3. Specification of the FSP Caseload Equation

The typical specification that has been used to estimate the impact of the economy and policy on FSP caseloads can be written as follows. For state i at time t, write the natural log of per capita food stamp caseloads FSP_{it} as,

$$(10) \quad FSP_{it} = \mu_i + \beta' T_{it} + \alpha' IP_{it} + \phi' P_{it} + \theta' E_{it} + \lambda' D_{it} + \gamma AFDC_{it} + \varepsilon_{it}$$

where *T*, *IP*, *P*, *E* and *D* denote vectors of time trend variables, intervention policy variables, political variables, economic variables, and demographic variables respectively. AFDC denotes the natural log of per capita AFDC/TANF caseloads, μ_i denote a state fixed effect, and ε_{it} is an error term. The scalars μ_i, γ, and vectors β, α, θ, ϕ, λ are model coefficients to be estimated. Except for the state fixed effects (and, perhaps the vector β if the trend specification includes state-specific time trends) previous studies have assumed a common response for all states so that the caseload equation is estimated as a homogeneous panel.

Previous versions of (8) have been estimated using annual state-level panel data. In this paper, observations for (federal fiscal year) 1980 through 1999 are used. This covers the same period as used by ZGF (2001, 2003). Other studies have used aggregate state level data but for different time periods: FGZ, 1980-98; Wallace and Blank, 1980-96; Kornfeld, 1987-99; and Currie and Grogger, 1980-98 (calendar year). These studies have used administrative data to measure FSP caseload levels. Currie and Grogger also report results for a specification in which FSP participation levels are measured by aggregating Current Population Survey (CPS) data across states.

3.1 Intervention Policy Variables (IP)

This type of policy variable corresponds to points in time at which specific legislative and/or program regulatory changes are instituted. Conceptually, policies that are captured by these variables are identified as intervening in the long-run underlying relationship between FSP caseloads and the other determinants that existed prior to the change. Modeling policy change in this fashion is an example of intervention analysis in which policy changes are modeled as structural breaks in the underlying long-run relationship.

The intervention policy variables are constructed as discrete dummy variables that correspond to explicit changes in FSP provisions. For example, for time periods prior to the passage of the Hunger Prevention Act of 1988 a dummy variable is assigned the value zero, and for time periods including 1988 and later, the value one. The estimated coefficient of the intervention dummy variable measures the shift in the mean FSP caseload associated with this policy change. Dummy variables may also be defined to capture policy changes in program that are closely associated with the FSP. These indirect policy changes have typically included policy changes in AFDC/TANF program, but can also include changes in programs, such as legislative changes in the Earned Income Tax Credit (ETIC) provisions. These variables may also be state-specific.

Intervention policy variables are also constructed as continuous variables. For example, ZGF (2001,2003) define the fraction of a state's ABAWD (able-bodied adults without dependents) population not waived from work requirements to account for the affect of the ABAWD provision in PRWORA. Kornfeld, and Currie and Grogger also used continuous state-specific policy variables associated with PRWORA in their specifications of the FSP caseload equation.

In this paper, we use a limited number of dummy intervention policy variables defined by direct and indirect legislative changes that have been identified in previous studies. These legislative changes are listed in table 1. The set also includes a state-specific dummy policy variable indicating whether the State had been granted any waiver in their AFDC/TANF program (prior to PRWORA).

Using intervention variables to account for policy changes has its limitations. One problem is that the policy impact measured by intervention analysis is limited to specific number of policy changes identified by the investigator. Knowledge of the investigator and the complexity of the various policy changes that occur in the individual states, however, can limit what is considered a change in policy. Even with detailed knowledge, determining what is, or is not, a policy change can be open to interpretation.

A second problem is the difficulty of distinguishing between when the legislation was passed and when FSP caseloads were actually affected. The uncertainty between the time when the change is approved and when it affects behavior can result in misspecifying the intervention variable.

Third, if the policy changes are frequent, the use of intervention variables may result in an intertemporal shape that looks very much like a polynomial trend. Including polynomial trends (or annual dummy variables) in the model in addition to frequent intervention variables can confound the effect of the intervention policy.

3.2 Political Variables (*P*)

These variables measure the political climate of a state. These variables are not typically characterized as either policy or economic variables. ZGF (2000, 2001) report that these variables explain only a small part of the variation in FSP caseloads between 1994-99. Since there are no avenues by which States can directly alter food stamp eligibility or payment rules through state legislation or regulations any impact of these variables on FSP caseloads must be indirect (Wallace and Blank). No political variables were included in our empirical specification.

3.3 Economic Variables (*E*)

In this paper, we follow previous studies by ZGF (2001,2003) and FGZ and use the state unemployment rate and the rate of employment growth to measure the impact of the economy on

FSP caseloads.[12] Whether these variables are adequate to capture the effect of the economy on FSP caseloads is an open question. The work of Goetz, Zimmerman and Tegegne (1999), for example, suggests that an unemployment measure that more accurately reflects the labor market conditions faced by potentially eligible welfare recipients, such as the unemployment rate of service workers, would be more appropriate than the overall state unemployment rate. Schoeni (2001) makes a similar, more general, point about the use of caseload equations like (8). He warns that in practice caseload equations like (8) are subject to uncertainty about whether there are sufficient controls for all unobservable factors that are correlated with caseloads. Our testing procedure, however, can assess whether the overall unemployment rate and employment growth are adequate measures of the economy by testing whether these variables are part of a cointegrated relationship with FSP caseloads.

3.4 Demographic Variables (D)

Like the political variables, the demographic variables are not typically characterized as either policy or economic variables. These variables are state level measures of demographic variables that have been used to explain cross-sectional variations in FSP caseloads. They include, for example, the percent of elderly and the percent of single-female headed households (Wallace and Blank); however, no demographic variables are included as regressors in our empirical specification.

3.5 AFDC/TANF Caseload (AFDC)

Including AFDC/TANF caseloads as a determinant of FSP caseloads recognizes the close association between these two assistance programs. Changes in the AFDC/TANF program can affect FSP participation directly by influencing the participation decision of recipients eligible for both programs. By statute, persons receiving or authorized to receive AFDC/TANF benefits are also eligible for the FSP implying a common set of potential recipients for both programs.

Caseload levels in the two programs are also linked indirectly through their implementation at the state level. In most states these programs are housed in the same administrative unit suggesting that there exists a common culture affecting the implementation of both programs. Any shared approach would imply that a state's practices or policies in one program might affect how it implements the other program. Evidence of this type of indirect effect between the programs is given by examples of state TANF diversion policies that provide certain one-time or temporary benefits and appear to reduce the likelihood of enrolling in the FSP (GAO, 1999).

Previous studies have faced problems when including AFDC/TANF caseloads in the FSP caseload equation because of the likely simultaneity between caseload levels in these two programs. ZGF (2001, 2003) report estimates of the FSP caseload equation using instrumental estimators. This raises, however, the problem of finding appropriate instruments for AFDC/TANF caseloads. ZGF (2001, 2003) report finding that AFDC/TANF caseloads are exogenous to FSP caseloads, and provide estimates of the FSP caseload equation with and

[12] Wallace and Blank use the unemployment rate, the log of median wage rate, and the log of the 20th quintile of the wage distribution as economic variables.

without AFDC/TANF caseloads as a regressor. Alternatively, the maximum combined FSP and AFDC/TANF benefits for a family for three as been employed as a proxy for AFDC/TANF caseloads, ZGF (2001, 2003). This variable, however, has been found to be statistically insignificant. Wallace and Blank, and Currie and Grogger report using just the maximum AFDC/TANF benefits as a proxy for AFDC/TANF caseloads. Currie and Grogger find this variable to be statistically significant but have difficult explaining why its estimated coefficient is negative. For Wallace and Blank the impact of this variable was negative but not statistically significant.

In cointegration analysis endogeneity between FSP and AFDC/TANF caseloads is not a concern because the estimation procedure allows for both contemporaneous and intertemporal correlation between regressors and model error terms. The important question in our analysis is, however, whether the inclusion of AFDC/TANF caseloads is needed to define a long-run equilibrium (cointegrated) relationship.

3.6 Time Trend Variables (*T*)

All previous studies of the FSP caseload equation have included year effects (annual dummies) in their trend specification. The studies by ZGF (2001,2003) and FGZ have in addition included state-specific linear time trends. Kornfeld and Currie and Grogger report, however, results both with and without state-specific time trends. Alternatively, Wallace and Blank prefer not to include any state specific time trend variables in their specification fearing that these may over-control for omitted variables (p.13).[13] They argue instead that trends in the regressors should explain trends in the caseload data. Schoeni (p. 238), commenting on the paper by Currie and Grogger, cautions against even the inclusion of year effects. He notes that these effects are typically quite large in FSP caseload regressions, and suggests that they may be capturing a large share of the effects of economic conditions.

Cointegration analysis can be used to test for the correct specification of time trends variables in the FSP caseload equation. If one of the regressors in a cointegrated regression contains a deterministic component that is explained by a linear combination of deterministic components in other regressors such that the resulting process has no trend, then no deterministic component needs to be added to the cointegrated regression. In this case, the regression is said to be *deterministically cointegrated*. Otherwise the regression is not deterministically cointegrated and a deterministic term is needed to achieve a purely stationary residual. Tests of whether a cointegrated FSP caseload equation is deterministically cointegrated indicate whether (polynomial) time trends should be included in the caseload equation. If the variables are found to be deterministically cointegrated, polynomial time trends are excluded from the model and vice versa. Tests of deterministic cointegration are included in our specification tests.

[13] Similar studies of the AFDC/TANF caseload equation have accounted for the impact of time trend variables using a much greater variety of specifications. It appears estimates of the relative importance of the economy and policy effects can be significantly influenced by how these trends are specified. Wallace and Blank, in fact, note that the major factor in explaining the differences between their results for AFDC/TANF caseloads and those of Ziliak and Figlio is in how the time trend is specified (p. 34).