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ABSTRACT

This paper uses state panel data to investigate changes in public assistance caseloads. Compared to other research, it uses more extensive data, both across states and over time; it utilizes a particularly rich set of control variables; it investigates the different subcomponents of the AFDC program separately; and it investigates the extent to which changes in caseloads are driven by changes in take-up rates versus in eligibility. The results indicate that an unexplained increase in AFDC-Basic caseloads started in the mid-1980s. This trend appears to be driven by three underlying components: a rise in child-only cases, an increase in take-up rates over the early 1990s during the economic slowdown, and a long-term increase in eligibility which is not well explained by a large set of control variables. In contrast, AFDC-UP caseload changes are relatively well explained by the model in this paper and are far more responsive to economic factors. Recent state policy changes are correlated with caseload declines, but more than half of their effect appears to precede their implementation, suggesting that other changes in client and caseworker behavior were occurring in states that adopted major policy changes.

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Introduction

This research investigates the determinants of growth in public assistance caseloads, focusing on participation in the Aid to Families with Dependent Children (AFDC) program. Growing caseloads in the early 1990s created great concern, and this phenomenon was frequently cited as a primary reason why welfare needed to be reformed. When declines in caseloads finally occurred in the mid-1990s, a number of Governors claimed that it was the changes they had enacted in welfare programs that led to this decline. Despite this policy discussion, there is a surprisingly sparse research literature on the determinants of aggregate caseload changes. This paper investigates the role of macroeconomic forces, public policies, and demographic change in explaining caseload changes over time.

The solid line in Figure 1 shows the total number of households receiving AFDC on a monthly basis from 1964 to the present. As the data indicate, there was a steep increase in AFDC caseloads in the late 1960s and early 1970s. Caseloads were then almost flat for 15 years until 1990 when they again began to increase sharply. In the last three years they have started to trend down. It is also worth noting that the back-to-back recessions in the early 1980s caused a mild uptick in caseloads, but this was quickly aborted when legislative changes in Reagan's first term ended AFDC eligibility for about 15 percent of the caseload.[1] This policy change makes it difficult to do any quick "eyeball" comparisons between the recession effects of the early 1980s and the early 1990s on caseloads.

The caseload increase in the late 1960s occurred at a time of enormous expansion in government public assistance programs. AFDC itself was substantially revised in 1967, and a series of court decisions forced states

[1] See GAO (1985).

to initiate more uniform procedures to review applications.[2] The Food Stamp program grew rapidly during this period and Medicaid was expanding, having just been established in 1965. A variety of groups, from the National Welfare Rights Organization to a cadre of legal aid lawyers, were working to empower poor families by encouraging them to claim the benefits available under these programs. In this environment, this early caseload increase is typically believed to be highly related to increasing participation among eligible women, both because states were more willing to admit applicants to the program, and because of an increased propensity by women to apply.[3]

This explanation for the caseload increase of the late 1960s makes the caseload increase of the early 1990s difficult to understand. A mild 1990-91 recession is not obviously sufficient to explain the magnitude and persistence of caseload growth. During this time period, the 1988 Family Support Act was being implemented in every state, mandating that "work eligible" AFDC recipients must participate in welfare-to-work programs. Rising Federal budget deficits and tight state budgets made public assistance programs the target of cutbacks in many of these years. AFDC benefit levels were declining in inflation-adjusted terms in all states throughout the 1980s and

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[2] Between 1968 and 1971, the Supreme Court abolished the absent father rule, residency requirements, and regulations that denied aid to families with "employable mothers." Welfare agencies were also required to provide fair hearings and proper notice to recipients threatened with termination.

[3] For instance, see the discussion in Patterson (1994). Moffitt (1987) argues that there was a structural shift in participation behavior in the late 1960s beyond what can be explained by economic or demographic forces, as take-up rates rose rapidly during this time period.

early 1990s.[4] In short, this was not a period of "expansiveness" toward low income families, and the rising caseloads are unexpected.

The majority of AFDC program dollars are spent in a program known as AFDC-Basic, which provides payments to single parent households and their children.[5] The remainder of the dollars are spent as part of the AFDC-Unemployed Parent program (AFDC-UP), which is paid (typically under stricter eligibility conditions) to low-income married couples and their children. The AFDC-UP program was available in only about half the states in the 1970s and 1980s.[6] Starting in 1990 all states were required to run such a program. Even after 1990, however, AFDC-UP accounted for less than 10 percent of overall AFDC caseloads and around 10 percent of all AFDC expenditures.[7] Because these two program components serve different populations (and, as we will see, exhibit quite different patterns), it is valuable to examine them separately.

Figure 2a shows caseloads in the AFDC-Basic program from 1975 on.[8] For comparison, the dotted line in Figure 2a plots the monthly unemployment rate. AFDC-Basic caseloads follow a similar pattern as total

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[4] Blank (1997) discusses these recent changes in program requirements and in the political debate about the best way to provide public assistance.

[5] AFDC-Basic also includes payments to "child-only" households where the caretaker is not eligible for AFDC, such as foster care payments or payments to children with a disabled parent who is receiving SSI. I discuss these child-only cases later in the paper.

[6] Between 1975 and 1989, the number of states participating in AFDC-UP varies from a low of 22 in 1981 and 1982 to a high of 29 in 1989. Note that some states initiate the program and then drop it over this time period.

[7] In 1995, AFDC-UP represents 6.9 percent of the total AFDC caseload and 10.1 percent of all AFDC expenditures.

[8] Prior to 1975, the data is not separately available on these two programs.

caseloads, not surprising given how large a share of the total they represent. A simple "eyeball comparison" suggests that there does not appear to be a strong relationship between unemployment and AFDC-Basic caseloads over this time period.

This aggregate pattern is not replicated in all states. While all states show a recent rise in caseloads, the magnitude of this rise and the caseload patterns during the 1970s and 1980s vary widely. For instance, Figure 3 plots data for Illinois, Texas, and New Jersey. Illinois shows little change in caseloads over the past 25 years. Texas shows no change until the mid-1980s and experiences a large and continuing caseload rise much sooner than the rest of the country. New Jersey exhibits a noticeable decline in caseloads over the 1980s. This type of variation suggests that the underlying determinants of caseloads must be moving quite differently across states.

In contrast, caseloads in the AFDC-UP program are shown in Figure 2b, with the unemployment rate again drawn as the dotted line. These data are not as easily interpretable as the AFDC-Basic data, since the UP program was available only in certain states before 1990. Hence, changes in UP caseloads reflect changes in the number of states offering the program as well as changes in AFDC-UP usage in those states where the program had always been available. AFDC-UP caseloads move more noticeably in line with the unemployment rate, although they too show a disproportionate increase over the past decade.[9]

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[9] Because all states were mandated to start an AFDC-UP program in 1990, it is less surprising to see an increase in AFDC-UP caseloads in the early 1990s.

Past Research on Caseloads

There is an extended literature on AFDC participation that measures the impact of family, personal, and program characteristics on individual participation decisions. This research investigates both point-in-time AFDC usage as well as spells of AFDC usage and the determinants of program participation and non-participation among eligibles.[10] The results indicate that certain types of family characteristics are correlated with a greater probability of AFDC usage and with longer AFDC spells, such as single parenthood outside of marriage, more and younger children, or lower education levels. But aggregating the results of these studies in order to derive expectations about aggregate caseloads is difficult. Few of these studies control for business cycle measures.[11] In addition, with cross-sectional or short-term longitudinal data this research cannot investigate the effect of changes in the economy over time on program participation.

The policy variables in these estimations are also problematic. Substantial cross-state differences in AFDC benefit levels are used to measure the elasticity of individual responses to benefits. This presumes that differences in behavior across states with different benefit levels can be used to predict the expected changes over time within a particular state should that state change its payments. This interpretation from cross-sectional results to longitudinal policy conclusions is common, but rarely convincing. Because of unmeasured differences in the populations and the environments of different states, panel data estimation that controls for state fixed effects often results

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[10] Moffitt (1992) provides a summary of this literature. See also Blank and Ruggles (1996).

[11] At best, state unemployment rates are included in the analysis. Fitzgerald (1995) and Hoynes (1996) are an exception.

in very different elasticities than estimation where most of the variation is cross-sectional.

There are few studies that attempt to model caseloads using longitudinal caseload data. Several state-specific studies seek to model caseload changes in order to forecast expected future program spending.[12] A few federally-sponsored internal reports on caseload changes have been recently written. Gabe (1992) and the Congressional Budget Office (1993) find that demographic changes, interacted with economic changes appear to explain some but not all of the caseload increases in the late 1980s and early 1990s. This work, however, is limited in the data it uses and small time period it focuses on. A recent report to HHS from the Lewin Group (1997) finds unusually large effects of unemployment on caseloads, but some unusual methodological choices make it difficult to compare these results with earlier studies.

A just-released report by the Council of Economic Advisers (1997) uses a relatively sparse specification to focus particularly on the role of recent state welfare policy changes, finding that Federal waivers which allowed states to change their AFDC programs in the mid 1990s had a significant negative effect on caseloads.[13] Work by Ziliak, et. al. (1997) uses an even sparser specification to relate AFDC caseloads to unemployment rates and state AFDC waivers over the 1990s and indicates that the economic changes were more important than the policy changes.

The present study uses more extensive data on caseloads, both across states and over time, than past research. Monthly public assistance data allow

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[12] See Plotnick and Lidman (1987), Brazzell, et.al. (1989), or Garasky (1990). An early Federal report that addresses this issue is Grossman (1985).

[13] Where the two papers are comparable, the results in this paper are quite similar to those in the CEA report.

me to look at the time series correlations between caseloads and monthly state unemployment rates. I also estimate effects from annual state panel data with controls for state and year effects, allowing the effects of economic, demographic, and policy changes to be more accurately measured as the effect of changes in these variables over time within a state. I control for a far wider variety of potential causal variables than earlier work; I investigate the different subcomponents of the AFDC program separately; and using data from the 12 largest states, I am also able to decompose recent caseload changes into changes in take-up rates versus changes in eligibility.

Data

Monthly state AFDC caseload data are available from 1964 to 1996. From 1975 on, these data are published separately for the AFDC-Basic and AFDC-UP programs.[14] There are 51 "states" in this data set since the District of Columbia is included. These data were collected from publicly available sources. The Data Appendix provides more information on sources. Table 1 shows the mean and standard deviation from annual caseload data from 1977 to 1995.

Given monthly caseload information, the other data available by state by month are state unemployment rates. State-level monthly unemployment rates were not reported prior to 1976. From 1976 to 1996, however, I have state-by-month data on caseloads and unemployment rates and can explore the time series relationship between these two series.

Because so little state data is available monthly, most of my analysis will focus on investigating the determinants of caseloads using a panel of

[14] Also available is data on the total number of individuals receiving each of these programs, as well as data on total expenditures. I use households rather than individuals to abstract away from large changes in average family size over this time period.

annual state caseload data. A host of state-by-year variables are collected from various publicly available sources. This includes unemployment rates, total population, number of women ages 15 to 44, black population, and the number of newly-admitted immigrants.[15] I also have information on the party affiliation of the governor and the majority party of the state House and state Senate. Table 1 provides the means and standard deviations of these variables from 1977 to 1995. The Data Appendix provides more thorough information on their sources.

Unfortunately, some key independent variables are not available from published sources by state. I utilized the Outgoing Rotation Group (ORG) data from the monthly Current Population Survey (CPS) to calculate annual state-specific information on a set of variables not elsewhere available. The ORG data provides information on those persons rotating out of the CPS each month during the year. This cumulates into around 350,000 annual observations in the early 1980s, decreasing to about 330,000 observations by the early 1990s as the CPS sample sizes fall. This provides enough data in each state to calculate state-specific variables. The smallest state sample in this data is 1659 observations in the District of Columbia in 1979. The largest state sample is 30,178 observations in the state of California in 1981. The mean number of observations per state is 6642.[16]

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[15] I have information on the number of naturalized immigrants in each state and year, but these data are highly correlated with newly-admitted immigrants.

[16] The ORG data is available from 1979 onward. For 1977-78, I utilize the May CPS to calculate the same variables I take from the ORG data in 1979-95, based on an admittedly smaller sample size (the May CPS in the late 1970s had around 60,000 observations.) Prior to 1977 not all states are individually identified in the Current Population Survey, which is one reason to limit the analysis to 1977 forward.

I use these CPS data sources to calculate a variety of demographic variables by state and year: the share of households headed by a single woman and including other related persons in the household[17]; the percent of the population that is over age 65, and average years of education. Most importantly, these data include wage information which allows me to calculate median log wage levels in each state and year, as well as the log wage at the 10th and 20th percentile in the wage distribution. The latter provides a measure of wage changes among lower-wage workers. See Table 1 for the means and standard deviations of these variables.

In addition, I want to control for key policy parameters. From 1975 through 1996 I have data on the primary state parameters of the AFDC program, including state maximum AFDC benefits and a dichotomous variable indicating the presence or absence of an AFDC-UP program. States with higher maximum AFDC benefit levels will have more eligible individuals in the population, hence higher AFDC benefit levels should result in higher caseloads, irrespective of any behavioral effect of AFDC benefits on work behavior. The presence of the AFDC-UP program might keep families off AFDC-Basic, if it affects the formation of female-headed households.[18]

I also have information on which states were granted Federal waivers after 1991 to implement state-wide changes in their AFDC program.[19] The

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[17] This is as close as one can come in the ORG data (which has limited demographic information) to the number of female-headed households with children. The vast majority of female-headed households with other relatives include children, and one would expect that trends in this data would be driven by the rise in female-headed households with children.

[18] Hoynes (1995) finds weak negative effects of AFDC-UP on female headship when she controls for both state and individual fixed effects.

[19] I use the same coding as the Council of Economic Advisers report (1997), which was created in consultation with the HHS department that

waiver variables are coded as the percent of the year in which the state has a particular type of waiver approved for implementation. These waivers are coded into six variables, depending on whether the waivers include time limits, work requirements, family caps (limiting AFDC benefits to women who have additional children while receiving AFDC), JOBS exemptions (typically expanding the categories of people who are mandatorily eligible for work programs), expanded earnings disregards, and strengthened sanctions. I also code a single variable for "any major waiver," which indicates the share of the year when a state has a waiver approved for any of the above items. These data allow me to investigate whether recent state welfare reforms affected state caseloads.

Finally, there were major changes in the Medicaid program over this time period. I have information on average Medicaid expenditures in each state for children and non-disabled, non-elderly adults. I combine this into a variable showing average Medicaid expenditures for a three-person family of 1 adult and 2 children. For many of these years families with children must be on AFDC in order to receive publicly funded health insurance, thus individuals in states with more generous Medicaid programs should have a greater incentive to participate in AFDC.[20] [21]

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granted these waivers. Most of these waivers were approved in 1994 or later, so these data affect only recent observations. There are admittedly problems with this coding. There is some discretion in the decision about which waivers affect a major share of the state welfare population (and hence are included in the coding) and which do not. For instance, waivers that were approved for only one or two counties in a state are not coded in my data. In addition, these waiver variables turn on when the waiver is approved. The actual implementation of the waivers within the states may be slower.

[20] Starting in the mid 1980s, progressively more children in low-income families were given access to Medicaid, regardless of the AFDC status of their family. I do not have any good controls for this change; some of it will be subsumed in the time effects since these were nationally-enacted changes (but

The Time Series Relationship Between Unemployment and Caseloads

The availability of monthly data on caseloads and unemployment rates for 51 states over an extended period of time makes it possible to explore some of the basic relationships in the data between these two variables with time series techniques. I estimate a simple two equation vector autoregression (VAR) model of the following type:

$$(1)\quad \log(Caseload)_{tj}=\sum_{s=1}^{q} \alpha_{1s}\log(Caseload)_{t-s,j}+\sum_{s=1}^{q} \beta_{1s}UnRate_{t-s,j}+\sum_{j=1}^{51} \gamma$$

$$(2)\quad UnRate_{tj}=\sum_{s=1}^{q} \alpha_{2s}\log(Caseload)_{t-s,j}+\sum_{s=1}^{q} \beta_{2s}UnRate_{t-s,j}+\sum_{j=1}^{51} \gamma_{2j}State_{j}$$

where log(Caseload) represents the log of either AFDC-Basic or AFDC-UP caseloads, UnRate represents the unemployment rate, α and β represent lag coefficients, t represents month, j represents state, and q represents the number of lags.[22] The 51 State dummy variables allow for 51 state fixed

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differences in income levels across states mean a different share of families were affected by these Medicaid expansions.) One would expect this policy change to lower caseloads, but as we shall see below, all of the unexplained time effects show increasing caseloads; hence, coding these Medicaid expansions would not help explain the unexplained part of the models.

[21] From 1981 onward, I also gathered information on maximum Supplemental Security Income (SSI) benefits in each state. (About half the states supplement Federal SSI benefit levels, creating state-specific variance in this program.) This variable was never significant in the regressions. Since it is available for only part of the time period, I do not use it in any of the reported regressions in this paper.

[22] I have also run this VAR model with differenced data on both caseloads and the unemployment rate and the results are similar. Note that the monthly data used here on caseloads is not seasonally adjusted. I have experimented

effects in each equation, estimated by 51 values of γ_1 and γ_2. With monthly data from 76:1 through 96:12, I have 12,852 observations on which to estimate this model (although I lose observations as I add lags.)

My primary interest is in the effects represented by the β_1 coefficients, which show the direct effect of unemployment on caseloads. The discussion below focuses on these coefficients. One might also be interested in the α_2 coefficients, the effect of caseloads on unemployment. These are smaller and generally less significant in the VAR models I have estimated than the β_1 coefficients, although they are significant.[23] The fact that current increases in caseloads are correlated with future increases in unemployment may be due to causal factors (as individuals go on AFDC they stop looking for work) or they may reflect the fact that caseload increases occur prior to increases in aggregate unemployment as problems among poor families emerge sooner than is signaled by the aggregate unemployment rate. It is worth noting that this effect is weaker in the AFDC-UP data than the AFDC-Basic data, which is consistent with the program fact that AFDC-UP recipients must typically engage in active job search to remain eligible.

Results for AFDC-Basic

Figure 4a presents the impulse response model for AFDC-Basic caseloads from a 1 unit change in the unemployment rate, estimated from the

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with various seasonal adjustment processes. It appears to make little difference to the results, while potentially adding quite a bit of error. In particular, in many states the seasonal patterns change over the time period, so using a single seasonal adjustment algorithm actually induces inappropriate seasonal patterns in the data.

[23] A Grainger causality test indicates that caseloads "Grainger cause" unemployment rates.

VAR model in equations (1) and (2) with 24 lags of monthly data.[24] Because the caseload data is in logs, one can interpret the numbers on the y axis as the percentage change in caseloads due to a 1 unit innovation in unemployment. A test of Grainger causality indicates that unemployment rates "Grainger cause" caseloads.

As is clear in Figure 4a, the impulse-response function rises rapidly over the first 18 months after the unemployment change, suggesting that a one-point increase in unemployment raises caseloads by over 3 ½ percent in the following 18 months. After 18 months, the caseload effect declines relatively slowly over time, and does not entirely disappear for years. In short, unemployment increases lead to long-term increases in AFDC-Basic caseloads.

Results for AFDC-UP

Figure 4b presents the impulse-response model for equivalent estimates on the AFDC-UP program. To estimate this model, I use data only from those 19 states which run an AFDC-UP program continuously from 1976 to 1996. This gives me 4,105 observations. I again show the results for a model with 24 lags.

The effect of unemployment innovations on AFDC-UP caseloads is much larger than on AFDC-Basic caseloads. A one-unit rise in unemployment results in steady increases in AFDC-UP caseloads for the first 18 months, culminating in around a 20 percent caseload rise, a very large effect. After 2½ years, the impulse-response function declines steadily and much more rapidly than AFDC-Basic. This suggests that unemployment-induced changes in AFDC-UP caseloads are not as permanent as in AFDC-Basic caseloads, although the magnitude of the short-term response is much larger.

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[24] These impulse-response models assume linear effects, hence the same effect would be calculated on an unemployment base of 4 percent as 8 percent. I have experimented with different lag lengths and one gets similar effects with any lag number greater than 18.

Both the AFDC-Basic and the AFDC-UP results suggest that caseloads are responsive to the macroeconomic environment. The increase in AFDC-Basic caseloads induced by a one-point increase in unemployment is estimated from a very different model than used in earlier studies, but it is in the range of those studies which generally find the effect of unemployment on caseloads to be around 3 percent. As we shall see, this result is also consistent with the results shown below using a panel data multivariate estimation process. The AFDC-UP effects are much larger and suggest that unemployment levels are highly important in determining AFDC-UP caseloads, with large swings in caseloads for this program as unemployment rises and falls.

Panel Data Analysis of the Determinants of Caseload Change

While the VAR analysis provides a description of the relationship between unemployment and caseloads in the raw data, it would be preferable to control for a wider range of factors. This means turning to annual data, in order to find more available state-specific variables.

I estimate a series of annual state panel data models, of the following form:

$$(3)\quad Caseload_{ts} = \gamma_1 X_{ts} + \gamma_2 D_{ts} + \gamma_3 P_{ts} + \nu_t + \rho_s + \omega_{ts}$$

where Caseload can be any one of a number of dependent variables measuring caseloads, X is a vector of economic factors, D is a vector of demographic factors, and P is a vector of policy parameters. The subscript t represents year and s represents state. The ν represents a vector of year fixed effects and ρ represents a vector of state fixed effects. The ω is an i.i.d. random error term. In some cases below, I also include a vector of state time trends. Note that with state and year effects, the only way in which a variable can influence caseloads is through its effect on caseload changes within a state over time.

Variables that are largely constant over time within states will have little effect, since their influence will be subsumed within the state fixed effect.

Equation (3) is estimated on annual data from 1977 through 1995 for 51 states, providing a total of 969 observations. The models are estimated with a weighted OLS procedure, where the weights are based on state population.

Results for AFDC-Basic

Table 2 presents the results of estimating equation (3) to explain changes in AFDC-Basic caseloads. In all columns except column 4, the dependent variable is the log of the ratio of the number of AFDC-Basic households divided by the female population ages 15-44 in state s at time t. This presents caseloads as a share of the population group that is most likely to be available as a household head for an AFDC-Basic case. I refer to this variable as the "caseload share," and it varies from 6 to 8 percent of the young female adult population over this time period. For comparison, column 4 uses the log of AFDC-Basic caseloads as the dependent variable without dividing through by population.

The results in column 1 provide a basic set of results. The economic variables are listed first. Changes in the unemployment rate have a strong effect on AFDC-Basic caseloads, operating with a 1 and 2 year lag. A current rise in unemployment raises the caseload share by 0.7 percent this year, 1.4 percent next year and 1.7 percent in the following year. These results are within the same order of magnitude as those estimated in the VAR models discussed above. Log median wages have a strong negative effect on caseloads; states with rising wage levels face declining caseload shares. Wages at the 20th percentile of the distribution have a further negative effect, but it is not highly significant. If wages at the bottom of the wage distribution increase along with median wages, caseloads decline somewhat more than a rise in median wages alone would suggest. To test this effect, I have also run the regressions in Table 2 using the log of the 10th percentile of wages and using the Median/20th percentile ratio. The results are strikingly similar.

Among the demographic variables, it is not surprising that the share of households with single female heads is important, the group which is eligible for AFDC-Basic if they find themselves in economic difficulty. If you believe that the formation of single-mother households is influenced by the presence and level of AFDC, then this variable is endogenous and its coefficient is biased upward, although the evidence suggests this is not a major problem.[25] Excluding the variable has little effect on the other coefficients. Years of education and racial composition have a less significant effect; the percent elderly is negatively correlated with caseloads. The share of newly-entered immigrants in a state has no current effect on caseloads, but the two-year lag on this variable is positive and significant indicating that a rising immigrant share is correlated with increased demand for public assistance over time.

The political variables show interesting effects. The party of the governor is strongly significant, with lower caseloads under Republican governors. This perhaps suggests that governors are able to shape the administrative processes by which public assistance is provided. In addition, states where both the House and Senate are controlled by the same party also have lower caseloads, regardless of whether that party is the Democrats or the Republicans. This is consistent with the fact that welfare policy is often a political hot potato in state legislatures, and states with split party control may have more difficulty passing welfare reform legislation.

The policy variables are strongly significant. As AFDC benefit levels rise, caseloads rise. As noted above, this must happen mechanically since

[25] For instance, see the summary of this literature in Moffitt (1992).

higher benefit levels mean more eligible households; whether it reflects any further behavioral change due to higher benefits is not interpretable in this regression. In addition, states which offer the AFDC-UP program also have higher AFDC-Basic caseloads. If one believes that the AFDC-UP program provides incentives for families to stick together by offering assistance to married couples, one would expect the sign on this variable to be negative. The evidence on the effect of the AFDC-UP program on family composition is limited, however.[26] It is likely that the presence of the AFDC-UP program is operating as a signal of state generosity. States that offer AFDC-UP tend to also be states that are more generous along a range of public assistance program dimensions, from the size of work expense disregards to the share of applicants approved for benefits. Hence, I interpret the coefficient on the AFDC-UP variable as a proxy for non-benefit related generosity in the AFDC-Basic program. Average family Medicaid expenditures also positively affect caseloads; states whose Medicaid policies have been more expansive have seen greater public assistance usage.

The final policy variable indicates that states which received program waivers in the 1990s saw significant caseload declines. This might suggest that these program changes had an important effect on caseloads. I discuss this issue further below.

Column 2 uses the same specification as column 1, but also includes state-specific time trends (i.e., 51 time trends) in the estimation. Including state time trends provides some indication of how many of the significant variables are significant simply because they are trending up (or down) in a linear way. The effect of such variables will be subsumed by a state time

[26] See Hoynes (1995). Hu (1997) finds a negative effect of AFDC-UP benefits on marriage among those in the program only (i.e., it encourages cohabitation over marriage.)

trend.[27] Not surprisingly, the inclusion of state time trends reduces the magnitude of most of the estimated coefficients. But the sign and significance of the variables are not greatly affected by the inclusion of state time trends. The unemployment rate continues to have a strong effect. The median wage has a smaller effect and the 20th wage percentile has a larger effect with state time trends included. The immigrant effect largely disappears with the inclusion of state time trends. Even though their coefficients are smaller, AFDC benefit levels, the AFDC-UP program, and AFDC waivers continue to have significant effects on caseloads. In short, the inclusion of state time trends changes few of the major conclusions from column 1.

Column 3 takes an alternative view and removes all time trends and time effects from the regression, except for the inclusion of a dummy variable equal to 1 in 1982 and all future years, controlling for the legislative changes to welfare in the first year of the Reagan administration. Column 3 provides information on the extent to which the variables included in the model explain the time trends in the data. The results in Column 3 are remarkably robust, and reasonably similar to the results in the earlier columns, although an F-test indicates that this model fits the data significantly less well. Column 4 uses the log of caseloads rather than the log of caseload share as the dependent variable. The results are generally consistent with those discussed above.

Columns 5 and 6 split the sample in half, pre- and post-1986. This provides a test of whether the estimated relationships are different between the early and the later part of the data. Of course, with fewer observations, the

[27] I do not view the coefficients estimated in column 2 as the most appropriate model, since the inclusion of such trends often overadjusts the data. Some variables with linear trends may be appropriately affecting caseloads. But column 2 provides diagnostic information on how much variation there is in these data and whether the effects estimated in column 1 are due to more than linear trends.

standard errors in columns 5 and 6 are necessarily larger. Column 6 (the later period) seems to show stronger effects than column 5 (the earlier period). Median wage levels appear to matter more in the later time period, while 20th percentile wages matter more in the earlier time period (when they declined more steeply.) The growth in single female heads and in immigrants is more important in the later time period, as is party affiliation in state legislatures. AFDC benefit levels are also significant in both time periods, although the AFDC-UP program has an effect only in the later time period.

Overall, table 2 suggests that the panel data estimation results for AFDC-Basic caseloads are generally robust to changes in specification and to various time periods. Caseloads are strongly affected by both macroeconomic factors and by programmatic and political factors. Demographic factors are important, but their significance varies across specifications.

The coefficients on the "any major waiver" variable are particularly important from a policy perspective, since they potentially indicate the effect of recent state experiments with the structure and rules of the AFDC program. Table 3 provides further information on the effects of waivers on caseloads, showing only the coefficients on variables relating to waivers.

Column 1 of Table 3 repeats the result of Column 1 of Table 2, indicating that waivers are correlated with a significant 10 percent reduction in caseloads. This is a very large effect, particularly since many of these waivers were implemented only slowly in the states and affected only a small share of the caseload at first. This raises the question of whether the waiver variable is measuring the effect of the direct program implemented by the waiver or whether it is acting as a proxy for a whole set of changes that occurred in states where waivers were implemented. Column 2 of Table 3 tests this by including not only the waiver variable, but also a lead of the waiver variable. Lead values cannot possibly signal program effects, and must indicate that the waiver variable is correlated with other changes in the state.

Column 2 indicates that the lead variable is larger and more significant than the current waiver variable. This suggests that something was changing in these states prior to the implementation of the waivers that reduced caseloads, and that the waiver programs themselves are not the primary cause of the caseload reductions. These other changes could include extensive media publicity about the fact that the state was going to "get tough" with welfare recipients, which might discourage applications or encourage current recipients to find alternative sources of support. They could also relate to changes in administrative procedures within the states, with front-line workers receiving the message to be tougher on new applicants and discouraging toward continuing recipients.

Column 3 breaks the waiver variable down into the six types of major waivers that were granted. Because only a relatively small number of states have different types of waivers (and only over a relatively small number of years in the 1990s), the disaggregated waiver data is estimated with less precision. The results suggest that family caps and JOBS exemptions had a negative and significant effect on caseloads. Sanctions actually show a positive and significant effect. The strongest effect is the effect of imposing a family cap, i.e., announcing that the state will no longer increase benefits for women who have additional children while on AFDC. In fact, the strength of this variable is further evidence that these waivers are proxying for effects beyond their direct program effect. The impact of family caps on the caseload in the short run should be minimal; it merely holds benefits constant for women who are already on the caseload, it does not remove anyone from the rolls. Even with extreme assumptions, it is hard to see how the implementation of a family cap, by itself, could result in a 18 percent reduction in caseloads during the year in which it was implemented, unless this variable were proxying for other changes in the state at the same time.[28]

Column 4 includes leads of the disaggregate waiver variables. These results suggest further problems interpreting the waiver coefficients as causal. Both time limits and work requirements show significant positive effects in the year before the waiver was granted (perhaps rising caseloads were an impetus for the waiver.) But earning disregards seem to show all of their negative effect in the year before they're implemented, while they and sanctions have significant and positive effects on caseloads during the year of implementation.

Overall, I conclude that these waivers are correlated with other changes occurring (and even preceding) their implementation that are causing caseloads to decline in states that seek waivers. It is hard to determine how much these effects might be due to the actual program implementation of the waiver, but it is surely no more than half, based on the fact that more than half of the waiver effect occurs in the year before the waiver is approved.

How effective is this model in explaining the caseload rise of the early 1990s? The estimated coefficients on the year fixed effects are one way to investigate this. Essentially, these coefficients indicate any time-related effects that are not explained by the other variables included in the data. Figure 5a graphs the year fixed effects from the model in column 1 of Table 2.

Figure 5a shows a sharp decline in caseloads in 1982. This is due to the implementation of the Reagan reforms, which removed about 15 percent of the caseload from eligibility for AFDC. (I cannot include a control variable for this other than the year fixed effect since it occurs in all states at the same

[28] Indeed, a study of the family cap in New Jersey indicates that AFDC use fell as much among those who were subject to the family cap as among a control group of AFDC families who were exempt from it.

time.) Hence, the sharp drop in the early 1980s is an indication of the policy effects of the eligibility changes in that time period.

From 1984 to 1995 the year effects rise steadily, particularly in the early 1990s. This indicates that there is a substantial unexplained rise in caseloads over this time period, which this model cannot account for. Even more surprisingly, these results indicate that the unexplained rise in caseloads started not in 1990 (when actual caseload numbers started to rise), but in the mid-1980s. In short, even though actual caseloads were not rising in the late 1980s, the economic, demographic, and program variables controlled for in this model would have suggested that caseloads should have fallen over this period; the fact that they remained constant is a puzzle, which none of the variables controlled for in this model adequately explain. I return to the question of how effectively the model explains caseload changes after discussing the regression results for the AFDC-UP program.

Results for AFDC-UP

I can estimate the determinants of AFDC-UP caseloads only for those periods when states were running an AFDC-UP program. While 20 states have an AFDC-UP program for the entire 1977-1995 period, 22 states have such a program only after 1990 when it was mandated by the federal government. Other states run the program for part but not all of the period between 1977 and 1990.

Table 4 presents the panel data results for the AFDC-UP program. As a dependent variable, I use the log of AFDC-UP caseloads. It is not clear what the appropriate population denominator is for this program.[29] The

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[29] One obvious choice is all married couples. But less than one percent of married couples ever utilize the AFDC-UP program, which makes this a poor proxy for eligibility. In addition, data on the number of married couples within each state each year is not readily available.

AFDC-Basic results were quite similar when the dependent variable was the log(caseloads) and when it was log(caseloads/eligible population).

Columns 1 and 2 are estimated using only information from the 20 states that run a continuous AFDC-UP program from 1977 to 1995. Columns 3 and 4 use information from these 20 states through 1989 and include data from all 51 states from 1990 on.[30]

The results in column 1 show much larger unemployment effects than for the AFDC-Basic program, consistent with the VAR results above. A one-point increase in unemployment causes an immediate 5.1 percent rise in AFDC-UP caseloads, with further lagged increases of 2.2 and 8.6 percent one and two years out. This underscores the greater importance of macroeconomic factors to the AFDC-UP program. The log of median wages has an insignificant negative relationship to caseloads, but the wage level at the 20th percentile of the distribution has strong and negative effects indicating that the wage opportunities in the less skilled labor market strongly affect the use of AFDC-UP

The demographic variables have generally insignificant effects on the AFDC-UP caseload, although the percent elderly in the state is strongly correlated with lower caseloads. Immigrant share does not appear to affect AFDC-UP usage. Among the political variables, the only important variable is whether the state House and Senate are Democratically controlled. This appears to be correlated with more generous AFDC-UP usage.

Benefit levels have a strong positive influence on AFDC-UP caseloads, as they did for AFDC-Basic. Medicaid expenditures have little

[30] Prior to 1990 I do not include data from the several states that start and/or stop the AFDC-UP program; one might believe that they are not running the program at full capacity.

influence on AFDC-UP. Most puzzling, state waivers appear to have a positive effect on the AFDC-UP population.

Alternative specifications and data samples do not change these conclusions. When state-specific time trends are included in the model (column 2), the coefficients do not change greatly, although the coefficients become much weaker on the variables measuring percent elderly, Democratic control of the state House and Senate, and the presence of state waivers.

When AFDC-UP caseloads are estimated including data from all 51 states after 1990 (columns 3 and 4), the results change somewhat. Unemployment rates become insignificant in these regressions, but the 20th percentile wage continues to have strong negative effects. With the inclusion of additional data from the 1990s, a negative effect of Republican governors on AFDC-UP caseloads is visible. AFDC benefit levels remain strongly significant. I investigate these differences further by estimating the determinants of AFDC-UP caseloads only in the 31 states from 1990-95 that entered the program because of a federal legislative mandate. This regression has almost no significant coefficients, and suggests that either because the state is discouraging applications or because married couples in these states have no information about AFDC-UP, there appears to be little responsiveness of the program in these specific states to economic or demographic factors (although there remains a significant effect of the share of black families on caseloads.) All of this suggests that the preferred regression for AFDC-UP is the one based only on the 20 states that run a continuous program throughout the period.

Figure 5b plots the estimated year fixed effects from column 1 of Table 4. Compared to the AFDC-Basic program, there is only a small unexplained rise in AFDC-UP caseloads between 1990 and 1992.[31] In short, the evidence suggests that the AFDC-UP program is far more driven by measurable macroeconomic and policy variables; there has been only a moderate increase in AFDC-UP caseloads over the past 10 years that is not explained by these variables.

Decomposing Recent Caseload Changes

It is an interesting exercise to see how much of the recent caseload changes can be explained by this model. Table 5A shows actual and predicted caseload changes for the AFDC-Basic program from 1990-94 (when caseloads rose sharply) and from 1994-95 (when caseloads began to fall.) The top row of Table 5A shows caseloads as a share of the prime-age female population. This share rose 21 percent between 1990 and 1994. Changes in the economic variables in the model (unemployment rates, median wages and 20th percentile wages) over this time period would have predicted only a 5 percent rise in caseloads. Changes in the demographic factors (percent single female heads, percent nonwhite, percent elderly, years of education, and percent immigrant) would have predicted no change. Changes in political and program factors (political affiliation of the governor and state house and senate, AFDC benefit levels, the AFDC-UP program, Medicaid expenditures, and the implementation of waivers) would have predicted an 8 percent decline. The bottom row of Table 5A shows the predicted change in caseloads, based on changes in all of these control variables. The model predicts a 3 percent *decline* in caseloads, in a period when they actually rose 21 percent.

Between 1994 and 1995, caseloads fell by over 5 percent. Changes in economic factors would have predicted a 3 percent decline, and demographic changes and program changes would also have predicted a

[31] Realize the dependent variable is different in Figures 5a and 5b, hence the y-axis scales are not comparable.

decline. In fact, the predicted decline based on changes in all control variables in the model is 7 percent. Between 1994-95, the model predicts that caseloads should have fallen even faster than they actually did during these two years.

The results in Table 5A underscore the mystery about AFDC-Basic caseload changes in the past decade. Over the first half of the 1990s, caseloads rose rapidly when a standard set of control variables suggests they should have fallen. Even after the caseload decline occurs between 1994 and 1995, that decline is slower than the model would predict.

In comparison, Table 5B produces similar numbers for the AFDC-UP program. As the discussion above indicated, there is very little unexplained movement in AFDC-UP caseloads. Between 1990 and 1994, the log of AFDC-UP caseloads rose by slightly less than 5 percent, while the model predicts 50 percent of this rise. Between 1994 and 1995, the log of AFDC-UP caseloads fell by 1.3 percent and the model predicts a 1.3 percent decline. In short, the model appears to be explaining recent trends in AFDC-UP reasonably well. The sharp unexplained run-up in the utilization of the AFDC-Basic did not occur in AFDC-UP.

Further Exploring the Recent Rise in AFDC-Basic Caseloads: Child-only Cases, Take-Up Rates, and Eligibility Changes

The model in the last section appears to predict year-to-year movement in caseloads within states, but has no power to explain the trend of rising caseloads over the 1990s. In fact, as the last section indicated, the model predicts a decline in caseloads over this period, when actual caseloads rose steeply. This section further explores the question of why AFDC-Basic caseloads were rising during this period. There are three obvious reasons why caseloads might rise which are sequentially explored: There may be changes in data definitions or composition; there may be a rise in participation rates (often called take-up rates) among eligible recipients; and there may be an increase in eligibility. Unfortunately, the data in this section will be more limited than that available earlier, as I discuss below.

Changes in Data -- The Role of Child-only Cases.[32]

The AFDC-Basic data includes all cases which are not part of the AFDC-UP program. Stereotypically, this means single-mother families with children. But not all cases fit this stereotype. In particular, there has been a sharp growth in so-called "child-only" cases in recent years. These cases occur when payments are made for a child, but where there is no payment to a caretaker adult. This includes payments to children in foster care, payments to children whose mother may be covered by SSI (and hence not eligible for AFDC), or payments to the children of immigrants (where the children are eligible because they are born in the U.S. and are U.S. citizens, but the parents are not.) All three of these categories have grown recently.

State data on child-only cases is available since 1983 as part of the quality-control state data surveys collected by the Federal government.[33] These surveys sample each state's caseload and provide an estimate of the total caseload in different categories, including the number of cases without a caretaker adult that are part of the AFDC-Basic program. Figure 6 plots AFDC-Basic cases for the U.S. (dark solid line) and AFDC-Basic cases less child-only cases (dashed line.) In 1984, child-only cases composed about 13 percent of the caseload; by 1995 they composed 21 percent of the caseload. Between 1990 and 1994 (the years of steep caseload increase), the number of child-only cases increased by 90 percent while the number of nonchild-only cases rose by only 13 percent. The raw data suggests that the growth in child-

[32] Special thanks are due to Don Oellerich, Department of Health and Human Services, who both suggested that I look at the role of child-only cases and helped make the data available.

[33] See the Data Appendix for more information on this variable.

only cases explains half of the AFDC-Basic caseload rise between 1990 and 1994 and forty percent of the caseload changes over the entire 1984-95 period.

I test this further in Table 6, which uses state panel data from 1983 to 1995. In column 1 I repeat the base specification shown in column 1 of Table 2, but estimated over this shorter time period. This uses the log of AFDC-Basic caseloads divided by the female population ages 15-44 as the dependent variable. In column 2, I replace AFDC-Basic caseloads with AFDC-Basic caseloads less child-only cases. The results in columns 1 and 2 are strikingly similar, except that the effect of newly-arrived immigrants becomes negative and insignificant in column 2. At the bottom of Table 6 I report the year dummy for 1995 from both regressions. The primary difference between these two regressions is that column 2 has a much lower unexplained caseload growth. The results suggest that removing child-only cases from the dependent variable removes 40 percent of the previously-unexplained rise in caseloads over this time period, consistent with the results in the raw data. This suggests that my specification is explaining almost none of the growth in child-only cases; they are unrelated to the included control variables and their impact is entirely subsumed in the time effects.

The last column of Table 3 uses the log of child-only cases as a share of female population as the dependent variable. As expected, most of the variables are insignificant in this regression. The median wage in the state is strongly negatively related to child-only cases, as is the share of the nonwhite population.[34] The presence of newly-arrived immigrants has a strong and positive cumulative effect on child-only cases, consistent with the growth of immigrant child-only cases. Democratic control of the state House and Senate is also associated with greater expansion of child-only cases.

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[34] Barth and Needell (1997) have noted that black children are far more likely to be placed in foster care than white children.

In short, the evidence suggests that part of the mystery of rising caseloads is purely a data composition issue. The growth of child-only cases, which are largely unrelated to the variables that determine caseloads among single-parent families, explains almost half of the rise in caseloads over the 1990s. Further research on the reasons for such rapid recent growth in child-only cases would be fruitful.

Changes in Eligibility and Take-up Rates

There are two primary reasons why nonchild-only caseloads might rise: Either more families become eligible for AFDC due to demographic, economic, or program changes, or there is an increase in take-up rates, that is, an increase in participation among the eligible population. As discussed earlier, most people assume the steep caseload increases of the early 1970s were due to increases in take-up rates. While the model estimated in Table 2 has controls for a variety of variables that might correlate with both eligibility and with take-up decisions, it is clear that there must remain an unexplained trend in either take-up or eligibility for which the variables in this model do not adequately control.

In order to investigate this question, it is necessary to know the number of persons eligible for the AFDC program, data that is not readily available. It is possible to estimate AFDC eligibility, as a number of earlier studies have done.[35] Many of these studies are interested only in national take-up rates. Since we want state panel data, we need a data source which will allow us to estimate eligibility numbers within states. We use the March CPS

[35] See Blank and Ruggles (1996) and its citations to earlier studies. Many of these studies use the Survey of Income and Program Participation (SIPP), which has the best available data for eligibility estimates. Unfortunately, the SIPP samples are too small for state-specific eligibility estimates. A paper which uses CPS data to estimate take-up rates in another social assistance program is Blank and Card (1991).

data for the 12 states with the largest AFDC caseloads. These 12 states contain an average of two-thirds of the AFDC caseload in any given year, hence by focusing on these 12 states we are discussing the majority of AFDC cases. Not coincidentally, these tend to be the states with the largest total population, which means they have more observations in the CPS and can provide more reliable estimates of the eligible population.[36]

I estimate eligibility among single-female family heads in each state and each year, using information on income sources over the past year combined with information on program parameters in each state. A detailed description of these eligibility calculations are provided in the Data Appendix. I can do this calculation from 1984 to 1995; in earlier years some of the program information necessary to calculate eligibility by state is lacking. There are clear problems with these estimates: the income information is annual rather than monthly, there is no information on the actual utilization of child care or work expense deductions, there is no information on assets, etc. Given data limitations, however, these estimates provide the best available measure of eligibility.[37]

Figure 7 shows how the eligibility estimates compare to caseload data for these 12 states. The top line in Figure 7 (the dotted line) shows estimated

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[36] The 12 states include CA, FL, GA, IL, MA, MI, NJ, NY, NC, OH, PA, and TX. Ranked by number of AFDC cases, these 12 states are at the top in both 1980 and 1995. The smallest state in this group (GA) has only 114 eligible observations in the CPS in 1995. Trying to estimate eligibility for states with smaller caseloads would produce very unreliable estimates.

[37] One measure of the accuracy of eligibility calculations is the share of observations that are obviously wrong, i.e., where an individual who reports receiving AFDC is estimated to not be eligible. This averages between 1.6 percent and 4.0 percent of all observations in these data each year, which is quite consistent with other efforts at estimating eligibility.

AFDC eligibility for the 12 states.[38] The next line (the solid line) shows AFDC-Basic caseloads less child-only cases in these states. The bottom line (the dashed line) shows the number of single female-headed families in the CPS data who report receiving AFDC in these states. This provides an alternative caseload calculation, based on CPS data. Public assistance usage is underreported in the CPS, as these lines indicate. Caseloads calculated from the CPS data are about 20 percent lower than the number of caseloads reported in administrative caseload data.[39] Both caseload series show a major rise in caseloads between 1990 and 1994, although the CPS data shows a slight decline over the 1984 to 90 period. Estimated eligibility also rises over this period.

I can calculate two alternative take-up rates with these data. I can divide actual caseload data by the eligibility estimates. Call this the administrative take-up rate. This has the advantage of using the more accurate administrative data to measure caseloads. Or I can divide the CPS-determined AFDC usage by eligibility. Call this the CPS take-up rate. This has the advantage of using a numerator and denominator from the same source, which might provide a more consistent estimate of take-up rates. Figure 8 shows these two take-up rates. The aggregate take-up rate in the 12 states calculated with administrative data is higher, as expected, ranging from about 80 percent to 90 percent. The 12-state take-up rate calculated with CPS data ranges from

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[38] I use the population weights in the CPS to produce aggregate AFDC eligibility numbers.

[39] Because of income under-reporting, the eligibility estimates are almost surely also under-estimated as well. Our interest is in observing trends within states over time, however. As long as there is no change in the level of under-reporting over time within states, these data should still provide reasonable estimates of the determinants of changes in eligibility and take-up rates using state panel data, although it may have the levels wrong.

about 60 percent to 70 percent.[40] Both series show generally similar movements through 1995. Both rise during the crucial 1990-94 period and decline from 1994-95.

Figures 7 and 8 suggest that both take-up rates and eligibility are rising over the early 1990s in these 12 states. I can do a simple decomposition of the change in caseloads into the share due to eligibility versus take-up. Caseloads in year t can be written as

(4) $\text{Caseloads}_t = \text{Elig}_t * \text{TUp}_t$,

where Elig represents the number eligible and TUp represents the take-up rate. Between years t and s, the change in caseloads can be decomposed as

(5) $\text{Caseloads}_t - \text{Caseloads}_s = (\text{Elig}_t - \text{Elig}_s)*\text{TUp}_t + \text{Elig}_s*(\text{TUp}_t - \text{TUp}_s)$

Table 7 shows the results of this calculation.[41]

Over the entire 1984-95 period, Table 7 indicates that all of the increase in caseloads is due to changes in eligibility; in fact, between 1984 and 1995 take-up rates fell slightly. Over the 1990-94 period, however, when caseloads were rising most rapidly, take-up changes accounted for about 40 percent of the changes in caseloads. In short, as Figure 8 indicates, take-up rates rose during and immediately following the recession of 1990-91, but fell afterwards.

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[40] Among states and years, the administrative take-up rate varies from 40 percent to 190 percent (because the administrative caseload data comes from an entirely different source than the eligibility data, nothing constrains the take-up rate to be less than 1.) The CPS take-up rate varies from 30 percent to 87 percent.

[41] Table 7 uses the take-up rate calculated with administrative caseload data. The results using CPS-reported caseload data and using the take-up rate based on this CPS data are similar. Note also that the decomposition could be written as

$\text{Caseloads}_t - \text{Caseloads}_s = (\text{Elig}_t - \text{Elig}_s)*\text{TUp}_s + \text{Elig}_t*(\text{TUp}_t - \text{TUp}_s)$.

Both of these decompositions produce almost identical results.

A visual representation of this is shown in Figure 6, where I present estimated AFDC caseloads holding take-up rates constant. The lower dotted line in Figure 6 shows estimated AFDC-basic caseloads (less child-only cases) holding take-up rates at their 1984 level throughout the time period. This figure indicates that, once child-only cases are removed from the data, removing changes in take-up rates lowers the caseload numbers by a only little bit more. The data used to plot Figure 6 indicate that, of the rise in AFDC-Basic caseloads between 1984 and 1994 (the high point for caseloads), 34 percent was due to an increase in child-only cases, 14 percent was due to a rise in take-up rates among single mother households, and the remaining 53 percent must be due to changes in eligibility over this time period. It is worth noting that eligibility changes can be due to multiple factors. They can reflect demographic changes in the population that change the potential pool of applicants, as well as changes in program parameters.

Table 8 investigates these changes in eligibility and take-up rates with regressions on the 12 states for which I have data over the 1984-95 period. Column 1 of Table 8 uses the log of the eligible population divided by the female population ages 15-44 as the dependent variable. Column 2 uses the log of the take-up rate (estimated using the administrative caseload data) as the dependent variable, while column 3 uses the log of the alternative take-up rate (estimated using the CPS caseload data.)

None of the coefficients in Table 8 are highly significant. This is a much smaller data sample than was used in previous regressions, and this means the coefficients are less precisely estimated. In addition, all of these regressions use a noisy (estimated) dependent variable. As long as the errors in the dependent variable are not correlated with the independent variables, this should not bias the results, but it will decrease the precision of the model.

The coefficients on eligibility are largely insignificant, although a number of the point estimates are quite large. In particular, several of the demographic variables appear to have large effects on eligibility. The policy variables have the expected effects but are imprecisely estimated. Most important, the year dummies for eligibility show a substantial positive and unexplained time trend. The bottom of Table 8 reports the year dummy for 1995, which is 53 percent higher than that for 1984 (the first year of the regression.)

The coefficients on the two take-up rates are particularly difficult to interpret. The signs and magnitude of the coefficients differ substantially between the two take-up rates, but are largely insignificant. The administrative take-up rate shows a more substantial decline by 1995 while the CPS take-up rate drops only slightly (see Figure 8). Both regressions show a substantial unexplained rise in the year effects between 1990 and 1992 (when the economy was entering and leaving a recession). This is maintained in the CPS take-up regression (the coefficient for 1995 shows an 18 percent increase versus 1984), but the decline in take-up rates in the administrative take-up data shows 1995 levels that are lower than those in 1984.

Overall, I conclude from the analysis of take-up rates and eligibility that both contributed to the increase in caseloads over the 1990s, although the effect of eligibility changes appears to be larger. In both cases, my specification is inadequate to fully explain the changes in either take-up or eligibility in the early 1990s; both show substantial unexplained increases. Further research on the causes behind these changes would be useful.

Conclusions

This paper investigates the major increase in AFDC caseloads over the past decade. Its primary conclusions are as follows:

1. Although the actual caseload numbers did not begin to rise until 1990, an unexplained increase in AFDC-Basic caseloads started in the mid-

1980s, when caseloads stayed constant at a time when changes in economic, demographic and program factors should have led caseloads to decline. A regression using state panel data with a rich set of control variables does a poor job of predicting this underlying trend toward higher caseloads, although the variables included in the model appear to be important determinants of the change in caseloads from year to year within the states.

2. The trend in AFDC-Basic caseloads which is not explained by the model appears to be driven by three underlying components. There has been a rise in child-only cases; this explains around 35 to 40 percent of the AFDC-Basic caseload rise over the 1984-95 period. In addition, both take-up rates and eligibility rose during the early 1990s among single-parent families. Once child-only cases are removed from the data, rising take-up rates explain a small additional share of remaining upward trend in caseloads through 1994, while rising eligibility explains most of the change. Take-up rates have declined since 1994. The increase in eligibility and the rise in take-up rates over the early 1990s is only partially explained by the control variables utilized in this paper; both show an unexplained upward trend in the early 1990s.

3. AFDC-UP caseload changes are relatively well explained by the variables in this model. These AFDC-UP/AFDC-Basic differences demonstrate the importance of analyzing these two programs separately.

4. The results in this paper underscore the importance of the macroeconomy on caseloads. This is particularly true for the AFDC-UP program, where changes in unemployment produce caseload changes of 15 to 20 percent. The AFDC-Basic program shows smaller but still significant effects, with about a 3 to 3½ percent change in caseloads over time as unemployment changes. Wage levels are also important to both programs.

5. Demographic variables appear to have a mixed effect on caseloads. The recent arrival of immigrants is important, particularly for child-only cases, as is the rise in single-female-headed families.

6. State political affiliations have mattered over the past two decades for the AFDC program. States with Republican governors have experienced lower caseloads. States whose House and Senate are Democratically controlled have experienced higher child-only caseloads and higher AFDC-UP caseloads, but having the House and Senate controlled by the same party is correlated with lower AFDC-Basic caseloads.

7. Not surprisingly, program parameters and operating rules affect caseloads. AFDC benefit levels are a major determinant of caseload levels. More recent state waivers, largely designed to strengthen the states' ability to enforce work requirements among recipients, are correlated with caseload declines. A substantial part of the effects of these waivers, however, precedes their implementation. This suggests that other changes in client and caseworker behavior was occurring in states at about the same time that these waivers were approved.

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Table 1

Summary Statistics for the Data
All dollars adjusted by the GDP-deflator.

	Number of Observations	Mean	Standard Deviation	Standard Deviation Across State Averages
1. Household Caseload Data				
AFDC-Basic	969	72,588	97,897	95,336
AFDC-UP	969	4,704	14,089	12,828
AFDC Total	969	77,292	109,680	106,390
AFDC-Child Only Cases	662	10,549	20,873	18,641
2. Data available by state from published sources				
Unemployment rate	969	6.583	2.102	1.352
State population (000)				
-- Total	969	4,725	5,120	5,086
-- Females ages 15-44	969	1,104	1,203	1,196
Percent black	969	.106	.123	.122
Percent new immigrants (00)	969	.196	.224	.188
Party affiliation				
--Republican governor?	969	.388	.487	.260
--Both House & Senate Republican?		969	.208	.406
	.335			
--Both House & Senate Democrat?	969	.578	.494	.411
3. Data calculated by state from ORG data				
log(median wage)	969	5.822	.242	.127
log(20th percentile wage)	969	5.194	.221	.130
Percent elderly	969	.155	.028	.024
Percent of households with single female heads	969	.107	.026	.024
Years of education	969	12.200	.632	.421
4. Policy variables				
AFDC max benefits (family of 4)	969	512	192	178
AFDC-UP program (1= yes)	969	.663	.473	.316
Average Medicaid expenditures (1 adult + 2 children)	969	1125	394	241
Any major waiver	969	.042	.187	.059
--Time limits	969	.006	.071	.021
--Work requirements	969	.011	.096	.034
--Family cap	969	.014	.107	.034
--JOBS exemptions	969	.024	.143	.050
--Earning disregards	969	.027	.154	.054
--Sanctions	969	.025	.142	.046

5. Data calculated by state from March CPS data				
Number of AFDC eligibles	144	214,968	133,285	127,637
CPS take-up rate (based on CPS AFDC usage)	144	.637	.116	.094
Administrative take-up rate (based on administrative caseload data)	144	.847	.185	.101

969 observations indicates data from 1977-95 for 51 states.
662 observations indicates data from 1983-95 for 51 states (with one missing observation).
144 observations indicates data from 1984-95 for 12 states.
For more information on these variables see the Data Appendix.

Table 2

Estimates of the Determinants of State AFDC-Basic Caseloads
Dependent Variable = log(AFDC-Basic caseloads/female population ages 15-44) except in column 4 where Dependent Variable = log (AFDC-Basic caseloads)

	Column 1 Basic Specification	Column 2 With state time trends	Column 3 With no time effects	Column 4 Alternative dep var	Column 5 1977- 1985	Column 6 1986- 1995
Unemployment Rate	.007 (.005)	.001 (.003)	.006 (.004)	.016 (.006)	.007 (.005)	.001 (.006)
Unemployment $Rate_{-1}$	.014 (.006)	.011 (.004)	.011 (.005)	.016 (.007)	.010 (.006)	.021 (.007)
Unemployment $Rate_{-2}$	.017 (.005)	.017 (.003)	.013 (.004)	.012 (.006)	.006 (.005)	.034 (.005)
Log(Median Wage)	-.774 (.118)	-.324 (.094)	-.721 (.124)	-.809 (.138)	.020 (.163)	-.727 (.148)
Log(20th Wage Percentile)	-.104 (.084)	-.260 (.057)	-.040 (.085)	.065 (.098)	-.129 (.085)	-.084 (.102)
% Black	.307 (.725)	3.742 (1.079)	2.658 (.819)	-2.063 (.846)	1.363 (1.411)	-2.280 (.993)
% Single Female Heads	1.353 (.466)	.584 (.332)	1.943 (.500)	1.485 (.544)	.188 (.549)	1.533 (.475)
Yrs of Education	-.046 (.027)	.025 (.023)	.217 (.020)	-.088 (.031)	-.015 (.028)	.125 (.045)
% Elderly	-1.502 (.404)	.107 (.322)	-.958 (.439)	-2.012 (.471)	-.556 (.541)	.008 (.463)
% $Immigrants_{-1}$ (x100)	-.031 (.024)	-.011 (.016)	.077 (.024)	-.004 (.028)	-.237 (.088)	-.008 (.018)
% $Immigrants_{-2}$ (x100)	.074 (.025)	-.022 (.017)	.128 (.025)	.110 (.029)	.007 (.087)	.032 (.019)
Party of Governor (1=Republican)	-.030 (.008)	-.030 (.005)	-.016 (.009)	-.021 (.009)	-.024 (.009)	-.056 (.008)
Both State Senate & House Democratic	-.026 (.012)	-.013 (.009)	-.058 (.014)	-.036 (.014)	.006 (.015)	-.021 (.013)
Both State Senate & House Republican	-.019 (.017)	-.008 (.011)	-.052 (.019)	-.025 (.020)	.018 (.020)	-.029 (.015)
Log (Maximum AFDC Benefit Level)	.559 (.080)	.218 (.046)	.306 (.040)	.779 (.049)	.248 (.054)	.419 (.052)

AFDC-UP program	.113	.085	.178	.158	.040	.133
	(.014)	(.012)	(.015)	(.017)	(.025)	(.014)
Log(Avg Family Medicaid Expenditures)[1]	.039	-.008	.063	.051	-.071	.039
	(.009)	(.008)	(.011)	(.011)	(.028)	(.008)
Any Major Waiver	-.107	-.041	.006	-.088	na	-.078
	(.020)	(.016)	(.021)	(.023)		(.015)
State Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	No[2]	Yes	Yes	Yes
State Time Trends	No	Yes	No	No	No	No
Number of obs.	510	969	969	969	969	459

Standard errors in parentheses. All regressions based on data for 51 states from 1977-95.

[1] Average state expenditures for a family with one adult and two children.

[2] Includes dummy variable for legislative (OBRA) changes implemented in 1982.

Table 3

Effects of Waivers on State AFDC-Basic Caseloads

Dependent Variable = log(AFDC-Basic Caseloads/Female Population ages 15-44)

Regressions include all variables listed in Table 2 plus a full set of year and state fixed effects.

	Column 1	Column 2	Column 3	Column 4
Any Major Waiver	-.107	-.051		
	(.020)	(.027)		
Any Major Waiver$_{+1}$		-.077		
		(.024)		
Time Limits			.045	-.049
			(.061)	(.075)
Time Limits$_{+1}$				.121
				(.045)
Work Requirements			-.059	-.175
			(.044)	(.076)
Work Requirements$_{+1}$				.118
				(.053)
Family Cap			-.179	-.095
			(.041)	(.056)
Family Cap$_{-1}$				-.063
				(.038)
JOBS Exemptions			-.104	-.189
			(.043)	(.063)
JOBS Exemptions$_{+1}$				.059
				(.046)
Earning Disregards			-.036	.092
			(.027)	(.039)
Earning Disregards$_{-1}$				-.170
				(.035)
Sanctions			.111	.167
			(.046)	(.064)
Sanctions$_{+1}$				-.010

(.044)

Standard errors in parentheses.

Table 4

Estimates of the Determinants of State AFDC-UP Caseloads

Dependent Variable = log(AFDC-UP Caseloads)

Columns 1 and 2 estimated on the 20 states which have a continuous AFDC-UP program from 1977-95; Columns 3 and 4 estimated on these 20 states from 1977-89 and on all 51 states from 1990-95.

	Based on 20 States, 1977-95		Based on 20 States, 1977-89; 51 states, 1990-95	
	Column 1 Basic Specification	Column 2 With state time trends	Column 3 Basic Specification	Column 4 With state time trends
Unemployment Rate	.051 (.027)	.030 (.022)	.035 (.040)	.014 (.033)
Unemployment Rate_{-1}	.022 (.033)	.038 (.027)	.009 (.049)	.022 (.039)
Unemployment Rate_{-2}	.086 (.024)	.082 (.020)	.033 (.036)	.079 (.030)
Log(Median Wage)	-.437 (.656)	-.308 (.660)	1.034 (.987)	-1.827 (1.030)
Log(20th Wage Percentile)	-1.174 (.439)	-1.585 (.397)	-2.508 (.696)	-1.596 (.633)
% Black	-2.589 (3.082)	-10.003 (6.420)	-4.756 (5.272)	-6.122 (11.058)
% Single Female Heads	4.191 (2.633)	1.932 (2.247)	5.281 (3.870)	5.546 (3.432)
Years of Education	-.158 (.158)	-.032 (.195)	-.445 (.249)	-.130 (.307)
% Elderly	-9.564 (2.413)	.822 (2.305)	-13.736 (3.456)	5.570 (3.402)
% Immigrants_{-1} (x100)	.072 (.100)	.013 (.083)	.251 (.148)	.134 (.128)
% Immigrants_{-2} (x100)	-.126 (.106)	-.100 (.088)	-.500 (.154)	-.528 (.128)
Party of Governor (1=Republican)	.041 (.038)	-.009 (.033)	-.181 (.058)	-.185 (.052)
Both State Senate & House Democratic	.137 (.055)	.056 (.048)	.124 (.083)	.131 (.076)
Both State Senate & House Republican	-.048 (.077)	.023 (.066)	-.104 (.117)	.125 (.103)

Log (Maximum AFDC Benefit Level)	.712 (.308)	1.244 (.294)	1.284 (.493)	1.532 (.492)
Log(Avg Family Medicaid Expenditures)[1]	-.019 (.098)	-.001 (.089)	.067 (.094)	.237 (.098)
Any Major Waiver	.196 (.095)	.006 (.091)	-.055 (.128)	.119 (.138)
State Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
State Time Trends	No	Yes	No	Yes
Number of obs.	380	380	566	566

Standard errors in parentheses.

Table 5

How Well Does This Model Explain Recent Caseload Changes?

A. AFDC-Basic Caseloads

	1990	1994	Pct change wrt/ 1990	1994	1995	Pct change wrt/ 1994
Caseloads/Female population ages 15-44	.062	.075	21.0%	.075	.071	-5.3%
Predicted 1994(95) value based on changes in						
1. Economic factors only		.065	4.8%		.073	-2.7%
2. Demographic factors only		.062	0.0%		.075	0.0%
3. Political & program factors only		.057	-8.1%		.072	-4.0%
4. All independent variables		.060	-3.2%		.070	-6.7%

B. AFDC-UP Caseloads

	1990	1994	Pct change wrt/ 1990	1994	1995	Pct change wrt/ 1994
Log(Caseloads)	9.276	9.703	+4.6%	9.703	9.579	-1.3%
Predicted 1994(1995) value based on changes in						
1. Economic factors only		9.643	+4.0%		9.609	-1.0%
2. Demographic factors only		9.148	-1.4%		9.704	+0.0%
3. Political & program factors only		9.251	-0.3%		9.665	-0.4%
4. All independent variables		9.490	+2.3%		9.574	-1.3%

Economic factors include unemployment rates (current and lagged one and two periods), log(median wages), and log(20th wage percentile).
Demographic factors include percent nonwhite, percent single female head, percent elderly, years of education, immigrant share (lagged one and two periods) and population percent in each state.
Policy factors include log(maximum AFDC benefit levels), the presence of an AFDC-UP program (part A only), average medicaid expenditures for a nondisabled adult and two children, whether the state enacted a major AFDC waiver, whether the governor is Republican, whether the House and Senate are both Republican, and whether the state House and Senate are both Democratic.

Table 6

The Determinants of AFDC-Basic less Child Only Cases and of Child Only Cases, 1983-95

Dependent Variable = log(X/female population ages 15-44) where X is defined in each column

A full set of state and year effects are included in each regression.

	Column 1 X=AFDC-Basic Caseloads	Column 2 X=AFDC-Basic less Child Only	Column 3 X=Child only Caseloads
Unemployment Rate	.008	.008	.004
	(.005)	(.006)	(.021)
Unemployment $Rate_{-1}$	.017	.016	.043
	(.006)	(.007)	(.024)
Unemployment $Rate_{-2}$	.029	.034	.016
	(.005)	(.005)	(.018)
Log(Median Wage)	-1.197	-1.171	-2.727
	(.135)	(.155)	(.528)
Log(20th Wage Percentile)	-.032	-.075	1.185
	(.094)	(.108)	(.368)
% Black	-.707	.292	-7.377
	(.870)	(1.002)	(3.405)
% Single Female Heads	1.674	1.537	2.586
	(.467)	(.538)	(1.829)
Yrs of Education	.088	.127	.085
	(.041)	(.047)	(.161)
% Elderly	-.165	.016	2.323
	(.436)	(.502)	(1.705)
% $Immigrants_{-1}$ (x100)	-.023	-.037	.182
	(.020)	(.023)	(.077)
% $Immigrants_{-2}$ (x100)	.036	-.023	.097
	(.021)	(.024)	(.081)
Party of Governor (1=Republican)	-.042	-.051	.045
	(.008)	(.009)	(.030)
Both State Senate & House Democratic	-.033	-.059	.175
	(.012)	(.014)	(.047)
Both State Senate & House Republican	-.031	-.037	.068
	(.016)	(.019)	(.063)
Log (Maximum AFDC Benefit Level)	.535	.600	.175
	(.065)	(.075)	(.254)

AFDC-UP program	.130	.122	.191
	(.013)	(.015)	(.050)
Log(Avg Family Medicaid Expenditures)[1]	.032	.031	.007
	(.008)	(.009)	(.032)
Any Major Waiver	-.089	-.093	-.006
	(.016)	(.019)	(.064)
Year dummy for 1995	.408	.244	1.338
	(.040)	(.046)	(.156)
Number of obs.	662	662	662

Standard errors in parentheses. All regressions based on data for 51 states from 1983-95.

[1] Average state expenditures for a family with one adult and two children.

Table 7

Decomposition of Recent Caseload Changes in in 12 Largest States

Based on AFDC-Basic Caseloads less Child Only Cases

	Percent of Change due to	
	Eligibility	Takeup
A. 1984-95	1.240	-.240
B. 1990-94	.602	.398

In year t, $\text{Caseloads}_t = \text{Eigibility}_t * \text{Takeup Rate}_t$

Between years t and s, the change in caseloads is decomposed as

$$\text{Caseload}_t - \text{Caseload}_s = (\text{Elig}_t - \text{Elig}_s)*\text{TUp}_t + \text{Elig}_s*(\text{TUp}_t - \text{TUp}_s).$$

Table 8

Determinants of Eligibility, TakeUp Rates and Caseloads Holding Take-up Constant

Based on eligibility estimates in the 12 largest states, 1984-95

A full set of state and year effects are included in each regression.

Dependent Variable:	Column 1 log(Eligibility/ Fem Pop 15-44)	Column 2[1] log(Administrative Take-up Rate)	Column 3[1] log(CPS Take-up Rate)
Unemployment Rate	.001 (.028)	.008 (.030)	.008 (.023)
Unemployment $Rate_{-1}$	.036 (.033)	-.014 (.035)	-.008 (.028)
Unemployment $Rate_{-2}$	.0002 (.024)	.015 (.025)	.010 (.020)
Log(Median Wage)	.296 (.651)	-1.366 (.692)	-.172 (.547)
Log(20th Wage Percentile)	-.030 (.544)	-.149 (.579)	.913 (.457)
% Black	-11.356 (4.226)	8.621 (4.496)	-.878 (3.552)
% Single Female Heads	5.707 (2.933)	-5.134 (3.121)	2.096 (2.465)
Yrs of Education	-.328 (.217)	.567 (.231)	-.232 (.182)
% Elderly	5.054 (2.734)	-4.981 (2.909)	-3.090 (2.298)
% $Immigrants_{-1}$ (x100)	-.039 (.074)	.011 (.079)	-.061 (.062)
% $Immigrants_{-2}$ (x100)	.071 (.073)	-.117 (.078)	.041 (.062)
Party of Governor (1=Republican)	.069 (.034)	-.120 (.036)	-.029 (.029)
Both State Senate & House Democratic	.004 (.055)	-.084 (.059)	-.026 (.046)
Both State Senate & House Republican	.023 (.072)	-.088 (.076)	-.127 (.060)
Log (Maximum AFDC Benefit Level)	.191 (.402)	.473 (.428)	-.240 (.338)
AFDC-UP program	.133	.102	.049

	(.066)	(.070)	(.055)
Log(Avg Family Medicaid Expenditures)[2]	.058	-.140	.059
	(.112)	(.120)	(.095)
Any Major Waiver	-.147	.052	-.064
	(.063)	(.067)	(.053)
Year dummy for 1995	.530	-.211	.179
	(.186)	(.198)	(.157)
Number of obs.	144	144	144

Standard errors in parentheses. All regressions based on data for 12 states from 1984-95.

[1] Column 2 is based on take-up rates calculated using administrative caseload data; column 3 is based on take-up rates calculated using reported AFDC usage in CPS data. Both use estimated eligibility from the CPS.

[2] Average state expenditures for a family with one adult and two children.

Figure 1

AFDC-Total Caseloads

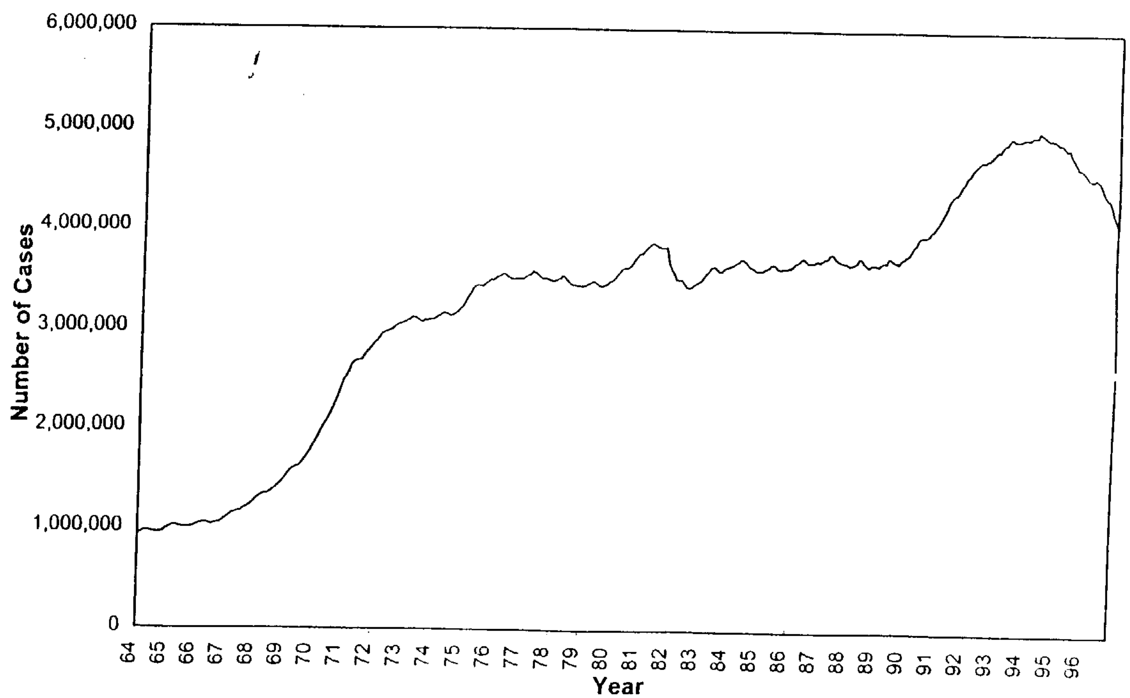


Figure 2a

AFDC-Basic Caseloads vs. the Unemployment Rate

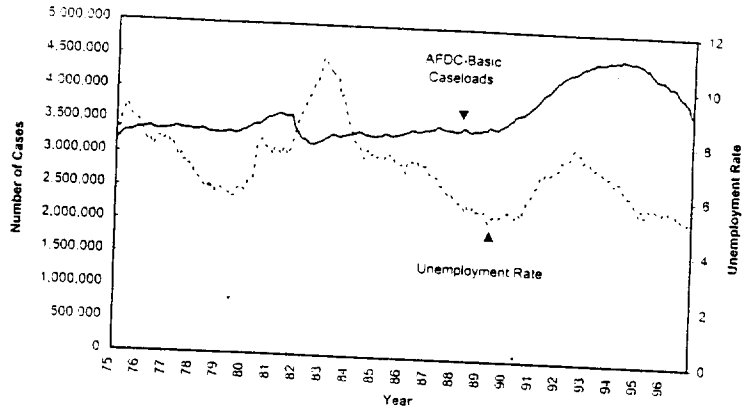


Figure 2b

AFDC-UP Caseloads vs. the Unemployment Rate

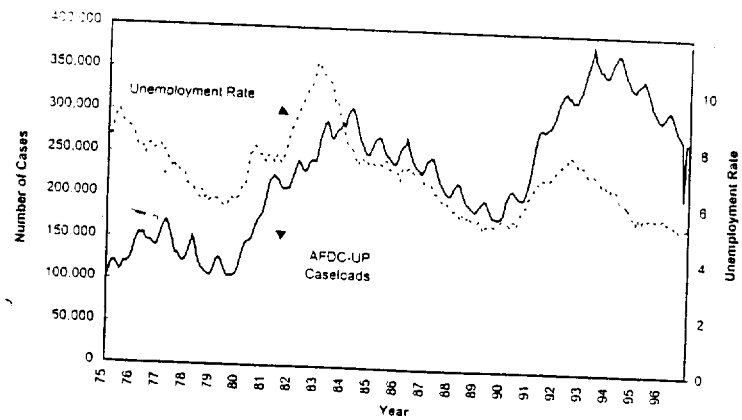


Figure 3

AFDC-Basic Caseloads
(Selected States)

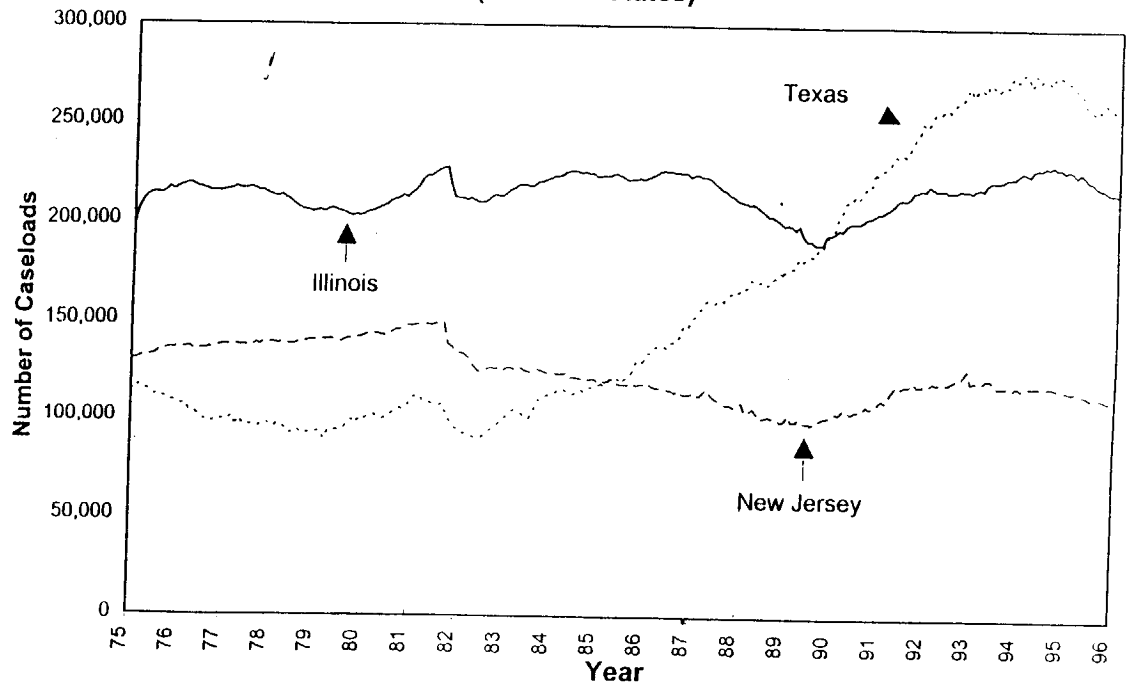


Figure 4a

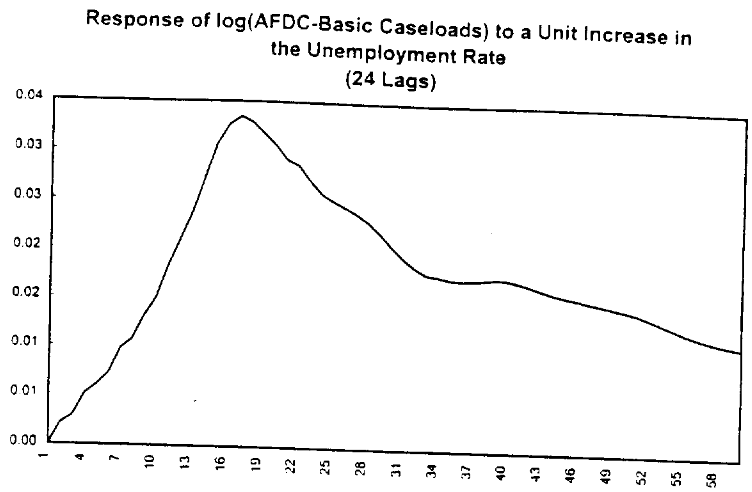


Figure 4b

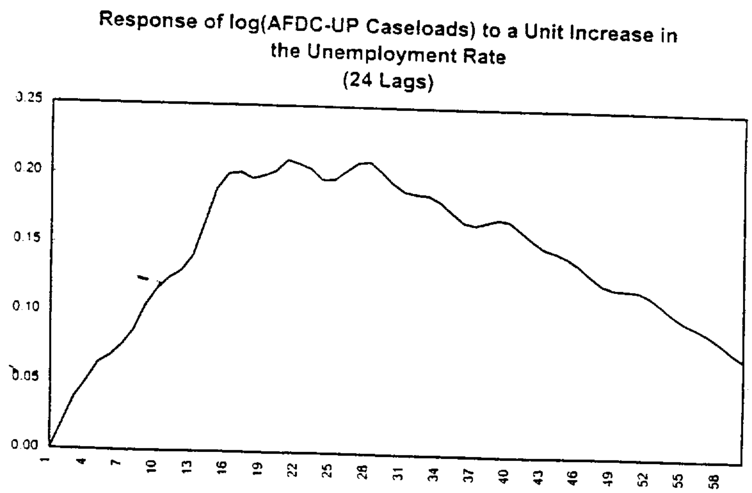


Figure 5a

Year Fixed Effects From a Regression with log(AFDC-Basic Caseloads/State Female Population ages 15 to 44) as the Dependent Variable

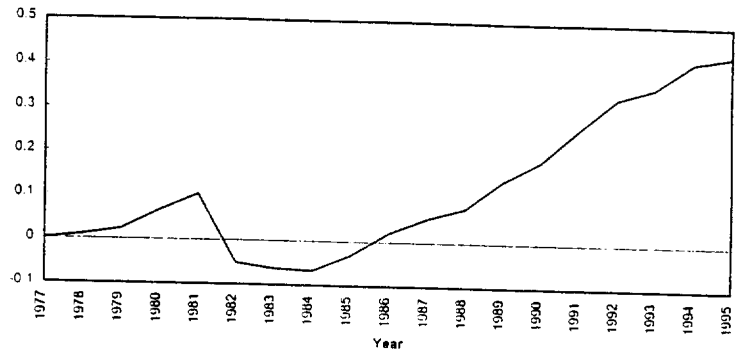


Figure 5b

Year Fixed Effects From a Regression with log(AFDC-UP Caseloads) as the Dependent Variable

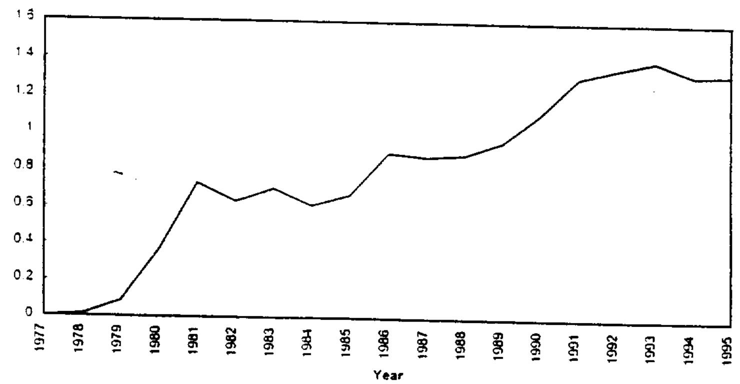


Figure 6

AFDC-Basic Cases, AFDC-Basic net Child-Only Cases, and AFDC-Basic Cases net Child-Only Cases Holding Take-Up Constant at 1984 Levels (12 States)

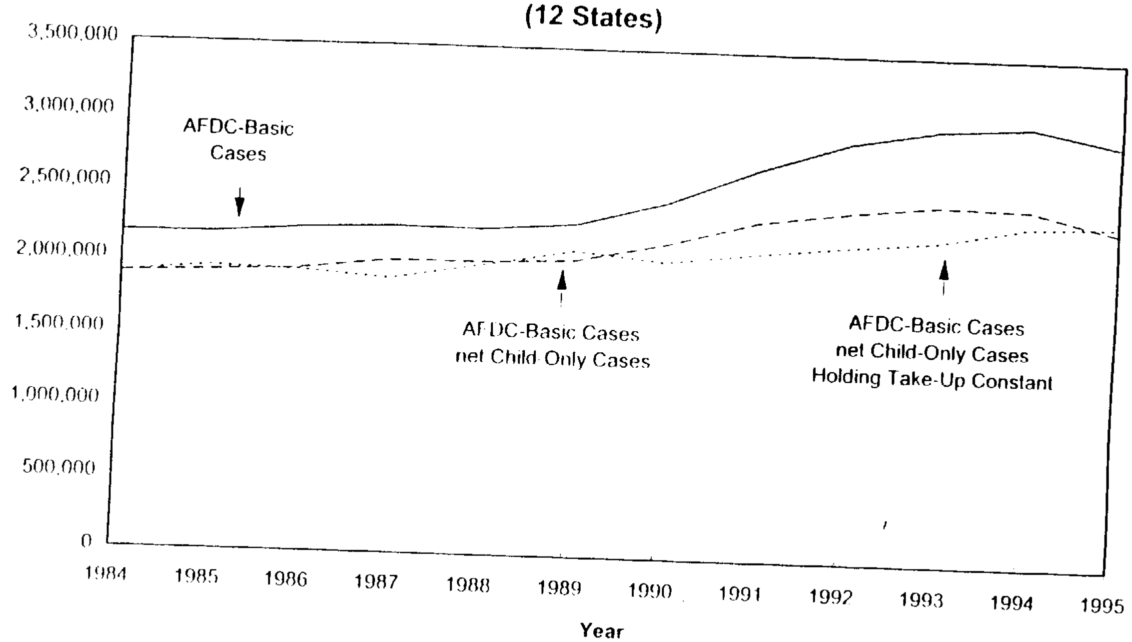


Figure 7

Estimated AFDC Eligibility, Administrative Caseloads, and Caseloads Based on CPS Reporting (12 States)

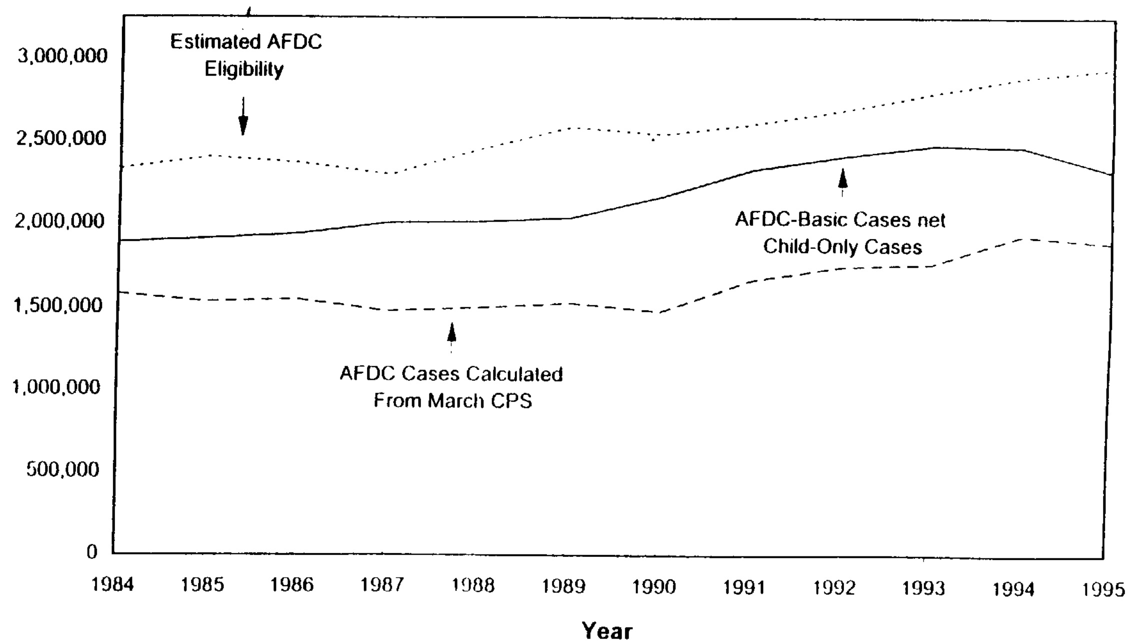
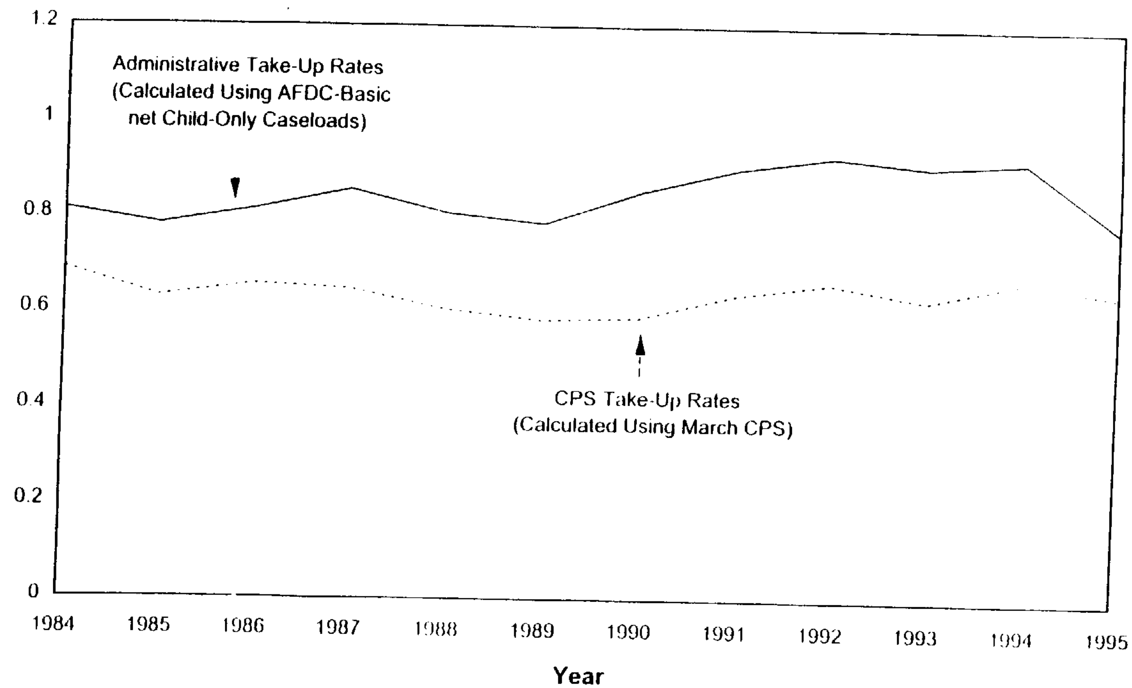


Figure 8

Two Measures of Take-Up Rates for Single Mother Families



Data Appendix

This appendix lists sources of data used in this paper, and indicates any adjustments to the data that were made.

I. Administrative Caseload Data

1. AFDC aggregate caseload data. Available monthly by state from 1964-96. From 1964-68 these data are from *Welfare in Review* published by the U.S. Department of Health, Education and Welfare (HEW.) From 1969-80 they are found in *Public Assistance Statistics* (HEW.) From September 1982-March 1988, they are in *Monthly Benefit Statistics*, published by the U.S. Department of Health and Human Services (HHS). *Quarterly Public Assistance Statistics* (HHS) also published these data from 1981-93. Sheila Zedlewski at the Urban Institute kindly made the monthly data from October 1981 through December 1995 available to us electronically. Data for 1996 were acquired electronically from the U.S. Department of Health and Human Services. A modest amount of data cleaning was done on these numbers, typically eliminating obviously incorrect monthly reports with interpolated numbers.

2. AFDC-Basic and AFDC-UP caseload data. Available monthly by state from 1975-96. See notes above on sources for AFDC aggregate caseload data.

3. AFDC child-only cases. Available annually by state from 1983-95 in *Characteristics and Financial Circumstances of AFDC Recipients*, published annually by the Office of Family Assistance, HHS. See table headed "AFDC Families With No Adult Recipient."

II. Data collected from publicly available sources

A. Demographic and economic variables

1. State population by year. Available for all years through the *Current Population Reports*, P25 series. Recent years available on Census web site.

2. *Female population, ages 15-44.* From 1974-1979, total population by state and age is available in *Current Population Reports*, P25 series. We calculate the female share by dividing the relevant age group in half. From 1980-1995, total population by state and age and sex is available in *Current Population Reports*, P25 series.

3. Unemployment rates. Available monthly by state from 1976-96; available annually from 1973-96. Monthly data for 1976-77 were acquired from the Council of Economic Advisers, and are not released publicly by the Bureau of Labor Statistics. The data for 1978-96 come from the Bureau of Labor Statistics web site. (These data are also published in *Employment and Earnings*, U.S. Department of Labor.

4. Percentage black. Number blacks divided by total state population. Number black is available by state and year for 1974, 1975, 1976, 1980-1985, and 1988-1995. Missing years interpolated. Data from the *Current Population Reports*, Series P23 (1973 and 1975), Series P20 (1976), and Series P25 (1980 and forward). Recent years on Census Bureau web site.

5. *Percentage new immigrants.* Number of newly-arrived immigrants divided by total state population. Number of newly-arrived immigrants is available by state and year from 1975-95 from *The Statistical Yearbook*, U.S. Immigration and Naturalization Service.

B. Political Variables

6. *Dummy variable for whether state governor is Republican.* Coded from information in various editions of *The Book of the States*. Where possible, we confirmed this information using *American Governors and Gubernatorial Elections, 1979-87.* We count D.C. as Democratic.

7. *Dummy variable for whether state Senate is Republican-controlled.* Coded from information in various editions of *The Book of the States*. In years where there is an exact tie between the number of Republican and Democratic senators, we code the variable 0.5. D.C. is considered Democratic. Nebraska, which has a unicameral and nonpartisan legislature is coded Republican (reflecting their gubernatorial and U.S. Congressional delegation choices).

8. *Dummy variable for whether state House is Republican-controlled.* Same source as previous variable.

C. Policy Variables

9. *AFDC maximum benefit levels for a family of 4.* Available by state and year for 1974-1996. Data for 1974-1980 from *Characteristics of State AFDC Plans*, various years; 1981-1996 data

from various editions of *The Green Book* (U.S. House of Representatives). Modest changes were made in these data, to make them consistent with the data used by the Council of Economic Advisers in its report; the author of that report compared multiple sources of AFDC benefits, attempting to achieve a consistent series over years within states.

10. Dummy variable for the presence of an AFDC-UP program. Available by state and year for 1975-96. Data for 1975-1980 from *Characteristics of State AFDC Plans*, various years; 1981-1989 data from various editions of *The Green Book* (U.S. House of Representatives). As of 1990 all states were required to run such a program.

11. Average Medicaid expenditures. The Health Care Financing Administration, Division of Medicaid Statistics, kindly provided total Medicaid expenditures by state and year on children and on non-disabled, non-elderly adults, as well as the number of recipients in each state and year. (These variables are highly correlated with each other.) From this I calculated per adult and per child expenditures by state and year. To create the variable used in the regressions I added the per adult expenditures to twice the per child expenditures to get an average expenditure for a family with one adult and two children.

12. Dummy variables for state waivers. Equals one for all years after the Federal government approved a major state request for a waiver to the national AFDC program rules. For waivers granted in the middle of the year, the variable equals the share of the year after the waiver was approved. These six different variables are coded only when a state waiver was granted that covered a substantial share of the state AFDC population (i.e., not for demonstration programs in one or two counties). This data was originally coded by the Council of Economic Advisers, in consultation with the agency at HHS who grants these waivers. The six dummy variables code state plans that include the following provisions:

A. Does the waiver include *time limits*?

B. Does the waiver include expanded *work requirements*?

C. Does the waiver include a *family cap* (limiting AFDC benefits to women who have additional children while receiving AFDC),

D. Does the waiver include *JOBS exemptions* (expanding the categories of people who are mandatorily eligible for work programs)

E. Does the waiver include expanded *earnings disregards*;

F. Does the waiver include strengthened *sanctions* for public assistance recipients who do not comply with existing rules.

13. Dummy variable for any major waiver. Equals one if any of the above six dummy variables equal one. For waivers granted in the middle of the year, the variable equals the share of the year after the waiver was approved.

III. Data calculated by state from ORG data

The Outgoing Rotation Group (ORG) data is available from 1979 on (an annual extract for 1979-93 is available from the National Bureau of Economic Research.) For 1977 and 1978 the March Current Population Survey (CPS) was used instead. All of the following series were calculated on this data by state and year:

1. Median wages in the state. Based on weekly wages.

2. 20th percentile wages in the state. Based on weekly wages

3. Percentage elderly. Percentage age 65 or older.

4. Years of education. Average years of completed schooling.

5. Percentage of households with single female heads. The share of households headed by a single woman and including other related persons in the household.

IV. Eligibility and take-up data calculated from the March CPS

The annual 1984-1995 March CPS each provides data on income in the previous year for a national sample of families. This was used to calculate the number of single female-headed families eligible for AFDC in 1984-95 in the 12 states with the largest AFDC caseloads in these years. These states are CA, FL, GA, IL, MA, MI, NJ, NY, NC, OH, PA, and TX.

1. AFDC Eligibility. Eligibility is estimated for all single female-headed families (both primary families and subfamilies) for the years 1984-95. State AFDC benefit levels by state and family size are the same as discussed above under "AFDC maximum benefit levels." We lack information on benefit levels for families with more than 6 persons. The specific formulas used by states to calculate benefits for 1984-96 were made available by Tom Gabe at the Congressional Research Service (CRS). CRS collects this information in an annual telephone survey. Lacking any CPS information on work expense disregards or child care disregards, I used the information from various years of *Characteristics and Financial Circumstances of AFDC Recipients* (HHS) on average disregards for work expenses and child care by state. All individuals who report themselves working over 5 weeks per year and 21 hours per week are allowed the average state disregard for work expenses. All families with a child under age 6 are allowed the average state disregard for child care. (Several alternative calculations were also tried, and produced virtually identical eligibility estimates.) Because SSI income is not reportable against AFDC income, but an SSI-eligible individual is typically ineligible for AFDC, if anyone in the family reported receiving SSI we subtracted one from the family size but did not add in SSI benefits in calculating eligibility.

The result of this calculation is an estimated number of eligible persons in each state, produced by weighting the eligible observations by the CPS population weights. Both individuals estimated to be eligible for AFDC and individuals estimated not eligible for AFDC but who report receiving it are counted as eligible in the data.

2. *Administrative take-up rates*. Calculates take-up rates by dividing administrative data on AFDC-Basic caseloads less child only cases in each state and year by the eligibility estimates.

3. *CPS take-up rates*. Calculates take-up rates by dividing CPS data on the number of individuals in each state and year who report receiving AFDC by the number who are estimated to be eligible.