RE-EVALUATING THE EFFECTS OF SNAP ON REDUCING FOOD INSECURITY: THE ROLES OF ECONOMETRIC METHODS AND HETEROGENEITY

by

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(Under the Direction of Travis A. Smith)

ABSTRACT

This paper examines how different econometric models, each with distinct functional form assumptions, influence estimates of the Supplemental Nutrition Assistance Program (SNAP) effect on food insecurity. To address potential endogeneity in SNAP participation, we employ a range of instrumental variables methods, including two-stage least squares, control function approaches, bivariate probit, and recursive bivariate probit models, analyzing SNAP's impact under various linear and nonlinear specifications in both first-stage reduced form and second-stage structural equations. Using data from the 1996, 2001, and 2004 panels of the Survey of Income and Program Participation (SIPP), our findings reveal that the magnitude and direction of SNAP's effect on food insecurity vary across model specifications, with estimates ranging from null effects to reductions of approximately 20 percentage points. Furthermore, heterogeneity analysis indicates that SNAP's effectiveness is more pronounced among certain subpopulations.

INDEX WORDS: Supplemental Nutrition Assistance Program, SNAP, Food Stamps, Food Security, Instrumental Variables, Control Functions

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DEDICATION

To my parents, whose love and support have been my greatest strength.

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CHAPTER 1

INTRODUCTION

Over the past two decades, food insecurity in the United States has persisted in more than 10% of households, peaking at 15% during the Great Recession (2008-2012). In 2023, 13.5% of households experienced food insecurity, with 8.4% classified as having low food security and 5.1% as having very low food security (Rabbitt et al., 2024).[1] The primary tool for addressing food insecurity is the Supplemental Nutrition Assistance Program (SNAP), formerly known as the Food Stamp Program. As the nation's largest food assistance program, SNAP accounts for nearly two-thirds of the United States Department of Agriculture (USDA)'s spending on food and nutrition assistance in recent years (Jones & Toossi, 2024). Given its significant government funding and vital role in supporting low-income households, especially during economic downturns, it is crucial to assess SNAP's effectiveness using alternative econometric approaches, and to identify which populations benefit the most in order to ensure that the program effectively reduces food insecurity and enhances resilience among vulnerable groups.

In this paper, we aim to fill this gap by quantifying the relationship between SNAP and food insecurity, utilizing different functional form assumptions and treatment effect heterogeneity. We begin by replicating the methodology of Ratcliffe et al. (2011) as closely as possible. For this, we use the Survey of Income and Program Participation (SIPP) 1996, 2001, and 2004 panels for household-level data, complemented by the USDA SNAP Policy Database

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[1] Ratcliffe et al. (2011) used the USDA's classification of "low food security" and "very low food security" to create their two indicators of food-related hardship. They referred to households experiencing either level as "food insecure" and those experiencing only "very low food security" as "very food insecure." Our study follows the USDA terminology to maintain clarity and ensure comparability with most of the literature.

(USDA, 2024b) to generate four instrumental variables (IVs) reflecting state SNAP policies: biometric technology, outreach spending per capita, full immigrant eligibility, and partial immigrant eligibility. After replicating Ratcliffe et al.'s (2011) dataset, we estimate SNAP's effectiveness across various econometric specifications, starting with a simple probit model without IVs. We then proceed to include IVs, beginning with minimal assumptions of linearity in both the first-stage reduced and second-stage structural equations, using the two-stage least squares (2SLS) model. Next, we introduce control function methods (Wooldridge, 2015) to account for a nonlinear first-stage reduced form equation by adding a normality assumption, specifically using a probit model. We move one step further by incorporating nonlinearity and normality assumptions in both the reduced form and structural equations, resulting in a bivariate probit model and a recursive bivariate probit model (to address simultaneity). These control function and (recursive) bivariate probit models allow us to explore the heterogeneity of treatment effects following Wooldridge (2015) – specifically, how SNAP's effectiveness varies across different demographic segments.

Our results can be grouped into two main categories. First, we find that varying assumptions about the functional form can significantly influence the results. For example, in our re-analysis of Ratcliffe et al. (2011), we find SNAP is significantly associated with an increased likelihood of food insecurity and very low food security in the probit model without IVs, a result that is well-documented (Smith & Gregory, 2023). However, when we introduce IVs with minimal assumptions using 2SLS, we find null results – meaning that SNAP is no longer significantly associated with food insecurity and very low food security, despite the coefficient remaining positive. When we assume a probit functional form for the first-stage reduced form equation, the results change dramatically. We find that SNAP reduces food insecurity by nearly

20 percentage points and very low food security by 10 percentage points, relative to baseline rates of 29.20% and 13.18%, respectively, in non-participating households. Further assuming a probit functional form for the structural equation (in the bivariate probit and recursive bivariate probit models), SNAP is estimated to reduce food insecurity by approximately 15 percentage points and very low food security by around 4 percentage points over their respective baselines of 30.58% and 12.07%. These findings emphasize the critical role of functional form assumptions in shaping the results.

The second set of results quantifies the effectiveness of SNAP across different demographic groups. Specifically, we examine interaction effects between SNAP participation and demographic characteristics in the control function model and (recursive) bivariate probit models to assess treatment effect heterogeneity. Our analysis shows that SNAP benefits are more effective at reducing food insecurity and very low food security among certain groups. Specifically, its impact is greater for Black and Hispanic households compared to White households, for those with lower educational attainment compared to households with more than a high school education, for single-adult-headed households (regardless of gender) compared to two-adult-headed households, and for households with disabled members compared to those without. Additionally, participating in SNAP has stronger effects for households with more children, and for households with younger heads (around 20 years old) or older heads (70+ years) compared to those with middle-aged heads. In comparisons between models, we find that the (recursive) bivariate probit model provides more precise estimates and highlights SNAP's stronger impact in alleviating food insecurity and very low food security.

Extensive research over the past two decades has established that SNAP mitigates food insecurity (Smith & Gregory, 2023). Various studies have examined this relationship using different econometric approaches. Swann (2017), Shaefer & Gutierrez (2013), and Ratcliffe et al. (2011) employed nonlinear selection models, specifically the bivariate probit model. Gundersen et al. (2017) and Kreider et al. (2012) used partial identification techniques that account for endogenous selection and nonrandom misclassification of SNAP participation, providing bounds rather than point estimates for average treatment effects (ATE). Nord & Prell (2011) applied a difference-in-differences (DID) approach, leveraging the increased SNAP benefits from the American Recovery and Reinvestment Act (ARRA) of 2009 as a “natural experiment.” Nord (2011) analyzed food insecurity among SNAP recipients and leavers, while Nord & Golla (2009) constructed a two-year synthetic panel to examine household food insecurity before and after SNAP receipt. Both studies used multivariate logistic regression models. Mykerezi & Mills (2010) and Yen et al. (2008) employed instrumental variable (IV) models with maximum likelihood estimation to assess the relationship between SNAP participation and food insecurity reduction.

Our study contributes to this literature in several key ways. First, we employ a more flexible approach, the control function methods, which addresses the endogeneity of SNAP participation within both linear and nonlinear frameworks. The control function method has the advantage of being computationally simpler and allowing us to explore the nature of self-selection into SNAP participation. However, this advantage comes with the cost of correctly specifying the first-stage regression. Second, we show how the estimated effects of SNAP on food insecurity vary under different functional form assumptions, offering general guidance for econometric approaches and their related assumptions when using instrumental variable methods. Third, as noted by Smith & Gregory (2023), many prior studies did not report first-stage statistics related to the relevance of instrumental variables, such as the first-stage Fstatistic. In contrast, we explicitly evaluate the strength of our IVs across different model specifications. Fourth, we employ both the control function and (recursive) bivariate probit models to examine heterogeneous treatment effects, further contributing to the understanding of SNAP's impact across different subpopulations.

From a policy perspective, understanding whether and to what extent SNAP reduces food insecurity is crucial. Our study directly addresses this question. Moreover, identifying which groups benefit the most from SNAP is equally important for policy implementation, and our findings provide valuable insights into this issue.

The paper proceeds as follows. Section 2 outlines the identification strategy for estimating SNAP's effect on food insecurity under different functional form assumptions using an instrumental variable approach. Section 3 describes the data, particularly how we replicate the dataset constructed by Ratcliffe et al. (2011). Section 4 presents the treatment effect estimates and their heterogeneity across various model specifications. Finally, Section 5 concludes.

CHAPTER 2

METHODS – INSTRUMENTAL VARIABLES

In this study, our focus is on examining the impact of SNAP participation (D_{ist}) on food insecurity (Y_{ist}) for household i in state s at month t.[2] To quantify this relationship, we specify the following regression:

$$Y_{ist} = \alpha + \beta D_{ist} + \boldsymbol{X\delta} + u_{ist} \tag{1}$$

Equation (1) represent a linear probability model (LPM), where the coefficient of interest is β. Here, $\boldsymbol{X}$ denotes a set of exogenous control variables, including state and year fixed effects, which account for time-invariant unobserved heterogeneity and time-varying unobserved common shocks, respectively.[3] The term u_{ist} represents the error term. However, since Y_{ist} is a binary variable, we can also specify a nonlinear binary response model as follows:

$$Y_{ist} = 1[\alpha + \beta D_{ist} + \boldsymbol{X\delta} + u_{ist} > 0] \tag{2}$$

where $1[\cdot]$ is an indicator function that equals 1 if the condition inside is true and 0 otherwise. If we assume that the function $1[\cdot]$ follows a standard logistic cumulative distribution function (CDF), $L(\cdot)$, the model is referred to as logit model. Alternatively, if $1[\cdot]$ follows a standard normal CDF, $\Phi(\cdot)$, the model is a probit model.

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[2] Food insecurity status, Y_{ist}, represents either a dummy variable for food insecurity or a dummy variable for very low food security.

[3] The matrix $\boldsymbol{X}$ includes all control variables used by Ratcliffe et al. (2011), covering individual and household characteristics, economic conditions, and state and year dummies. These controls consist of the household head's age and age squared, race/ethnicity indicators (Black non-Hispanic, Hispanic, Other non-Hispanic, White non-Hispanic (Reference group)), noncitizen immigrant household indicator, household's educational attainment (< high school, = high school, > high school (Reference group)), the number of children (age<18) and adults (age 18-64) in the household, household type (Female-headed, Male-headed, Two-adult headed (Reference group)), presence of disabled person in household, household's metropolitan status, state monthly unemployment rate, state monthly employment to population ratio, state annual per capita income, quarterly GDP, states dummies (covering 46 states, including D.C.), and years dummies (1998, 2003, 2005(Reference year)).

To estimate β, one could use either the linear model in equation (1) or the nonlinear models in equation (2), assuming that u_{ist} is independent of D_{ist}. However, these approaches are problematic because SNAP participation (D_{ist}) is potentially endogenous. SNAP participation is not randomly assigned – eligible low-income households self-select into the program, which may introduce endogeneity. Specifically, D_{ist} may be systematically related to unobserved factors, leading to:

$$E(D_{ist}u_{ist}) \neq 0 \tag{3}$$

Endogeneity in D_{ist} results in a biased estimator of β. To some extent, this issue can be mitigated by including observable confounders in $\boldsymbol{X}$, thereby reducing omitted variable bias. However, it is crucial to avoid including variables in $\boldsymbol{X}$ that may themselves be affected by the treatment D_{ist}, as these are considered "bad controls" (Angrist & Pischke, 2009).

A widely used method to solve endogeneity is the instrumental variable (IV) approach. Let $\boldsymbol{Z_{st}}$ be a matrix of instruments representing SNAP policies in state s at month t. Following Ratcliffe et al. (2011), there are four elements in $\boldsymbol{Z_{st}}$.

$$\boldsymbol{Z_{st}} = (Z_{st}^1, Z_{st}^2, Z_{st}^3, Z_{st}^4) \tag{4}$$

where $\boldsymbol{Z_{st}}$ has the following elements: Z_{st}^1 is biometric technology, Z_{st}^2 is state's outreach spending, Z_{st}^3 is full immigrant eligibility, and Z_{st}^4 is partial immigrant eligibility. For $\boldsymbol{Z_{st}^n}$ to be a valid instrument, it must satisfy the instrument exogeneity condition,

$$Cov(\boldsymbol{Z_{st}^n}, u_{ist}) = 0, \quad \forall\, n \tag{5}$$

and instrument relevance condition,

$$Cov(\boldsymbol{Z_{st}^n}, D_{ist}) \neq 0, \quad \forall\, n \tag{6}$$

Equation (5) states that valid instruments must be uncorrelated with the error term u_{ist}, which cannot be directly tested as the error term is unobservable. Therefore, we rely on strong theoretical arguments to ensure that the instrument $\boldsymbol{Z_{st}}$ has no direct effect on the outcome variable Y_{ist}. In other words, $\boldsymbol{Z_{st}}$ does not belong in the main outcome equation (1), a condition known as the exclusion restriction. This restriction implies that $\boldsymbol{Z_{st}}$ affects Y_{ist} only through its impact on the endogenous regressor D_{ist}.[4] This, in turn, leads to the instrument relevance condition in equation (6), requiring $\boldsymbol{Z_{st}}$ and D_{ist} to be sufficiently correlated, even after controlling for the exogenous regressors $\boldsymbol{X}$. Instrument relevance can be empirically tested by examining the significance of $\boldsymbol{Z_{st}}$ in the first-stage regression of D_{ist} on $\boldsymbol{Z_{st}}$, as shown below.

2.1 Two Stage Least Square (2SLS)

The 2SLS method addresses endogeneity by breaking the estimation process into two stages, both of which follow the LPM framework. In the first stage, we estimate the following reduced form equation:

$$D_{ist} = \pi_o + \boldsymbol{Z_{st}}\boldsymbol{\pi} + \boldsymbol{X}\boldsymbol{\gamma} + v_{ist} \tag{7}$$

For the instrument relevance condition in equation (6) to hold, we require $\pi \neq 0$ or, equivalently, we should be able to reject the null hypothesis $H_0\colon \pi = 0$. Here, D_{ist} is decomposed into two components: (i) a problematic component, the reduced form error v_{ist}, which may be correlated with the structural error u_{ist}, and (ii) a problem-free component, $\pi_o + \boldsymbol{Z_{st}}\boldsymbol{\pi} + \boldsymbol{X}\boldsymbol{\gamma}$, which is uncorrelated with u_{ist}. We estimate equation (7) using OLS to obtain the predicted probability of SNAP participation:

$$\widehat{D}_{\text{ist}} = \hat{\pi}_{\text{o}} + \mathbf{Z_{st}}\hat{\boldsymbol{\pi}} + \mathbf{X}\hat{\boldsymbol{\gamma}} \tag{8}$$

This first stage effectively removes the endogenous variation in D_{ist}, ensuring that $\widehat{D}_{ist}$ is exogenous.

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[4] Refer to Ratcliffe et al. (2011) for justification of instrument exogeneity, explaining how state SNAP policies influence SNAP participation D_{ist} but are not directly associated with food insecurity outcomes Y_{ist}.

In the second stage, we substitute $\widehat{D}_{ist}$ into the structural equation (1) as follows:

$$Y_{ist} = \alpha + \beta \widehat{D}_{ist} + \boldsymbol{X\delta} + u_{ist} \tag{9}$$

Since all regressors in equation (9) are now exogenous, β can be consistently estimated using OLS, thereby addressing the endogeneity problem in D_{ist}.

2.2 Control Function (CF)

Compared to the 2SLS method, the CF approach is more flexible with regard to functional form, provided the underlying assumption hold, and can accommodate both linear and nonlinear models to address endogeneity in D_{ist}. Like 2SLS, the CF method operates in two stages. However, instead of isolating the exogenous variation of the instruments $\boldsymbol{Z_{st}}$ (as in 2SLS), CF uses the problematic component – the residuals or generalized residuals – from the first stage as a control variable in the second stage. This ensures that D_{ist} becomes exogenous in the structural equation.

Since both the endogenous explanatory variable (EEV) D_{ist} and the outcome Y_{ist} are binary, the CF approach allows for different combinations of linear and nonlinear specifications in the first and second stages, leading to four possible model structures.[5]

2.2.1 CF-Linear Reduced Form: Linear Reduced Form-Linear Structural Model

The CF approach assumes a relationship between the structural error (u_{ist}) and the reduced form error (v_{ist}):

$$u_{ist} = \tau v_{ist} + e_{ist} \tag{10}$$

where, by definition,

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[5] Among the four possible CF specifications, we exclude two from our analysis: (1) Linear Reduced Form-Nonlinear Structural Model and (2) Nonlinear Reduced Form-Nonlinear Structural Model. The first specification aligns with the *ivprobit* approach in Stata; however, it is advised against applying *ivprobit* when the endogenous explanatory variable is binary. For the second specification, which involves nonlinear probit models in both the structural and reduced form equations, we instead adopt the (recursive) bivariate probit model, which is more appropriate for addressing endogeneity in this context.

$$E(v_{ist}e_{ist}) = 0 \tag{11}$$

and

$$E\left(\boldsymbol{Z^{n\prime}}_{\boldsymbol{st}}e_{ist}\right) = 0 \tag{12}$$

Moreover, in addition to the assumption in equation (5) that the instrumental variables $\boldsymbol{Z_{st}}$ are uncorrelated with the second-stage structural error term u_{ist}, as in the 2SLS approach, the CF methods require an additional assumption. Specifically, it assumes that the instrumental variables $\boldsymbol{Z_{st}}$ are also uncorrelated with the first-stage reduced form error term v_{ist}, i.e., $E(\boldsymbol{Z^{n\prime}}_{\boldsymbol{st}}v_{ist}) = 0$. In our case, this means we must assume that changes in a state's SNAP policies are uncorrelated with unobserved factors, such as unemployment rates, that could influence SNAP take-up rates. Since Ratcliffe et al. (2011) include state- and national-level macroeconomic variables, this may help alleviate some of these concerns.

From equations (7), (11), and (12), it follows that

$$E(D_{ist}e_{ist}) = 0 \tag{13}$$

The first stage of CF follows equation (7), where we now focus on its residuals $\hat{v}_{ist}$. In the second stage, the predicted residuals is included as a control variable in the structural equation (1):

$$Y_{ist} = \alpha + \beta D_{ist} + \boldsymbol{X\delta} + \tau\hat{v}_{ist} + e_{ist} \tag{14}$$

Equation (13) ensures a valid estimation of β from equation (14), which is expected to be identical to the 2SLS results from equation (9) (Wooldridge, 2015). An additional feature of the CF approach is that $\hat{v}_{ist}$ can be used to conduct a heteroskedasticity-robust Hausman test for exogeneity, where the null hypothesis $H_0 : \tau = 0$ implies D_{ist} is exogenous.

2.2.2 CF-Probit Reduced Form: Nonlinear Reduced Form-Linear Structural Model

The CF approach allows for a probit specification in the reduced form equation to capture generalized residuals. The nonlinear binary response model for equation (7) is given by:

$$D_{ist} = 1[\pi_o + \boldsymbol{Z_{st}\pi} + \boldsymbol{X\gamma} + v_{ist} > 0] \tag{15}$$

Assuming $v_{ist} \sim N(0,1)$, the probit model is:

$$P(D_{ist} = 1 \,\big|\, \boldsymbol{Z_{st}}, \boldsymbol{X}) = \Phi(\pi_o + \boldsymbol{Z_{st}\pi} + \boldsymbol{X\gamma}) \tag{16}$$

where (u_{ist},v_{ist}) is independent of each element of $\boldsymbol{Z_{st}}$, which is a stronger than the zero-correlation assumption used in Section 2.2.1 (the linear-linear CF estimator). Equation (10) is also assumed here. Unlike the usual 2SLS approach, which relies only on zero correlation assumptions, this approach makes explicit distributional assumptions about D_{ist}, specifically that it follows a normal distribution given $\boldsymbol{Z_{st}}$, $\boldsymbol{X}$.

After estimating equation (16), we obtain the generalized residuals $\hat{r}_{ist}$:

$$\hat{r}_{ist} = D_{ist}\,\lambda(\hat{\pi}_o + \boldsymbol{Z_{st}\hat{\pi}} + \boldsymbol{X\hat{\gamma}}) - (1 - D_{ist})\lambda\big(-(\hat{\pi}_o + \boldsymbol{Z_{st}\hat{\pi}} + \boldsymbol{X\hat{\gamma}})\big) \tag{17}$$

where $\lambda(\cdot) = \phi(\cdot)/\Phi(\cdot)$ is the inverse Mills ratio.

We then include $\hat{r}_{ist}$ as a control in the structural equation:

$$P(Y_{ist} = 1|D_{ist}, \boldsymbol{X}, \boldsymbol{Z_{st}}) = \alpha + \beta D_{ist} + \boldsymbol{X\delta} + \eta\hat{r}_{ist} \tag{18}$$

to obtain consistent estimates for β. A heteroskedasticity-robust t-test on $\hat{r}_{ist}$ provides a direct test of the exogeneity of D_{ist}.

2.3 (Recursive) Bivariate Probit

Instead of using the LPM as in equation (18), we specify a nonlinear probit structural model:

$$P(Y_{ist} = 1|D_{ist}, \boldsymbol{X}) = \Phi(\alpha + \beta D_{ist} + \boldsymbol{X\delta}) \tag{19}$$

In conjunction with this, we consider the reduced form probit equation (16) under the key distributional assumption that error terms (u_{ist},v_{ist}) follow a standard bivariate normal distribution with correlation ρ and are independent of ($\boldsymbol{Z}_{st}, \boldsymbol{X}$):

$$\begin{pmatrix} u_{ist} \\ v_{ist} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right] \tag{20}$$

Given these assumptions, the system of equations (16) and (19) with binary dependent variables following probit specifications constitutes a bivariate probit model, enabling joint estimation of the structural and reduced form equations using maximum likelihood estimation (MLE).

If $\rho \neq 0$, then u_{ist} and v_{ist} are correlated, and a probit estimation of equation (19) produces inconsistent parameter estimates (Wooldridge, 2010). A key feature of our model is that the binary endogenous variable D_{ist} in equation (19) is itself determined by the reduced form probit equation (16), allowing the errors terms of both probit equations to be correlated. This structure makes it, in particular, a recursive bivariate probit model, which is a special case of a simultaneous equations model of bivariate probit nature (Greene, 2003). Unlike a standard bivariate probit model, which allows for correlation between the error terms of two probit equations without imposing a specific directional relationship between the binary dependent variables, a recursive bivariate probit model introduces a structural dependence by specifying that one binary outcome (D_{ist}) in equation (16) acts as an endogenous regressor in the other equation (19).

2.4 Treatment effect estimators

Given that our primary explanatory variable, SNAP participation (D_{ist}), is binary, the estimated average partial effect (APE) or average marginal effect (AME) is synonymous with the average treatment effect (ATE). Thus, the estimated parameter $\hat{\beta}$ provides an estimate of the

ATE within the context of the linear structural model specified in Section 2.2.2. In general, the ATE represents the expected effect of treatment when shifting the entire population from the untreated to the treated state, formally expressed as:

$$ATE = E[Y_{ist}(1) - Y_{ist}(0)] \tag{21}$$

where $Y_{ist}(1)$ and $Y_{ist}(0)$ denote the food insecurity (or very low food security) outcomes under SNAP receipt and non-receipt, respectively.

Unlike the ATE, which measures the average treatment effect across the entire population, the 2SLS estimator introduced in Section 2.1 identifies the local average treatment effect (LATE), which captures the treatment effect for the subpopulation of compliers. Formally, LATE is given by:

$$LATE = E[Y_{ist}(1) - Y_{ist}(0) \mid D_{ist}(z) - D_{ist}(z') = 1] \tag{22}$$

where LATE quantifies the mean effect on food insecurity (or very low food security) for individuals whose SNAP participation status (D_{ist}) changes from 0 to 1 due to a shift in the instrumental variables $\boldsymbol{Z_{st}}$ from z' to z. Additionally, it is important to note that our CF specification of the linear reduced form – linear structural model, as outlined in Section 2.2.1, is numerically equivalent to the 2SLS estimator (Wooldridge, 2015).

In contrast, the coefficient estimates derived from nonlinear structural models, such as the (recursive) bivariate probit model presented in Section 2.3, do not have a direct economic interpretation. However, the estimated coefficient can be used to compute the ATE as follows:

$$ATE = \Phi(\alpha + \beta + \boldsymbol{X\delta}) - \Phi(\alpha + \boldsymbol{X\delta}) \tag{23}$$

Furthermore, the average treatment effect on the treated (ATT)[6], which measures the average treatment effect specifically for individuals who actually participated in SNAP, is given by:

$$ATT = \Phi\left(\frac{\alpha + \beta + \boldsymbol{X\delta} - \rho(\pi_0 + \boldsymbol{Z_{st}\pi} + \boldsymbol{X\gamma})}{\sqrt{1-\rho^2}}\right) - \Phi\left(\frac{\alpha + \boldsymbol{X\delta} - \rho(\pi_0 + \boldsymbol{Z_{st}\pi} + \boldsymbol{X\gamma})}{\sqrt{1-\rho^2}}\right), \qquad \forall\, D_{ist} = 1 \tag{24}$$

2.5 Heterogeneity in Treatment effect

To examine heterogeneity in the treatment effect of SNAP participation, we extend both the control function (CF) and (recursive) bivariate probit models. First, we consider the CF-probit reduced form approach outlined in Section 2.2.2, which incorporates the reduced form equation (16) and the structural equation (18). In this extension, we modify only the structural equation by allowing the SNAP participation, D_{ist}, to interact with exogenous variables:

$$P(Y_{ist} = 1|D_{ist}, \boldsymbol{X}, \boldsymbol{Z_{st}}) = \alpha + \beta D_{ist} + \boldsymbol{X\delta} + \eta\hat{r}_{ist} + D_{ist}\boldsymbol{X\theta} \tag{25}$$

Alternatively, if we allow the effect of D_{ist} to depend on unobservables following Garen (1984), we obtain a correlated random coefficient β_{ist}^{r} using the model:

$$Y_{ist} = \alpha + \beta_{ist}^{r}\, D_{ist} + \boldsymbol{X\delta} + \varepsilon_{ist} \tag{26}$$

We assume:

$$E(\beta_{ist}^{r}\,|\,D_{ist}, \boldsymbol{X}, \boldsymbol{Z_{st}}\,) = \beta + \psi r_{ist} \tag{27}$$

and

$$E(\varepsilon_{ist}|v_{ist}) = \eta r_{ist} \tag{28}$$

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[6] For the recursive bivariate probit model, we used the formulation and codes for estimating the treatment effects from Coban (2022).

where r_{ist} is the reduced form equation error, β represents the average treatment effect (ATE) of SNAP participation, and ψr_{ist} captures the self-selection effect. In CF models, it is also assumed that all unobservables are independent of $\boldsymbol{X}$ and $\boldsymbol{Z_{st}}$. Under these assumptions, the structural equation can be estimated as:

$$P(Y_{ist} = 1|\boldsymbol{X}, D_{ist}, r_{ist}, \boldsymbol{Z_{st}}) = \alpha + \beta D_{ist} + \boldsymbol{X\delta} + \eta \hat{r}_{ist} + \psi \hat{r}_{ist} D_{ist} \qquad (29)$$

To further account for heterogeneity in treatment effects, we modify the assumption in equation (27) as follows:

$$E(\beta_{ist}^{r}|D_{ist}, \boldsymbol{X}, \boldsymbol{Z_{st}}) = \beta + \psi r_{ist} + \boldsymbol{\theta X} \qquad (30)$$

where $\boldsymbol{\theta X}$ represents heterogeneity in the treatment effect with respect to covariates $\boldsymbol{X}$.[7] With this extension, the corresponding structural equation is:

$$P(Y_{ist} = 1|\boldsymbol{X}, D_{ist}, r_{ist}, \boldsymbol{Z_{st}}) = \alpha + \beta D_{ist} + \boldsymbol{X\delta} + \eta \hat{r}_{ist} + \psi \hat{r}_{ist} D_{ist} + D_{ist}\boldsymbol{X\theta} \qquad (31)$$

As before, r_{ist} is the reduced form equation error, β denotes the ATE of SNAP participation, and ψr_{ist} represents self-selection. A joint test of $(\hat{r}_{ist}, \hat{r}_{ist} D_{ist})$ in equations (29) and (31) provides a valid test of the null hypothesis $H_0 : D_{ist}$ is exogenous.

Finally, an analogous (recursive) bivariate probit model, which accounts for self-selection and treatment effect heterogeneity, is specified as:

$$P(Y_{ist} = 1|\boldsymbol{X}, D_{ist}) = \Phi(\alpha + \beta D_{ist} + \boldsymbol{X\delta} + D_{ist}\boldsymbol{X\theta}) \qquad (32)$$

As in the CF specifications, interaction effects in the (recursive) bivariate probit model are included only in the structural equation and not in the reduced form equation. Thus, equations (16) and (32) are jointly estimated in the (recursive) bivariate probit model for heterogenous analysis.

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[7] In our heterogenous analysis, we include only household demographic characteristics for $\boldsymbol{X}$ in the interaction terms.

CHAPTER 3

DATA

Our study replicates and improves upon the work of Ratcliffe et al. (2011) by primarily following their study design while incorporating additional refinements on data and methods. We primarily use data from the Survey of Income and Program Participation (SIPP), a nationally representative panel survey conducted by the U.S. Census Bureau. These data are augmented with state- and national-level economic conditions and SNAP-related policies.

3.1 Survey of Income and Program Participation (SIPP)

The SIPP provides detailed individual- and household-level data on demographic characteristics, household composition, government assistance program participation, and financial resources. We use data from the 1996, 2001, and 2004 SIPP panels, each comprising approximately 35,000 to 45,000 households surveyed over three to four years. The survey follows a rotating panel structure, with questions referencing the four months preceding the interview. Each cycle of interviews covering this period is referred to as a "wave." While core questions are consistently asked in every wave, additional questions on specific topics are included in topical modules administered only in selected waves.

For demographic information, we primarily rely on core questions collected during the periods when food insecurity was measured. For other key variables like food insecurity, assets, and citizenship, we relied on the Adult Well-being, Asset and Liabilities, and Migration History topical modules, respectively.

Food Insecurity

The questions on food insecurity, found in the Adult Well-being topical module, were asked in Wave 8 of the 1996 and 2001 panels, and in Wave 5 of the 2004 panel. The reference period covered by these waves were April–October 1998 for the 1996 panel, February–August 2003 for the 2001 panel, and February–August 2005 for the 2004 panel. Information is captured during these periods for the identification of our empirical model.

To estimate household food insecurity status, the SIPP uses the following five food security questions referencing the four months prior to the survey:[8]

1. The food that (I/WE) bought just didn't last and (I/WE) didn't have money to get more. Was that often, sometimes or never true for you in the last four months?
2. (I/WE) couldn't afford to eat balanced meals. Was that often, sometimes or never true for you in the last four months?
3. In the past four months did you or the other adults in the household ever cut the size of your meals or skip meals because there wasn't enough money for food? [Yes/No]
4. In the past four months did you or the other adults in the household ever eat less than you felt you should because there wasn’t enough money to buy food? [Yes/No]
5. In the past four months did you or the other adults in the household ever not eat for a whole day because there wasn't enough money for food? [Yes/No]

Using Nord’s (2006) methodology, responses to the five SIPP questions are used to classify households into two levels of food insecurity: “low food security” and “very low food security.” Households with 0 or 1 affirmative responses are considered **food secure**, those with 2 or 3

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[8] As compared to the SIPP, the USDA uses the Current Population Survey Food Security Supplement (CPS-FSS) for its official food security measures, which include 10 to 18 questions depending on whether household have children. However, according to Nord (2006), the SIPP food security scale, derived from those 5 questions, is reasonably reliable when compared to the USDA’s standard scale.

affirmative responses are classified as having **low food security**, and households with 4 or 5 affirmative responses are classified as having **very low food security**.[9] Thus, households are considered food insecure if they experience either low or very low food security. While Ratcliffe et al. (2011) refer to the most severe category as “very food insecurity,” we adopt the USDA terminology of “very low food security.”

SNAP participation

SIPP core files provide monthly data on SNAP participation at the individual level. A household is considered to participate in SNAP during a given month if any member reports receiving SNAP benefits.

Demographic variables

Using SIPP core files, our study incorporates a range of demographic variables to characterize both household-level attributes and the characteristics of the household reference person, whom we refer to as the household head. For household heads, we include age, and race and ethnicity. At the household level, we classify educational attainment based on the highest level of education reported by any member, record household composition by counting the number of children and adults (ages 18-64), and account for household structure based on headship, as well as whether the household contains a disabled member.[10] Additionally, we include household location, including metropolitan status and state of residence.

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[9] Responses are considered affirmative for food insecurity if respondents answer 'often' or 'sometimes' for questions 1 and 2, and 'yes' for questions 3, 4, and 5.

[10] Race and ethnicity are categorized into four groups: non-Hispanic Black, non-Hispanic White, Hispanic, and Other non-Hispanic. Educational attainment is classified as less than high school, high school, or more than high school. Household structure, based on headship, distinguishes between male-headed, female-headed, and two-adult-headed households, with the latter indicating households headed by both a husband and wife.

To identify households with noncitizen immigrants, we use data from the Migration History topical module.[11] Households are classified as noncitizen immigrants if at least one member is identified as a noncitizen.

3.2 Macroeconomic variables

We control for both state and national economic conditions. Data on the monthly state unemployment rate and employment-to-population ratio are based on the civilian labor force population and are sourced from the U.S. Bureau of Labor Statistics (2024), while annual state per capita personal income and national quarterly GDP are obtained from the U.S. Bureau of Economic Analysis (2024).

3.3 Instruments

The instrumental variables used in this study are state-level monthly SNAP policies obtained from the USDA SNAP Policy Database (2024). Unlike Ratcliffe et al. (2011), our study benefits from publicly available policy data that were not accessible in the same format during their research period. SNAP policy variation across states following the 1996 welfare reform provided an opportunity to use state-level policy differences as instruments.

The four instruments used are:

Biometric technology: This variable captures whether a state requires fingerprinting as part of the SNAP application process, either statewide or in selected regions.

Outreach Spending per Capita: Following Ratcliffe et al. (2011), we construct a measure of state monthly SNAP outreach spending per capita as:

$$Outreach\ spending\ per\ capita = \frac{state\ outreach\ spending\ (monthly\ measure)}{\begin{array}{c} state\ population\ below\ 150\%\ of\ the\ federal\ poverty\ threshold\ (annual\ measure) - \\ number\ of\ state\ SNAP\ recipients\ (monthly\ measure) \end{array}}$$

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[11] The Migration History topical module, collected in Wave 2 of the 1996 and 2001 panels, provides citizenship information only once, whereas the 2004 panel includes citizenship status monthly in the core data.

State outreach spending is sourced from the USDA SNAP Policy Database (2024), the population below 150% of the federal poverty threshold is obtained from the U.S. Census Bureau (2024), and the number of state SNAP recipients comes from the USDA Food and Nutrition Service (2024).[12]

Full Immigrant Eligibility and Partial Immigrant Eligibility: These two instruments capture the interaction between noncitizen immigrant households and state SNAP policies that extend eligibility to legal noncitizens. Following the terminology used in Ratcliffe et al. (2011), *Full Immigrant Eligibility* corresponds to the interaction term “All Legal Immigrants Eligible × Noncitizen Immigrant”, while *Partial Immigrant Eligibility* represents “Some Legal Immigrant Eligible × Noncitizen Immigrant”.[13]

3.4 Study Population and Sample Selection

In general, for households to qualify for SNAP benefits, they must meet specific income and asset limits. The gross monthly income limit is set at 130% of the federal poverty line, and the net monthly income limit is 100% of the poverty line. Regarding assets, households must meet specific thresholds: the limit for countable resources (e.g., cash or money in a bank account) is $3,000 for regular households, and $4,500 for households with elderly (aged 60+) or disabled members. Additionally, households that receive TANF, SSI, or general assistance may automatically qualify for SNAP based on their eligibility for these programs (USDA, 2025).

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[12] The monthly measure of state outreach spending is derived from annual figures by distributing them evenly across 12 months. For 1998, data on the population below 150% of the poverty threshold was unavailable, so we used data for those below 125% of the threshold as a substitute. This adjustment ensures consistency with the outreach spending per capita measure used by Ratcliffe et al. (2011), as reflected in the descriptive statistics in Table 1.
[13] The “All Legal Immigrants Eligible” variable reflects policies that allow all lawful noncitizen adults (aged 18-64), who meet other SNAP eligibility criteria such as income and asset limits, to qualify for federal SNAP or state-funded food assistance. In contrast, the “Some Legal Immigrant Eligible” variable applies to policies that extend eligibility only to a subset of lawful noncitizen adults (aged 18-64), while maintaining the same general SNAP eligibility requirements.

For our study, we defined the study population to include both low-income and low-asset households, following the approach used by Ratcliffe et al. (2011). Low-income households are defined as those with total monthly income below 150% of the poverty threshold,[14] while low-asset households are those with liquid assets less than or equal to $4,000, or $5,000 if at least one household member is 60 years or older.[15] This approach differs from studies by Mykerezi & Mills (2010), Shaefer & Gutierrez (2013), and Swann (2017), which focused primarily on households with income below 150% of the poverty line. The rationale for using a broader population, rather than strictly simulating SNAP eligibility rules, is that households near the eligibility threshold may adjust their income or assets to qualify. By including this broader population, we avoid excluding households on the margin that could become eligible with minor changes in behavior.

In the 1996 and 2001 SIPP panels, states such as Maine, North Dakota, South Dakota, Vermont, and Wyoming are not uniquely identifiable, making it impossible to match them with state-level SNAP policy and economic data. Consequently, observations from these states are excluded from our analysis.[16] Additionally, to ensure the accuracy of our analysis, we exclude households with imputed values for food insecurity and SNAP receipt data provided by the SIPP.

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[14] The SIPP core files provide monthly income and poverty threshold data for each household, which are used to classify low-income households. We followed the U.S. Census Bureau's official poverty measure to estimate total monthly household income, excluding non-cash benefits.

[15] Household asset information in the SIPP is collected through the Asset and Liabilities topical modules. In the 1996 panel, asset data were collected in waves 3, 6, 9, and 12; in the 2001 panel, in waves 3, 6, and 9; and in the 2004 panel, in waves 3 and 6. For this study, asset values were drawn from waves preceding the food security measurement – before wave 8 in the 1996 and 2001 panels, and before wave 5 in the 2004 panel. Individual asset values were averaged across waves and then aggregated across household members to determine total household assets. The study considers only liquid assets, including interest and non-interest bearing checking accounts, savings accounts, money market deposit accounts, and certificates of deposit.

[16] Although the 2004 panel resolves this issue by identifying each state individually, for consistency across panels, we have excluded data for these five states in all our analyses. As a result, our study covers 46 states, including D.C.

CHAPTER 4

RESULTS

In this section, we first present and compare our descriptive statistics with those reported by Ratcliffe et al. (2011). We then examine the effect of SNAP participation on food insecurity across different model specifications, followed by an analysis of the heterogeneity in treatment effects arising from interactions between SNAP participation and household demographic characteristics. All results are weighted using SIPP household weights.

Table 1 presents the weighted summary statistics. Column (1) reports result from Ratcliffe et al. (2011), while Column (2) shows the statistics for our full sample. The close alignment between these two sets of results suggests that our study builds upon Ratcliffe et al. (2011) while reinforcing its validity as an extension of their work under different modeling frameworks. Column (3) and (4) further break down the sample into SNAP participants and non-participants. To assess differences between these groups, we include the absolute value of t-statistics and p-values for mean equality tests. The results indicate significant differences between SNAP participants and non-participants across several characteristics.

Of particular importance to this study, food insecurity and very low food security levels are notably higher among SNAP participants. Specifically, 35.6% of SNAP-participating households experience food insecurity, and 15.8% face very low food security, compared to 18.9% and 7.9%, respectively, among non-participating households. While these figures suggest that SNAP participants are more likely to be food insecure (or very low food secure), they do not imply causation, as selection on observables has not been accounted for in this analysis.

Further examination of Table 1 reveals that SNAP households exhibit distinct demographic and socioeconomic characteristics. Compared to SNAP non-participating households, they tend to have younger household heads, a higher proportion of U.S. citizens, and a greater representation of non-Hispanic Black households. They are also more likely to have lower educational attainment, a larger number of children and adults, and a higher prevalence of female-headed households and disabled individuals. Additionally, SNAP participation is more common in non-metropolitan areas and is positively associated with higher state unemployment rates, greater state outreach spending, and lower adoption of biometric technology in program administration.

Table 1: Comparison of Descriptive Statistics with Ratcliffe et al. (2011)

Variable	Ratcliffe et al. (2011)	Our Study				
	All Households (1)	All Households (2)	SNAP participants (3)	SNAP Nonparticipants (4)	|t| (5)	p-value (6)
Program Participation and Food-Related Hardship						
SNAP Receipt	0.286	0.286	1.000	0.000	-	-
Food Insecure	0.244	0.237	0.356	0.189	37.83	0.000
Very Low Food Secure	0.103	0.102	0.158	0.079	22.55	0.000
Demographic Characteristics						
Age	47.982	48.297	44.795	49.701	29.29	0.000
	(18.547)	(18.732)	(17.054)	(19.185)		
Noncitizen immigrant	0.112	0.126	0.099	0.136	12.34	0.000
White, non-Hispanic (omitted reference group)	0.537	0.549	0.437	0.594	33.26	0.000
Black, non-Hispanic	0.231	0.218	0.326	0.175	36.11	0.000
Hispanic	0.189	0.182	0.187	0.180	1.61	0.108
Other, non-Hispanic	0.043	0.050	0.050	0.050	0.01	0.990
Education less than high school	0.271	0.280	0.345	0.254	20.90	0.000
Education high school only	0.354	0.319	0.337	0.312	5.51	0.000
Education more than high school (omitted reference group)	0.375	0.401	0.319	0.434	25.05	0.000
Number of children in household	1.010	1.002	1.445	0.824	45.21	0.000
	(1.385)	(1.383)	(1.557)	(1.264)		
Number of adults in household	1.544	1.267	1.331	1.241	10.87	0.000
	(0.747)	(0.931)	(0.871)	(0.953)		
Female-headed household	0.518	0.521	0.659	0.466	41.02	0.000
Male-headed household	0.198	0.199	0.147	0.219	20.19	0.000
Two adult-headed household (omitted reference group)	0.284	0.280	0.195	0.315	28.49	0.000
Disabled person in household	0.294	0.295	0.451	0.232	48.67	0.000

Metropolitan area	0.747	0.746	0.731	0.751	4.88	0.000
Economic Variables						
State monthly unemployment	5.290	5.188	5.221	5.175	4.77	0.000
	(1.040)	(1.043)	(1.034)	(1.046)		
State monthly employment-population ratio	0.947	0.947	0.947	0.947	4.38	0.000
	(0.010)	(0.011)	(0.011)	(0.011)		
State annual per capita income	29,361	31,452	31,514	31,427	1.74	0.083
	(4,058)	(5,305)	(5313)	(5301)		
Quarterly GDP (in billions)	10,275	11,238	11,370	11,185	12.92	0.000
	(730)	(1,595)	(1588)	(1595)		
Instrumental Variables						
Biometric technology	0.257	0.304	0.272	0.317	10.18	0.000
Outreach spending per capita	0.024	0.023	0.029	0.021	10.73	0.000
	(0.083)	(0.084)	(0.095)	(0.079)		
Full immigrant eligibility (All legal immigrants eligible × noncitizen immigrant)	0.026	0.031	0.020	0.035	10.01	0.000
Partial immigrant eligibility (Some legal immigrants eligible × noncitizen immigrant)	0.078	0.075	0.064	0.079	6.04	0.000
Number of Observations	65,269	65,311	20,212	45,099		

Note: Sample includes low-income and low-asset households for each reference months. Figures represent weighted sample means, with standard deviations in parentheses.

To establish a causal relationship between SNAP participation and food insecurity, we conduct a multivariate analysis and employ an instrumental variable (IV) approach, as presented in Table 2. Column (1) reports results from a naïve probit model that does not account for the endogeneity of SNAP participation. Unsurprisingly, the estimated coefficient for SNAP participation is positive and statistically significant for both food insecurity (Panel A) and very low food security (Panel B), suggesting that SNAP receipt is associated with a higher likelihood of being food insecure and very low food secure. This positive correlation between SNAP and food insecurity is most likely due to unobserved factors driving both self-selection into SNAP and increased food insecurity (or very low food security).

However, when we address endogeneity using an IV approach through 2SLS in Column (2), the coefficient for SNAP participation – representing the local average treatment effect (LATE) for compliers – is no longer statistically significant from zero, though it remains positive. Notably, these 2SLS results are identical to those obtained from the control function (CF) linear reduced form model in Column (3).

Further adding assumptions, we introduce a probit specification for the reduced form equation while maintaining a linear specification for the structural equation, as outlined in Section 2.2.2. The results are presented in Column (4) and indicate that the coefficient of SNAP participation is now negative and statistically significant. Specifically, for the average household in our sample, SNAP participation reduces the probability of food insecurity by 19.3 percentage points (from an estimated 29.2% to 9.9%) and very low food security by 10.5 percentage points (from an estimated 13.1% to 2.6%).

Expanding the analysis, we apply a bivariate probit model in Column (5), incorporating a probit specification in both the reduced form and structural equations. The estimated average treatment effect (ATE) remains negative and statistically significant, although slightly smaller than in Column (4). In this specification, SNAP participation reduces the probability of food insecurity by 15.5 percentage points (from 30.6% to 15.1%) and very low food security by 4 percentage points (from 12% to 8%) on average. These results remain consistent in the recursive bivariate probit model in Column (6), which accounts for simultaneity. Importantly, our findings align closely with those reported by Ratcliffe et al. (2011).[17]

Focusing on the average treatment effect on the treated (ATT) from the bivariate probit model in Column (5), we find that for households that actually receive SNAP benefits, the probability of food insecurity decreases by 24.3 percentage points (from 60.1% to 35.8%), while the probability of very low food security declines by 6.7 percentage points (from 22.7% to 16%). As expected, these effects are larger than the ATE estimates, reflecting self-selection into the program – households that enroll in SNAP tend to be more food insecure initially. The ATT estimates from the recursive bivariate probit model in Column (6) are 23.1 percentage points for food insecurity and 5.4 percentage points for very low food security, closely mirroring those from Column (5).

Overall, our results in Table 2 suggest that the estimated impact of SNAP participation on food insecurity and very low food security is sensitive to the chosen model specification and the accompanying assumptions. In particular, introducing a probit specification in the reduced form equation (Column 4) and further incorporating it into both the reduced form and structural equations (Column 5 and 6) meaningfully alters the findings compared to the models with linear reduced form equation (Column 2 and 3). Additionally, the IV approach plays a crucial role in

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[17] In addition to Ratcliffe et al. (2011), multiple studies have found that SNAP participation reduces food insecurity, including Gundersen et al. (2017), Swann (2017), Mabli et al. (2013), Shaefer & Gutierrez (2013), Kreider et al. (2012), Nord (2011), Nord & Prell (2011), Mykerezi & Mills (2010), Nord & Golla (2009), and Yen et al. (2008).

modifying the estimated effect of SNAP participation, as evidenced by the difference between the naïve probit model (Column 1) and the IV-based models (Column 2 to 6).[18]

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[18] In the case of the (recursive) bivariate probit model, the estimated treatment effects (ATE and ATT) remain similar whether instrumental variables (IVs) are included or excluded. This suggests that identification in the (recursive) bivariate probit model does not primarily rely on the IVs but rather stems from the model's structural assumptions. A similar observation was made by Shaefer & Gutierrez (2013). Our estimated ATE and ATT in the (recursive) bivariate probit model using IVs are reported in Table 2. Without IVs, the estimated treatment effects are as follows: For food insecurity, the ATE in the (recursive) bivariate probit model is -0.155, while the ATT is -0.244 in the standard bivariate probit model and -0.232 in the recursive bivariate probit model. For very low food security, the ATE in the (recursive) bivariate probit model is -0.041, while the ATT is -0.068 in the standard bivariate probit model and -0.054 in the recursive bivariate probit model.

Table 2: Effects of SNAP participation on Food Insecurity and Very Low Food Security Likelihood

	Probit	2SLS	CF-Linear Reduced Form	CF-Probit Reduced Form	Bivariate Probit			Recursive Bivariate Probit	
	(1)	(2)	(3)	(4)	(5)			(6)	
					Ratcliffe et al. (2011)	Our study			
	ATE	LATE	LATE	ATE	AME/ATE	AME/ATE	ATT	ATE	ATT
A. Food Insecure									
SNAP participation	0.092***	0.027	0.027	-0.193***	-0.162	-0.155***	-0.243***	-0.155***	-0.231***
	(0.009)	(0.455)	(0.461)	(0.059)		(0.016)	(0.030)	(0.016)	(0.026)
(Generalized) Residuals			0.071	0.172***					
			(0.459)	(0.036)					
Errors correlation (ρ)					0.509***	0.533***		0.533***	
					(0.054)	(0.038)		(0.038)	
B. Very Low Food Secure									
SNAP participation	0.042***	0.088	0.088	-0.105*	-0.039	-0.040***	-0.067***	-0.040***	-0.054***
	(0.007)	(0.315)	(0.307)	(0.062)		(0.011)	(0.021)	(0.011)	(0.015)
(Generalized) Residuals			-0.042	0.089**					
			(0.305)	(0.037)					
Errors correlation (ρ)					0.284***	0.297***		0.297***	
					(0.035)	(0.041)		(0.041)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes		Yes	

Observations	65,311	65,311	65,311	65,311	65,269	65,311	20,212	65,311	20,212

Note: Observations include low-income and low-asset households for each reference month. The figures corresponding to the errors correlation (ρ) represent coefficient estimates. Standard errors (SE), clustered at the state level, are reported in parentheses. Coefficient estimates use robust SE, while ATE is reported with unconditional SE, and LATE and ATT are reported with delta-method SE. All models include controls for age, age squared, race/ethnicity indicators (non-Hispanic Black, non-white non-Hispanic, and Hispanic), noncitizen immigrant household status, household educational attainment (less than high school and high school only), number of children and adults in the household, household type (Female-headed and Male-headed), disabled person in household, metropolitan status, state monthly unemployment rate, state monthly employment to population ratio, state annual per capita income, quarterly GDP, states dummies (covering 46 states, including D.C.), and year dummies (1998 and 2003). Instruments for first-stage reduced form equations include biometric technology, outreach spending per capita, full immigrant eligibility, and partial immigrant eligibility. *** p<0.01, ** p<0.05, * p<0.1

Understanding the factors driving SNAP participation and food insecurity (or very low food security) is crucial. These relationships can be inferred from the estimated coefficient signs presented in Appendix Tables 1 and 2, with most variables exhibiting expected directional effects. Across all models, SNAP participation is negatively associated with the household head's age, being a noncitizen immigrant, having more adults in the household, and residing in a metropolitan area. Conversely, it is positively associated with identifying as a racial/ethnic minority (Non-Hispanic Black, Hispanic, Other Non-Hispanic), having lower educational attainment (high school or less), having more children, being in a single-adult-headed household (male or female), and having a disabled household member. Notably, SNAP participation decreases during periods of higher state monthly unemployment rates—contrary to expectations—but, as anticipated, it is negatively associated with higher state monthly employment-to-population ratios, state annual per capita income, and national quarterly GDP.

Instrumental variable relevance is assessed in Table 3. Among the instruments, only biometric technology is statistically significant, showing a negative association with SNAP participation. Outreach spending per capita is positively associated with SNAP participation, while full and partial immigrant eligibility unexpectedly exhibit negative relationships. This finding contrasts with Ratcliffe et al. (2011), possibly due to differences in SNAP policy data availability—our study relies on publicly accessible USDA data, whereas Ratcliffe et al. (2011), faced with data limitations at the time, supplemented their database with additional documents obtained directly from the USDA.

The joint significance test indicates that the four instruments are jointly significant at the 1% level in the CF-Probit reduced form model and at the 5% level in the remaining models. While the commonly used rule of thumb for detecting weak instruments in linear 2SLS models suggests that the first-stage F-statistics should exceed 10 (Stock & Watson, 2020), no analogous diagnostic currently exists for nonlinear models (Donohue et al., 2024). For completeness, we report the first-stage F-statistics across models, and in the 2SLS model, the instruments do not satisfy the conventional threshold. However, weak instruments are generally considered less problematic in nonlinear two-equation systems compared to linear settings (Donohue et al., 2024). As noted in footnote 18 of our paper, the results indicate that identification in nonlinear frameworks such as the (recursive) bivariate probit model mainly relies on the model's structure and underlying assumptions rather than on instruments.

Table 3: Evaluating instruments performance for SNAP participation across models

Instrumental Variables	2SLS	CF-Linear Reduced Form	CF-Probit Reduced Form	Bivariate Probit/Recursive Bivariate Probit		Ratcliffe et al. (2011) Bivariate Probit	
	(1)	(2)	(3)	(4)		(5)	
	Food Insecurity/Very Low Food Security	Food Insecurity/Very Low Food Security	Food Insecurity/Very Low Food Security	Food Insecurity	Very Low Food Security	Food Insecurity	Very Low Food Security
SNAP participation							
Biometric technology	-0.082***	-0.082***	-0.294***	-0.260***	-0.271***	-0.269***	-0.261**
	(0.023)	(0.023)	(0.086)	(0.074)	(0.083)	(0.095)	(0.108)
Outreach spending per capita	0.026	0.026	0.015	0.059	0.005	0.402*	0.384*
	(0.084)	(0.084)	(0.321)	(0.283)	(0.303)	(0.228)	(0.223)
Full immigrant eligibility	-0.023	-0.023	-0.121	-0.103	-0.134	0.370**	0.418**
	(0.025)	(0.025)	(0.106)	(0.111)	(0.114)	(0.201)	(0.179)
Partial immigrant eligibility	-0.033	-0.033	-0.132	-0.146	-0.140	0.312*	0.365**
	(0.031)	(0.031)	(0.126)	(0.118)	(0.130)	(0.180)	(0.174)
Joint Significance test							
$\chi^2(4)$	14.68	14.68	14.35	12.52	13.28	15.8	14.9
F-stat	3.67	3.67	3.59	3.13	3.32	3.95	3.73
p-value	0.011	0.011	0.006	0.014	0.010	0.003	0.005
Observations	65,311	65,311	65,311	65,311	65,311	65,269	65,269

Note: Observations include low-income and low-asset households for each reference month. Robust standard errors, clustered at the state level, are reported in parentheses. In addition to the instrumental variables, the first-stage reduced form for all models include the full set of controls described in the note to Table 2. The reported F-statistics are converted to χ^2 statistics (and vice versa) using the formula: $\chi^2 = numerator\ degree\ of\ freedom \times F$. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Regarding food insecurity and very low food security, models in Columns (3) and (4) of Appendix Tables 1 and 2 suggest that households with an older head, racial/ethnic minority status, lower educational attainment, more children, and single-adult headship (male or female) are more vulnerable to both food insecurity and very low food security. Additionally, the presence of a disabled household member and residence in a metropolitan area are associated with an increased risk. In contrast, noncitizen immigrant households exhibit a lower likelihood of experiencing food insecurity and very low food security.

In Table 2, as well as Appendix Tables 1 and 2, the results from the bivariate probit and recursive bivariate probit models are presented, accounting for the error correlation (ρ) between the SNAP participation equation and the food insecurity (or very low food security) equations. The estimated correlation (ρ) is positive and statistically significant, supporting the self-selection hypothesis: unobserved factors increase the likelihood of both SNAP participation and food insecurity (or very low food security). As a result, households that are more likely to participate in SNAP also tend to face an increased risk of food insecurity and very low food security.

Moreover, self-selection implies that households choose to participate in SNAP when their returns to participation are higher. This is empirically supported by the results in Table 4, where the coefficient on the interaction term SNAP participation × Generalized residuals is positive and statistically significant. This finding further reinforces the selection hypothesis, suggesting that households self-select into SNAP when the expected benefits of participation are higher.

Table 4: Average Marginal Effects from the Heterogenous Analysis

	CF-Probit Reduced Form (1)	CF-Probit Reduced Form (2)	CF-Probit Reduced Form (3)	(Recursive) Bivariate Probit (4)
A. Food Insecure				
SNAP participation	0.052	0.030	-0.026	-0.127**
	(0.060)	(0.085)	(0.081)	(0.056)
SNAP participation × non-Hispanic Black		-0.103***	-0.062***	-0.109***
		(0.020)	(0.023)	(0.014)
SNAP participation × Hispanic		-0.034	-0.015	-0.051*
		(0.028)	(0.024)	(0.026)
SNAP participation × Less than High school		-0.013	0.033	-0.040**
		(0.025)	(0.026)	(0.016)
SNAP participation × High school only		-0.018	0.001	-0.022*
		(0.018)	(0.019)	(0.012)
SNAP participation × Female-headed		-0.049**	0.026	-0.074***
		(0.022)	(0.024)	(0.019)
SNAP participation × Male-headed		-0.042	-0.013	-0.065***
		(0.028)	(0.027)	(0.023)
SNAP participation × Disabled person in household		-0.048**	0.045	-0.101***
		(0.019)	(0.028)	(0.023)
Generalized residuals	-0.078	0.049	-0.077	
	(0.048)	(0.048)	(0.049)	
SNAP participation × Generalized residuals	0.161***		0.220***	
	(0.032)		(0.044)	
Errors correlation (ρ)				0.473***
				(0.121)
B. Very Low Food Secure				
SNAP participation	0.072	0.086	0.053	-0.066
	(0.064)	(0.083)	(0.079)	(0.069)
SNAP participation × non-Hispanic Black		-0.064***	-0.040**	-0.060***
		(0.015)	(0.018)	(0.017)
SNAP participation × Hispanic		-0.046**	-0.034*	-0.036
		(0.021)	(0.019)	(0.023)
SNAP participation × Less than High school		-0.030	-0.003	-0.037**
		(0.019)	(0.021)	(0.018)
SNAP participation × High school only		0.003	0.013	0.007
		(0.015)	(0.016)	(0.009)
SNAP participation × Female-headed		-0.049**	-0.006	-0.076**
		(0.021)	(0.022)	(0.035)

SNAP participation × Male-headed		-0.019	-0.002	-0.053*
		(0.021)	(0.022)	(0.028)
SNAP participation × Disabled person in household		-0.023	0.031	-0.076
		(0.018)	(0.024)	(0.050)
Generalized residuals	-0.092*	-0.016	-0.090*	
	(0.048)	(0.047)	(0.052)	
SNAP participation × Generalized residuals	0.116***		0.128***	
	(0.029)		(0.043)	
Errors correlation (ρ)				0.385
				(0.240)
Controls	Yes	Yes	Yes	Yes
Observations	65,311	65,311	65,311	65,311

Note: Observations include low-income and low-asset households for each reference month. Figures for Errors correlation (ρ), Generalized residuals, and SNAP participation × Generalized residuals represent coefficient estimates, while all other results are reported as average marginal effects (AME). Standard errors (SE), clustered at the state level, are reported in parentheses. Coefficient estimates use robust SE, whereas AME are reported with unconditional SE. All models include the full set of controls described in the note to Table 2. Models (2), (3), and (4) include additional interactions between SNAP participation and household demographic characteristics in the structural equation. Instruments for the first-stage reduced form equation are as specified in the note to Table 2. Full model specifications are provided in Appendix Tables 3 and 4. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

A joint test of the Generalized residuals and SNAP participation × Generalized residuals in the control function models (1) and (3) indicates statistical significance at the 1% level for food insecure in Panel A (F(2, 45) = 16.89, p-value = 0.000 for Model (1); F(2, 45) = 12.62, p-value = 0.000 for Model (3)). In Panel B, the joint test is significant at the 1% level for very low food secure in Model (1) (F(2, 45) = 9.03, p-value = 0.001) and at the 5% level in Model (3) (F(2, 45) = 4.56, p-value = 0.0158).

Additionally, Table 4 confirms the endogeneity of SNAP participation through a joint test of the Generalized residuals and the SNAP participation × Generalized residuals in the control function (CF) models 1 and 3, with the test statistics provided in the Note section of Table 4. The presence of endogeneity is further validated by the statistically significant coefficient on the Generalized residuals in the control function model 4 of Table 2, indicating that SNAP participation is indeed endogenous.

Beyond addressing endogeneity and self-selection, Table 4 provides valuable insights into the heterogeneity of treatment effects by examining the interactions between SNAP participation and various household demographic characteristics. Specifically, the models in Columns 2, 3, and 4 focus on treatment effect heterogeneity, complemented by Figures 1 through 4. These figures show the average marginal effects for all groups, including the reference group. The average marginal effects for selected groups are presented in parentheses in the descriptive paragraphs below, while Table 4 highlights how the returns to SNAP participation differ across specific demographic groups relative to the reference group.

In general, the results from Table 4 and Figures 1 to 4 suggest that the effects on food insecurity (Panel A) and very low food security (Panel B) are more pronounced and statistically significant in the (recursive) bivariate probit model (Column 4) compared to the CF specification models in Columns 2 and 3. As we progress from CF Model 2 to CF Model 3 and then to the (recursive) bivariate probit Model 4, the average marginal effect of SNAP participation becomes increasingly negative. This indicates that SNAP participation is more likely to reduce food insecurity and very low food security, with the effect being strongest in Model 4. The differences in the likelihood of reduction in food insecurity and very low food security across CF Model 2, CF Model 3, and the (recursive) bivariate probit Model 4 are clearly depicted in Figures 1 and 2.

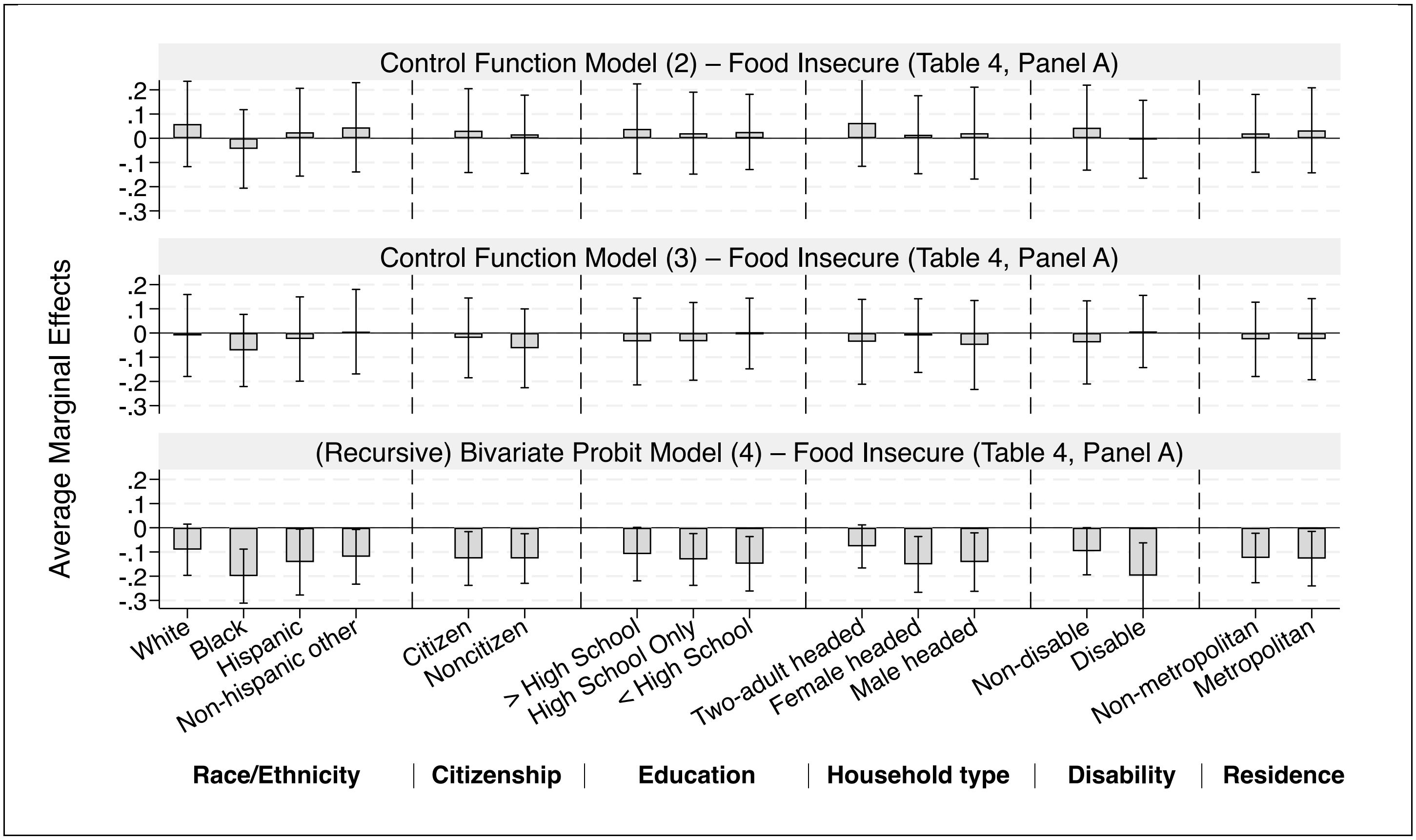

Figure 1: Average Marginal Effects of SNAP participation on Food Insecurity for discrete household demographics

Note: Estimated average marginal effects are derived from Panel A (Food Insecure) of Table 4. Plot titles correspond to the respective models presented in Table 4. The top of each bar represents the mean estimate, while the lines with caps indicate the upper and lower bounds of the 95% confidence interval.

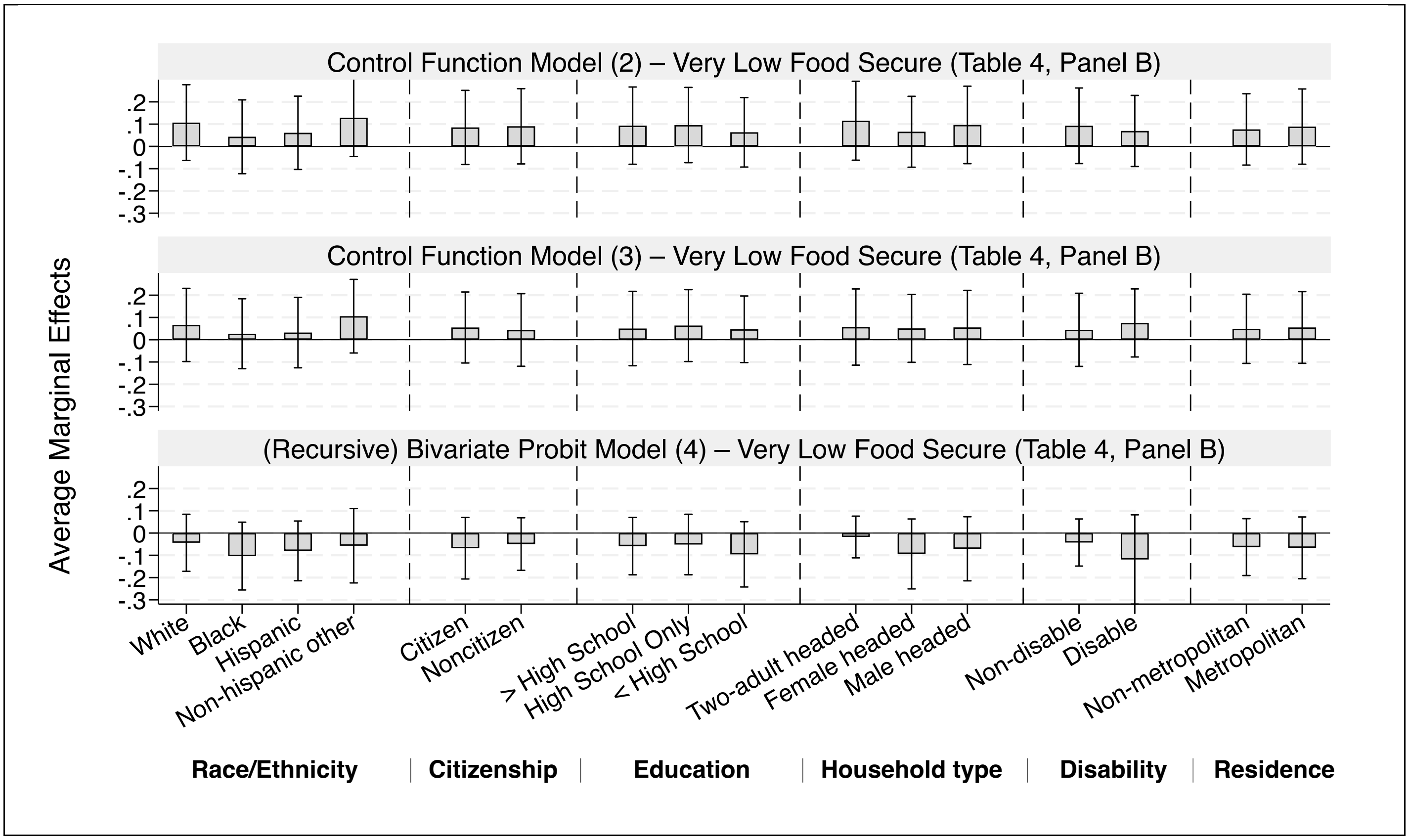

Figure 2: Average Marginal Effects of SNAP participation on Very Low Food Security for discrete household demographics

Note: Estimated average marginal effects are derived from Panel B (Very Low Food Secure) of Table 4. Plot titles correspond to the respective models presented in Table 4. The top of each bar represents the mean estimate, while the lines with caps indicate the upper and lower bounds of the 95% confidence interval.

A notable heterogeneity in treatment effects is observed among racial/ethnic groups, particularly among Black non-Hispanic households. Across all specifications in Table 4, the average marginal effect of SNAP participation for Black households, compared to White households, significantly lowers the likelihood of both food insecurity and very low food security. Specifically, for food insecurity (Panel A), Black households experience an additional 10.3 percentage point reduction (from 5.9% to -4.4%) in Column (2), an additional 6.2 percentage point reduction (from -1% to -7.2%) in Column (3), and an additional 10.9 percentage point reduction (from -9.1% to -20%) in Column (4) due to SNAP participation, compared to White households. Furthermore, the effect of SNAP participation on food insecurity is more evident for households with disabled members and female-headed households, with the strongest effect observed in Model 4. In this model, households with disabled members experience a 10.1 percentage point greater reduction (from -9.7% to -19.8%) in food insecurity due to SNAP, compared to those without disabled members. Similarly, SNAP is associated with a 7.4 percentage point larger reduction (from -7.7% to -15.1%) in food insecurity for female-headed households relative to two-adult headed households. Compared to households with more than a high school education, those with less than a high school education experiences a 4 percentage point greater reduction (from -10.9% to -14.9%) in food insecurity due to SNAP.

For very low food security (Panel B), the results follow a similar pattern, although the marginal effect of SNAP between households with and without disabled members is no longer statistically significant. Black households, however, experience an additional 6.4 percentage point reduction (from 10.7% to 4.3%) in very low food security in Column (2), an additional 4 percentage point reduction (from 6.6% to 2.6%) in Column (3), and an additional 6 percentage point reduction (from -4.4% to -10.4%) in Column (4) due to SNAP participation, compared to

White households. The effects of education and headship variables are more markedly evident in Model 4 than in Models 2 and 3. In Model 4, SNAP reduces very low food security by an additional 3.7 percentage points (from -5.9% to -9.6%) for households with less than a high school education, compared to those with educational attainment of more than high school. Likewise, in female-headed households, SNAP reduces very low food security by an extra 7.6 percentage points (from -1.8% to -9.4%) compared to two-adult headed households.

Figures 3 and 4 show the average marginal effects of SNAP participation on food insecurity and very low food security, respectively, at different levels of household children and household head age across the three model specifications (Columns 2, 3, and 4 of Table 4). The trends in both figures indicate that as the number of children in the household increases, SNAP participation is expected to increasingly reduce the risk of food insecurity and very low food security, although this relationship is less clear in CF Model 3. Regarding household head age, the effect of SNAP differs between the CF models (2 and 3) and the (recursive) bivariate probit model (4). In CF Models 2 and 3, SNAP participation has a much greater effect in reducing food insecurity and very low food security for households with younger heads (around 20 years old) and older heads (70+ years) compared to those with medium-aged heads, with the strongest effect observed for households with older heads. However, in the (recursive) bivariate probit model (4), the effect of SNAP participation on reducing food insecurity and very low food security decreases as the household head's age increases.

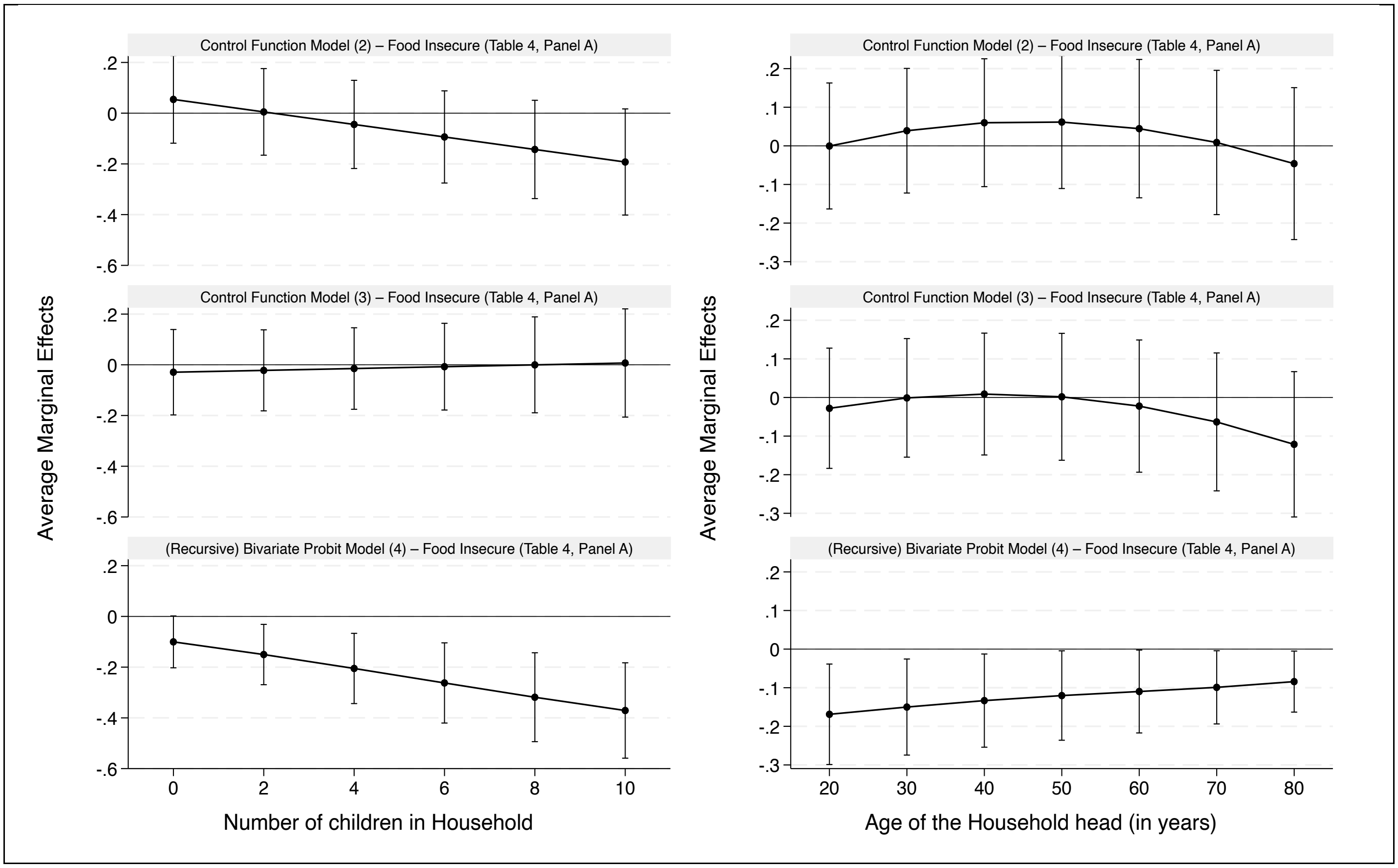

Figure 3: Average Marginal Effects of SNAP participation on Food Insecurity at different levels of household children and head's age

Note: Estimated average marginal effects are derived from Panel A (Food Insecure) of Table 4. Plot titles correspond to the respective models presented in Table 4. The points represent the mean estimate, while the lines with caps indicate the upper and lower bounds of the 95% confidence interval.

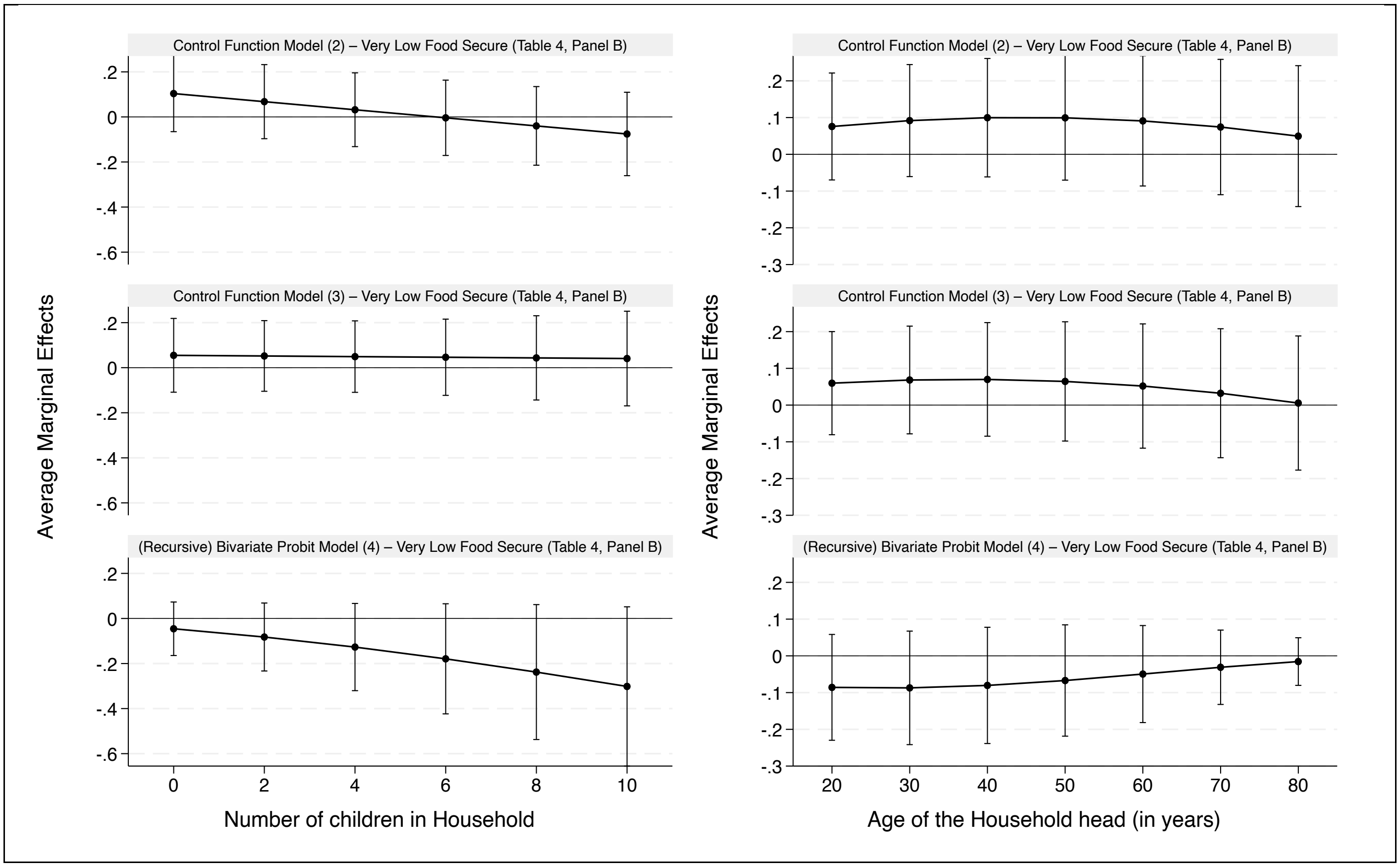

Figure 4: Average Marginal Effects of SNAP participation on Very Low Food Security at different levels of household children and head's age

Note: Estimated average marginal effects are derived from Panel B (Very Low Food Secure) of Table 4. Plot titles correspond to the respective models presented in Table 4. The points represent the mean estimate, while the lines with caps indicate the upper and lower bounds of the 95% confidence interval.

Overall, SNAP is more effective at reducing food insecurity and very low food security for Black and Hispanic households compared to White households, for less educated households compared to those with more than a high school education, for single-adult headed households (whether male or female) compared to two-adult headed households, for households with disabled members compared to those without, for households with more children, and for households with younger heads (around 20 years old) and older heads (70+ years). It is important to note that the heterogeneity in treatment effects, similar to the average treatment effects (ATE) of SNAP participation in Table 2, is influenced by the functional form assumptions. The bivariate probit model provides more precise estimates and reveals larger effects of SNAP in reducing food insecurity and very low food security.

CHAPTER 5

CONCLUSIONS

In this study, we examine the relationship between SNAP participation and food insecurity using various econometric models to address potential endogeneity and explore the robustness of our findings under different functional form assumptions. Our results indicate that SNAP benefits play a significant role in reducing food insecurity, though the magnitude and direction of the effect vary depending on model specification.

In the probit model without instrumental variables (IV), we find that SNAP participation significantly increases food insecurity by 9.2 percentage points and very low food security by 4.2 percentage points. However, when applying IV approaches such as 2SLS and the control function (linear reduced form), the estimated coefficients remain positive but are not statistically significant. Notably, introducing a nonlinear specification in the first-stage reduced form equation through the control function (probit reduced form) shows that SNAP participation significantly reduces food insecurity by 19.3 percentage points and very low food security by 10.5 percentage points. Further applying nonlinear probit assumptions to both the reduced and structural equations through bivariate probit and recursive bivariate probit models reveals that SNAP participation significantly reduces food insecurity by 15.5 percentage points and very low food security by 4 percentage points. These results should be interpreted with an important qualifier: the findings from the (recursive) bivariate probit models appear to be driven by their underlying structural assumptions, as the results remain consistent regardless of whether instrumental variables are used.

Our findings suggest that the effectiveness of SNAP in reducing food insecurity is more marked among specific subpopulations. Larger effects are observed among Black non-Hispanic households, households with less than a high school education, those with disabled members, single-adult-headed households, households with more children, and those with either very young (around 20 years old) or older heads (70+ years). Policymakers and program administrators can benefit by identifying these groups that gain the most from the program and tailoring interventions to better support them, thereby enhancing SNAP's overall effectiveness. This study underscores the crucial role of SNAP as a safety net that alleviates food insecurity for many American households, with particularly strong impacts for the subpopulations mentioned above.

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APPENDICES

Appendix Table 1: Regression estimates for Food Insecurity across models

	2SLS		CF-Linear Reduced Form	CF-Probit Reduced Form		Bivariate Probit/Recursive Bivariate Probit	
	(1)		(2)	(3)		(4)	
	SNAP participation	Food Insecurity	Food Insecurity	SNAP participation	Food Insecurity	SNAP participation	Food Insecurity
SNAP participation		0.027	0.027		-0.193***		-0.590***
		(0.455)	(0.461)		(0.059)		(0.065)
<u>Instrumental variables</u>							
Biometric technology	-0.082***			-0.294***		-0.260***	
	(0.023)			(0.086)		(0.074)	
Outreach spending per capita	0.026			0.015		0.059	
	(0.084)			(0.321)		(0.283)	
Full immigrant eligibility	-0.023			-0.121		-0.103	
	(0.025)			(0.106)		(0.111)	
Partial immigrant eligibility	-0.033			-0.132		-0.146	
	(0.031)			(0.126)		(0.118)	
<u>Household demographic characteristics</u>							
Age	-0.004***	0.004*	0.004*	-0.015***	0.003**	-0.015***	0.019***
	(0.001)	(0.002)	(0.002)	(0.004)	(0.001)	(0.004)	(0.005)
Age squared	0.000**	-0.000***	-0.000***	0.000**	-0.000***	0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Race/Ethnicity (Reference group: non-Hispanic White)							
Non-Hispanic Black	0.124***	0.058	0.058	0.404***	0.086***	0.409***	0.292***
	(0.008)	(0.055)	(0.055)	(0.024)	(0.012)	(0.024)	(0.026)
Hispanic	0.065*	0.054*	0.054*	0.244**	0.068***	0.250**	0.237***
	(0.035)	(0.031)	(0.030)	(0.115)	(0.019)	(0.115)	(0.071)
Other non-Hispanic	0.081***	0.032	0.032	0.268***	0.050**	0.269***	0.175**
	(0.017)	(0.041)	(0.041)	(0.062)	(0.020)	(0.061)	(0.070)
Noncitizen immigrant	-0.022	-0.019	-0.019	-0.032	-0.029*	-0.022	-0.090
	(0.038)	(0.020)	(0.020)	(0.145)	(0.016)	(0.137)	(0.057)
Educational Attainment (Reference group: More than high school)							
Less than high school	0.121***	0.055	0.055	0.429***	0.082***	0.432***	0.287***
	(0.011)	(0.059)	(0.060)	(0.037)	(0.013)	(0.037)	(0.036)
High school only	0.047***	0.021	0.021	0.172***	0.031***	0.180***	0.108***
	(0.009)	(0.024)	(0.025)	(0.033)	(0.008)	(0.033)	(0.027)
Number of children	0.079***	0.011	0.011	0.259***	0.028***	0.257***	0.089***
	(0.004)	(0.038)	(0.038)	(0.016)	(0.005)	(0.015)	(0.014)
Number of adults	-0.008*	0.013*	0.013*	-0.022	0.011*	-0.023	0.036*
	(0.004)	(0.008)	(0.007)	(0.015)	(0.006)	(0.015)	(0.021)
Household type (Reference group: Two-adult headed)							
Female-headed	0.192***	0.082	0.082	0.662***	0.125***	0.664***	0.416***
	(0.008)	(0.088)	(0.089)	(0.034)	(0.013)	(0.033)	(0.048)
Male-headed	0.077***	0.066*	0.066*	0.261***	0.083***	0.264***	0.281***
	(0.011)	(0.038)	(0.038)	(0.045)	(0.011)	(0.043)	(0.046)
Disabled person in household	0.237***	0.150	0.150	0.787***	0.202***	0.789***	0.623***
	(0.015)	(0.109)	(0.111)	(0.040)	(0.014)	(0.040)	(0.032)
Metropolitan area	-0.023*	0.023	0.023	-0.082**	0.018	-0.085**	0.052
	(0.012)	(0.016)	(0.016)	(0.042)	(0.011)	(0.041)	(0.036)

Macroeconomic characteristics							
State monthly unemployment rate	-0.012	-0.010	-0.010	-0.042	-0.012	-0.041	-0.040
	(0.008)	(0.011)	(0.011)	(0.028)	(0.010)	(0.029)	(0.035)
State monthly employment to population ratio	-0.551	-3.193***	-3.192***	-1.265	-3.364***	-1.479	-11.187***
	(0.914)	(0.953)	(0.945)	(3.262)	(0.828)	(3.337)	(3.239)
State annual per capita income (in $100s)	-0.001**	0.001	0.001	-0.005*	0.001	-0.005*	0.002
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	(0.002)
Quarterly GDP (in trillions)	-0.006	-0.065***	-0.065***	-0.031	-0.067***	-0.030	-0.226***
	(0.022)	(0.021)	(0.022)	(0.080)	(0.022)	(0.081)	(0.065)
Year							
1998	-0.203*	-0.152	-0.152	-0.752*	-0.194*	-0.741*	-0.652*
	(0.114)	(0.130)	(0.131)	(0.421)	(0.108)	(0.430)	(0.362)
2003	-0.089*	-0.111**	-0.111*	-0.324**	-0.131***	-0.324*	-0.447***
	(0.045)	(0.056)	(0.056)	(0.164)	(0.042)	(0.170)	(0.138)
Residuals/Generalized residuals			0.071		0.172***		
			(0.459)		(0.036)		
Intercept	1.193	3.615***	3.615***	2.035	3.915***	2.168	11.374***
	(0.946)	(1.097)	(1.091)	(3.212)	(0.869)	(3.291)	(3.342)
Errors correlation (ρ)						0.533***	
						(0.038)	
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,311		65,311	65,311		65,311	

Note: Observations include low-income and low-asset households for each reference month. Robust standard errors, clustered at the state level, are reported in parentheses. The first-stage reduced form equation for SNAP participation in Model (2) (CF-Linear reduced form) is identical to that in Model (1) (2SLS). *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2: Regression estimates for Very Low Food Security across models

	2SLS (1)		CF-Linear Reduced Form (2)	CF-Probit Reduced Form (3)		Bivariate Probit/Recursive Bivariate Probit (4)	
	SNAP participation	Very Low Food Security	Very Low Food Security	SNAP participation	Very Low Food Security	SNAP participation	Very Low Food Security
SNAP participation		0.088	0.088		-0.105*		-0.252***
		(0.315)	(0.307)		(0.062)		(0.071)
<u>Instrumental variables</u>							
Biometric technology	-0.082***			-0.294***		-0.271***	
	(0.023)			(0.086)		(0.083)	
Outreach spending per capita	0.026			0.015		0.005	
	(0.084)			(0.321)		(0.303)	
Full immigrant eligibility	-0.023			-0.121		-0.134	
	(0.025)			(0.106)		(0.114)	
Partial immigrant eligibility	-0.033			-0.132		-0.140	
	(0.031)			(0.126)		(0.130)	
<u>Household demographic characteristics</u>							
Age	-0.004***	0.003**	0.003**	-0.015***	0.002**	-0.015***	0.030***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.004)	(0.006)
Age squared	0.000**	-0.000***	-0.000***	0.000**	-0.000***	0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Race/Ethnicity (Reference group: non-Hispanic White)							
Non-Hispanic Black	0.124***	0.000	0.000	0.404***	0.024*	0.407***	0.114***
	(0.008)	(0.039)	(0.038)	(0.024)	(0.012)	(0.024)	(0.044)
Hispanic	0.065*	-0.004	-0.004	0.244**	0.008	0.246**	0.041
	(0.035)	(0.022)	(0.020)	(0.115)	(0.011)	(0.116)	(0.058)

Other non-Hispanic	0.081***	0.028	0.028	0.268***	0.044**	0.268***	0.220**
	(0.017)	(0.024)	(0.024)	(0.062)	(0.021)	(0.062)	(0.100)
Noncitizen immigrant	-0.022	-0.014	-0.014	-0.032	-0.024**	-0.024	-0.126**
	(0.038)	(0.015)	(0.014)	(0.145)	(0.011)	(0.149)	(0.058)
Educational Attainment (Reference group: More than high school)							
Less than high school	0.121***	0.004	0.004	0.429***	0.027***	0.430***	0.135***
	(0.011)	(0.036)	(0.035)	(0.037)	(0.009)	(0.037)	(0.047)
High school only	0.047***	-0.006	-0.006	0.172***	0.003	0.175***	0.003
	(0.009)	(0.015)	(0.015)	(0.033)	(0.005)	(0.033)	(0.033)
Number of children	0.079***	-0.002	-0.002	0.259***	0.013***	0.259***	0.047**
	(0.004)	(0.026)	(0.025)	(0.016)	(0.004)	(0.016)	(0.019)
Number of adults	-0.008*	-0.001	-0.001	-0.022	-0.003	-0.023	-0.005
	(0.004)	(0.005)	(0.005)	(0.015)	(0.005)	(0.015)	(0.027)
Household type (Reference group: Two-adult headed)							
Female-headed	0.192***	0.039	0.039	0.662***	0.076***	0.662***	0.408***
	(0.008)	(0.062)	(0.060)	(0.034)	(0.011)	(0.034)	(0.054)
Male-headed	0.077***	0.041	0.041	0.261***	0.056***	0.261***	0.336***
	(0.011)	(0.028)	(0.028)	(0.045)	(0.008)	(0.045)	(0.063)
Disabled person in household	0.237***	0.067	0.067	0.787***	0.113***	0.788***	0.519***
	(0.015)	(0.076)	(0.074)	(0.040)	(0.013)	(0.040)	(0.034)
Metropolitan area	-0.023*	0.019	0.019	-0.082**	0.014*	-0.083**	0.094**
	(0.012)	(0.012)	(0.012)	(0.042)	(0.008)	(0.041)	(0.047)
Macroeconomic characteristics							
State monthly unemployment rate	-0.012	0.001	0.001	-0.042	-0.002	-0.041	0.004
	(0.008)	(0.006)	(0.006)	(0.028)	(0.006)	(0.028)	(0.036)
State monthly employment to population ratio	-0.551	-1.256*	-1.256*	-1.265	-1.406**	-1.212	-6.951*
	(0.914)	(0.669)	(0.689)	(3.262)	(0.630)	(3.260)	(3.940)

State annual per capita income (in $100s)	-0.001**	0.000	0.000	-0.005*	0.000	-0.005*	0.001
	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)	(0.003)	(0.003)
Quarterly GDP (in trillions)	-0.006	-0.010	-0.010	-0.031	-0.012	-0.031	-0.074
	(0.022)	(0.019)	(0.019)	(0.080)	(0.020)	(0.079)	(0.111)
Year							
1998	-0.203*	-0.006	-0.006	-0.752*	-0.043	-0.751*	-0.213
	(0.114)	(0.083)	(0.084)	(0.421)	(0.087)	(0.420)	(0.496)
2003	-0.089*	-0.023	-0.023	-0.324**	-0.040	-0.324**	-0.217
	(0.045)	(0.038)	(0.038)	(0.164)	(0.034)	(0.164)	(0.196)
Residuals/Generalized residuals			-0.042		0.089**		
			(0.305)		(0.037)		
Intercept	1.193	1.188*	1.188	2.035	1.453**	1.965	4.896
	(0.946)	(0.718)	(0.743)	(3.212)	(0.665)	(3.190)	(4.180)
Errors correlation (ρ)						0.297***	
						(0.041)	
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,311		65,311	65,311		65,311	

Note: Observations include low-income and low-asset households for each reference month. Robust standard errors, clustered at the state level, are reported in parentheses. The first-stage reduced form equation for SNAP participation in Model (2) (CF-Linear reduced form) is identical to that in Model (1) (2SLS). *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3: Regression estimates for Food Insecurity from the Heterogenous Analysis

	CF-Probit Reduced Form		CF-Probit Reduced Form	CF-Probit Reduced Form	(Recursive) Bivariate Probit	
	(1)		(2)	(3)	(4)	
	SNAP participation	Food Insecure	Food Insecure	Food Insecure	SNAP participation	Food Insecure
SNAP participation		0.052	-0.032	-0.147		-0.308
		(0.060)	(0.116)	(0.118)		(0.327)
Instrumental variables						
Biometric technology	-0.294***				-0.270***	
	(0.086)				(0.078)	
Outreach spending per capita	0.015				0.055	
	(0.321)				(0.293)	
Full immigrant eligibility	-0.121				-0.104	
	(0.106)				(0.113)	
Partial immigrant eligibility	-0.132				-0.144	
	(0.126)				(0.119)	
Household demographic characteristics						
Age	-0.015***	0.004***	0.002	0.003*	-0.014***	0.015**
	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)	(0.007)
Age squared	0.000**	-0.000***	-0.000***	-0.000***	0.000**	-0.000***

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Race/Ethnicity (Reference group: non-Hispanic White)						
Non-Hispanic Black	0.404***	0.047***	0.097***	0.076***	0.407***	0.410***
	(0.024)	(0.012)	(0.014)	(0.014)	(0.024)	(0.038)
Hispanic	0.244**	0.045**	0.061**	0.052**	0.246**	0.269***
	(0.115)	(0.020)	(0.025)	(0.024)	(0.115)	(0.094)
Other non-Hispanic	0.268***	0.025	0.037**	0.022	0.268***	0.193***
	(0.062)	(0.020)	(0.017)	(0.017)	(0.061)	(0.072)
Noncitizen immigrant	-0.032	-0.017	-0.018	-0.009	-0.024	-0.091
	(0.145)	(0.017)	(0.019)	(0.019)	(0.138)	(0.072)
Educational Attainment (Reference group: More than high school)						
Less than high school	0.429***	0.043***	0.059***	0.038***	0.431***	0.305***
	(0.037)	(0.013)	(0.014)	(0.013)	(0.037)	(0.044)
High school only	0.172***	0.016**	0.025***	0.017**	0.177***	0.123***
	(0.033)	(0.008)	(0.008)	(0.008)	(0.033)	(0.029)
Number of children	0.259***	0.004	0.021***	0.006	0.259***	0.115***
	(0.016)	(0.005)	(0.006)	(0.006)	(0.016)	(0.019)
Number of adults	-0.022	0.013**	0.012	0.013*	-0.023	0.042
	(0.015)	(0.006)	(0.008)	(0.008)	(0.015)	(0.027)
Household type (Reference group: Two-adult headed)						

Female-headed	0.662***	0.065***	0.099***	0.064***	0.661***	0.473***
	(0.034)	(0.016)	(0.017)	(0.017)	(0.033)	(0.058)
Male-headed	0.261***	0.060***	0.080***	0.065***	0.261***	0.349***
	(0.045)	(0.012)	(0.015)	(0.015)	(0.044)	(0.052)
Disabled person in household	0.787***	0.127***	0.162***	0.117***	0.787***	0.672***
	(0.040)	(0.017)	(0.018)	(0.019)	(0.040)	(0.055)
Metropolitan area	-0.082**	0.026**	0.019	0.024*	-0.084**	0.057
	(0.042)	(0.011)	(0.012)	(0.012)	(0.041)	(0.043)
Macroeconomic characteristics						
State monthly unemployment rate	-0.042	-0.008	-0.010	-0.008	-0.041	-0.039
	(0.028)	(0.009)	(0.009)	(0.009)	(0.029)	(0.034)
State monthly employment to population ratio	-1.265	-3.209***	-3.177***	-3.155***	-1.455	-11.717***
	(3.262)	(0.813)	(0.820)	(0.813)	(3.355)	(3.232)
State annual per capita income (in $100s)	-0.005*	0.001*	0.001	0.001	-0.005*	0.003
	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Quarterly GDP (in trillions)	-0.031	-0.063***	-0.064***	-0.063***	-0.031	-0.225***
	(0.080)	(0.022)	(0.022)	(0.022)	(0.081)	(0.066)
Year						
1998	-0.752*	-0.124	-0.146	-0.129	-0.747*	-0.602*
	(0.421)	(0.111)	(0.110)	(0.109)	(0.430)	(0.358)

2003	-0.324**	-0.100**	-0.109**	-0.102**	-0.326*	-0.435***
	(0.164)	(0.043)	(0.043)	(0.043)	(0.169)	(0.137)
Interaction terms (SNAP participation × Household demographics)						
SNAP participation × Age			0.009***	0.007**		0.013
			(0.003)	(0.003)		(0.008)
SNAP participation × Age squared			-0.000***	-0.000***		-0.000
			(0.000)	(0.000)		(0.000)
SNAP participation × Non-Hispanic Black			-0.103***	-0.062**		-0.329***
			(0.020)	(0.023)		(0.056)
SNAP participation × Hispanic			-0.034	-0.015		-0.142*
			(0.028)	(0.024)		(0.077)
SNAP participation × Other non-Hispanic			-0.014	0.016		-0.075
			(0.029)	(0.034)		(0.077)
SNAP participation × Noncitizen Immigrant			-0.015	-0.043*		-0.027
			(0.025)	(0.026)		(0.076)
SNAP participation × Less than High school			-0.013	0.033		-0.087
			(0.025)	(0.026)		(0.068)
SNAP participation × High school only			-0.018	0.001		-0.062

			(0.018)	(0.019)		(0.049)
SNAP participation × Number of children			-0.025***	0.004		-0.073***
			(0.007)	(0.010)		(0.020)
SNAP participation × Number of adults			0.000	-0.002		-0.013
			(0.014)	(0.014)		(0.039)
SNAP participation × Female-headed			-0.049**	0.026		-0.199***
			(0.022)	(0.024)		(0.054)
SNAP participation × Male-headed			-0.042	-0.013		-0.194**
			(0.028)	(0.027)		(0.078)
SNAP participation × Disabled person in household			-0.048**	0.045		-0.214***
			(0.019)	(0.028)		(0.047)
SNAP participation × Metropolitan area			0.013	0.001		0.004
			(0.023)	(0.022)		(0.069)
Generalized residuals		-0.078	0.049	-0.077		
		(0.048)	(0.048)	(0.049)		
SNAP participation × Generalized residuals		0.161***		0.220***		
		(0.032)		(0.044)		
Intercept	2.035	3.517***	3.596***	3.500***	2.176	11.662***

	(3.212)	(0.838)	(0.830)	(0.822)	(3.298)	(3.260)
Errors correlation (ρ)					0.473***	
					(0.121)	
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,311	65,311	65,311	65,311	65,311	65,311

Note: Observations include low-income and low-asset households for each reference month. Robust standard errors, clustered at the state level, are reported in parentheses. The first-stage reduced form equation for SNAP participation in Models (2) and (3) is identical to that in Model (1). *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 4: Regression estimates for Very Low Food Security from the Heterogenous Analysis

	CF-Probit Reduced Form	CF-Probit Reduced Form	CF-Probit Reduced Form	(Recursive) Bivariate Probit	
	(1)	(2)	(3)	(4)	
	Very Low Food Secure	Very Low Food Secure	Very Low Food Secure	SNAP participation	Very Low Food Secure
SNAP participation	0.072	0.097	0.030		0.127
	(0.064)	(0.087)	(0.092)		(0.378)
<u>Instrumental variables</u>					
Biometric technology				-0.263***	
				(0.081)	
Outreach spending per capita				0.000	
				(0.299)	
Full immigrant eligibility				-0.133	
				(0.116)	
Partial immigrant eligibility				-0.140	
				(0.130)	
<u>Household demographic characteristics</u>					
Age	0.003***	0.002***	0.003***	-0.014***	0.028***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.007)
Age squared	-0.000***	-0.000***	-0.000***	0.000**	-0.000***

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Race/Ethnicity (Reference group: non-Hispanic White)					
Non-Hispanic Black	-0.004	0.025*	0.012	0.407***	0.265***
	(0.013)	(0.014)	(0.014)	(0.023)	(0.079)
Hispanic	-0.008	0.009	0.003	0.244**	0.128
	(0.010)	(0.016)	(0.015)	(0.116)	(0.111)
Other non-Hispanic	0.026	0.024	0.015	0.269***	0.243***
	(0.020)	(0.015)	(0.014)	(0.061)	(0.093)
Noncitizen immigrant	-0.014	-0.019**	-0.014	-0.025	-0.174**
	(0.010)	(0.009)	(0.009)	(0.149)	(0.074)
Educational Attainment (Reference group: More than high school)					
Less than high school	-0.000	0.014	0.002	0.430***	0.222***
	(0.010)	(0.011)	(0.011)	(0.038)	(0.070)
High school only	-0.008	-0.008	-0.013**	0.175***	-0.011
	(0.006)	(0.005)	(0.005)	(0.033)	(0.035)
Number of children	-0.004	0.006	-0.002	0.259***	0.106***
	(0.005)	(0.006)	(0.007)	(0.016)	(0.039)
Number of adults	-0.002	-0.001	-0.000	-0.023	-0.004
	(0.004)	(0.005)	(0.005)	(0.015)	(0.032)
Household type (Reference group: Two-adult headed)					

Female-headed	0.033**	0.057***	0.037**	0.660***	0.585***
	(0.014)	(0.014)	(0.015)	(0.034)	(0.101)
Male-headed	0.040***	0.050***	0.042***	0.260***	0.459***
	(0.011)	(0.010)	(0.011)	(0.045)	(0.074)
Disabled person in household	0.058***	0.073***	0.047**	0.788***	0.629***
	(0.016)	(0.018)	(0.019)	(0.040)	(0.097)
Metropolitan area	0.020**	0.015*	0.018**	-0.082**	0.083
	(0.008)	(0.008)	(0.008)	(0.041)	(0.057)
Macroeconomic characteristics					
State monthly unemployment rate	0.001	0.001	0.002	-0.041	0.004
	(0.005)	(0.005)	(0.005)	(0.028)	(0.034)
State monthly employment to population ratio	-1.294**	-1.220*	-1.207*	-1.231	-7.272*
	(0.624)	(0.606)	(0.604)	(3.288)	(3.897)
State annual per capita income (in $100s)	0.000	0.000	0.000	-0.005*	0.001
	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)
Quarterly GDP (in trillions)	-0.009	-0.009	-0.009	-0.031	-0.066
	(0.020)	(0.020)	(0.020)	(0.079)	(0.108)
Year					
1998	0.008	-0.003	0.006	-0.752*	-0.200
	(0.088)	(0.089)	(0.088)	(0.419)	(0.493)
2003	-0.018	-0.022	-0.018	-0.326**	-0.221

	(0.036)	(0.036)	(0.036)	(0.163)	(0.196)
<u>Interaction terms (SNAP participation × Household demographics)</u>					
SNAP participation × Age		0.004*	0.003		0.000
		(0.002)	(0.002)		(0.011)
SNAP participation × Age squared		-0.000**	-0.000*		0.000
		(0.000)	(0.000)		(0.000)
SNAP participation × Non-Hispanic Black		-0.064***	-0.040**		-0.309***
		(0.015)	(0.018)		(0.068)
SNAP participation × Hispanic		-0.046**	-0.034*		-0.221*
		(0.021)	(0.019)		(0.123)
SNAP participation × Other non-Hispanic		0.022	0.039		-0.021
		(0.031)	(0.035)		(0.106)
SNAP participation × Noncitizen Immigrant		0.005	-0.011		0.071
		(0.021)	(0.022)		(0.105)
SNAP participation × Less than High school		-0.030	-0.003		-0.156*
		(0.019)	(0.021)		(0.086)
SNAP participation × High school only		0.003	0.013		0.049
		(0.015)	(0.016)		(0.059)
SNAP participation × Number of children		-0.018***	-0.001		-0.088***

		(0.006)	(0.009)		(0.029)
SNAP participation × Number of adults		-0.004	-0.005		-0.016
		(0.008)	(0.008)		(0.038)
SNAP participation × Female-headed		-0.049**	-0.006		-0.361***
		(0.021)	(0.022)		(0.096)
SNAP participation × Male-headed		-0.019	-0.002		-0.268***
		(0.021)	(0.022)		(0.095)
SNAP participation × Disabled person in household		-0.023	0.031		-0.216***
		(0.018)	(0.024)		(0.073)
SNAP participation × Metropolitan area		0.013	0.006		0.014
		(0.015)	(0.013)		(0.067)
Generalized residuals	-0.092*	-0.016	-0.090*		
	(0.048)	(0.047)	(0.052)		
SNAP participation × Generalized residuals	0.116***		0.128***		
	(0.029)		(0.043)		
Intercept	1.164*	1.142*	1.086*	1.984	5.029
	(0.652)	(0.624)	(0.621)	(3.211)	(4.091)
Errors correlation (ρ)				0.385	
				(0.240)	
State Fixed Effects	Yes	Yes	Yes	Yes	Yes

Observations	65,311	65,311	65,311	65,311	65,311

Note: Observations include low-income and low-asset households for each reference month. Robust standard errors, clustered at the state level, are reported in parentheses. The first-stage reduced form equation for SNAP participation in Models (1), (2), and (3) of Appendix Table 4 is identical to that in Model (1) of Appendix Table 3. *** p<0.01, ** p<0.05, * p<0.1