Section IV. Empirical Model

Our empirical analysis is designed to examine how employment characteristics affect FSP participation. We estimate the determinants of FSP participation in models that do and do not control for unobserved heterogeneity. Unobserved heterogeneity is of concern if unmeasured characteristics, such as preferences, affect both food stamp participation and employment status. For example, people who have a distaste for work may have a strong preference for transfer programs. Ignoring this heterogeneity would wrongly ascribe the part of program participation due to the preference for transfer programs to employment status. If this is the case, then models that do not control for these unmeasured characteristics would overstate the effect of employment status on food stamp participation.

We begin with a logit model of FSP participation that does not provide controls for unobserved heterogeneity (Model 1). We then control for individual-specific unobserved heterogeneity using Chamberlain's fixed effects logit model (Model 2). A comparison of Models 1 and 2 will allow us to examine how the results differ for models that do and do not control for unobserved heterogeneity and to test whether there is indeed heterogeneity using a Hausman specification test. If there is no unobserved heterogeneity, then Model 1 is the preferred specification because it is more efficient than Model 2, as explained below. These two models are discussed in turn.

Model 1: Food Stamp Program Participation Model

The Food Stamp Program participation model is based on a utility maximization framework where the net benefit of FSP participation (***P****)—the benefit minus the cost of participation—for individual *i* is a linear function of explanatory variables (X and Emp), estimated coefficients (β and δ), plus an error term (ε):

$$\begin{aligned} &P_i^* = \alpha + \beta' X_i + \delta' Emp_i + \varepsilon_i \\ &P_i = 1 \text{ if } P_i^* > 0, \text{ and } 0 \text{ otherwise} \end{aligned} \qquad [4]$$

Based on the conceptual model, the explanatory variables include employment characteristics that affect the benefit and cost of FSP participation, denoted by the vector Emp. The explanatory variables also include FSP policies, household composition, demographic characteristics, allowable income deductions, economic conditions and time period, denoted by the vector X.

In this analysis we do not observe the net benefit of FSP participation (P*), only whether individuals participate (P=1)—the benefit is greater than the cost—or do not participate (P=0)—the benefit is less than or equal to the cost. With this discrete outcome, we assume the error term has a logistic distribution and estimate FSP participation using a logit model. In this standard model, the probability of the two outcomes (no food stamp receipt and food stamp receipt) can be written as:

$$\mathrm{Prob}(P_i = 0) = \mathrm{P}_{\text{No Food Stamps, i}} = \frac{1}{1+e^{z_i}}$$

$$\mathrm{Prob}(P_i = 1) = \mathrm{P}_{\text{Food Stamps, i}} = \frac{e^{z_i}}{1+e^{z_i}} \qquad [5]$$

where $z_i = \alpha + \beta' X_i + \delta' \mathrm{Emp}_i$.

An important issue is the timing of the employment variables. Most of the employment characteristics included in the model are measured last month (*m-1*). With this timing, we measure how employment characteristics last month affect FSP participation this month. One exception is that we measure number of employer changes with two quarterly lags—number of employer changes last quarter and two quarters ago. We use this lag structure on these change variables because employer changes, which require reporting to the food stamp agency, may not result in an immediate withdrawal from the Food Stamp Program, but rather, the withdrawal may occur three months down the line if quarterly recertification is required, or six months down the line if semi-annual recertification is required. We rewrite the above equation as:

$$z_{im} = \alpha + \beta' X_{im} + \delta_1 E_{im\text{-}1} + \delta_2 EC_{iq\text{-}1} + \delta_3 EC_{iq\text{-}2}, \qquad [6]$$

where *i* represent the individual, *m* represents the current month, *m-1* represents last month, and *q-1* and *q-2* represent one and two quarterly lags, respectively. The vector E represents employment characteristics measured at time *m-1* and EC represents the variables measuring the number of employer changes. In this model, the coefficients on the employment variables (δ_1, δ_2, δ_3) provide information about the relationship between employment characteristics and FSP participation.

We examine the relationship between employment and FSP participation separately before (years 1990-1992) and after welfare reform (years 1996-1999). In addition, we combine all years of data in one model and interact all of the model's covariates with a variable indicating the later (1996-1999) time period, and then conduct a Chow test for structural change across the two time periods.

The longitudinal data we use for the analysis allow us to observe individuals in multiple periods. To take advantage of these data we include persons in the model multiple times (each time observed), and adjust the standard errors for the non-independent observations.

Model 2: Food Stamp Program Participation Model with Fixed Effects

Unobserved heterogeneity is of concern if unmeasured characteristics (e.g., household preferences) affect both food stamp participation and employment status. For instance, if individuals have some unmeasured fixed characteristics that lead them to both not work and take-up food stamp benefits (e.g., a distaste for work and a taste for transfer programs), then our estimate of the effect of employment status on Food Stamp Program participation would be overstated. Consistent with this concern, Fraker and Moffitt (1988) find evidence that unobserved factors affecting employment are negatively related to unobserved factors affecting FSP participation: individuals that are less likely to work are more likely to participate in the FSP. The model described below expands Model 1 to include a component that captures this potential fixed unobserved heterogeneity component.

To show the individual-specific unobserved heterogeneity component we expand the equation for z_{im} above to:

$$\widetilde{z}_{im} = \alpha + \beta' X_{im} + \delta_1 E_{im-1} + \delta_2 EC_{iq-1} + \delta_3 EC_{iq-2} + \mu_i, \qquad [7]$$

where μ_i represents the individual-specific heterogeneity component. A standard approach for dealing with this unobserved heterogeneity term is to estimate a fixed effects model. A fixed effects logit model can be written as above:

$$P_{\text{Food Stamps, it}} = \frac{e^{\widetilde{z}_{im}}}{1 + e^{\widetilde{z}_{im}}} \qquad [8]$$

where $\widetilde{z}_{im}$ includes the unobserved individual-specific term, μ_i.

Controlling for unobserved heterogeneity using fixed effects in a discrete, nonlinear framework is not as straightforward as doing so in a linear model. "In this nonlinear model, it is not possible to sweep out the heterogeneity by taking differences or deviation from group means" (Greene 2000, p. 839). However, using Chamberlain’s conditional (fixed effects) logit model we can obtain both consistent and efficient estimates.[16] Chamberlain’s model controls for unobserved individual-level fixed effects by focusing on changes in each individual’s food stamp participation over time. Accordingly, only individuals who change their food stamp participation status are included in the model.

[16] Greene (2000) describes how the logit model lends itself to the fixed-effects framework, while the probit specification does not (pp. 837, 839).

More formally, Chamberlain's approach is based on maximizing a conditional logit model, where the likelihood function is conditioned on the sum of each individual's outcomes (i.e., $\sum_t p_{it}$). The conditional likelihood function can be written as:

$$L = \prod_i \text{Prob}\left[P_{i1} = p_{i1}, P_{i2} = p_{i2}, \ldots, P_{iT_i} = p_{iT} \middle| \sum_t p_{it} \right], \qquad [9]$$

where T_i represents the number of months FSP participation is observed for person *i*. The estimated coefficients from this model are based on the data in which individuals change their FSP participation over the T time periods. Individuals who do not change their participation do not contribute to the conditional likelihood function. Chamberlain's model is inefficient if used when there is no unobserved heterogeneity because it often does not use all the data, among other reasons. With no unobserved heterogeneity, the standard logit estimator used in Model 1 is both consistent and efficient. However, if there is unobserved heterogeneity, the Chamberlain's conditional (fixed effects) logit is both consistent and efficient, and the standard logit model is inconsistent (Greene 2000, p. 841). We use a Hausman specification test—as recommended by Greene (2000, p. 841) specifically for use with Chamberlain's fixed effects model—to test whether there is indeed unobserved heterogeneity.

Model 2 identifies the effect of employment characteristics on FSP participation by looking at individuals who experience a change in food stamp receipt, and examining how changes in their employment characteristics are related to that change in food stamp receipt. For example, this model estimates how a person with the same employment status, same level of income, and same demographic characteristics, etc. changes his or her FSP participation with a change in hours worked.

This model is designed to provide unbiased estimates of the relationship between employment status and food stamp participation if individuals' unobserved components are fixed overtime. That is, the model can only eliminate bias from unobserved characteristics that are fixed over time, not unobserved characteristics that change over time. Additionally, the model does not control for the possibility of reverse causation—that the Food Stamp Program affects employment status. Although these limitations exist, this analysis examines unique employment outcomes and takes steps to control for potential endogeneity that has been given limited attention in the literature.

Study Population

Our primary study population is working-aged adults (age 18 through 59) ever observed living in a low-income household. In this analysis, a low-income household is defined as one in which the household is below 175 percent of the poverty threshold and readily available assets are less than or equal to $4,000, or $5,000 if at least one household member is age 60 or older.[17]

This study population is a trade-off between a population that is too broadly defined and a population that is too narrowly defined. If the study population is defined too narrowly, then it likely results in select group of individuals. Individuals at the margin can slightly alter their behavior to become eligible for benefits, so if the elasticity of labor supply does not equal zero, the pool of persons that should be examined as eligible is larger than those who would actually qualify for the program under current income and asset limits (Ashenfelter 1983). Suppose, for example, that in the absence of the FSP the economic status of two households is identical, with both households having incomes and assets that are slightly above the current FSP eligibility criteria. Now suppose food stamps are made available to these two households. The members of the first household enjoy working and have a strong distaste for welfare programs, so the introduction of food stamps does not changed their behavior. Conversely, the members of the second household have a distaste for work and a taste for welfare programs, so the introduction of food stamps reduces their work effort making them eligible to collect food stamp benefits. In this example, narrowly defining the study population to be food stamp eligible households will result in a study population that has an above average distaste for work and taste for welfare programs (i.e., a select population), which in turn can lead to biased estimates of the effect of employment characteristics on FSP participation. If, on the other hand, the study population is defined too broadly, the estimated effect of employment characteristics on FSP participation may be washed out even if the effect on low-income households is substantial.[18,19]

Our primary study population of adults ever observed living in a household below 175 percent of the poverty threshold (and readily available assets of $4,000 to $5,000) was designed with these two competing concerns in mind.[20] To test the sensitivity of our results to our choice of study population, we carry out our multivariate analysis with a more restricted secondary population. This secondary population is defined as adults ever observed living in a household below *130 percent of the poverty threshold* (and readily available assets of $4,000 to $5,000), which more closely approximates the food stamp eligible population.

By using both income and assets as inclusion criteria, we ensure that the sample excludes short-term low-income, high asset households (such as professors in summer). We use persons *ever* observed living in a low-income household, as opposed to living in a low-income household

[17] Readily available assets include checking, savings, money market, non-retirement stocks (1990 SIPP panel only), and bonds.
[18] Grogger (2000, p.11) argues a similar point in his analysis of welfare reform and time limits.
[19] Gleason et al. (1998) do not limit their study population based on income or assets. They use (1) adults over age 18 and (2) households as the unit of analysis, but the main focus is on the analysis of adults. In general, they find similar results for the two populations.
[20] The average income-to-needs ratio for individuals in this study population who are not food stamp recipients is 2.6.

in a particular month or year, because it allows us to capture a population that does not change over the panel and exploits the longitudinal nature of our data. By observing people in multiple time periods, we can examine how FSP participation changes under alternative employment patterns and statuses.