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TWO ESSAYS ON THE APPLICATION OF ORDERED PROBABILITY MODEL

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To the Graduate Council:

I am submitting herewith a thesis written by Jun Zhang entitled "TWO ESSAYS ON THE APPLICATION OF ORDERED PROBABILITY MODEL." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Agricultural Economics.

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TWO ESSAYS ON THE APPLICATION OF ORDERED PROBABILITY MODEL

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DEDICATION

I dedicate this thesis to my parents, friends, mentors and people who helped me.

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ABSTRACT

This thesis includes two essays on health issues of mental health and household food insecurity, and how socioeconomic, demographic, and other factors may influence these health issues are explored. The first essay investigates the effects of regular physical activity and socio-demographic factors on depressive symptoms for both men and women. Data for this study come from the 2011 Behavioral Risk Factor Surveillance System (BRFSS) and an ordered probability model with binary endogenous physical activity is developed to accommodate the ordinal nature of depression outcomes. Results suggest that physical activity is most beneficial for mild and moderate depressed individuals and the effect of regular physical activity is most notable on mild depressed females. In addition, socio-demographic factors are found to vary significantly between gender, and factors of age, income, race, education, employment status and recent mental health condition play important roles in affecting depressive symptoms. With data from the 2010 and 2011 Current Population Survey (CPS), the second essay investigates the effectiveness of the Supplemental Nutrition Assistance Program (SNAP) in reducing household food insecurity with a simultaneous equation model among husband-wife families with children (HW-C). Parental resource variables are used to better explore the effects of HW-C's SNAP participation on FI. Our results suggest the participation of SNAP can reduce the probability of being food insecure among adults only (FIA) by 4.2%, but increases the probability of being low food security among children (LFSC) by 3% and increases the probability of being very low food security among children (VLFSC) by 1.2%. Parental resource variables and socio-demographic variables are also found to play important role in determining household food insecurity.

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CHAPTER I

INTRODUCTION

This thesis contains two essays on important health issues, mental health and household food insecurity, and how socioeconomic, demographic, and other factors may influence these issues. According to the World Health Organization (WHO), more than 350 million people of all ages suffered from depression in all regions of the world in 2012 (WHO 2012). It is estimated that 1 out of 20 people reported having an episode of depression in the previous year worldwide (Kessler et al. 2008), and by the year of 2020, depression will be the second leading cause of world disability (WHO 2001) and by 2030, it is expected to be the largest contributor to disease burden (WHO 2008). Physical activity is generally believed by doctors and physicians as an efficient way to reduce depressive symptoms, and academic studies in clinical research also confirm this point of view (e.g. Babyak et al. 2000; Foley et al. 2008; Mota-Pereira et al. 2011). To provide more comprehensive understanding on the association between physical activity and depression, further investigations with better statistical techniques are necessary. In addition to mental health problems, household food security is closely related to general health problems. Adults in food insecure households are found to be more likely to report poor health status (Stuff et al. 2004), and household food insecurity has bad effects on children's health condition and development (Cook and Frank 2008). In 2012, 14.5 percent of households in the U.S. were food insecure at least some time during the year, including 5.7 percent with very low food security (VLFS) (Coleman-Jensen et al. 2013). To fight against food insecurity problems, the U.S. government implements several food and nutrition assistance programs. The Supplemental Nutrition Assistance Program (SNAP) is one of such programs aiming at reducing household food insecurity (FI) and many researchers have evaluated its effect on reducing FI, but the results are not consistent. Further research in the relation between SNAP participation and household FI, especially for children is required.

The first essay in Chapter II is about the effect of physical activity on depressive symptoms. The outcome variable comes from the 2011 U.S. Behavioral Risk Factor Surveillance System (BRFSS), which is measured by the eight-item self-reported Patient Health Questionnaire Depression Scale (PHQ-8) and classified into five categories in terms of the severity of such symptoms. To address the categorical nature of outcome variable and potential endogenous physical activity, a treatment effect ordered probability model and its more generalized extension, switching probability model are developed separately. Compared with ordered probability model without treatment, treatment effect model can provide more information on how endogenous physical activity affects depressive symptoms by calculating average treatment effects (ATE). In terms of model selection between treatment effect and switching probability models in fitting data, several statistical information criteria are constructed and calculated. With the model selected from information criteria results, average marginal effects are calculated to investigate the effects of socio-demographic variables on depressive symptoms.

The second essay in Chapter III investigates the effectiveness of the Supplemental Nutrition Assistance Program (SNAP) in reducing household food insecurity (FI) among husband-wife households with children (HW-C). Data of this study come from the 2010 and 2011 U.S. Current Population Survey (CPS). The household food insecurity is measured by 18 questionnaires, 8 of which concerns children's FI. Based on the numbers of affirmative responses to the 18 questionnaires and to the 8 children-specific items, household food insecurity is classified into four mutually exclusive categories. With the ordinal nature of FI and endogeneity of SNAP, treatment effect ordered probability is used. In addition, a simultaneous ordered probability equation system is developed and estimated in addressing the mutual causality between SNAP and FI. Applying the model selected from information criteria, average treatment and marginal effects are calculated to gauge the effects of SNAP participation and parental resources on FI among adults and children.

CHAPTER II

DEPRESSIVE SYMPTOMS AND PHYSICAL ACTIVITY

2.1 Introduction and Objectives

Depression is a common mental disorder involving the brain and is commonly characterized by sadness, loss of interest or pleasure, feelings of guilt or low self-esteem, disturbed sleep or appetite, feelings of tiredness, and poor concentration. Depression can be long-lasting or recurrent, substantially impairing an individual's ability to function at work or school or cope with daily life. At its most severe, depression can lead to suicide (WHO 2013). Almost one million lives are lost due to suicide, which translated to 3000 suicide deaths every day, for every person who complete a suicide, 20 or more may attempt to end his or her life (WHO 2012).

Many people in developed countries suffer from depression and other diseases related to depression. In the year of 2006 and 2008, about 9% Americans met criteria for current depression and 3.4% met criteria for major depression (Centers for Disease Control and Prevention (CDC) 2010)[1]. Depression was the third leading cause of disease burden worldwide and a leading cause of disability in high-income countries in 2004 (WHO 2008). Depression can adversely affect the outcome of common chronic conditions, such as arthritis, asthma, cardiovascular disease, cancer, diabetes, and obesity (Chapman et al. 2005), it can also result in increased work absenteeism, short-term disability, and decreased productivity (Goetzel et al. 2003).

[1] Current depression was defined as meeting BRFSS criteria for either major depression or "other depression" during the 2 weeks preceding the survey.

Factors contributing to depression are complicated and include both biological and social factors. Some researchers attribute depression primarily to biological factors (e.g. Ranga and Krishnan 2002; Riso, Miyatake, and Thase 2002) while a number of other studies suggest that depression is mainly caused by social factors rather than biological factors (e.g. Jorm et al. 1997; Hansson et al. 2009). Many traditional socio-demographic factors are known to contribute to depression, such as marital status, gender, income and age (e.g. Addis 2008; De-Velde, Bracke, and Levecque 2010), and other factors like physical activity level are also generally believed to affect depression level (e.g. Camacho1991; Robertson 2012; Goodwin 2003; De-Moor et al. 2006).

A number of studies have investigated the relationship between physical activity and mental health problems (e.g. Farmer et al. 1988; Camacho et al. 1991; Paluska and Schwenk 2000), and physical activity is also regarded as an important way to alleviate depressive symptoms (Salmon 2001; Mota-Pereira et al. 2011).One popular explanation for the relation between exercise and depression is based on the theory that exercise has a positive effect on depression due to an increased release of beta-endorphins following exercise and endorphins are related to positive mood and thus enhanced the sense of well-being (Craft et al. 2004). Another explanation related to the theory of self-efficacy is that exercise would increase the feeling of coping self-efficacy which is inversely related to depression (Craft 2005). However, Chalder et al. (2012) suggest that adding a physical activity intervention to usual care does not reduce symptoms of depression more than usual care alone. This finding challenges the current clinical guidance which recommends exercise to help those suffering from depression (Babyak et al. 2000; Foley et al. 2008; Hoffman et al. 2011).

Although findings have not been totally consistent, many studies suggest that physical activity or exercise could reduce symptoms of mild to moderate depression (e.g. Babyak et al. 2000; Foley et al. 2008; Mota-Pereira et al. 2011). Most of these studies rely on small and selected clinical samples which do not represent the general population. In addition, few studies (e.g. Farmer et al. 1988; Goodwin 2003) take other socio-demographic factors into account when studying the relation between physical activity and depression. Analysis not accounting for other factors can be misleading if both physical activity and socio-demographic factors affect the level of depressive symptoms simultaneously. In this study, large national datasets from the U.S. Behavioral Risk Factor Surveillance System (BRFSS) are used and over 10,000 samples are included. When exploring the effects on depressive symptoms, physical activity and socio-demographic factors will be applied at the same time.

Research Objectives

The general objective of this study is to determine the quantitative effects of physical activity and other socio-demographic factors on the level depressive symptoms, and to investigate gender difference in such effects. Specific objectives are as follows:

1. Investigate the role of economics and socio-demographic characteristics, such as marital status, race, age and household income, in depressive symptoms.
2. Evaluate the effects of physical activity on depressive symptoms.
3. Investigate gender differences in the effects above.

2.2 Literature Review

2.2.1 Physical Activity and Depression

The empirical literature on depression and physical activity has provided much evidence that physical activity is negatively related to the level of depressive symptoms, and many researchers employ a variety of methods and data from either surveys or clinical samples. Early examples of the research have shown solid evidence that physical activity is likely to affect the level of depressive symptoms. In the 1980s, Farmer et al. (1988) find a negative association in white individuals between physical activity and depressive symptoms by using the National Health and Nutrition Examination Survey and logistic models that include demographic variables of age, race, education, employment status, self-reported health, household income and length of follow-up. Camacho et al. (1991) use a method similar to Farmer et al. but a different dataset. Based on samples from 1965 to 1983 in the Alameda County, California, they find that men and women who report a low activity level at baseline have greater risk of depression than those who report high activity levels. This finding suggests that high activity level can indeed reduce the risk of depression in the long term.

Many recent studies on depression also confirm that physical activity or exercise can reduce the level of depressive symptoms. Goodwin (2003) estimates the impacts of self-reported physical activity and socio-demographic factors on mental disorders by using samples from the National Comorbidity Survey. Results from logistic regressions indicate that regular physical activity is associated with a significantly decreasing likelihood of having current major depression. De-Moor et al. (2006) empirically show that regular exercisers are on average less depressed than non-exercisers by using large national samples from the Netherland. Hamer, Stamatakis and Steptoe (2008) use data from the Scottish Health Survey to further supplement different types of physical activity in relation to mental health, and demonstrate strong associations between physical activity and the reduced odds of psychological distress. Sieverdes et al. (2012) focus on leisure time physical activities of men and divide individuals into categories according to time spent on physical activities per week. They find that men in median and high physical activity categories are 51% less likely to have depressive symptoms compared with men who do not participate in any physical activities.

In clinical research, physical activity is shown to be an effective treatment to alleviate mild and moderate depressive symptoms. Babyak et al. (2000) show that among individuals with major depressive disorder (MDD), after 4 months treatment with exercise 60.4% of patients in the exercise group no longer meet DSM-IV (American Psychiatric Association 1994) criteria for MDD[2]. Foley et al. (2008) find that both aerobic and stretching exercises are associated with significant decreases in severity of depression and increased in coping efficacy and episodic memory over 12 weeks. Mota-Pereira et al. (2011) suggest a 12 week exercise program of 30-45 minutes walks 5 times a week results in the improvement of all studied parameters of depression and this improvement is not due to social interaction. Hoffman et al. (2011) find that among clinical samples of depressed elder adults, 46% were fully remitted at the end of the original 4-month study treatment with exercise, and 66% were fully remitted 1 year after the end of treatment. This finding suggests a lasting effect of physical activity in reducing depressive symptoms. Most recently, Chalder et al. (2012) use samples from 361 depressed adults age 18-69 and find no evidence that participants offered the physical activity intervention reported improvement in mood by the four month follow-up point compared with those in the usual care

[2] DSM-IV is short for the Diagnostic and Statistical Manual of Mental Disorders, 4thedition.

group. However, the result is questionable because the effect of exercise on depression was not tested and further, the samples are very small.

2.2.2 Socio-demographic Factors and Depression

Besides physical activity, other socio-demographic factors are also found to play a role in affecting depression. Age is generally accepted as an important factor, but the relation between age and depression is not consistent in previous findings. Mirowsky and Ross (1992) suggest a U-shape relation between age and depression and find depression reaches its lowest level around age 45 with samples of 1985 and 1990 in the United States. Kessler et al. (1992) show a similar relationship with samples from two national surveys of the United States. Wade and Cairney (1997) find a steady decline across age groups after other socio-demographic factors are controlled for, by using Canadian samples. Schieman et al. (2002) reinforce the notion of negative linear relationship between age and depression with data from physically disabled and nondisabled residents respectively. Streiner et al. (2006) provide evidence of a linear decrease for all disorders after age 55 for men and women, for both people born in Canada and people who immigrated to Canada after age 18.

Gender is another important factor that affects depression, and most of earlier studies have concluded that women have higher risk than men of having depressive symptoms. Kessler et al. (1993) suggest that depressive disorders are more common in women, who have lifetime rates for major depressive episodes of 21.3%, compared with 12.7% in men. Using logistic regression, Goodwin and Gotlib (2004) find that being female is associated with an increased likelihood of major depression. De-Velde, Bracke and Levecque (2010) estimate the gender difference in depression with large datasets of 23 European countries and their results indicate that women report higher levels of depression than men do in all countries. They also confirm that socio-demographic factors have strong association with depression in both men and women.

Plenty of previous studies suggest that income, race, education, marriage and employment status can affect depressive symptoms. Whooley et al. (2002) find low-income young adults are more likely to have depressive symptoms than high-income young adults by using data from 5115 adults age 18 to 30. Zimmerman and Katon (2005) report a negative relation between income and depression symptoms with Kernel regression both for men and women. Somervell et al. (1989) use large samples from 5 communities in the United States to test the difference in major depression between white and black adults. Results show that in the 18-24 years age group, white men have higher prevalence of depression than black men while white women have lower prevalence of depression than black women. Bromberger et al. (2004) indicate that compared with white women, African American and Hispanic women have higher odds and Chinese woman have lower odds, of a CES-D score of 16 or higher[3]. Craig and Natta (1979) studied the influence of education on depressive symptoms and find that less educated individuals are more likely to exhibit depressive symptoms. Jang et al. (2009) investigate the relation between marital status and depression with large samples for Korean individuals age 45 and above. The results reveal that both male and female who are divorced, separated or widowed have higher scores for depression than married individuals. Based on logistic regression with panel data, Dooley et al. (1994) find that unemployment does increase the risk of depressive symptoms.

[3] CES-D is short for the Center for Epidemiologic Studies Depression Scale. See Radloff 1977.

2.3 Conceptual Framework

The empirical model of this study is derived from the utility maximization framework where utility is specified as a function of the level of depressive symptoms, level of physical activity and a set of socio-demographic variables. Let each individual's current level of depressive symptoms be $D = D(H_{\mathrm{M}}, E; Z_1)$, be determined by recent mental health status (H_{M}), recent physical activity or exercise (E), and socio-demographic variables (Z_1). Deriving utility from the level of depressive symptoms, current mental health status, and recent physical activity, each individual has a utility function

$$U = U(D(H_M, E;\ Z_1), E;\ Z_2) \tag{2.1}$$

where Z_2 is another set of socio-demographic variables. Under the assumption that health condition of each individual is restricted by age, this utility function is maximized subject to the health condition constraint

$$g(E, H_M, H_P) \leq f(A) \tag{2.2}$$

where $g(\cdot)$ is a function which reflects current health status in numerical values, $f(\cdot)$ is a function of age which reflects optimal possible health status of normal people at age A, and H_P is recent physical health condition.[4] Solving the constrained utility maximization problem in equations (2.1) and (2.2) yields the optimal level of current depressive symptoms, recent mental health status, recent physical activity, and socio-demographic variables. The optimal level of depressive symptoms (D^*) can be denoted as

[4] We posit that previous mental and physical health conditions, especially recent conditions will affect current health status.

$$D^* = D^*(H_M{}^*(H_p, A\,; Z_1, Z_2)\,, E^*(H_p, A\,; Z_1, Z_2); Z_1) \tag{2.3}$$

which is a function of recent mental health status, physical activity level and socio-demographic variables. Drawing on the optimal depression level of equation (2.3), one relevant empirical specification is the treatment effect model (Barnow, Cain, and Goldberger, 1980), the other empirical approach is the switching regression model, which is a more generalized case of treatment effect model. With the endogenous variables of physical activity, recent mental health condition, age and other socio-demographic variables, the optimal level of depressive symptoms of each individual i is expressed by a linear equation:

$$y_i = x_i^{'}\beta + \gamma d_i + u_i \qquad i = 1 \ldots n \tag{2.4}$$

Where y_i denotes the observed level of depressive symptoms, x_i denotes as recent mental health condition, age and other socio-demographic variables (with corresponding parameter vector β), d_i is the endogenous variable of physical activity (with corresponding parameter γ), and u_i is random error which reflects the unobservable.

2.4 Data and Samples

The data of this study comes from the 2011 Behavioral Risk Factor Surveillance System (BRFSS) collected by state health departments in collaboration with the Centers for Disease Control (CDC). The BRFSS is a state-based system of health surveys that collects information on health risk behaviors, and the 2011 BRFSS is the most recent large national survey which provides adequate information for depression and socio-demographic factors. After removing missing values for each variable, the pooled sample consists of 11,560 individuals aging from 18 to 99, of which 4,798 are males and 6,762 are females.

2.4.1 Dependent Variable

The dependent variable of this study is the current depression level, which is measured by the eight-item self-reported Patient Health Questionnaire Depression Scale (PHQ-8).[5] PHQ-8 covers eight of the nine criteria from the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV) for diagnosis of major depressive disorder (CDC 2010). The ninth criterion in the DSM-IV is omitted because it is to access extreme depressive symptom, such as suicide which is out of this study. PHQ-8 is turned out to be one of the valid diagnostic and severity measures for depression in large clinic studies (e.g. Kroenke et al. 2009; Dhingra et al. 2011). Compared with the Center for Epidemiologic Studies Depression Scale (CES-D), the PHQ-9 (with additional suicide item than PHQ-8) is reliable and advantageous because it is just half the length of CES-D (Milette et al. 2010).

The BRFSS questionnaire section of depression provides eight self-reported items which belong to the PHQ-8 system. Each depression level indicator was calculated based on the eight PHQ-8 items from BRFSS and the dependent variable which measures depression level is denoted as PHQ-8. The value of PHQ-8 in this study is a non-negative integer ranging from 0 (no depressive symptoms) to 4 (severe depressive symptoms). And depression is classified as major depression (PHQ-8≥2) and other depression due to corresponding PHQ-8 scores (Kroenke et al. 2009). The pooled sample is restricted to individuals age >18 with a sample size of 11,560. The frequencies for PHQ-8 are 8,802(76.1%) for value 0, 1,702(14.7%) for value 1, 578(5.0%) for value 2, 315(2.7%) for value 3 and 163(1.4%) for value 4. The sample size for men is 4,798 and corresponding frequencies for PHQ-8 are 3,834(79.9%) for value 0, 597(12.4%) for value 1, 207(4.3%) for value 2, 105(2.2%) for value 3 and 55(1.2%) for value 4. Among 6,762 female individuals, the frequencies for PHQ-8 are 4,968(73.5%) for value 0, 1105(16.3%) for value 1,

[5] Details of PHQ-8 classification are included in Appendix A.1 and A.2.

371(5.5%) for value 2, 201(3.0%) for value 3 and 108(1.6%) for value 4. Compared to males, there are more females suffering from all levels of depressive symptoms, and the sample statistics are consistent with previous research (e.g. Kessler et al. 1993; Goodwin and Gotlib 2004).

2.4.2 Endogenous Variable-Physical Activity

To better differentiate the effects of physical activity on depression level, physical activity is specified as a binary variable (physical activity =1 denotes regular exerciser, physical activity =0 denotes seldom exerciser). The measurement for physical activity is drawn from BRFSS questionnaire item "How many times per week or per month did you take part in this activity during the past month". Regular exercisers are defined as those who did physical activity or exercise at least 15 times during last month, while seldom exercisers are those who did less than 15 times during last month. In the pooled sample of 11,560 individuals, about 39% are regular exercisers. Considering gender difference, about 38.5% of male and 38.6% of female are regular exercisers, there is no big gender difference in regular exercisers and seldom exercisers.

2.4.3 Explanatory Variables

Table 2.1 provides sample statistics and definitions of all explanatory variables in this study. The socio-demographic variables include age, income, race, education, household composition, gender, home ownership, employment status and marital status. In addition, seasonal dummies are also included.

Recent mental health condition plays a notable role in affecting the current level of depressive symptoms. The measurement for the recent mental health condition is drawn from

BRFSS questionnaire item “For how many days during the past 30 days was your mental health not good”. The sample mean of not good mental health days in the last 30 days are 3.49 for the pooled sample and 2.93 and 3.89 for male and female. About 7,811(67.6%) pooled sample individuals, 3,513(73.2%) male individuals and 4,298(63.6%) female individuals reported excellent recent mental health conditions (0 mental health not good days). The statistical results suggest that male individuals are less likely to have mental health problems than female individuals.

The measurement for the recent physical health condition is drawn from BRFSS questionnaire item “For how many days during the past 30 days was your physical health not good?” The sample mean of not good physical health days in the last 30 days are 4.31 for the pooled sample and 4.13 and 4.43 for male and female. About 7,323(63.4%) pooled sample individuals, 3,161(65.9%) male individuals and 4,162(61.6%) female individuals reported excellent recent physical health conditions (0 physical health not good days).

In the clinical research of depression, season is found to affect depression (e.g. Rosenthal et al. 1984; Harmatz et al. 2000), because mood is closely related to seasonal variation (Harmatz et al. 2000). In this study, each season is indicated by a binary variable. The pooled sample frequencies are 0.25, 0.21, 0.27 and 0.27for the season of fall, winter, spring and summer respectively.

The age range in this study is 18 to 99, and the mean age of the pooled sample is about 54.4, and the average ages are almost the same for male and female samples which are 54.3 and 54.5 respectively. To simplify the calculation process, age is scaled down by 10 and age square is scaled down by 1000. The mean of annual household income level is 5.61 (5 denotes annual household income between 25,000 to 35,000 and 6 denotes annual household income between

35,000 to 50,000) for the pooled sample and 5.84 and 5.44 for male and female samples. Considering the difference between races, white individuals take the percentage of 71.5%, 70.9% and 72.0% among pooled sample, male sample and female sample while the percentages for Hispanic individuals in all three samples are 21.3%, 21.9% and 20.8%.

About 39% of the pooled sample individuals have a bachelor’s degree or above, and more male have bachelor’s degree or above compared to female (40% of the male sample and 38% of the female sample). Referring to the household composition, one variable is used to measure the number of children under 18 years old in each family, and the sample means of that variable are 0.55 for the pooled sample, 0.53 for the male sample and 0.58 for the female sample. The pooled sample contains 9,021(78.0%) home owners while home owners are 3,769(78.6%) and 5,252(77.7%) for male and female samples respectively.

Among pooled sample individuals, 4,880 (38.8%) are employed and 2,591(22.4%) are retired, these figures are 2,162(45.1%) and 1,181(24.6%) for male sample and 2,718(40.2%) and 1,410(20.9%) for female sample. Compare with female individuals, the proportions of male individuals being employed and retired are higher. Taking marriage status into consideration, about 54.4% of the pooled sample individuals are get married, and 16.3% of them are divorced. In the male sample, 59.8% are married and 14.4% are divorced. In contrast with male individuals, less female individuals are married (50.5%) and more are divorced (17.7%).

2.5 Methods

2.5.1 Treatment Effect Model

The empirical approaches used by most previous studies are either logistic regression or OLS. With the large portion of zeroes in outcome (PHQ-8), OLS will be biased and logistic regression cannot reflect the ordinal depression level accurately. Facing such ordinal outcome problems, recent studies in the field of applied economics provide more efficient and accurate procedures. Yen, Shaw and Yuan (2010) implement an ordinal health model with an ordinal endogenous treatment to study the effect of cigarette smoking on ordinal outcome variable of health condition. Driven by the theoretical framework in equation (2.3) and (2.4), an ordered probability model with binary treatment is implemented.

For current application, consider a selection equation for being regular exerciser ($d_i = 1$)

$$d_i = \begin{cases} 1, \text{ } if \quad z_i'\alpha + v_i > 0 \\ 0, \text{ } if \quad z_i'\alpha + v_i \le 0 \end{cases}, \tag{2.5}$$

and the outcome variable of depression (y_i) for each individual i

$$y_i = k \quad if \quad \xi_{k-1} < x'\beta + \gamma d_i + u_i < \xi_k, \ \ k = 0 \ldots K; \tag{2.6}$$

where z_i and x_i are vectors of explanatory variables of each individual, α and β are conformable parameter vectors, γ is the coefficient parameter for endogenous physical activity, u_i is random error for each individual, and ξ_k is threshold variable parameter such that $\xi_{-1} = -\infty, \xi_0 = 0, \xi_K = \infty$, and $\xi_1 \ldots \xi_{K-1}$ are estimable. Assume that the random error vectors v ($v = [v_1, v_2, \ldots, v_n]'$) and u ($u = [u_1, u_2, \ldots, u_n]'$) are bivariate normally distributed with zero mean, unitary variance and correlation ρ

$$\begin{bmatrix} v \\ u \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right) \tag{2.7}$$

The parameters in equation (2.5), (2.6) and (2.7) are estimated by the Maximum-likelihood procedure. Before constructing the likelihood contribution for the sample observation, first define a bivariate standard normal cumulative function (CDF) $\Phi_2(x, y, \rho) = \Pr(\mathrm{X} \le x, \mathrm{Y} \le y)$ with correlation ρ and marginal CDFs $\Phi_1(x) = \Pr(\mathrm{X} \le x)$ and $\Phi_1(y) = \Pr(\mathrm{Y} \le y)$. Then given the distribution of error terms in equation (2.7) and information from equation (2.5) and (2.6), the likelihood contributions for the two distinctive sample regimes ($d_i = 0$ and $d_i = 1$) are:

$$\Pr(y_i = k, d_i = 0) = \Phi_2(-z_i'\alpha, \xi_k - x_i'\beta, \rho) - \Phi_2(-z_i'\alpha, \xi_{k-1} - x_i'\beta, \rho) \tag{2.8}$$

$$\Pr(y_i = k, d_i = 1) = \Phi_2(z_i'\alpha, \xi_k - x_i'\beta - \gamma, -\rho) - \Phi_2(z_i'\alpha, \xi_{k-1} - x_i'\beta - \gamma, -\rho) \tag{2.9}$$

and the likelihood function for the entire sample is:

$$L = \prod_{i=1}^{n} \prod_{k=1}^{K} \left\{ \left[\Pr(y_i = k, d_i = 0) \right]^{1-d_i} \left[\Pr(y_i = k, d_i = 1) \right]^{d_i} \right\}^{g(y_i, k)} \tag{2.10}$$

where n is the number of observations, K is the number of outcome levels and $g(y_i, k)$ is a dichotomous indicator function which equals 1 if $y_i = k$ holds and 0 otherwise. Thus by maximizing the likelihood function in above, unknown parameters can be estimated with the Maximum-likelihood procedure.[6]

To facilitate interpretation of the effects on explanatory variables, marginal effects of explanatory variables on the probabilities of depression categories and treatment effect of physical activity on the depression categories are calculated. Specially, for each individual, the

[6] All econometric models in this thesis are estimated by the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm with MATLAB, and standard errors of coefficients are calculated from the inverse hessian matrix.

marginal effects of explanatory variables on the probabilities of being regular or seldom exercisers is

$$\Pr(d_i = 1) = \Phi_1(z_i'\alpha) \tag{2.11}$$

$$\Pr(d_i = 0) = 1 - \Phi_1(z_i'\alpha) \tag{2.12}$$

applying equations of (2.8),(2.9),(2.11) and (2.12), the probabilities of each depression category conditional on being seldom exerciser and regular exerciser are

$$\Pr(y_i = k, d_i = 0 \mid d_i = 0) = \frac{\Phi_2(-z_i'\alpha\ , \xi_k - x_i'\beta, \rho) - \Phi_2(-z_i'\alpha\ , \xi_{k-1} - x_i'\beta, \rho)}{1 - \Phi_1(z'\alpha)} \tag{2.13}$$

$$\Pr(y_i = k, d_i = 1 \mid d_i = 1) = \frac{\Phi_2(z_i'\alpha\ , \xi_k - x_i'\beta - \gamma, -\rho) - \Phi_2(z_i'\alpha\ , \xi_{k-1} - x_i'\beta - \gamma, -\rho)}{\Phi_1(z_i'\alpha)} \tag{2.14}$$

and treatment effect of physical activity on each depression category is

$$TE_k = \Pr(y_i = k | d_i = 1) - \Pr(y_i = k | d_i = 0),\ k = 1 \ldots K \tag{2.15}$$

By differentiating equations (2.11)-(2.15), marginal effects of explanatory variables and treatment effects of physical activity will be obtained. When interpreting the effects of explanatory variables on the dependent variable, average marginal effects and average treatment effects are calculated approximately by numerical differentiation approach, and the standard errors of all average marginal and treatment effects are calculated by delta method (e.g. Papke and Wooldridge 2004).[7]

[7] Details on the calculation of standard errors of marginal effects with delta method are in appendix A.3.

2.5.2 Switching Probability Model

Switching regression models date back to Roy (1951) who concerns with an individual's decision between earning income as fisher or hunters, and have been extensively used in economics. Unlike the ordered treatment effect model, the switching regression model specifies the ordinal outcome y_i (PHQ-8) with two different processes. Following Li and Tobias (2008) and Yen, Bruce and Jahns (2012), the ordered probability model with binary switching (switching regression model) is developed to accommodate the ordinality of dependent variable and better differentiate the effect of seldom and regular exercise on the depression categories. Similar to the approach in treatment model above, consider a binary switching equation for endogenous binary variable d_i (being regular exerciser or not)

$$d_i = \begin{cases} 1, \ if \quad z_i'\alpha + v_i > 0 \\ 0, \ if \quad z_i'\alpha + v_i \le 0 \end{cases} \tag{2.16}$$

and a set of ordered probability models for outcome variable (depression category), for the regular exerciser($d_i = 1$) and seldom exerciser ($d_i = 0$) regimes

$$y_i^{(s)} = k \quad if \quad \xi_{k-1}^{(s)} < x_i'\beta^{(s)} + u_i^{(s)} < \xi_k^{(s)}, \ \ k = 0\ldots K; s = 0,1 \tag{2.17}$$

where $y_i^{(1)}$ denotes the outcome received by each individual with treatment state ($d_i = 1$) and $y_i^{(0)}$ denotes the outcome received by each individual without treatment state ($d_i = 0$). And only one outcome, denotes as y_i (depression category), is observed for each individual, and thus

$$y_i = d_i y_i^{(1)} + (1-d_i)y_i^{(0)} \tag{2.18}$$

in equation (2.16) and (2.17), z_i and x_i are vectors of explanatory variables of each individual, α and $\beta^{(s)}$ are conformable parameter vectors, v_i and $u_i^{(s)}$ are random errors for each individual, and $\xi_k^{(s)}$ is threshold variable parameter such that $\xi_{-1}^{(s)} = -\infty$, $\xi_0^{(s)} = 0$, $\xi_K^{(s)} = \infty$, and

$\xi_1^{(s)}$ ... $\xi_{K-1}^{(s)}$ are estimable. Assume that the random error vectors v ($v = [v_1, v_2, \dots, v_n]'$) and $u^{(0)}$ ($u^{(0)} = [u_1^{(0)}, u_2^{(0)}, \dots, u_n^{(0)}]'$), v and $u^{(1)}$ ($u^{(1)} = [u_1^{(1)}, u_2^{(1)}, \dots, u_n^{(1)}]'$) are bivariate normally distributed with zeros means, unitary variances and correlation ρ_0 and ρ_1 respectively

$$\begin{bmatrix} v \\ u^{(0)} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_0 \\ \rho_0 & 1 \end{bmatrix} \right) \quad , \quad \begin{bmatrix} v \\ u^{(1)} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_1 \\ \rho_1 & 1 \end{bmatrix} \right) \tag{2.19}$$

The corresponding parameters in (2.16), (2.17) and (2.19) are estimated by the Maximum-likelihood procedure.

Following the approaches in treatment model above, with the distribution of error terms in equation (2.19) and information from equation (2.16)-(2.18), the likelihood contributions for the two distinctive sample regimes ($d_i = 0$ and $d_i = 1$) are:

$$\Pr(y_i^{(0)} = k, d_i = 0) = \Phi_2(-z_i'\alpha\ , \xi_k^{(0)} - x_i'\beta^{(0)}, \rho_0) - \Phi_2(-z_i'\alpha\ , \xi_{k-1}^{(0)} - x_i'\beta^{(0)}, \rho_0) \tag{2.20}$$

$$\Pr(y_i^{(1)} = k, d_i = 1) = \Phi_2(z_i'\alpha\ , \xi_k^{(1)} - x_i'\beta^{(1)}, -\rho_1) - \Phi_2(z_i'\alpha\ , \xi_{k-1}^{(1)} - x_i'\beta^{(1)}, -\rho_1) \tag{2.21}$$

and the likelihood contribution for the pooled sample is:

$$L = \prod_{i=1}^{n} \prod_{k=1}^{K} \left\{ \left[\Pr(y_i^{(0)} = k, d_i = 0) \right]^{1-d_i} \left[\Pr(y_i^{(1)} = k, d_i = 1) \right]^{d_i} \right\}^{g(y_i, k)} \tag{2.22}$$

where n is the number of observations, K is the number of outcome levels and $g(y_i, k)$ is a dichotomous indicator function which equals 1 if $y_i = k$ holds and 0 otherwise. Unknown parameters can be estimated with the Maximum-likelihood procedure by maximizing the likelihood function above.

For the switching probability model, marginal effects can be estimated as well. The marginal effects of explanatory variables on the probabilities of being regular or seldom exercisers is the same as treatment effect model in equation (2.11) and (2.12). Applying equations of (2.11), (2.12), (2.20) and (2.21), the probabilities of each depression category conditional on seldom exerciser and regular exerciser are

$$\Pr(y_i^{(0)} = k, d_i = 0 \mid d_i = 0) = \frac{\Phi_2(-z_i'\alpha \ , \xi_k^{(0)} - x_i'\beta^{(0)}, \rho_0) - \Phi_2(-z_i'\alpha \ , \xi_{k-1}^{(0)} - x_i'\beta^{(0)}, \rho_0)}{1 - \Phi_1(z_i'\alpha)} \quad (2.23)$$

$$\Pr(y_i^{(1)} = k, d_i = 1 \mid d_i = 1) = \frac{\Phi_2(z_i'\alpha \ , \xi_k^{(1)} - x_i'\beta^{(1)}, -\rho_1) - \Phi_2(z_i'\alpha \ , \xi_{k-1}^{(1)} - x_i'\beta^{(1)}, \rho_1)}{\Phi_1(z_i'\alpha)} \quad (2.24)$$

and treatment effect of physical activity on each depression category is

$$TE_k = \Pr(y_i = k|d_i = 1) - \Pr(y_i = k|d_i = 0), \ k = 1 \ldots K \quad (2.25)$$

Average marginal effects and average treatment effects are calculated approximately by differentiating equations (2.11), (2.12), (2.23), (2.24) and (2.25) with the similar procedure in treatment model.

2.5.3 Model Selection via Information Criteria

Information criteria are used to compare between treatment effect model and switching probability model. Akaike's (1973) information criterion (AIC) is widely used in statistics and social sciences, and it provides an efficient procedure for model selection. The AIC form is given as

$$AIC = -2 \log L(\hat{\theta}) + 2k \quad (2.26)$$

where $L(\hat{\theta})$ is the maximized likelihood function, $\hat{\theta}$ is a vector of estimated parameters and k is the number of unknown parameters in the model, and the model with minimum AIC value is chosen as the best model in fitting data.

Based on Akaike's information criterion, Bozdogan (1987) developed a more accurate new Information Complexity Criterion (ICOMP). In contrast to AIC, ICOMP is based on the structural complexity of an element or set of random vectors via a generalization of the information-based covariance complexity index of Van Emden (1971). Bozdogan's ICOMP is defined as

$$ICOMP = -2\log L(\hat{\theta}) + 2C_1(\hat{F}^{-1}(\hat{\theta})) \tag{2.27}$$

and $\hat{F}^{-1}(\hat{\theta})$ is estimated inverse Fisher information matrix of parameter $\hat{\theta}$ and $C_1(\cdot)$ is a maximal information theoretic measure of complexity of the ICOMP of a multivariate normal distribution given by

$$C_1(\hat{F}^{-1}(\hat{\theta})) = \frac{s}{2}\log\left[\frac{tr(\hat{F}^{-1}(\hat{\theta}))}{s}\right] - \frac{1}{2}\log\left|\hat{F}^{-1}(\hat{\theta})\right| \tag{2.28}$$

where $s = \dim(\hat{F}^{-1}) = rank(\hat{F}^{-1})$.

The second component in equation (2.27) takes into account of the accuracy of the estimated parameters and implicitly adjusts for the number of free parameters included in the model. ICOMP controls the risks of both insufficient of over-parameterized models and the model with minimum ICOMP is chosen to be the best model.

2.6 Results

An important problem in estimation is the identification of model parameters and endogenous effects. For instrumental variables estimation, at least one variable which is correlated with the endogenous variable, uncorrelated with the error term of the outcome equation, and does not affect the outcome equation is required for parameter identification. However, for the Maximum-likelihood estimation of current model, the nonlinear identification criteria are met without exclusion restrictions owing to the distributional assumption of the error term. Nonlinear functional form relying solely on distributional assumptions often fails to generate sufficient variation to identify model parameters which can be capricious. To avoid over-burdening the nonlinear functional forms for parameter identification, exclusion restrictions with different sets of explanatory variables in the switching (physical activity) and PQH-8 equations are imposed. Recent mental health condition is used solely in the PHQ-8 equation and recent physical health condition is only placed in the switching (physical activity) equation.

2.6.1 Model Selection and Statistical Tests

This subsection performs model selection procedure and several empirical tests to compare between treatment and switching model, and thus choose the best one in fitting data. Table 2.2 presents the AIC and ICOMP values for both treatment and switching model with pooled, male and female samples. According to the information criteria, both AIC and ICOMP have smaller values on switching model than treatment model with pooled, male and female samples, which suggest switching model performs better than treatment effect model. In addition to information criteria, empirical tests are used to compare these two models. Since treatment effect model and switching model are nested[8], the tests for the equality of parameters can be achieved by restricting parameters in switching model. And the null hypothesis that coefficients of seldom exerciser and regular exerciser in the switching model are equal is equivalent to the alternative null hypothesis that the switching model performs better than treatment effect model. Under the alternative hypothesis, the Likelihood ratio (LR) and Wald tests are be carried out with standard routines. Considering the test statistics, the Likelihood ratio statistics are significant at the 1% level of significance for pooled, male and female samples, and the Wald test statistics are significant at the 1% level of significance for pooled sample and female samples[9] (Table 2.3), which suggest that switching model is better than the treatment effect model in fitting data. Since switching model is preferred by information criteria and empirical tests, the rest part of this study will be implemented by switching model.

To further investigate the gender difference between depression categories, the empirical test for the equality of parameters across male and female samples is required. The test is fulfilled with a likelihood ratio test, which is similar to the Chow test in linear regression models. Specifically, define the log-likelihood values for the pooled sample, male and female samples as $logL$, $logL_m$ and $logL_f$, with corresponding number of parameters k, k_m and k_f. Thus under the null hypothesis that parameters are equal across gender, the test statistics $LR = 2(logL_m + logL_f - logL)$ is Chi-square distributed with $k_m + k_f - k$ degrees of freedom (df). For the switching regression model, the hypothesis of equal slope coefficients between male and female samples is rejected (LR=117.82, df=80, p-value=0.0038), which suggests the estimation of the model by segmented samples is justifiable. Thus the rest of this study will be implemented on segmented sample.

[8] Treatment effect model is a special case of switching model which restricts both sets of slope and threshold coefficients (except constant coefficients) and correlations of the switching model to be equal.
[9] Wald test statistics for the male sample is significant at the 5% level of significance.

2.6.2 Maximum-Likelihood Estimates

Table 2.4 present the ML estimates for the switching model with male and female samples respectively. All threshold parameter estimates are positive and significant at the 1% level of significance or lower, which suggest that the ordered probability model (switching model) is successful in delineating the PHQ-8 categories for regular exercisers and seldom exercisers with gender-segmented samples. The error correlation estimates between the switching equation (physical activity equation) and the PHQ-8 equations for both regular exercisers and seldom exercisers are all significant at the 1% level or lower, which supports the endogeneity of regime switching. In addition these positive error correlations suggest that unobserved characteristics affect physical activity and PHQ-8 in the same direction for both males and females.

For the switching equation for male individuals, only 6 explanatory variables are significant at the 10% level of significance or lower out of 25 variables, while for female individuals, 14 variables are significant out of the same 25 variables. The exclusion variable of recent physical health condition in the switching equation is significant at the 1% level of significance in both male and female samples. For the PHQ-8 equation of male seldom exercisers, only 3 variables are significant at the 10% level of significance or lower out of 25 variables, including season (summer), race (Hispanic), marriage (married individual), but among female seldom exercisers, variables measure season (winter), age, income, education (have some college), employment (employed, retired and unable individuals) and home ownership are significant. The estimates also differ greatly among male and female regular exercisers. In the PHQ-8 equation of male regular exercisers, explanatory variables measure season (summer), age, income and marriage (married individual) are significant, but among female regular exercisers explanatory variables which measure income, race (white and Hispanic), employment (employed, student and unable individuals) and home ownership are significant at the 10% level of significance of lower. To further exploit the effects of explanatory variables and physical activity on the level of depressive symptoms between male and female in greater detail, average treatment effects, marginal effects of explanatory variables are discussed below.

2.6.3 Average Treatment Effects of Physical Activity on Depression

The primary purpose of estimating the switching probability model is to investigate the effect of physical activity on the probabilities of depressive symptom categories. Average treatment effects (ATEs) are calculated to quantify such effects. The results, presented in Table 2.5, suggest that regular exercise decreases the probabilities of some levels of depressive symptoms among males and females. For a randomly selected male, regular exercise decreases the probabilities of moderate depressive symptoms by 0.87% and moderately severe depressive symptoms by 0.83%. The corresponding effects of regular exercise for females are 2.34% lower probabilities of mild depressive symptoms and 1.00% lower probability of moderate depressive symptoms. In terms of ameliorating depressive symptoms, physical activity is most beneficial for mildly and moderately depressed individuals and the effect of regular activity is most notable on mildly depressed females.

2.6.4 Marginal Effects of Explanatory Variables: Males

Marginal effects of explanatory variables are calculated by differentiation and differencing (described above) for all individuals and averaged over each sample. Conditional on exercise categories, these average marginal effects allow further exploration for the effects of explanatory variables on depression category probabilities. Results are presented in Table 2.6 for males and Table 2.7 for females.

Age is a key determinant of depression, and it has a negative effect on all depression categories for both seldom and regular exercisers among males. Conditional on seldom exercise, a 10-year increase in age is associated with a 0.24% (0.11%, 0.07%) decrease in the probability of moderate (moderately severe, severe) depressive symptoms, but conditional on regular exercise, a 10-year increase in age is associated with 1.09%, 0.37%, 0.18% and 0.24% decreases in the probabilities of mild, moderate, moderately severe, and severe depressive symptoms.

As expected, income plays a role in affecting the level of depressive symptoms for males, regular exercise or not. The marginal effects of income on the probabilities of all depression categories are negative, which suggest that higher income decreases the probabilities of depressive symptoms; thus, poor males are more likely to have depressive symptoms than rich ones. Specifically, for a man who seldom exercises, a one-category increase in income level decreases the probabilities of mild, moderate, moderately severe, and severe depressive symptoms by 0.50%, 0.20%, 0.09%, and 0.06%, and decreases the corresponding probabilities by 0.75%, 0.22%, 0.10%, and 0.14% conditional on regular exercise.[10]

Season affects depressive symptoms of men who seldom exercise but not those who exercise regularly. For no obvious reason, the probabilities of mild, moderate, moderately severe, and severe depressive symptoms are 1.70%, 0.68%, 0.31%, and 0.20% higher in the spring season than in the fall.

Supporting the hypothesis that mental health condition in previous conceptual framework, recent mental health condition has a positive impact on the level of depressive

[10] Income in this study in divided into categories from 1 to 8.

symptoms among males regardless of exercise category. A one-day increase in recent bad mental health decreases the probabilities of mild, moderate, moderately severe, and severe depressive symptoms by 0.97% (0.93%), 0.38% (0.27%), 0.17% (0.12%), and 0.11% (0.17%), conditional on seldom (regular) exercise.

Race affects some categories of depressive symptoms among men who exercise regularly but not among those who seldom exercise. Among regular exercises, a black man has a 4.92% (0.88%) lower probability of mild (severe) depression than men of other races.

Education only affects seldom exercisers among men, and compared with men who only have high school diplomas, those who have bachelor's degrees or above are less likely to be depressed. Seldom exercisers who have bachelor's degrees or above are 2.67%, 1.06%, 0.43%, and 0.29% less likely to have mild, moderate, moderately severe, and severe depressive symptoms.

Employment status affects depressive symptoms of men with regular exercise but not men without. Compared with male homemakers, a male student has 7.12%, 2.11%, 1.10%, and 1.28% lower probabilities of having mild, moderate, moderately severe, and severe depression conditional on regular exercise.

Marital status affects men, regular exercise or not. Married men who seldom exercise have 2.23%, 0.82%, 0.40%, and 0.24% lower probabilities of mild, moderate, moderately severe, and severe depressive symptoms than their single counterparts, and married males who exercise regularly have 2.34% and 0.46% higher probabilities of mild and severe depressive symptoms than single ones.

2.6.5 Marginal Effects of Explanatory Variables: Females

Similar to results for males, age affects the depression category probabilities of females negatively. Conditional on seldom (regular) exercise, a 10-year increase in age is associated with a 0.89%, 0.27%, 0.11%, and 0.09% (1.52%, 0.53%, 0.33% and 0.30%) decrease in the probabilities of mild, moderate, moderately severe, and severe depressive symptoms. Our finding that depressive symptoms taper off as men and women age is consistent with findings in some of the previous studies (Wade and Cairney 1997; Schieman et al. 2002; Streiner et al. 2006).

Income affects depressive symptoms of women as well, as higher income decreases the probabilities of depressive symptoms, regular exercise or not. Specifically, a one-category increase in income decreases the probabilities of mild, moderate, moderately severe, and severe depressive symptoms by 0.44%, 0.16%, 0.08%, and 0.07% among seldom exercisers, while the corresponding decreases are 0.73%, 0.25%, 0.15%, and 0.14% among regular exercisers. Finding from this study that higher income ameliorates depression for both men and women are similar to finding reported by Zimmerman and Katon (2005).

As is true among men, recent mental health condition has a positive impact on all depression category probabilities among women. A one-day increase in recent bad mental health decreases the probabilities of mild, moderate, moderately severe, and severe depressive symptoms by 1.22%, 0.44%, 0.21%, and 0.18% for women who seldom exercise. With regular exercise, the effects of recent bad mental health are slightly lower, by 0.92%, 0.31%, 0.19% and 0.17%, in probabilities.

Race plays a different role on women than men, with more notable effects on mental health among women who exercise regularly. Among women who exercise regularly, a white (Hispanic) has 6.53%, 2.34%, 1.49% and 1.35% (9.36%, 3.53%, 2.09% and 1.93%) higher probabilities of mild, moderate, moderately severe, and severe depressive symptoms than women of other races. The findings suggest that Hispanic women are more likely to be depressed than white women and this is consistent with the findings by Bromberger et al. (2004) who find Hispanic women having higher odds of depression than white women.

While education affects mental health only among men who seldom exercise, education affects women's mental health regardless of exercise categories. Compared with women who only have high school diplomas, those who have bachelor's degrees or above are less likely to be depressed. Seldom (regular) exercisers who have bachelor's degrees or above are 1.85%, 0.73%, 0.27%, and 0.26% (1.99%, 0.63%, 0.39% and 0.34%) less likely to have mild, moderate, moderately severe and severe depressive symptoms. Relating these results to those of males, more educated people have lower risks of being depressed, which echoes previous finding by Craig and Van-Natta (1979).

Unlike the effects on men, employment status plays important roles among women who exercise regularly and women who do not. Conditional on seldom exercise, unemployed women have 3.18%, 1.42%, 0.59%, and 0.51% higher probabilities of mild, moderate, moderately severe, and severe depressive symptoms than homemakers. Compared to female homemakers who exercise regularly, a female student has 4.83%, 1.54%, 0.96%, and 0.81% lower probabilities of mild, moderate, moderately severe, and severe depressive symptoms. In addition, unable women are more likely to be depressed than homemakers, with unable seldom (regular) exercisers having 7.12%, 3.31%, 1.46%, and 1.18% (4.49%, 1.65%, 0.99% and 0.85%) higher probabilities of being mild, moderate, moderately severe, and severe depressed.

2.7 Conclusion

This paper examines the effects of physical activity and socio-demographic factors on the level of depressive symptoms, using data from a large national sample of the general population. PHQ-8 scores are used as indicators of depressive symptoms, and an endogenous switching ordered probability model is developed to address the ordinal depression outcome and binary endogenous physical activity.

One of the primary finding in this study is that regular physical activity ameliorates depressive symptoms, decreasing the probabilities of moderate and moderately severe depressive symptoms for men, and decreasing the probabilities of mild and moderate depressive symptoms for women. This finding also suggests mildly and moderately depressed women will benefit more from regular physical activity.

This study is the first to evaluate the role of physical activity on depression and the roles of socio-demographic factors on depression by exercise categories. By comparing marginal effects of socio-demographic variables between seldom and regular exercisers for both men and women, some differences in the mechanism of depression among seldom and regular exercisers are found. For men, season and education play significant roles in affecting depression of seldom exercisers while being black and being student influence depression of regular exercisers. For women, race plays a prominent role in affecting depression of regular exercisers, and being white or Hispanic are found to increase the probabilities of all depression categories significantly.

CHAPTER III

SUPPLEMENTAL NUTRITION ASSISTANCE PROGRAM AND FOOD INSECURITY AMONG HUSBAND-WIFE HOUSEHOLDS WITH CHILDREN

3.1 Introduction

Food security is a globally essential issue for household and personal well-being which guarantees household members have dependable access to sufficient food for an active and healthy lifestyle. Over the past several decades, researchers and policy makers have devoted attention to food security related issues. Food insecurity is still one of the most pressing problems we are facing today, even in the developed countries like the United States. Indeed, some low income families still experience food insecurity (FI) due to the lacking of monetary or other resources. In 2005, 37 million people (12.6%) lived in households with incomes below the poverty threshold in the United States, and 38.5% of all people in the United States with incomes below the poverty thresholds were food insecure (Cook Frank 2008).

To increase the food security of low-income households, the U.S. Department of Agriculture (USDA) implemented the Supplemental Nutrition Assistance Program (SNAP) which is formerly known as Food Stamp Program (FSP) to provide food assistance via benefit payments to households meeting eligibility criteria.[11] Other food assistance programs such as the Special Supplemental Nutrition Program for Women, Infants and Children (WIC), National

[11] SNAP eligible households should have gross income below the 130 percent of the federal poverty level of the state where they live.

School Lunch Program, and informal (private) food assistance (IFA) programs are also designed to combat food insecurity and hunger. In 2011, SNAP provided benefits to 44.7 million people in the U.S. and the total federal expenditures for the program were over $75 billion. Despite this strong program support from the government, the rate of households reporting food insecurity still increased in some years. For instance, the percentage of food insecure households increased largely (3.5%) from 2007 to 2008 (Nord et al. 2009) and increased slightly (0.4%) from 2010 to 2011 (Coleman-Jensen et al. 2012). Such phenomenon seems brings the effectiveness of SNAP in diminishing food insecurity into question. Hence, detailed research of the simultaneous relationship of SNAP and food insecurity is needed.

3.2 Literature Review

A better understanding of the relation between the SNAP participation and FI is important for policy makers to assess effectiveness of food assistance policies. During the past decade, a number of studies have investigated the relationship between SNAP participation and FI, but findings of the effects of SNAP on household FI are mixed. A number of studies find that SNAP or FSP participants are more likely to be food insecure (e.g. Jensen 2002; Ribar and Hamrick 2003; Wilde and Nord 2005). Other studies find no significant statistical relation between SNAP participation and FI (e.g. Gundersen and Oliveira 2001; Huffman and Jensen 2008). While many studies provide no evidence that SNAP (FSP) participation reduces FI, some recent studies still find evidence that SNAP (FSP) alleviates FI to some extent (e.g. Borjas 2004; Bartfeld and Dunifon 2006; DePolt et al. 2009; Nord and Golla 2009; Yen et al. 2008; Mykerezi and Mills 2010).

Among studies reporting either positive or no statistically significant relation between SNAP (FSP) and FI, Jensen (2002) implements an ordered probability model to deal with the categorical nature of household FI and find evidence that FSP participation and FI are not independent. Wilde and Nord (2005) use a panel data approach with two-year samples from the Current Population Survey (CPS) to estimate the association between FSP and FI.The results suggest that food security status more commonly deteriorated for households entered FSP during 2001-2002. Gunderson and Oliveira (2001) employ a simultaneous probit model and find Food Stamps have no significant effect on food insufficiency using data from the 1991–1992 Survey of Income and Program Participation (SIPP). Similar to Gunderson and Oliveira’s simultaneous equation approach, Huffman and Jensen (2008) develop a structural simultaneous model to jointly estimate the effects of FSP and labor force participation on FI. Their results suggest being food insecure increases the probability that a household participates in FSP even though the effect of FSP on FI is not significant.

Positive or insignificant effect of SNAP (FSP) on household FI is generally believed to be the result of a household’s self-selection into SNAP that is likely not properly accounted for (Nord and Golla 2009). This inconsistency among previous results calls for a more thorough investigation of the role of SNAP participation in FI. Recent analyses on the subject feature more careful attention to the selection issue of SNAP (FSP) participation (e.g. Yen et al. 2008; DePolt et al. 2009; Mykerezi and Mills 2010; Ratcliffe and McKernan 2010) and find that participation in SNAP generally alleviates FI (e.g. Wilde 2007).

Yen et al. (2008) develop an instrumental variable approach to control for selection into FSP with data from the 1996–1997 National Food Stamp Program Survey. By calculating the treatment effect of FSP participation on the FI score, they further point out that FSP participation lowers the FI score by 0.4 among those who are food insecure. Following Yen's approach, Mykerezi and Mills (2010) use the treatment effect model to deal with the endogeneity of FSP for each income group and estimate the effect of losing FSP benefits due to a government decision. Their result is consistent with Yen et al. (2008) that FSP participation lowers the severity of FI and they find an even larger reduction in the magnitude. DePolt et al. (2009) use a longitude data from low-income families with children living in Boston, Chicago and San Antonio to evaluate the effect of FSP on food hardships. By implementing a quasi-fixed-effects procedure to control for unobservable household characteristics, the authors find a strong negative association between FSP and food hardship. Most recently, with large national data from the SIPP, Ratcliffe and McKernan (2010) use a dummy endogenous variable model with instrumental variables of state SNAP policies to control for selection bias. Results from their specification suggest the participation in SNAP reduces the probability of FI by 31.2% and reduces the probability of being very food insecurity by 20.2%.

Most of recent empirical studies with the result of negative association of SNAP and FI use the instrumental variables to deal with the endogeneity of SNAP participation, and shortcomings of these studies are identified. First is use of old data. For instance, Yen et al. (2008) use the 1996–97 National Food Stamp Program Survey (NFSPS). Second, most studies address household FI in general, and do not include low and very low food security levels among children (Nord 2009), one exception is the study by Ratcliffe and McKernan (2010). Without such food insecure levels among children in measuring household FI, the effects of SNAP cannot be fully exploited. A third shortcoming, which is the most important and thus motivates this study, is the lack of simultaneous nature of SNAP participation and FI. Without such simultaneous decision about SNAP participation and FI, the probability that food insecure households are more likely to participate in SNAP than food secure households will be neglected, and thus the effect of SNAP participation on FI will be biased.

3.3 Methods and Model

3.3.1 Conceptual Framework

The empirical model of this study is motivated by a utility maximization framework where utility is specified as a function of income and leisure.[12] Assume each SNAP eligible household derives utility from total income (*Y*) and leisure (*L*), then the utility function can be written as

$$U = U(Y, L) \tag{3.1}$$

This utility is maximized subject to the time constraint

$$L + W = \bar{T} \tag{3.2}$$

where W is working hours and $\bar{T}$ is total time available, both for household members. Household income is a function of working hours and SNAP participation

$$Y = Y(W, SNAP) \tag{3.3}$$

where *SNAP* equals to 1 if any household member participates SNAP. Assume there is a disutility function $C = C(S)$ that affects household's choice for SNAP participation, where *S* is a set of factors, such as state SNAP policies, that affects the participation decision of an eligible household. Then, SNAP participation decision of a household can be expressed as

$$P_{SNAP} = U(Y_{SNAP=1}, L) - U(Y_{SNAP=0}, L) - C(S) \tag{3.4}$$

A household will participate in SNAP if $P_{SNAP} > 0$ but will not if $P_{SNAP} \leq 0$.

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[12] The conceptual framework is an extension of Jensen (2002).

Assume food insecurity is a function of household income (*Y*) and a set of economic and demographic variables (*Z*) such that $FI_j = F(Y, Z)$. Then, maximizing the utility yields the reduced-form equation for household food insecurity:

$$\begin{aligned} FI_j^* &= F(W, SNAP^P, Z) \qquad \text{if} \quad P_{SNAP} > 0 \\ &= F(W, SNAP^{NP}, Z) \qquad \text{if} \quad P_{SNAP} \leq 0 \end{aligned} \tag{3.5}$$

where FI_j is household FI index at category *j*; $SNAP^P$ equals 1 and $SNAP^{NP}$ equals 0, and $FI_j = j$ if $\xi_{j-1} < FI_j^* \leq \xi_j$ where ξ_{j-1} and ξ_j are threshold parameters.

3.3.2 Econometric Models

Driven by the theoretical model, a two-equation simultaneous system is developed to deal with the mutual effects of ordinal FI (y_1) and binary SNAP (y_2). The model is characterized by two structural equations for corresponding latent variables y_1^* and y_2^*

$$y_1^* = \gamma_1 y_2^* + x'\alpha_1 + z'\alpha_2 + u_1 \tag{3.6}$$

$$y_2^* = \gamma_2 y_1^* + x'\beta_1 + w'\beta_2 + u_2 \tag{3.7}$$

where x, z and w are vectors of exogenous variables with conformable parameters of α_1, β_1, α_2 and β_2; γ_1 and γ_2 are scalar parameters, and the error terms are assumed to be bivariate normal distributed with zeroes means and unitary variances, correlation ρ and covariance matrix:

$$\begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right) \tag{3.8}$$

The variance of u_1 and u_2 are assumed to be unitary because y_1 is ordinal outcome with only unit increment in each category and y_2 is a binary variable. The reduced-form equations are

$$y_1^* = x'\Pi_{11} + z'\Pi_{12} + w'\Pi_{13} + v_1 \tag{3.9}$$

$$y_2^* = x'\Pi_{21} + z'\Pi_{22} + w'\Pi_{23} + v_2 \tag{3.10}$$

where Π_{11}, Π_{12}, Π_{13}, Π_{21}, Π_{22} and Π_{23} are functions of the structural parameters in equation (3.6) and (3.7), and the composite error vector $v = [v_1, v_2]'$ is distributed as a bivariate normal with zero means, correlation τ, standard deviations ω_1 and ω_2, and covariance matrix:

$$\begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \omega_1^2 & \omega_1\omega_2\tau \\ \omega_1\omega_2\tau & \omega_2^2 \end{bmatrix}\right) \tag{3.11}$$

Being more specific, we have $w_1^2 = (1+\gamma_1^2 + 2\rho\gamma_1)/(1-\gamma_1\gamma_2)^2$, $w_2^2 = (1+\gamma_2^2 + 2\rho\gamma_2)/(1-\gamma_1\gamma_2)^2$ and $\tau = [\gamma_1 + \gamma_2 + (1+\gamma_1\gamma_2)\rho]/[(1+\gamma_1^2 + 2\rho\gamma_1)(1+\gamma_2^2 + 2\rho\gamma_2)]^{1/2}$.

Based on the reduced form of equation (3.9) and (3.10), the model with ordinal outcome y_1 and binary outcome y_2 is characterized as

$$y_1 = k \quad \text{if} \quad \xi_{k-1} < y_1^* < \xi_k^{(s)}, \;\; k = 0\ldots K \tag{3.12}$$

$$\begin{aligned} y_2 &= 1 \quad \text{if} \quad y_2^* > 0 \\ &= 0 \quad \text{if} \quad y_2^* \le 0 \end{aligned} \tag{3.13}$$

where ξ_k is threshold parameter such that $\xi_0 = -\infty$, $\xi_1 = 0$, $\xi_K = \infty$, and $\xi_2 \ldots \xi_{K-1}$ are estimable.

Maddala (1983) suggests a two-step estimation of such simultaneous equation system. Although estimates of the two-step procedure are consistent, efficiency cannot be guaranteed. To overcome the shortcoming of two-step estimator, a more efficient maximum-likelihood (ML) procedure is developed.

Before constructing the likelihood contribution for the sample observation, first define $\psi\Pi_1 = x'\Pi_{11} + z'\Pi_{12} + w'\Pi_{13}$ and $\psi\Pi_2 = x'\Pi_{21} + z'\Pi_{22} + w'\Pi_{23}$, where $\psi = [x', z', w']$. The likelihood contribution for an observation with outcomes $(y_1 = k, y_2 = 0)$ and $(y_1 = k, y_2 = 1)$ are

$$\Pr(y_1 = k, y_2 = 0) = \int_{-\infty}^{-\psi\Pi_2} \int_{\xi_{k-1}-\psi\Pi_1}^{\xi_k-\psi\Pi_1} f(v_1, v_2)\, dv_1 dv_2 \tag{3.14}$$

$$\Pr(y_1 = k, y_2 = 1) = \int_{-\psi\Pi_2}^{\infty} \int_{\xi_{k-1}-\psi\Pi_1}^{\xi_k-\psi\Pi_1} f(v_1, v_2)\, dv_1 dv_2 \tag{3.15}$$

and the sample likelihood function for an independent sample of *n* observations is

$$\begin{aligned} L = \prod_{i=1}^{n}\prod_{k=1}^{K} \Bigg\{ & \Phi_2\left(\frac{\xi_k - \psi_i\Pi_1}{w_1}, \frac{(-1)^{j+1}\psi_i\Pi_2}{w_2}; (-1)^j\tau \right) \\ & -\Phi_2\left(\frac{\xi_{k-1} - \psi_i\Pi_1}{w_1}, \frac{(-1)^{j+1}\psi_i\Pi_2}{w_2}; (-1)^j\tau \right) \Bigg\}^{g(y_{1i},k)} \end{aligned} \tag{3.16}$$

where $\Phi_2(x, y; \rho) = \Pr(\mathrm{X} \le x, \mathrm{Y} \le y)$ is a bivariate standard normal cumulative function (CDF) with correlation ρ, $g(y_i, k)$ is a dichotomous indicator function which equals 1 if $y_{1i} = k$ holds and 0 otherwise, and $j = y_{2i}$.

The model reduces to the recursive model of SNAP participation (Yen et al., 2008; Mykerezi and Mills, 2010) by restricting γ_2 to be zero in equation (3.7) and tests for such restriction can be carried out by regular means, using likelihood-ratio (LR), Wald, or Lagrange multiplier (LM) test.

To facilitate interpretation of the effects on explanatory variables, marginal effects of explanatory variables on the probabilities of SNAP participation and FI are calculated. In addition, to better gauge the effect of SNAP on each FI category, the average treatment effects of SNAP participation are also estimated. Specially, for each individual, the probability of SNAP participant or nonparticipant is

$$\Pr(y_{2i} = j) = \Phi_1[(-1)^{j+1}\psi_i\Pi_2 / w_2], \quad j = 0,1 \tag{3.17}$$

where $\Phi_1(\cdot)$ is a standard normal cumulative function (CDF). Applying equations (3.16)-(3.17), the joint probability of each FI category and SNAP participant or nonparticipant is

$$\Pr(y_{1i} = k, y_{2i} = j) = \Phi_2\left(\frac{\xi_k - \psi_i\Pi_1}{w_1}, \frac{(-1)^{j+1}\psi_i\Pi_2}{w_2}; (-1)^j\tau\right) - \Phi_2\left(\frac{\xi_{k-1} - \psi_i\Pi_1}{w_1}, \frac{(-1)^{j+1}\psi_i\Pi_2}{w_2}; (-1)^j\tau\right) \tag{3.18}$$

Applying equation (3.17) and (3.18), the conditional probability of FI (y_1) is

$$\Pr(y_{1i} = k \mid y_{2i} = j) = \Pr(y_{1i} = k, y_{2i} = j) / \Phi_1[(-1)^{j+1}\psi_i\Pi_2 / w_2] \tag{3.19}$$

and the conditional probability of SNAP (y_2) is

$$\Pr(y_{2i} = j \mid y_{1i} = k) = \frac{\Pr(y_{1i} = k, y_{2i} = j)}{\Phi_1[(\xi_k - \psi_i\Pi_1)/w_1] - \Phi_1[(\xi_{k-1} - \psi_i\Pi_1)/w_1]} \tag{3.20}$$

Marginal effects of each continuous (binary) explanatory variable can be derived by differentiating (differencing) equations (3.17)-(3.20). In addition, the treatment effect of SNAP participation on FI categories conditional on food insecurity $(y_{1i} > 0)$ is

$$\begin{aligned} TE_k &= \Pr(y_{1i} = k \mid y_{2i} = 1, y_{1i} > 0) - \Pr(y_{1i} = k \mid y_{2i} = 0, y_{1i} > 0) \\ &= \frac{\Pr(y_{1i} = k, y_{2i} = 1)}{\Pr(y_{2i} = 1) - \Pr(y_{1i} = 0, y_{2i} = 0)} - \frac{\Pr(y_{1i} = k, y_{2i} = 0)}{\Pr(y_{2i} = 0) - \Pr(y_{1i} = 0, y_{2i} = 0)}, k = 1,2,3 \end{aligned} \tag{3.21}$$

For statistical inference, standard errors of the marginal and treatment effects can be derived by the delta method (Papke and Wooldridge 2005).

3.4 Data

Data come from the 2010–2011 Current Population Survey-Food Security Supplement (CPS-FSS). The CPS-FSS data are the basis of USDA's series of annual reports on food security of U.S. households and are collected in the December CPS. The primary purpose of this study is to investigate the effects of SNAP participation on FI among husband-wife families with children (HW-C). The sample is thus limited to SNAP eligible HW-C households. The income criterion is used to determine SNAP eligibility—by restricting households to those with annual income below 130% of Federal Poverty Level (FPL). After removing missing values for important variables, the final sample consists of 1826 SNAP eligible households. Table 3.1 presents sample statistics of all variables.

3.4.1 Measuring Food Insecurity and SNAP Participation

Household food insecurity is measured by the 18 questions in CPS-FSS, 8 of which concern children's FI during 12 months prior to the survey. Table 3.2 presents the classification of household food insecurity.[13] Based on the numbers of affirmative responses to the 18 questions and to the 8 children-specific items, household FI is categorized into four mutually exclusive categories (Nord et al., 2010): food secure (FS, with < 3 affirmative responses); and three categories among those with ≥ 3 affirmative responses: FI among adults only (FIA, with < 2 children-specific responses), low food security among children (LFSC, with 2–4 children-specific responses), and very low food security among children (VLFSC, with ≥ 5 children-specific responses). The above are coded into four categories, with FI scores of 0,1,2, and 3,

[13] Details on the household food insecurity survey module are included in Appendix B.1, which come from the U.S. Department of Agriculture (2012).

respectively. The endogenous variable is household SNAP participation—a binary indicator of whether anyone in the household received SNAP in the past 12 months. Table 3.3 and Figure 3.1 present the distribution and two-way frequencies of FI categories by SNAP participation status.

3.4.2 Identification Variables

For ML estimation of the current model, the nonlinear identification criteria are met without exclusion restrictions owing to distributional assumption of the error term. Nonlinear functional form relying solely on distributional assumptions often fails to generate sufficient variation to identify model parameters which can be capricious. To avoid over-burdening the nonlinear functional forms for parameter identification, exclusion restrictions are imposed, with different sets of explanatory variables in the SNAP and FI equations.

In the SNAP equation, five state SNAP policy variables are used uniquely, and in order to better evaluate the effects of SNAP policies on participation decision, the policies one year ahead of the FSS data collection time are used.[14] A one year lag in SNAP policy variables is reasonable because household decisions of SNAP participation are normally made awhile before SNAP benefits are received. The first variable is the proportion of SNAP units with earnings (Short 1), and the second variable without earnings (Short 2), both with a 1–6 month recertification period. Yen et al. (2008) use a binary indicator of recertification period shorter than six months to identify FSP equation as frequent recertification of FSP eligibility may discourage participation. The third variable is a dummy indicator of simplified reporting option for households with earnings (Report simplified), which may encourage households to participate in SNAP due to easier administrative process. The fourth variable is the broad-based

[14] The SNAP policy in June 2009 and 2010 of each state are used with the FSS data in December 2010 and 2011 respectively.

categorical eligibility (BBCE) for SNAP. BBCE eliminates the asset tests for most households, thus simplifying the process and reducing potential eligibility determination errors. Mabli and Ferrerosa (2010) find that state offering BBCE have a 6.2 percent higher per capital participant count than states without this policy. Finally, the fifth variable refers to the Vehicle test, measured by a binary indicator of whether the state excludes at least one, but not all, vehicles in the household from the SNAP asset test. Vehicle exemption may reduce the difficulty to be SNAP eligible and thus will encourage households to participate in SNAP. Recent studies suggest a positive association between vehicle exemption and SNAP participation (e.g., Gregory et al. 2013).

Four variables are used solely in the FI equation, under the exclusionary hypothesis that they have no direct effect on SNAP participation. Motivated by our theoretical model, two variables are used to measure participation in other food assistance programs, which may have large positive or negative effect on FI (e.g., Kreider et al. 2012). These are binary indicators of whether anyone in the household received food through the WIC during past 30 days, and whether any children in the household received free or reduced-cost food at day care or the Head Start program. The third and fourth variables reflect household financial status and food consumption, which come from questions "Did you run short of money in past 12 months and tried to make food money go further" and "Do you need to spend more money to buy enough food to meet needs than you do now", respectively.

3.4.3 Parental Resource and Other Explanatory Variables

Besides SNAP effects, the second focus is on the role of parental resource variables in SNAP participation and FI among HW-C households. Parental resources have been found to play a key role in child abuse and neglect in the economics literature (Paxson and Waldfogel 1999), and these variables are assumed to affect other aspects of children's welfare such as FI. Household head's educational status, race, husband (wife)'s ages, employment status, and working hours belong to this category. In the HW-C sample, about 70% of the household heads graduated from high school or above, including 18% with a bachelor's degree or above. About 82% of the household heads are white. Age of husband (wife) averages to 36.33 (33.48), and working hours of husband (wife) to 27.38 (12.07) hours per week. About 73% of the household have husbands employed and 39% have wives employed.

Other explanatory variables are household annual income, household size, number of children, and locations of residence.[15] Average household income is $20,500 per year, and mean household size is 4.89. Each HW-C household has 2.48 children on average, and about 76% of households live in Metropolitan Statistical Areas. Of the sample of households, 34% live in the South, 12% Northeast, 34% West, and 20% Midwest.

3.5 Results and Discussion

3.5.1 Model Selection and Statistical Tests

Even though simultaneous equation system is driven by the mutual causality between FI and SNAP, further model selection procedure and statistical tests are still needed to choose the best model in fitting data. Regardless the effect of FI on SNAP participation, treatment effect model (Chapter II, equation (2.6)) and recursive system (a special case of simultaneous equation system, by restricting γ_2 to zero in equation (3.7)) are also potential econometric procedures to

[15] Household income in the CPS data is categorical which ranges from 1–16. The household income used in this study is the mean number of dollars corresponds to each category. Since the HW-C samples are restricted to SNAP eligible households, the highest income category will not be reached.

address the endogenous SNAP and ordinal FI. To justify the simultaneous equation system among potential treatment effect model and recursive system (Yen et al. 2008; Mykerezi and Mills 2010), model selection procedure with information criteria are carried out. Model selection results in table 3.4 show that the simultaneous equation system has the smallest AIC and ICOMP values among other models (AIC=5149.981, ICOMP=5171.908), which suggest simultaneous equation system performs better than recursive system and treatment effect model. In addition, statistical tests are also carried out to assess the suitability of the simultaneous equation system vis-à-vis the recursive system. Results of LR and Wald tests suggest significance of the coefficient for latent FI (γ_2) (LR = 98.96, p-value < 0.001; Wald = 8.90, p-value = 0.003), both with df = 1, suggesting that the simultaneous equation system is more appropriate than the recursive system in fitting the data, in that two-way relationship is allowed between SNAP participation and FI. Since both information criteria and statistical tests justify the use of simultaneous equation system, the rest empirical part of this study will be carried out by simultaneous equation system along.

3.5.2 Maximum Likelihood Estimates of the Simultaneous Equation System

Table 3.5 presents Maximum Likelihood estimates for the simultaneous probability model. All threshold parameter estimates are positive and significant at the 1% level (of significance), suggesting that the ordered probability specification is successful in delineating the FI categories. The error correlation (ρ) estimate is positive (0.493) and significant at the 5% level, suggesting simultaneity of FI and SNAP participation. The positive error correlation suggests that unobserved characteristics affect SNAP and FI in the same direction.

Latent FI has a significant and positive (0.687) coefficient, at the 1% level, in the SNAP equation. Thus, more insecure households are more likely to participate in SNAP than less insecure households. This positive effect of FI on SNAP is consistent with the independent probit estimates but contradicts the simultaneous probit estimates Gundersen and Oliveira (2001).[16] Similar to findings by Yen et al. (2008) and Mykerezi and Mills (2010), SNAP has a significant and negative coefficient (–0.759) in the FI equation at the 1% level, suggesting that participation in SNAP ameliorates FI. Of the 28 explanatory variables in the SNAP equation, 13 are significant at the 10% level, including the two identification variables (BBCE and simplified reporting). As to parental resources, husband and wife's ages and working hours are significant in the SNAP equation. Of the 27 explanatory variables in the FI outcome equation, 17 are significant at the 10% level; all of the four identification variables are significant at the 5% level, rejecting the hypothesis of weak instrument and justifying use of the variables for parameter identification. Husband and wife's working hours, household income, number of children, and household size are significant at 5% level of lower. To further exploit effects of SNAP participation on FI and effects of explanatory variables on SNAP participation and FI, treatment effects and marginal effects are discussed below.

3.5.3 Average Treatment Effects of SNAP Participation on FI

To quantify effects of SNAP participation on FI among households who are food insecure (FI > 0), average treatment effects (ATEs) are calculated conditional on food insecurity. Yen et al. (2008) and Mykerezi and Mills (2010) estimate the ATEs of SNAP on continuous FI scores of households with older data, and both of their results suggest SNAP participation decreases the mean FI scores of food insecure households; neither address the effect of SNAP

[16] Gundersen and Oliveira (2001) find no significant relation between FSP and FI when using simultaneous probit equation due to the insignificance of coefficients FI in FSP equation and FSP in FI equation.

participation on FI of children separately from adults. Without differentiating between adults' FI and children's FI, the actual effect of SNAP cannot be fully explored, and the ATEs will be misleading for LFSC and VLFSC households since the average effect of SNAP on FI in all food insecure households may be dominated by the comparatively larger number of FIA samples and larger magnitude of SNAP effects on FIA households. With mutually exclusive classification of FI for adults and children, ATEs for adults and children can be calculated separately. The results, presented in Table 3.6, suggest that SNAP participation decreases the probability of FIA, but increases the probabilities of LFSC and VLFSC. According to these ATE estimates, for a randomly selected HW-C household, a SNAP-participating household has a 4.2% lower probability of FIA than non-participating households, while a SNAP participating household has 3% and 1.2% higher probabilities of LFSC and VLFSC than non-participating households. Although SNAP participation increases the probabilities of being LFSC and VLFSC, the positive effects are small in magnitude.

3.5.4 Marginal Effects on the Probability of SNAP Participation

Determinants of SNAP participation are presented in Table 3.7.[17] Household income shows a negative association with SNAP participation, with a $10,000 increase in income decreasing the marginal (unconditional) probability of SANP participation by 8.33%. This increase in income also has negative effects on the probabilities of SNAP participation, conditional on FI status, ranging from a decrease in probability of 2.13% conditional on VLFSC to 11.11% conditional on FIA.

The two state policy variables have positive signs as expected, with the state policies of

[17] Besides marginal effects on the probability of SNAP participation (unconditional on FI), table 3.7 also presents probabilities of SNAP participation conditional on all FI categories.

BBCE and Simplified reporting increasing the marginal probability of SNAP participation by 4.34% and 5.00%, respectively. Conditional on FS and FIA, these variables also have positive effects on SNAP participation probability. However, their effects on SNAP participation are negative conditional on LFSC and VLFSC, suggesting that these policies work opposite to expectation, *viz*., interfering with SNAP participation among the LFSC and VLFSC households. All FI identification variables (WIC, Free food, Out of money, and More money) contribute to SNAP participation indirectly, having positive effects on marginal probability and on probabilities conditional on most of the FI categories.

As to parental resources, husband and wife's ages and working hours are negatively associated with SNAP participation. A 10-year increase in husband's (wife's) age is associated with a 4.43% (6.60%) decrease in the marginal probability of SNAP participation, and a 10-hour increase in husband's (wife's) weekly working hours is associated with a 3.58% (3.27%) decrease in the marginal probability. Compared with households with husband (wife) not in labor force, household with unemployed husband (wife) is 15.32% (8.05%) more likely to participate in SNAP. A college educated household has an 8.88% lower probability of participating in SNAP compared with high-school educated households.[18] The effects of these variables on probabilities of SNAP participation conditional on FI categories are more or less similar to the effects on marginal probability.

Household size and number of children play positive roles in SNAP participation, with one additional member increasing the probability of SNAP participation by 3.76%, while that probability increases by 2.28% with one additional child in the household. Compared with non-metropolitan residents, households residing in a metropolitan area are 7.00% less likely to

[18] Education status of household is drawn from the respondent's education status. "College educated" status includes with a bachelor's degree or above.

participate in SNAP. Compared with households in the West, households in Southern U.S. are 4.98% more likely to participate in SNAP. Hispanic households are 8.05% less likely to participate in SNAP than non-Hispanic households.[19]

3.5.5 Marginal Effects on the Joint Probability of SNAP and FI

Marginal effects on the joint probabilities of SNAP participation and FI categories are presented in Table 3.8. Household income is one of the key determinants. Among households not participating in SNAP, a $10,000 increase in income is associated with 6.25%, 1.23%, and 0.78% increases in the joint probabilities of being FS, FIA and LFSC (and non-participation); while among SNAP participants the effects are opposite, with that same income increase decreases the joint probabilities of being FS, FIA, LFSC and VLFSC (and SNAP participation) by 4.05%, 1.83%, 2.00%, and 0.46%. Household size affects the joint probabilities of SNAP non-participants negatively but participants positively. One additional member in the non-participating household decreases the joint probabilities of (non-participation and) FS, FIA, LFSC and VLFSC by 2.13%, 0.82%, 0.70%, and 0.11%; it increases the joint probabilities of FS and FIA by 2.52% and 0.72% among SNAP participants. Children do not affect the joint probability of food insecure households among non-participants, but for SNAP participants, one additional child increases the joint probability of FIA by 0.56% and LFSC by 0.76%. Location of residency also plays a role for both participants and non-participants.

Residing in a metropolitan area increases the joint probabilities of FS by 4.12%, FIA and LFSC by FIA by 1.47%, and LFSC by 1.22% among non-participants; it decreases the joint probabilities of FS by 4.64% and FIA by 1.33% among participants. In terms of state policy variables, among non-participants, BBCE and Simplified reporting are negatively associated

[19] Race of household is drawn from the respondent's race.

with the joint probabilities of being FIA, LFSC and VLFSC, and they are positively associated with the joint probability of being FS. The marginal effects of all four identification variables in the FI equation (WIC, Free food, Out of money, and More money) are significant for both non-participants and participants; they are all negatively associated with the joint probability of FS but positively associated with the joint probabilities of FIA, LFSC and VLFSC.

Parental resource variables play key roles. Husband and wife's ages have opposite effects on the joint probabilities of FI between SNAP non-participants and participants. A 10-year increase in husband's (wife's) age increases the joint probabilities of FIA, LFSC, and VLFSC by1.25%, 1.19%, and 0.22% (1.77%, 1.65%, and 0.29%) among non-participants; it decreases the probabilities of FS and FIA by 3.70% and 0.73% (5.25% and 1.12%) among participants.

Effects of working hours also differ notably between non-participants and participants. A 10-hour increase in husband's (wife's) working hours per week increases the joint probabilities of FS and FIA (FS) by 2.94% and 0.43% (2.42%) among non-participants; it decreases the joint probabilities of FS and FIA (FS) by 2.94% and 0.43% (2.42%) among non-participants; and it decreases the joint probabilities of being FS, FIA, LFSC and VLFSC (FS, FIA and LFSC) by 1.49% and 0.83%, 1.01% and 1.26% (1.62%, 0.71% and 0.77%).

Compared to households with a husband not in the labor force, for SNAP non-participants (participants), households with an unemployed husband have 10.49%, 2.64% and 1.93% lower (8.51%, 3.17% and 3.03% higher) joint probabilities of FS, FIA and LFSC. Considering wife's employment status, wife unemployment decreases the joint probability of FS by 6.37% among SNAP non-participants; it increases the probabilities of FIA and LFSC by 1.84% and 2.26% among participants.

Education has more influence on the joint probability of SNAP participants than non-participants. Among SNAP participants, a college educated household has 2.33%, 3.27% and 0.86% lower joint probabilities of being FIA, LFSC and VLFSC. Finally, among SNAP non-participants (participants), a Hispanic household has 2.47%, 2.44%, and 0.45% (7.02% and 1.31%) higher (lower) joint probabilities of FIA, LFSC and VLFS (FS and FIA).

3.5.6 Marginal Effects of FI Condition on SNAP Participation

Table 3.9 presents marginal effects of conditional probabilities. Unlike the marginal effects of joint probabilities which focus on two events occurring at the same time, the marginal effects of conditional probabilities concern more about the probability of each FI category when SNAP participation is (or is not) in place. Household income affects FI categories similarly regardless of SNAP participation status. Conditional on non-participation a $10,000 increase in household income increases the probability of FS by 1.64%, and decreases the probability of being FIA by 0.54%; while conditional on participation, the same increase in household income increases the probability of being FS by 1.71% and decreases the probabilities of being LFSC and VLFSC by 0.97% and 0.34%. Considering state policy variables, BBCE and Simplified reporting affect the probabilities conditional on SNAP non-participation and participation in the same direction. BBCE and Simplified reporting affect the probability of FS positively but the probabilities of FIA, LFSC and VLFSC negatively regardless of SNAP participation status. Similar to their effects on joint probabilities above, all four identification variables (WIC, Free food, Out of money, and More money) are negatively associated with the probability of FS but positively associated with the probabilities of FIA, LFSC and VLFSC, conditional on SNAP non-participation and participation.

Turning to parental resources, marginal effects of husband's (wife's) age, working hours, and employment status are not significant conditional on SNAP participation or non-participation, but household's education status and race are significant. Compared with high school educated households, households with less than high school education have 3.69% lower probability of FS, and 1.13% and 2.02% higher probabilities of FIA and LFSC conditional on SNAP non-participation; while conditional on SNAP participation, households with less than high school education are 3.86% less likely to be FS and 0.94% and 2.17% more likely to be FIA and LFSC. For both non-participants and participants, college educated households are more likely to be food secure. Specifically, conditional on SNAP non-participation, college educated households are 6.08% more likely to be FS, and 2.08%, 3.23% and 0.77% less likely to be FIA, LFSC and VLFSC comparing with high school educated household; while conditional on SNAP participation, college educated households are 6.39% more likely to be FS and 1.73%, 3.55% and 1.11% less likely to be FIA, LFSC and VLFSC. Compared with non-Hispanic households, Hispanic households have 4.86% (5.10%) lower probability of FS and 1.47%, 2.67% and 0.72% (1.27%, 2.85% and 0.98%) higher probabilities of FIA, LFSC and VLFSC conditional on SNAP non-participation (participation). Compared with black households, a white household has 5.23% (1.58%) higher (lower) probability of FS (FIA) conditional on SNAP non-participation, and 5.53% (1.28% and 3.21%) higher (lower) probability of FS (FIA and LFSC) conditional on SNAP participation.

3.6 Conclusion

This paper investigates the effects of parental resources and other socio-demographic variable on SNAP participation and FI, and the relationship between SNAP and FI, among HW-C households, using data from the most recent CPS-FSS. FI is used as ordinal outcome variable to measure the severity of food insecure among both adults and children. A simultaneous ordered probability model is developed to address simultaneity between ordinal FI and binary SNAP participation, and estimated by maximum-likelihood.

One of the primary findings is that among food insecurity households, participation in SNAP reduces the probability of FIA, but increases probabilities of LFSC and VLFSC slightly. This result is consistent with previous findings that SNAP participation ameliorates FI among FIA households (Mykerezi and Mills 2010; Yen et al. 2008). Contradictory results of SNAP participation are found among LFSC and VLFSC households. This positive association between SNAP participation and being LFSC or VLFSC, while small in magnitudes, is reasonable when taking into account that households more likely to participate in SNAP are also more likely to be food insecure, and estimates of the simultaneous equation system also justify such impacts of FI on SNAP participation.

This study is the first to evaluate the implication of SNAP participation and FI across parental resource variables and FI categories among HW-C households. Findings can inform policy makers concerned about household food security issues. By calculating marginal effects of explanatory variables for SNAP non-participants and participants, parental resource and socio-demographic variables are found to affect SNAP non-participants and participants differently. For SNAP nonparticipants, husband’s (wife’s) age and working hours are all positively correlated with each FI category and for SNAP participants, these parental variables are negatively correlated with each FI category. Findings from this study also suggest that state policy of BBCE and simplified reporting can encourage SNAP participation and thus lower the probabilities of being FIA, LFSC and VLFSC conditional on SNAP participation.

CHAPTER IV

CONCLUSION

Findings of these two essays can inform clinical professionals and doctors who are concerning mental health issues, and policy makers who are dealing with household food insecurity problems.

Findings from the first essay suggest that the probabilities of depression are higher among low income, less educated, unemployed, and unable individuals, and those who report bad mental health recently, policy makers should pay more attention to individuals with poor living status. In clinical treatment for depression, doctors can recommend mild or moderate depressed patients to take part in physical activity regularly, an effective means known to reduce mild and moderate depressive symptoms. While this research represents one of the first attempts to investigate the role of physical activity in ordinal depression, further studies might consider the use of panel data and investigation of the depression issues among various sub-populations, such as teenagers, minorities, and the disabled. Further, physical activity and other socio-demographic factors are likely to be important for general health besides depression, and interesting insights may emerge with a similar study for general health.

Results from the second essay suggest that SNAP participation can reduce the probability of FIA, but increases probabilities of LFSC and VLFSC slightly among husband-wife households with children. Findings from this study can inform policy makers that for severe food insecure household (LFSC, VLFSC), SNAP is no longer an effective way to help them combat with hunger, other policies aiming at children's food insecurity must be implemented together with SNAP. In addition, parental resource factors are also found to be effective in determining household food insecurity among husband-wife households with children. While this paper represents one of the first attempts to investigate the role of SNAP participation in ordinal FI of adults and children, future studies might consider the use of panel data and investigation of FI and other food assistance programs, such as WIC and informal food assistance programs. Further, SNAP and parental resource factors are likely to be important for diet quality and nutrition, and interesting insights may emerge with a similar study for this field.

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APPENDIX

A.1 Patient Health Questionnaire Eight-Item Depression Measures (PHQ-8)

Over the last 2 weeks, how often (many days) have you been bothered by any of the following problems?	PHQ-8 Score of Each Item			
	Not at all (0–1 day)	Several days (2–6 days)	More than half the days (7–11 days)	Nearly everyday (12–14days)
1. Had little interest or pleasure in doing things	0	1	2	3
2. Felt down, depressed or hopeless	0	1	2	3
3. Had trouble falling asleep or staying asleep or sleeping too much	0	1	2	3
4. Felt tired or had little energy	0	1	2	3
5. Had a poor appetite or eaten too much	0	1	2	3
6. Felt bad about yourself or that you were a failure or had let yourself or your family down	0	1	2	3
7. Had trouble concentrating on things, such as reading the newspaper or watching the TV	0	1	2	3
8. Have moved or spoken so slowly that other people could have noticed or the opposite– being so fidgety or restless that you were moving around a lot more than usual	0	1	2	3

Notes: Classification of PHQ-8 scores is consistent with that in Kroenke et al. (2009) and Dhingra et al. (2011).

A.2 PHQ-8 Scores and the Levels of Depressive Symptoms

Depressive Symptoms	PHQ-8 Total Score (0–24)
No depressive symptoms (PHQ-8 = 0)	0–4
Mild depressive symptoms (PHQ-8 = 1)	5–9
Moderate symptoms (PHQ-8 = 2)	10–14
Moderately severe symptoms (PHQ-8 = 3)	15–19
Severe depressive symptoms (PHQ-8 = 4)	19–24

Notes: Classification of depression categories is consistent with that in Dhingra et al. (2011).

A.3 Delta Method for Standard Errors of Marginal Effects

Assume that a linear model is defined as

$$y = x\beta + u \tag{A.1.1}$$

where β is a vector of coefficients and u is a vector of error terms.

Define $V = A\text{var}(\beta)$ as the asymptotic variance matrix of estimated coefficient β. Since marginal effect θ is a function of coefficient β, it can be noted as

$$\theta = r(\beta) \tag{A.1.2}$$

Let $g(\beta)$ be the of $1 \times k$ gradient of $r(\beta)$, the asymptotic standard deviation of θ can be expressed as

$$se(\theta) = \sqrt{g(\beta)V\,g(\beta)'} \tag{A.1.3}$$

With equation (A.1.3), standard errors of marginal effects θ can be estimated.

B.1 Food Insecurity Survey Module

Notes: The questionnaires below come from the U.S. Department of Agriculture (2012). Responses of "yes," "often," "sometimes," "almost every month," and "some months but not every month" are coded as affirmative. Household food insecurity is measured by the number of affirmative questions for both adults and children.

Household Stage 1: Questions HH2-HH4 (asked of all households; begin scale items).

HH2. Now I'm going to read you several statements that people have made about their food situation. For these statements, please tell me whether the statement was <u>often</u> true, <u>sometimes</u> true, or <u>never</u> true for (you/your household) in the last 12 months—that is, since last (name of current month).

The first statement is "(I/We) worried whether (my/our) food would run out before (I/we) got money to buy more." Was that <u>often</u> true, <u>sometimes</u> true, or <u>never</u> true for (you/your household) in the last 12 months?

- [ ] Often true
- [ ] Sometimes true
- [ ] Never true
- [ ] DK or Refused

HH3. "The food that (I/we) bought just didn't last, and (I/we) didn't have money to get more." Was that <u>often</u>, <u>sometimes</u>, or <u>never</u> true for (you/your household) in the last 12 months?

- [ ] Often true
- [ ] Sometimes true
- [ ] Never true
- [ ] DK or Refused

HH4. "(I/we) couldn't afford to eat balanced meals." Was that <u>often</u>, <u>sometimes</u>, or <u>never</u> true for (you/your household) in the last 12 months?

- [ ] Often true
- [ ] Sometimes true
- [ ] Never true
- [ ] DK or Refused

Adult Stage 2: Questions AD1-AD4 (asked of households passing the screener for Stage 2 adult-referenced questions).

AD1. In the last 12 months, since last (name of current month), did (you/you or other adults in your household) ever cut the size of your meals or skip meals because there wasn't enough money for food?

[ ] Yes
[ ] No (Skip AD1a)
[ ] DK (Skip AD1a)

AD1a. [IF YES ABOVE, ASK] How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?

[ ] Almost every month
[ ] Some months but not every month
[ ] Only 1 or 2 months
[ ] DK

AD2. In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food?

[ ] Yes
[ ] No
[ ] DK

AD3. In the last 12 months, were you every hungry but didn't eat because there wasn't enough money for food?

[ ] Yes
[ ] No
[ ] DK

AD4. In the last 12 months, did you lose weight because there wasn't enough money for food?

[ ] Yes
[ ] No
[ ] DK

Adult Stage 3: Questions AD5-AD5a (asked of households passing screener for Stage 3 adult-referenced questions).

AD5. In the last 12 months, did (you/you or other adults in your household) ever not eat for a whole day because there wasn't enough money for food?

[ ] Yes
[ ] No (Skip AD5a)
[ ] DK (Skip AD5a)

AD5a. [IF YES ABOVE, ASK] How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?

[ ] Almost every month

[ ] Some months but not every month
[ ] Only 1 or 2 months
[ ] DK

Child-Referenced Questions:
Now I'm going to read you several statements that people have made about the food situation of their children. For these statements, please tell me whether the statement was OFTEN true, SOMETIMES true, or NEVER true in the last 12 months for (your child/children living in the household who are under 18 years old).

CH1. "(I/we) relied on only a few kinds of low-cost food to feed (my/our) child/the children) because (I was/we were) running out of money to buy food." Was that <u>often</u>, <u>sometimes</u>, or <u>never</u> true for (you/your household) in the last 12 months?

[ ] Often true
[ ] Sometimes true
[ ] Never true
[ ] DK or Refused

CH2. "(I/We) couldn't feed (my/our) child/the children) a balanced meal, because (I/we) couldn't afford that." Was that <u>often</u>, <u>sometimes</u>, or <u>never</u> true for (you/your household) in the last 12 months?

[ ] Often true
[ ] Sometimes true
[ ] Never true
[ ] DK or Refused

CH3. "(My/Our child was/The children were) not eating enough because (I/we) just couldn't afford enough food." Was that <u>often</u>, <u>sometimes</u>, or <u>never</u> true for (you/your household) in the last 12 months?

[ ] Often true
[ ] Sometimes true
[ ] Never true
[ ] DK or Refused

Child Stage 2: Questions CH4-CH7 (asked of households passing the screener for stage 2 child-referenced questions).

CH4. In the last 12 months, since (current month) of last year, did you ever cut the size of (your child's/any of the children's) meals because there wasn't enough money for food?

[ ] Yes
[ ] No

[ ] DK

CH5. In the last 12 months, did (CHILD'S NAME/any of the children) ever skip meals because there wasn't enough money for food?

[ ] Yes
[ ] No (Skip CH5a)
[ ] DK (Skip CH5a)

CH5a. [IF YES ABOVE ASK] How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?

[ ] Almost every month
[ ] Some months but not every month
[ ] Only 1 or 2 months
[ ] DK

CH6. In the last 12 months, (was your child/were the children) ever hungry but you just couldn't afford more food?

[ ] Yes
[ ] No
[ ] DK

CH7. In the last 12 months, did (your child/any of the children) ever not eat for a whole day because there wasn't enough money for food?

[ ] Yes
[ ] No
[ ] DK

Table 2.1

Definitions and Sample Statistics of Variables in Pooled, Male and Female Samples

Variable	Definitions	Sample Mean		
		Pooled	Male	Female
Dependent Variable				
PHQ-8	Indicator of depression level ranging from 0-4	0.39	0.32	0.43
		(0.82)	(0.76)	(0.86)
Endogenous Variables				
Physical activity	Individual did physical activities more than 10 times during the past 30 days (1=yes, no=0)	0.39	0.38	0.39
Mental health	Self-report to the question " For how many days during the past 30 days was your mental health not good"	3.49	2.93	3.84
		(7.75)	(7.28)	(8.04)
Continuous Explanatory Variables				
Age/10	Age of respondent in years/10	5.44	5.43	5.45
		(1.63)	(1.64)	(1.61)
Income	Annual household income level from 1 to 8	5.61	5.84	5.44
		(2.16)	(2.09)	(2.18)
Children18	Number of children in household under18 years old	0.55	0.53	0.58
		(1.03)	(1.03)	(1.04)
Physical health	Self-report to the question "For how many days during the past 30 days was your physical health not good"	4.31	4.13	4.43
		(8.81)	(8.87)	(8.76)
Binary Explanatory Variables				
Fall	Fall (Reference)	0.25	0.25	0.26
Winter	Winter	0.21	0.21	0.21
Spring	Spring	0.27	0.27	0.26
Summer	Summer	0.27	0.27	0.27
White	Race is White	0.72	0.71	0.72
Black	Race is Black	0.01	0.01	0.01
Hispanic	Race is Hispanic	0.21	0.22	0.21
Other race	Other race (Reference)	0.06	0.06	0.06
Base	Do not have high school diploma	0.08	0.08	0.08
High school	Has a high school diploma or GED (Reference)	0.27	0.28	0.26
Some college	Has some college but do not get a bachelor's degree	0.26	0.24	0.28
Graduate	Has a bachelor's degree or above	0.39	0.40	0.38
Employed	Employed	0.53	0.57	0.51
Unemployed	Unemployed	0.06	0.07	0.05
Retired	Retired	0.26	0.27	0.24
Student	Student	0.02	0.02	0.03
Unable	Unable to work	0.07	0.06	0.07

Table 2.1 Continued

Definitions and Sample Statistics of Variables in Pooled, Male and Female Samples

Homemaker	Homemaker (Reference)	0.06	0.00	0.11
Male	Male	0.42		
Home owner	Home owner	0.78	0.79	0.78
Married	Married	0.54	0.60	0.51
Divorced	Divorced	0.16	0.14	0.18
Widowed	Widowed	0.11	0.06	0.14
Separated	Separated	0.02	0.02	0.02
Single	Single (Reference)	0.16	0.19	0.15

Notes: Sample sizes are 11560 for pooled, 4792 for males and 6762 for females. Standard errors are in parentheses. Income in this study is the annual household income reported as categories from 1 to 8: 1 = less than $10,000, 2= $10,000 to $15,000, 3= $15,000 to $20,000, 4= $20,000 to $25,000, 5= $25,000 to $35,000, 6= $35,000 to $50,000, 7= $50,000 to $75,000 and 8= $75,000 or more.

Table 2.2

AIC and ICOMP Information Criteria for Model Selection

Sample	Treatment Effect Model		Switching Probability Model	
	AIC	ICOMP	AIC	ICOMP
Pooled	29399.9460	29377.8789	29369.1940	29344.6727
Male	11648.7778	11716.1918	11644.7348	11695.0112
Female	17777.0762	17755.2892	17762.5922	17740.0461

Table 2.3

Likelihood Ratio and Wald Tests for Switching Regression Model against Treatment Effect model

Sample	Degree of freedom	Test statistics	
		Likelihood ratio	Wald
Pooled sample	29	88.75***	69.01***
Male sample	28	59.96***	43.30**
Female sample	28	70.48***	53.65***

Notes: Asterisks indicate level of significance: *** = 1%, ** = 5%, * = 10%.

Table 2.4

Maximum-likelihood Estimation of Ordinal PHQ-8 Equation with Binary Endogenous Switching for Male Sample and Female Sample

Variable	Male Sample: Switching: Physical Activity	Male Sample: PHQ-8: Seldom Exerciser	Male Sample: PHQ-8: Regular Exerciser	Female Sample: Switching: Physical Activity	Female Sample: PHQ-8: Seldom Exerciser	Female Sample: PHQ-8: Regular Exerciser
Constant	0.256(0.412)	0.601(0.486)	0.240(0.551)	–0.323(0.185)*	–0.094(0.199)	–0.928(0.306)***
Winter	–0.074(0.055)	–0.020(0.060)	–0.031(0.105)	–0.236(0.047)***	–0.147(0.050)***	–0.132(0.083)
Spring	0.018(0.051)	0.091(0.057)	0.034(0.096)	–0.070(0.043)	–0.045(0.047)	–0.057(0.073)
Summer	0.154(0.051)***	0.157(0.058)***	0.152(0.091)*	0.105(0.042)**	0.077(0.047)	0.012(0.069)
Age/10	0.026(0.073)	–0.026(0.079)	–0.365(0.125)***	0.115(0.065)*	0.177(0.070)**	–0.126(0.109)
Age2/1000	–0.007(0.068)	0.009(0.076)	0.273(0.120)**	–0.117(0.061)*	–0.205(0.066)***	0.017(0.103)
Income	0.005(0.012)	–0.021(0.013)	–0.055(0.020)***	0.012(0.010)	–0.021(0.011)*	–0.045(0.017)***
Children18	–0.025(0.021)	–0.006(0.023)	0.016(0.037)	–0.038(0.018)**	–0.025(0.019)	–0.000(0.029)
White	–0.196(0.078)**	–0.135(0.086)	–0.110(0.125)	–0.021(0.066)	–0.042(0.069)	0.503(0.128)***
Black	–0.060(0.193)	–0.008(0.207)	–0.500(0.386)	–0.056(0.165)	–0.059(0.183)	–0.179(0.360)
Hispanic	–0.195(0.084)**	–0.203(0.092)**	–0.178(0.136)	–0.126(0.071)*	–0.106(0.074)	0.526(0.135)***
Base	–0.070(0.079)	–0.111(0.082)	0.095(0.129)	0.018(0.067)	0.052(0.066)	0.156(0.107)
Some college	0.002(0.052)	–0.046(0.055)	0.067(0.093)	0.166(0.043)***	0.120(0.045)***	0.073(0.073)
Graduate	0.188(0.049)***	–0.006(0.056)	0.024(0.092)	0.263(0.043)***	0.074(0.048)	–0.029(0.076)
Employed	–0.592(0.360)	–0.458(0.434)	–0.711(0.444)	–0.215(0.055)***	–0.186(0.060)***	–0.216(0.090)**
Unemployed	–0.363(0.366)	–0.190(0.439)	–0.393(0.453)	–0.184(0.086)**	0.040(0.089)	0.106(0.131)
Retired	–0.349(0.363)	–0.279(0.438)	–0.583(0.452)	–0.117(0.064)*	–0.129(0.072)*	–0.082(0.108)
Student	–0.460(0.384)	–0.387(0.456)	–1.010(0.500)**	–0.057(0.113)	0.025(0.120)	–0.394(0.185)**
Unable	–0.252(0.368)	0.039(0.440)	–0.084(0.456)	0.036(0.084)	0.327(0.083)***	0.295(0.126)**
Home owner	0.038(0.052)	–0.043(0.055)	–0.016(0.091)	–0.140(0.043)***	–0.155(0.045)***	–0.136(0.067)**
Married	–0.130(0.060)**	–0.185(0.065)***	0.132(0.111)	0.003(0.052)	–0.016(0.055)	–0.088(0.086)
Divorced	0.048(0.070)	0.095(0.075)	0.194(0.122)	0.013(0.058)	0.043(0.061)	0.089(0.096)
Widowed	–0.112(0.101)	–0.046(0.109)	0.209(0.182)	0.077(0.067)	0.041(0.073)	0.087(0.112)
Separated	0.045(0.145)	0.102(0.153)	0.119(0.239)	0.061(0.111)	0.058(0.113)	0.152(0.167)
Physical health	–0.018(0.002)***			–0.022(0.002)***		
Mental health		0.046(0.003)***	0.070(0.006)***		0.054(0.002)***	0.062(0.004)***
$\mu 2$, $\xi 2$		0.529(0.036)***	0.825(0.068)***		0.665(0.033)***	0.853(0.052)***
$\mu 3$, $\xi 3$		0.981(0.065)***	1.409(0.110)***		1.177(0.055)***	1.405(0.082)***
$\mu 4$, $\xi 4$		1.613(0.107)***	1.917(0.150)***		1.791(0.082)***	2.024(0.122)***
$\rho 0$, $\rho 1$		0.901(0.020)***	0.615(0.106)***		0.876(0.020)***	0.618(0.079)***
Log likelihood	–5741.389			–8798.296		

Notes: Asymptotic standard errors are in parentheses. Asterisks indicate level of significance: *** = 1%, ** = 5%, *= 10%.

Table 2.5

Average Treatment Effects of Physical Activity on Probabilities of PHQ-8

	Average Treatment Effects (ATE)	
Depressive symptoms (PHQ-8)	Male	Female
No depressive symptoms (PHQ-8=0)	2.58 (0.99)***	4.10 (0.93)***
Mild depressive symptoms (PHQ-8=1)	–1.41 (0.94)	–2.34 (0.89)***
Moderate symptoms (PHQ-8=2)	–0.87 (0.52)*	–1.00 (0.50)**
Moderately severe symptoms (PHQ-8=3)	–0.83 (0.37)**	–0.56 (0.38)
Severe depressive symptoms (PHQ-8=4)	0.54 (0.30)*	–0.20 (0.30)

Notes: All effects of probability are multiplied by 100. Asymptotic standard errors are in parentheses. Asterisks indicate the level of significance: *** = 1%, ** = 5%, * = 10%.

Table 2.6

Marginal Effects of Explanatory Variables on the Probability of PHQ-8 Categories by Physical Activity of Male Sample

	Conditioned on Physical Activity = 0 (Seldom Exerciser)					Conditional on Physical Activity = 1 (Regular Exerciser)				
Variable	PHQ-8 = 0	PHQ-8 = 1	PHQ-8 = 2	PHQ-8 = 3	PHQ-8 = 4	PHQ-8 = 0	PHQ-8 = 1	PHQ-8 = 2	PHQ-8 = 3	PHQ-8 = 4
Continuous explanatory variables										
Age/10	0.99 (0.59)*	–0.58 (0.36)	–0.24 (0.14)*	–0.11 (0.06)*	–0.07 (0.04)*	1.88 (0.74)**	–1.09 (0.46)**	–0.37 (0.15)**	–0.18 (0.07)**	–0.24 (0.09)***
Income	0.84 (0.37)**	–0.50 (0.22)**	–0.20 (0.09)**	–0.09 (0.04)**	–0.06 (0.03)**	1.21 (0.42)***	–0.75 (0.26)***	–0.22 (0.08)***	–0.10 (0.04)**	–0.14 (0.05)***
Children18	–0.35 (0.65)	0.21 (0.38)	0.09 (0.15)	0.03 (0.07)	0.02 (0.04)	–0.56 (0.76)	0.35 (0.47)	0.10 (0.14)	0.05 (0.06)	0.06 (0.09)
Physical health	–0.40 (0.05)***	0.24 (0.03)***	0.10 (0.01)***	0.04 (0.01)***	0.03 (0.00)***	–0.15 (0.04)***	0.09 (0.02)***	0.03 (0.01)***	0.01 (0.00)***	0.02 (0.00)***
Mental health	–1.63 (0.08)***	0.97 (0.06)***	0.38 (0.03)***	0.17 (0.02)***	0.11 (0.01)***	–1.49 (0.08)***	0.93 (0.07)***	0.27 (0.03)***	0.12 (0.02)***	0.17 (0.02)***
Binary explanatory variables										
Winter	–0.95 (1.75)	0.55 (1.03)	0.25 (0.42)	0.09 (0.19)	0.06 (0.12)	0.04 (2.17)	–0.03 (1.35)	–0.01 (0.39)	–0.00 (0.18)	–0.00 (0.25)
Spring	–2.89 (1.69)*	1.70 (0.99)*	0.68 (0.41)*	0.31 (0.19)*	0.20 (0.12)*	–0.59 (2.03)	0.37 (1.26)	0.11 (0.37)	0.05 (0.17)	0.07 (0.23)
Summer	–2.12 (1.73)	1.28 (1.02)	0.45 (0.41)	0.25 (0.19)	0.15 (0.12)	–2.02 (1.98)	1.24 (1.23)	0.38 (0.37)	0.17 (0.17)	0.23 (0.23)
White	0.35 (2.47)	–0.23 (1.48)	–0.03 (0.57)	–0.06 (0.26)	–0.03 (0.17)	0.75 (2.61)	–0.46 (1.62)	–0.15 (0.48)	–0.06 (0.22)	–0.08 (0.30)
Black	–1.05 (6.01)	0.61 (3.49)	0.27 (1.45)	0.11 (0.65)	0.07 (0.41)	7.89 (4.69)*	–4.92 (2.89)*	–1.39 (0.85)	–0.70 (0.47)	–0.88 (0.52)*
Hispanic	2.76 (2.44)	–1.66 (1.45)	–0.59 (0.56)	–0.32 (0.26)	–0.19 (0.17)	2.08 (2.64)	–1.29 (1.64)	–0.39 (0.47)	–0.17 (0.23)	–0.24 (0.31)
Base	2.26 (2.16)	–1.36 (1.30)	–0.50 (0.49)	–0.25 (0.23)	–0.15 (0.15)	–2.76 (2.96)	1.71 (1.83)	0.50 (0.56)	0.23 (0.25)	0.32 (0.34)
Some college	1.64 (1.51)	–0.98 (0.90)	–0.38 (0.35)	–0.17 (0.16)	–0.11 (0.10)	–1.43 (1.99)	0.88 (1.23)	0.26 (0.36)	0.12 (0.17)	0.16 (0.23)
Graduate	4.45 (1.52)***	–2.67 (0.93)***	–1.06 (0.35)***	–0.43 (0.17)***	–0.29 (0.10)***	1.01 (1.87)	–0.64 (1.17)	–0.17 (0.34)	–0.09 (0.16)	–0.12 (0.21)
Employed	2.90 (12.80)	–1.74 (7.80)	–0.52 (2.93)	–0.41 (1.33)	–0.23 (0.75)	11.06 (10.47)	–6.64 (5.97)	–2.24 (2.33)	–1.01 (1.10)	–1.17 (1.12)
Unemployed	–1.00 (12.75)	0.49 (7.22)	0.37 (3.21)	0.08 (1.47)	0.07 (0.86)	4.67 (7.41)	–2.88 (4.55)	–0.84 (1.30)	–0.40 (0.67)	–0.54 (0.90)
Retired	2.20 (11.95)	–1.34 (7.13)	–0.42 (2.76)	–0.28 (1.28)	–0.15 (0.78)	8.77 (8.01)	–5.45 (4.87)	–1.62 (1.57)	–0.76 (0.76)	–0.95 (0.85)
Student	3.67 (11.10)	–2.24 (6.60)	–0.73 (2.57)	–0.46 (1.23)	–0.25 (0.71)	11.60 (4.23)***	–7.12 (2.45)***	–2.11 (0.91)**	–1.10 (0.52)**	–1.28 (0.47)***
Unable	–7.40 (15.16)	3.95 (7.73)	2.08 (4.43)	0.87 (2.03)	0.50 (1.00)	–0.39 (9.62)	0.26 (6.01)	0.05 (1.73)	0.03 (0.80)	0.04 (1.09)
Home owner	2.45 (1.64)	–1.44 (0.96)	–0.59 (0.40)	–0.25 (0.18)	–0.16 (0.11)	0.66 (1.92)	–0.41 (1.19)	–0.12 (0.35)	–0.06 (0.16)	–0.08 (0.22)
Married	3.69 (1.89)*	–2.23 (1.14)*	–0.82 (0.44)*	–0.40 (0.20)**	–0.24 (0.12)**	–3.80 (2.22)*	2.34 (1.35)*	0.68 (0.42)	0.32 (0.20)	0.46 (0.28)*
Divorced	–2.35 (2.25)	1.39 (1.32)	0.54 (0.54)	0.26 (0.24)	0.16 (0.15)	–3.99 (2.88)	2.45 (1.76)	0.75 (0.56)	0.34 (0.25)	0.46 (0.33)
Widowed	–0.83 (3.16)	0.47 (1.84)	0.23 (0.77)	0.08 (0.35)	0.05 (0.21)	–6.06 (4.71)	3.72 (2.83)	1.13 (0.94)	0.50 (0.41)	0.71 (0.56)
Separated	–2.73 (4.69)	1.60 (2.69)	0.64 (1.16)	0.30 (0.52)	0.19 (0.32)	–2.26 (5.45)	1.40 (3.34)	0.42 (1.02)	0.19 (0.46)	0.26 (0.63)

Notes: All effects on probabilities are multiplied by 100. Asymptotic standard errors are in parentheses. Asterisks indicate level of significance: *** = 1%, ** = 5%, * = 10%.

Table 2.7

Marginal Effects of Explanatory Variables on the Probability of PHQ-8 Categories by Physical Activity of Female Sample

	Conditioned on Physical Activity = 0 (Seldom Exerciser)					Conditional on Physical Activity = 1 (Regular Exerciser)				
Variable	PHQ-8 = 0	PHQ-8 = 1	PHQ-8 = 2	PHQ-8 = 3	PHQ-8 = 4	PHQ-8 = 0	PHQ-8 = 1	PHQ-8 = 2	PHQ-8 = 3	PHQ-8 = 4
Continuous explanatory variables										
Age/10	1.37 (0.52)***	–0.89 (0.32)***	–0.27 (0.11)**	–0.11 (0.05)**	–0.09 (0.05)**	2.69 (0.67)***	–1.52 (0.40)***	–0.53 (0.14)***	–0.33 (0.09)***	–0.30 (0.08)***
Income	1.04 (0.33)***	–0.62 (0.20)***	–0.23 (0.07)***	–0.10 (0.03)***	–0.09 (0.03)***	1.26 (0.41)***	–0.73 (0.24)***	–0.25 (0.08)***	–0.15 (0.05)***	–0.14 (0.05)***
Children18	0.10 (0.58)	–0.06 (0.35)	–0.01 (0.13)	–0.01 (0.06)	–0.01 (0.05)	–0.37 (0.72)	0.22 (0.42)	0.07 (0.14)	0.04 (0.09)	0.04 (0.08)
Physical health	–0.49 (0.04)***	0.29 (0.03)***	0.11 (0.01)***	0.05 (0.01)***	0.04 (0.00)***	–0.23 (0.04)***	0.13 (0.02)***	0.04 (0.01)***	0.03 (0.01)***	0.02 (0.01)***
Mental health	–2.06 (0.06)***	1.22 (0.06)***	0.44 (0.03)***	0.21 (0.02)***	0.18 (0.01)***	–1.60 (0.07)***	0.92 (0.06)***	0.31 (0.03)***	0.19 (0.02)***	0.17 (0.02)***
Binary explanatory variables										
Winter	0.41 (1.53)	–0.27 (0.90)	–0.01 (0.34)	–0.07 (0.16)	–0.05 (0.14)	0.88 (2.02)	–0.50 (1.18)	–0.19 (0.39)	–0.11 (0.24)	–0.09 (0.21)
Spring	0.16 (1.47)	–0.10 (0.87)	–0.01 (0.32)	–0.02 (0.15)	–0.02 (0.13)	0.73 (1.80)	–0.42 (1.04)	–0.15 (0.35)	–0.09 (0.21)	–0.08 (0.19)
Summer	–0.57 (1.49)	0.35 (0.89)	0.09 (0.32)	0.07 (0.15)	0.06 (0.13)	0.76 (1.69)	–0.45 (0.98)	–0.14 (0.33)	–0.09 (0.20)	–0.08 (0.18)
White	1.12 (2.20)	–0.67 (1.31)	–0.24 (0.48)	–0.11 (0.22)	–0.10 (0.20)	–11.71 (2.51)***	6.53 (1.31)***	2.34 (0.57)***	1.49 (0.40)***	1.35 (0.36)***
Black	0.99 (5.56)	–0.59 (3.33)	–0.20 (1.18)	–0.11 (0.56)	–0.09 (0.49)	3.76 (7.94)	–2.21 (4.73)	–0.72 (1.49)	–0.44 (0.93)	–0.39 (0.79)
Hispanic	1.21 (2.27)	–0.73 (1.35)	–0.22 (0.49)	–0.14 (0.23)	–0.12 (0.20)	–16.91 (4.20)***	9.36 (2.13)***	3.53 (1.02)***	2.09 (0.64)***	1.93 (0.57)***
Base	–1.57 (2.15)	0.93 (1.26)	0.34 (0.48)	0.16 (0.22)	0.14 (0.19)	–4.01 (2.91)	2.29 (1.65)	0.80 (0.60)	0.48 (0.36)	0.44 (0.32)
Some college	–0.85 (1.43)	0.52 (0.85)	0.14 (0.31)	0.11 (0.14)	0.09 (0.13)	–0.18 (1.80)	0.09 (1.04)	0.05 (0.35)	0.02 (0.21)	0.02 (0.19)
Graduate	3.12 (1.46)**	–1.85 (0.89)**	–0.73 (0.31)**	–0.27 (0.14)*	–0.26 (0.13)**	3.36 (1.83)*	–1.99 (1.08)*	–0.63 (0.36)*	–0.39 (0.22)*	–0.34 (0.19)*
Employed	2.27 (1.90)	–1.36 (1.14)	–0.43 (0.41)	–0.26 (0.19)	–0.22 (0.17)	3.35 (2.26)	–1.92 (1.31)	–0.67 (0.45)	–0.40 (0.28)	–0.35 (0.24)
Unemployed	–5.70 (3.02)*	3.18 (1.64)*	1.42 (0.77)*	0.59 (0.34)*	0.51 (0.29)*	–4.99 (3.69)	2.87 (2.08)	0.98 (0.76)	0.59 (0.45)	0.55 (0.42)
Retired	2.27 (2.18)	–1.37 (1.31)	–0.45 (0.46)	–0.24 (0.22)	–0.21 (0.19)	0.87 (2.67)	–0.50 (1.56)	–0.18 (0.52)	–0.10 (0.31)	–0.09 (0.28)
Student	–2.24 (3.85)	1.30 (2.22)	0.52 (0.88)	0.22 (0.40)	0.20 (0.35)	8.14 (3.33)**	–4.83 (2.02)**	–1.54 (0.64)**	–0.96 (0.41)**	–0.81 (0.32)**
Unable	–13.06 (3.19)***	7.12 (1.55)***	3.31 (0.96)***	1.46 (0.43)***	1.18 (0.30)***	–7.98 (3.81)**	4.49 (2.08)**	1.65 (0.84)*	0.99 (0.51)*	0.85 (0.42)**
Home owner	2.81 (1.49)*	–1.68 (0.88)*	–0.57 (0.33)*	–0.30 (0.15)**	–0.26 (0.13)**	2.11 (1.74)	–1.21 (1.01)	–0.43 (0.35)	–0.25 (0.21)	–0.22 (0.18)
Married	0.68 (1.73)	–0.40 (1.03)	–0.15 (0.37)	–0.07 (0.17)	–0.06 (0.15)	2.30 (2.16)	–1.34 (1.26)	–0.45 (0.42)	–0.27 (0.26)	–0.24 (0.22)
Divorced	–1.37 (1.94)	0.81 (1.14)	0.30 (0.43)	0.14 (0.20)	0.12 (0.17)	–2.20 (2.49)	1.27 (1.43)	0.43 (0.50)	0.26 (0.30)	0.24 (0.27)
Widowed	0.17 (2.28)	–0.10 (1.36)	–0.06 (0.48)	–0.01 (0.23)	–0.01 (0.20)	–1.45 (2.87)	0.83 (1.64)	0.29 (0.57)	0.17 (0.34)	0.16 (0.32)
Separated	–0.84 (3.65)	0.50 (2.16)	0.16 (0.80)	0.09 (0.36)	0.08 (0.33)	–3.43 (4.53)	1.95 (2.55)	0.69 (0.92)	0.41 (0.55)	0.38 (0.51)

Notes: All effects on probabilities are multiplied by 100. Asymptotic standard errors are in parentheses. Asterisks indicate level of significance: *** = 1%, ** = 5%, *=10%.

Table 3.1

Definition and Sample Statistics of Variables

Variable	Definitions	Mean	SD
FI	Household food insecurity category (0–3)	0.59	0.84
SNAP	Any member in the household got SNAP in the past 12 months	0.46	0.50
Age (H)	Age of husband	36.33	8.40
Age (W)	Age of wife	33.48	7.19
Work hours (H)	Husband's actual working hours per week	27.38	20.58
Work hours (W)	Wife's actual working hours per week	12.07	17.65
Income	Household income in 10000 dollars	2.05	0.97
HH size	Number of persons living in household	4.89	1.57
Children	Number of children < 18 years of age	2.48	1.28
Short 1	Proportion of SNAP units in state with earnings and with 1-6 month recertification periods	0.50	0.44
Short 2	Proportion of SNAP units in state without earnings and with 1-6 month recertification periods	0.40	0.33
Binary explanatory variables (yes = 1, no = 0)			
Year 2011	Data collected in year 2011	0.56	
< High school	Reference person has < school education	0.30	
High school	Reference person is high school graduate (reference)	0.36	
Some college	Reference person attended college (no degree)	0.17	
College	Reference person has college education or higher	0.18	
Employed (H)	Husband is employed	0.73	
Unemployed (H)	Husband is unemployed	0.15	
Not in labor force (H)	Husband is not in labor force (reference)	0.12	
Employed (W)	Wife is employed	0.39	
Unemployed (W)	Wife is unemployed	0.09	
Not in labor force (W)	Wife is not in labor force (reference)	0.52	
Hispanic	Reference person is Hispanic	0.39	
White	Reference person is white	0.82	
Black	Reference person is black (reference)	0.09	
Other race	Reference person is of other race	0.09	
MSA	Reference person resides in Metropolitan Statistical Area	0.76	
South	Reference person resides in South	0.34	
Northeast	Reference person resides in Northwest	0.12	
West	Reference person resides in West (reference)	0.34	
Midwest	Reference person resides in Midwest	0.20	
BBCE	State uses BBCE categorical eligibility for SNAP	0.63	
Vehicle test	State excludes at least one, but not all, vehicles in the household from the SNAP asset test	0.08	

Table 3.1 Continued

Definition and Sample Statistics of Variables

Report simplified	For households with earnings, the State uses simplified reporting option for SNAP participants to report changes	0.85	
Short of money	Run short of money in past 12 months and tried to make food money go further	0.53	
More money	Need to spend more money to buy enough food to meet needs than you do now	0.31	
WIC	Any member of household get food through the WIC program during past 30 days	0.32	
Free food	Any children in household received free/reduced cost food in past 30 days	0.12	
Sample size			1826

Table 3.2

Classification of Household Food Insecurity

Food Insecurity Category	Classification Criteria
FI = 0 (Food Secure)	with < 3 affirmative responses
FI = 1 (Food Insecure among Adults only)	with ≥ 3 affirmative responses, with < 2 children-specific responses
FI = 2 (Low Food Insecurity among Children)	with ≥ 3 affirmative responses, with 2–4 children-specific responses
FI = 3 (Very Low Food Insecurity among Children)	with ≥ 3 affirmative responses, with ≥ 5 children-specific responses

Table 3.3

Frequency Distribution of SNAP Participation and FI categories

	Household Food Insecurity (FI)				
SNAP Participation	FS	FIA	LFSC	VLFSC	Total
Participants	419	219	168	27	833
Nonparticipants	710	137	130	16	993
Total	1129	356	298	43	1826
Ratio of participants	37%	62%	56%	63%	46%

Table 3.4

AIC and ICOMP Information Criteria for Model Selection

Model	AIC	ICOMP
Simultaneous Equation System	5149.981	5171.908
Recursive System	5246.944	5247.055
Treatment Effect Model	5251.427	5228.780

Table 3.5

ML Estimates of SEQ Model

Variable	SNAP Participation	Food Insecure
Latent variables		
SNAP		–0.759 (0.174)***
FI	0.687 (0.230)***	
Other explanatory variables		
BBCE	0.199 (0.074)***	
Vehicle test	0.132 (0.136)	
Short 1	–0.070 (0.308)	
Short 2	–0.116 (0.413)	
Report simplified	0.230 (0.114)**	
Short of money		1.114 (0.162)***
More money		0.608 (0.101)***
WIC		0.132 (0.064)**
Free food		0.211 (0.087)**
Year 2011	0.023 (0.071)	0.172 (0.063)***
Age / 10 (H)	–0.162 (0.065)**	–0.061 (0.068)
Age / 10 (W)	–0.233 (0.076)***	–0.100 (0.090)
< High school	–0.125 (0.087)	0.019 (0.089)
Some college	–0.080 (0.097)	–0.171 (0.096)*
College	–0.170 (0.100)*	–0.350 (0.094)***
Employed (H)	0.099 (0.150)	0.212 (0.141)
Unemployed (H)	0.421 (0.132)***	0.383 (0.137)***
Employed (W)	0.030 (0.139)	0.133 (0.120)
Unemployed (W)	0.196 (0.121)	0.246 (0.110)**
Work hours / 10 (H)	–0.087 (0.028)***	–0.113 (0.027)***
Work hours / 10 (W)	–0.087 (0.040)**	–0.092 (0.036)***
Income	–0.219 (0.038)***	–0.237 (0.046)***
HH size	0.119 (0.038)***	0.078 (0.040)**
Children	0.050 (0.044)	0.080 (0.037)**
Hispanic	–0.305 (0.081)***	–0.091 (0.107)
White	0.034 (0.122)	–0.147 (0.131)
Other race	0.089 (0.158)	0.116 (0.154)
MSA	–0.216 (0.085)**	–0.147 (0.089)*
South	0.127 (0.094)	0.146 (0.084)*
Northeast	0.098 (0.121)	0.194 (0.118)*
Midwest	0.131 (0.109)	0.046 (0.105)
Constant	1.320 (0.276)***	–0.427 (0.542)

Table 3.5 Continued

ML Estimates of SEQ Model

ξ1		0.461 (0.151)***
ξ2		1.252 (0.405)***
ρ		0.493 (0.210)**
Log likelihood	–2514.9906	

Notes: Asymptotic standard errors in parentheses. Asterisks indicate level of significance: *** = 1%, ** = 5%, * = 10%.

Table 3.6

Average Treatment Effects of SNAP on Probabilities of Food Insecurity (Conditional on FI > 0)

Food insecure category	ATE
Food insecurity among adults (FIA, FI = 1)	–0.042 (0.014)***
Low food security among children (LFSC, FI = 2)	0.030 (0.010)***
Very low food security among children (VLFSC, FI = 3)	0.012 (0.004)***

Notes: Asymptotic standard errors are in parentheses. Asterisks indicate the level of significance: *** = 1%, ** = 5%, * = 10%.

Table 3.7

Average Marginal Effects of Explanatory Variables on the Probability of SNAP Participation

Variable	Probability of SNAP participation				
	Conditional on FI = 0	Conditional on FI = 1	Conditional on FI = 2	Conditional on FI = 3	Unconditional
Continuous explanatory variables					
Age / 10 (H)	–5.340 (1.579)***	–4.818 (0.503)***	–1.534 (0.858)*	0.138 (0.226)	–4.443 (2.038)**
Age / 10 (W)	–7.720 (2.007)***	–7.319 (0.637)***	–2.684 (1.091)**	0.013 (0.290)	–6.595 (2.417)***
Work hours / 10 (H)	–2.976 (0.818)***	–4.961 (0.257)***	–3.859 (0.445)***	–1.129 (0.121)***	–3.583 (0.833)***
Work hours / 10 (W)	–2.949 (0.974)***	–4.340 (0.305)***	–3.064 (0.530)***	–0.813 (0.140)***	–3.270 (1.200)***
Income	–7.444 (0.997)***	–11.108 (0.310)***	–7.935 (0.547)***	–2.133 (0.148)***	–8.330 (1.133)***
HH size	3.974 (0.962)***	4.520 (0.304)***	2.375 (0.522)***	0.392 (0.137)***	3.761 (1.133)***
Children	1.727 (1.125)	3.297 (0.355)***	2.791 (0.612)***	0.876 (0.161)***	2.283 (1.313)*
Short 1	–2.277 (7.619)	–1.306 (2.382)	0.334 (4.143)	0.455 (1.095)	–1.531 (6.732)
Short 2	–3.759 (10.255)	–2.157 (3.203)	0.551 (5.579)	0.752 (1.475)	–2.527 (9.019)
Binary explanatory variables					
Year 2011	1.028 (1.825)	5.541 (0.591)***	6.363 (0.991)***	2.402 (0.275)***	3.085 (2.167)
< High school	–4.015 (2.201)*	–1.888 (0.666)***	1.253 (1.216)	1.103 (0.337)***	–2.424 (2.756)
Some college	–2.893 (2.594)	–6.547 (0.875)***	–5.964 (1.383)***	–1.957 (0.346)***	–4.279 (3.067)
College	–6.321 (2.671)**	–13.520 (0.971)***	–11.856 (1.411)***	–3.750 (0.328)***	–8.877 (2.988)***
Employed (H)	3.462 (4.046)	7.873 (1.317)***	7.275 (2.173)***	2.437 (0.566)***	5.203 (4.375)
Unemployed (H)	14.702 (3.357)***	19.515 (1.038)***	12.628 (1.828)***	3.035 (0.492)***	15.318 (4.275)***
Employed (W)	1.139 (3.540)	4.449 (1.077)***	4.884 (1.932)**	1.818 (0.540)***	2.642 (4.199)
Unemployed (W)	6.713 (3.088)**	11.085 (0.909)***	8.612 (1.698)***	2.528 (0.486)***	8.050 (3.824)**
Hispanic	–10.021 (2.200)***	–8.704 (0.674)***	–2.224 (1.224)*	0.587 (0.333)*	–8.047 (2.565)***
White	1.022 (3.216)	–3.511 (0.911)***	–5.784 (1.784)***	–2.547 (0.547)***	–1.459 (4.091)
Other race	3.040 (3.861)	5.109 (1.176)***	4.009 (2.109)*	1.185 (0.578)**	3.687 (5.196)
MSA	–7.358 (2.142)***	–8.387 (0.686)***	–4.473 (1.159)***	–0.771 (0.299)***	–6.998 (2.675)***
South	4.343 (2.462)*	6.714 (0.764)***	4.944 (1.342)***	1.373 (0.358)***	4.976 (2.815)*
Northeast	3.356 (3.387)	7.599 (0.973)***	7.087 (1.872)***	2.408 (0.552)***	5.075 (3.865)
Midwest	4.346 (2.924)	3.715 (0.962)***	1.028 (1.573)	–0.183 (0.392)	3.548 (3.250)
BBCE	6.427 (1.949)***	3.887 (0.588)***	–0.797 (1.072)	–1.275 (0.323)***	4.339 (2.061)**
Vehicle test	4.328 (3.299)	2.215 (1.135)*	–0.803 (1.758)	–0.872 (0.414)**	2.898 (3.101)
Report simplified	7.385 (3.076)**	4.942 (0.835)***	–0.622 (1.720)	–1.457 (0.552)***	5.004 (2.836)*
Out of money	5.402 (1.985)***	45.678 (1.058)***	44.701 (1.341)***	13.358 (0.506)***	17.339 (1.773)***
More money	0.056 (1.964)	19.385 (0.758)***	25.528 (1.201)***	9.763 (0.479)***	9.270 (1.193)***
WIC	0.163 (1.863)	3.895 (0.572)***	5.028 (1.018)***	2.007 (0.296)***	1.981 (0.945)**
Free food	0.069 (2.528)	5.956 (0.682)***	8.156 (1.416)***	3.406 (0.476)***	3.170 (1.262)**

Notes: All effects on probabilities are multiplied by 100. Asymptotic standard errors are in parentheses. Asterisks indicate level of significance: *** = 1%, ** = 5%, * = 10%.

Table 3.8

Marginal Effects of Explanatory Variables on the Joint Probability of SNAP and FI

	SNAP = 0 and				SNAP = 1 and			
Variable	FI = 0	FI = 1	FI = 2	FI = 3	FI = 0	FI = 1	FI = 2	FI = 3
Continuous explanatory variables								
Age / 10 (H)	1.79 (1.51)	1.25 (0.50)**	1.19 (0.51)**	0.22 (0.11)**	–3.70 (1.47)**	–0.73 (0.43)*	–0.14 (0.59)	0.12 (0.19)
Age / 10 (W)	2.89 (1.87)	1.77 (0.60)***	1.65 (0.62)***	0.29 (0.13)**	–5.25 (1.73)***	–1.12 (0.52)**	–0.34 (0.75)	0.12 (0.25)
Work hours/10 (H)	2.94 (0.67)***	0.43 (0.23)*	0.21 (0.24)	0.00 (0.05)	–1.49 (0.65)**	–0.83 (0.18)***	–1.01 (0.29)***	–0.26 (0.11)**
Work hours/10 (W)	2.42 (0.86)***	0.49 (0.31)	0.32 (0.32)	0.03 (0.06)	–1.62 (0.91)*	–0.71 (0.25)***	–0.77 (0.34)**	–0.17 (0.12)
Income	6.25 (0.88)***	1.23 (0.29)***	0.78 (0.30)***	0.07 (0.06)	–4.05 (0.83)***	–1.83 (0.26)***	–2.00 (0.37)***	–0.46 (0.13)***
HH size	–2.13 (0.83)**	–0.82 (0.30)***	–0.70 (0.31)**	–0.11 (0.06)*	2.52 (0.86)***	0.72 (0.24)***	0.49 (0.33)	0.04 (0.11)
Children	–2.07 (0.95)**	–0.20 (0.35)	–0.04 (0.36)	0.02 (0.07)	0.76 (1.02)	0.56 (0.27)**	0.76 (0.38)**	0.21 (0.13)
Short 1	0.12 (0.73)	0.62 (2.72)	0.66 (2.87)	0.13 (0.57)	–1.76 (7.74)	–0.17 (0.77)	0.25 (1.11)	0.16 (0.69)
Short 2	0.20 (1.06)	1.03 (3.66)	1.08 (3.86)	0.22 (0.77)	–2.91 (10.38)	–0.29 (1.03)	0.41 (1.51)	0.26 (0.94)
Binary explanatory variables								
Year 2011	–4.29 (1.64)***	0.31 (0.56)	0.70 (0.57)	0.20 (0.12)*	–0.45 (1.62)	1.00 (0.46)**	1.91 (0.65)***	0.63 (0.24)***
< High school	–0.32 (2.07)	1.17 (0.69)*	1.31 (0.72)*	0.27 (0.15)*	–3.21 (1.91)*	–0.23 (0.59)	0.66 (0.83)	0.37 (0.29)
Some college	4.41 (2.50)*	0.16 (0.76)	–0.19 (0.78)	–0.10 (0.15)	–1.01 (2.18)	–1.13 (0.67)*	–1.67 (0.93)*	–0.47 (0.29)
College	9.11 (2.48)***	0.34 (0.82)	–0.38 (0.83)	–0.18 (0.15)	–2.42 (2.24)	–2.33 (0.66)***	–3.27 (0.88)***	–0.86 (0.27)***
Employed (H)	–5.36 (3.52)	–0.19 (1.18)	0.23 (1.21)	0.11 (0.24)	1.21 (3.32)	1.35 (0.92)	2.04 (1.38)	0.60 (0.49)
Unemployed (H)	–10.49 (3.11)***	–2.64 (0.96)***	–1.93 (0.90)**	–0.25 (0.18)	8.51 (3.30)***	3.17 (0.93)***	3.03 (1.41)**	0.61 (0.50)
Employed (W)	–3.31 (3.05)	0.12 (1.09)	0.42 (1.13)	0.13 (0.24)	–0.07 (3.18)	0.79 (0.87)	1.45 (1.25)	0.48 (0.46)
Unemployed (W)	–6.37 (2.75)**	–1.06 (0.91)	–0.59 (0.91)	–0.03 (0.19)	3.35 (2.87)	1.84 (0.81)**	2.26 (1.22)*	0.59 (0.45)
Hispanic	2.68 (2.00)	2.47 (0.66)***	2.44 (0.71)***	0.45 (0.16)***	–7.02 (1.79)***	–1.31 (0.56)**	–0.04 (0.81)	0.33 (0.28)
White	3.60 (3.17)	–0.71 (0.93)	–1.13 (0.99)	–0.30 (0.23)	1.82 (2.59)	–0.67 (0.91)	–1.88 (1.35)	–0.73 (0.50)
Other race	–3.00 (3.91)	–0.45 (1.17)	–0.23 (1.16)	–0.00 (0.24)	1.50 (3.54)	0.85 (1.12)	1.06 (1.59)	0.27 (0.54)
MSA	4.12 (1.97)**	1.47 (0.65)**	1.22 (0.64)*	0.19 (0.13)	–4.64 (2.04)**	–1.33 (0.56)**	–0.93 (0.80)	–0.10 (0.27)
South	–3.83 (2.04)*	–0.70 (0.75)	–0.42 (0.77)	–0.03 (0.16)	2.30 (2.21)	1.11 (0.58)*	1.26 (0.86)	0.30 (0.30)
Northeast	–4.91 (2.94)*	–0.33 (0.94)	0.08 (1.00)	0.09 (0.22)	1.16 (2.80)	1.30 (0.84)	2.00 (1.32)	0.61 (0.50)
Midwest	–1.42 (2.41)	–1.01 (0.87)	–0.95 (0.86)	–0.17 (0.17)	3.06 (2.65)	0.55 (0.67)	0.05 (1.01)	–0.11 (0.34)
BBCE	–0.26 (1.39)	–1.77 (0.63)***	–1.91 (0.69)***	–0.40 (0.16)**	4.93 (1.71)***	0.53 (0.41)	–0.66 (0.58)	–0.46 (0.24)*
Vehicle test	–0.36 (1.05)	–1.15 (1.15)	–1.17 (1.12)	–0.22 (0.20)	3.42 (3.59)	0.27 (0.34)	–0.51 (0.66)	–0.29 (0.29)
Report simplified	–0.09 (1.60)	–2.09 (1.02)**	–2.33 (1.22)*	–0.50 (0.29)*	5.54 (2.55)**	0.71 (0.56)	–0.70 (0.71)	–0.55 (0.36)
Out of money	–31.66 (1.78)***	5.62 (0.60)***	7.52 (0.64)***	1.18 (0.21)***	–7.17 (1.36)***	9.47 (0.69)***	12.55 (0.88)***	2.49 (0.38)***
More money	–15.82 (1.53)***	1.85 (0.30)***	3.80 (0.47)***	0.90 (0.17)***	–4.93 (0.77)***	3.76 (0.48)***	8.04 (0.88)***	2.40 (0.40)***
WIC	–3.27 (1.53)**	0.39 (0.18)**	0.71 (0.34)**	0.19 (0.10)*	–0.83 (0.41)**	0.72 (0.34)**	1.56 (0.74)**	0.54 (0.27)**
Free food	–5.19 (2.00)***	0.56 (0.20)***	1.13 (0.44)**	0.33 (0.15)**	–1.43 (0.63)**	1.08 (0.41)***	2.56 (1.03)**	0.96 (0.43)**

Notes: All effects on probabilities are multiplied by 100. Asymptotic standard errors in parentheses. Asterisks indicate level of significance: *** = 1%, ** = 5%, * = 10%.

Table 3.9

Marginal Effects of Explanatory Variables on the Conditional Probability of SNAP Participation

	Conditional on SNAP = 0				Conditional on SNAP = 1			
Variable	FI = 0	FI = 1	FI = 2	FI = 3	FI = 0	FI = 1	FI = 2	FI = 3
Continuous explanatory variables								
Age / 10 (H)	–2.19 (1.58)	0.68 (0.50)	1.20 (0.86)	0.32 (0.23)	–2.30 (1.66)	0.59 (0.42)	1.28 (0.93)	0.43 (0.32)
Age / 10 (W)	–2.79 (2.01)	0.86 (0.64)	1.53 (1.09)	0.41 (0.29)	–2.93 (2.11)	0.76 (0.53)	1.63 (1.18)	0.55 (0.41)
Work hours/10 (H)	1.22 (0.82)	–0.39 (0.26)	–0.65 (0.45)	–0.17 (0.12)	1.27 (0.86)	–0.31 (0.22)	–0.71 (0.48)	–0.25 (0.17)
Work hours/10 (W)	0.59 (0.97)	–0.19 (0.31)	–0.31 (0.53)	–0.08 (0.14)	0.61 (1.02)	–0.14 (0.26)	–0.35 (0.57)	–0.12 (0.19)
Income	1.64 (1.00)*	–0.54 (0.31)*	–0.88 (0.55)	–0.22 (0.15)	1.71 (1.04)*	–0.40 (0.27)	–0.97 (0.58)*	–0.34 (0.20)*
HH size	0.63 (0.96)	–0.19 (0.30)	–0.35 (0.52)	–0.09 (0.14)	0.67 (1.01)	–0.18 (0.25)	–0.37 (0.56)	–0.12 (0.19)
Children	–1.15 (1.12)	0.37 (0.36)	0.62 (0.61)	0.16 (0.16)	–1.21 (1.18)	0.29 (0.30)	0.68 (0.66)	0.23 (0.22)
Short 1	–1.74 (7.62)	0.54 (2.38)	0.95 (4.14)	0.25 (1.10)	–1.82 (7.99)	0.46 (2.03)	1.02 (4.45)	0.34 (1.51)
Short 2	–2.87 (10.26)	0.90 (3.20)	1.56 (5.58)	0.41 (1.48)	–3.01 (10.75)	0.76 (2.73)	1.68 (5.99)	0.57 (2.03)
Binary explanatory variables								
Year 2011	–4.52 (1.83)**	1.44 (0.59)**	2.45 (0.99)**	0.64 (0.28)**	–4.74 (1.92)**	1.18 (0.50)**	2.65 (1.07)**	0.90 (0.38)**
< High school	–3.69 (2.20)*	1.13 (0.67)*	2.02 (1.22)*	0.54 (0.34)	–3.86 (2.29)*	0.94 (0.54)*	2.17 (1.30)*	0.75 (0.47)
Some college	3.10 (2.59)	–1.02 (0.88)	–1.66 (1.38)	–0.41 (0.35)	3.25 (2.74)	–0.84 (0.76)	–1.82 (1.51)	–0.60 (0.48)
College	6.08 (2.67)**	–2.08 (0.97)**	–3.23 (1.41)**	–0.77 (0.33)**	6.39 (2.85)**	–1.73 (0.86)**	–3.55 (1.57)**	–1.11 (0.46)**
Employed (H)	–3.80 (4.05)	1.23 (1.32)	2.04 (2.17)	0.52 (0.57)	–3.98 (4.26)	1.00 (1.13)	2.22 (2.35)	0.76 (0.79)
Unemployed (H)	–0.92 (3.36)	0.33 (1.04)	0.48 (1.83)	0.12 (0.49)	–1.06 (3.49)	0.21 (0.85)	0.62 (1.95)	0.24 (0.69)
Employed (W)	–3.20 (3.54)	1.00 (1.08)	1.73 (1.93)	0.46 (0.54)	–3.34 (3.69)	0.81 (0.89)	1.87 (2.07)	0.66 (0.74)
Unemployed (W)	–2.46 (3.09)	0.77 (0.91)	1.33 (1.70)	0.36 (0.49)	–2.59 (3.20)	0.59 (0.74)	1.47 (1.80)	0.53 (0.67)
Hispanic	–4.86 (2.20)**	1.47 (0.67)**	2.67 (1.22)**	0.72 (0.33)**	–5.10 (2.31)**	1.27 (0.54)**	2.85 (1.32)**	0.98 (0.47)**
White	5.32 (3.22)*	–1.58 (0.91)*	–2.92 (1.78)	–0.82 (0.55)	5.53 (3.33)*	–1.28 (0.71)*	–3.12 (1.89)*	–1.14 (0.75)
Other race	–1.25 (3.86)	0.40 (1.18)	0.67 (2.11)	0.18 (0.58)	–1.31 (4.02)	0.31 (0.96)	0.74 (2.26)	0.26 (0.81)
MSA	–0.98 (2.14)	0.29 (0.69)	0.54 (1.16)	0.15 (0.30)	–1.02 (2.24)	0.28 (0.57)	0.56 (1.25)	0.18 (0.42)
South	–1.19 (2.46)	0.39 (0.76)	0.64 (1.34)	0.17 (0.36)	–1.25 (2.57)	0.29 (0.64)	0.71 (1.44)	0.25 (0.50)
Northeast	–3.40 (3.39)	1.04 (0.97)	1.85 (1.87)	0.51 (0.55)	–3.54 (3.51)	0.82 (0.78)	2.00 (1.98)	0.73 (0.76)
Midwest	1.86 (2.92)	–0.59 (0.96)	–1.01 (1.57)	–0.26 (0.39)	1.95 (3.07)	–0.51 (0.81)	–1.08 (1.71)	–0.35 (0.55)
BBCE	4.95 (1.95)**	–1.50 (0.59)**	–2.70 (1.07)**	–0.74 (0.32)**	5.18 (2.04)**	–1.27 (0.49)***	–2.89 (1.15)**	–1.02 (0.44)**
Vehicle test	3.24 (3.30)	–1.06 (1.14)	–1.74 (1.76)	–0.43 (0.41)	3.40 (3.48)	–0.92 (0.99)	–1.88 (1.92)	–0.60 (0.58)
Report simplified	5.79 (3.08)*	–1.68 (0.83)**	–3.19 (1.72)*	–0.92 (0.55)*	6.05 (3.20)*	–1.40 (0.67)**	–3.39 (1.81)*	–1.25 (0.74)*
Out of money	–36.61 (1.99)***	15.64 (1.06)***	18.15 (1.34)***	2.82 (0.51)***	–39.30 (1.99)***	13.86 (1.09)***	21.20 (1.41)***	4.24 (0.66)***
More money	–20.02 (1.96)***	6.36 (0.76)***	11.11 (1.20)***	2.55 (0.48)***	–20.74 (1.99)***	4.94 (0.63)***	12.13 (1.29)***	3.67 (0.60)***
WIC	–3.95 (1.86)**	1.23 (0.57)**	2.15 (1.02)**	0.57 (0.30)*	–4.13 (1.94)**	1.01 (0.47)**	2.32 (1.09)**	0.81 (0.40)**
Free food	–6.41 (2.53)**	1.87 (0.68)***	3.52 (1.42)**	1.02 (0.48)**	–6.65 (2.59)**	1.48 (0.53)***	3.75 (1.48)**	1.42 (0.63)**

Notes: All effects on probabilities are multiplied by 100. Asymptotic standard errors in parentheses. Asterisks indicate level of significance: *** = 1%, ** = 5%, * = 10%.

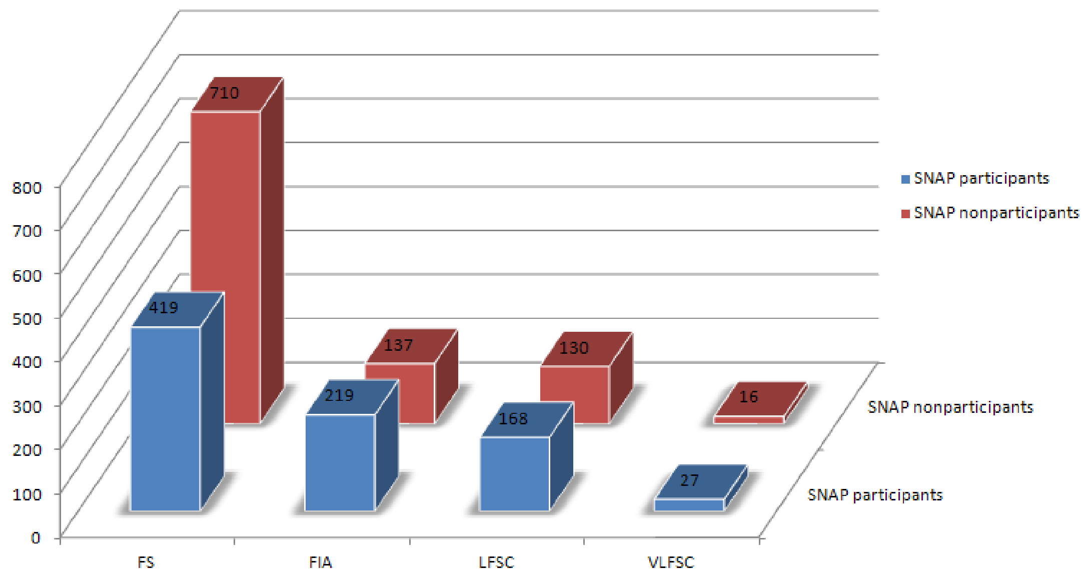

Figure 3.1

Frequency Distribution of SNAP Participation and Food Insecurity Categories

VITA

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