What Causes Public Assistance Caseloads to Grow?

Rebecca M. Blank
University of Michigan and
National Bureau of Economic Research

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Abstract

This paper uses state panel data to investigate changes in public assistance caseloads through the end of the AFDC program in 1996, with particular attention to the rapid increase in caseloads between 1990 and 1994. Previous research has focussed on total caseloads, with attention to economic and policy variables, and does a relatively poor job of explaining this caseload increase. This paper utilizes a much richer set of control variables to investigate the causes of caseload change; it separates AFDC caseloads into three subcomponent programs, separately investigates changes within the AFDC-UP program, AFDC child-only cases, and the remaining "core" AFDC cases (with benefits paid to single mothers and their children); and it explores whether this caseload rise was driven by changes in take-up rates versus in eligibility. The results indicate a large unexplained rise in total AFDC caseloads, even with a very rich specification. A good share of this is due to sharp increases in child-only cases, driven by program and demographic shifts. To a lesser extent, this rise was caused by the expansion of AFDC-UP to all states. These two factors explain half of the overall rise, and all of the unexplained rise in AFDC caseloads. The remaining increase in "core" AFDC cases – with benefits paid to single mothers and their children -- is well explained within the model, and is the result of economic, demographic, political and policy changes. These variables appear to have increased eligibility among the core AFDC population in the early 1990s during the economic slowdown. Take-up rates also increased during this time period, but not by a large amount.

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 through 1996, when AFDC was replaced by the Temporary Assistance to Needy Families (TANF) block grant. Growing caseloads in the early 1990s created great concern, and this phenomenon was frequently cited as a primary motivation for the national welfare reform legislation passed in 1996. When caseloads finally began to decline in the mid-1990s, a number of state governors claimed that it was the changes they had enacted in welfare programs that led to this decline.

This paper investigates caseload changes over time in greater detail than previous research, utilizing a larger set of explanatory variables (including more extensive macroeconomic and demographic variables, state political configuration, and state policy parameters). It also separately investigates the determinants of changes in different subcomponents of the AFDC program. The results indicate a large unexplained rise in total AFDC caseloads, even with a very rich specification. A good share of this is due to sharp increases in child-only cases, driven by program changes and demographic shifts. To a lesser extent, this rise was caused by the expansion of AFDC-UP to all states. These two factors explain over half of the total rise, and all of the unexplained rise in AFDC caseloads. The remaining increase in "core" AFDC cases – with benefits paid to single mothers and their children -- is well explained within the model, and is the result of economic, demographic, political and policy changes. These variables appear to have increased eligibility among the core AFDC population in the early 1990s during the economic slowdown. Take-up rates also increased during this time period, but not by a large

amount.

The solid line in Figure 1 shows the total number of households receiving cash public assistance through the AFDC program on a monthly basis from 1964 to 1996 and from the TANF program in 1997 to 1998. 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. Note 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 (US GAO, 1985). This policy change makes it difficult to do any quick Aeyeball@ comparisons between the recession effects of the early 1980s and the early 1990s on caseloads.

The recent caseload increase peaked in 1994 when caseloads started to trend down. The dotted vertical line indicates the passage of welfare reform legislation in late 1996 that fundamentally changed the structure of cash public assistance. States were given almost total control over the design and operation of cash assistance programs. Most states implemented major changes in 1997 and 1998 as they transformed their AFDC programs to TANF programs, typically enacting stronger work incentives, enforcing stronger work requirements, reorganizing case management procedures, and taking new measures to limit program entry and hasten exit. While there is intense interest in the effect of these recent changes, it is hard to evaluate these new programs in their first few years when states were still experimenting with various program options and trying to effectively implement new program configurations.

This paper limits its attention to the AFDC program, using data through the end of 1996,

the last full year in which most states ran an AFDC program.[1] Although current attention has focused almost entirely on the amazing decline in caseloads since 1994, the run-up in caseloads during 1990 to 1994 occurred almost as quickly as the recent decline. For instance, while caseloads fell by half between 1994 and 1999, they rose by 24 percent between 1990 and 1994. Understanding this increase in the early 1990s is clearly as important as understanding the decline in the later 1990s (which coincided with major policy changes, many of them designed to reduce reliance on public assistance.) Most existing papers on caseloads do quite a poor job of explaining this early 1990s increase, however. Understanding this large and rapid rise in caseloads from the early 1990s may be critical in evaluating the long-term prognosis for permanently reduced caseloads in the 2000s; if similar factors could recur, then one might be less optimistic that the recent caseload decline is permanent. Although many of the new state TANF-funded programs differ substantially from AFDC, they do serve a similar population and B at least in some states and for some populations B provide similar services as AFDC.

Decomposing AFDC Caseload Changes

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 to initiate more uniform procedures to review applications.[2]

[1] States were given until July 1997 to design a TANF-funded program and abolish their AFDC programs. About half the states moved to a TANF-funded program in the last quarter of 1996. In many of these cases, states started to receive TANF funding before they were able to implement much in the way of actual program changes.

[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.

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 ascribed 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 Awork eligible@ AFDC recipients 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 early 1990s. In short, this was not a period of Aexpansiveness@ toward low income families, and the rising caseloads are unexpected.

While all states show a recent rise in caseloads, the magnitude and timing of these changes over the 1980s and 1990s vary widely. For instance, Figure 2 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

[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.

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 and promises state-level variation to identify different causal factors.

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. 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.[4] 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. Because these two program components serve different populations (and, as we will see, exhibit quite different patterns), it is valuable to examine them separately.

A frequently unrecognized fact is that AFDC-Basic caseloads themselves are composed of two distinct subgroups. While most AFDC-Basic cases involve payments to a single parent and children, there has been a sharp growth in so-called Achild-only@ cases in recent years. These cases occur when payments are made to a child, but where there is no payment to a caretaker adult. They may occur, for example, when children in the foster care system are placed in unlicensed kinship care and are ineligible for foster care payments, when a family is sanctioned and the caretaker portion of the benefits removed for noncompliance with welfare-to-

[4] 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.

work rules, or when payments are made to the U.S.-born children of immigrants.

State data on child-only cases is available since 1983 as part of the quality-control state data surveys collected by the Federal government. 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. Child-only cases increased rapidly between the mid-1980s and mid-1990s. In 1984, child-only cases composed about 12 percent of the total caseload; by 1996 they composed 22 percent of the caseload. Between 1990 and 1994 (the years of steep caseload increase), the number of child-only cases increased by 89 percent while the number of non-child-only cases rose by only 16 percent. The raw data suggests that the growth in child-only cases explains 42 of the total AFDC caseload rise between 1990 and 1994 and 71 percent of the rise over the entire 1984-96 period. This suggests that analyzing and understanding more about the recent increase in child-only cases is critical for understanding overall AFDC caseload growth.

Figure 3 decomposes total AFDC caseloads into these three programs. The top gray shading is the number of households in the core AFDC program, in which both a single parent and children receive payments. The white dotted shading shows the strong rise in child-only cases. Both of these two together constitute the AFDC-Basic program. The black dotted shading at the bottom shows the AFDC-UP program. AFDC-UP also increases over this time period, as the number of states offering the program increases after 1990.

This quick look at the aggregate data suggests that AFDC caseload increases between 1990 and 1994 can be decomposed into changes among these three distinct groups: increases in AFDC child only cases, which explain 42 percent of the overall caseload rise between 1990 and

1994; increases in core AFDC cases, which explain 43 percent of the aggregate increase; and increases in AFDC-UP cases, which explain the remaining 15 percent. Because these different components of the AFDC program serve distinct populations, one might believe that their caseloads respond to different causal factors. The next three sections summarize existing research on caseload changes, describe the data used in this paper, and present estimates of aggregate caseload change which provide a useful baseline to compare the results in this paper to existing research. Following that, I separately analyze caseload changes in each of these three categories.

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.[5] The results indicate that certain characteristics, such as nonmarital births or lower education levels, are correlated with a greater probability of AFDC usage and with longer AFDC spells. 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,[6] while their policy variables are difficult to interpret. 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

[5] Moffitt (1992) provides a summary of this literature, or see Blank and Ruggles (1996).

[6] At best, state unemployment rates are included. Fitzgerald (1995) and Hoynes (2000) are an exception.

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

A growing number of recent studies use state panel data to model caseloads. Two federally-sponsored reports from the early 1990s[7] investigated caseload changes with only a few years= data. More recent papers utilize state panel data from the 1980s through the mid-1990s to investigate changes in aggregate AFDC caseloads. The Council of Economic Advisers (1997) used a relatively sparse specification to focus particularly on the role of state welfare policy changes prior to the implementation of TANF, finding that Federal waivers which allowed states to change their AFDC programs in the mid 1990s had a significant negative effect on caseloads. Subsequent studies examined changes in welfare caseloads during this and earlier periods (Ziliak, et al, 1997; Levine and Whitmore, 1998; Bartik and Eberts, 1999; Moffitt, 1999; Figlio and Ziliak, 1999; Wallace and Blank, 1999.) These studies use a limited number of control variables and estimate the determinants of changes in total AFDC caseloads through 1996.[8] Their primary focus is on the extent to which economic and policy variables determine caseloads. Two recent studies try to investigate the role of policy changes on caseloads post 1996, and indicate that policy changes since the 1996 welfare reform have had a substantial effect on caseload decline (CEA, 1999; Schoeni and Blank, 2000).

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[7] Gabe (1992) and the Congressional Budget Office (1993). An early Federal report that addresses this issue is Grossman (1985). Earlier studies of state-specific caseloads include Plotnick and Lidman (1987), Brazzell, et al (1989) or Garasky (1990).

[8] Wallace and Blank (1999) are an exception and use a richer specification to look at AFDC-Basic cases.

As we shall see, the specifications used in these papers tend to leave a substantial share of the recent caseload change unexplained, particular the steep increase between 1990 and 1994. The present study attempts to provide a more complete explanation in three ways. First, I have collected and/or tabulated a much larger set of control variables, and am able to control for a wider range of economic, demographic, political, and policy-related factors than these earlier studies. Second, as noted above, I separately investigate caseload changes among child-only, core AFDC, and AFDC-UP populations, as a way of understanding the AFDC caseload increases in the early 1990s at a more micro level. Third, using data from the 12 largest states, I am also able to decompose recent core AFDC caseload changes into changes in take-up rates versus changes in eligibility. Taken as a whole, this analysis provides a much better understanding of caseload changes within the AFDC program, and particularly the rise in caseloads in the early 1990s.

Data

I use data on the number of households in each state receiving AFDC from 1977 to 1996, both because I cannot separate AFDC-UP from AFDC-Basic in earlier data and because some of my independent variables are not available for earlier years.[9] Although caseload data is available monthly, I use annual panel data because there are few monthly control variables available at the state level. There are 51 "states" in this data set since the District of Columbia is included. Columns 1 and 2 of Table 1 show the mean and standard deviation from 1977 to 1996

[9] Also available are data on the total number of individuals receiving AFDC, as well as total expenditures. I use households rather than individuals to abstract away from changes in average family size over this time period.

in annual caseload data and for the other included control variables in the models. Column 3 shows the standard deviation across state averages; comparison of columns 2 and 3 provides an indication of how much of the data variation is due to differences within versus across states.

A number of state-by-year variables were collected from publicly available sources. These include unemployment rates, total population, black population share, out-of-wedlock births, and the number of newly-admitted immigrants.[10] I also have information on the party affiliation of the governor and the majority party of the state House and state Senate.

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.[11]

I use these CPS data sources to calculate a variety of demographic variables by state and

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

[11] 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.

year: the share of households headed by a single woman and including other related persons in the household[12]; 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 of the wage distribution. The latter provides a measure of wage changes among lower-wage workers.

In addition, I want to control for key policy parameters. From 1977 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.[13]

I also have information on which states were granted Federal waivers after 1991 to implement state-wide changes in their AFDC program.[14] The waiver variables are coded as the

[12] 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. One would expect that trends in this data would be driven by the rise in female-headed households with children.

[13] Hoynes (1997) finds weak negative effects of AFDC-UP on female headship when she controls for both state and individual fixed effects.

[14] Re-estimation of the models presented here using actual implementation rather than approval dates results in virtually no changes to the results. I use the same coding as the Council of Economic Advisers report (1997), which was created in consultation with the HHS department that 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.

percent of the year in which the state has a major state waiver approved for implementation. These data allow me to investigate whether state welfare reforms enacted prior to the 1996 federal reform legislation 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.[15] [16]

Panel Data Analysis of the Determinants of Caseload Change

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

$$(1)\quad Caseload_{ts} = \gamma_1 X_{ts} + \gamma_2 D_{ts} + \gamma_3 P_{ts} + \nu_t + \rho_s + \omega_{ts}$$

where Caseload can be any one of a number of dependent variables measuring caseloads, X is a

[15] 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 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.

[16] From 1981 onward, I also gathered information on maximum Supplemental Security Income (SSI) benefits in each state, available to the elderly and disabled. (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.

vector of economic factors, D is a vector of demographic factors, and P is a vector of political and policy parameters. The subscript t represents year and s represents state. The v 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. 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 (1) is estimated on annual data from 1977 through 1996 for 51 states, providing a total of 1020 observations. The models are estimated with a weighted OLS procedure, where the weights are based on state population.

For comparison with existing studies, I start with an extremely sparse specification. Column 1 of Table 2 shows the results of this estimation, using the specification established by CEA (1997) and emulated in much of the other literature. Column 2 uses the much richer specification that my data allows. In particular, I am hoping that the inclusion of information on wages and wage inequality, and on more detailed demographic, political, and policy factors will provide a better explanation of AFDC caseload changes over the last decade of the program. Column 3 includes state-specific time trends, in addition to the state and year effects in columns 1 and 2. In all columns in Table 2 the dependent variable is the log of the ratio of the number of AFDC households divided by the total population in state s at time t. I call this variable the "caseload share."[17]

[17] The results change little if I estimate these models using female population, ages 15-44, as the denominator. I use total population throughout this paper since that is the variable used in most of the existing literature.

The results in column 1 are very similar to those seen elsewhere in the literature. A one-point rise in the unemployment rate raises caseloads by 6.2 percent over a three-year period. This is comparable to the unemployment effects estimated in similar annual panel data (see Table 1 in Wallace and Blank). The other results in column 1 are also similar to earlier work, and indicate that AFDC-related policy can affect caseloads. States with higher AFDC benefits have higher caseloads, while states that implemented waivers in the 1990s experienced a caseload decline.

Column 2 utilizes the much richer set of explanatory variables to estimate caseloads. The inclusion of these other variables has little effect on the estimated effect of unemployment or of AFDC policy on caseloads. A one-point rise in unemployment raises the caseload share by 4.8 percent over three years, very similar to the estimates in column 1.

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, suggesting that change in the distribution of wages affects caseloads. 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 non-marital births and the share of households with single female heads are important, since both signal an increase in single-parent households, the group which is eligible for AFDC-Basic if they find themselves in economic difficulty. If one believes that fertility and the formation of single-mother households is influenced by the presence and level of AFDC, then these variables are endogenous and their coefficients are biased upward, although the evidence suggests this is not a

major problem.[18] Excluding these variables has little effect on the other coefficients.

Years of education and the percent elderly are both strongly negatively correlated with caseloads; racial composition has a less significant effect. 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 Democratic or Republican. 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 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 caseloads, which is to be expected since the AFDC-UP program makes a number of two-parent families eligible for AFDC benefits. Average family Medicaid expenditures also positively affect caseloads; states whose Medicaid policies have been more expansive have seen

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

greater public assistance usage.

The final policy variable indicates that states that received program waivers in the 1990s saw significant caseload declines. The magnitude of this effect is consistent with the estimates elsewhere in the literature, and I do not discuss this further since these policy changes are the focus of many of the previously-cited papers.[19]

Column 3 uses the same specification as column 2, 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 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 trend.[20] Not surprisingly, the inclusion of state time trends reduces the magnitude of most of the estimated coefficients. But the sign and significance of the economic, political and policy variables are not greatly affected by the inclusion of state time trends. The primary effect of adding state time trends is to eliminate significance on the demographic variables (except for the share of nonmarital births), all of which change only slowly over time. In short, the inclusion of state time trends changes few of the major conclusions from column 2.

How much more effective is the richer model shown in column 2 in explaining the caseload rise of the early 1990s, compared to the model in column 1 used elsewhere in the

[19] Blank (1997) shows that the negative effect of waivers on caseloads are apparent even before a waiver is approved for implementation. This suggests that there may be a behavioral "demonstration" effect, as women hear that the state is going to "get tough" on welfare recipients. It is also consistent with the possibility that waivers are endogenously determined, however Schoeni and Blank (2000) indicate that there are few differences between waiver and nonwaiver states once economic differences are controlled for.

[20] I do not view the coefficients estimated in column 3 as the most appropriate model, since the inclusion of such trends often overadjusts the data. Some variables with linear trends (such as education rates) may be appropriately affecting caseloads. But column 3 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.

literature? The coefficients on the year fixed effects indicate any over-time changes that are not explained by the other variables included in the data. At the bottom of Table 2, I indicate by how much the year fixed effects increase between 1985 and 1994. If all of the trends in caseloads were explained by this model, there would be no difference in the year fixed effects between these two years. Table 2 indicates that column 1's specification leaves a substantial unexplained rise in caseloads over this period. The richer specification in Column 2 reduces the unexplained increase in the year fixed effects by one-third; i.e., column 2 explains one-third more of the unexplained variation in the data than does column 1. The inclusion of state time trends reduces the unexplained variation by another 25 percent.

Figure 4 provides a graphical analysis of the year fixed effects from columns 1 and 2 of Table 2. Figure 4 shows a sharp unexplained decline in caseloads in 1982 in both models. 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 time.) Hence, the sharp drop in the early 1980s is an indication of the policy effects of the eligibility changes in that time period.

After 1984 the year effects from both models rise steadily, particularly in the early 1990s. This indicates that there is a substantial unexplained rise in caseloads over this time period, which these models 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. 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.

Figure 4 also indicates that the additional variables in the regression in column 2 help to explain the underlying trend increase in caseloads in the late 1980s and early 1990s. The richer specification (dotted line) has a substantially lower unexplained increase in caseloads than does the sparse specification (solid line). On the one hand, it may be surprising that this much richer specification does not explain all of the caseload change over this period. On the other hand, it does much better than the more limited specification in Column 1.

Another way to investigate the fit of the model in column 2 is provided in Table 3, where Part A shows actual and predicted total caseload changes for AFDC between 1990 and 1994 (when caseloads rose sharply), and 1994 and 1996 (when caseloads began to fall.) The top row of Table 3 shows that caseloads as a share of the total population rose 19 percent between 1990 and 1994. Changes in the economic variables in the model (unemployment rates and wage rates) over this time period would have predicted only a 6 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 a 10 percent decline. The bottom row in Part A of Table 3 shows the predicted change in caseloads, based on changes in all of these control variables. The model predicts a 1 percent *decline* in caseloads, in a period when they actually rose 19 percent.

Between 1994 and 1996, caseload share fell by 13 percent. Changes in economic factors would have predicted an 8 percent decline, and demographic changes and program changes

would also have predicted declines. In fact, the predicted decline based on changes in all control variables in the model is 14 percent, very close to the actual decline that occurred.

The results in Part A of Table 3 underscore the mystery about AFDC caseload changes in the past decade. Over the first half of the 1990s, caseloads rose rapidly when an extensive set of control variables suggests they should have fallen slightly. In contrast, the post-1994 decline appears well explained by my model. These results lead me to investigate each of the components of the AFDC program in more detail in the next three sections. I start with the two smaller components of the program, AFDC-UP and AFDC child-only cases, and then investigate any remaining increase in the core AFDC program.

AFDC-UP and The Rise in Caseloads

The Family Support Act of 1988 mandated that all states run AFDC-UP programs by 1990 (previously only about half of the states had been operating such programs). As a number of two-parent families became eligible for AFDC under this new mandate, at least some of the Aunexplained@ increase may be due to rises in AFDC-UP cases as this program expands in states in which it was previously not offered. A large unexplained increase in the utilization of AFDC-UP in the early 1990s would be consistent with this hypothesis.

The raw data on caseloads indicates that the AFDC-UP program cannot be a major explanation of the aggregate caseload rise, however, simply because it is a small program. The AFDC-UP program does grow between 1990 and 1994, from 212,000 to 358,000 cases (a 69 percent growth rate), but this growth explains only 15 percent of the aggregate caseload rise.

More sophisticated estimation results indicate that AFDC-UP expansions are a part of the

puzzle of rising overall caseloads, even if they do not explain the entire amount observed. Column 1 of Table 4 repeats the results in column 2 of Table 2, showing the determinants of the total AFDC caseload share. Columns 2a and 2b of Table 4 reports estimates using AFDC-UP caseloads as a share of the total population as the dependent variable.

I can estimate the determinants of AFDC-UP caseloads only for those periods when states were running an AFDC-UP program. All states have such a program after 1990 when it was mandated by the federal government. Column 2a uses information from the 20 states that run a continuous AFDC-UP program from 1977 to 1989, and uses data from all 51 states from 1990 on.[21] Column 2b uses information from only the 20 states that run a continuous program from 1977 through 1996.

A comparison of the results in columns 1 versus 2a or 2b indicate that AFDC-UP is much more responsive to unemployment changes than is the overall AFDC program, although the coefficients are less precisely estimated. A one-point increase in unemployment causes a 9.3 percent rise in AFDC-UP caseloads in column 2a (a 17.2 percent rise in column 2b) over the next three years.[22] The wage level at the 20th percentile of the distribution also has much stronger and more negative effects, indicating that the wage opportunities in the less skilled labor market strongly affect the use of AFDC-UP. This underscores the greater importance of macroeconomic factors to the AFDC-UP program.

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[21] 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.

[22] This is consistent with simple time-series VAR models that correlate monthly changes in state unemployment rates with monthly changes in state AFDC-UP benefits. Those models suggest that a one-point rise in unemployment results in steady increases in AFDC-UP caseloads for the next 18 months, culminating in a 20 percent aggregate caseload rise. For details see Blank, 1997.

The demographic variables have generally insignificant effects on the AFDC-UP caseload, although the percent elderly and the percent of immigrants in the state are both correlated with lower caseloads. Among the political variables, a Republican in the governorship reduces AFDC-UP caseloads in column 2a, but not 2b. This suggests that the impact is on the expansiveness of the AFDC-UP program in states that start the program after 1990.

Benefit levels have a strong positive influence on AFDC-UP caseloads in column 2a. Waivers have a strong positive effect on AFDC-UP caseloads in column 2b, an unexpected effect. The insignificance of waivers in column 2a suggests that waivers must have a negative effect on caseloads in the states that start an AFDC-UP program in 1990. This suggests that the states which started AFDC-UP programs in 1990 are running somewhat different programs than are the 20 states that run an AFDC-UP program continuously over this period.

Alternative specifications and data samples do not change these conclusions. When state-specific time trends are included in the model 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.

Part B of Table 3 investigates the extent to which the model in column 2a explains the changes in AFDC-UP over time. Between 1990 and 1994, the AFDC-UP caseload share rose by 62 percent. The independent variables in the model predict a 74 percent decline. But this is exactly the period when all states were mandated to begin the program, an effect that is not captured in this prediction. There is a steep increase in the unexplained year effects between 1989 and 1991, and little increase afterward. If we predict the 1994 value using the 1992 year effect rather than the 1990 year effect, we would predict a 42 percent rise in AFDC-UP

caseloads, close to the actual change of 62 percent. In short, the unexplained rise in AFDC-UP caseloads over the 1990-94 period appears to be largely due to a step-function increase in caseloads immediately after all states are mandated to run AFDC-UP programs.

The evidence suggests that the AFDC-UP program is far more driven by macroeconomic variables than are overall AFDC caseloads. This underscores the differences between AFDC-UP and other components of the program and is an argument for dealing separately with AFDC-UP versus AFDC-Basic in analyzing caseloads and other aspects of the AFDC program. (And is an argument for separating out support for two-parent families when analyzing the current TANF block grant caseloads, as well.)

Child-Only Cases and the Rise in Caseloads

As noted at the beginning of this paper, there has been a sharp increase in so-called "child only" cases within the AFDC-Basic caseload, with child-only cases growing 115 percent from 1984 and 1996, far faster than other AFDC cases. Fully 71 percent of the total AFDC caseload growth between 1984 and 1996 (42 percent of the growth from 1990 to 1994) can be accounted for by growth in child-only cases. This fact was largely unrecognized throughout the early 1990s when caseload increases were used to justify greater enforcement of work requirements on adults.

Child-only cases occur when payments are made for a child, but where there is no payment to a caretaker adult. The most common child-only case occurs when the child is not living with his or her parents, but is still eligible to receive AFDC payments. This may occur for children placed by the foster care system into kinship care. Foster care parents must meet strict

licensing requirements for their homes, which kin often cannot meet. Over the past decade, the foster care system has increasingly encouraged kinship care placements for children, if at all possible. To deal with the licensing problems this creates, 41 states by 1997 had different standards for kinship care. In 19 of these states, however, the kin caregiver is eligible only for AFDC payments, not foster care payments (Boots and Geen, 1999). (Any family that could receive foster care payments presumably would, since these are typically substantially higher than child-only AFDC payments.)

Furthermore, there may be low-income relatives who informally choose to care for children whose parents are incapacitated (and who may explicitly desire to avoid the oversight of the foster care system, which can be highly intrusive.) In these cases, the child's custodian (even if not formally assigned custody through the courts) can receive AFDC benefits for the child. (If these relatives are themselves low-income, they may be able to receive a full benefit – with both child and adult components -- from AFDC.) In fact, there was an slight increase in the number of children living with relatives who are not parents between the mid-1980s and the mid-1990s (from around 2.0 percent of all children to 3.0 percent of all children), which might signal an increase in the number of potential child-only-eligible households. There is no data that would allow me to separate children in child-only cases by whether they were under the oversight of the foster care system, or simply living more informally with a non-parental relative.[23]

There are three additional situations where child-only cases can arise even though a parent is present in the home. If a parent is disabled or elderly and eligible for SSI they will

[23] For further information on both formal and informal kinship care arrangements, see US HHS (1997) and Child Welfare (1996).

typically be ineligible for AFDC (SSI payment levels are higher than AFDC payment levels), but their children=s eligibility is not affected by this. If parents are non-citizens, but the child was born in the U.S. and is a citizen, a child-only case can result. Finally, over the last decade states have begun to enforce work requirements and other behavioral requirements for AFDC more strongly, imposing a variety of sanctions on families that don't meet these requirements. In many states, such sanctions can take the form of removing the adult share of the AFDC benefit and paying the family at a lower rate as a child-only case.

The research literature on child-only cases in AFDC is virtually non-existent, and there are many things we don't know or can only guess at. State data on child-only cases is only available since 1983 as part of the quality-control state data surveys collected by the Federal government. These surveys sample each state's caseload and provide an estimate of the total caseload in different categories, including the number and type of child-only cases. Table 5 shows the distribution of child-only cases in 1988, 1994 and 1996 by type.[24] Between 1988 and 1996, child-only cases increased from 9.8 percent to 21.4 percent of the caseload, acccording to these data.[25]

While the majority (57 percent) of child-only cases were in households without parents in 1988, this shrank to 40 percent by 1996, largely because other child-only categories grew faster. (The absolute number of these non-parental child-only cases increased even though their share shrank.) In 1996, about one-fifth (20 percent) of the child-only cases occurred in families where

[24] The data in Table 5 come from special tabulations of the Quality Control data by the Urban Institute for the Assistance Secretary for Planning and Evaluation in DHHS, and were made available by Don Oellerich in that office.

[25] This is quite similar to, although not identical with, the data we use elsewhere in this paper.

the parent received SSI, 16 percent were in families where the parent was a non-citizen, and 11 percent were in families that had been sanctioned. All three of these "parent present" categories have grown over the past decade, with the fastest growth among non-citizens and sanctioned families. A substantial Aother@ category remains in the data (13 percent), which is not well understood.[26]

Growth in all of these categories is consistent with our general knowledge about how public assistance is changing. States steadily increased their use of sanctioning as work requirements (and other behavioral requirements) grew steadily stronger. Many states, as AFDC caseloads grew in the early 1990s, carefully screened their AFDC rolls, looking for individuals who might qualify for SSI and hence move from AFDC benefits (shared by state and federal government) to SSI benefits (paid entirely by the federal government.) Finally, throughout this decade, immigration remained at a very high level, increasing the number of families with non-citizen parents but eligible citizen children.

It is difficult to estimate the determinants of child-only cases in a rigorous way. Some key variables that one would want to include would be information on state foster care utilization of kinship care, on the extent to which states have moved people from AFDC to SSI, on the

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[26] Conversations with those at Urban Institute who tabulated the data in Table 5 suggest a variety of reasons for the "other" category: It could reflect miscoding, where someone is misreported as a parent in the QC data but not in the AFDC benefit calculation. Many types of sanctioning (particularly by the mid-1990s) may not be picked up by the limited question which focuses only on sanctioning due to nonparticipation in employment programs. Finally, caseworkers needn't put the parent into the payment unit if there's a reason not to.

immigrant population, on the sanctioning policies of the state, and on the number of children in kinship care (in or out of the foster care system). Only the immigrant information is actually available by state and by year, as we need for our panel data estimates. Hence, I present regression estimates with some hesitation, since I do not have the optimal set of control variables to understand the determinants of child-only cases. On the other hand, it is useful to compare the estimated determinants of child-only to those of other AFDC components and see how they differ.

Column 3 of Table 4 provides these estimates, using state panel data from 1983 to 1996. As expected, most of the variables are insignificant in this regression. For instance, the state of the economy, as measured by unemployment rates, appears to have little effect on child-only cases. The median wage in the state is strongly negatively related to child-only cases, as is the share of the nonwhite population.[27] Interestingly, the 20th percentile wage is positively correlated with child-only cases, perhaps indicating a greater willingness by relatives to take in children when their own income is higher. 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.

Although I don't have state-by-year data on the foster care system, I do have 1997 information from state kinship care requirements (Boots and Geen, 1999). I can correlate the state fixed effects from the estimates in column 3 of Table 4 with an indicator of whether states

[27] Barth and Needell (1997) have noted that black children are far more likely to be placed in foster care than white children. They are also more likely to live with relatives.

by the end of this period utilized child-only AFDC as their primary form of cash assistance to children in kinship care in the foster care system. The results indicate a very low correlation between this aspect of the foster care system in 1997 and state variation on average child-only caseloads over the earlier time period (correlation coefficient = 0.03). This result suggests that differences in state foster care systems do not appear to be the primary cause behind higher child-only cases in some states, consistent with the fact that non-parental cases are not the primary cause of growth in child-only cases, as Table 5 demonstrates. This is also consistent with the fact that many non-parental child-only cases may occur through informal kinship care arrangements, rather than from formally established kinship care under the aegis of the foster care system.

Table 3, Part C, indicates that child-only caseload share grew 81 percent between 1990 and 1994 (and another 11 percent from 1994 to 1996, when other caseloads were falling). Our model explains none of this growth, suggesting that child-only increases are a primary reason for unexplained increases in the overall AFDC caseload.

Core AFDC Cases and the Rise in Caseloads

The previous results suggest that increases in AFDC-UP and in AFDC child-only cases explain about half the rise in total caseloads during the late 1980s and early 1990s. This leaves the "core" AFDC cases B those cases including a single parent and one or more children, all of whom receive AFDC benefits. This is the traditional population of AFDC recipients that most people think of when considering caseload increases. This section will first investigate how much of an unexplained increase in caseloads occurs in core AFDC cases, and then try to further understand the underlying changes in core AFDC cases.

Column 4 of Table 4 shows the results of estimating the determinants of core AFDC cases, to be compared with similar estimates for total AFDC cases (column 1), and for AFDC-UP and child-only cases (columns 2 and 3). The results in columns 1 and 4 are reasonably similar, except that the effect of newly-arrived immigrants becomes negative and insignificant in column 4. The economy has a strong effect on core AFDC cases (although not as strong as on AFDC-UP); demographic and political factors also matter, as do program factors. As expected, AFDC benefit levels, waivers, and Medicaid generosity all affect core AFDC 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.[28] 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.

At the bottom of Table 4 I report the difference in the unexplained year dummies for 1994 and 1985, a measure of how much unexplained caseload growth is subsumed in the year effects. While both AFDC-UP and AFDC child-only cases had large unexplained increases in caseloads over this period, this model explains most of the change in AFDC-Core cases.

This is also apparent in Table 3, Part D, which shows that there is no unexplained increase in core-AFDC caseloads between 1990 and 1994 in this model. Once AFDC-UP and child-only cases are removed from the data, core AFDC caseloads increase only 8 percent

[28] Hoynes (1997). Hu (1998) finds a negative effect of AFDC-UP benefits on marriage among those in the

between 1990 and 1994. In fact, our model overexplains this increase, predicting a 15 percent increase (in sharp contrast to the other regressions, the year fixed effects actually fall over this period for core AFDC caseloads). Between 1994 and 1996, core caseloads decrease 18 percent and our model predicts a 14 percent decline. In short, once other AFDC components are removed, our model does a good job of explaining the remaining movement in core AFDC cases.

Results not shown here suggest that the panel data estimates for core AFDC caseloads are quite robust to specification changes and to various time periods. Including state time trends lowers the significance levels on several variables but does not change the fundamental results. If the sample is split in half, pre- and post-1986, the results are generally similar. The 20th percentile wage level matters more in the earlier time period (when it 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.

Eligibility vs. Take-Up: Which Is Changing More? The estimates above suggest that there were substantial increases in AFDC utilization, including increases in core AFDC rates. Most of these changes in core AFDC are explainable by changes in economic, demographic, policy, or political variables. An alternative way to think about the increases in core AFDC is to realize that any change must be due to the combined effects of changes in *eligibility*, that is, an increase in the eligible population, and changes in *take-up rates*, that is, an increase in participation among the eligible population. The regression model in Table 4 shows the combined effects of these two underlying factors. For instance, it is not possible to tell whether the increase in non-marital births primarily impacted AFDC caseloads by increasing the eligible

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program only (i.e., it encourages cohabitation over marriage).

population or by increasing the propensity of single-mother families to take-up AFDC. (For instance, London (1996) suggests that never married women participate in AFDC at a higher rate than divorced women). As discussed earlier, most people assume the steep caseload increases of the early 1970s were due to increases in take-up rates, not eligibility.

In order to investigate this question, it is necessary to know the number of persons eligible for the AFDC program, data that are not readily available. It is possible to estimate AFDC eligibility, however, as a number of earlier studies have done.[29] Many of these studies are interested only in national take-up rates. Since I want state panel data, I need a data source which will allow me to estimate eligibility numbers within states. I use the March CPS 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 I am dealing with 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.[30]

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. (Note that by default I am estimating eligibility among core AFDC

[29] 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).

[30] 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.

cases B I cannot determine child-only eligibility nor eligibility among two-parent families.) I can do this calculation from 1984 to 1996; 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. [31]

Figure 5 shows how the eligibility estimates compare to caseload data for these 12 states. The top dotted line in Figure 5 shows estimated core AFDC eligibility for the 12 states.[32] The solid line shows core AFDC caseloads in these states (as reported in administrative data). The administrative caseload data actually exceeds estimated eligibility in a number of years, due to income underreporting in the CPS. There is little evidence that income under-reporting has changed over time, however, which means these data should provide reasonable estimates of the changes in eligibility over time within states, although the estimated levels may be wrong. 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 receipt is also underreported in the CPS, as these numbers

[31] 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.

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

indicate, and this underreporting has increased over the 1990s (Bavier, 1999).[33]

Both caseload series show very similar trends, however, with a major rise in caseloads between 1990 and 1994. Estimated eligibility also rises steeply at exactly the same time as caseloads are rising. This rise in eligibility starts with the economic slowdown in 1990 and continues through 1993. Clearly, Figure 5 suggests that much of the caseload rise of the early 1990s is due to increases in the number of eligible households. Eligibility falls rapidly in the mid-1990s, however, and by 1996 is nearly back to its level during the late 1980s.

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 6 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 94 percent to 109 percent. The take-up rate calculated with CPS data ranges from 68 percent to 76 percent.[34]

Both series are relatively flat over this period. While both rise during the crucial 1990-94 period and decline from 1994-96, the administrative take-up rate shows a small increase over time, while the CPS take-up rate is slightly lower in 1996 than in 1984. The flatter CPS take-up

[33] States are running a growing number of programs under state-specific names during this time period. Women may report income from these programs, but not realize they are public assistance programs.

[34] Among states and years, the administrative take-up rate varies from 50 percent to 248 percent (because the administrative caseload data comes from an entirely different source, nothing constrains this take-up rate to be less than 1.) The CPS take-up rate varies from 47 percent to 96 percent.

rate is expected given the increased underreporting of public assistance receipt, discussed above. For this reason, I believe the administrative take-up rate is more accurate and use it in the calculations below.

Figures 5 and 6 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) $Caseloads_t = Elig_t * TUp_t$,

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) $Caseloads_t - Caseloads_s = (Elig_t - Elig_s)*TUp_t + Elig_s*(TUp_t - TUp_s)$

Table 6 shows the results of this calculation.[35]

Over the entire 1984-96 period, Table 6 indicates that 90 percent of the increase in caseloads is due to increases in take-up rates. But caseloads rise by only 7 percent over this entire period. This essentially says that the relatively small long-term rise in AFDC usage between 1984 and 1996 was entirely due to a relatively small increase in take-up over this period.

Over the 1990-94 period, however, when caseloads were rising most rapidly, take-up changes accounted for only 32 percent, while eligibility increases accounted for 68 percent of the caseload increase. Both take-up rates and eligibility were rising in this period, but the rise in eligibility was more important to overall caseloads. Similarly, over the 1994-96 period, eligibility fell rapidly and accounts for 85 percent of the decline in overall caseloads.

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[35] Table 6 uses the take-up rate calculated with administrative caseload data. The decomposition could also be written as: $Caseloads_t - Caseloads_s = (Elig_t - Elig_s)*TUp_s + Elig_t*(TUp_t - TUp_s)$.
Both of these decompositions produce almost identical results.

One can regress the eligibility and take-up data against our standard set of control variables. With only 156 observations (12 states in 13 years), it pushes the data to estimate coefficients on a full set of variables, state, and year fixed effects. The dependent variable in these regressions is also measured with error, since it includes the estimated eligibility numbers, which will not bias the coefficients but will decrease their precision. For all of these reasons, I take these regressions as less reliable and do not report their results here. Most of the coefficients are insignificant, with a notable exception. Even with problems of small sample size and noisy data, eligibility appears to be highly related to the demographic variables in these regressions, particularly the share of nonmarital births, the share of single female heads, years of education, and the racial and education mix of the state. This is reassuring, since these are exactly the variables one would expect to affect long-run eligibility trends. The macroeconomic variables have the expected signs and quite large coefficients, but are imprecisely determined, suggesting that unemployment and wages also affect AFDC eligibility.

Overall, I conclude that increases in eligibility during the economic slowdown were the most important component of the rise (and subsequent fall) in caseloads between 1990 and 1996. This makes the 1990-94 caseload increase quite different from that experienced in the late 1960s. Take-up rates also rose over this period, although their effects were smaller than the eligibility changes. These eligibility changes are closely related to the economic and demographic variables that are controlled for in the regression model, and this is consistent with the fact that this model appears to explain the underlying trends in core AFDC caseloads reasonably well.

Conclusions

This paper investigates changes in AFDC caseloads over a two-decade period, with particular attention to the large increase in AFDC caseloads in the early 1990s. Its primary conclusions are as follows:

1. AFDC caseloads have three primary components: AFDC-UP, AFDC child-only, and the remaining core AFDC caseloads of single mothers and their children. Distinguishing between these components is important, particularly in understanding the caseload changes prior to 1996 welfare reform legislation. These sub-programs are received by different types of families and respond to different causal factors.
2. Although the actual caseload numbers did not begin to rise until 1990, an unexplained increase in AFDC 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. AFDC-UP caseloads increase between 1989 and 1991 when all states are mandated to begin operating this program. Outside of the changes that occur at this time, our model does a reasonably good job of explaining movements in AFDC-UP, which is far more responsive to economic factors than are other AFDC program components.
3. There has been a rise in child-only cases; this explains around 71 of the overall rise in AFDC caseloads rise over the 1984 to 1996 period. This is driven by changes in the population

(increases in immigration), in state behavior (increase in the use of SSI among single mothers, increases in state sanctioning, changes in the foster care system), and changes in family behavior (increases in the number of children living with relatives who are not their parents.)

4. Once AFDC-UP and child only cases are removed from the data, movements in core AFDC cases are relatively well-explained by the regression results in this paper, and there is no further unexplained increase in core AFDC caseloads between 1990 and 1994. Most of this increase appears to be due to a rise in eligibility in the early 1990s, which falls again once the economy improves. Small increases in take-up rates also contribute to this caseload rise.
5. These results provide a much richer sense of the variables which impact caseloads, particularly core AFDC caseloads. The macroeconomy is important, including both wage levels and unemployment rates. Demographic variables matter, as does the political configuration within the state. As others have found, program parameters and operating rules affect caseloads, including AFDC benefit levels and Medicaid generosity. State waivers, granted in the period prior to the 1996 welfare reform legislation and largely designed to strengthen the states= ability to enforce work requirements among recipients, are correlated with caseload declines.

These results indicate that the economic slowdown, together with some long-term demographic changes, led to the very rapid caseload rise of the early 1990s among single mothers, largely by creating increases in the eligible population. In addition, policy changes were highly important, particularly policies that increased the number of child-only cases and mandated AFDC-UP programs in all states. This suggests that recent caseload declines cannot be assumed permanent. Should long-term demographic trends or economic recession start to expand the potentially eligible population, or should legislative and policy changes produce greater demand for or availability of public assistance programs,

caseloads could increase again. In fact, the increased reliance on labor market earnings rather than public assistance among low-income families (due to strong work requirements) may actually increase cyclicality in the demand for TANF. Other policy changes may offset this, however, if the enforcement of time limits or strict sanctions limits access to public assistance even during a recession.

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Table 1

Summary Statistics for the Data

	Number of Observations	Mean	Standard Deviation	Standard Deviation Across State Averages
1. Household Caseload Data				
AFDC-Basic	1020	72,966	99,022	96,368
AFDC-UP	1020	4,757	14,600	13,245
AFDC Total	1020	77,723	111,245	107,788
AFDC-Child Only Cases	713	11,158	21,780	19,435
2. Data available by state from published sources				
Unemployment rate	1020	6.515	2.088	1.328
State population (000)	1020	4,749	5,152	5,117
Percent black	1020	.107	.122	.122
Percent new immigrants (00)	1020	.196	.224	.188
Party affiliation				
--Republican governor?	1020	.399	.489	.256
--Both House & Senate Republican?	1020	.217	.412	.336
--Both House & Senate Democrat?	1020	.568	.496	.408
3. Data calculated by state from ORG data				
log(median wage)	1020	5.898	.139	.126
log(20th percentile wage)	1020	5.269	.159	.128
Percent elderly	1020	.156	.028	.024
Percent nonmarital births	1020	.233	.094	.073
Percent of households with single female heads	1020	.107	.026	.024
Years of education	1020	12.236	.640	.416
4. Policy variables				
AFDC max benefits (family of 4)	1020	507	192	177
AFDC-UP program (1=yes)	1020	.679	.467	.300
Average Medicaid expenditures (1 adult + 2 children)	1020	928	346	204
Any major waiver	1020	.071	.243	.072
5. Data calculated by state from March CPS data				
Number of AFDC eligibles	156	177,674	114,089	108,924
CPS take-up rate (based on CPS AFDC usage)	156	.731	.097	.074
Administrative take-up rate (based on administrative caseload data)	156	1.047	.239	.123

1020 observations indicates data from 1977-96 for 51 states.
713 observations indicates data from 1983-96 for 51 states (with one missing observation).
156 observations indicates data from 1984-96 for 12 states.

Table 2

Estimates of the Determinants of Total State AFDC Caseloads
Dependent Variable = log(AFDC caseloads/Total population)

	Column 1 Short specification	Column 2 Full specification	Column 3 Column 2 with state time trends
Unemployment Rate	.001 (.006)	.012** (.005)	.005 (.003)
Unemployment Rate$_{-1}$	.017* (.008)	.015** (.006)	.015** (.004)
Unemployment Rate$_{-2}$	.044** (.005)	.021** (.005)	.017** (.003)
Log(Median Wage)		-.450** (.116)	-.225** (.088)
Log(20th Wage Percentile)		-.242** (.083)	-.362** (.055)
% Nonmarital Births		1.128** (.235)	.695** (.214)
% Single Female Heads		.831* (.454)	.482 (.310)
Yrs of Education		-.085** (.026)	.029 (.022)
% Black		-.257 (.685)	1.691 (1.042)
% Elderly		-1.402** (.388)	.287 (.298)
% Immigrants$_{-1}$ (x100)		-.030 (.024)	-.011 (.015)
% Immigrants$_{-2}$ (x100)		.050* (.024)	.030* (.016)
Party of Governor (1=Republican)		-.039** (.008)	-.039** (.005)
Both State Senate		-.027*	-.020**

& House Democratic		(.012)	(.008)
Both State Senate & House Republican		-.044** (.015)	-.018* (.011)
Log (Maximum AFDC Benefit Level)	.576** (.052)	.574** (.046)	.240** (.038)
AFDC-UP program		.136** (.014)	.137** (.012)
Log(Avg Family Medicaid Expenditures)[1]		.027** (.009)	-.006 (.009)
Any Major Waiver	-.081** (.020)	-.064** (.018)	.047** (.013)
State Effects	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes
State Time Trends	No	No	Yes
Change in year fixed effects, 1994-1985	.466	.321	.220
Number of obs.	1020	1020	1020

Standard errors in parentheses. All regressions based on data for 51 states from 1977-96.
** Significant at 1 percent level; * Significant at 5 percent level.
[1] Average state expenditures for a family with one adult and two children.

Table 3

How Well Do These Models Explain Recent Caseload Changes?

A. Total AFDC Caseloads/Total Population (*1000)

	1990	1994	Pct change wrt/ 1990	1994	1996	Pct change wrt/ 1994
Actual data	15.98	19.05	19.2%	19.05	16.52	-13.3%

Predicted 1990-1994 (1994-1996) change based on model in Table 4, Column 1:

Economic factors only	5.6%	-7.8%
Demographic factors only	-.3%	-2.7%
Political & program factors only	-9.9%	-7.5%
All independent variables	-1.3%	-14.3%

B. AFDC-UP Caseloads/Total Population (*1000)

	1990	1994	Pct change wrt/ 1990	1994	1996	Pct change wrt/ 1994
Actual data	0.85	1.38	61.6%	1.38	1.11	-19.2%

Predicted 1990-1994 (1994-1996) change based on model in Table 4, Column 2b:

Economic factors only	-60.2%	-24.6%
Demographic factors only	-74.3%	-14.7%
Political & program factors only	-71.9%	-26.5%
All independent variables	-73.9%	-34.3%

C. AFDC-Child Only Caseloads/Total Population (*1000)

	1990	1994	Pct change wrt/ 1990	1994	1996	Pct change wrt/ 1994
Actual data	1.82	3.31	81.4%	3.31	3.67	10.74

Predicted 1990-1994 (1994-1996) change based on model in Table 4, Column 3:

Economic factors only	-1.1%	-7.3%
Demographic factors only	-0.7%	-4.6%
Political & program factors only	-11.5%	-2.0%
All independent variables	0.8%	-13.5%

D. AFDC-Core Caseloads/Total Population (*1000)

	1990	1994	Pct change wrt/ 1990	1994	1996	Pct change wrt/ 1994
Actual data	13.30	14.36	7.9%	14.36	11.74	-18.2%

Predicted 1990-1994 (1994-1996) change based on model in Table 4, Column 4:

Economic factors only	9.6%	-9.5%
Demographic factors only	11.8%	0.3%
Political & program factors only	-9.1%	-6.7%
All independent variables	15.1%	-14.2%

Economic factors include unemployment and wage variables. Demographic factors include percent nonwhite, percent single female head, percent nonmarital births, percent elderly, years of education, and immigrant share. Political and policy factors include all program variables and all political configuration variables.

Table 4

Estimates of the Determinants of Components of State AFDC Caseloads
Dependent Variable = log(AFDC caseloads/Total population)

	Column 1 Total AFDC Caseloads	Column 2a[1] AFDC-UP Caseloads	Column 2b[1] AFDC-UP Caseloads	Column 3[2] Child Only Caseloads	Column 4[2] AFDC Core Caseloads
Unemployment Rate	.012** (.005)	.041 (.038)	.056* (.026)	-.001 (.020)	.007 (.006)
Unemployment Rate$_{-1}$	.015** (.006)	.006 (.046)	.016 (.032)	.041* (.023)	.018** (.007)
Unemployment Rate$_{-2}$	.021** (.005)	.046 (.034)	.100** (.023)	.012 (.018)	.040** (.006)
Log(Median Wage)	-.450** (.116)	1.655* (.909)	.216 (.634)	-2.343** (.489)	-.758** (.155)
Log(20th Wage Percentile)	-.242** (.083)	-2.635** (.646)	-1.210** (.424)	1.000** (.344)	-.184* (.109)
% Nonmarital Births	1.128** (.235)	3.059* (1.605)	2.359* (1.047)	.875 (.846)	1.708** (.268)
% Single Female Heads	.831* (.454)	3.916 (3.470)	4.104 (2.509)	1.891 (1.686)	.751 (.534)
Yrs of Education	-.085** (.026)	-.410* (.226)	-.111 (.152)	.057 (.144)	.139** (.046)
% Black	-.257 (.685)	-5.138 (4.718)	-4.549 (2.806)	-5.618* (3.079)	.536 (.974)
% Elderly	-1.402** (.388)	-10.377** (3.095)	-7.228** (2.291)	1.580 (1.534)	-.044 (.485)
% Immigrants$_{-1}$ (x100)	-.030 (.024)	.242* (.137)	.049 (.094)	.173** (.073)	-.027 (.023)
% Immigrants$_{-2}$ (x100)	.050* (.024)	-.580** (.142)	-.173* (.099)	.105 (.076)	-.045* (.024)
Party of Governor (1=Republican)	-.039** (.008)	-.177** (.054)	.017 (.037)	.050* (.028)	-.065** (.009)
Both State Senate & House Democratic	-.027* (.012)	.091 (.077)	.111* (.053)	.197** (.044)	-.066** (.014)

Both State Senate & House Republican	-.044** (.015)	-.122 (.099)	-.096 (.068)	.099* (.054)	-.034* (.017)
Log (Maximum AFDC Benefit Level)	.574** (.046)	.951* (.462)	.370 (.296)	.125 (.240)	.541** (.076)
AFDC-UP program	.136** (.014)	-- --	-- --	.189** (.048)	.102** (.015)
Log(Avg Family Medicaid Expenditures)[3]	.027** (.009)	.072 (.091)	-.033 (.102)	.009 (.030)	.023** (.010)
Any Major Waiver	-.064** (.018)	- .009 (.106)	.147* (.081)	-.010 (.055)	-.082** (.017)
State Effects	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
Change in year fixed effects, 1994-1985	.321	.723	.292	.576	.091
Number of obs.	1020	616	399	713	713

Standard errors in parentheses. All regressions based on data for 51 states.
** Significant at 1 percent level; * Significant at 5 percent level.
[1] Column 2a includes the 20 states that run the UP program from 1977-89, and all states from 1990-96. Column 2b includes only the 20 states that run the UP program continuously between 1977-96.
[2] Columns 3 and 4 based on data for 1983-96 (with one missing observation).
[3] Average state expenditures for a family with one adult and two children.

Table 5

Changes in Child Only Cases by Reason

	1988	1994	1996
Total number of child only cases	350,725	868,646	978,312
Child only cases as percent of total caseload	9.8%	17.2%	21.4%
Reasons for child only cases as a percent of all child only cases			
No parent present in unit	56.7%	39.4%	39.7%
Parent present in unit, on SSI	16.9%	21.4%	19.9%
Parent present in unit, Noncitizen	11.2%	17.7%	16.3%
Parent present in unit, Sanctioned	3.7%	7.5%	11.4%
Parent present in unit, Other	11.6%	14.1%	12.7%

Data from unpublished tabulations provided by the Office of the Assistant Secretary of Planning and Evaluation, Department of Health and Human Services.

Table 6

Decomposition of Recent Caseload Changes in 12 Largest States

Based on AFDC-Core Caseloads

	Change in AFDC-Core Caseloads	Percent of Change due to Eligibility	Takeup
A. 1984-96	+6.7%	10.2	89.8
B. 1990-94	+12.7%	68.2	31.8
C. 1994-96	-16.7%	85.3	14.7

In year t, $Caseloads_t = Eigibility_t * Takeup\ Rate_t$

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

$Caseload_t - Caseload_s = (Elig_t - Elig_s)*TUp_t + Elig_s*(TUp_t - TUp_s)$.

Figure 1

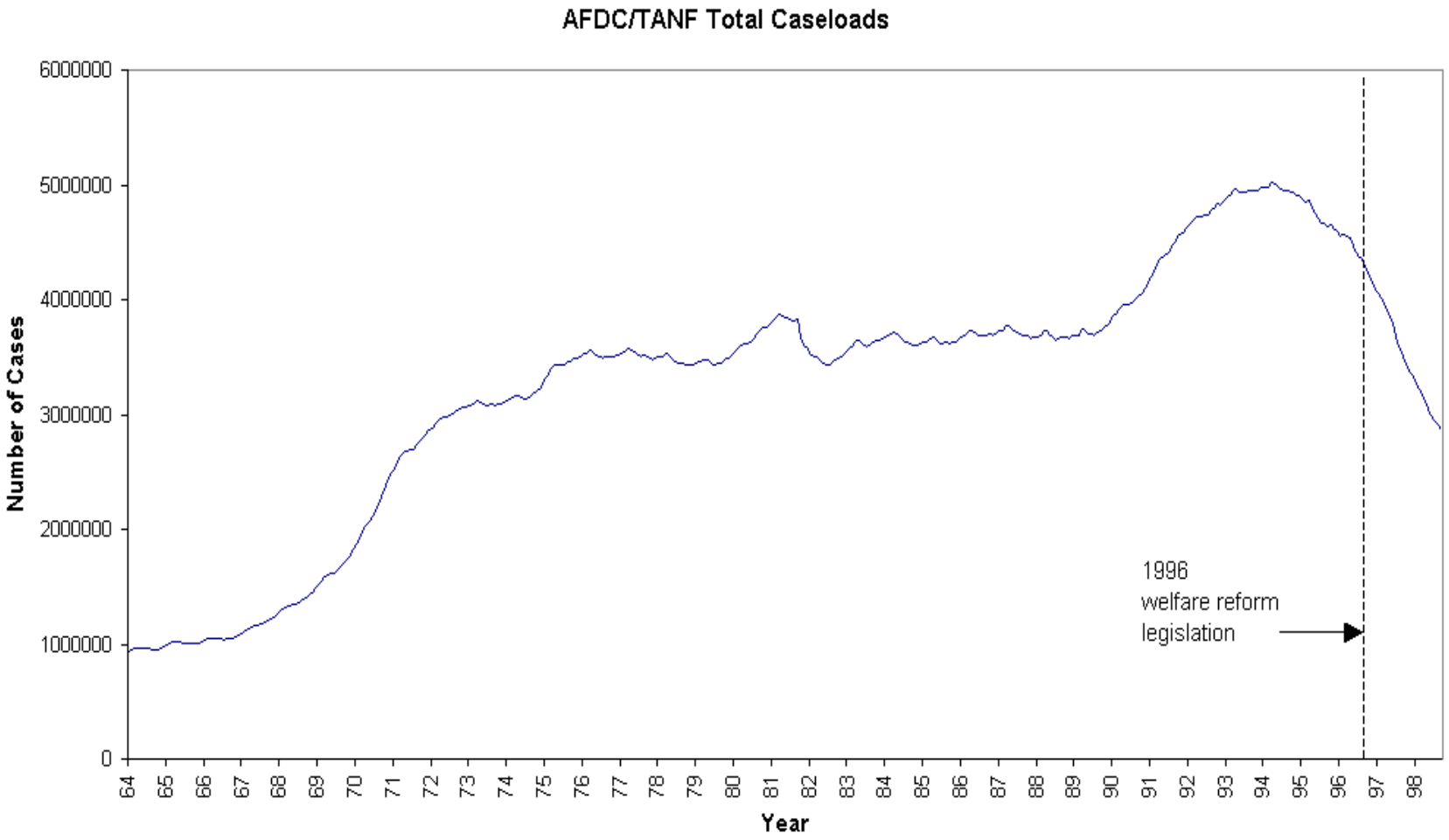

AFDC/TANF Total Caseloads
Number of Cases
6000000
5000000
4000000
3000000
2000000
1000000
0
64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98
Year
1996
welfare reform
legislation

Figure 2

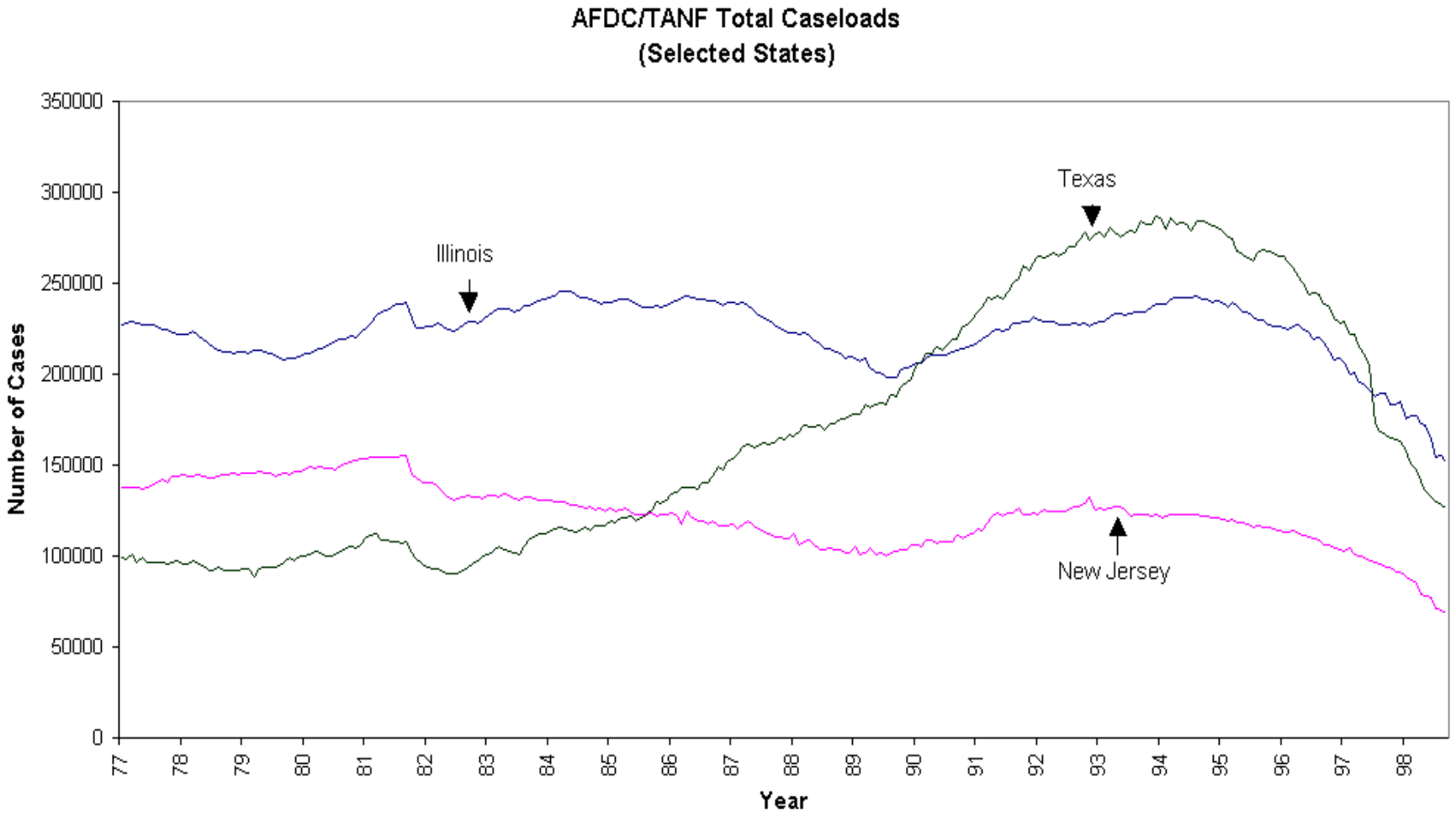

AFDC/TANF Total Caseloads
(Selected States)
Number of Cases
350000
300000
250000
200000
150000
100000
50000
0
Illinois
Texas
New Jersey
77
78
79
80
81
82
83
84
85
86
87
88
89
90
91
92
93
94
95
96
97
98
Year

Figure 3

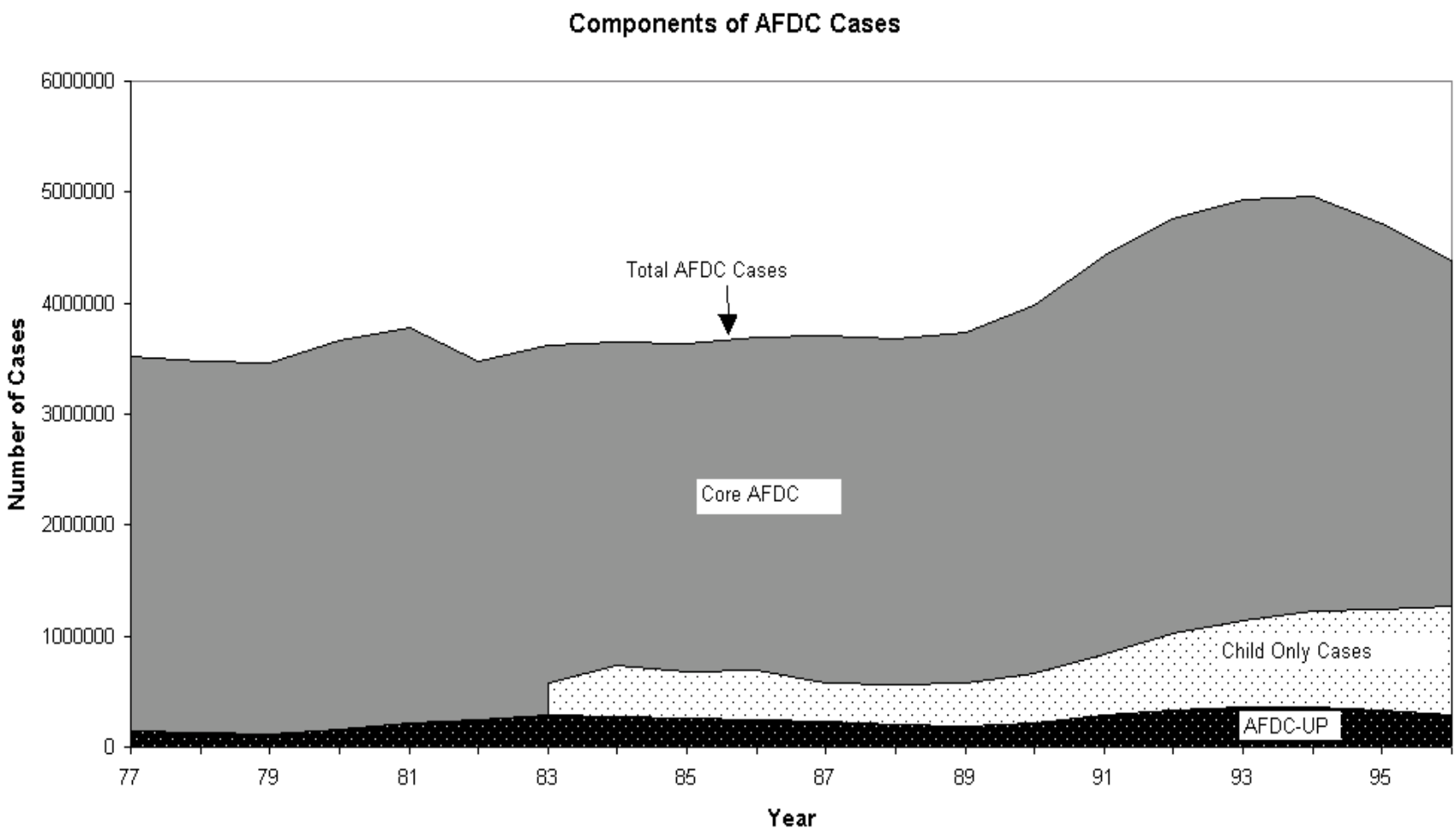

Components of AFDC Cases
6000000
5000000
4000000
3000000
2000000
1000000
0
Number of Cases
Total AFDC Cases
Core AFDC
Child Only Cases
AFDC-UP
77
79
81
83
85
87
89
91
93
95
Year

Figure 4

Year Fixed Effects for AFDC-Total Caseloads Regression

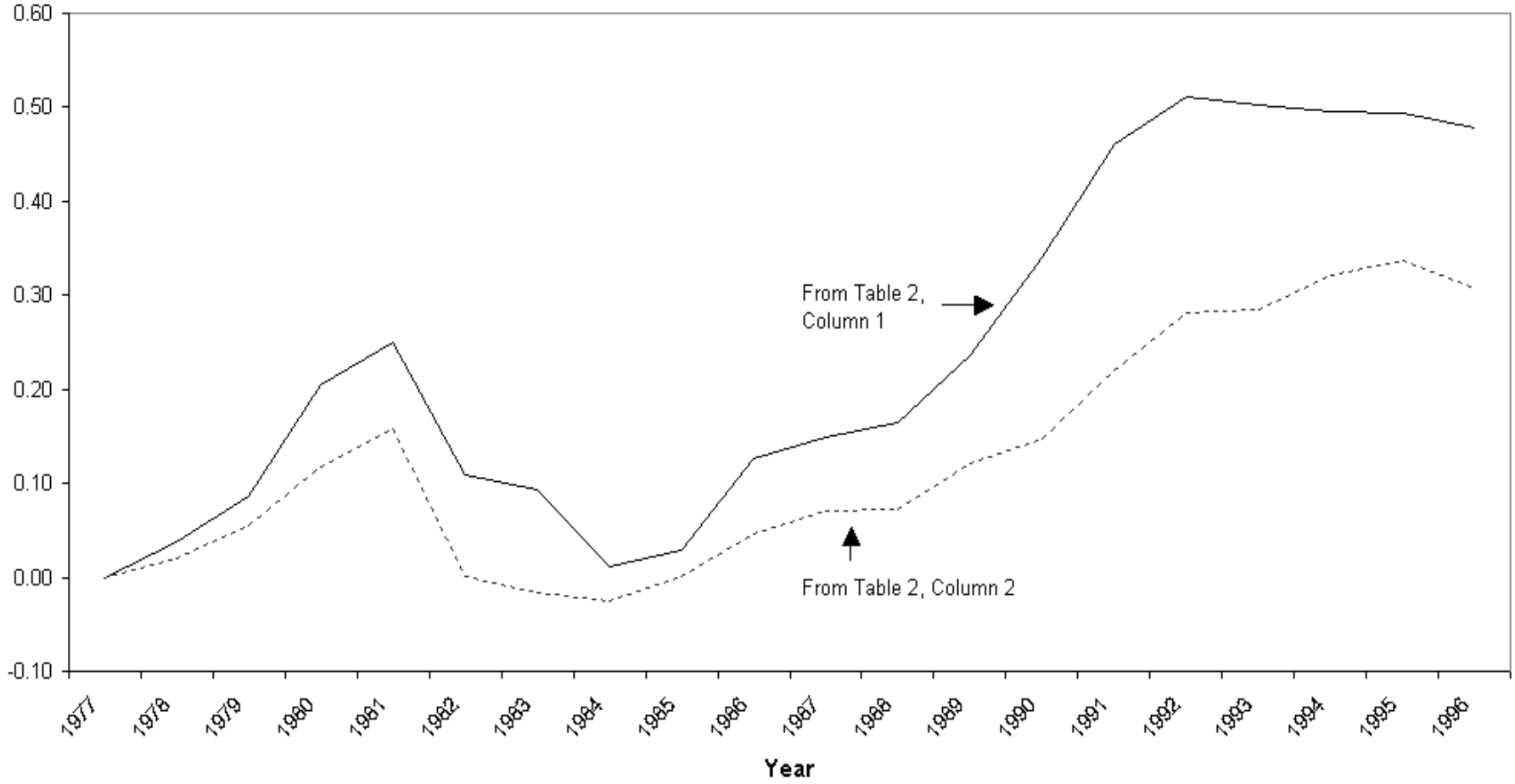


Figure 5

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

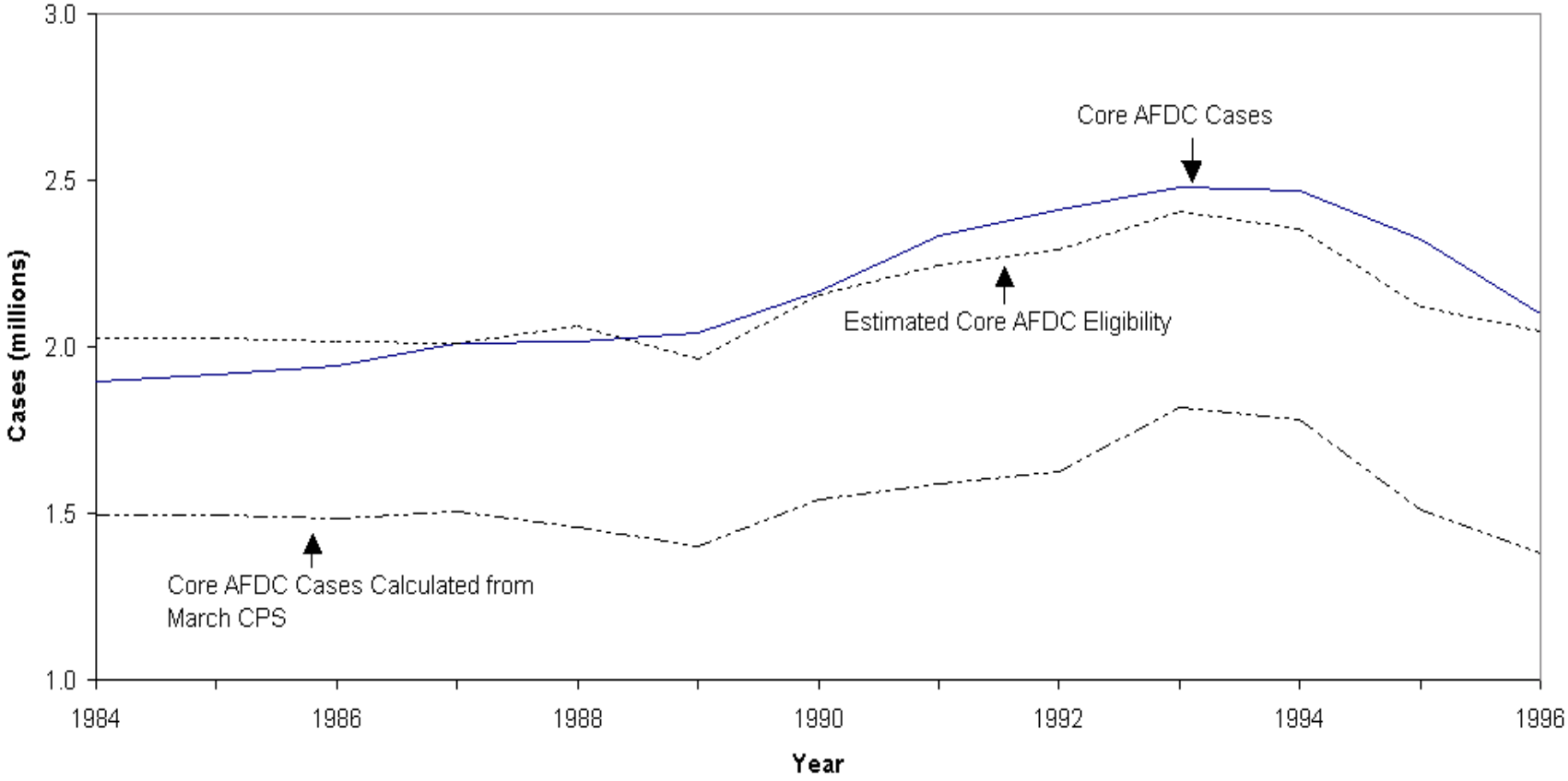


Figure 6

Two Measures of Take-Up Rates Among Core AFDC Recipients

