severely food insecure the 6 months prior to

SNAP take up which further supports the decision to treat SNAP as an endogenous measure in the food security model.

Addressing the exogenous selection problem has proven to be difficult in evaluations of SNAP. As noted above, the existing literature on SNAP participation effects and outcomes has highlighted the difficulty in measuring outcomes of SNAP due to the homogeneity in implementation and federal regulations on eligibility as well as misreporting in national surveys (Bronchetti et al., 2019; Kreider et al., 2012) . However, more recently there has been an implementation of policies at the state level aimed to incentivize SNAP participation or make the application process easier for potential recipients (Bronchetti, Christensen & Hoynes, 2019). In Almond, Hoynes and Schanzenbach (2011) the authors use different dates of SNAP introduction in different US counties to determine pregnancies introduced to the SNAP in the last trimester experienced higher birth weights and lower neonatal mortality rates.

Ratcliffe et al. (2021) utilise CPS data to determine how SNAP reduces food insecurity for households with children. They identify SNAP as endogenous in the food security regression and use broad based categorical eligibility and option for simplified reporting option in a state to instrument for SNAP. They find that SNAP benefits reduce the chance of being food insecure by 20%. The results I find in Section 6 corroborate the findings in Ratcliffe et al. (2021) for elderly single person households.

A 2013 study explored a similar question determining the impact of SNAP on food sufficiency levels of the 60 years and above population (Greenhalgh-Stanley and Patrick, 2013). They use state SNAP policies (CAP, fingerprinting, etc.) as an IV for endogenous SNAP participation. The authors find CAP results in a higher chance of elderly individuals to be of normal body weight and reduced out of pocket healthcare expenditure. However, the study does not restrict the results of CAP to single household SSI recipients, which is a criterion for CAP eligibility. Additionally, their paper focusses on data till 2008. I offer new results by extending the data to 2016. Between 2008 and 2016, 7 more states have implemented CAP. I present a model for food security and SNAP that specifies the effect of CAP on SSI recipients.

Mykerezi and Mills (2010) uses PSID in an endogenous treatment effect model and find SNAP participation reduces food insecurity by 18%. Ratcliffe and McKernan (2010) compare an IV model where SNAP is endogenous in food security alongside naïve models that use SNAP as exogenous. They find the naïve model results in inaccurate higher levels of food insecurity with

SNAP participation. In their IV model, they instrument SNAP using 4 primary state level SNAP policies – biometrics, outreach spending, partial and full immigrant eligibility. The IV model finds a 30% decrease in the chance of being food insecure and 20% decrease in likelihood of being very food insecure.

The model presented for food security in this paper only instruments SNAP using the Combined Application Project and an interaction for the policy with SSI recipients. I include the variables Ratcliffe and McKernan use in the food security equation because they relate to spending burdens and are more closely related to the environment of the state than CAP as policies. For this reason, I believe they are relevant to the food security model directly and not just through SNAP participation.

Section 3: Conceptual Framework

Food insecurity is considered to be a product of social and economic conditions of a household which limits access to (or creates uncertainty to the access of) sufficient food according (Office of Disease Prevention and Health Promotion). Ratcliffe and McKernan (2010) describe food insecurity as primarily a micro level function of income, public and private transfer and consumption or decision which are all inputs determined by members of the household. Their food security model included SNAP participation along with these determinants and state and year fixed effects[4].

Being disabled is hypothesized to increase chance of SNAP participation but reduce food security levels. Being female, a minority racial group or not having completed a high school degree is hypothesized to increase SNAP participation but reduce food security. This is because these groups are hypothesized to be associated with negative effects on income which has a higher chance of increasing their perceived need for SNAP. Additionally, this negative effect on income which is a determinant of food security would result in lower levels of food security. Finally, downturns in the economy like the period following the 2008 financial crisis are expected to be associated with lower levels of food security and higher levels of benefit participation like SNAP.

[4] This paper refers to the effect of SNAP on food security not on food insecurity levels as is more commonly seen in the literature. The main reason for this is to provide easier interpretation of regression tables and results presented.

3.1 Hypothesized effect of CAP on SNAP

SNAP participation is determined in part by the rules of eligibility and application. Program rules and processes impose a cost on the application process (Ratcliffe and McKernan, 2010). Programs that reduce the cost of application process – where cost can be financial or non-financial in nature – like removing fingerprinting requirements or implementing online applications can increase the SNAP participation (Yen et al., 2008; Mykerezi and Mills, 2010; Shaefer and Gutierrez, 2013). CAP is a program that reduces the cost to apply for SSI recipients so I hypothesize the implementation of CAP increases the participation of SNAP.

To better understand the hypothesized effect of CAP on SNAP we can think of SNAP as a good to consume. The market for this good consists only of eligible individuals. The price of this good for any consumer is the cost to apply and participate in SNAP. As stated previously, cost can be pecuniary or non-pecuniary. The implementation of CAP reduces the overall price of the good causing an increase in demand for SNAP. In this model, a shift in demand would also come about if income eligibility criteria expanded and more people were then eligible for SNAP, i.e., consumers in the market.

This micro level model highly simplifies the consumption of SNAP to demand and supply factors. To keep the model simple, we assume that the market for this specific case looks only at SSI recipients that are eligible for SNAP. An expansion of this model to better understand the impact of CAP is to include all elderly eligible individuals in the market and note how much demand increases for SSI recipients relative to non-SSI recipients which is not fully explored in this paper.

3.2 Hypothesized Effect on Food Security:

I hypothesize a direct effect of SNAP on increasing food security levels through increasing the funds provided to households to purchase foods. We can conceptualize food security as an outcome from a level of food consumption. Hoynes et al. (2014) presents the neoclassical model of food consumption with the implementation of SNAP. In Figure A we have a model with food on the X axis and consumption of all other goods on the Y axis. The introduction of food stamps, or SNAP, increases the budget constraint with a parallel shift outward shown by B_F.

In figure B, Hoynes et al. (2014) show how consumption behavior with the introduction of SNAP depends where on the initial budget constraint a consumer's utility function lies. Looking at individual A, we see that SNAP increases the amount of food consumption from F_0 to F_1 as well as increasing the consumption of other goods on the Y axis due to an overall outward shift of the utility curve on to the new budget constraint. This occurs because the conditional cash transfer through SNAP now expands the resources available for the individual to consume, to a certain extent (hence the kinked point at C). Now person A is able to consume at a higher utility curve at point A_1*. This can be thought of as an overall increase in self-sufficiency and the economic security or ability to consume. For the purpose of this extension, we can narrow this to increased food security due to increased food consumption.

Individual B differs from A in that they prefer relatively less consumption of food. When SNAP is introduced, they move from B_0* to B_1* using all their food voucher benefits to consume food goods and other cash resources to purchase all other goods. As seen in the Figure B they are situated at the kink point. If B was provided a cash transfer in place of food vouchers, they would choose to spend more on other goods and not food. For consumers like B, SNAP results in a higher increase in food consumption than a cash transfer would.

With this understanding of the Neoclassical model, Hoynes and Schanzenbach (2009) determine that access to SNAP increases food consumption levels by 18%. Additionally, the USDA results discussed earlier stated a larger increase in food consumption with SNAP than when a cash amount is given (20-45 cents compared to 5-10 cents). This would suggest that individuals are more likely to be like individual B than A.

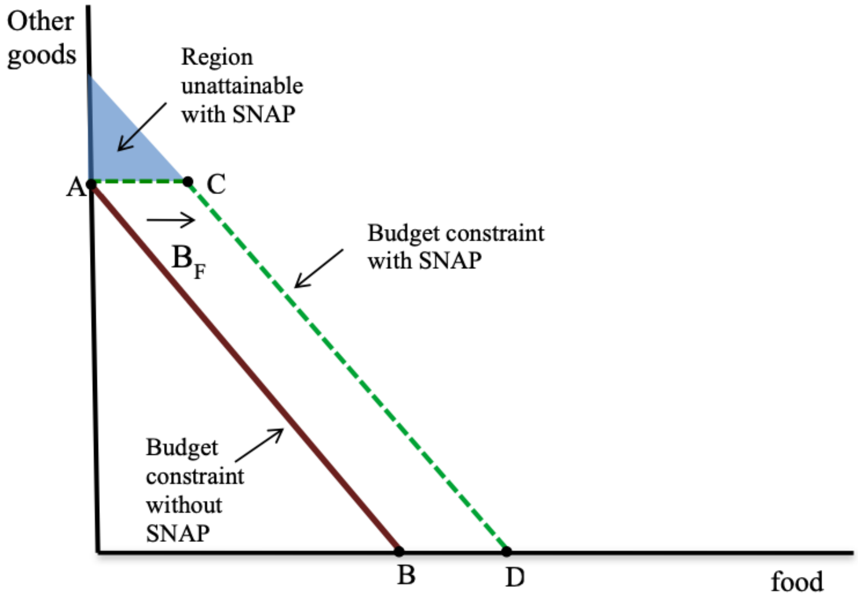

Figure A. Changing budget constraint with introduction of SNAP Source: Hoynes, H., McGranahan, L. & Schanzenbach, D. *SNAP and Food Consumption* (2014)

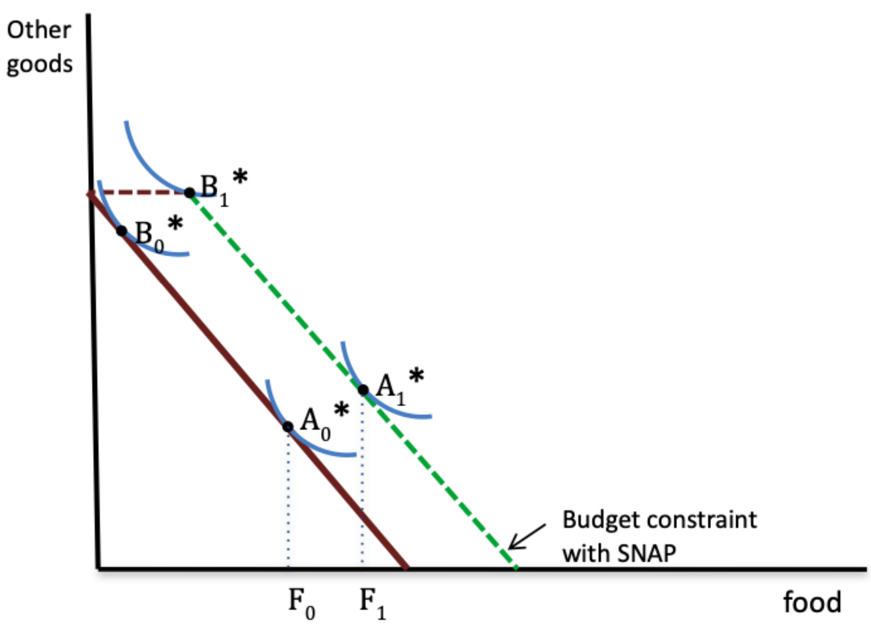

Figure B. Shifting utility curve and food consumption levels with SNAP Source: Hoynes, H., McGranahan, L. & Schanzenbach, D. *SNAP and Food Consumption* (2014)

Section 4: Data Description

I use data from four sources in the analysis: 1) Current Population Survey (CPS) 2) U.S. Department of Agriculture (USDA) SNAP Policy Database 3) Bureau of Labor Statistics (BLS) Labor Area Unemployment Statistics 4) Office of the Assistant Secretary for Planning and Evaluation Poverty Guidelines (ASPE).

The CPS is a monthly survey sponsored jointly by the BLS and U.S. Census Bureau and serves as the primary source of labor statistics in the country. Along with monthly surveys on labor and employment statistics, the CPS conducts supplemental surveys covering regarding food security levels[5]. I use each year's respective food security schedule to determine food security for each respondent. In the month of March, the CPS conducts an additional supplemental survey, the Annual Social and Economic Supplement, which collects data on household characteristics, participation in social safety net programs, more specific earnings amounts and additional demographic characteristics such as marital status, high school completion levels, etc. I link individuals in the March ASEC CPS supplement with their respective data in the Food Security supplement to create my primary dataset for this paper. This dataset allows me to observe SNAP participation as well as food security levels for a given individual in the data.[6] I also use data from the ASPE Poverty Guidelines to determine national poverty income threshold for a single household for the respective year. I further restrict the CPS data to only look at the elderly population (>65 years) in single households and utilize state income requirements stated in the USDA Policy Database to restrict the data to observations under the income threshold for single household elderly in the respective state. This represents the SNAP and CAP eligible elderly population.

The USDA SNAP Policy Database shows when each state implemented CAP, or if they are yet to implement CAP and other state wide SNAP policy variations. The database is used to identify CAP implementation dates as well as to control for other SNAP policies at the state levels such as if the state required fingerprinting, income thresholds, etc.

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[5] The food security supplement is conducted in December in each year since 2001. Prior to 2001, this supplement was conducted in different months each year – but largely in either April, August or September.

[6] One limitation with linking data across months is the CPS rotation pattern. Households are interviewed for 4 consecutive months, then not interviewed for 8 months and then are interviewed again for the next 4 months. So, households are only in the survey for 8 months total and the linking process only includes households that can be matched in the March ASEC and December, April, August or September surveys of a given year. This restricts the size of the sample significantly.

The total dataset has 4673 observations from 1996 to 2016[7]. I have omitted observations from California, Hawaii and Alaska. Hawaii and Alaska are omitted due to much larger thresholds for SNAP eligibility as well as varying eligibility for other assistance programs, etc. that make it harder to control for state effects. California is omitted (and commonly omitted in past work) due to the state's cash-out policy which restricted access to SNAP for SSI recipients until 2019 (Jones et al. 2021). The California cash-out policy allowed California to give SSI recipients an extra $10[8] instead of providing SNAP (called CalFresh in California) benefits (California Legislative Analyst's Office, 2018).

4.1 State Control Variables

I include several variables using the USDA Policy Database and Bureau of Labor Statistics that might affect SNAP participation and food security levels for a given individual in a state. First, I control for unemployment levels in the state in a given year using the Area Unemployment Statistics database from the BLS. Next, I include a vector of other policies on SNAP eligibility that are implemented at the state level. This includes measures of whether the state allows exemption from in person interviews, allows telephone interviews, requires fingerprinting, online applications for SNAP, total outreach spending and if non-citizen elderly are eligible (if they meet all other requirements). Some states have policies enacted in only some regions of the state so we treat such policies as categorical variables. For example, the categorical variable for fingerprinting takes values 0 (policy not implemented), 1 (policy implemented in the whole state) or 2 (policy implemented in some parts of the state).

Figure 1 below shows a timeline of CAP implementation in different states. South Carolina was the first state to implement CAP in 1996. The early 2000s saw a rise in CAP implementation for different states across the country. From the figure we can see that CAP implementation reached a peak in 2011 with 18 states. This dropped to 17 states in 2014 because New Mexico stopped offering CAP.

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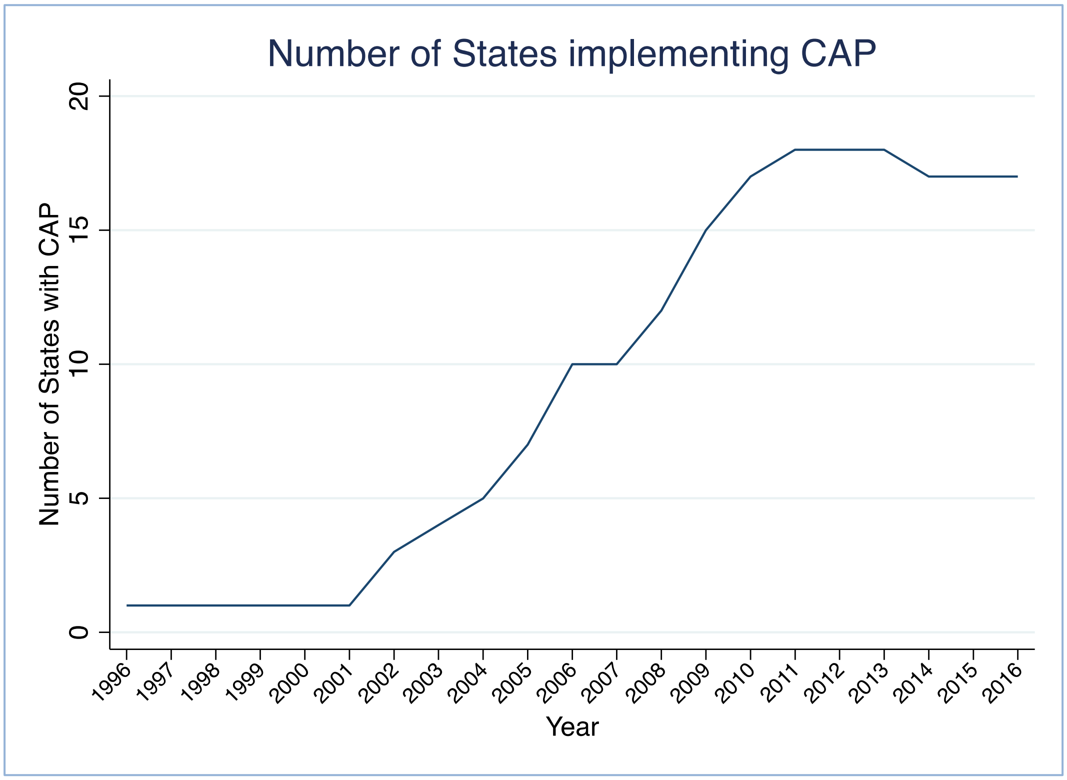
[7] This is largely because the USDA Snap policy database only provides compiled data on the extend of CAP, other SNAP policies implemented in each state and varying income threshold until 2016

[8] $10 was the average SNAP benefit amount in California in 1974 which was when the cash out policy was implemented. However, this additional benefit to SSI recipients never increased as average SNAP benefits increased. For context, in 2016 the national average of SNAP benefits for an individual was $125.40 (USDA)

Figure 1: Number of States implementing CAP from 1996 – 2016



Note: This graph shows the number of states which have CAP in a given year using data from the USDA SNAP Policy Database

Table 1 below provides an overview of the states in the dataset that currently implement the main state level SNAP policies. The first column lists the main SNAP policies that I include in the empirical model including CAP. The second column shows the number of states (excluding Hawaii, California and Alaska) and D.C. had implemented that policy in March of 2016. I also present the total number of states that have ever implemented the given policy. State policies changed over this period. For example, in 1996, all states and D.C. had provisions to allow non-citizen elderly that met income requirements to be eligible for SNAP benefits yet by 2016 only four states had this policy. Fingerprint and other biometric details were initially adopted by some states in the 90s but dropped in in the 2000s.

Table 1: State SNAP Policy Implementation Overview			
Policy Name	# of States in 2016	# of States implemented ever	Year of first implementation
Combined Application Project (CAP)	17	18	1996
Call centers	37	45	1999
Exempt from in person interviews	44	45	2006
Fingerprint required	1	7	1996
Non-citizen elderly eligible	4	48	1996
Online Application	45	45	2002
Broad based categorical eligibility	38	39	2000

Note: This table uses data from the 47 states and D.C. included in the analysis of this paper. Column 1 shows the number of states that has the respective policy in 2016, Column 2 shows the number of states that have ever implemented the policy and Column 3 shows the first year of implementation in any state in the given dataset.

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

4.2 Data Demographics

I use demographic variables from the CPS to control for socio-demographic factors such as age, gender, income, education levels and race. In Table 2 we can see the demographic breakdown of the sample population by SNAP participation.

Table 2: Weighted Means and Proportion for SNAP participants and non-participants

	Proportions - Participants	Means-Participants	Proportions-Nonparticipants	Means-Nonparticipants
Male	0.299		0.342	
Female	0.701		0.658	
White	0.811		0.904	
Black	0.155		0.074	
Other	0.034		0.022	
SSI=0	0.775		0.987	
SSI=1	0.225		0.013	

Not completed HS	0.412		0.244	
HS diploma or equivalent	0.588		0.756	
Age		74.62		75.03
Income as a percent of poverty line		93.70		102.4
Unemployment		6.699		6.647
Observations	504	504	4169	4169

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

Table 2 shows the basic demographic distribution of the population data for SNAP participants and non-participants. The ratio of male to female in both groups is roughly similar with around 29% male and 70% female for SNAP participants and 34% male and 66% female in the non-participant group. A study from the Administration for Community Living (ACL) found that in 2020 55% of the population of elderly people over the age of 65 were women (ACL, 2017). The number in our data differs from this number, however our data looks only at single household low income. One reason for the proportion of gender to not be representative of the national statistics for elderly population might be that according to the ACL, 70% of older men were found to be married compared to only 40% of older women. This could result in a larger share of the elderly male population being excluded when we look only at single-individual households.

The share of SNAP participants that are black is at 15% while the share of non-participants that are black is 7.4%. According to Census data, the national share of black residents is approximately 13% and white residents make up around 75% of the population. In the SNAP participant group, 22.3% receive SSI benefits compared to only 1.3% of the non-SNAP participant group. SNAP participants in the data also have a higher share of individuals who did not complete a high school degree at 41% compared to only 24% in the non-SNAP participation group. The average age of an individual is roughly the same for both groups as well as a measure of mean unemployment in each individual’s respective state. The mean measure of income level as a percentage of poverty level (pctpovhh) is lower for SNAP participants at 93.83 compared to 102.4 for non-SNAP participants.

It is important to note that only 11% of the respondents take part in SNAP despite every individual here being eligible. This number differs from the federal statistic provided earlier of 40% SNAP participation rate among the elderly. There are two potential reasons we have for this difference: 1. The dataset for this paper looks specifically at single household elderly instead of the elderly population as a whole 2. The CPS relies on self-reporting of SNAP participation are known to be underreported whereas the federal statistic is from administrative data (Brent et al. 2012). I do not address these measurement errors in this paper.

Table 3: Weighted Means and Proportion for Food Secure and Food Insecure

	Proportions - Food Insecure	Means-Food Insecure	Proportions- Food Secure	Means-Food Secure
Male	0.317		0.333	
Female	0.683		0.667	
White	0.774		0.917	
Black	0.188		0.0621	
Other	0.0379		0.0210	
SSI=0	0.883		0.981	
SSI=1	0.117		0.0195	
Not completed HS	0.342		0.199	
HS diploma or equivalent	0.658		0.801	
Disabled	0.480		0.331	
Not Disabled	0.520		0.669	
SNAP=0	0.699		0.918	
SNAP=1	0.301		0.0821	
Age		73.85		75.38
Income as a percent of poverty line		99.76		107.9
Unemployment		6.924		6.759
Observations	463	628	2003	2877

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

Table 3 shows the demographic characteristics of food secure and food insecure individuals. Both groups have almost identical share of male and female individuals. 77% of the food insecure group are white compared to 91% of the food secure group with black respondents taking up only 18% of the food insecure and 6% of the food secure group. The share of food insecure individuals that receive SSI benefits is at 11% compared to only 1.9% of the food secure group. The share of people in the food insecure group who have completed a high school diploma is 65% compared to 80% of the food secure group. This is not surprising as we would assume if high school completion is a determinant for income earnings and subsequently food security, that the food insecure category would have a smaller share of individuals who have completed high school. The share of people that are disabled is higher for food insecure at 48% than food secure group at 33%. The SNAP participation rate for the food insecure group is 30% compared to only 8% in the low food secure group. The mean age of the food insecure group is 73 and 75 for the food secure group, comparable to the dataset average of 74 years. The mean income as a percent of poverty line is higher for food secure at 107% while food insecure is at 99%.

Section 5: Empirical Framework

The method of analysis in this paper is a two stage least squares regression model to determine the impact of the Combined Application Project on food security levels through SNAP participation for a 20-year time period, 1996 to 2016. I also use non-linear models to further understand the impact of CAP on SNAP participation rates. The unit of observation is an individual *i* in a given state *s.* As explained in Section 4, I control for demographic features as well as state and year fixed effects. I estimate the causal impact of CAP implementation at the state level on food security through an increase in SNAP participation for low-income single-household elderly SSI recipients.

We can reasonably conclude that the CAP could only have an effect on food security through its impact on SNAP participation. This is because all CAP does is allow SSI recipients to directly apply for SNAP with a simplified application process at an SSA office, and does not otherwise provide additional resources to improve food security. One concern is that we might assume states that implement CAP are inherently different from states that do not implement CAP. I address this issue by including state characteristics and additional policies that are implemented at the state level to change SNAP participation in the food security and SNAP regression equations. For example, if a state that implements CAP is different than a state that does not implement CAP, I assume this difference is captured in the state fixed effects and time varying variables such as total outreach spending by the state for program participation, whether or not a state implements call centers to help with SNAP participation and if the state allows non-citizens that are satisfy income requirements for SNAP are eligible. For this reason, we can justify the use of only CAP and SSI&CAP as instruments for the endogenous variable SNAP.

5.1 Empirical Model for SNAP Participation

I use a binary measure for SNAP participation which is 1 when an individual *i* in state *s* at a given time *t* receives SNAP benefits and 0 when they do not. I use a logit model for SNAP participation with the following functional form:

$$E[SNAP_{ist}] = G[\beta_1 + \beta_2 X_{ist} + \beta_3 SSICAP_{ist} + \epsilon]$$

In this equation, G(.) is the standard logistic CDF, *X* is a vector of state characteristics and demographic variables of the individual *i*. The variable of interest, *SSICAP*, is an indicator variable which is 1 when the individual receives SSI benefits and lives in a state which implements CAP. This form borrows from the mechanism of difference-in-difference estimations where SSI&CAP measures the difference in SNAP take up for SSI recipients in CAP (treatment) vs non-CAP (control) states. However, it is not a perfect difference in difference setup since I do not measure the time difference[9]. Along with the logit model, I also present a linear probability model of the same functional form. Unlike the logit, the results from the linear probability model are statistically insignificant but do suggest a similar positive effect of SSI&CAP. This serves to motivate the food security equation discussed in 5.2.

5.2 Empirical Model for Food Security

I use a binary indicator variable for food security where a person with very low food security, low food security and marginal food security is foodsecure = 0 and a person with high food security is indicated as foodsecure =1. Moving forward, the variable for food security may be referred to as *FS* in the empirical model. The regression for food security I measure is a linear probability model of the form:

$$FS_{ist} = \alpha_1 + \alpha_2 \mathrm{Y} + \gamma \mathrm{SNAP} + \varepsilon$$

where Y is a vector of all state and year fixed effects as well as demographic identifiers of the individual *i* in state *s* in the year *t*. State-time varying factors include all SNAP policy variations at the state level except CAP. This is because I assume that CAP as a policy only impacts the

[9] I do use a dummy variable *financial crisis* to indicate if the observation is in the years immediately following the financial crisis 2009, 2010, 2011. I state that I do not measure the time difference because I do not control for the period of time that passes after implementation of CAP.

take up of SNAP participation and not directly determines the level of food security through any other channel. Additionally, out of all other state expansions, CAP has a relatively lower cost to the state (compared to expanding income thresholds, establishing call centers, etc.) and does not add an additional barrier to the consumer (fingerprint requirements) and thus can be assumed to not influence food security through any other channel besides SNAP participation. Additionally, since it has a relatively low cost it is less determined by state funds and tells us less about something inherent in a state, i.e., CAP states are not fundamentally different in one way than other CAP states.

I assume that SNAP is endogenous and correlated to the error term for the FS model, but CAP and Y are exogenous:

$$Cov(SNAP, \varepsilon) \neq 0$$
$$Cov(Y, \varepsilon) = 0$$
$$Cov(CAP, \varepsilon) = 0$$

To address this endogeneity problem, I model SNAP take-up using the following equation:

$$\text{SNAP}_{ist} = \beta_1 + \beta_2 \text{X} + \beta_3 SSICAP + \beta_4 CAP + \nu$$

where v is assumed to be uncorrelated with all of the righthand side variables including CAP and SSICAP. One concern with this model is I treat SSI as exogenous, which might not be accurate because we know that program participation in general varies across groups. However, I minimize this concern by controlling for demographic characteristics. Additionally, SNAP is more directly targeted to provision of food access and food security whereas SSI is not directly targeted at providing food. So, it is plausible that 1. SSI recipients are not taking up SSI only food security and 2. SSI is uncorrelated to unobserved factors for food security. So, I make the assumption that SNAP is endogenous to food security whereas SSI is exogenous. The functional form of SNAP used in the two-stage least squares regression is of the same form as the linear model discussed in Section 5.1.

Section 6: SNAP Participation

For both the logit and linear models, I provide regression results using a complete model, including all state effects and demographic characteristics, as a well as a model excluding the disability variable. As stated above, disability is removed to allow for a larger sample size and acts as a robustness check. The disability variable is only reported for the years 2009-2016, however the variable itself is seen to be statistically significant in the SNAP models.

6.1 Logit Model

I use a logit model to regress SNAP participation on the individual characteristics vector of variables and state policies. In Table 4 below and Table C in the appendix, I provide two models. The first includes all demographic and state policy variables, which I refer to as the complete model; and a second model which excludes the disability variable. Table C in the appendix provides the results of the same logit regression from Table 4 but includes the coefficient estimates for the SNAP policy measures (which is excluded from the results in Table 4 due to negligible statistical significance).

Table 4: Marginal Effects of Demographic factors on SNAP in the Logit Model

	Complete Model		Exclude Disability	
	(1)	(2)	(3)	(4)
Sex				
Male	0.117***	0.525***	0.0950***	0.504***
	(0.00911)	(0.0649)	(0.00688)	(0.0568)
female	0.134***	0.567***	0.114***	0.560***
	(0.00678)	(0.0617)	(0.00535)	(0.0534)
Race				
White	0.119***	0.535***	0.0990***	0.522***
	(0.00579)	(0.0626)	(0.00449)	(0.0544)
Black	0.183***	0.668***	0.149***	0.644***
	(0.0186)	(0.0622)	(0.0141)	(0.0559)
Other	0.165***	0.637***	0.163***	0.670***
	(0.0316)	(0.0833)	(0.0273)	(0.0684)
Disability				
Disabled	0.168***	0.644***		
	(0.0106)	(0.0600)		
Not Disabled	0.106***	0.502***		
	(0.00641)	(0.0640)		
High school completion				
Not completed HS	0.182***	0.671***	0.153***	0.653***
	(0.0129)	(0.0583)	(0.00976)	(0.0513)
HS diploma or equivalent	0.109***	0.515***	0.0899***	0.497***
	(0.00606)	(0.0640)	(0.00475)	(0.0552)
SSI recipient				0.0898***
SSI=0	0.108***	0.108***	0.0898***	(0.00427)
	(0.00570)	(0.00570)	(0.00427)	(0.00427)
SSI=1	0.553***	0.553***	0.541***	0.541***
	(0.0613)	(0.0613)	(0.0533)	(0.0533)
CAP State				

CAP=0	0.142***	0.585***	0.118***	0.565***
	(0.00870)	(0.0597)	(0.00659)	(0.0519)
CAP=1	0.115***	0.518***	0.0961***	0.504***
	(0.00798)	(0.0668)	(0.00657)	(0.0587)
SSI recipient & CAP state				
SSICAP=0	0.126***	0.551***	0.107***	0.540***
	(0.00566)	(0.0624)	(0.00442)	(0.0542)
SSICAP=1	0.207***	0.698***	0.136***	0.611***
	(0.0607)	(0.0647)	(0.0360)	(0.0583)
Restricted to SSI recipients	No	Yes	No	Yes
Includes disability variable	Yes	Yes	No	No

Note: Column 1 shows the marginal effects of for the total sample set for the complete model, Column 2 shows the marginal effects when we look only at SSI recipients for the complete model, Column 3 is the marginal effects of the logit model excluding disability for the total sample and Column 4 includes the marginal effect excluding disability for SSI recipients.

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

The main measure of interest is the binary SSI&CAP indicator variable which determines the impact of CAP on SNAP participation for an SSI recipient. However, I am most interested in the marginal effects of CAP when we know an individual is an SSI recipient. So, in Table 4 we see the marginal effects of SSI&CAP when an individual is an SSI recipient compared with the marginal effects when we do not restrict the population to SSI recipients. The complete model shows that CAP results in an increase in the chance for SNAP participation rate from 55% to 69% for an SSI recipient (2), i.e., CAP increases SNAP participation by approximately 14.7-percentage points (26.67%) for the average low-income, elderly SSI recipient. The second model without disability in Table 4 (and Column (3) in Table 5) results in a 7-percentage point increase (13%) in likelihood of SNAP participation for an SSI recipient. These results are statistically significant.

The marginal effects from the complete model for the average individual in the sample suggests that a female individual is 14.5% (percentage points) more likely to participate in SNAP than their male counterparts. Black individuals are 5% (7-percentage points) more likely than white respondents to receive SNAP. Lack of high school completion has a statistically significant impact with a 73% (8-percentage point) increase in probability of SNAP participation in model (1). The estimates for demographic controls provide qualitatively similar results in Model (2) and Model (3) as seen in Model (1). Irrespective of whether an individual is in a CAP state or not, being an SSI recipient increases SNAP participation by 80.4% (44.5-percentage points). disability results in an increase in SNAP participation by 64% (6.8-percentage points). The marginal effects for the demographic characteristics in both models are statistically significant at the 1% level so they provide a high level of precision. However, since we see statistically significant results of the disability measure, the complete model including disability (1) is the more accurate. The results for other SNAP related state policies used as state effects in this model all produce small and statistically insignificant marginal effects.

Table 5 below shows marginal effects when I run the logit model for SNAP participation including state and year fixed effects. The first two models produce percentage point increases of 15.8 and 14.9 respectively for SNAP participation. These results show a consistent increase in SNAP participation by approximately 27-29% when we restrict the effect of CAP to SSI recipients. Column (4) shows the marginal effects from a linear model discussed in Section 6.2. We notice that the estimated marginal effects in Tables 4 and 5 produce statistically significant and results suggesting that CAP has a substantial and statistically significant effect on SNAP participation.

Table 5: Marginal Effect of SSI&CAP on SNAP Participation

	(1)	(2)	(3)	(4)
SSICAP=0	0.538***	0.550***	0.540***	0.605*
	(0.0623)	(0.0624)	(0.0542)	(0.03)
SSICAP=1	0.696***	0.699***	0.611***	0.713*
	(0.0657)	(0.0646)	(0.0583)	(0.04)
Percentage-point	15.8	14.9	7.1	10.8
Percentage Change	29.36%	27.09%	13.14%	17.9%
State and Year Fixed Effects	Yes	No	No	Yes
Disability Included	Yes	Yes	No	Yes
Linear Model	No	No	No	Yes

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

6.2 Linear Model

I include a linear model for SNAP participation to understand the difference in results seen from the logit models. This is particularly useful to understand how to interpret the food security regression in Section 7 since I estimate SNAP participation using a linear regression. Table 6 below shows the regression results for a linear probability model of SNAP when I include state and year fixed effects. The state and year fixed effects control for measures apart from the state and year control variables used in the complete model in Section 6.1. I also vary the use of disability in the linear model.

The main estimates for demographic characteristics show that an increase in age by 1 year decreases the probability of an individual to participate in SNAP by 0.2 percentage points. In our main model, female respondents are more likely to participate in SNAP and black individuals are 5.5-8 percentage points more likely than white respondents to receive SNAP. As income levels increase, respondents are less likely to participate in SNAP although the marginal fall in probability to participate is fairly small. While small, this correlation makes sense as we might assume people with lower income are more ‘in need’ for SNAP despite the entire population being eligible. Lack of high school completion has a statistically significant impact with a 6-7.5 percentage point increase in probability of SNAP participation. The estimates for demographic controls provide qualitatively similar results across the models suggesting robust results. Higher levels of unemployment increase SNAP participation although at a marginally low rate of less than 1% for each unit increase in unemployment measure.

The estimate for the effect of SSI&CAP varies between 5-10 percentage point increase with the models including disability resulting in a larger effect of SSI&CAP on SNAP participation. The complete model with fixed effects in Column (1) in Table 6 increases SNAP participation from 12% to 23% when CAP is implemented in an SSI state. However, this estimate is not statistically significant with standard errors of the magnitude 1.89 for an estimate of 0.106 in the complete model (3). Column 4 in Table 5 shows the marginal effect of SSICAP in the linear model when I look only at SSI recipients as done in Section 6.1. The linear model results in a 10.8-percentage point increase in SNAP for SSI recipients in CAP states which translates into a 17% increase in SNAP participation. While the results are imprecise, and smaller in magnitude than the estimate from the logit model, it is consistent in providing a positive relation between CAP for SSI recipients and SNAP. The estimate of SSI on SNAP participation is robust at 49-percentage points. In the data, approximately 63% of SSI recipients are enrolled in SNAP. Thus, a 17% increase in this population would result in a non-negligible increase in SNAP recipients.

Table 6: Regression Results using Year and State Fixed Effects				
	(1)	(2)	(3)	(4)
SSI&CAP	0.108	0.0537	0.106	0.0526
	(1.92)	(1.15)	(1.89)	(1.14)
SSI	0.499***	0.488***	0.503***	0.499***
	(12.94)	(15.40)	(13.20)	(15.88)
CAP	-0.0813	0.00170	-0.0267*	-0.0235*
	(-1.28)	(0.08)	(-2.11)	(-2.22)
Age	-0.00226*	-0.00125	-0.00228*	-0.00144*
	(-2.52)	(-1.83)	(-2.56)	(-2.11)
Female	0.0198	0.0193*	0.0171	0.0198*
	(1.67)	(2.11)	(1.46)	(2.18)
Black	0.0808***	0.0650***	0.0700***	0.0554***
	(4.21)	(4.41)	(3.97)	(4.07)
Other	0.0452	0.0653**	0.0499	0.0707**
	(1.47)	(2.67)	(1.65)	(2.93)
Income as a percent of poverty line	-0.000236	-0.000218*	-0.000232*	-0.000177*
	(-1.94)	(-2.38)	(-2.03)	(-2.19)
Disabled	0.0610***		0.0621***	
	(5.08)		(5.21)	
Unemployment	0.00342	-0.00391	0.000800	0.00462*
	(0.37)	(-0.58)	(0.28)	(2.03)
Not completed HS	0.0741***	0.0629***	0.0751***	0.0615***
	(5.60)	(6.34)	(5.73)	(6.27)
State and Year Fixed Effects	Yes	Yes	No	No
Include Disability	Yes	No	Yes	No

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

While the results seen in the linear model are imprecise with large standard error, they are used in the next section to determine changes in food security levels since SNAP is instrumented through a linear model.

Section 7: Food Security

In the first stage equation, I instrument SNAP using CAP and SSI&CAP as the instruments. The effect of SSI&CAP in the first equation of this model is 0.04. The coefficient here is not exactly the same but is consistent in magnitude with what we see in Section 6.2 (5-10 percentage points).[10]

[10] This is because there is underreporting in the CPS for food security. In Section 6, I include all observations in the sample for size but in this section, the data is reduced to 2459 observations when I regress food security.

Table 7: Two stage least squares regression instrumenting SNAP with CAP and SSICAP

	(1) First equation	(2) Second equation
SSI&CAP	0.0487	
	(0.0652)	
SSI	0.493***	-0.400
	(0.0426)	(0.302)
CAP	-0.0311*	
	(0.0148)	
SNAP		0.247
		(0.580)
Age	-0.00238*	0.00762***
	(0.00105)	(0.00190)
Female	0.0164	-0.0140
	(0.0137)	(0.0197)
Black	0.0783***	-0.221***
	(0.0202)	(0.0511)
Other	0.0789*	-0.136*
	(0.0359)	(0.0638)
Income as a percent of poverty line	-0.000218	0.000238
	(0.000134)	(0.000215)
Unemployment	0.000613	-0.00637
	(0.00331)	(0.00406)
Not completed HS	0.0716***	-0.103*
	(0.0154)	(0.0454)
Disabled	0.0631***	-0.111**
	(0.0138)	(0.0410)

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

The second stage equation regresses food security of an individual *i* in a state *s* on the vector of demographic characteristics, vector of state effects and SSI participation of that individual. In this second stage equation, our main measure of interest is the coefficient on the endogenous variable SNAP. We see the results for this model in Table 7. In this model, food security for an individual increases by 30% (24-percentage points as seen in Table 7) when an individual participates in SNAP. We can interpret this result as CAP increases SNAP participation for 17% (from Section 6.2) of the SSI recipient population resulting in a 30% increase in the likelihood for food security (moving from food insecure / low secure to food secure).

Table 7 shows the regression results on the demographic groups. We see that age, race, high school completion, disabilities and policies on SNAP accessibility have significant effects on if an individual is food secure or not. Converse to the result seen in the SNAP regression, an increase in age results in 0.762 percentage point increase in food security whereas an increase in age results in a decrease in SNAP participation. A black individual is 20-percentage points less likely to be food secure compared to their white counterparts. Similarly, an individual that has not completed a high school degree is 10.3-percentage points less likely to be food secure and 7-percentage points more likely to participate in SNAP than an individual in this population that has a high school degree. We see similar results when an individual is disabled, they are 11-percentage points less likely to be food secure and 6-percentage points more likely to participate in SNAP with statistical significance.

Importantly, the coefficient on SNAP participation has large standard errors (in magnitude greater than the coefficient measure). We know our results are not precise for the approximation of the effect of SNAP on food security. However, the results do support the existing literature on the positive effect of SNAP on food security. Additionally, it is important to note the reduction in sample size due to underreporting in the CPS for food security and disability. This causes the data to shrink to around 2459 observations when I have to include the food security variable. We implement the food security regression in Table E in the appendix removing the disability and find an effect of 20.1 percentage points of SNAP on food security with a standard error of 0.548 (for a coefficient of 0.201). These results are quantitatively similar with very low statistical significance. However, we know from the linear and logit models in Section 6 that disability has a statistically significant impact on SNAP participation and is crucial to the approximation model for the first stage equation in Table 7 so the estimates in Table E with a larger sample size but excluding disability are not representative.

Section 8: Discussion

The findings in this paper tell us two significant results on SNAP participation and elderly food security: 1. The Combined Application Project results in an increase in SNAP participation for elderly SSI recipients; and 2. SNAP appears to increase food security among the elderly (irrespective of SSI participation), although the results are very imprecise.

This paper presents two models for SNAP participation – a linear probability model which is most commonly used in the literature and a logit model. The linear probability model presents a 17% increase in SNAP participation with CAP for SSI recipients. We also see that SSICAP in general for the total sample increases SNAP participation by 88% (from 12% to 23%). While the results in the linear probability model are robust and consistent, they are accompanied by large standard errors. For this reason, we do not see that these results are statistically significant. We can conclude that the results from the linear probability model provide more suggestive evidence to a positive causal relation of CAP on SNAP participation while the estimates of 17% found are likely imprecise. We determine that this might be because a linear model is not the most appropriate model of SNAP participation.

The logit model presented in Section 6 for SNAP participation uses the same functional form as the linear probability model. This model produces robust marginal effects of an approximate 26% (15-percentage points) increase in SNAP participation for SSI recipients when CAP is implemented in a state. The marginal effects here are also statistically significant ($p<0.0001$) providing a more precise measure compared to the linear model. Robustness checks in Table 5 provide slight variation in percentage point increases with 15.8-percentage points when I expand state and year fixed effects.

Jones et al. (2021) provides a comprehensive evaluation of state expansionary policies and the impact on elderly SNAP participation in general. They utilise a similar linear probability model find CAP results in a 1.3% increase in SNAP participation with marginal statistical significance on SNAP participation for senior households. However, their model did not limit sample size to single household seniors which is the particular demographic for which CAP is eligible and the step taken in this paper. This might be why the results found in this paper are higher in magnitude.

We identify sample size restrictions as a limitation of the results, particularly for the linear probability model on SNAP participation. The data used is nationally representative data for all states and D.C. excluding Hawaii, Alaska and California. If we add California, the data adds around 250 additional observations. I ran the same logit and linear probability models presented in Sections 5.2 and 5.1. in Table F and Table G in the Appendix respectively. To recall, California was excluded due to specific policies restricting SNAP access to SSI elderly recipients, the state's cash-out policy. The marginal effects from logit model including California shown in Table G shows a 32.5-percentage point increase in SNAP participation for an SSI recipient in a CAP state, an 86.43% increase. In the linear model including California I find statistically significant results (at the 1% level) of SSICAP of a 33-percentage point increase in SNAP participation. SSI overall increase SNAP take up by 28.5%, significant at the 1% level., in SNAP participation for SSI recipients in CAP states. We would expect this overestimation due to California's absence of CAP along with the cash-out policy. Since SSI recipients in California are actively restricted from receiving SNAP, and since California is a non-CAP state during this period of time, there is an upward bias on the effect of CAP states for SSI recipients. This produces an estimate of an 86% increase on SNAP participation when SSICAP=1.

The results in Section 6.2 also show that just being an SSI recipient results in a 49% increase in the likelihood to participate in SNAP. We might assume that an individual that participates in SSI are more likely to be aware of their eligibility for SNAP and thus this could address the information effect in Wu (2009). Additionally, a person on SSI just might be more vulnerable and thus have a higher perceived need of benefits and aid which would corroborate findings in Nord and Golla (2009). The results on SSI effect on SNAP participation are robust with an approximate of 49-51% determined in Table A, Table B and Table D. Logit marginal effects in Table 4 show a slightly higher effect of SSI recipient on SNAP participation with a 54% increase at the 1% significance level. It is interesting to note that Table F which includes California in the linear model only estimates 28% for the effect of SSI recipiency on SNAP participation. This could be attributed to the cash out policy which results in SSI recipients who would otherwise participate in SNAP not being able to apply for SNAP, thus underestimating the effect of SSI.

The model on food security provides results with negligible statistical significance of SNAP participation on food security levels. The results suggest a 30% increase in food security levels with a wide standard error almost thrice in magnitude (SE of 0.604 for a 0.209 coefficient). However, a 30% increase in food security corroborates results found in the literature. Ratcliffe and McKernan use an IV approach and find a 30% decrease in chance of food insecurity through SNAP participation while Mykerezi and Mills (2010) use PSID data and determine an 18% reduction in food insecurity through SNAP. It is important to note that while both methods use an IV approach, the model for SNAP participation slightly varies by utilizing an interaction term with SSI and CAP to more precisely determine the effect of CAP on SNAP participation. This could explain the differences in results along with the difference in sample populations. Additionally, we might expect the sample size when reduced so drastically with the underreporting of food security and disability would result in nationally representative results.

Of course, a strong limitation in the food security model presented in Section 7 is the exogeneity assumption of SSI. If we claim behavioral differences, information asymmetry or perception on need for benefits as contributing factors to low SNAP participation and thus low food security, we have to consider that SSI recipiency is also endogenous like SNAP participation. However, it is more difficult to model the endogenous equation of SSI within food security. If we were to simply run the same regression but include SSI as endogenous and instrument SSI as well as SNAP with CAP and SSICAP we get drastically different coefficient estimates as seen in Table H. Here, SSI results in a -16% change in food security levels and SNAP results in a -7% increase in food security, with standard errors 0.327 and 0.06 (for coefficients of -0.16 and -0.07) respectively. However, this result is inconsistent with basic theoretical model in Section 3. While instrumenting SSI considers endogeneity, there are likely other variables outside of CAP that are correlated with the error term in food security. If knowledge of information programs results in a large effect on program participation, we would want to observe if the SSI recipients received benefits prior to being 65 and eligible for SSI through the elderly low-income channel. We might assume that disabled elderly is more likely to participate in SSI after turning 65 than non-disabled elderly. For this reason, longitudinal data might be the most appropriate to more accurately SSI within the food security regression model.

Expanding the work done in this paper utilizing longitudinal data could contribute to the understanding of the causal effect between CAP and SNAP. Additionally, a proposed extension of this paper would be to include a measure to observe the period of time following the implementation of CAP which could tell us if CAP results in an immediate change in SNAP and food security or gradual (does food security really happen with a snap). Of course, one limitation of this paper is the level of statistical significance provided by the linear SNAP and food security model. One potential way to address this is to expand the data to the most recent year. While the USDA SNAP Policy Database is only updated to 2016, manual collection of each state's SNAP policies could provide the necessary data to expand the analysis to more recent years and increase sample size. Additionally, further work should involve the use of additional control groups beyond comparing CAP and non-CAP states and SSI and non-SSI recipients. Such extensions could involve expanding the analysis to include married low-income elderly households, or observations prior to the first implementation of CAP (1996) as a control group. These extensions are limited to the extent that the CPS reports food security and SNAP levels consistently prior to 1996, otherwise the methods in this paper could be replicated using alternative datasets.

This paper also contributes to the overall discussion on mechanisms to improve both targeting and take up of SNAP. Specifically, it offers a relatively low-cost policy that, when targeted to the elderly incentivizes program participation. The implications of these results point towards a positive outcome if other social safety net programs were to adopt a similar 'bundling' or shortening of applications when an individual is enrolled in another. Research by the U.S. Government Accountability Office (GAO) finds that because each welfare program is enacted by different federal statutes with varying income requirements, it is complicated to enact a blanket one application fits all social safety net programs (GAO, 2017). However, the findings from CAP show that for some demographic groups like elderly low-income, eligibility criteria are similar and can allow a streamlined process. This paper suggests that this demographic group benefits from a policy like CAP. Further work in this area would be to view the applicability of policies like CAP in other welfare programs for the elderly as well.

The results from this paper provide robust results of approximately 26-29% increase in SNAP participation for elderly low-income, single household recipients of SSI residing in states with CAP. The logit model provides strong statistically significant and consistent results to understand SNAP participation in the context of other state SNAP expansionary policies. This paper also provides consistent results on the increase in food security by 30% from SNAP participation, although there is low confidence in the magnitude of this increase. The consistency of a positive impact of SNAP on food security seen in this paper however corroborates similar results in the literature.

The CAP policy differs from programs like broad based categorical eligibility or establishing call centers because it has a relatively lower implementation cost. The process of using information already known through SSI applications does not impose higher costs to administrative offices or the state and is still seen to have high effects. The results from this paper provide a compelling argument for the implementation of CAP at a national scale to address the crisis of low SNAP participation rates for this particularly vulnerable population through an easy and low-cost avenue.

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Appendix Tables

Table A: LPM Models for SNAP Participation

	(1) Complete Model	(2) Without disability	(3) Individual characteristics	(4) State Effects
SSI	0.503***	0.499***	0.516***	0.510***
	(0.0381)	(0.0314)	(0.0381)	(0.0314)
CAP	-0.0267*	-0.0235*	-0.0158	-0.0242*
	(0.0127)	(0.0106)	(0.0112)	(0.0106)
SSI&CAP	0.106	0.0526	0.110*	0.0458
	(0.0558)	(0.0461)	(0.0559)	(0.0463)
Age	-0.00228*	-0.00144*	-0.00184*	
	(0.000891)	(0.000680)	(0.000891)	
Female	0.0171	0.0198*	0.0113	
	(0.0117)	(0.00907)	(0.0117)	
Black	0.0700***	0.0554***	0.0783***	
	(0.0176)	(0.0136)	(0.0174)	
Other	0.0499	0.0707**	0.0624*	
	(0.0302)	(0.0241)	(0.0303)	
Income as a percent of poverty line	-0.000232*	-0.000177*	-0.000286*	
	(0.000114)	(0.0000808)	(0.000114)	
Disabled	0.0621***		0.0669***	
	(0.0119)		(0.0119)	
Unemployment	0.000800	0.00462*		0.00453*
	(0.00287)	(0.00228)		(0.00228)
Not completed HS	0.0751***	0.0615***		0.0652***
	(0.0131)	(0.00980)		(0.00963)
Exempt from in person interview	-0.00680	0.0173		0.0171
	(0.0158)	(0.0117)		(0.0118)
call=1	-0.0225	-0.00758		-0.00555
	(0.0146)	(0.0118)		(0.0119)
call=2	-0.0272	-0.0269*		-0.0260*
	(0.0179)	(0.0124)		(0.0124)
Fingerprint=1	-0.0268	-0.0206		-0.0215
	(0.0291)	(0.0183)		(0.0183)
Fingerprint=2	-0.0392	-0.0511		-0.0522*
	(0.0422)	(0.0262)		(0.0263)
Non-citizen Elderly Eligible for SNAP	-0.00691	0.00669		-0.00296
	(0.0184)	(0.0130)		(0.0129)
Online	0.0348*	0.0430***		0.0369**

Application=1				
	(0.0160)	(0.0121)		(0.0121)
Online Application=2	-0.0276	0.0214		0.0137
	(0.0522)	(0.0318)		(0.0319)
Outreach spending	0.000114^{**}	0.000110^{**}		0.000118^{**}
	(0.0000440)	(0.0000376)		(0.0000377)
Constant	0.234^{**}	0.121^{*}	0.239^{***}	0.0206
	(0.0715)	(0.0526)	(0.0666)	(0.0157)
Observations	3225	4673	3225	4673

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

Table B: Linear Probability Model for SNAP Participation using Clustered Standard Errors and Varying State and Year Fixed Effects

	(1)	(2)	(3)	(4)
SSI	0.499^{***}	0.503^{***}	0.502^{***}	0.502^{***}
	(0.0528)	(0.0381)	(0.0516)	(0.0381)
CAP	-0.0815^{*}	-0.0251^{*}	-0.0597^{*}	-0.0154
	(0.0383)	(0.0128)	(0.0279)	(0.0113)
SSI&CAP	0.108	0.109	0.101	0.104
	(0.0689)	(0.0558)	(0.0692)	(0.0557)
Age	-0.00226^{**}	-0.00229^{*}	-0.00230^{**}	-0.00233^{**}
	(0.000801)	(0.000891)	(0.000800)	(0.000891)
female	0.0198	0.0174	0.0194	0.0169
	(0.0140)	(0.0117)	(0.0139)	(0.0117)
Black	0.0808^{**}	0.0706^{***}	0.0793^{**}	0.0689^{***}
	(0.0248)	(0.0177)	(0.0243)	(0.0175)
Other	0.0452	0.0491	0.0449	0.0509
	(0.0402)	(0.0302)	(0.0395)	(0.0302)
Income as a percent of poverty line	-0.000236^{*}	-0.000230^{*}	-0.000237^{*}	-0.000216
	(0.000105)	(0.000114)	(0.000106)	(0.000114)
Disabled	0.0610^{***}	0.0623^{***}	0.0620^{***}	0.0615^{***}
	(0.0107)	(0.0119)	(0.0107)	(0.0119)
Unemployment	0.00343	0.00282	-0.00621	-0.00225
	(0.00770)	(0.00418)	(0.00342)	(0.00270)
Financial Crisis	-0.0525	-0.0425		
	(0.0539)	(0.0354)		
Not completed HS	0.0741^{***}	0.0749^{***}	0.0726^{***}	0.0737^{***}
	(0.0153)	(0.0131)	(0.0149)	(0.0131)
Observations	3225	3225	3225	3225
Clustered Standard Errors	Yes	No	Yes	No

State and Year FEs	Yes	Yes	No	No

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

Table C: Logit Models for SNAP Participation

	(1) Complete Logit Model	(2) Marginal Effects	(3) Logit without disability	(4) Marginal Effects
SSI	2.488***	0.464***	2.636***	0.207***
	(0.276)	(0.0660)	(0.239)	(0.0200)
CAP	-0.294*	-0.0274*	-0.266*	-0.0209*
	(0.136)	(0.0126)	(0.126)	(0.00989)
SSICAP	0.682	0.0636	0.317	0.0249
	(0.431)	(0.0403)	(0.359)	(0.0283)
Age	-0.0242*	-0.00226*	-0.0180*	-0.00141*
	(0.00945)	(0.000879)	(0.00823)	(0.000645)
female	0.185	0.0168	0.242*	0.0184*
	(0.126)	(0.0112)	(0.112)	(0.00825)
Black	0.594***	0.0657**	0.537***	0.0494***
	(0.159)	(0.0206)	(0.140)	(0.0150)
Other	0.448	0.0468	0.660**	0.0638*
	(0.276)	(0.0334)	(0.236)	(0.0284)
Income as a percent of poverty line	-0.00256*	-0.000239*	-0.00227*	-0.000179*
	(0.00122)	(0.000113)	(0.00101)	(0.0000790)
Disabled	0.618***	0.0621***		
	(0.121)	(0.0129)		
Unemployment	0.00415	0.000388	0.0519	0.00408
	(0.0303)	(0.00283)	(0.0269)	(0.00211)
Not completed HS	0.687***	0.0739***	0.683***	0.0612***
	(0.124)	(0.0150)	(0.109)	(0.0109)
Exempt from in person interview	-0.0942	-0.00903	0.237	0.0183
	(0.167)	(0.0164)	(0.145)	(0.0110)
call=1	-0.212	-0.0210	-0.0773	-0.00643
	(0.149)	(0.0152)	(0.138)	(0.0115)
call=2	-0.275	-0.0266	-0.323*	-0.0243*
	(0.190)	(0.0183)	(0.158)	(0.0117)
Fingerprint=1	-0.306	-0.0259	-0.282	-0.0205
	(0.332)	(0.0250)	(0.238)	(0.0157)
Fingerprint=2	-0.345	-0.0287	-0.662	-0.0413*

	(0.474)	(0.0345)	(0.377)	(0.0180)
Non-citizen Elderly Eligible for SNAP	-0.0485	-0.00446	0.107	0.00873
	(0.197)	(0.0178)	(0.160)	(0.0134)
Online Application=1	0.352*	0.0306*	0.527***	0.0400***
	(0.171)	(0.0137)	(0.149)	(0.0109)
Online Application=2	-0.527	-0.0319	0.294	0.0201
	(0.678)	(0.0337)	(0.445)	(0.0339)
Outreach spending	0.00117**	0.000109**	0.00118**	0.0000929**
	(0.000444)	(0.0000413)	(0.000407)	(0.0000319)
Constant	-0.782		-1.980**	
	(0.754)		(0.635)	
Observations	3225	3225	4673	4673

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

Table D: Two stage least squares regression instrumenting SNAP with CAP and SSICAP

	(1) First equation	(2) Second equation
Age	-0.00238*	0.00762***
	(0.00105)	(0.00190)
Female	0.0164	-0.0140
	(0.0137)	(0.0197)
Black	0.0783***	-0.221***
	(0.0202)	(0.0511)
Other	0.0789*	-0.136*
	(0.0359)	(0.0638)
Income as a percent of poverty line	-0.000218	0.000238
	(0.000134)	(0.000215)
Unemployment	0.000613	-0.00637
	(0.00331)	(0.00406)
Not completed HS	0.0716***	-0.103*
	(0.0154)	(0.0454)
Disabled	0.0631***	-0.111**
	(0.0138)	(0.0410)
Exempt from in person interview	-0.00789	-0.0150
	(0.0181)	(0.0232)
Call=1	-0.0317	0.0495
	(0.0171)	(0.0279)

Call=2	-0.0494*	0.0571
	(0.0204)	(0.0379)
Fingerprint=1	-0.00271	-0.0133
	(0.0337)	(0.0421)
Fingerprint=2	0.000327	-0.0356
	(0.0501)	(0.0621)
Non-citizen Elderly Eligible for SNAP	-0.0151	0.0518*
	(0.0210)	(0.0261)
Online Application=1	0.0359	-0.00851
	(0.0184)	(0.0291)
Online Application=2	-0.0552	0.0566
	(0.0610)	(0.0833)
Outreach spending	0.000120*	-0.000180*
	(0.0000513)	(0.0000808)
SSI=1	0.493***	-0.400
	(0.0426)	(0.302)
CAP=1	-0.0311*	
	(0.0148)	
SSI&CAP	0.0487	
	(0.0652)	
SNAP		0.247
		(0.580)
Constant	0.254**	0.349
	(0.0836)	(0.182)
Observations	2459	2459

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

Table E: Food Security Model Removing Disability

	SNAP	**Food Security**
SSI	0.493***	-0.355
	(0.0346)	(0.270)
CAP	-0.0281*	
	(0.0123)	
SSI&CAP	-0.00884	
	(0.0528)	
SNAP		0.201
		(0.548)
Age	-0.00159*	0.00509***
	(0.000794)	(0.00134)
female	0.0194	-0.0163

	(0.0105)	(0.0173)
Black	0.0624***	-0.216***
	(0.0155)	(0.0389)
Other	0.0924**	-0.142*
	(0.0288)	(0.0630)
Income as a percent of poverty line	-0.000184	0.0000487
	(0.0000942)	(0.000163)
Unemployment	0.00462	-0.00941*
	(0.00259)	(0.00383)
Not completed HS	0.0606***	-0.108**
	(0.0113)	(0.0361)
Exempt from in person interview	0.0179	-0.0270
	(0.0135)	(0.0197)
call=1	-0.0164	0.0342
	(0.0138)	(0.0196)
call=2	-0.0450**	0.0310
	(0.0141)	(0.0300)
Fingerprint=1	0.00414	-0.0387
	(0.0213)	(0.0269)
Fingerprint=2	-0.0351	0.00641
	(0.0302)	(0.0429)
Non-citizen Elderly Eligible for SNAP	0.00403	0.0227
	(0.0147)	(0.0194)
Online Application=1	0.0486***	-0.0291
	(0.0139)	(0.0298)
Online Application=2	0.0171	-0.00586
	(0.0368)	(0.0471)
Outreach spending	0.000111*	-0.000112
	(0.0000439)	(0.0000693)
Constant	0.141*	0.583***
	(0.0613)	(0.111)
Observations	3632	3632

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

Table F: LPM SNAP Participation Including State of California

	(1)	(2)
SSI&CAP	0.330***	0.106

	(0.0507)	(0.0558)
SSI	0.285***	0.503***
	(0.0301)	(0.0381)
CAP	-0.0169	-0.0269*
	(0.0119)	(0.0127)
Age	-0.00265**	-0.00229*
	(0.000854)	(0.000891)
Female	0.0190	0.0171
	(0.0112)	(0.0117)
Black	0.0621***	0.0699***
	(0.0171)	(0.0177)
Other	0.00480	0.0499
	(0.0265)	(0.0303)
Income as a percent of poverty line	-0.000236*	-0.000232*
	(0.000110)	(0.000114)
Not Disabled	-0.0562***	-0.0621***
	(0.0114)	(0.0119)
Unemployment	-0.000503	0.00104
	(0.00326)	(0.00343)
HS diploma or equivalent	-0.0756***	-0.0752***
	(0.0124)	(0.0131)
Exempt from in person interview	-0.000294	-0.00737
	(0.0163)	(0.0164)
call=1	-0.0147	-0.0224
	(0.0145)	(0.0146)
call=2	-0.0253	-0.0268
	(0.0179)	(0.0181)
Fingerprint=1	-0.0167	-0.0261
	(0.0259)	(0.0296)
Fingerprint=2	0.0316	-0.0386
	(0.0384)	(0.0425)
Non-citizen Elderly Eligible for SNAP	-0.0207	-0.00661
	(0.0179)	(0.0185)
Online Application=1	0.0245	0.0346*
	(0.0159)	(0.0160)
Online Application=2	-0.0713	-0.0270
	(0.0412)	(0.0524)
Outreach spending	-0.0000421	0.000114*
	(0.0000232)	(0.0000446)
Financial Crisis	0.000257	-0.00207
	(0.0160)	(0.0163)
Observations	3485	3225

Includes California	Yes	No

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

Table G: Logit Model Marginal Effects for SNAP Participation including State of California

	(1)	(2)
SSI&CAP = 0	0.376***	0.551***
	(0.0475)	(0.0624)
SSI&CAP = 1	0.701***	0.698***
	(0.0641)	(0.0647)
Observations	3485	3225
Including California	Yes	No

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

Table H: Food Security Model Instrumenting SSI along with SNAP

	SNAP	Food Security
SSI&CAP	0.0487	
	(0.0652)	
SSI	0.493***	-0.161
	(0.0426)	(0.327)
SNAP		-0.0786
		(0.587)
CAP=1	-0.0311*	
	(0.0148)	
Age	-0.00238*	0.00707***
	(0.00105)	(0.00182)
female	0.0164	-0.00894
	(0.0137)	(0.0188)
Black	0.0783***	-0.197***
	(0.0202)	(0.0505)
Other	0.0789*	-0.108
	(0.0359)	(0.0628)
Income as a percent of poverty line	-0.000218	0.000172
	(0.000134)	(0.000206)
Disabled	0.0631***	-0.0924*
	(0.0138)	(0.0404)
Unemployment	0.000613	-0.00633
	(0.00331)	(0.00380)

Not completed HS	0.0716***	-0.0840
	(0.0154)	(0.0445)
Exempt from in person interview	-0.00789	-0.0197
	(0.0181)	(0.0220)
call=1	-0.0317	0.0398
	(0.0171)	(0.0270)
call=2	-0.0494*	0.0411
	(0.0204)	(0.0371)
Fingerprint=1	-0.00271	-0.0156
	(0.0337)	(0.0394)
Fingerprint=2	0.000327	-0.0384
	(0.0501)	(0.0581)
Non-citizen Elderly Eligible for SNAP	-0.0151	0.0502*
	(0.0210)	(0.0245)
Online Application=1	0.0359	0.00326
	(0.0184)	(0.0284)
Online Application=2	-0.0552	0.0399
	(0.0610)	(0.0788)
Outreach spending	0.000120*	-0.000153*
	(0.0000513)	(0.0000778)
Constant	0.254**	0.413*
	(0.0836)	(0.176)
Observations	2459	2459

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