Determinants of Food Resource Utilization among Low-Income Households in North Alabama, USA

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Abstract The objective of this study is to examine the food security status of selected low-income households in north Alabama and to assess the factors believed to influence their participation in public-funded and private/community-based food assistance programs. The analysis draws on primary data from food security and a socio-economic survey administered to 700 low-income households. The main tools of analysis include descriptive statistics and logistic regression models. The descriptive results show that roughly 21 percent of the low-income families, who completed the questionnaire, are characterized as being food insecure; while the participation rate in food assistance programs is estimated at 21 percent. The factors that predict households' participation in food assistance programs, based on the logit model results, include gender of household head, education, household size, income, and ethnicity. The results can assist local leaders in designing appropriate strategies to reduce food insecurity among low-income households in North Alabama.

Keywords: food insecurity, urban households, food assistance programs, logit model

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1. Introduction

While both public and private agencies have exerted enormous resources and efforts in the U.S. through a wide range of policies and programs designed to address household food inequalities [1,2,3], and while these policies and programs have improved the security of many communities, food insecurity prevalence has continued, especially among low-income households and those with children. Anderson *et al*. [4] blame the continued prevalence of food insecurity to the low-participation in food assistance programs by many food-insecure households. Other studies have also explored potential reasons for the low participation rates in food security programs [1,5,6], particularly for SNAP. By focusing on Alabama, the study examines low-income households' participation in public and community-based food assistance programs and the factors that predict their participation.
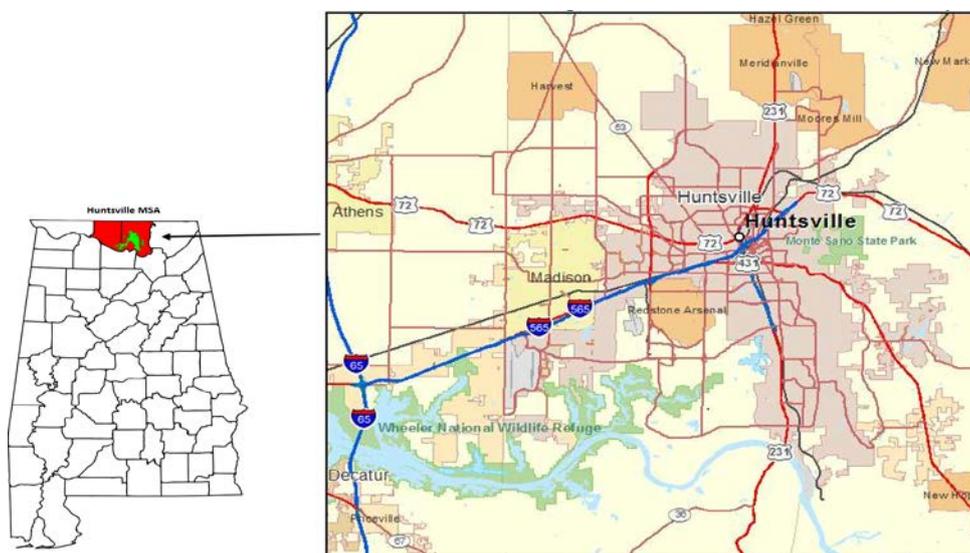

Figure 1. Huntsville Metropolitan Statistical Area, Alabama

Indeed, Alabama is one of the states in the U.S. with the most food-insecure households (just behind Mississippi and Louisiana). Recent data from the U.S. Department of Agriculture (USDA) reveals that over three years (2014-2016), 18.1% of households in Alabama were food-insecure [7]. Furthermore, Alabama's high food hardship rate (20% of the population in 2016) and poverty rate (17% in 2016) has meant that a large number of low-income households in the state are struggling to cover their basic food needs [2]. According to the Center on Budget and Policy Priorities [8], 804,000 Alabamians—or roughly 17% of the state's population—received Supplemental Nutrition Assistance Program (SNAP) benefits in 2017. Of those, 71% were families with children; 38% were in families with members who are elderly or have disabilities, and 37% were in working families [8].

The study area is in a low-income neighborhood of the Huntsville Metropolitan Statistical Area (MSA), Alabama (Figure 1). Located in two North Alabama Counties (Madison and Limestone), the Huntsville MSA is the fastest growing and second largest MSA in Alabama. The MSA has experienced tremendous growth in the past seven years, expanding from a population of about 417,593 in 2010 to 455,631 in 2017—a change of 38,038 or 9.1%. Such growth is a testament to the MSA's robust economy. The MSA is comprised of nineteen cities (Huntsville, Ardmore, Athens, Brownsboro, East Limestone, Elkmont, Gurley, Harvest, Hazel Green, Madison, Meridianville, Monrovia, Moores Mill, New Hope, New Market, Owens Cross Roads, Redstone Arsenal (U.S. Army post), Toney and Triana) of which, Huntsville is the largest.

Food insecurity within the Huntsville MSA is a continuing problem. As the economy fluctuates, more people are seeking assistance from public and private food security programs, such as SNAP, Women, Infants, and Children (WIC), food banks, food pantries, and community gardens. In 2016 for instance, 11.6% and 12.4% of families in Madison and Limestone Counties, respectively received SNAP benefits. The Counties also had some of the highest food insecurity rates in the state (14.3% Madison and 12.4% Limestone) [9]. Furthermore, the 2016 childhood food insecurity rates were above the national average (17.5%) in Madison (22%) and Limestone (20.2%) Counties [9].

2. Literature Review

In addressing the different aspects of the food insecurity problem, previous empirical studies have revealed an interesting ethnic/racial difference in response to food security support [10]. For instance, Yu, Lombe, and Nebbitt [11] found that food insecurity was much higher in African American households (48%) that participated in a food stamp program when compared to Caucasian households (29%) participating in the same program. Furthermore, Caucasian households were found to score significantly lower in food insecurity when receiving supplemental informal food supports than African Americans who also received supplemental food support. Similarly, a report released by the USDA Economic

Research Service for data collected in 2016 revealed that rates of food insecurity were higher than the national average for African American and Hispanic households under or near the poverty line with children that were headed by single parents [3]. Specifically, African American households had a 22.5% rate of food insecurity, while Hispanic households had 18.5% rate. Furthermore, single mother households had a rate of 13.9% food insecurity.

Studies have also documented significant differences in food security resource utilization across racial, demographic, and social dimensions [5,12]. Using data from the 1999 Current Population Survey, Bhattarai *et al.* [13] examined food stamp and food pantries participation for low-income households. They revealed that household income, the level of food insecurity, household structure, and metro versus nonmetro residence affected participation decisions in both programs. Within the general population, Anderson *et al.* [4] contend that a family's resources relative to its size are vital in determining its food security. Other determinants have been reported to include access to and use of food security programs, such as SNAP, WIC, food pantries and community gardens [14]. Studies have also found an elevated risk of food insecurity among low-income individuals, families with children in the household, residents of ''food deserts,'' migrants, and other socially and economically disadvantaged population [12,15,16].

The potential reasons for the observed low participation rates in food assistance programs were also explored [1,5,6]. Mainly, Fuller-Thomson and Redmond [6] argue that barriers to information and confusion regarding eligibility, level of benefits, and program policies discourage potential participants from applying for SNAP. Other obstacles that may further discourage participation include a lack of transportation or difficulty reaching program administration offices, as well as, language barriers [6]. The fear of being stigmatized for seeking social assistance often discourages individuals from seeking food assistance [6]. The level of benefits offered by the program also influences the level of participation. This observation has been supported by the Food and Nutrition Service, noting that the likelihood of participation in food assistance programs increases as the level of benefit increases [1].

The current study contributes to the existing literature by examining the factors that influence participation among low-income households in North Alabama. As Martin *et al.* [5] have noted, it is important to identify why some choose to utilize food assistance to develop appropriate programs and policies to address the needs of those who are eligible.

3. Methodology

The study uses econometric approach to examine the factors that can help predict low-income households' participation in public and private/community-based food security programs. The variables explained in the model are dichotomous, taking a value of one if a household indicates participation in public/private food security

programs and the value of zero otherwise. In the current case where Y is a dummy variable, a binary choice model is applied to find the relationship between the probability (P_i) that Y will take a 1-value and the characteristics of the considered individual/household. A general class of binary choice models assumes that,

$$P_i = P(y_i = 1) = F(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_k x_{ki}) \quad (1)$$

Where

P_i =probability, $i = 1, 2, ..., n$,

$F(.)$ =cumulative distribution function (CDF),

β_j =parameters, $j = 0, 1, 2, ..., k$,

x_{ji} =value of explanatory variables,

x_j for *i*-th household,

k =number of explanatory variables,

n =sample size.

The two common binary choice models are the binomial logit model and the binomial probit model. The current analysis employs the former, which is presented as:

$$P_i = \Lambda(\mathbf{X}_i^T \boldsymbol{\beta}) = \frac{1}{1 + \exp(-\mathbf{X}_i^T \boldsymbol{\beta})} \quad (2)$$

Where $\mathbf{X}_i^T \boldsymbol{\beta} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_k x_{ki}$ and $\Lambda(.)$ denotes the logistic cumulative distribution function. The explanatory variables can have the form of both dichotomy and quantitative variables. For a quantitative variable x_j, Greene [17] shows that:

$$\frac{\partial P(y_i = 1 | \mathbf{x}_i)}{\partial x_j} = \beta_j f(\mathbf{X}_i^T \boldsymbol{\beta}) \quad (3)$$

where f(.) is the density function that corresponds to the cumulative distribution function F(.). Because the CDF is monotonically increasing in its argument, the second term in the chain rule derivative given in (3) is always positive. As a result, the sign of the parameters will always equal the sign of the partial derivative of interest. The partial derivatives are given by:

$$\frac{\partial P(y_i = 1 | \mathbf{x}_i)}{\partial x_j} = \beta_j f(\Lambda(\mathbf{X}_i^T \boldsymbol{\beta}).(1 - \Lambda(\mathbf{X}_i^T \boldsymbol{\beta}))) \quad (4)$$

$$= \beta_j . P_i . (1 - P_i)$$

where $\Lambda(.)$ is the logistic CDF.

The advantage of the logit model over the probit model is that the effects of changes in explanatory variables are also interpreted as odds ratios. Odds are defined as the ratio of two probabilities P_i and (1- P_i), i.e., the ratio of the likelihood of occurrence of an event to that of non-occurrence [17]. The logit model odds equal $\exp(\mathbf{X}_i^T \boldsymbol{\beta})$, because

$$Odds = \frac{P_i}{1 - P_i} = \frac{(\frac{1}{1 + \exp(-\mathbf{X}_i^T \boldsymbol{\beta})})}{(\frac{\exp(-\mathbf{X}_i^T \boldsymbol{\beta})}{1 + \exp(-\mathbf{X}_i^T \boldsymbol{\beta})})} = \exp(\mathbf{X}_i^T \boldsymbol{\beta}). \quad (5)$$

The exponential relationship provides an interpretation of odds ratio. For a unit change in x_j, the odds are expected to change by a factor of $\exp(\beta_j)$, holding all other variables constant. The logit model parameters are estimated using the maximum likelihood method (ML).

In the current study, the estimated models use the household response to the question of whether a household has participated in any of the listed food security programs (Yes, No) as the dependent variables. The actual realization of the dependent variables y_i are assumed to follow,

$$y_i = \begin{cases} 0 \text{ if No} \\ \\ 1 \text{ if Yes} \end{cases}, \quad (6)$$

and are hypothesized to predict respondents' utilization of the various food assistance programs (SNAP, WIC, SCHOOL, FBANK, FPANTRY, and CGARDEN). Because of the nature of the data [i.e., the categorical question with two choices: yes ($y_i = 1$) or no ($y_i = 0$)], a binary logit regression model was adopted to assess the factors that are expected to predict utilization of food assistance programs. Overall, six logit models are estimated using the following general specification:

$$\begin{aligned} &\text{Program\_Utilization} \\ &= \beta_0 + \beta_1 * Ethnicity + \beta_2 * Gender \\ &\quad + \beta_3 * Education + \beta_4 * Marital\_status \\ &\quad + \beta_5 * Income + \beta_6 * Household\_size + e \end{aligned} \quad (7)$$

where β_i are parameters to be estimated and *e* represents the error term.

3.1. Data and Sampling

Primary data collected through a household food security and socio-economic telephone survey, conducted on August 27 through September 17, 2016, are used. The questionnaire was reviewed and approved by the Institutional Review Board and pre-tested before data collection. The survey was administered in 14 low-income neighborhoods (Chelsea, West Huntsville, Huntsville Park, Brandontown, Oakwood, Rutledge Heights, Lakewood, Vaughn Corners, Rideout Village, Terry Heights, Brookhurst, Meadow Hills, Cavalry Hill, and Edmonton Heights) within the City of Huntsville [18]. The neighborhoods were selected from a cluster of census tracts defined as food desert [19]. These neighborhoods are typical in many ways of inner-city communities in the South. Their populations include a large proportion of minorities, female-headed households, with incomes below the poverty line, high unemployment rates, high crimes, among other disparities. Within these neighborhoods, three-stage cluster random sampling with probability proportional to size sampling technique was used to select a sample of 700 households. After removing the incomplete responses, a sample of 679 households was compiled.

The food security section of the survey was based on the shorter version of Household Food Security Survey

Module (HFSSM) administered annually in the Current Population Survey (CPS), the Food Security Supplement [20]. This version consists of a six-question subset. In addition to the six food security questions, the survey corrected information on food security programs (SNAP, WIC, School-operated, food banks, pantries, and community gardens) utilized by the respondents. Furthermore, opinions about services received from selected programs, and socio-economic background variables (age of household head, employment status, marital status, ethnicity, education, the presence of children in the household, household income and household size) were solicited.

3.2. Assessment of Household Food Security

Responses to the six questions on the short form of the HFSSM were scored for each respondent and summed up to generate each respondent's raw score (Figure 2). The raw scores (ranging from 0 to 6) were used to group the respondents into food secure and food insecure households.

Out of the 679 low-income households in the sample, 144 were characterized as being food insecure (Table 1). The food insecure sub-sample (144 households) is used in the current study to examine the factors that predict participation in food security programs. Household responses are analyzed based on answers to questions related to their participation in each of the six food security programs: SNAP, WIC, School-operated, Food Bank, Pantries and Community Gardens. The breakdown of the self-reported participation is presented in Table 1. As shown in the table, the overall participation rate across the sample (food secure and food insecure households) is 21%. Similar low participation rates have been reported in previous studies [4]. Regarding public-funded versus private/community-based food assistance programs, respondents utilized more of the private/community-based programs (28%) compared to public-funded programs (20%). SNAP was the most utilized (12%) public food assistance program, while food banks (12%) and food pantries (10%) were the most used among the private/community-based food assistance programs in North Alabama.
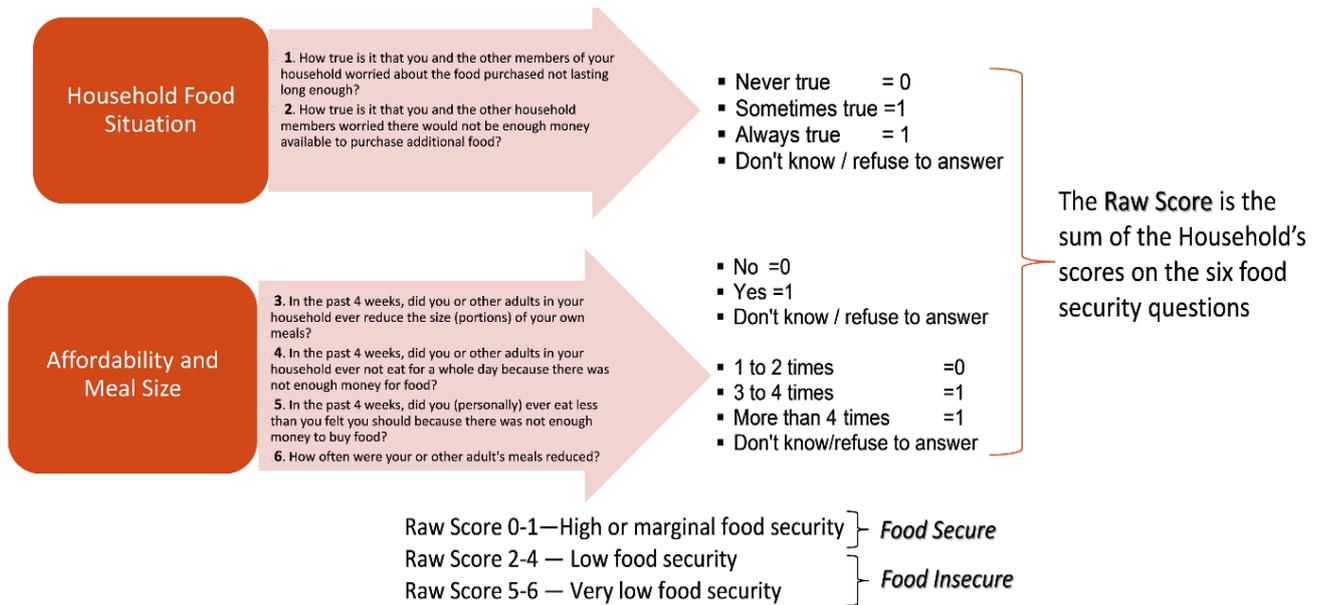

Figure 2. U.S. Household Food Security Questions (USDA/ERS 6-item Module) (*Source*: Generated by Bukenya [18] using information from Bickel *et al*. [20])

Table 1. Participation in Food Assistance Programs Among Low-Income Households*

	Total sample (n = 679)	Food secure (n = 535)	Food insecure (n = 144)
Not participating in food insecurity programs	79%	95%	19%
Participation in food insecurity programs	21%	5%	81%
Participation in government programs	*20%*		
SNAP	12%	0%	57%
WIC	3%	0%	14%
SCHOOL	5%	1.5%	18%
Participation in non-government programs	*28%*		
FOOD BANK	12%	0.5%	55%
COMMUNITY GARDEN	6%	3%	17%
FOOD PANTRY	10%	0%	47%

*Note: In some instances, the percentages do not equal 100% because respondents reported participation in more than one food assistance program.

Table 2. Variable Descriptions

Variable	Description	Mean	Std. Dev
Dependent Variables (Resource Utilization)			
SNAP	=1 if received SNAP benefits; 0 otherwise.		
WIC	=1 if received WIC benefits; 0 otherwise.		
SCHOOL	=1 if participation in the national school lunch program, summer feeding programs or school breakfast program; 0 otherwise.		
FBANK	=1 if received food assistance from a food bank; 0 otherwise.		
FPANTRY	=1 if received food assistance from outlets typically operated by churches and other community non-profit organizations; 0 otherwise.		
CGARDEN	=1 if received food assistance from community gardens; 0 otherwise.		
Independent Variables		Mean	Std. Dev
ETHNICITY	=1 if African American; 0 otherwise.	0.57	0.497
GENDER	=1 if female-headed household; 0 otherwise.	0.85	0.361
EDUCATION	=1 if high school or lower education; 0 otherwise.	0.47	0.501
MARITAL	=1 if divorced; 0 otherwise.	0.47	0.501
INCOME	=1 if household income <$25k; 0 otherwise.	0.34	0.475
HOUSEHOLD SIZE	= Number of people in the household.	2.41	1.40

3.3. Econometric Analysis

The analysis utilizes the logit regression to model the six food security program variables (SNAP, WIC, SCHOOL, CBANK, CPANTRY, and CGARDEN), which are coded into dichotomous variables. Detailed description and descriptive statistics of the dependent and independent variables included in the analysis are presented in Table 2. For instance, respondents who indicated that they had received SNAP benefits were coded 1 and 0 otherwise; those who reported receiving assistance from food pantries in the past twelve months were coded 1 and 0 otherwise; and so on. In a logit model, the dependent variable is expressed as the natural log of the odds of being categorized in one category as opposed to the other. Therefore, an odd expresses the ratio between the frequencies of those in one group against the rate of not being in that category. This odd is dependent on the independent variables used in the particular logit model. Thus, the impact of the predictor variable may be explained using odds ratios. Parameter estimates known as logit coefficients, which are estimators of the change in the dependent variable caused by a unit change in the independent variable are also calculated [21]. Regarding interpretation, a positive logit coefficient suggests that the presence of the independent variable would increase the odds of the dependent variable, and conversely, a negative logit coefficient would decrease the odds.

4. Results and Discussion

The logit model was employed to identify factors that predicted participation in food security programs. Before fitting the model, it was essential to check whether severe multicollinearity problems and association exist among explanatory variables. For this purpose, variance inflation factor and contingency coefficient tests are used for continuous and discrete variables, respectively. The choice of the final variables in equation 7 was best on the analyses as mentioned earlier. Table 3 and Table 4 present the logit regression results, showing that the models fit the data reasonably. The estimated coefficients of determination (count R-square) are reasonably high across the six models, suggesting that between 68% and 77% of the responses to program participation are predicted correctly among public-funded food security programs (Table 3). Similarly, between 72% and 76% of the reactions for the involvement in private/community-based food security programs are correctly predicted (Table 4). It must be noted here though, that in binary choice models, the goodness of fit measures are of secondary importance—what matters are the expected signs of the slope parameters and their statistical significance [22].

Table 3 presents the estimated logit model coefficients for the three public-funded food security programs (SNAP, WIC, and SCHOOL). Based on the results, ethnicity appears capable of influencing low-income households' decision to participate in public-funded food security programs. The variable reveals a strong relationship between ethnicity (African American) and household participation in all three public-funded food security programs. In Model 1 (SNAP), the expected odd ratio of ethnicity is equal to 2.2, which indicates that low-income households headed by African American have 2.2 times chance to participate in SNAP compared to low-income White-headed households. Model 2 (WIC program) and Model 3 (SCHOOL-operated programs) yield similar results, suggesting that the odds of participating in public-funded food security programs (WIC and SCHOOL) are higher among African American headed households compared to White-headed households. Education is another significant predictor of households' participation, but only in Model 3 (SCHOOL-operated programs). The expected odds ratio of education is equal to 2.8, which implies that less educated (high school or lower) households have 2.8 times chance to utilize school-operated food security programs (national school lunch, summer feeding, and school breakfast program) than households headed by individuals with more than high school education.

Table 3. Participation in Public Food Security Programs

	Model 1: SNAP			Model 2: WIC			Model 3: SCHOOL		
	Coefficient	SE	Odds ratio	Coefficient	SE	Odds ratio	Coefficient	SE	Odds ratio
Constant	-1.383**	0.645	--	-1.680**	0.715	--	-2.242***	0.739	--
Ethnicity	0.797**	0.399	2.218	0.863*	0.457	2.371	1.022**	0.451	2.779
Gender	0.601	0.502	0.548	0.679	0.538	0.507	0.023	0.576	1.023
Education	0.238	0.382	1.269	0.438	0.426	1.549	1.043**	0.433	2.839
Marital status	0.047	0.405	1.048	0.092	0.447	1.096	-0.453	0.454	0.636
Income	0.212	0.388	1.236	0.474	0.422	1.607	-0.562	0.443	0.570
Household size	0.178	0.137	1.195	0.020	0.157	1.020	0.105	0.143	1.161
Pseudo R^2	0.043			0.053			0.079		
Count R^2	68%			77%			75%		
Log-likelihood	-86.36			-73.44			-75.55		
Observations	144			144			144		

*,**,*** denotes significance at the 10%, 5% and 1% levels, respectively.

Table 4. Participation in Community Food Security Programs

	Model 4: FBANK			Model 5: FPANTRY			Model 6: CGARDEN		
	Coefficient	SE	Odds ratio	Coefficient	SE	Odds ratio	Coefficient	SE	Odds ratio
Constant	-0.667	0.655	--	-2.347***	0.744	--	-1.928***	0.73	--
Ethnicity	-1.235***	0.442	0.291	-0.264	0.451	0.734	0.125	0.418	1.133
Gender	1.065***	0.53	0.345	0.652	0.570	0.441	0.083	0.57	1.087
Education	-0.405	0.414	0.667	0.429	0.432	1.689	-0.411	0.41	0.663
Marital status	1.161**	0.459	3.194	1.136***	0.483	2.066	0.803*	0.435	2.233
Income	1.156***	0.429	3.178	0.543	0.440	1.036	0.511	0.41	1.667
Household size	0.147	0.150	1.158	0.290*	0.153	1.240	0.097	0.147	1.101
Pseudo R^2	0.123			0.075			0.038		
Count R^2	78%			72%			76%		
Log-likelihood	-73.81			-69.38			-76.82		
Observations	144			144			144		

*,**,*** denotes significance at the 10%, 5% and 1% levels, respectively.

The results are supported by previous studies. For instance, Biggerstaff *et al*. [23] identified age (under 18 years), single parent, low education, minority, gender (being a woman), and being unemployed as predictor variables for participation in public-funded food security programs. Smith *et al*. [24] reported that those more likely to participate in government programs, such as SNAP, included non-Hispanic blacks and less educated. While the other variables (gender, marital status, household size, and income) in the models carry the expected signs, they are not significant predictors of households' participation in public-funded food security programs, among the studied sample. Thus, the results for a sample of low-income food insecure households in North Alabama reveals that ethnicity and education are critical predictors of whether a household will participate in public-funded food security programs, such as SNAP.

Turning to the private/community-based food security programs (food banks, pantries and community gardens), the logit model results are reported in Table 4. For Models 4 and 5, the sign for the estimated coefficient for the ethnicity variable is contrary to the positive effect observed in the public-funded food security models. Furthermore, the coefficient for ethnicity is statistically

significant only in the food bank model (Model 4), with an expected odd ratio equal to 0.29. Although too small in magnitude, the result suggests that there is a 0.29 times chance of low-income households headed by African American not utilizing food banks in addressing their food insecurity situation compared to their White counterparts. Marital status is another significant predictor of household participation across the three private/community-based food security programs. The expected odd ratios of marital status (being divorced) are equal to 3.2, 2.1 and 2.2 in Model 4 (Food Banks), Model 5 (Pantries) and Model 6 (Community Gardens), respectively. The results suggest that low-income households headed by someone divorced/separated have 3.2 times chance to utilize food banks, 2.1 times chance to use food pantries, and 2.2 times to utilize community gardens in addressing their food insecurity situations compared to households with the married couple. Household size also appears to be a significant predictor of participation, but only in Model 5 (Food Pantry). The expected odds ratio of household size is equal to 1.2, suggesting that, households with two or more members have 1.2 times chance to utilize food pantries to address their food insecurity situation compared to households with one member. In support of

this result, Cohen *et al.* [25] have indicated that most households visiting food pantries are small—with the average client household size of 2.7 persons.

Previous studies have also reported that participation rate in food assistance programs is influenced by gender [5,26,27]. Generally, women are more likely to participate in food security programs than men, and this finding was supported by the food bank model (Model 4). Although small in magnitude, the expected odd ratio of gender is equal to 0.35, indicating that, female-headed households have 0.35 times chance to utilize food banks to address household food insecurity situation compared to households headed by men. Income is another significant predictor of participation, but only in the food bank model. The expected odds ratio of income is equal to 3.2, indicating that, low-income households have 3.2 times chance to utilize food banks to address household food insecurity situation compared to households with higher income.

Overall, the results across the private/community-based food security programs highlight the role that food banks play in helping low-income households in dealing with food insecurity issues. Food banks, utilized by 12% of low-income households in the sample are indeed a valuable food resource. Notably, many people who use public-funded programs also used food banks. It is observed that 6.6% of the 12% of households that received SNAP benefits also used food banks in addressing their food insecurity situations. As others have noted, it is a clear indication of how private/community-based food security programs have helped to prevent even higher rates of hunger in America's low-income population by playing a valuable, complementary role to federal assistance programs.

5. Conclusions

This paper aimed to examine the food security status of selected low-income households and to assess their participation in food security programs. Also, the factors that predict their participation in public and private/community-based food security programs were examined. The descriptive results showed that out of the 679 low-income households who completed the questionnaire, 144 were characterized as being food insecure. The overall participation rate in food security programs among low-income households was estimated at 21%—such a low participation rate has been typical in previous studies.

The logit model results revealed that participation in food assistance programs among low-income households in North Alabama was strongly related to predisposing and need factors, such as female-headed households, living without a spouse, low education levels and ethnicity, as well as enabling factors, such as low household income. The results suggest that thus far, a significant response to household food insecurity in the study area has been local-level community-based initiatives, predominantly food banks, but also community-based food pantries and programs such as community gardens, aimed at enhancing food access. While some studies have argued that such

initiatives do not address the economic issues that underlie food insecurity, the perception that these programs play a valuable role in addressing the unmet food needs of food-insecure households persists and is supported by the findings in the current study. The results highlight the need for systematic evaluations of community-based food initiatives to determine their relevance and accessibility for food-insecure households in North Alabama. As noted in other studies [28], these findings will be helpful in identifying segments of the population to be targeted for food assistance programs and thus increasing the effectiveness and target population penetration of these food assistance programs.

Limitations: The study has some limitations that should be considered when drawing broader conclusions from the results. First, the sample size is relatively small for this type of analysis. Second, both the predictor and outcome variables were based on self-reported conditions. As some studies have reported, fear of being stigmatized for seeking social assistance often discourages individuals from revealing their food security situation. Despite these limitations, the results can assist local leaders in designing appropriate strategies to curb food insecurity among low-income households in North Alabama.

Acknowledgments

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