Estimating Longrun Food Stamp Program Caseloads

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Abstract

This study analyzes the relationship between Food Stamp Program (FSP) caseloads and the macroeconomy using annual State-level panel data for 1980-99. It is the first study to link the time-series properties of the data to an interpretation of public assistance program policy. A longrun relationship involving FSP caseload equation and the macroeconomy is estimated but requires that Aid to Families with Dependent Children/Temporary Assistance for Needy Families (AFDC/TANF) caseloads be included as an explanatory variable. The resulting equation that connects trends in the economy with the trend in FSP caseloads indicates that the economic expansion in the 1990s permanently lowered future FSP caseloads below what they would be otherwise. The potential for the economy to change the trend in FSP caseloads is in contrast to its role presented in previous studies in which the economic expansion of the 1990s is seen as causing only a temporary decrease in FSP caseloads that dies out over time. Tests of the estimated equation also indicate that the common practice of including year effects (annual dummy variables) or State-specific time trend in the FSP caseload equation may overcontrol for omitted variables. Instead, trends in the regressors should be allowed to explain the trend in FSP caseloads.

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1. Introduction

Between federal fiscal years 1994 and 1999 caseloads in the Aid to Families with Dependent Children (AFDC) declined by approximately 41 percent and those in the Food Stamp Program (FSP) declined by approximately 31 percent. Efforts to identify how much of the reduction in caseloads was due to the Responsibility and Work Opportunity Reconciliation Act (PRWORA)[1] and various waivers to AFDC program provisions that were granted to individual states beginning in the early 1990's have been confounded by the strong performance of the economy during the decade.

Several studies have attempted to determine what part of the caseload reduction was due to PRWORA and the waivers, and what part was due to the economy by employing a regression strategy based on state level panel data. The studies by Blank (1997), Council of Economic Advisers (1997, 1999), Figlio and Ziliak (1999), Wallace and Blank (1999), and Ziliak *et. al.* (2000) include estimates for AFDC/TANF caseloads. Estimates for FSP caseloads are presented in the studies by Wallace and Blank (1999), Figlio, Gundersen, and Ziliak (2000) (hereafter denoted as FGZ), Ziliak, Gundersen and Figlio (2001, 2003) (hereafter denoted as ZGF), Currie and Grogger (2001), and Kornfeld (2002).[2]

All of these papers have used regression procedures that apply to data generated by *trend stationary* processes. Evidence from previous studies and additional tests indicates, however, that FSP and AFDC/TANF caseloads as well as the variables that have been used to measure economic activity may be generated by *integrated* or *unit root non-stationary* data processes. In the following sections of this paper, the different methods associated with analyzing data containing unit-roots, compared to trend stationary data, are illustrated and applied to the annual state level panel caseload data set from 1980 to 1999. (The data set consisting of FSP and AFDC/TANF caseloads plus the variables measuring economic activity is referred to as the *caseload data set* in this paper.)

However before proceeding to these results it is important to first discuss how the nature of the data process affects the interpretation of policies regarding public assistance programs; and in particular, how the role of the economy in evaluating the consequences of welfare reform changes when the caseload data set follows unit-root processes.

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* We would like to thank Craig Gundersen for making the data available to us.

[1] In 1996, PRWORA replaced the AFDC program with a new state block grant program called Temporary Assistance for Needy Families (TANF). In what follows, we refer to the AFDC/TANF program. PRWORA also involved changes in the FSP but these were less far reaching.

[2] Some authors (Wallace and Blank, Currie and Grogger, and Kornfeld) have included estimates of the FSP caseload equation for different segments of the caseload. In this paper, any comparisons are limited to aggregate caseload equation.

Assume that a (discrete) time series contains a unit-root.[3] Then, according to the Beveridge-Nelson (1981) decomposition the series can be written as the sum of two terms: one where the effect of (current and past) random shocks to the series is permanent; and the other where the effect of shocks is transitory. Shocks accumulate in the permanent component so that a shock at any point in time contributes the same amount to all future realization of the time series. In this sense, the shock alters the future path of the series by imparting a permanent effect on the time series. The effect of the same shock in the transitory component, on the other hand, dies out over time. The relative strength of the permanent component measures the proportion of a given shock that would persist into the future.[4]

The accumulation of shocks in the permanent component means that at any given time this component contains a complete history of the time series. The permanent component is often referred to as a trend, but because this component is determined by random shocks to the series, the series is said to display a *stochastic trend*. For public assistance programs the effect of the permanent component might reflect some notion of persistence in program enrollment.

Multiple regression analysis undertaken in the previously cited studies have implicitly characterized movements in the time series of the caseload data as consisting of stationary movements around deterministic trends.[5] Under this characterization, the resulting regression analysis relates random shocks in the economy (conceptually through transitory changes in FSP eligibility) to transitory changes in FSP caseload levels. The finding that the caseloads data are integrated implies, however, that shocks to the economy can be associated with changes in the stochastic trend as well as with transitory changes in FSP caseloads.

With integrated data, shocks to the economy, even though they are transitory, can have a permanent effect on FSP caseloads. Such an effect might happen, for example, if greater employment (such as associated with cyclical improvement in the economy in the late 1990's) provided added work experience to the (potentially) FSP-eligible population. This added work experience in turn may translate into greater future employment opportunities and a permanent reduction in future FSP caseloads below what they would be otherwise. For some analysts, such as Rector (2001), this type of human capital accumulation seems to describe the lesson of welfare reform.

The potential for the economy to change the trend in FSP caseloads is in contrast to its role presented in previous studies. In these studies, the assumption that FSP caseloads and the variables used to measure economic activity are trend stationary leads to conclusion that changes in FSP caseloads attributed to an improved economy are temporary changes (from a deterministic trend) that will be reversed in the future when the economy reverted back to its deterministic trend (see, for example, Blank 2001, p.28).

[3] A discrete time series is defined as a sequence of random variables in which each element of the sequence is indexed by an integer value of time.
[4] Of course the relative strength of the permanent and transitory components depends on the particular time series.
[5] A deterministic trend changes the series each time period by a fixed (non-random) function of time.

The finding that the caseload data contain unit-roots implies, however, that an analysis of these data based only on their transitory component is incomplete. While for certain policy questions it may be useful to know how *changes* in FSP caseloads respond to *changes* in economic activity, the existence of a permanent component in FSP caseloads means that changes in economic activity does not provide sufficient information to explain the *level* of FSP caseloads.

Given the existence of unit-roots in the caseload data, the objective of this paper is to extend the analysis of these data by evaluating whether or not there exits a stable relationship connecting the (stochastic) trend in FSP caseloads levels with the (stochastic) trends of other variables in the caseload data set (and, in particular with the stochastic trends of the variables measuring macro-economic activity). Such a relationship will be referred to as the *long-run food stamp caseload equation.*

The plan of the paper is as follows. In the next section, a more detailed comparison of differences between stationary and integrated time series and resulting regression methods is presented. This section also include a discussion of how the recent advances by Phillips and Moon (1999) on estimation with non-stationary panel data are used in obtaining the long-run FSP caseload equation using annual state level panel data.

In section 3, the specification of the FSP caseload equation that has been estimate with annual state level panel data is introduced and a discussion of the types of explanatory variables that have been used is provide. In section 4, formal evidence that the caseload data follow unit-root processes is presented. This section also reports on the results of several specification tests of the FSP caseload equation based on tests of cointegration. Here we report the important result that in order to estimate a long-run (cointegrated) FSP caseload equation AFDC/TANF caseloads must be included in the regression. In this section the estimated coefficients of the long-run FSP caseload equation are also reported and the contributions of the different regressor variables to explaining variations in FSP caseload over the sample period 1980-1999 are evaluated.

Section 5 addresses the issue of how much of the decline in FSP caseloads in the mid-1990's was due to the economy and how much was due to PRWORA and the waivers. This question has been addressed by all previous caseload studies. However, since AFDC/TANF caseloads are themselves a function of the economy and policy, and since they must be included in the FSP caseload equation in order to define a stable long-run relationship, it is not possible to calculate the *unconditional* impact of the economy and policy on FSP caseload using *only* the FSP caseload equation. Partial measures conditional on the level of AFDC/TANF caseloads is the best that can be done if the analysis is limited to the FSP caseload equation.

In section 6, a brief discussion of how the long-run FSP caseload equation could be used in making period-by-period estimates of FSP caseloads from the error correction form of the data is presented. The final section provides conclusions.

2. Stationary versus Cointegrated Regressions Models

In this paper the relationship between FSP caseloads and the macro-economy is analyzed based on evidence that these data follow unit-root processes. To understand how the approach with unit-root processes differs from the one used in previous FSP caseload studies it is necessary to review some fundamentals of cointegration econometrics by comparing them with a more familiar regression theory.

Previous studies have measured the relative importance of policy and economic variables on *FSP* or *AFDC/TANF* caseloads by regressing caseloads on a vector of economic and policy variables. All these studies use methods that are correctly applied to *stationary regression models* in which the model is formed from variables that follow stationary time series. In this section, stationary regression models are compared to integrated regression models. Integrated regressions are regression models constructed from variables that follow unit root time series. [6] The fundamental difference between a stationary and a unit root series is the response of the series to a transitory shock in a single period. Differences in regression methods, predictive reliability, and most importantly for the purposes of this paper, coefficient interpretation can all be traced to this difference.

This section proceeds in three parts. First, a brief overview of the difference between stationary and cointegration regression models is presented. A more formal discussion of difference between stationary versus integrated data and between regression analyses with stationary versus integrated data follows. Finally, unique features of estimating cointegated regression models using panel data are discussed.

2.1 Overview

Suppose initially that the time series of food stamp caseloads can be described as a trend stationary (or stationary) process. Following a transitory shock in the present period food stamp caseloads first deviate from, and then return to their original time trend (to their mean if stationary). The transitory shock imparts a *short-run* effect on the series in the sense that FSP caseloads returns to the same path they would have followed had the stock not occurred. If economic and policy variables are also trend stationary, each would display the same temporary deviation from their time trends. Because past deviations from these trends have been temporary, the future paths of these variables are predictable. This means that a regression of food stamp caseloads on economic and policy variables yields stable estimates and that these estimates describe a short-run relationship between deviations of food stamp caseload and economic and policy variables from their time trends.

The sequence of events is different if the FSP caseload data are drawn from unit root processes. In this case a transitory shock to one of these variables forever alters the future path of its series and so imparts a *long-run* or permanent effect on the time series. Past responses do not

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[6] There are a number of different classes of integrated time series and in this paper we follow the convention that an integrated series is taken to mean an integrated series of order 1 or equivalently, that the time series contains a single unit root. This section draws heavily on Chapters 15-19 of Hamilton for the discussion of unit root nonstationary series and cointegration.

‘trace out’ a stable path; instead, any time trend would be stochastic and future paths cannot be reliably predicted from past patterns.

Even though the individual unit-root data series are each non-stationary it is possible that a linear combination of these variables is stationary and thus predictable. Such a linear combination defines a *cointegrated* relationship between the variables, and explains how the individual data series move together in a way that can be reliably predicted from past realizations of their stationary combination. In this sense, a cointegrating regression among FSP caseloads, economy, and policy variables describes a stable long-run (equilibrium) relationship between permanent movement in the FSP caseloads and permanent movements in the economic and policy variables.

If no such linear combination exists, the estimated OLS relationship among the variables would be *spurious* and the linear combination defined by the OLS coefficients would behave like a non-stationary time series and yield unreliable predictions. Tests of cointegration are, therefore, tests of the existence of long-run equilibrium relationships, and can be interpreted as tests of model specification. It is this aspect of cointegration analysis that is emphasized in this paper. In particular, our specification tests find evidence that estimates of the FSP caseload equation that *do not* include a measure of AFDC/TANF caseloads are incomplete and do not define a long-run stable relationship.

2.2 Derivation of Results

This comparison will first look at differences in the time series properties of a single (univariate) random variable generated by a stationary versus a unit root process. The section then addresses how these properties affect stationary versus integrated regressions.

For a given a random variable, x_t, let the process or time series be denoted as $\{x_t\}$. Stationary time series have well-defined first and second moments that make them relatively easy to predict. For example suppose that an economy or policy random variable, x_t, follows an auto-regressive process of order 1 (i.e., $AR(1)$) and so that it satisfies

$$x_t = c + \rho x_{t-1} + \varepsilon_t$$

where ε_t is a serially uncorrelated or transitory shock with $Var(\varepsilon_t) = \sigma^2$ for all t, and where $|\rho|<1$. The condition $|\rho|<1$ represents the absolute summability condition for a stationary $AR(1)$ time series. Let E denote the mathematical expectations operator, then the mean of this process is $E(\{x_t\}) \equiv \mu = c/(1- \rho)$, its variance is $Var(\{x_t\}) \equiv \gamma_o = \sigma^2/(1-\rho^2)$, and its jth auto-covariance, γ_j, is $\sigma^2[\rho^j/(1-\rho^2)]$. In this stationary $AR(1)$ example, finite unconditional moments of the process are independent of t and the covariance of variables separated by longer time periods decays (i.e., $\gamma_j \rightarrow 0$) as the distance between the variables grows larger (i.e., $j \rightarrow \infty$). It is the summability condition that ensures the existence of finite moments and is responsible for the type of decay exhibited by stationary time series. As discussed below it also has important implications for prediction.

A more general representation of a stationary process satisfies

$$(1) \qquad x_t = \mu + \varepsilon_t + \rho_1 \varepsilon_{t-1} + \rho_2 \varepsilon_{t-2} + \rho_3 \varepsilon_{t-3} + \ldots$$

where $E(\{x_t\}) = \mu$, and where $\sum_{i=0}^{\infty}|\rho_i| < \infty$ is the absolute summability condition. Besides ensuring finite moments, absolute summability also ensures that as a forecast horizon grows, the forecast converges to μ, the unconditional mean of the series. That is if $\sum_{i=0}^{\infty}|\rho_i| < \infty$, then $E(x_{t+s}|x_t, x_{t-1}, \ldots) \rightarrow E(\{x_t\}) = \mu$ as $s \rightarrow \infty$.

The problem with *(1)* is it does not generate the type of trends that are commonly observed in economic data. One possibility that does generate typical patterns is a *trend-stationary* series

$$(2) \qquad x_t = \mu + \delta t + \varepsilon_t + \rho_1 \varepsilon_{t-1} + \rho_2 \varepsilon_{t-2} + \rho_3 \varepsilon_{t-3} + \ldots$$

In this case absolute summability ($\sum_{i=0}^{\infty}|\rho_i| < \infty$) ensures that forecasts of x_{t+s}, given by $E(x_{t+s} | x_t, x_{t-1}, \ldots)$ converge (in mean square) to the time trend $\mu + \delta(t+s)$ and the mean-squared error *(MSE)* of the forecast converges to the bounded unconditional variance of the series (i.e.,) as $s \rightarrow \infty$. That is, MSE $\equiv E[x_{t+s} - E(x_{t+s} | x_t, x_{t-1}, \ldots)]^2 \rightarrow Var\{(x_t\}) = \sigma^2 [1 + \rho_1 + \rho_2 + \rho_3 + \ldots]$ as $s \rightarrow \infty$ and the added uncertainty of forecasting further into the future becomes negligible.

Another way to generate trends commonly observed with economic data is through a unit root non-stationary series. The first difference of a unit-root series is a stationary series but the series itself is not. This means the first-differenced series satisfies absolute summability but the level series does not. Violating absolute summability not only means finite moments do not exist, it also has dramatic consequences for prediction.

A unit root series that allows for trends satisfies

$$(3) \qquad x_t - x_{t-1} = (1-L)\, x_t = \delta + \varepsilon_t + \rho_1 \varepsilon_{t-1} + \rho_2 \varepsilon_{t-2} + \rho_3 \varepsilon_{t-3} + \ldots$$

where the symbol L denotes the lag operator, which transforms x_t into x_{t-1} upon multiplication. Note that *(3)* is similar to *(1)* except that $(1-L)\, x_t$ replaces x_t, and the drift term, δ, replaces the unconditional mean μ. It can be shown (e.g., see Hamilton, Chapter 15) that the s-step-ahead forecast of a series that follows *(3)* is

$$E(x_{t+s} | x_t, x_{t-1}, \ldots) = s\,\delta + x_t + T(\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots)$$

where T is some function of current and past realizations of $\{\varepsilon_t\}$. Even in the case in which the function T equals zero (i.e., a random walk with drift) the above relationship indicates that an s-step ahead forecast is a random variable that grows at a constant rate (δ) from the current realization of x_t. This means that over time the prediction of x_{t+s} changes as new values x_{t+1}, $x_{t+2}, \ldots$ are realized. It can also be shown that the *MSE* associated with such a prediction grows linearly with the forecast horizon (Hamilton, Chapter 15).

The above discussion suggests stationary series are much easier to predict than unit root series. For a trend stationary process the forecast of x_{t+s} converges to the *value* $\mu + \delta(t+s)$. On the other hand, for a random walk with drift process, the forecast of x_{t+s} does not converge to a single value but constantly changes as future values of the series are realized. This means that it is virtually impossible to accurately predict the future values of a unit root series.

Differences in the time series characteristics of stationary and integrated data affect the properties of linear regression. Let y_t represents food stamp caseloads, $\mathbf{x}_t$ is represents a k-vector of policy and economic variables, β a corresponding vector of true parameters and u_t a model error. (A variable in bold indicates a vector.) Write a regression model relating food stamp caseloads to policy and economic variables as,

$$(4) \qquad y_t = \mathbf{x}_t'\beta + u_t$$

Conditional on current values of economy and policy regressors equation *(4)* can be viewed as providing a prediction of current food stamp caseloads. Given the general unreliability of forecasts of integrated series, a central question is whether y_t can be reliably predicted from $\mathbf{x}_t$ if y_t and $\mathbf{x}_t$ follow unit root processes.

Given the regression framework by (4) three separate cases are considered. First suppose that the $\{[y_t \;\; \mathbf{x}_t']\}$ are jointly covariance stationary. Any linear combination of these series forms a stationary series. Hence the model errors

$$[y_t \;\; \mathbf{x}_t'] \; [1 \; -\beta]' \equiv u_t$$

would be stationary. Suppose $E(u_t | \mathbf{x}_t') = 0$ and suppose u_t is a serially uncorrelated process with a constant and finite variance σ^2 for all t.[7] Denote $\mathbf{b}_T$ as the vector of *OLS* estimates of β based on T observations, so the model residuals, $u_t^* = [y_t \;\; \mathbf{x}_t'] \; [1 - \mathbf{b}_T]'$ and the residual sum of squares is $RSS_T = \sum_{t=1}^{T}(u_t^*)^2$. Then *OLS* estimation yields the following well- known results: $\mathbf{b}_T$ is a consistent estimate of β, $s^2 = (1/T\text{-}k)\, RSS_T$ is a consistent estimate of σ^2, and as $T \rightarrow \infty$, $\mathbf{b}_T$ is approximately distributed multivariate normal with mean β and variance $\sigma^2[\sum_{t=1}^{T}(\mathbf{x}_t \mathbf{x}_t')]^{-1}$. Thus if observations on $[y_t \;\; \mathbf{x}_t']$ $(t=1,\ldots, T)$ are drawn from jointly stationary or trend-stationary processes, standard *OLS* yields consistent estimates of β and the usual t and F tests yield valid inference. Furthermore, these results do not change if one or more of the elements of $\mathbf{x}_t'$ are deterministic time trends. In short, if $\{[y_t \;\; \mathbf{x}_t']\}$ are jointly covariance stationary, *(4)* provides a stable prediction of food-stamp caseloads, and this prediction can be estimated consistently and efficiently using *OLS*. These are the standard type of results that are used by previous FSP caseload studies.

Now consider the second case in which $\{[y_t \;\; \mathbf{x}_t']\}$ is a vector of unit root non-stationary processes. In this case the model is

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7 For serially correlated u_t one can appeal to a *GLS* transformation that achieves serially uncorrelated errors.

(4a) $y_t = \mathbf{x}_t'\beta + u_t$

(5) $\mathbf{x}_t = \delta + \mathbf{x}_{t-1} + \mathbf{v}_t.$

where *(4a)* is an integrated regression, and the data generating process of the regressor variables has been written out explicitly in (*5*) with error vector $\mathbf{v}_t$ consisting of stationary terms. The properties of *(4a)* depend crucially on the properties of the model errors.

It might be expected that a linear combination of unit-root non-stationary processes would be a unit root non-stationary process. Specifically $\{[y_t \ \ \mathbf{x}_t'] \ [1 \ -\beta]'\} \equiv \{u_t\}$ would be a unit root non-stationary process and *(4a)* would represent an integrated regression with integrated model errors. The above discussion on univariate time series states that the prediction of unit root variables is both unstable and uncertain. The relevance of that discussion for regression analysis derives from the view that the *OLS* residual

(6) $u_t^* = [y_t \ \ \mathbf{x}_t'] \ [1 \ - \mathbf{b}_T]'$

represents a prediction of the model error based on values of $[y_t \ \ \mathbf{x}_t']$. Recall from above that $\mathbf{b}_T$ denotes the *OLS* estimate of β based on *T* observations. The above discussion on the prediction of univariate unit root process indicates that the predictor u_t^* varies even as the sample size becomes infinitely large. From *(6)* this means that even in large samples $\mathbf{b}_T$ continues to vary and fails to converge to β. The *MSE* calculated from the predicted residuals, $s^2 = (1/(T\text{-}k))\ RSS_T = (1/T\text{-}k) \sum_{t=1}^{T}(u_t^*)^2$ grows at the rate T^2 . This divergence of the RSS_T means that *F*-statistics calculated from the OLS residuals grow at the rate *T*. As the sample size grows, *F* tests would be more likely to reject the null that $\mathbf{x}_t$ has *no* relationship with y_t even though $\mathbf{b}_T$ remains unstable in large samples. Phillips (1986) was the first to formally show that these properties indeed represent the hallmark of integrated regressions with integrated model errors. Integrated regressions with integrated model errors are called *spurious regressions*.

Finally, consider the third case; the case of an integrated regression with stationary model errors. The above discussion of the prediction of univariate stationary time series suggests that in this case the model residuals, $[y_t \ \mathbf{x}_t'] \ [1 \ \ - \mathbf{b}_T]$ converges to $[y_t \ \mathbf{x}_t'] \ [1 \ \ -\beta]$ as the sample size increases which suggests $\mathbf{b}_T$ converges to β. Integrated regressions with a stationary model error are called *cointegrated regressions.*

It is important to note that in the case of cointegrated regressions, the consistency of $\mathbf{b}_T$ does not depend on econometric exogeneity. That is, with cointegrated regressions OLS is consistent even when Cov $(u_t,v_t) \neq 0$, i.e., the error terms in (4a) and (5) are correlated. To see this, note that

$$\mathbf{b}_T = [\textstyle\sum_{t=1}^{T} (\mathbf{x}_t \ \mathbf{x}_t')]^{-1} [\sum_{t=1}^{T} \mathbf{x}_t \, y_t] = [\sum_{t=1}^{T} (\mathbf{x}_t \ \mathbf{x}_t')]^{-1} [\sum_{t=1}^{T} \mathbf{x}_t \, (\mathbf{x}_t'\beta + u_t)]$$

$$= \beta + [\textstyle\sum_{t=1}^{T} (\mathbf{x}_t \ \mathbf{x}_t')]^{-1} \sum_{t=1}^{T} (\mathbf{x}_t \, u_t).$$

The bias term, $[\sum_{t=1}^{T} (\mathbf{x}_t \ \mathbf{x}_t')]^{-1} \sum_{t=1}^{T} (\mathbf{x}_t \, u_t)$, is the sum of the product of a unit root vector of variables and a stationary variable (i.e., $\sum_{t=1}^{T} (\mathbf{x}_t \, u_t)$) divided by the sum of squares of a unit root vector of variables (i.e., $\sum_{t=1}^{T} (\mathbf{x}_t \ \mathbf{x}_t'))$. It can be shown that in the special case of a cointegrated regression $\sum_{t=1}^{T} (\mathbf{x}_t u_t)$ grows at the rate T and $\sum_{t=1}^{T} (\mathbf{x}_t \ \mathbf{x}_t')$ grows at rate T^2. Because the denominator of the bias term grows at a rate in time greater than the numerator, the bias term converges (in law) to zero and *OLS* estimates converge to β.

In the context of the present study the above result means that if food stamp caseloads and the policy and economy variables in $\mathbf{x}_t$ are cointegrated, then *OLS* would provide consistent estimates of the cointegrating vector $[1 \ \ -\beta]$ even though economic and policy variables may not be econometrically exogenous. Moreover this regression would represent a long-run relationship in the sense that the cointegrating vector $[1 \ \ -\beta]$ relates permanent changes in food stamp caseloads to permanent changes in the economic and policy variables.

To illustrate the nature of the long-run relationship described by the cointegrated regression (*4a*), consider a single element of the integrated vector $\mathbf{x}_t$ which is a unit root process without drift. According to *(3)*, this element satisfies

$$(3a) \qquad x_t - x_{t-1} = u_t$$

where $u_t = \delta + \varepsilon_t + \rho_1 \ \varepsilon_{t-1} + \rho_2 \ \varepsilon_{t-2} + \rho_3 \ \varepsilon_{t-3} + \ldots$. Repeated substitution gives

$$x_t = x_o + u_1 + u_2 + u_3 + \ldots + u_t$$

so the change to x_t from x_o is the sum of serially correlated events. Note the realization of u in period 1 affects every realization of $\{x_t\}$ drawn in any future time period ($t>1$) in exactly the same way. The Beveridge-Nelson decomposition shows that *(3a)* can be expressed as

$$(7) \qquad x_t = x_o + \rho(1) \ (\varepsilon_1 + \varepsilon_2 + \varepsilon_3 + \ \ldots + \varepsilon_t) + \eta_t - \eta_o$$

where ε is a serially uncorrelated or transitory shock, η_t is a stationary process, x_o and η_o are initial conditions, $\rho(1) = \sum_{k=0}^{\infty}(\rho_k)$, and $\rho(1) \ (\varepsilon_1 + \ \varepsilon_2 + \varepsilon_3 + \ \ldots + \varepsilon_t)$ represents a random walk.[8] *The permanent or long run component of an integrated time series is described by the random walk component of a unit root series*. This random walk component shows that a purely transitory event that occurs in say, the first period (ε_1), imparts a permanent effect on all future realizations of the random variables x_t , x_{t+1} , $x_{t+2}, \ldots$ in exactly the same manner. Furthermore, for unit root series without drift, it is only this permanent component that matters when characterizing the distribution of a unit root time series (Hamilton, Ch. 17).

Hence if food stamp caseloads $\{y_t\}$ is an integrated process (without drift) and if $\{\mathbf{x}_t\}$ is comprised of integrated policy and economy variables (without drift), and if $\{[y_t \ \ \mathbf{x}_t]\}$ are cointegrated with cointegrating vector [1 **-β**] then if the permanent component or long run component of $\mathbf{x}_t$ is

$$(\varepsilon_1 + \varepsilon_2 + \varepsilon_3 + \ \ldots + \varepsilon_t)' \ \boldsymbol{\rho(1)}$$

[8] More precisely it is the product of a constant and a random walk.

the long run component of $\{y_t\}$ can be represented as

$$(\varepsilon_1 + \varepsilon_2 + \varepsilon_3 + \ldots + \varepsilon_t)' \rho(1)\, \boldsymbol{\beta}.$$

Therefore the cointegrated food stamp caseload regression links through the coefficient vector **β** the long-run components of economic and policy variables to the long-run component of food stamp caseloads.

If a food stamp caseload regression is a cointegrated regression, the long-run components of unit-root economic and policy variables dominates the distribution of food stamp caseloads. It even affects the short-run fluctuations or stationary component of caseloads. To see this, write the period-by-period change in FSP caseloads in an *error-correction form*. This form can be obtained by substitute *(5)* into *(4a)* and subtract y_{t-1} from both sides.

$$(8) \qquad \Delta y_t = (\mathbf{x}_{t-1}'\boldsymbol{\beta} - y_{t-1}) + \Delta \mathbf{x}_t' \boldsymbol{\beta} + u_t$$

where 'Δ' is the first difference operator (i.e., $\Delta y_t = y_t - y_{t-1}$). Equation *(8)* shows that period-by-period changes in food stamp caseloads can be expressed in terms of the cointegrating vector and lagged *levels* of integrated food stamp caseloads and economic and policy variables (the error-correction term) and period-by-period changes in the economic and policy variables. Equation *(8)* shows that a simple first-difference representation of *(4a)*, although stationary, is misspecified since it does not include the error-correction term and thus severs the link between short-run dynamics and the long-run relationship.

Even though *OLS* yields consistent estimates of β, the usual *t* and *F* hypothesis tests associated with estimating *(4a)* yield correct inference only under the stringent condition of econometric exogeneity. Strict econometric exogeneity is achieved in *(4a)* and *(5)* when $Cov(u_t, \mathbf{v}_t) = 0$, however in general, one should expect that this condition will be violated. Phillip and Hanson (1990) have developed a *fully modified (FM) estimator* that corrects for the effects of this correlation. FM estimation involves a transformation the data. The usual t and F tests calculated from OLS estimates applied to the transformed data results in asymptotically valid tests of β. Park's (1992) *Canonical Cointegrating Regressions (CCR)* estimator used in this paper is also a fully modified estimator.

In order to determine whether an integrated regression model is described by second case (spurious regression) or by the third case (cointegrated regression) tests of cointegration are conducted. All cointegration tests are based on whether regression residuals behave like a stationary or a unit-root nonstationary process. One approach to testing for cointegration is to check whether the model residuals behave like a unit root process. This approach tests the null hypothesis that the relationship is *not* cointegrated. In this case one applies the Dickey-Fuller (1981) or augmented Dickey Fuller tests (for residuals) or the tests described by Phillips and Ouliaris (1990). Rejecting the null of integrated model residuals rejects the null that the integrated regression is spurious. A problem with these residual tests is their low power, which owes to the fact that residuals must be estimated before they can be tested (Dickey, Jansen, and Thornton, 1991). Another approach to testing for cointegration is to test the null hypothesis that the regression *is* cointegrated using a procedure developed by Park (1990). His variable addition test exploits the fact that under the null of cointegration the stationary model error tests are uncorrelated with additional integrated variables or deterministic time trends. In this case, an *F*-test (on transformed regression variables) will fail to reject the null of zero coefficients associated with additional integrated regressors. That is, under the null of cointegration, the additional integrated regressors are superfluous and an *F*-test will imply that coefficients of the added variables are zero. Under the alternative, the model residuals are unit-root non-stationary and the *F*-test rejects the null of zero coefficients.

In this paper, cointegration is tested using variable addition tests. This approach to testing cointegration is taken because we believe that there exists a long-run relationship between the FSP and AFDC/TANF caseloads and the economy and look for evidence to refute this belief. Given this belief, variable addition tests provide an advantage over residual tests. The low power of residual based tests of the null of unit-root nonstationary, like the augmented Dickey-Fuller test, means that these tests are not good at detecting relationships that are, in fact, cointegrated. A second advantage of variable additions test is that they are based on standardized distributions. This avoids complications associated with relying on non-standard testing procedures that are not currently well developed for testing residual from regressions of panel data.

We use tests of cointegration as tests of model specification. If a regression model is found to be spurious, this is interpreted to imply that the specification is misspecified. One way this could happen would be if too few integrated regressors were included in the model. For example, if there were a cointegrating relationship between FSP caseloads, the economy, and AFDC/TANF caseloads but an FSP caseload equation was estimated that included only economy regressors then the regression would be spurious. This distinction between cointegrated and spurious regression equations provides a criterion for evaluating previously estimated specifications of the FSP caseload equation.

2.3 Panel Cointegrating Regressions

Versions of the FSP caseload equation will be estimated using annual state level panel data from 1980 to 1999. The obvious advantage of these data is they include both the variation of FSP caseloads over time as well as the variation across states. It is anticipated that the additional variation will improve the quality of the estimated FSP caseload equation.

Let y_{it} denote *FSP* caseloads and $\mathbf{x}_{it}$ denote the vector of policy and economic variables in the *i*th panel in time *t*. The panel model that is estimated in this paper is of the form

$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + u_{it}$$

This specification of the caseload equation assumes that the relationship between the model variables is the same or *homogeneous* across the states.[9] Previously studies that have estimated

[9] Methods by which standard panel models adjust for individual panel fixed or random effects, such as demeaning or detrending, can be incorporated within the homogeneous panel case so that these individual effect do not make the panels heterogeneous.

the FSP caseload equation using state level panel data have assumed a homogenous relationship across states. In order to faciliate the comparison with these studies, we also assume of a homogeneous relationship across the states. The rationale for assuming a homogenous panel is quite different, however, depending on whether the data are generated by trend stationary versus integrated data processes.

With integrated data, the justification for a homogenous response in each state is based on the notion that the FSP is a national program with uniform eligibility requirements in which states are subjected to standardized performance criteria and are provided the same (percentage) reimbursement for administrative costs. Under these circumstances we might reasonably expect a common (homogenous) *long-run* relationship linking FSP caseloads, economy, and policy variables in each of the states. With integrated data, the assumption of a common long-run relationship implies that in any state a given change in a regresssor will cause the same change in the long-run FSP caseload level; however, the path of adjustment to the new equilibrium may be different for each state.[10] On the other hand, for trend stationary data the notion of a homogeneous panel implies much stronger assumptions. Under the assumption of trend stationary data, a homogenous panel implies that the short-run (year-to-year) path of adjustment of FSP caseloads to their time trend would be the same in each state.

Assume the elements of $[y_{it}\ \mathbf{x}_{it}']$ are drawn from unit root non-stationary processes, and for any fixed time period t, the $[y_{it}\ \mathbf{x}_{it}']$ are identically and independently distributed across *panels*. Let Ω_i denote the long-run covariance matrix of $\{[y_{it}\ \mathbf{x}_{it}']\}$ for the ith panel, and note the Ω_i are distributed *iid* across panels. Given mild moment and summability conditions, this matrix is integrable and therefore can be averaged over panels so that $\Omega = \mathrm{E}(\Omega_i)$ denotes the long-run average covariance matrix of $[y_{it}\ \mathbf{x}_{it}']$. Elements of Ω include Ω_{yy} (i.e., the long-run average moment matrix of y_{it}), Ω_{xx} (i.e., the long-run average moment matrix of $\mathbf{x}_{it}$), and Ω_{xy}(i.e., the long-run average cross-moment vector of $[y_{it}\ \mathbf{x}_{it}']$). Then $\beta = \Omega_{xx}^{-1}\Omega_{xy}$ denotes the long-run average regression coefficient associated with the long-run average covariance matrix of $[y_{it}\ \mathbf{x}_{it}']$.

Given T observations on n panels, Phillips and Moon show that under the null of homogeneous panel cointegration the pooled OLS estimator

(9) $\mathbf{b}_{n,T} = \sum_{i=1}^{n} \sum_{t=1}^{T} [\mathbf{x}_{it}\, \mathbf{x}_{it}'\,]^{-1}[\mathbf{x}_{it}\, y_{it}\,]$

is a $\sqrt{n}$ consistent estimate of β with a limiting normal distribution when $n/T \rightarrow 0$, and $[1\ {-\beta}]$ is the cointegrating vector. Phillips and Moon also show that a Fully Modified estimator of the pooled relationship, which includes the CCR estimator, is a $\sqrt{nT}$ consistent estimator of β with a limiting normal distribution providing $n/T \rightarrow 0$.

With homogenous panels the results discussed above for single equation cointegration carry over to pooled estimation. In particular, with homogeneous panels the pooled estimator (9) will converge to a stable long-run relationship when the specification is cointegrated; if the panel

[10] With cointegrated data, the path of adjustment is obtained from estimates of the error correction specification given in (8). For a further discussion of assumptions underlying short-run and long- run adjustments in dynamic heterogenous panel models see Pesaran, Shin, and Smith (1999).

specifications are spurious the pooled estimator diverges. Tests of cointegration, therefore, have the same interpretation with the pooled estimator as with the single equation estimator. This means that either the residual based tests or the variable addition test for cointegration discussed above could be used to evaluate the completeness of the model specification in the case of a homogenous panel.[11]

[11] The results of Phillips and Moon are much more powerful than are required for this paper. In particular they show that in the case of heterogeneous panels stable average long-run relationships can be estimated whether or not the individual panels are cointegrated or spurious. This means that panel methods allow for the estimation of long-run relationship even in cases where considerations of the time dimension alone would lead to the regression being characterized as spurious. To see this result write the heterogeneous panel as $y_{it} = \mathbf{x}_{it}'\beta_i + u_{it}$ with β_i random, and rewrite this equation as $y_{it} = \mathbf{x}_{it}'\beta + u_{it}^*$ where $u_{it}^* = \mathbf{x}_{it}'(\beta_i - \beta) + u_{it}$. The pooled estimator (7) provide a consistent estimator of the parameter vector β even though u_{it} (for all $i = 1,\ldots,n$) is drawn from a unit-root process because in this case the linear combination of integrated variables $\mathbf{x}_{it}'(\beta_i - \beta)$ offsets a diverging variance of $\{u_{it}\}$. The result is an error process (u_{it}^*) with converging second moments. The estimator $\mathbf{b}_{n,T}$ represents a consistent estimate of β in this case because averaging over independent panels decreases the second moments of $\{u_{it}^*\}$ relative to the second moments of the integrated vector $\{\mathbf{x}_{it}\}$, although the speed of convergence of $\mathbf{b}_{n,T}$ will, in general, be slower than in the homogenous panel case. The pooled estimator in this case is defined by the long-run average variance matrix of the panel. In general, it is not equal to the average of the cointergration coefficients.

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

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[12] Wallace and Blank use the unemployment rate, the log of median wage rate, and the log of the 20^{th} 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).

4. Analysis of Annual State-Level Panel Caseload Data, 1980-1999

4.1 Evidence of Unit Root Non-stationarity From Previous Studies

Variables characterized by unit root non-stationarity exhibit a high degree of persistence. This is due to the fact that shocks to unit root processes do not die out over time.[14] The necessity of including a large number of lags in any dynamic model specification to account for this persistence is an indication of unit root non-stationarity or a root in the lag structure close to one. Both long lags of the FSP caseload variable and a high degree of persistence are evident in the preferred dynamic specification of the FSP caseload equation reported by FGZ and ZGF (2001,2003). In these specifications, four years, or one-fifth of the sample, are required to account for dynamic feedback. ZGF (2001,2003) report choosing a lag length based on the Schwartz information criterion. This criterion, however, tends to find shorter lag lengths than other methods (Ng and Perron, 1995) indicating that even longer lag lengths might be appropriate.

To illustrate the persistence implied by the lag structure reported in these studies we simulated the impulse response function of a one time shock implied by the coefficients of the lagged FSP caseload variables. The impulse response function is illustrated in figure 1 for the estimated lag structure given in table 1 of ZGF (2001). This lag structure implies that it takes 10 years for 90% of the impact of a shock to be realized but that the shock does not completely die out for approximately 30 years.[15]

As is common with models estimated with long dynamic lags, the impulse response function calculated from the estimated lag structure implies a complicated pattern of adjustment that appears difficult to interpret. In figure 1, the impulse response function of FSP caseloads indicates two cycles, one of 3 years and another of 12 years with an initially positive response that becomes negative after 5 years. The weights then cycle around zero until finally dampening out.

The simulation of the impulse response function implied by the lag structure estimated by ZGF (2001, 2003) shows clear evidence of a high degree of persistence in the FSP caseload data. The advantage of modeling the data assuming unit root non-stationarity in this case is that the long-run persistence in the data is embedded directly into the model specification. *Even if* the data were, in fact, stationary, but with a root close to but less than unity, assuming unit root non-stationarity would provides a more parsimonious method of incorporating persistence compared to stationary models requiring long lags.[16] Modeling the data as if it were unit root non-stationary, in this case, would adhere to the Box-Jenkins' principle of "parsimonious parameterization". Parsimony is valued as a criterion for model selection since an excessive number of parameters often leads to multicollinearity, instability of parameter estimates, a loss of

[14] See the discussion around (7).
[15] ZGF (2001, p. 9, footnote 7) note that their estimates implies that ". . .it takes about a decade for a shock to completely filter through the system"
[16] Clark and Spriggs (1992) provide an example in which unit root and stationary models with roots are close to unity have similar predictions, at least for the first few years.

degrees of freedom and hence a loss in the precision of estimation (Fuss, McFadden, and Mundlak, 1978, p.224).

Studies that estimate static FSP caseload equations (i.e., those that do not include lagged FSP caseload variables) such as, for example Wallace and Blank, do not report the combination of regression statistics that usually indicate the existence of unit root non-stationarity. For a single equation model that does not include dynamics, evidence of unit root non-stationary typically would be indicated by highly significant t-values of the estimated coefficients, high R^2, and low Durbin-Watson statistics (Granger and Newbold, 1977). In the context of panel data, however, it is unclear how statistics based on estimated model residuals, such as R^2 or the Durbin-Watson statistic ought to be interpreted.

4.2 Unit Root Tests for Panel Data

Table 2 reports test results of the null hypothesis that unit-root time series generate the FSP caseload-related data. Tests for each state individually would have low power because each test would be based on only 20 observations. The tests in table 2 treat the data as generated from a panel of 50 states with 20 observations per state, and hence are panel unit root tests (Im, Pesaran, and Shin, 1997).

Two types of tests are reported. One type, denoted as ‘no trend’, is a test of the null that the sample data is generated by a time series with a single unit root. The second type, denoted as ‘trend’, tests the null that the data are generated by a series with a single unit root and a time trend. Observed test statistics that are less than the corresponding critical value (reported in a footnote) reject the null hypothesis of a unit root.

Whether or not a trend is included, tests in table 2 fail to reject the null that both the log of per capita FSP caseloads and log of per capita AFDC/TANF caseloads are integrated. Unit root tests for the employment growth and the unemployment rate appear to depend, however, on whether a trend is included in the test regression. In particular, the tests fail to reject that the employment growth and the unemployment rate were generated by integrated processes with no trend, but do reject (again, at conventional levels) the null that these variables were generated by integrated processes with a trend.

Visual inspection of the plots of aggregate employment growth and the unemployment rate indicate that the appropriate test regressions may be the ones without trend. The employment growth series appears to exhibit no trend over the sample period, and the unemployment rate exhibits no strong evidence of a trend. Under the alternative hypothesis that these series are stationary (around a non-zero mean) the appropriate test regression for these variables would exclude a time trend (Hamilton, pp. 501-3). These tests in table 2 do not reject the null hypothesis that employment growth and the unemployment rate are integrated.

The results from table 2, and the indication of persistence in the data, provide evidence that the FSP caseload data behave as if they were generated by unit-root processes. It is not, of course, possible to determine definitively whether or not these data were generated by a nonstationary processes. Based on our examination of these date we assume that state level time-series of the log of per capita FSP caseloads, the log of per capita AFDC/TANF caseloads, the unemployment rate, and employment growth are described by unit-root processes.

4.3 Tests of Cointegration

Previous estimates of the FSP caseload equation using annual state level panel data have assumed a homogenous panel structure in which response coefficients are the same for each state (except for the effect of state fixed effects or, if present, state specific time trends). We make the same assumption in this paper. The difference is that we assume that there exists the same cointegrating relationship for all the states. In a subsequent section, we provide evidence that supports this assumption.

Our estimation procedure is based on the results of Phillips and Moon for the case in which the number of cross-sections (n) and time series observations (T) are such that $n/T \rightarrow 0$. In our analysis this assumption is satisfied since we will assume that the number of states is fixed and the panel grows over time.

Under this condition, Phillips and Moon show that the average panel can be estimated using a fully-modified panel estimator if an individual homogeneous (or near homogeneous) cointegrating relationship exist for the cross sections. In this study, estimates are obtained using Park's (1992) canonical cointegrating regression (CCR) estimator. This estimator is a version of Phillips and Hansen's fully-modified (FM) estimator. Tests for cointegration are conducted using Park's (1990) variable addition test. This testing framework assumes that there exists a long-run relationship (a null of cointegration) and looks for evidence to refute this hypothesis.

The empirical analysis is based on the following specification of the FSP caseload equation (*10*) that removes the state level fixed effects.

$$(10a) \quad \mathrm{FSP}_{it} - \mathrm{FSP}_{i.} = \mu + \beta' T_t + \alpha' IP_{it} + \theta' (E_{it} - E_{i.}) + \gamma(\mathrm{AFDC}_{it} - \mathrm{AFDC}_{i.}) + \varepsilon_{it}$$

The state-level economic variables (E) consist of a 2 element column vector with the unemployment rate (UM) and employment growth (EMP) measured as deviations from their time means, $(E_{it} - E_{i.})' = [\mathrm{UM}_{it} - \mathrm{UM}_{i.} \ \ \mathrm{EMP}_{it} - \mathrm{EMP}_{i.}]$. The time means of the variables are denoted as $\mathrm{FSP}_{i.} = \mathrm{T}^{-1} \Sigma_t \mathrm{FSP}_{it}$, $\mathrm{AFDC}_{i.} = \mathrm{T}^{-1} \Sigma_t \mathrm{AFDC}_{it}$, $\mathrm{UM}_{i.} = \mathrm{T}^{-1} \Sigma_t \mathrm{UM}_{it}$, and $\mathrm{EMP}_{i.} = \mathrm{T}^{-1} \Sigma_t \mathrm{EMP}_{it}$, respectively.

The economic variables and the log of per capita ADFC/TANF caseloads are the unit root regressors. The deterministic regressors consist of the trend variables (T), which include both linear and quadratic trend terms, a common intercept (μ), and the intervention policy variables (IP). The intervention policy variables include the dummy variables defined by the set of explicit changes in FSP provisions given in table 1 and the any waiver dummy variable. We will refer to (*10a*) as the full model. Conceptually, we hypothesize that any possible cointergrated relationship exists between the caseloads of these program and the economic variables. The policy variables are viewed as intervening into this long-run equilibrium relationship. Park and Phillips (1988) have shown that stationary regressors such as the policy and deterministic variables are asymptotically orthogonal to any integrated variables in a cointegrating regression.

Hence, asymptotically, the inclusion of the policy variables does not affect the asymptotic results. These policy variables are included in the model specification to better account for shocks to the system generated by changes in policy, which should more accurately model short-term fluctuations in the system during this sample period.

Since previous studies have generally estimated the FSP caseload equation without including AFDC/TANF caseloads as a regressor, we begin the evaluation of the specification of this equation by first addressing the question of whether a FSP caseload equation that consists of just economic and policy variables can be considered correctly specified. The null hypothesis is that a FSP caseload equation given in (10a) that *excludes* the log of per capita AFDC/TANF caseloads forms a long-run equilibrium relationship. We test this hypothesis using two versions of Park's variable addition test for cointegration.

In the first version, third, fourth, and fifth powers of time are used as superfluous variables. The first row of table 3 reports the results of these variable addition tests for the specification of the FSP caseload equation (*10a*) that includes only the economic, policy and deterministic variables. [17]

The results suggest that the FSP/economy/policy-only equation may be misspecified. At the 10% level the null hypothesis of cointegration is rejected. This provides evidence that the model residuals act like an integrated process so that the economy and dummy policy variables, by themselves, are not sufficient to define a long-run equilibrium relationship with FSP caseloads.[18] These test results indicate, therefore, that the estimated relationship leaves out AFDC/TANF caseloads may not be stable and may not provide consistent estimates of the relationship between FSP caseloads and the economy and policy.

In the second version of Park's variable addition test the log of per capita AFDC/TANF caseloads is added to the FSP/economy/policy-only equation as a superfluous variable. Coefficient estimates of the full model (*10a*) given in the third column of table 4 indicate that the impact of AFDC/TANF caseloads is highly significant with an observed t-value that exceeds ten. As a superfluous variable, the significance of the log of per capita AFDC/TANF caseloads is strong evidence against the cointegration of a FSP/economy/policy-only caseload specification.

The evidence from both versions of the variable addition test supports a conclusion that the FSP/economy/policy-only regression is not cointegrated. Next, we test the specification of the full model (*10a*) that includes the impact of the log of per capita AFDC/TANF caseloads for cointegration. Cointegration tests of the full specification of (8a) using powers of time as superfluous variables are reported in the second and third rows of table 3. In the second row of table 3 test results are reported when trend variables (*T*) are included. The large observed probability values for each of the variable addition tests indicate support for the null hypothesis

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[17] The tests consist of adding these superfluous variables to the regression, beginning with the cubic time trend, and testing the joint hypothesis that the coefficients of the superfluous variables are all equal to zero.

[18] More precisely, the variables used to measure economic activity do not appear to be cointegrated with FSP caseloads. This does not exclude the possibility that FSP caseloads, the economy and intervention policy variables could be cointegrated with different measures of economic activity.

that the full model is stochastically cointegrated.[19] Removal of the trend variables allows for a test of deterministic cointegration (see the discussion on page 12). The results of this test are presented in the third row of table 3 and indicate that deterministic cointegration is not rejected at conventional level in the full model.[20, 21]

The finding that the full model specification is deterministically cointegrated means that (*10a*) is correctly specified without including the trend variables (*T*). Any trend in the log of per capita FSP caseloads is cancelled by a linear combination of trends in the regressors. The implication of this finding is that the common practice of including year effect and/or state specific time trends is not recommended for these data. Including these trends appears to overcontrol for variation that can be explained by variation in the regressors. Take, for example, the estimate of the importance of policy and economic variables in explaining the FSP caseload reduction during 1994-99. For the specification that most closely corresponds to the cointegrated FSP caseload equation we estimate, results reported by ZGF (2001, table 3, column 2) imply that the deterministic and residual components represent about 34 percent of the actual change in FSP caseloads between during these years. In our case, (table 5) the net effect of the deterministic and residual components represent only about 4 percent of the actual change in FSP caseloads for this period. This comparison suggests that the admonition by Wallace and Blank and by Schoeni concerning over-differing with time trends is important (see the discussion on page 12).[22]

4.4 Coefficient Estimates

Table 4 presents the parameter estimates of the full model specification given in (*10a*). Even though OLS estimates of the panel cointegrating relationship are consistent, non-zero correlation between the stationary component of the stochastic regressors and the error term will cause the OLS estimates to exhibit a finite sample bias that invalidates the usual asymptotic t-test of parameter significance. The CCR estimator transforms the variables of the regression so that these problems are asymptotically corrected. Hence, test statistics presented along with the CCR estimates are large sample test.[23]

A comparison of the parameter point estimates obtained from the OLS and CCR estimators in table 4 illustrates the implications of endogeneity caused by correlation between the model errors and the explanatory variables. The effect of this correlation on tests of significant is illustrated by the estimates of Omnibus Budget Reconciliation Acts in 1990 and 1993, and the

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[19] The null hypothesis of cointegration between log of AFDC/TANF caseloads, trend, the intervention policy and economic variables was rejected at the 5% level of significance using these superfluous variables.
[20] Deterministic cointegration is discussed on page 16.
[21] The fact that we find cointegration using the same measures of the economy as have been used in previous studies suggests that the misspecification of FSP caseload equation estimated in these studies results because the variables included to measure the impact of policy do not sufficiently capture the range of policy changes that occurred during the sample period.
[22] Currie and Grogger report specifications with and without state-specific time trends (table 2). The inclusion of state-specific time trends reduced the magnitudes of the unemployment rate coefficient and a AFDC waiver variable, however, from their results it is not possible to calculate how the inclusion of these trends affects the proportion of the change in FSP caseloads due to the deterministic components.
[23] The results of Phillips and Moon implies that the CCR estimator converges to this distribution at the rate $\sqrt{n}T$.

estimate of the intercept term. In each case, OLS estimation indicates that the impact of the variable is statistically positive at conventional levels but is statistically insignificant with CCR.

The adjustment of OLS estimates for correlation between the first-difference in the explanatory variables and the model error and any serial correlation by CCR also causes the sign of some parameter estimates to change; however, this mostly involves coefficients that are not statistically significant at conventional levels. The notable except is the impact of employment growth which changes from a statistically positive effect with OLS to a marginally significant negative effect with CCR. This switch in sign is similar to the effect observed by ZGF (2001, p. 18) when they proceeded from a "static" model to a "dynamic" model.

Results in column 4 indicate that the elasticity of FSP caseloads with respect to AFDC/TANF caseload, given by the estimated coefficient, is positive as expected and very precisely estimated. Column 3 of table 4 also reports CCR estimates for the FSP caseload equation that does not include the AFDC/TANF caseload variable. Our tests of conintegration indicate that meaningful inference can not be conduced with this equation; however, it is interesting to observe what effect the exclusion of AFDC/TANF caseloads has on the estimated effects of the economic variables. When AFDC/TANF caseloads are excluded both economic variables have a greater absolute affect on FSP caseloads. This likely reflects the fact that AFDC/TANF caseloads are themselves a function of the economy. This effect is discussed further in Section 6 when estimates of the relative effect of policy versus economy are compared.

4.5 Variable Contribution

Previous studies of the FSP caseload equation have reported on the relative importance of the economy versus policy by comparing the percentage of the actual change in FSP caseloads predicted from changes in each type of variable around the time of PRWORA. Following these studies, measures are also calculated using our estimate of the FSP caseload equation for the time interval 1994-98. A comparison of these measures with those from other studies is postponed, however, until section 6. In this section, measures of the importance of the various regressor variables in explaining variations in FSP caseloads are presented for the *entire* sample period 1980-99.

Variable performance is evaluated based on two comparisons. The contribution of each type of variable used in (*10a*) is evaluated based on its contribution to the statistically fit measured by incremental R^2, and a graphical analysis, using a sample of 5 states and the aggregate US, that illustrates how well each variable type tracks movements in FSP caseloads over the sample period. The CCR estimates of the cointegrated caseload equation given in column 3 of table 4 are used in the comparisons.

Table 6 reports values of incremental R^2 for each type of variable used in (8a).[24] The incremental R^2 of a variable provides a measure of its importance in the estimated equation (Theil, 1971, p.168). A given value of the incremental R^2 measures the addition to (overall) R^2 when the variable is added to the regression. Incremental R^2 is a conditional measure that

[24] Incremental R^2 values were calculated using the transformed data from the CCR estimator.

depends on the order in which the variables are added to the equation. That is, the value of the incremental R^2 of a variable depends upon the variables already included in the regression.

Since we are interested in assessing the impact of adding AFDC/TANF caseloads to the FSP/economy-only specification, the incremental R^2 associated with the log per capita AFDC/TANF caseloads variable is calculated after accounting for the other determinants in the regression. The results in table 6 illustrate that the impact of this variable is quite large, roughly five times more important than the economic variables in achieving the overall fit of the FSP caseload equation. This result suggests the importance of variations in AFDC/TANF caseloads in explaining movements in FSP caseloads extends to the entire sample period 1980-99 and is not limited to the particular subset of years surrounding the passage of welfare reform legislation.

To illustrate how the estimated cointegrated specification tracks the time path of FSP caseloads over the sample period, five states consisting of California, Florida, Illinois, Texas, and Wisconsin plus the aggregate US were chosen. Each of these states had relatively large FSP caseload and as a group exhibited a diverse caseload pattern over the period. The model's ability to track the path of FSP caseloads in these states provides evidence of the overall fit of the estimated cointegrated FSP caseload equation.

Time plots of the deviations in the log of per capita FSP caseloads from their sample mean for the five individual states and the US are given in figures 2. Since the end of the 1980's FSP caseloads for each of the states have generally followed the overall US pattern, however, prior to that time the states exhibited much greater diversity in their FSP caseloads. During the decade of the 1980's, both California and Florida exhibited generally declining FSP caseloads until the run-up at the end of the decade (similar to the US aggregate). The other states, however, exhibited an increase in FSP caseloads through the first part of this decade, either to a plateau and then a decline (Illinois and Wisconsin), or simply a general increase throughout (Texas). At the beginning of the decade of the 1990's, FSP caseloads were increasing for all the states and peaked at their highest levels around 1993-94 before declining throughout the second half of the 1990's.[25] The experience in Wisconsin differed somewhat from this pattern. FSP caseloads in Wisconsin did not start to increase until 1991-92 and then peaked in 1993 at a level below their peak level in the 1980's.

In figure 3 the plot of the mean deviations of the log of per capita FSP caseloads predicted by the full model (*10a*) using the CCR estimates is graphed against the actual FSP caseload data for each state and the aggregate US. These plots indicate that the model does a reasonably good job of tracking the diverse patterns of FSP caseloads illustrated by this sample of individual states. The overall performance of the specification (*10a*) in tracking FSP caseloads in these states appears to support the decision to model the state level data as a homogeneous (or near homogeneous) panel with the same cointegrating vector for each state.

[25] The peak in per capital FSP caseloads in the 1980's (1981) in Florida was only slightly less than the peak in the 1990's (1993).

Additional insight into the performance of (*10a*) can be gained by illustrating the contribution of each variable type in explaining movements in FSP caseloads. In these illustrations a ‘hat’ denotes an estimated CCR coefficient.

In figure 4 the mean deviations in the log of per capita FSP caseloads predicted by per capita AFDC/TANF caseloads [$\hat{\gamma}$ ($AFDC_{it}$ – $AFDC_{i.}$)] is graphed for each state along with the deviations in the log of per capita FSP caseloads, FSP_{it} – $FSP_{i.}$. The plots indicate that per capita AFDC/TANF caseloads track the general overall pattern of per capita food stamp caseloads fairly well. The general fluctuations of per capita food stamp caseloads are fairly consistently tracked by concomitant rise and fall predicted by per capita AFDC/TANF caseloads.

Next, the portion of the deviations in the log of per capita FSP caseloads predicted by AFDC/TANF caseloads is subtracted from the deviations in the log of per capita FSP caseload, [(FSP_{it} –$FSP_{i.}$) - $\hat{\gamma}$ ($AFDC_{it}$ – $AFDC_{i.}$)]. In figure 5 the resulting series is graphed along with the log of per capita FSP caseloads predicted by deviations in the economic variables, $\hat{\vartheta}^{/}(E_{it} - E_{i.})$. Once the influence of per capita AFDC/TANF caseloads has been taken out, the remaining portion of the deviations in the log per capita FSP caseloads is much more variable. However, the predictions obtained from unemployment rate and employment growth variables do a credible job in tracking the fluctuations unexplained by variations in AFDC/TANF caseloads.

Finally, both the influence predicted by the AFDC/TANF caseloads and the economic variables are removed from deviations in the log of per capita FSP caseload variable, (FSP_{it} - $FSP_{i.}$) - $\hat{\gamma}$ ($AFDC_{it}$ – $AFDC_{i.}$) - $\hat{\vartheta}^{/}(E_{it} - E_{i.})$. In figure 6 these unexplained variations are graphed along with the deviations in the log of per capita FSP caseloads predicted by the intervention policy variables, $\hat{\alpha}^{/} IP_{it}$. These plots illustrate that these intervention policy variables do not tract the remaining portion of log per capita FSP caseloads in the individual states well. Interestingly, the policy dummy variables do a better job tracking the residual log per capita FSP caseloads for the US than for any of the individual states. This may indicate that these policy dummies, in the aggregate, are picking up differences in the proportion of states that implement policy changes during a given year.

5. Economy versus Policy

One of the original objectives of estimating the FSP caseload equation was to obtain measures of the relative importance of the economic versus policy variables for explaining movements in FSP caseloads during the 1990's. Most of the previous studies have provided a comparison of these two influences by calculating the percentage of the actual change in FSP caseloads predicted by these two types of variables. Wallace and Blank report this measure of variable importance over the entire decade up to 1998 (1990-94, 1994-96, and 1996-98). Other studies have concentrated on the time period around the passage of PRWORA. ZGF (2001) and Kornfeld report these measures of variable contribution for the periods 1994-99 and 1996-99. FGZ report this measure but for only the 1994-99 period.

A similar measure of variable importance is calculated here for the time period 1994-98 for each type of regressor variable use in the estimation of the cointegrated FSP caseload equation. The percentage reduction in the log of per capita FSP caseloads during 1994-98 attributed to the trend, dummy, the economic variables, the log of per capita AFDC/TANF caseloads, and the residuals are reported in table 5. The contribution of the economic variables to the reduction in per capital FSP caseload is about one and one-half times that of the intervention policy variables (16 versus 10 percent). In this time period the effect of the policy dummy variables reflect the effect of the dummy variable that signals the enactment of PRWORA in 1996 and the any waiver variable. The contribution of both the intervention policy and economic variables, however, pales by comparison to the effect attributed the AFDC/TANF caseloads. Table 5 indicates that the reduction in the log of per capita AFDC/TANF caseloads predicts roughly 80% of the actual reduction in the log of per capita FSP caseloads during this period.

Of the previous studies, only Wallace and Blank and ZGF (2001) report specifications of the FSP caseload equation that include AFDC/TANF caseloads as a regressor, however, only ZGF (2001) use estimates of this specification to calculate measures of variable contribution. Wallace and Blank are concerned about the endogeneity problems and included estimates of the FSP caseload equation only "as a comparison", (p.15) with their preferred specifications that do not account for AFDC/TANF caseloads.

Adding the contemporaneous log of per capita AFDC/TANF caseload as a regressor in the specification estimated by these author is not, however, sufficient to insure cointegration. In a recent paper Pesaran and Shin (1997) showed that it is possible to estimate cointegrating relationships using an autoregressive-distributed-lag (*ARDL*) specification such as used by ZGF (2001) and Wallace and Blank. The method proposed by Pesaran and Shin requires tests of the regression residual to make sure that all variables enter with the correct number of lags to insure that the residuals are stationary. In particular, since ZGF (2001) provide no information on the nature of their residuals, it is not possible for us to determine whether the specification that includes AFDC/TANF caseloads is in fact cointergrated.

Having stated this qualification, we can proceed to compare the measures of variable contribution that are reported in table 5 with the measures reported by ZGF (2001) for their specification that includes the log of per capita AFDC/TANF caseloads as a regressor. ZGF

(2001) report that for this specification the economic variables predicted 23 percent, their policy variables predicted 7 percent, and AFDC/TANF caseloads predicted 32 percent of the reduction in caseloads during 1994-99. The predicted effects of the economic and policy variables are similar in magnitude to the effects given in table 5, however, the predicted effect of AFDC/TANF caseloads is substantially lower than what we calculate. There appear to be two possible reasons for ZGF (2001) finding AFDC/TANF caseloads during this period to be less important than we do. One, ZGF (2001) did not include the effects of lagged AFDC/TANF caseloads in their estimated specification of the FSP caseload equation. Two, annual effects or the state-specific time trends employed by ZGF (2001, 2003) control for effects that may be, in fact, associated with changes in AFDC/TANF caseloads.

The requirement that the effect of AFDC/TANF caseloads be included in the FSP caseload equation to achieve cointegration means that measures of the contribution of the economy and policy calculated using just the FSP caseload equation are only partial measures conditional on the level of AFDC/TANF caseloads. Since changes in AFDC/TANF caseloads themselves reflect both effects of economy and policy, it is not possible conceptually to measure the total effect of either economy or policy using the estimated FSP caseload equation alone.[26, 27]

ZGF (2001) handle this problem by assuming a recursive structural system in which AFDC/TANF caseloads affects FSP caseloads but not visa versa. Their structural AFDC/TANF caseload equation is based on previous work by Figlio and Ziliak, and specifies AFDC/TANF caseloads as a function of only the economic variables and a set of policy indicators defined for the AFDC/TANF program. The empirical results presented in section 5.3 suggest, however, FSP caseloads, AFDC/TANF caseloads plus the economic and policy variables are all needed to define a cointegrated relationship. Regressions involving subsets of any of these variables would be spurious. In this case, ZGF (2001) attempt to identify the impact of the economy on AFDC/TANF caseloads from an equation that *excludes* FSP caseloads would be invalid for the same reason that the FSP caseload equation without AFDC/TANF caseloads is invalid.

This suggests that in order to calculate the *total* effect of the economy on either FSP or AFDC/TANF caseloads a full simultaneous equation system for the two programs must be estimated. Such a system would consist of long-run structural equations in which there are two potentially cointegrating relationships connecting the caseload data. This system would define a reduced form specification from which the total impact of economy on both ADFC/TANF and FSP caseloads could be determined.

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[26] This can also be a problem with other variables, for example, ZGF (2001, p.12) recognize that their "policy" variable ABAWD also reflect economy effects.

[27] The impact of the economy on AFDC/TANF caseloads is probably the reason why excluding this variable from the FSP caseload equation results in both economic variables having a greater absolute affect. CCR estimates of the FSP caseload equation (10'), without and with the inclusion of the log of per capita AFDC/TANF caseloads are given in columns 2 and 3 of table 4.

6. Predicting Period-by-Period Changes in FSP Caseloads

The assumption that unit-root non-stationarity processes generate the data implies that variables have both permanent and transitory components. Any shock will, thus in general, impart *both* permanent and transitory effects. If the variables are cointegrated, the relationship among permanent components identifies the long run equilibrium relationship among the variables whereas the relationship among the transitory components identifies the short run relationship. In this paper, we have concentrated only on identifying and estimating the (long-run) relationship between permanent components of the FSP caseload data.

To predict the short run (transitory) period-by-period response of FSP caseloads to changes in the regressors requires the estimation of the *error correction* form given in (8). This specification of the data uses information from the cointegrating regression (specifically, the estimated error term) in combination with a vector autoregression that captures the short run response. In error correction models, the short run response tracks the adjustment process from one steady state level (equilibrium) to another. A characteristic of cointegration theory is that the existence of a cointegrating relationship implies an error correction model and vice-versa. Hence, “long run” and “short run” are tied together using a “permanent” and “transitory” decomposition of the variables. If the variables are cointegrated, it is not necessary to explicitly decompose them into permanent and transitory components since this distinction is accounted for by the estimation procedure. We find in this paper evidence that the economy does have a permanent effect on FSP caseloads. Our findings indicate that a *permanent* lower rate of unemployment or greater employment growth result in *permanently* lower FSP caseloads. What we have not done in this paper is to provide the decomposition of changes in FSP caseloads into permanent and transitory components which would be available from the estimation of (8).

For data that is trend stationarity the long-run permanent levels are given by their time trends. Model estimates measure the affects of deviations from the time trends in the regressor variables on deviations in the regressand variable from its time trend. If the data are trend stationary then the pattern of period-by-period changes caused by a changes in a regressor variable is useful in summarizing the short-run transitory influences on, say, FSP caseloads. These changes in FSP caseload may occur over more than one period, however, their cumulative effect does not reflect a permanent change in the level of FSP caseloads. This pattern of period-by-period change in FSP caseloads for a unit change in, say, the economy is illustrated in Figure 1 by the plot of the impulse response function estimated from the distributed lag structure given in ZGF (2001). This function measures the year-by-year response in FSP caseloads from a unit change in a regressor variable. In the long-run the response vanishes and FSP caseloads return to their time trend.

A comparison between the stationary and integrated characterization of the FSP caseload data could be performed by evaluation predictions of the year-by-year changes in FSP caseloads. The error correction specification given in (8) implies that a correct characterization of period-by-period changes in FSP caseloads incorporates the connection between permanent components of FSP caseloads and the regressor variables. An implication of (8) is that knowledge of this connection will result in better predictions of the period-by-period changes in FSP caseloads than formulations that rely on the stationary components of the regressor variables.

7. Conclusion

In this paper we analyze time series of the underlying FSP and AFDC/TANF caseload data assuming they behave like integrated processes. An examination of the lag structure of previously estimated FSP caseload equations indicated a high degree of persistent in the caseload data. This result suggests that a root in the dynamic structure is close to, or perhaps, equal to one. Formal tests of the hypotheses that these data were generated by unit-root processes could not be refuted.

Tests of cointegration are used to test specifications of the FSP caseload equation for completeness. These tests find strong evidence that AFDC/TANF caseloads must be included, along with measures of economic activity, in the FSP caseload equation in order to define a long-run equilibrium (cointegrated) relationship. This result implies that specifications of the FSP caseload equation that include measure of economic activity but fail to include AFDC/TANP caseloads may be spurious. Regression estimates of the FSP caseload equation that do not include AFDC/TANF caseloads will, therefore, imply coefficients that vary over time and *do not* converge to the true relationship. This means larger sample sizes *will not* improve model performance. In such a case, reliable measures of the extent to which the economy has affected FSP caseload cannot be made. Nor is it possible to obtain reliable predictions of how changes in the economy are likely to affect future FSP caseloads.

When the effect of AFDC/TANF caseloads is added to the FSP caseload regression evidence of a long-run (cointegrated) relationship connecting FSP caseloads with the economy is found. The existence of such a relationship between *long-run* or *permanent* components of the economy and the *long-run* or *permanent* component of FSP caseloads implies that even short-lived economic benefits can result in *permanently* lower FSP caseloads. This finding implies that the robust economy of the 1990's, by itself, resulted in a lower *long-run or permanent* level of FSP caseloads than would otherwise have been observed. It is hypothesized that this lower level of FSP caseloads is associated with the added work experience the FSP-eligible population gained during the economic expansion.

The requirement that the effect of AFDC/TANF caseloads be included in the FSP caseload equation in order to achieve cointegration implies that it is not possible to calculate the full impact of the economy on FSP caseloads using estimates of only the FSP caseload equation. This is a consequence of the fact that AFDC/TANF caseloads are themselves a function of economic variables. At best only a partial measure of the economy's effect on FSP caseloads can be obtained if the analysis is limited to just the FSP caseload equation. What are required in order to estimate the total effect of the economy are estimates of a (cointegrated) system of FSP and AFDC/TANF caseloads equations. The total effect of the economy on both FSP and AFDC/TANF caseloads could then be calculated from the resulting reduced form.

Our test results also indicate that the common practice of including year effects (annual dummy variables) or state-specific time trend in the FSP caseload equation may over-control for omitted variables. Instead, trends in the regressors should be allowed to explain trends in the caseload data. Both Wallace and Blank and Schoeni have expressed concern with the inclusion of various time trends in the FSP caseload equation, suggesting, in particular, that such trends might affect measures of the importance of the economy and welfare reform. Our results indicate that this is a legitimate concern.

Table 1: Intervention Policy Dummy Variables Affecting the Food Stamp Program

Year	Dynarski, Rangarajan and Decker (1991)	Ziliak, Gundersen and Figlio (2001)
1981	Omnibus Budget Reconciliation Act	Family Recovery Act
1985	Food Securities Act	
1986	Immigration Reform Act	
1988	Hunger Prevention Act	Family Support Act
1990	Food Agriculture Conservation and Trade Act	Omnibus Budget Reconciliation Act
1993		Omnibus Budget Reconciliation Act
1996		Personal Responsibility And Work Opportunity Reconciliation Act

Table 2: Average T-statistic Panel Unit Root Tests

Variable	No Trend	Trend
Log per capita FSP Caseloads	-1.230	-0.798
Log per capita AFDC/TANF Caseloads	0.027	-0.048
Unemployment Rate	-1.146	-2.583
Employment Growth	-0.048	-3.578

Critical values (and rejection region) of average t-statistic, T=50, N=20
No trend: -1.69 (0.10), -1.73 (0.05), -1.82 (0.01)
Trend: -2.33 (0.10), -2.38 (0.05), -2.46 (0.01)

Source: Im, Pesaran and Shin, Table 4 (1997)

Table 3: Variable Addition Tests of Cointegration[1]

Model	Number of superfluous regressors[2]		
	1	2	3
FSP caseloads, trends, intervention policy and economic variables	4.59 (0.03)	5.13 (0.08)	7.35 (0.06)
FSP caseloads, log of AFDC/TANF, caseloads, intervention policy and economic variables,			
with trend variables	0.52 (0.46)	0.55 (0.75)	1.10 (0.77)
without trend variables	0.65 (0.42)	0.68 (0.71)	1.35 (0.72)

1. Observed values of the test statistic which are asymptotically distributed as χ^2 with degrees of freedom equal to the number of superfluous variables. Values in parentheses are observed p-values.
2. Cubic, quartic and quintic powers of time are used as superfluous variables.

Table 4: Parameter estimates of the FSP Caseloads Equation[1]

	Estimator		
Regressor	OLS	CCR	CCR
Intercept	-0.094	0.19	0.056
	(-4.77)	(1.18)	(0.20)
Trend	0.001	-0.090	-0.051
	(0.12)	(-1.95)	(-1.07)
Trend Squared	0.001	0.002	0.002
	(1.20)	(1.15)	(1.11)
Policy Dummy 1985	-0.040	0.223	0.115
	(-1.54)	(1.74)	(0.94)
Policy Dummy 1986	-0.036	0.051	-0.014
	(-1.59)	(0.45)	(-0.18)
Policy Dummy 1988	0.011	0.144	0.046
	(0.54)	(1.48)	(0.49)
Policy Dummy 1990	0.085	0.345	0.158
	(4.10)	(3.41)	(1.62)
Policy Dummy 1993	0.101	0.228	0.129
	(4.69)	(2.36)	(0.69)
Policy Dummy 1996	-0.003	0.041	-0.020
	(-0.11)	(0.35)	(-0.18)
Any Waiver	-0.006	-0.091	-0.014
	(-0.28)	(-0.92)	(-0.15)
Unemployment Rate	0.034	0.057	0.036
	(9.54)	(6.57)	(4.07)
Employment Growth	0.406	-2.760	-1.853
	(2.12)	(-2.72)	(-1.92)
Log per capita AFDC/TANF Caseloads	0.490	-----	0.522
	(21.67)		(10.88)

1. Values in parentheses are asymptotic t-values. The asymptotic t-values for the OLS parameters are incorrect because they do not account for serial correlation or correlation between model errors and stochastic regressors.

Table 5: Percent of Per Capita Food Stamp Caseload Decline, 1994-98 Predicted by Regressor Variables

Variable:	Trends	Intervention Policy	Economy	Log Per Capita AFDC/TANF Caseloads	Residual
	-21.0%	10.0%	16.0%	78.0%	17.0%

Table 6: Incremental R^2 for the Regressor Variables in the Cointegrated FSP Caseload Equation[1,2]

Variable:	Trend	Intervention Policy	Economy	Log Per Capita AFDC/TANF Caseloads
	0.004	0.018	0.076	0.395

1. Estimated FSP caseload equation is given in table 4 column 3.
2. Because incremental R^2 is a conditional measure, their sum will not in general equal one.

Figure 1
Food Stamp Impulse Response Function

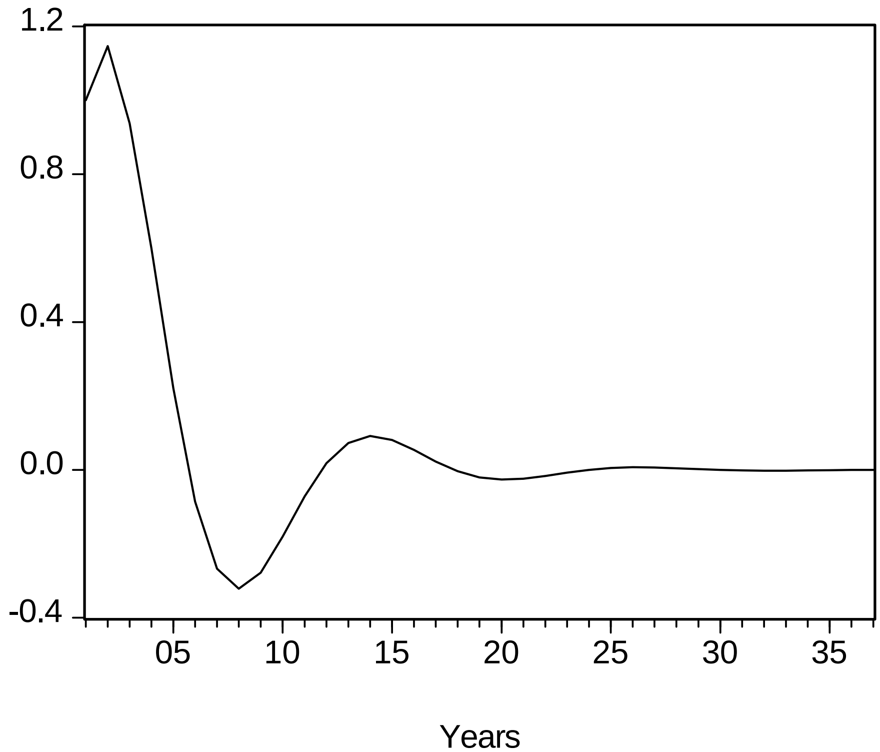


FIGURE 2

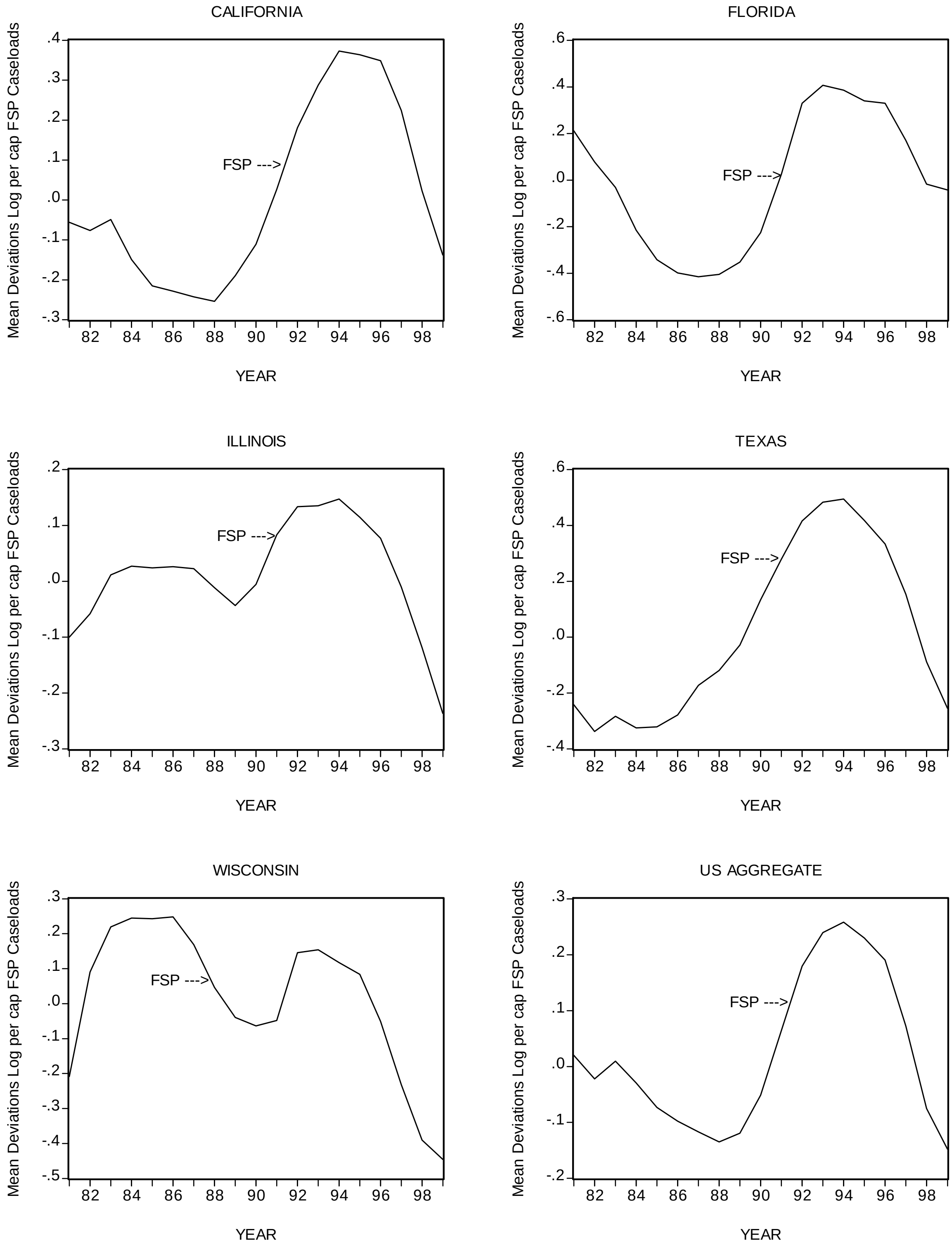

CALIFORNIA
FLORIDA
ILLINOIS
TEXAS
WISCONSIN
US AGGREGATE
Mean Deviations Log per cap FSP Caseloads
FSP --->
YEAR

FIGURE 3

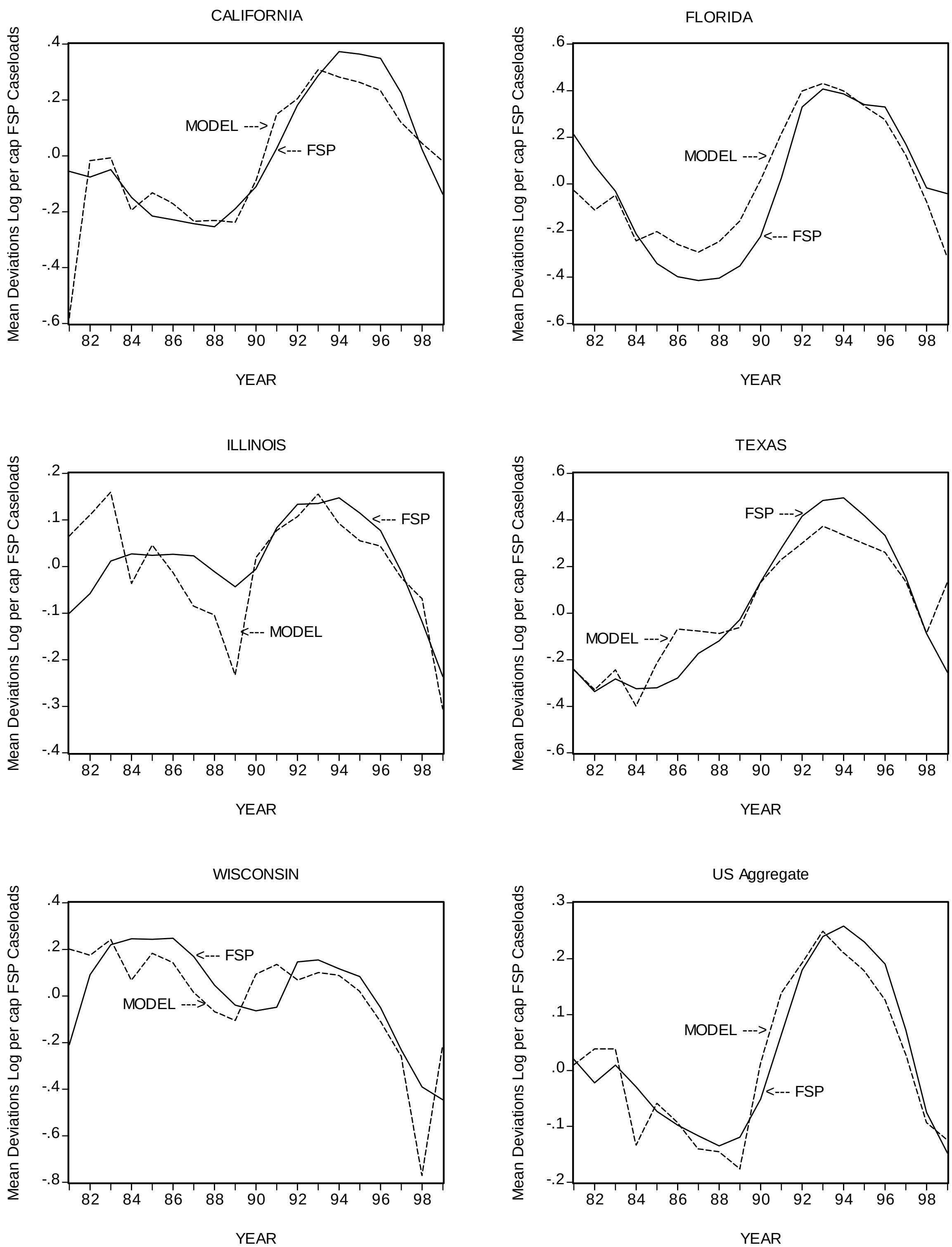

CALIFORNIA
MODEL --->
<--- FSP
FLORIDA
MODEL --->
<--- FSP
ILLINOIS
<--- FSP
<--- MODEL
TEXAS
FSP --->
MODEL --->
WISCONSIN
<--- FSP
MODEL --->
US Aggregate
MODEL --->
<--- FSP
Mean Deviations Log per cap FSP Caseloads
YEAR
82
84
86
88
90
92
94
96
98

FIGURE 4

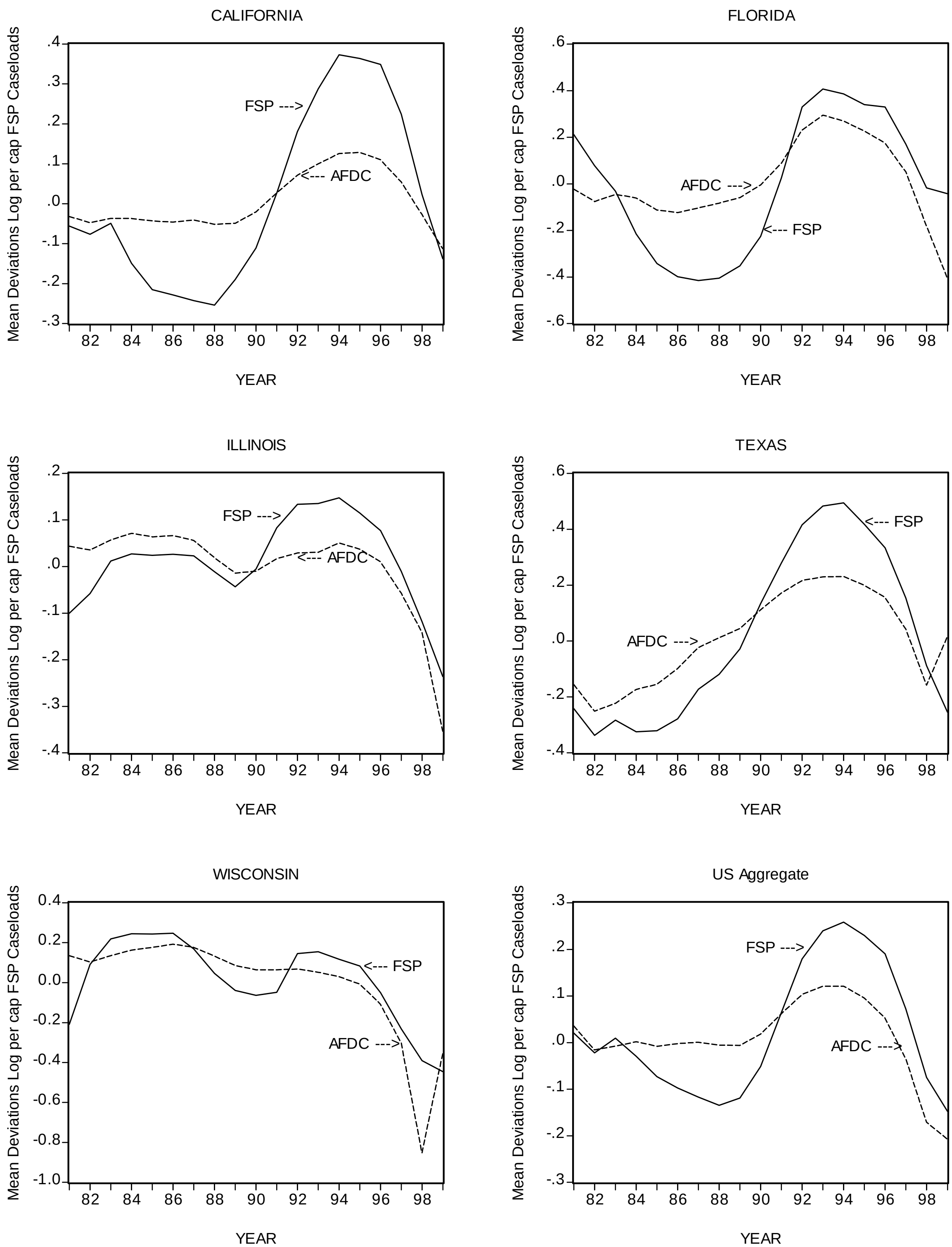

CALIFORNIA
Mean Deviations Log per cap FSP Caseloads
.4
.3
.2
.1
.0
-.1
-.2
-.3
82 84 86 88 90 92 94 96 98
YEAR
FSP --->
<--- AFDC
FLORIDA
Mean Deviations Log per cap FSP Caseloads
.6
.4
.2
.0
-.2
-.4
-.6
82 84 86 88 90 92 94 96 98
YEAR
AFDC --->
<--- FSP
ILLINOIS
Mean Deviations Log per cap FSP Caseloads
.2
.1
.0
-.1
-.2
-.3
-.4
82 84 86 88 90 92 94 96 98
YEAR
FSP --->
<--- AFDC
TEXAS
Mean Deviations Log per cap FSP Caseloads
.6
.4
.2
.0
-.2
-.4
82 84 86 88 90 92 94 96 98
YEAR
<--- FSP
AFDC --->
WISCONSIN
Mean Deviations Log per cap FSP Caseloads
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
82 84 86 88 90 92 94 96 98
YEAR
<--- FSP
AFDC --->
US Aggregate
Mean Deviations Log per cap FSP Caseloads
.3
.2
.1
.0
-.1
-.2
-.3
82 84 86 88 90 92 94 96 98
YEAR
FSP --->
AFDC --->

FIGURE 5

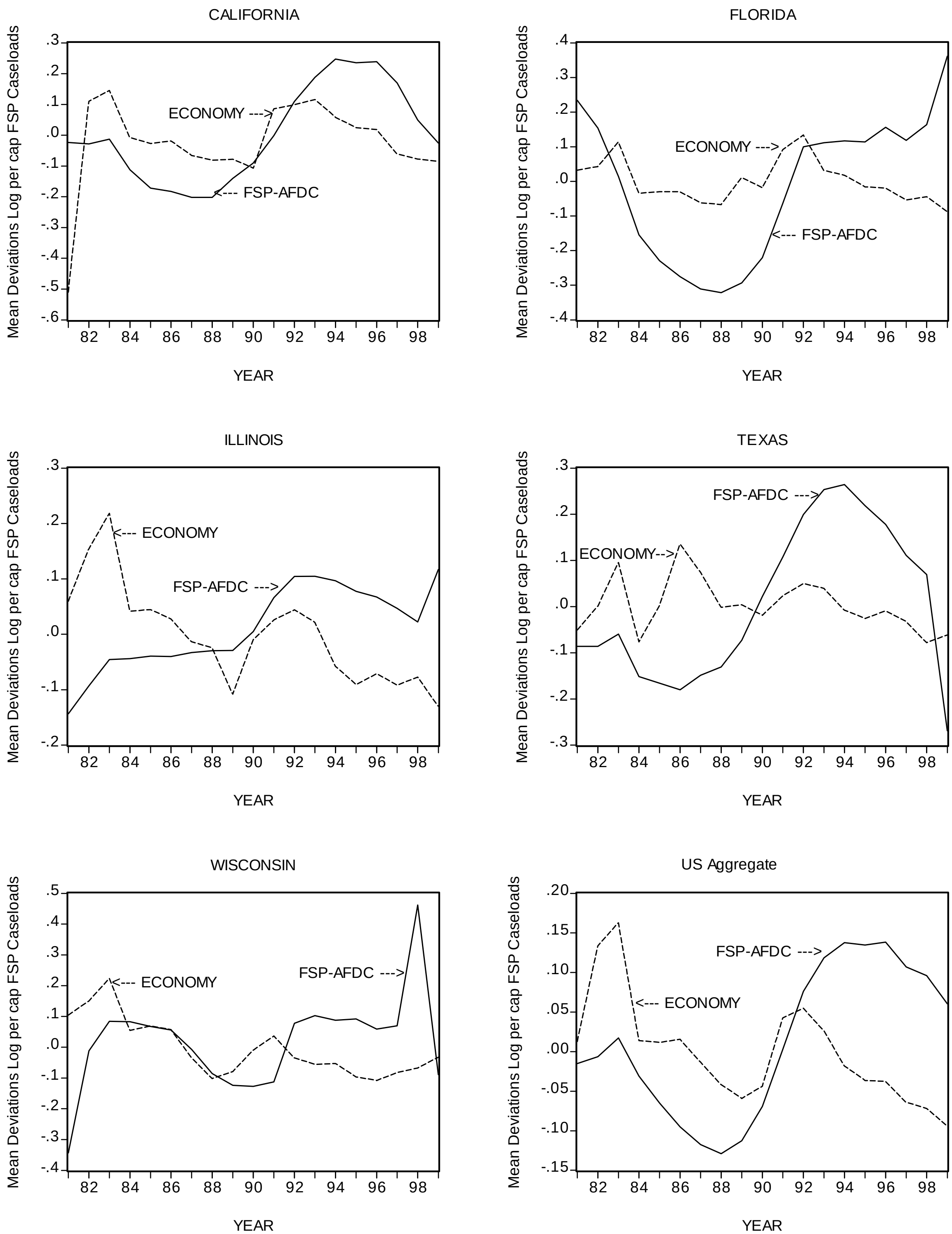
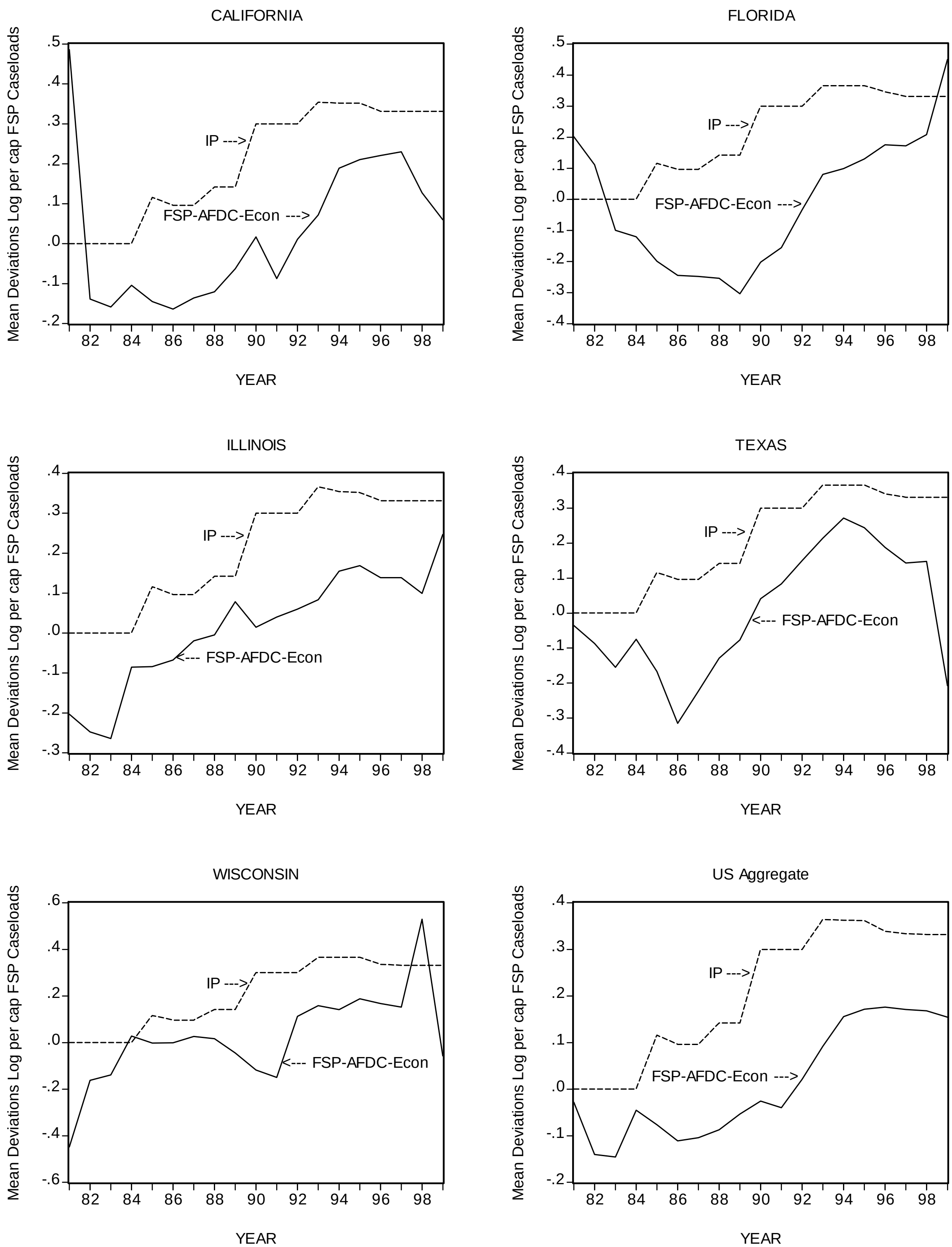

CALIFORNIA
Mean Deviations Log per cap FSP Caseloads
.3
.2
.1
.0
-.1
-.2
-.3
-.4
-.5
-.6
ECONOMY --->
<--- FSP-AFDC
82 84 86 88 90 92 94 96 98
YEAR
FLORIDA
Mean Deviations Log per cap FSP Caseloads
.4
.3
.2
.1
.0
-.1
-.2
-.3
-.4
ECONOMY --->
<--- FSP-AFDC
82 84 86 88 90 92 94 96 98
YEAR
ILLINOIS
Mean Deviations Log per cap FSP Caseloads
.3
.2
.1
.0
-.1
-.2
<--- ECONOMY
FSP-AFDC --->
82 84 86 88 90 92 94 96 98
YEAR
TEXAS
Mean Deviations Log per cap FSP Caseloads
.3
.2
.1
.0
-.1
-.2
-.3
FSP-AFDC --->
ECONOMY-->
82 84 86 88 90 92 94 96 98
YEAR
WISCONSIN
Mean Deviations Log per cap FSP Caseloads
.5
.4
.3
.2
.1
.0
-.1
-.2
-.3
-.4
<--- ECONOMY
FSP-AFDC --->
82 84 86 88 90 92 94 96 98
YEAR
US Aggregate
Mean Deviations Log per cap FSP Caseloads
.20
.15
.10
.05
.00
-.05
-.10
-.15
FSP-AFDC --->
<--- ECONOMY
82 84 86 88 90 92 94 96 98
YEAR

FIGURE 6


CALIFORNIA
FLORIDA
ILLINOIS
TEXAS
WISCONSIN
US Aggregate
Mean Deviations Log per cap FSP Caseloads
YEAR
IP --->
FSP-AFDC-Econ --->
<--- FSP-AFDC-Econ
82
84
86
88
90
92
94
96
98

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