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The Impact of Welfare Programs on Poverty Rates: Evidence from the American States

Abstract

There is spirited debate between those who maintain that public assistance to the poor *decreases* poverty by raising their incomes (an *income enhancement* effect) and those who contend that welfare *increases* poverty by discouraging the poor from working (a *work disincentive* effect). Extant studies have been inconclusive because they have focused on the effect of welfare benefits on the poverty rate, but have not employed designs that allow researchers to sort out distinct income enhancement and work disincentive effects. We develop a model of poverty rates in the American states that permits estimation of these distinct effects – based on state-level time-series data observed annually for the years 1960-90 – and we find that welfare had *both* effects during our period of analysis. We also calculate the *net* impact on the poverty rate of an increase in welfare benefits (taking into account both income enhancement and work disincentives), and we conclude that it has varied across states and time. In general, however, the ability of marginal increases in welfare spending to reduce the poverty rate by enhancing incomes has declined since the 1970s.

Introduction

In 1996, the United States embarked on a new era of public assistance with the passage of the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA). An important assumption underlying this legislation was that the existing welfare system, partly due to the expansion of programs and benefits associated with the War on Poverty, was ineffective in reducing poverty. Much of the criticism was directed at the Aid to Families with Dependent Children (AFDC) program, which until 1996 was the largest cash assistance program for the able-bodied poor. Critics of AFDC claimed that in combination with in-kind benefits provided by the Food Stamp and Medicaid programs, AFDC had come to undermine work incentives. Consequently, it was argued, AFDC not only failed to reduce poverty; it may even have served to increase poverty by encouraging the poor to choose welfare over work.

The most influential account of this perspective is offered by Murray (1984), who observed that prior to the public assistance expansion of the late 1960s, poverty had been decreasing at a significant and steady rate. He noted, however, that by the 1970s, poverty had stabilized, and by some interpretations may have even increased. Murray adamantly claimed that this "poverty-spending paradox" could not be attributed to economic stagnation, since "poverty quit dropping as per capita GNP continued to grow" (59). The culprit, he claimed, was public assistance. By the 1980s, this "failure thesis," as some have termed it, had come to be the conventional wisdom not only among many conservatives, but among the mass public as well (Marmor, Mashaw and Harvey 1990).

Many scholars offered an alternative perspective, however, maintaining that welfare is not the problem, and that work disincentive effects are relatively small, if they exist at all. Acknowledging the fact that poverty did not decline as much as the architects of the War on Poverty had hoped, they argued that this was due to a combination of factors, including the decline of the manufacturing sector in the economy, the failure of wages and public assistance benefits to keep pace with inflation, and demographic changes promoting the growth of economically vulnerable female-headed families (e.g., Greenstein 1991; Marmor, Mashaw and Harvey 1990; Wilson 1987). According to this perspective, the net impact of the public assistance system has been to reduce poverty, although the magnitude of this reduction has been masked by other forces.

Over the years, several studies have attempted to test these suppositions by estimating the aggregate effect of public assistance on poverty, using a variety of research designs and levels of analysis. The results of these studies have been decidedly mixed, thus offering little guidance as to the validity of the two perspectives on the role of welfare in reducing poverty. One likely reason for this confusion, we argue, is that previous studies have not employed designs that allow the researcher to sort out the potential *income enhancement* (and therefore, poverty reducing) effect of welfare from its possible *work disincentive* (and thus, poverty increasing) effect. In other words, previous research has used a single variable (welfare benefits) to model what are potentially two separate causal processes.

In this paper, we reexamine the relationship between welfare and poverty, controlling for a variety of economic and demographic variables. Our research is unique in several respects. First, while past studies have relied on national-level or state-level data observed over a relatively short period of time, we utilize state-level time-series data, observed annually for the years 1960-90. This three decade period reflects substantially more variation in public assistance benefits than has been observed in previous research. Second, we utilize a design that allows us to derive separate estimates of the income enhancement and work disincentive effects of welfare on state poverty rates. Using this approach, we find that welfare programs have exhibited both types of effects during the period of our analysis, although their relative magnitude is dependent upon program characteristics and the economic environment. Third, based on our estimates, we are able to calculate the net effect of public assistance on the poverty rate under a variety of contexts. Consistent with historical trends in cash benefit levels and unskilled wage levels over the last forty years, we conclude that the ability of welfare to reduce the poverty rate has decreased significantly over the years.

Previous Empirical Studies of the Relationship Between Welfare and Poverty

Much research has been done to assess the aggregate impact of public assistance on poverty to try to settle the debate between those who contend that welfare's effect has been to decrease poverty by raising the income of the poor above the poverty threshold, and those who maintain that its impact has been to increase poverty by discouraging work. One approach has been to compare pre-transfer and post-transfer poverty rates. Most studies of this type proceed in two stages. First, the researcher calculates the poverty rate (i.e., the percentage of the population that is below the official poverty threshold) using income data that does not include welfare benefits. Second, the poverty rate is recomputed taking into account public assistance transfers, and the pre-transfer and post-transfer rates are compared. These studies rely on a variety of data sets and employ a wide range of assumptions concerning the calculation of transfer income. However, their results have been fairly consistent. According to a review by Danziger, Haveman and Plotnick (1981), these studies find that welfare programs reduce poverty. The estimated poverty reduction has varied, from as little as 10% (Levy 1976) to as much as 78% (Hoagland 1980), depending on the types of transfers accounted for and the time period examined. More recent studies employing this technique report similar effects, although the estimated ameliorative effects of welfare programs seem to have decreased by the 1980s (e.g., Danziger, Haveman and Plotnick 1986; Jensen, Eggebeen and Lichter 1993).

Despite the consistency of these findings, this approach to measuring the impact of welfare has rightly been criticized as ignoring the behavioral effects of public assistance. In other words, in the calculation of pre-transfer income it is assumed that income levels would be exactly the same if welfare did not exist. Yet a rather large literature suggests that this is not the case, and that in fact, more poor people would choose to work if public assistance were not available.[1] Given the likelihood of this behavioral effect, comparisons of pre- and post-transfer poverty rates probably exaggerate the poverty-reducing impact of welfare programs.

A different body of research attempts to examine the net impact of public assistance on poverty by using national level (aggregate) data to estimate the relationship between welfare benefits and poverty rates. Perhaps the most well known of these studies is Murray's (1984), which examined trends in national-level data to support his claim that increases in welfare generosity associated with the War on

[1] Numerous studies have attempted to estimate the effect of welfare programs on work incentives by examining a range of dependent variables including work effort, welfare entry, welfare exit, and the duration of welfare spells. According to reviews of this research by Danziger, Haveman and Plotnick (1981) and by Moffitt (1992), the findings are relatively consistent. As Moffitt concludes, AFDC benefit levels have generally been found to "generate nontrivial work disincentives" and to be significantly related to welfare participation and turnover. The magnitude of this effect, however, is a matter of dispute.

Poverty led to increases in poverty rates. This conclusion sparked a series of rebuttals. Some claimed that the trends in national-level poverty observed by Murray were driven by economic stagnation and demographic changes (Cogan 1982; Jencks 1992; Schwarz 1983; Wilson 1987). Schram (1991) extended Murray's analysis through the 1980s, concluding that contrary to Murray's thesis, reductions in welfare spending caused an increase, rather than a decrease, in poverty. Finally, in a recent study, Kenworthy (1999) examined the relationship between welfare spending and poverty across fifteen industrial democracies and found welfare spending to have a negative effect on poverty.

Recognizing the small number of observations available when analyzing national poverty rates, a few scholars have examined the relationship between welfare and poverty at the state level. The findings of these studies are mixed as well. Gallaway and Vedder (1985) concluded that AFDC benefit levels were positively related to annual changes in child poverty across the 1970-80 period. These results are consistent with those of Peterson and Rom (1989), who found AFDC benefits to be positively related to changes in state poverty rates over five-year intervals spanning the period 1970-85. However, these conclusions are contradicted to some extent by Schram, Turbett and Wilken (1988). Upon replicating Gallaway and Vedder's analysis, they found a negative relationship between AFDC benefits and child poverty when the dependent variable is the poverty rate *level* (rather than the percentage change) in a state. Finally, Morgan and Kickham (2001) examined the relationship between the child poverty rate and AFDC benefits using yearly data from 1987 to 1996. They report mixed results, as the effect of AFDC was negative and significant in one model, but insignificant in two others.

An Alternative Strategy for Assessing the Impact of Welfare on Poverty

A fundamental flaw of the studies examining the relationship between public assistance benefit levels and poverty rates is that they offer no vehicle for separating out a possible income enhancement (and therefore, poverty reducing) effect of welfare from a potential work disincentive (and thus, poverty increasing) effect. If one finds little relationship between benefit levels and poverty rates, this may indicate that there is neither a strong income enhancement effect nor a strong work disincentive effect. But it may also mean that both these effects are powerful, yet in aggregate, they cancel each other out to yield a weak relationship between welfare and poverty. Even if one finds a large negative relationship (consistent with an income enhancement effect) or a strong positive relationship (consistent with a work disincentive effect), one does not learn whether one effect is entirely absent, or if it is present but overwhelmed in magnitude by the other effect.

Ideally, we could conduct experiments to sort out the income enhancement and work disincentive effects of welfare. In each American state, the poor that are eligible for public assistance receive both *cash* and *in-kind* (primarily for food and health care) benefits.[2] Assume we observe the *poverty rate* in a state, that is, the percentage of individuals in a state that earn less than the "poverty threshold" (i.e., the income level deemed necessary to maintain a "minimally adequate" standard of living.) Imagine that we could intervene to increase the real (i.e., adjusted for inflation) level of cash assistance to the poor in the state. At the same time, we would fix the real poverty threshold (so the rules for determining who is poor are stable)[3], and we would hold real wage levels for unskilled workers constant, so we do not let the income of the working poor change, perhaps moving some from one side of the poverty threshold to the other. We would also make sure that the total real welfare benefit to the poor remained constant (by reducing in-kind benefits the same amount that we increased cash assistance). Finally, we would also fix all other variables. If, after the intervention, the observed poverty rate is lower, the decrease cannot be due to changes in the incentive to work because the ratio of the total welfare benefit to the wage level for unskilled workers was unchanged. Since all other variables were also fixed, the decrease in the poverty rate would have to be due to the increased income of welfare recipients resulting from the higher cash benefit level.[4]

Of course, such a controlled experiment is unfeasible in the real world. But the experimental design suggests an econometric model that capitalizes on statistical control toward the same end. We

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[2] Since 1996, most of the cash assistance comes from Temporary Assistance for Needy Families (TANF); previously, it came from AFDC. The vast majority of in-kind assistance is provided by the Food Stamp and Medicaid programs.

[3] In fact, the real poverty threshold *is* fixed in the United States, as the nominal threshold automatically increases each year by the rise in the consumer price index (CPI).

[4] When measuring the poverty rate in a state, the poverty status of individuals is based solely on cash income, and ignores any in-kind assistance received.

collect annual data for the American states for a multi-year period, and regress a state's poverty rate on (*i*) its real cash welfare benefit [***Cash Benefit***], (*ii*) the wage level for unskilled workers [***Unskilled Wage***], (*iii*) the ratio of the state's total welfare benefit (cash and in-kind together) to the wage level for unskilled workers [***Total Welf Benefit*** / ***Unskilled Wage***] and (*iv*) a variety of other likely determinants of the poverty rate. (The real poverty threshold is constant, since the nominal threshold is indexed to the CPI, and thus the poverty threshold is not included in the model.) Since ***Unskilled Wage*** and ***Total Welf Benefit*** / ***Unskilled Wage*** are included as independent variables, *the slope coefficient estimate for* ***Cash Benefit*** *reflects the change in the poverty rate resulting from an increase in the cash welfare benefit, when the real wage level for unskilled workers is fixed* (so incomes of the working poor do not change, moving some working poor from one side of the poverty threshold to the other), *the ratio of the total welfare benefit to the wage level for unskilled workers is constant* (so there is no change in the incentive to work), *and all other independent variables are fixed*. Therefore, a *negative* coefficient for ***Cash Benefit*** would imply that an increase in the real value of cash assistance prompts a decrease in the poverty rate, and would indicate an *income enhancement effect* of welfare.

In another idealized experiment, we could intervene to increase the total real welfare benefit level, by increasing in-kind assistance and keeping cash assistance constant. Again, we would fix both the real poverty threshold (keeping the rules for calculating the poverty rate stable) and real wage levels for unskilled workers (holding constant the income of the working poor). This means that the ratio of the total welfare benefit to the wage level for unskilled workers would rise. We would fix all other variables. Now, any observed increase in the poverty rate could not be due to an income enhancement effect of welfare, because the cash assistance benefit was unchanged. Indeed, given that all other variables were fixed, an increase in the poverty rate would have to be traceable to the increased attractiveness of welfare relative to the wage level for unskilled workers, and therefore, a work disincentive effect.

Although this experiment, too, is infeasible, the same regression model offers a statistical analog. Since ***Cash Benefit*** and ***Unskilled Wage*** are in the model, *the slope coefficient for* ***Total Welf Benefit*** / ***Unskilled Wage*** *measures the response of the poverty rate to an increase in the total welfare benefit relative to the wage level for unskilled workers, when the real wage level for unskilled workers is fixed* (so there is no movement of the working poor from one side of the poverty threshold to the other due to increases in income), *the real cash welfare benefit is constant* (so there is no income enhancement effect), *and all other independent variables are fixed*. Consequently, a *positive* coefficient for ***Total Welf Benefit / Unskilled Wage*** would imply that an increase in ratio of the total welfare benefit to the wage level for unskilled workers (and thus a decline in the incentive to work) leads to a rise in the poverty rate, and would indicate a *work disincentive effect* of welfare.

A Model of State Poverty Rates

Prior to 1996, the vast majority of cash assistance to the able-bodied poor was provided through Aid to Families with Dependent Children (AFDC).[5] In 1996, Congress eliminated ADFC, and replaced it with Temporary Assistance for Needy Families (TANF). Thus, a study implementing our regression design focusing on the most recent period would measure ***Cash Benefit*** by the size of the TANF benefit given to recipients in a state. Unfortunately, reliable information about state TANF programs is still being assembled (Moffitt and Ver Ploeg 2001), and, therefore, conducting our study with post-1996 data is not feasible. Consequently, we rely on an historical analysis of AFDC. Given that the debate about the effects of welfare on poverty has been framed primarily in terms of impacts of AFDC, our historical focus is actually quite fitting.

Data for the variables in our model are not systematically available across all states before 1960. Various changes in the AFDC program after the implementation of the Family Support Act in 1990 made the program after that time noncomparable to the program during the 60s, 70s and 80s.[6] Thus, we

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[5] The only other public assistance program to provide cash benefits to the able-bodied poor is General Assistance, which refers to a collection of diverse programs run entirely by state and local governments. These programs have traditionally been meagerly funded compared to AFDC.

[6] These changes included mandatory coverage of unemployed parents, stricter child support provisions, and implementation of the Job Opportunities and Basic Skills program. The new provisions expanded the range of options available to policy makers for regulating public assistance and fundamentally altered AFDC and its dynamics. In the 1990s, the federal government also approved a variety of state waivers to the AFDC program that allowed the states to operate their programs under different terms. The waivers represent an additional complication to extending our analysis after 1990.

estimate our model using pooled annual data from the 48 continental states for the 1960-1990 period.[7]

Our model is specified in equation 1, where the subscripts *i* and *t* denote the state and year of observation, respectively.

$$\textbf{\textit{Poverty Rate}}_{i,t} = \beta_0 + \beta_1\textbf{\textit{Poverty Rate}}_{i,t-1} + \beta_2\textbf{\textit{Cash Benefit}}_{i,t} + \beta_3\textbf{\textit{Unskilled Wage}}_{i,t}$$
$$+ \beta_4\textbf{\textit{Total Welf Benefit}} / \textbf{\textit{Unskilled Wage}}_{i,t} + \Sigma(\beta j \textbf{\textit{Z}}_j) + \varepsilon_{i,t} \quad [1]$$

Our dependent variable, ***Poverty Rate***, is the Census Bureau's measure of the poverty rate. The key independent variables are operationalized as follows:

Cash Benefit **=** the maximum monthly AFDC payment for a family of four with no income in real (2000) dollars.[8]

Total Welf Benefit / ***Unskilled Wage*** **=** [(the maximum monthly AFDC payment for a family of four with no income) plus (the monetary value of the in-kind benefits to which such a family is entitled)] divided by [the typical wage that an unskilled AFDC recipient could earn in a private sector job].

Unskilled Wage = the typical wage that an unskilled AFDC recipient could earn in a private sector job [measured by the average monthly wage in the retail trade sector (in real dollars)].

Ideally, ***Unskilled Wage*** would be based on wages earned by unskilled women of child-rearing age. Unfortunately, annual state-level data are not available for wages earned by this subpopulation. However, we can measure the average wage in a state's retail trade sector annually, and this is a reasonable indicator of the wage that a welfare recipient is likely to earn in the private sector. Based on the Census Bureau's classification system, the retail sector includes several traditionally low paying occupational categories, such as "eating and drinking places," "food stores," "retail general merchandise stores," and "apparel and accessory stores," among others. All these jobs require little education and few skills and, on average, pay significantly less than jobs in the other nonagricultural sectors.[9]

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[7] Because of the inclusion of a lagged variable, the model ultimately is estimated using observations of the dependent variable from 1961 through 1990 (n = 1440).

[8] The Consumer Price Index (CPI) is used to deflate all variables measured in real terms to 2000 dollars.

[9] There is empirical evidence that the average retail wage is a good surrogate for the typical wage earned by unskilled women of child-rearing age. We used Current Population Survey [CPS] (March Supplement) data to calculate an average wage earned by women between the ages of 18 and 50 with less than a high school education, in each state for every year between 1975 and 1995 (to be denoted ***Female Wage***). Since CPS samples of this population were too small in most states for reliable analysis, we aggregated the data in two ways. First, we computed the average values across states (weighted by

To measure the numerator of ***Total Welf Benefit* / *Unskilled Wage***, we add to the maximum monthly AFDC benefit for a family of four with no income the monetary value of the in-kind assistance to which such a family is entitled. There are two primary in-kind benefits for which AFDC families are eligible: Food Stamps and Medicaid.[10] The Food Stamp benefit is determined by the national government, using a formula that is the same for all states in any year. We include in our measure of the total welfare benefit the monetary value of the monthly allotment of food coupons for which the AFDC family is eligible. The value of Medicaid benefits, on the other hand, is not as easy to determine, since the subjective demand for medical services among the poor is difficult to anticipate and likely varies a great deal across individuals. Indeed, some might question whether poor persons attach a *monetary* value to medical services in the same way they do the more easily valued cash and food assistance they receive. We believe that access to health care is of great concern to Americans, and that as a consequence, the poor do count Medicaid benefits among the tangible benefits they receive. Thus, our measure of the total welfare benefit includes the average Medicaid expenditure per AFDC family in a state. Yet, to test the sensitivity of our results to the inclusion of Medicaid benefits, we estimate our model with measures of the total welfare benefit package including and excluding Medicaid – which we label ***Total Welf Benefit (<u>with</u> Medicaid)* / *Unskilled Wage*** and ***Total Welf Benefit (<u>w/out</u> Medicaid)* / *Unskilled Wage***. If results are consistent across the two indicators, it will be clear that our findings do not hinge on any debate about whether health care benefits are valued in the same way as cash and food benefits.

The term $\Sigma(\beta j Z_j)$ in equation 1 represents a set of statistical control variables. The large literature on the determinants of poverty suggests that our model should reflect hypothesized impacts on the poverty rate of (*i*) economic conditions, (*ii*) interstate migration, (*iii*) social insurance programs, and (*iv*)

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population) of ***Female Wage*** and ***Unskilled Wage*** in each year. After adjusting for inflation, the time-series correlation between these two series is .85 (n=21). We also averaged observations of ***Female Wage*** and ***Unskilled Wage*** over all years to produce measures of the mean wage in a state across the 21-year period. The cross-sectional correlation between the two wage measures is also strong, at .70 (n=48).

[10] Food Stamp data were provided by Russell Hanson, Indiana University. Medicaid data are from Robert Moffitt's (Johns Hopkins University) *Welfare Benefits Database*: http://www.econ.jhu.edu/People/Moffitt/DataSets.html. Details on the construction of ***Total Welf Benefit*** are reported in an unpublished appendix.

state demographic factors. We began with a model containing all independent variables in Berry, Fording and Hanson's (2003) recently published model of state poverty rates, and including all the interactions among these variables originally specified. Berry, Fording and Hanson's model emphasizes economic conditions and interstate migration, and we were satisfied with their model's coverage of these forces. But the only demographic variable included by these authors tapped the presence of female-headed families with children. We added a second variable reflecting the special susceptibility to poverty of children: the number of out-of-wedlock births (as a percentage of population). Because African-Americans have been especially vulnerable to poverty (Rodgers 2000), we also include a measure of the size of a state's black population. Finally, to reflect the role of social insurance programs in reducing poverty, we include both the number of social security recipients in a state and the average monthly benefit for retired workers.[11]

This model proved to be characterized by extreme multicollinearity.[12] We deleted several variables to reduce multicollinearity; we also removed variables that were consistently estimated to have little effect on the dependent variable – or an effect contrary to that hypothesized – across a variety of specifications involving different combinations of variables. This yielded equation 2:

$$\begin{aligned} \textbf{\textit{Poverty Rate}}_{i,t} = {} & \beta_0 + \beta_1 \textbf{\textit{Poverty Rate}}_{i,t-1} + \beta_2 \textbf{\textit{Cash Benefit}}_{i,t} + \beta_3 \textbf{\textit{Unskilled Wage}}_{i,t} \\ & + \beta_4 \textbf{\textit{Total Welf Benefit / Unskilled Wage}}_{i,t} + \beta_5 \textbf{\textit{Relative Wage}}_{i,t} + \beta_6 \textbf{\textit{Soc Sec Recipients}}_{i,t} \\ & + \beta_7 \textbf{\textit{Income}}_{i,t} + \beta_8 \textbf{\textit{Unemployment}}_{i,t} + \beta_9 \textbf{\textit{Relative Unemployment}}_{i,t} + \beta_{10} \textbf{\textit{Manuf Jobs}}_{i,t} \\ & + \beta_{11} \textbf{\textit{Out of Wedlock Births}}_{i,t} + \varepsilon_{i,t} \end{aligned} \quad [2]$$

The control variables in this final version of the model are as follows:

[11] Data on Social Security recipients were obtained from *Social Security Bulletin* and the *Statistical Abstract of the United States*. Annual data for out of wedlock births were taken from *Vital Statistics of the United States*. Details on the estimation of missing values are reported in an unpublished appendix. Data for all other control variables were provided by Berry, Fording and Hanson (and are described in detail in their 2003 article).

[12] Regressing an independent variable on the remaining independent variables yielded an R^2 greater than .99 in the case of four variables, and greater than .98 in three other cases. This high degree of multicollinearity was not surprising given that the model included several product terms to specify interaction.

Relative Wage = ratio of the average wage in a state's retail sector to the average retail wage in neighboring states.[13]

Soc Secur Recipients = number of recipients (retired, survivors, and disabled) of Social Security (OASDI) [per 100 population]

Income = state per capita income in thousands (in real dollars).

Unemployment = average monthly unemployment rate.

Relative Unemployment = ratio of the unemployment rate in a state to the average rate in neighboring states.

Manuf Jobs = number of people employed in the manufacturing sector (per 100 population).

Out of Wedlock Births = number of out of wedlock births (per 100 population)

Although equation 2 is substantially revised from our initial model including a full set of control variables, and coefficient estimates for some variables are sensitive to the precise specification of the model, it is important to note that the coefficient estimates for the variables of theoretical interest in this paper -- ***Cash Benefit*** and ***Total Welf Benefit / Unskilled Wage*** – are robust across specifications.

Empirical Analysis

Equation 2 is estimated as a fixed-effects model (i.e., with a set of dummy variables for the states) using OLS regression. Consistent with Beck and Katz's (1995) advice, a lagged dependent variable is included to model dynamics within states. The presence of the lagged dependent variable casts the equation as a partial adjustment model. In such a model, the slope coefficients reflect the *immediate* impacts of independent variables (i.e., that experienced in the first year). But the *total* effects of independent variables are also dynamically distributed over time through the lagged dependent variable, so that the dependent variable is assumed to respond gradually to changes in the independent variables (Gujarati 1995, 599-600).

Also following Beck and Katz, panel corrected standard errors (PCSEs) are reported. The results are in Table 1. Column 1 presents results when ***Total Welf Benefit*** / ***Unskilled Wage*** is measured "with

[13] For ***Relative Wage*** (and for ***Relative Unemployment***) – which compare a state's value to the average value of its neighbors – we employ a weighted average based on population.

Medicaid"; column 2 shows findings when Medicaid benefits are excluded.[14] Only one independent variable (***Unskilled Wage***, which shows a slightly stronger effect in the model "with Medicaid") has a t-ratio that is more than 10 percent greater in magnitude in one version than the other; thus the results prove to be robust with regard to the choice about whether to include Medicaid benefits when calculating total welfare benefits. In the text interpretations to follow, we rely on the results for the model including Medicaid benefits in the calculation.

(Table 1 about here)

The appendix summarizes our findings regarding the control variables. Here, we turn to the results of greatest theoretical interest: those pertaining to the effects of welfare benefits. The coefficient estimate for ***Cash Benefit*** (-.0011) is negative, and statistically significant at the .01 level, reflecting a substantial income enhancement effect of welfare. In particular, this coefficient estimate implies the following. Assume that the real AFDC benefit in a state is increased by one hundred (2000) dollars, while (1) the real wage level for unskilled workers, (2) the ratio of the total welfare benefit to the wage level for unskilled workers, and (3) all other variables, are held constant. This $100 increase in the AFDC benefit would lead, on average, to a decrease of .11 points in the poverty rate in one year, and a total increase (distributed over time) of .40 points.[15] The average within-state difference between the minimum AFDC benefit and the maximum benefit during the period of analysis is $495. An increase of roughly this amount ($500) would prompt an average decrease of .55 points in a state's poverty rate in the first year, and eventually, a total decrease of 2.01 points. Since this response in the poverty rate occurs even when the ratio of the total welfare benefit to the wage for unskilled workers remains constant, the response cannot be due to a change in the relative attractiveness of work and welfare. Thus, there is

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[14] Both equations showed nearly no autocorrelation; a Lagrange multiplier test (regressing residual_t on residual_{t-1}) yielded an estimated slope coefficient of .16 for residual_{t-1} "with Medicaid" and .15 "without."

[15] The total effect (distributed over time) of a change in an independent variable is calculated by the magnitude of that change multiplied by [(the slope coefficient estimate for the variable) divided by (one minus the slope coefficient estimate for the lagged dependent variable)]. Thus, the total expected response of the poverty rate to a $100 increase in the AFDC benefit is a decrease of .40 = 100[(-.0011)/(1-.726)] points.

empirical evidence that increases in cash benefits prompt significant reductions in poverty by boosting the incomes of poor individuals, implying that welfare has a sizeable income enhancement effect.

The parameter estimate for ***Total Welf Benefit / Unskilled Wage*** (1.25) is also statistically significant at the .01 level and suggests an appreciable work disincentive effect. Assume that the ratio of the total welfare benefit to the wage level for unskilled workers grows by 10%, while (1) the real wage level for unskilled workers, (2) the real welfare cash benefit, and (3) all other variables, are fixed.[16] This 10% increase in welfare benefits relative to the unskilled wage would lead to an expected increase in the poverty rate of .125 points in one year, and ultimately a cumulative increase of .46 points. The variation in the ratio of welfare benefits to wages is considerable: the average within-state difference between the minimum and maximum ratios during the period of analysis is .65. A 65% increase in welfare benefits relative to the unskilled wage would prompt, on average, a first-year increase of .81 points in a state's poverty rate, and over time, a total change of 2.37 points. Note that this response of the poverty rate occurs despite the fact that the cash benefit is fixed. Therefore, the response cannot be due to any income-enhancement effect of welfare, and can be interpreted as a *work disincentive effect*. Our results indicate that an increase in the value of the total welfare benefit package relative to the wage for unskilled labor leads to an increase in poverty by increasing the attractiveness of welfare relative to that of employment.

The results thus far provide support for both the income enhancement and work disincentive propositions. In the next section, we return to the theoretical logic underlying these hypotheses to generate additional testable propositions regarding the impact of public assistance on poverty. One of these involves a refinement of the original poverty model to better specify the income enhancement hypothesis. The other involves the construction of a model explaining the AFDC recipient rate in a state to further test the work disincentive hypothesis. To the extent that these propositions receive empirical support, we can claim a greater degree of confidence in our conclusions regarding the impact of welfare.

[16] Note that this condition is identical to the total welfare benefit growing by 10%, while (1) the real wage level for unskilled workers, (2) the real welfare cash benefit, and (3) all other variables, are fixed.

Refining the Poverty Model: A Further Test of the Income Enhancement Hypothesis

Given that the poverty rate is measured as the number of persons whose income is below an established poverty threshold, if cash assistance reduces poverty by enhancing incomes, an increase in the real AFDC benefit should have the greatest marginal impact on the poverty rate when the benefit is at the level that provides an income *equal* to the poverty threshold (i.e., when the ratio of the nominal AFDC benefit to the nominal poverty threshold – ***Cash Benefit / Poverty Threshold*** – equals one). It is at this benefit level that an increase in benefits is most likely to move AFDC recipients from below the threshold to above it. As the distance of the AFDC benefit from this point of maximal impact widens (i.e., as ***Cash Benefit / Poverty Threshold*** moves away from one in either direction), the benefit level should have less effect on the poverty rate because the income changes generated by adjustments in welfare benefits are less likely to move recipients from one side of the poverty threshold to the other. Indeed, as the AFDC benefit approaches zero, the marginal impact of the benefit level on the poverty rate should also approach zero, as a slight increase in the benefit level should prompt no reduction in poverty when the benefit level starts at zero. Thus, whereas our original model assumed that the effect of ***Cash Benefit*** on the poverty rate is linear, we now recognize that the income enhancement hypothesis anticipates that this effect should be nonlinear.

Unfortunately, there are insufficient observations in our data set to test this hypothesis over the range of AFDC benefit levels for which ***Cash Benefit / Poverty Threshold*** is greater than one: only nine (of the 1440) cases in our sample have ***Cash Benefit / Poverty Threshold*** values exceeding one.[17] Thus, we must restrict the empirical test of the hypothesis to the range of ***Cash Benefit / Poverty Threshold*** values less than one (which turns out to be the range in which ***Cash Benefit*** is less than $1430). In this range, the income enhancement hypothesis predicts that the negative effect of ***Cash Benefit*** on the poverty rate should gradually decline in magnitude as the value of ***Cash Benefit*** decreases toward zero, and when ***Cash Benefit*** equals zero, the effect should reach zero. To test this proposition, we modify

[17] In our sample, ***Cash Benefit / Poverty Threshold*** ranges from .12 to 1.12; the 5th percentile is .23; the 95th is .88.

equation 2 by adding a squared term for ***Cash Benefit***, and then estimate the model using all cases for which ***Cash Benefit / Poverty Threshold*** is less than one. If the proposition is true, the coefficient for ***Cash Benefit*** should be zero (indicating that ***Cash Benefit*** has no effect on the poverty rate when ***Cash Benefit*** equals zero) and the coefficient for ***Cash Benefit***^{2} should be negative.

OLS estimates for the revised model relying on both versions of ***Total Welf Benefit / Retail Wage*** are consistent with these predictions. In both versions, the coefficient estimate for ***Cash Benefit*** is weak (failing a test of statistical significance with a t-value less than 1.20), and the parameter estimate for ***Cash Benefit***^{2} is strongly negative (with t-ratios having magnitudes in excess of 2.07).[18] Given the empirical evidence that the coefficient estimate for ***Cash Benefit*** is near zero, we delete this term from the equation, thereby allowing for a more efficient estimate of the coefficient for ***Cash Benefit***^{2}.[19]

Estimates for the resulting model are presented in columns 3 and 4 of Table 1.[20] Figure 1 displays the estimated relationship between the real AFDC benefit and the poverty rate (based on the coefficient estimates for the model "with Medicaid" in column 3). The effect of the AFDC benefit on the poverty rate (i.e., the slope of the curve) is constrained to be zero when the benefit level is zero. But the effect gradually increases as ***Cash Benefit / Poverty Threshold*** rises; when the ratio reaches one, the slope of the curve is strongly negative at -.0021.[21] This slope implies that if the real AFDC benefit in a state increases by $100, while (1) the real wage level for unskilled workers, (2) the ratio of the total welfare benefit to the wage level for these workers, and (3) all other variables are held constant, the poverty rate decreases, on average, by .21 points in the first year, and in time, a total of .77 points. This

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[18] Our unpublished appendix presents the full set of coefficient estimates for these models.

[19] Since ***Cash Benefit*** and ***Cash Benefit***^{2} are highly correlated, removing ***Cash Benefit*** reduces collinearity considerably, thus lowering the standard error of the coefficient estimate for ***Cash Benefit***^{2}.

[20] A Lagrange multiplier test for serial autocorrelation (regressing residual_t on residual_{t-1}) showed almost no autocorrelation (with an estimated slope coefficient of .16 for residual_{t-1} "with Medicaid" and .15 "without.")

[21] This maximum slope of the curve is more than 2 times the size of the estimated constant slope for the relationship between ***Cash Benefit*** and ***Poverty Rate*** (-.0011) in the nonlinear model of equation 2 (see column 1 of Table 1).

provides additional support for the supposition that increases in welfare reduce poverty by enhancing incomes.

(Figure 1 about here)

A Further Test of the Work Disincentive Hypothesis

We can subject the work disincentive hypothesis to a further empirical test by constructing a model of the AFDC recipient rate in a state (i.e., the number of AFDC recipients per 100 population). The work disincentive hypothesis predicts that as the total welfare benefit rises relative to the wage level for unskilled workers, welfare's attractiveness relative to that of employment increases, and the poverty rate grows as more poor people choose welfare over work. Thus, according to the hypothesis, an increase in the total welfare benefit relative to the wage level for unskilled workers should prompt an increase not only in poverty, but in AFDC caseloads as well. To test this prediction, we include ***Total Welf Benefit* / *Unskilled Wage*** in a model of the AFDC recipient rate:

$$\begin{aligned} \textit{\textbf{AFDC Recipients}}_{i,t} = {} & \beta_0 + \beta_1 \textit{\textbf{AFDC Recipients}}_{i,t-1} + \beta_2 \textit{\textbf{AFDC Recipients}}_{i,t-2} \\ & + \beta_3 \textit{\textbf{Total Welf Benefit / Unskilled Wage}}_{i,t} + \beta_4 \textit{\textbf{Citizen Ideology}}_{i,t} \\ & + \beta_5 \textit{\textbf{Government Ideology}}_{i,t} + \beta_6 \textit{\textbf{PartyCompetition}}_{i,t} + \beta_7 \textit{\textbf{Tax Capacity}}_{i,t} + \beta_8 \textit{\textbf{Tax Effort}}_{i,t} \\ & + \beta_9 \textit{\textbf{Unemployment}}_{i,t} + \beta_{10} \textit{\textbf{Female Headed Families}}_{i,t} + \beta_{11} \textit{\textbf{Out of Wedlock Births}}_{i,t} \\ & + \beta_{12} \textit{\textbf{Urbanization}}_{i,t} + \beta_{13} \textit{\textbf{Mass Insurgency}}_{i,t} + \varepsilon_{i,t} \end{aligned} \qquad [3]$$

where ***AFDC Recipients*** denotes the number of AFDC recipients per 100 population, and the rest of the new variables are defined in the appendix. The model incorporates controls for a number of variables suggested by past research, including various economic (***Unemployment, Tax Capacity***), political (***Citizen Ideology***, ***Government Ideology***, ***Party Competition***, ***Tax Effort***, ***Mass Insurgency***) and social (***Urbanization***, ***Out of Wedlock Births***, ***Female Headed Families***) influences on state welfare caseloads.[22] While the poverty models previously analyzed include a single lagged dependent variable, this model includes two lagged variables (both *t-1* and *t-2*). We include the second lag because a model

[22] For research supporting the inclusion of these variables, see (among others), Isaac and Kelly (1981), Peterson and Rom (1989), Fording (1997, 2001), and Hill and Leighley (1992).

with just one lag showed evidence of substantial remaining autocorrelation.[23] Yet models with two lags are interpreted very similarly to those with just one; the slope coefficients reflect immediate impacts in the first year, but the total effects of variables are distributed over time.

The results are presented in columns 1and 2 of Table 2. Many of the independent variables have very weak estimated effects – which is not surprising, since even one lagged dependent variable can be expected to suppress the effects of other independent variables (Achen 2000), and our model contains two lags. But the coefficient estimate for ***Total Welf Benefit*** / ***Unskilled Wage*** is positive and statistically significant for both the version that includes Medicaid benefits (column 1) and the version that does not (column 2). The parameter estimate of .346 in column 1 implies that when the total welfare benefit rises by 10%, but the wage level for unskilled workers and all other independent variables remain constant, the AFDC recipient rate will increase in the first year, on average, .035 points (i.e., the number of AFDC recipients per 100 population should increase by approximately .035); over time, the recipient rate will increase a total of .38 points.[24] This lends further empirical support to the claim that welfare contributes to poverty by lessening the incentive to find work and encouraging people to seek public assistance.

(Table 2 about here)

The Net Effect of Welfare on the Poverty Rate

Thus far we have found evidence that supports both sides of the welfare debate. Consistent with critics of welfare programs, we have found that an increase in welfare benefits contributes to work disincentives that lead to an increase in the poverty rate. At the same time, we have found that a rise in cash assistance has an income enhancement effect, which results in a decrease in the poverty rate. Thus,

[23] For the models with one lag, a Lagrange multiplier test for autocorrelation (regressing residual_t on residual_{t-1}) yields an estimated slope coefficient of .44 for residual_{t-1} (t = 18.38) "with Medicaid," and .44 "without" (t = 18.33)]. When the second lag is added, these coefficients drop to less than .01 both "with" and "without Medicaid."

[24] In a model with dependent variables lagged both one and two periods, the total effect (distributed over time) of a change in an independent variable is calculated by the magnitude of that change multiplied by {[the slope coefficient estimate for the variable] / [1 – (the slope coefficient estimate for the variable lagged one period) – (the slope coefficient estimate for the variable lagged two periods)]}(Harvey 1990; Stevenson 2001).

increases in welfare benefits have two distinct effects on the poverty rate acting in opposite directions – one increasing the poverty rate, the other decreasing it. A key element of the welfare debate concerns the *net effect* of welfare: Taking into account *both* income enhancement and work disincentive effects, what is the *net* impact of a marginal increase in welfare benefits on the poverty rate?

The net impact of welfare cannot be discerned from a *direct* inspection of the coefficients in Table 1, for two reasons. First, the variables representing the work disincentive effect (i.e., ***Total Welf Benefit / Unskilled Wage)*** and the income enhancement effect (i.e., ***Cash Benefit***) are measured in metrics that are not immediately comparable. Second, because the poverty rate is measured as the percentage of the population with income less than an established threshold, the effect of ***Cash Benefit*** on the poverty rate is nonlinear, varying with the size of the cash benefit (relative to the poverty threshold) at which the effect is calculated (see Figure 1). Below, we present analyses of the net effect of welfare on the poverty rate that take both these complications into account. Also, as we shall see, the net effects of cash and in-kind assistance are quite different, and must be considered separately.

We first consider the net impact of *cash* assistance by examining the net effect of a $100 increase in the monthly AFDC benefit (measured in real 2000 dollars), assuming in-kind benefits remain unchanged. To do so, we start by (*i*) setting ***Cash Benefit*** at some value, **CB***, (*ii*) setting ***Unskilled Wage*** at some value, **UW***, (*iii*) fixing the remaining independent variables at specified values, and then (*iv*) using the coefficient estimates (from column 2 of Table 1) for the nonlinear version of equation 2 (which substitutes ***Cash Benefit***^{2} for ***Cash Benefit***) to calculate a predicted value for ***Poverty Rate***. We then increase ***Cash Benefit*** by $100, which (since in-kind benefits are assumed to be constant) also increases the numerator of ***Total Welf Benefit / Retail Wage*** by $100, but hold all other variables constant, and calculate a new predicted value for ***Poverty Rate***. The difference between the two predicted values can be interpreted as the net effect of the $100 increase in cash assistance. Since the two predicted values fix most independent variables at the same values, the calculation of this net effect simplifies to a function of just the initial value of ***Cash Benefit***, **CB***, and the value, **UW***, of ***Unskilled Wage***:

Estimated Net Effect (**CB***, **UW***) =

$$1.411\ (100 / \mathbf{UW^*}) - .000000729\ [(\mathbf{CB^*} + 100)^2 - (\mathbf{CB^*})^2] \qquad [4]$$

The first term on the right side of the equation (involving **UW***) constitutes the work disincentive effect of the $100 boost in ***Cash Benefit***; the last term (containing **CB***) is the income enhancement effect of the increase; added together, they yield the net effect.

Figure 2 shows the estimated net effect on the poverty rate of a $100 increase in ***Cash Benefit*** across the range of ***Cash Benefit*** values in our sample for which ***Cash Benefit / Poverty Threshold*** is less than one,[25] when ***Unskilled Wage*** is fixed at its median ($1,372) across the state-years in our sample. The figure also shows 95% confidence intervals for the estimated net effect at various values of cash benefit spread across its range.[26] It is at a real ***Cash Benefit*** level of $655 – the 38th percentile of the benefit distribution – that the estimated income enhancement effect of a $100 increase in monthly cash benefits becomes larger than the work disincentive effect, so that the point estimate of the net effect on the poverty rate switches from positive to negative. At ***Cash Benefit*** levels lower than $655, the $100 increase in ***Cash Benefit*** is estimated to increase poverty; at values in excess of $655, the benefit increase is predicted to decrease poverty. However, for all ***Cash Benefit*** levels between $280 (the 3rd percentile) and $1112 (the 85th percentile), the confidence interval for the estimated net effect includes zero, indicating that the net effect is not statistically significant. It is only for extremely low benefit levels that we can conclude with confidence that the net effect of the $100 increment in ***Cash Benefit*** is to increase the poverty rate, and only at the highest benefit levels that we can be confident that the ***Cash Benefit*** rise serves to decrease the poverty rate.

(Figure 2 about here)

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[25] Recall that the regression model on which Figure 2 is based is estimated using only cases for which ***Cash Benefit / Poverty Threshold*** is less than one 1 (i.e., ***Cash Benefit*** < 1430). Therefore, it would not be appropriate to apply equation 4 to calculate a net effect when ***Cash Benefit / Poverty Threshold*** is greater than one. Only nine of the 1440 cases in our sample have ***Cash Benefit*** values in this excluded range, and all of them are observations prior to 1973.

[26] Our estimated net effects, along with the confidence intervals, were calculated in Stata 8.0 using the *lincom* command.

The net effects examined thus far (in Figure 2) assume that ***Unskilled Wage*** is fixed at its median across all states. We relax this assumption in Figure 3 to assess the impact wage levels have on the estimated net effect on the poverty rate of a $100 increase in cash benefits. The *direction* of the impact is clear even before we inspect the graph: since a decrease in the wages available to unskilled workers in the private sector does not influence the magnitude of the income enhancement component of the net effect, but it increases the size of the work disincentive component (by decreasing the denominator of ***Total Welf Benefit / Retail Wage***), a decrease in ***Unskilled Wage*** shifts the net effect of welfare toward a smaller reduction (or a larger increase) in the poverty rate. Figure 3, however, shows the estimated *magnitude* of the impact of a wage decrease on the net effect. Consider the three negatively sloped solid lines in the graph. The lower, middle and upper lines show the predicted net change in the poverty rate given a $100 increase in cash benefits, at various values of ***Cash Benefit***, when ***Unskilled Wage*** is fixed at its 90th, 50th and 10th percentile values, respectively. (Thus, the middle line in the figure is identical to the line in Figure 2.) Movement from the high-wage context to the low-wage context increases the estimated poverty rate change accompanying a $100 boost in ***Cash Benefit*** by .033 points – the vertical distance between the low and high lines – a value significantly different from zero at the .01 level.[27] For example, when ***Cash Benefit*** is fixed at its median and ***Unskilled Wage*** is at the 90th percentile, an increase of $100 in ***Cash Benefit*** is expected to *decrease* the poverty rate by .028 points, but when ***Unskilled Wage*** is at the 10th percentile, at the same benefit level, an increase of $100 in ***Cash Benefit*** *increases* the poverty rate, on average, by .005 points.

(Figure 3 about here)

We now shift our attention to the horizontal lines at the top of Figure 3. These also represent the estimated net effect of a $100 increase in welfare benefits, but this time assuming that the entire increase comes in in-kind benefits, and the cash benefit remains constant. Since the poverty rate relies on the Census Bureau definition of income, which takes into account cash assistance but not in-kind benefits, an

[27] The 95% confidence interval for the distance between the lines runs from .011 to .055 (calculated using Stata's *lincom* procedure).

increase of \$100 in in-kind benefits cannot – by definition – prompt any reduction in the poverty rate at *any* ***Cash Benefit*** level. Thus, the estimated net effect on the poverty rate of a \$100 increase in in-kind benefits consists of only a work disincentive component. When ***Unskilled Wage*** is at its median, an increase of \$100 in in-kind benefits is expected to increase the poverty rate by .103 points, regardless of the ***Cash Benefit*** level. Furthermore, the same wage effect described above in the case of a \$100 increase in cash benefits applies in the case of a \$100 increase in in-kind assistance: at the 90th percentile value of ***Unskilled Wage***, an increase of \$100 in in-kind benefits results in an average increase in the poverty rate of .088 points. At the 10th percentile value, the expected increase in the poverty rate is .121.

We have seen that the net effect of an increase in *cash* assistance is a function of two variables: the size of the initial cash benefit, and the wage level earned by unskilled workers. The ability of an increase in cash benefits to reduce the poverty rate decreases as either of these variables declines in value. In contrast, the net effect of an increase in *in-kind* assistance is unaffected by the initial cash benefit level and is a function of just the unskilled wage. As with the case of cash benefits, the effectiveness of an increase in in-kind benefits in lowering the poverty rate diminishes as wages decline. By comparing the net effects of increases in cash and in-kind assistance, we derive another important conclusion: the net impact of an increase in welfare benefits is a function of the relative shares of the increase distributed as cash and in-kind assistance. The smaller the share of an increase in welfare benefits allocated as cash assistance, the smaller the capacity of the benefit increase to lower the poverty rate. To illustrate, the three dashed lines in Figure 3 show the estimated net effect on the poverty rate of a \$100 increase in benefits split evenly between cash and in-kind assistance. At any fixed levels for the unskilled wage and the initial cash benefit, the predicted change in the poverty rate accompanying a \$100 benefit increase is greater (i.e., more positive or less negative) when the benefit increase is split evenly between cash and in-kind assistance than when the benefit increase is exclusively cash.

Thus, we conclude that the net impact of an increase in welfare benefits on the poverty rate is contingent on three factors. Specifically, the ability of an increase in welfare benefits to reduce the poverty rate declines as three other variables decrease: (*i*) the size of the initial cash benefit in relation to the poverty threshold, (*ii*) the relative share of the benefit increment that is provided via cash, as opposed to in-kind, assistance, and (*iii*) the wage level earned by unskilled workers. It is important to recognize that all three of these variables have seen declines since the 1970s; Figure 4 shows the historical trends during our period of analysis, from 1960 to 1990.

(Figure 4 about here)

First, let us examine trends in two important characteristics of state welfare programs – the average cash benefit level and the average share of the total welfare benefit that is devoted to cash assistance. These are displayed in the top panel of Figure 4. The total shaded area in the graph represents the combined monetary value of the average total welfare benefit – including AFDC, Food Stamps and Medicaid – guaranteed to an AFDC family of four with no other income, in constant (2000) dollars. [28] The total area is broken into three sections, allocating the total welfare benefit into the portions derived from the three programs. We can see that the cash portion (AFDC) of the total benefit was relatively high during the 1960s and early 1970s, peaking at $937 (approximately 66% of the poverty threshold) in 1968. But since the early 1970s, the average real AFDC benefit has eroded steadily, reaching $581 (approximately 40% of the poverty threshold) in 1990. While this was happening, the cash portion of the total benefit was dropping, and a growing share of welfare benefits was provided through in-kind assistance. Prior to the introduction of the Food Stamp and Medicaid programs in the mid-1960s, cash benefits made up 100% of the total welfare benefit; by 1990 the share had declined to 40%. Finally, the bottom panel of Figure 4 displays trends in the average real retail-sector wage. As can be seen, unskilled wage levels peaked at a value of $1,565 per month in 1973. By 1990, largely due to a decline in the real value of the minimum wage, the average retail wage had decreased 23% to $1,201.

Therefore, all three determinants of the net impact of an increase in welfare benefits have moved in tandem since the 1970s in a direction which diminishes the capacity of welfare benefit increases to reduce the poverty rate: cash benefits have declined relative to the poverty threshold, the share of welfare benefits provided through cash rather than in-kind assistance has dipped, and real wages for unskilled

[28] All data represented in Figure 4 are calculated as the simple (unweighted) average across the 48 continental United States.

workers have dropped. The inevitable conclusion is that since the 1970s, welfare spending by the American states has become increasingly less effective in reducing the poverty rate. While this conclusion is a direct implication of the results presented in Figures 1-4, this fact is confirmed by the data presented in Figure 5, which presents historical trends in the poverty-reducing effectiveness of cash assistance during the period of our analysis (1961-90).

(Figure 5 about here)

To generate Figure 5, we first calculated the predicted net effect of a marginal increase of $100 in the cash portion of the welfare benefit for every state-year observation in our sample, based on observed values of ***Cash Benefit*** and ***Unskilled Wage***. For each year from 1961-1990, we then calculated both the average net effect across all 48 states and the percentage of states for which the predicted net effect was less than 0. The results are displayed in Figure 5. As can be seen, our results suggest that prior to the mid 1970s, the average net effect of welfare on the poverty rate hovered between -.03 and -.05, while the vast majority of states (approximately 70%) generated predicted net effects that were below 0. Thus, for the first half of our period of analysis, welfare spending appears to have had the intended effect of reducing the poverty rate in many states. Beginning in the mid 1970s, however, the poverty-reducing effectiveness of state welfare spending began to decrease. By the early 1980s only 30% of the states generated a predicted net effect that was below 0, while the average net effect of welfare across all states was considerably greater than 0. These trends continued through the last year of our analysis (1990), and suggest that declining cash benefit levels and declining wages have had a profound effect on the impact of welfare spending.

Conclusion

Since the expansion of public assistance during the late 1960s, many analysts have attempted to assess the impact of welfare on poverty. Generally speaking, two views have been offered. Many have criticized public assistance expansion, claiming that increases in welfare benefits have created work disincentives, thus contributing to rising caseloads, welfare dependence, and ultimately an increase (or at the very least, a stabilization) in poverty rates after 1970. Defenders of welfare, however, claim that if welfare expansion creates work disincentives, these effects are trivial and dwarfed by the reduction in poverty due to income enhancement. These defenders of welfare maintain that the stabilization of poverty rates during the 1970s was largely due to changing economic conditions and decreases in real AFDC benefits since 1970.

Using a design that allows us to isolate the income enhancement and work disincentive effects of welfare, we have shown that each perspective is correct to some degree regarding the impact of welfare on poverty. Real increases in cash benefits do indeed have the hypothesized negative effect on the poverty rate, and increases in total welfare benefits relative to the wage rate for unskilled workers contribute to an increase in the poverty rate, much as the individual-level evidence on work disincentives suggests (Moffitt 1992).

Our results suggest that the net impact of an increase in the welfare benefit (taking into account both income enhancement and work disincentive effects) on the poverty rate is complex, and highly contingent on three factors: the initial level of real cash benefits, wage levels for unskilled workers, and the share of the benefit increase provided through cash rather than in-kind assistance. Historical trends in these important contextual factors make clear that since the 1970s, welfare spending has become increasingly less effective in reducing the poverty rate. This historical observation reveals an interesting irony in welfare policymaking over the last three decades. At least partly motivated by criticism that welfare spending was ineffective in reducing poverty rates, since the early 1970s policymakers have (*i*) systematically reduced cash benefit levels, and (*ii*) gradually shifted the majority of the total welfare benefit package to more politically acceptable in-kind programs. It is these very two features of today's welfare system, however, that virtually insure that *additional* welfare spending will fail to reduce the poverty rate in most states.

Yet it is important to recognize that this conclusion characterizes the net impact of welfare benefits on the official *poverty rate*, and not necessarily on the concept the poverty rate is intended to measure – namely, the *extent of impoverishment*. Presumably, any welfare benefits that enhance the ability of recipients to provide for their material needs and improve the quality of their lives ought to be reflected in an assessment of the income enhancement effect of welfare benefits. While there is debate about whether it is more appropriate for society to assist the poor with in-kind or cash support, there is no doubt that in-kind assistance in the form of Food Stamps and Medicaid provide important material benefits to the poor that improve the quality of their lives. Recall that the construction of the poverty rate excludes consideration of in-kind assistance when calculating individuals' incomes to determine whether they are poor. This failure of the poverty rate to take into account the value of in-kind assistance to the poor undoubtedly makes it so that our conclusion about the ability of welfare to reduce the poverty *rate* underestimates welfare's ability to diminish the *true* extent of poverty.

Another reason why our findings about the net impact of welfare on the poverty *rate* cannot be extended to conclusions about welfare's impacts on the true extent of impoverishment is the poverty rate's reliance on counting persons whose income is less than an established poverty threshold. As we have seen, when welfare benefit levels are near an amount that would provide an income equivalent to the poverty threshold, a small boost in benefit levels can lift a substantial number of poor persons above the poverty line, thereby appreciably reducing the poverty rate. But when benefit levels are low in relation to the poverty threshold, the same small boost in benefit levels will not bring many above the poverty line, so that the poverty rate will be left nearly unchanged. Yet there is no reason to believe that an additional $100 leads to less improvement in the quality of life for a person who has nearly no income than for a person who already has income close to the poverty threshold. If anything, additional assistance should have *diminishing* marginal value as pre-increment income rises. One hundred dollars given to an individual who has no income at all may, indeed, be life saving; the same amount given to someone with income approaching the poverty threshold should have a less dramatic impact. The fundamental problem is that the poverty rate's construction completely ignores the value of increasing a poor person's income unless the increase is sufficient to lift the person above the poverty threshold. Thus, in an environment in which cash benefits are substantially less than the poverty threshold – as they currently are in most states – findings about the net effect of welfare on the poverty *rate* will almost certainly underestimate welfare's ability to reduce the *true* extent of poverty.

Using our research design, however, the poverty rate is a sufficiently good indicator of the extent of poverty to generate strong empirical evidence that welfare has both the income enhancement and work disincentive effects their proponents have claimed. Although the estimated magnitude of these effects would certainly change if we were able to use a perfect measure of the extent of poverty instead of the poverty rate, we are confident that we would still detect substantial income enhancement and work disincentive effects. Nevertheless, an assessment of the *net* effect of an increase in welfare benefits on poverty requires a much better measure of the extent of poverty, because it depends on accurate point estimates of the magnitudes of the income enhancement and work disincentive effects. When the official poverty rate was first calculated in the early 1960s, cash benefit levels were relatively high and the relative share of in-kind assistance was very low. Perhaps in this environment the poverty rate was adequate for assessing the net impact of welfare benefit changes. However, for the current public assistance system characterized by low cash benefit levels and a relatively high share of in-kind benefits, a valid assessment of the net effect of welfare on the extent of poverty in the United States will require an improved measure of poverty.

References

Achen, Christopher H. 2000. "Why Lagged Dependent Variables Can Suppress the Explanatory Power of Other Independent Variables." Paper presented at the Annual Meeting of the Political Methodology Society, UCLA, July 2001.

Beck, Nathaniel and Jonathan Katz. 1995. "What to Do (and Not to Do) with Time-Series Cross-Section Data." *American Political Science Review* 89:634-47.

Berry, William D., Richard C. Fording, Russell H. Hanson. 2003. "Reassessing the 'Race to the Bottom' in State Welfare Policy: Resolving the Conflict Between Individual-Level and Aggregate Research." *Journal of Politics* 65 (May): 327-49.

Berry, William D., Evan J. Ringquist, Richard C. Fording and Russell L. Hanson. 1998. "Measuring Citizen and Government Ideology in the American States, 1960-93." *American Journal of Political Science* 41:327-48.

Berry, William D. and Richard C. Fording. 1997. "Measuring State Tax Capacity and Effort." *Social Science Quarterly* 78:158-66.

Cogan, John. 1982. "The Decline in Black Teenage Employment: 1950-70." *American Economic Review* 72:621-38.

Danziger, Sheldon, Robert Haveman, and Robert Plotnick. 1981. "How Income Transfer Programs Affect Work, Savings, and the Income Distribution: A Critical Review." *Journal of Econometric Literature* 19 (Sept.): 975-1028.

Danziger, Sheldon, Robert Haveman, and Robert Plotnick. 1986. "Poverty and Policy: Lessons of the Last Two Decades." *Social Service Review* 60: 34-51.

Fording, Richard C. 1997. "The Conditional Effect of Violence as a Political Tactic: Mass Insurgency, Welfare Generosity, and Electoral Context in the American States." *American Journal of Political Science* 41:1-29.

Fording, Richard C. 2001. "The Political Response to Black Insurgency: A Critical Test of Competing Theories of the State." 2001. *American Political Science Review* 95(1):115-130.

Gallaway, Lowell, and Richard Vedder. 1985. "Suffer the Little Children: The True Casualties of the War on Poverty." Paper Submitted to the United States Congress, Joint Economic Committee.

Greenstein, Robert. 1991. "Universal and Targeted Approaches to Relieving Poverty: An Alternative View," in Christopher Jencks, Paul E. Peterson, eds., *The Urban Underclass*. Washington, D.C.: Brookings Institution.

Gujarati, Damodar N. 1995. *Basic Econometrics*. 3rd ed. New York: McGraw-Hill.

Harvey, A.C. 1990. *The Econometric Analysis of Time Series*. New York: Philip Allan.

Hill, Kim Quaile, Jan Leighley, and Angela Hinton-Andersson. 1995. "Lower Class Mobilization and Policy Linkage in the United States." *American Journal of Political Science* 39:75-86.

Hoagland, G. William. 1980. "The Effectiveness of Current Transfer Programs in Reducing Poverty." Paper presented at the Middlebury College Conference on Welfare Reform.

Isaac, Larry, and William R. Kelly. 1981. "Racial Insurgency, the State, and Welfare Expansion: Local and National Level Evidence from the Postwar United States." *American Journal of Sociology* 86 (May): 1348-86.

Jencks, Christopher. 1992. *Rethinking Social Policy: Race, Poverty, and the Underclass*. Cambridge: Harvard University Press.

Jensen, Leif, David J. Eggebeen, and Daniel T. Lichter. 1993. "Child Poverty and the Ameliorative Effects of Public Assistance." *Social Science Quarterly* 74 (Sept.):542-59.

Kenworthy, Lane. 1999. "Do Social-Welfare Policies Reduce Poverty? A Cross-National Assessment." *Social Forces* 77(3):1119-39.

Levy, Frank. 1976. "The Labor Supply of Female Households Heads, or AFDC Work Incentives Don't Work Too Well." *Journal of Human Resources* 14(1):76-97.

Marmor, Theodore R., Jerry L. Mashaw, and Philip L. Harvey. 1990. *America's Misunderstood Welfare State: Persistent Myths, Enduring Realities.* New York: Basic Books.

Moffitt, Robert. 1992. "Incentive Effects of the U.S. Welfare System: A Review." *Journal of Economic Literature* 30:1-61.

Morgan, David R., and Kenneth Kickham. 2001. "Children in Poverty: Do State Policies Matter?" *Social Science Quarterly* 82(3): 478-494.

Murray, Charles. 1984. *Losing Ground: American Social Policy, 1950-1980*. New York: Basic Books.

Peterson, Paul E. and Mark C. Rom. 1989. “American Federalism, Welfare Policy and Residential Choices.” *American Political Science Review* 83:711-28.

Ranney, Austin. 1976. “Parties in State Politics,” in Herbert Jacob and Kenneth Vines, eds., *Politics in the American States*, 3rd ed. Boston: Little Brown.

Rodgers, Harrell R. 2000. *American Poverty in a New Era of Reform*. New York: M.E. Sharpe.

Schram, Sanford F. 1991. “Welfare Spending and Poverty: Cutting Back Produces More Poverty, Not Less.” *American Journal of Economics and Sociology* 50 (April):129-41.

Schram, Sanford F., Patrick J. Turbett, Paul H. Wilken. 1988. “Child Poverty and Welfare Benefits: A Reassessment with State Data of the Claim that American Welfare Breeds Dependence.” *American Journal of Economics and Sociology* 47 (Oct.):409-22.

Schwarz, John E. 1983. *America's Hidden Success: A Reassessment of Twenty Years of Public Policy.* New York: Norton.

Stevenson, Randolph T. 2001. “The Economy and the Policy Mood: A Fundamental Dynamic of Democratic Politics?” *American Journal of Political Science* 45 (July):620-33.

Wilson, William Julius. 1987. *The Truly Disadvantaged*. Chicago: University of Chicago Press.

Appendix

Findings Regarding Control Variables in Poverty Model (Equation 2)

Our interpretations are based on the coefficient estimates in column 1 of Table 1, which rely on the measure of ***Welf Benefit*** / ***Unskilled Wage*** taking into account Medicaid benefits. All of these coefficients, and thus the effects we discuss below, represent the immediate impact of these variables on the poverty rate. As the models are estimated with a lagged dependent variable, it is assumed that the effects are distributed through time, so that the total effect of each variable is significantly larger than its immediate effect.

Out-of-wedlock births have a strong effect on poverty; the coefficient estimate of .305 for ***Out-of-Wedlock Births*** implies that an increase of 100 in the number of unmarried births increases the poor population by an average of 30.5. While the elderly population is at high risk of poverty, Social Security prevents much poverty among the elderly; when the number of Social Security recipients grows by 100, the size of the poor population decreases, on average, by 26.5.

Not surprisingly, there is also evidence that the strength of a state's economy has a powerful impact on its poverty rate. Each addition of 100 persons to the ranks of the unemployed pushes, on average, 16 people into poverty. Furthermore, an increase in per capita income of $4,390 (2000) dollars (i.e., a one standard deviation increase in income) is associated with an expected reduction of .83 percentage points in the poverty rate (i.e., a decrease in the percentage of the population that is poor of .83).[29] There is also evidence that the availability of manufacturing jobs and the prevailing wage levels for retail jobs have a very strong impact on the level of poverty in states. An increase in the number of manufacturing jobs sufficient to employ one percent of the population decreases the poverty rate by an average of .11 percentage points. Turning to the retail-sector of the economy, an increase of 176 (2000)

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[29] The average value for per capita income across the state-years in our sample is $18,079, with a standard deviation of $4,390.

dollars in the average monthly wage (i.e., an increase of one standard deviation) yields a decrease of .60 points in the poverty rate.[30]

Compared to the impacts of a state's internal economic conditions, magnetic effects – the impacts of conditions relative to those in other states – on the poverty rate seem much smaller. Assume that a state's average retail-sector wage is equal to the mean prevailing wage in surrounding states (i.e., ***Relative Wage*** = 1.00). The slope coefficient of 4.987 for ***Relative Wage*** implies that if real wages in the state remained constant, but those in neighboring states dropped 10%, the poverty rate would increase by approximately .5 points. The magnetic impact of unemployment is considerably weaker. Assume a similar hypothetical situation: the unemployment rate in a state is the same as the average value among its neighbors. The statistical results suggest that if the state's unemployment level remained fixed, but the average level in neighboring states increased 10%, the state's poverty rate would rise by .08 points.

<u>Definition of Variables in AFDC Recipients Model (Equation 3)</u>

AFDC Recipients: number of AFDC recipients (per 100 population), averaged over the months of January, April, July and October for each year. Data obtained from *Social Security Bulletin,* various years.

Citizen Ideology: Berry, Ringquist, Fording and Hanson (1998)'s measure [running from 0 (most conservative) to 100 (most liberal)].

Female Headed Families: number of female-headed families with children under 18 (per 100 population).

Government Ideology: Berry, Ringquist, Fording and Hanson (1998)'s measure of the ideological orientation of the institutions of state government [running from 0 (most conservative) to 100 (most liberal)].

Party Competition: interparty competition, measured by a folded Ranney (1976) index ranging from .50 to 1.00. Data provided by Laura Langer, University of Arizona.

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[30] The average value for average retail wage across the state-years in our sample is $1,381, with a standard deviation of $176.

Mass Insurgency: number of acts of "violence on behalf of blacks or minorities, either spontaneous or planned, which is either framed as, or can be construed as politically motivated" measured by Fording (1997).

Tax Capacity: state tax capacity [as measured by the Advisory Commission on Intergovernmental Relations, and estimated by Berry and Fording (1997) in years for which ACIR does not provide data].

Tax Effort: state tax effort (same source as ***Tax Capacity***).

Urbanization: annual change in the percentage of state population residing in metropolitan areas. Data obtained for decennial years from the U.S. Census, and for intervening years from the Census Bureau's *Current Population Reports* (P-25). Missing years estimated by linear interpolation.

Table 1. Regression Results for Equation 2

Independent Variable	(1)	(2)	(3)	(4)
Poverty Rate$_{t-1}$	.726**	.725**	.723**	.722**
	(.029)	(.029)	(.029)	(.029)
Cash Benefit	-.0011**	-.0015**	---	---
	(.0003)	(.0005)		
Cash Benefit^2	---	---	-7.29e-07**	-9.27e-07**
			(1.92e-07)	(2.60e-07)
Total Welf Benefit (with Medicaid) / Unskilled Wage	1.245**	---	1.411**	---
	(.462)		(.473)	
Total Welf Benefit (w/out Medicaid) / Unskilled Wage	---	1.997**	---	2.141**
		(.776)		(.752)
Soc Sec Recipients	-.265**	-.265**	-.276**	-.275**
	(.057)	(.056)	(.056)	(.056)
Income	-.00020**	-.00018**	-.00020**	-.00020**
	(.00004)	(.00004)	(.00004)	(.00004)
Unemployment	.161**	.161**	.166**	.169**
	(.048)	(.047)	(.050)	(.049)
Relative Unemployment	-.808**	-.788**	-.803**	-.779**
	(.258)	(.252)	(.266)	(.260)
Unskilled Wage	-.0035**	-.0032**	-.0033**	-.0031**
	(.0010)	(.0011)	(.0010)	(.0010)
Relative Wage	4.987**	4.722**	5.040**	4.777**
	(.721)	(.728)	(.716)	(.724)
Manuf Jobs	-.113*	-.111*	-.109*	-.104*
	(.052)	(.052)	(.056)	(.056)
Out of Wedlock Births	.305*	.314*	.332**	.351**
	(.137)	(.137)	(.141)	(.139)
R^2	.983	.983	.983	.983
N	1440	1440	1431	1431

**$p < .01$, one-tailed
*$p < .05$, one-tailed

Note: Column entries are unstandardized slope estimates, with panel corrected standard errors (PCSE) in parentheses. All models were estimated with the inclusion of unit effects (i.e., state dummies), however we do not report these coefficients. All estimates were generated by STATA 8.0, using the XTPCSE procedure.

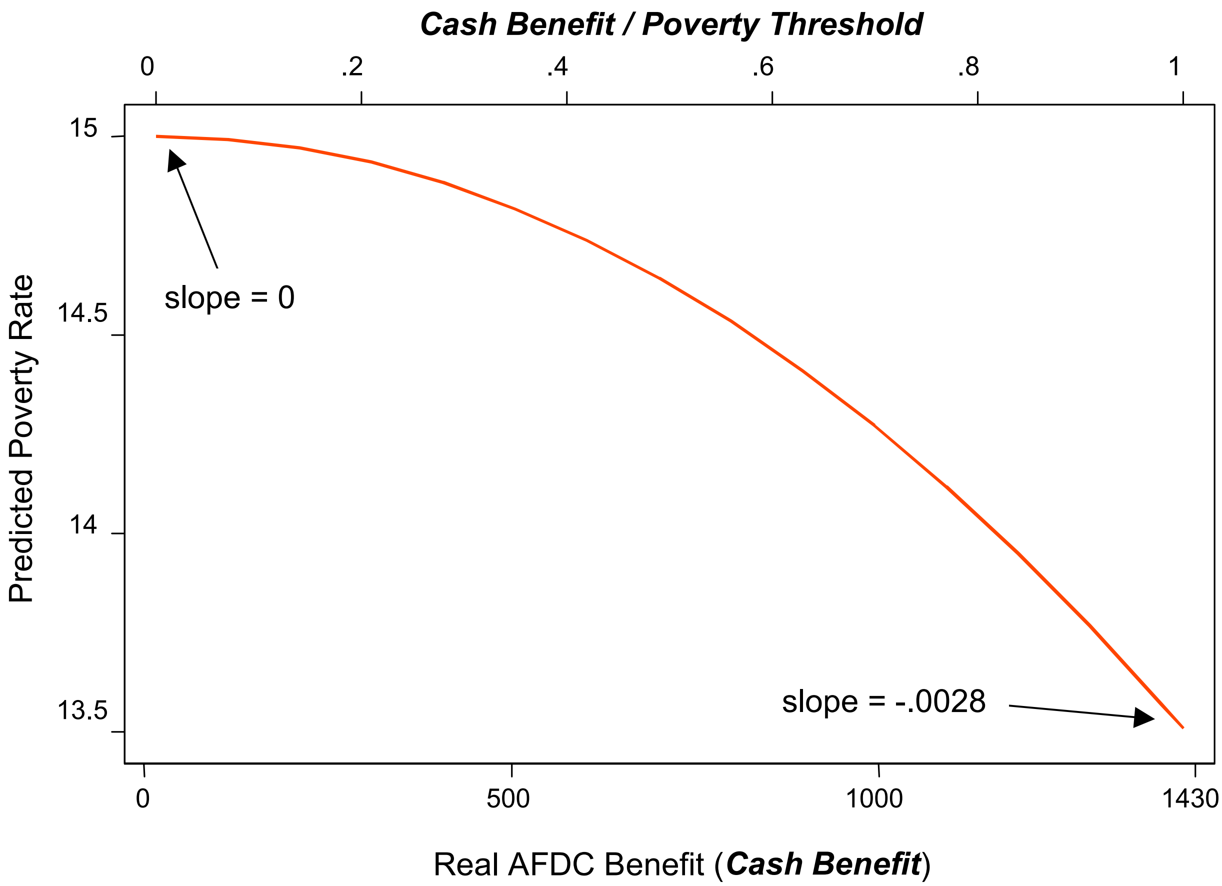
Table 2. Regression Results for Equation 3

Independent Variable	(1)	(2)
AFDC Recipients$_{t-1}$	1.412**	1.413**
	(.065)	(.066)
AFDC Recipients$_{t-2}$	-.503**	-.502*
	(.063)	(.064)
Total Welf Benefit (with Medicaid) / Retail Wage	.346**	---
	(.113)	
Total Welf Benefit (w/out Medicaid) / Retail Wage	---	.308*
		(.142)
Citizen Ideology	-.0020	-.0018
	(.0020)	(.0020)
Government Ideology	-.00011	-.00018
	(.00057)	(.00058)
Party Competition	.050	.047
	(.156)	(.158)
Tax Capacity	-.00082	-.0010
	(.0011)	(.0011)
Tax Effort	.0013	.0015
	(.001)	(.0013)
Unemployment	.0172	.015
	(.0132)	(.013)
Female-Headed Families	-.184*	-.119
	(.094)	(.087)
Out of Wedlock Births	.050	.053
	(.042)	(.042)
Urbanization	.0049	.0057
	(.0050)	(.0051)
Mass Insurgency	.017**	.018**
	(.005)	(.005)
R^2	.975	.974
N	1392	1392

**p<.01, one-tailed, *p < .05 , one-tailed

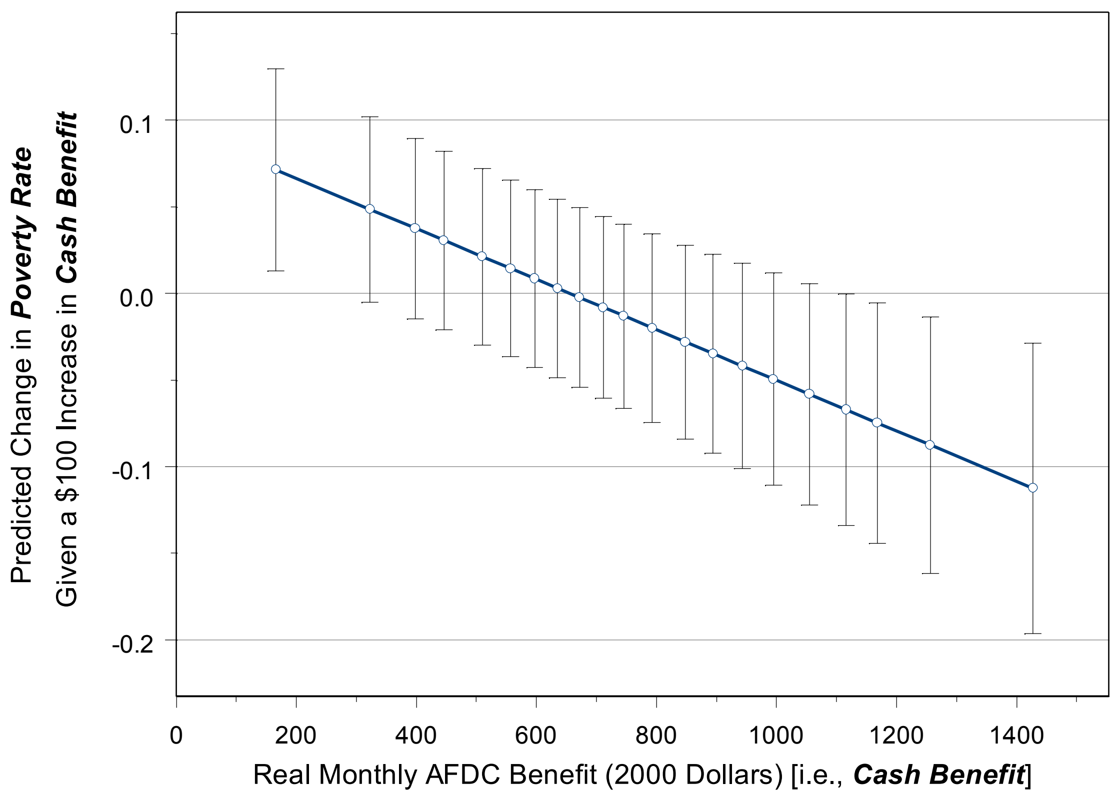
Note: Entries are unstandardized slope estimates, with panel corrected standard errors (PCSE) in parentheses. All models are estimated with the inclusion of unit effects (i.e. state dummies), however we do not report these coefficients due to space considerations. All estimates were generated by STATA 8.0, using the XTPCSE procedure.

Figure 1. Predicted Effect of *Cash Benefit* on the Poverty Rate by Value of *Cash Benefit* and *Cash Benefit/Poverty Threshold*



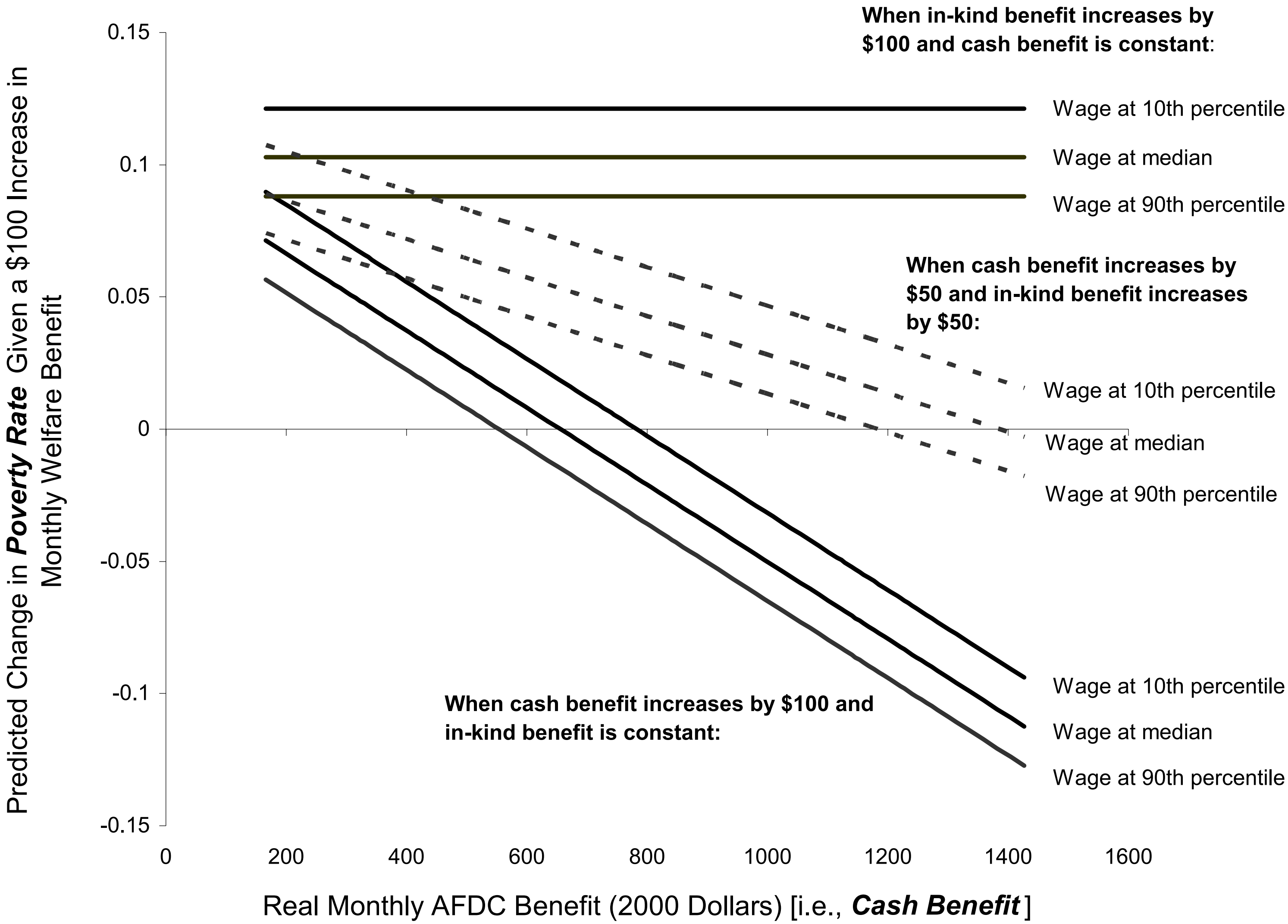
Notes:
(1) The graph is based on the coefficient estimates in Table 1, column 3.
(2) The scale for the vertical axis is determined by fixing all other independent variables besides ***Cash Benefit*** at their mean. Yet the values at which these other variables are fixed influence only the height of the curve; the slope of the curve at any point is independent of these values.

Figure 2. Estimated Net Effect on the Poverty Rate of a $100 Increase in *Cash Benefit* When *Unskilled Wage* is at its Median, by Benefit Level



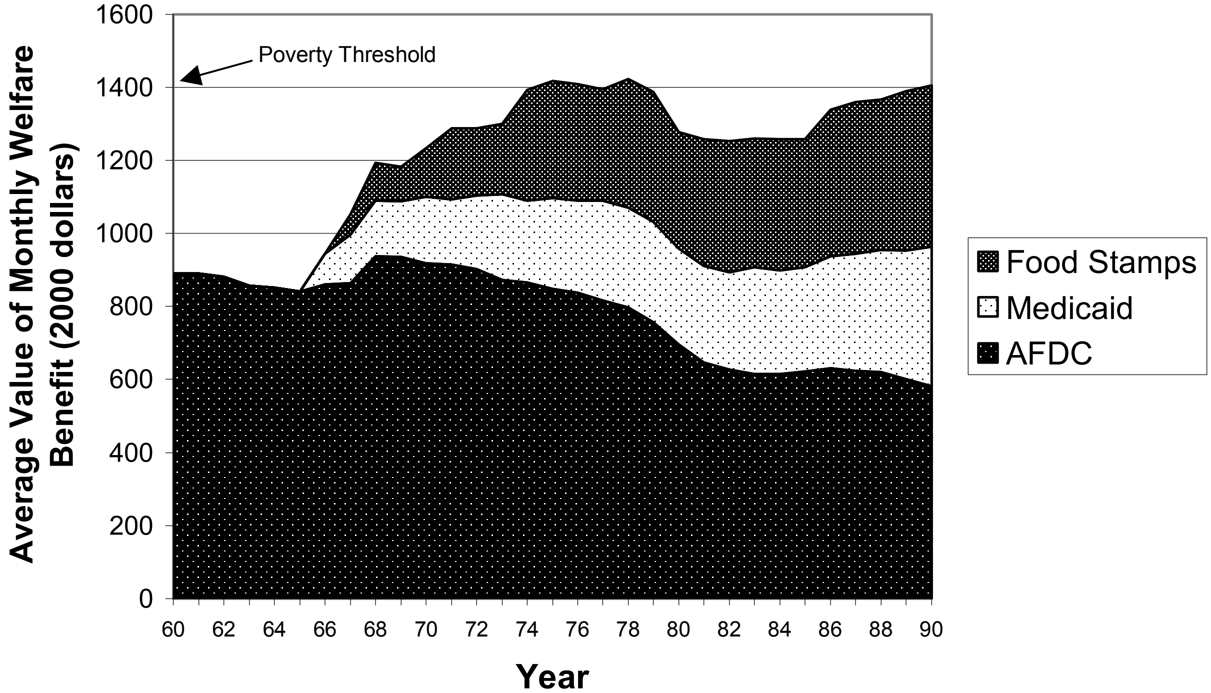
<u>Notes</u>:
(1) Vertical bars indicate 95% confidence interval.
(2) This graph is based on the coefficient estimates in Table 1, column 3.

Figure 3. Estimated Net Effect on the Poverty Rate of a $100 Increase in Real Welfare Benefit Level, by *Cash Benefit* Level



Notes:
(1) Confidence intervals for predicted changes in ***Poverty Rate*** are not shown to enhance readability of the graph.
(2) This graph is based on the coefficient estimates in Table 1, column 3.

Figure 4. Historical Trends in Variables Influencing the Poverty-Reducing Impact of Welfare



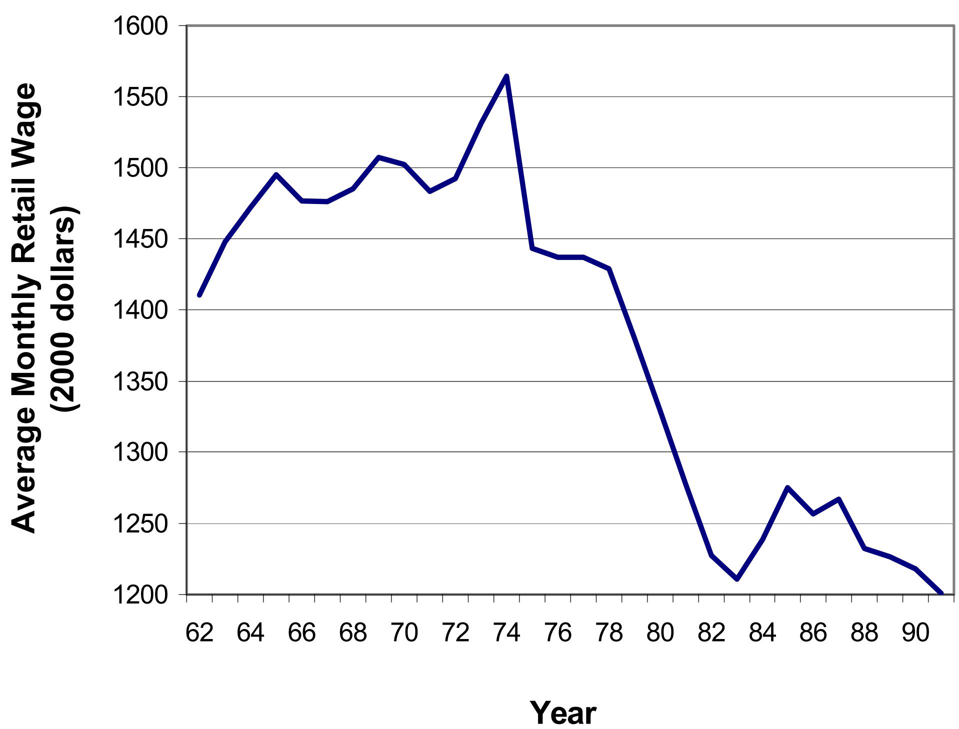
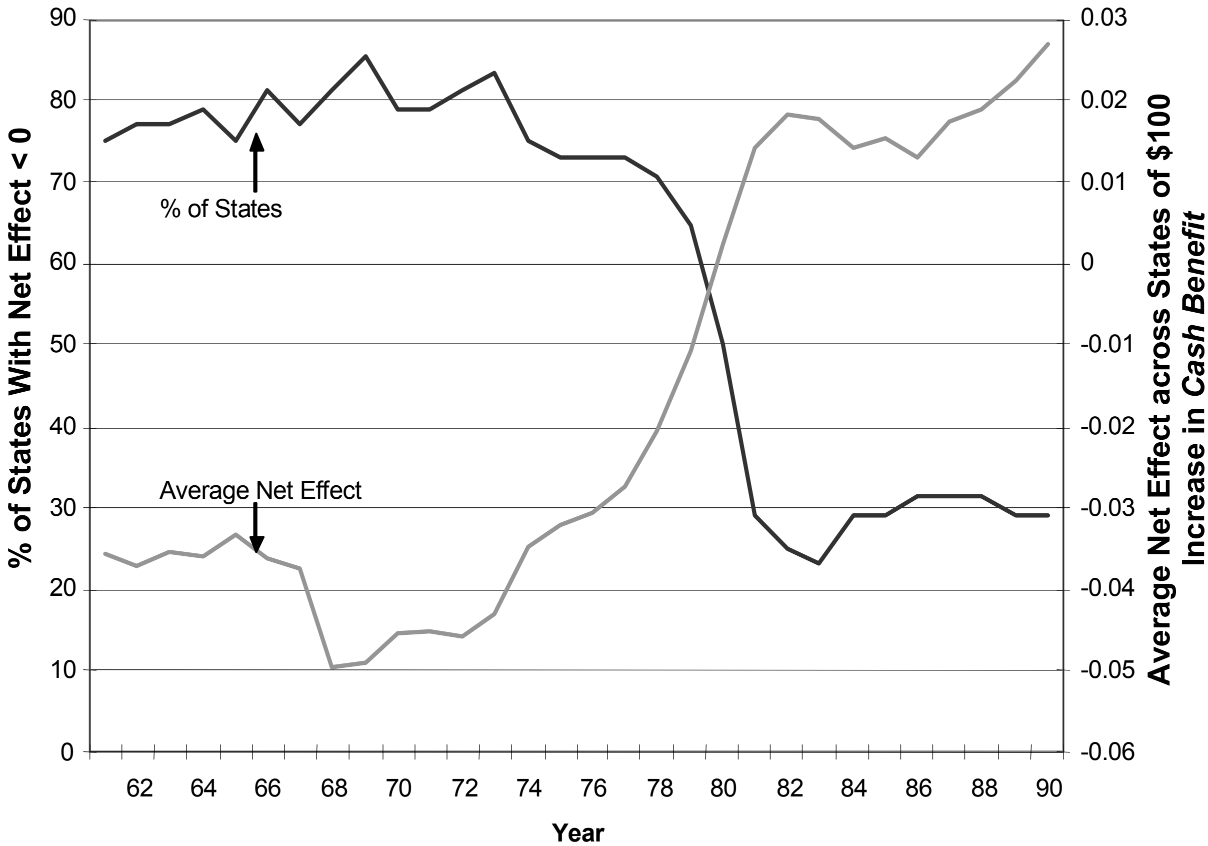


Figure 5. Historical Trends in Poverty-Reducing Effectiveness of State Welfare Spending



Notes:

(1) Excludes Alaska and Hawaii

(2) This graph is based on the coefficient estimates in Table 1, column 3, and net effects are calculated given observed state values for ***Cash Benefit*** and ***Unskilled Wage***.

Unpublished Supplement to

"The Impact of Welfare Programs on Poverty Rates: Evidence from the American States"

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Contents

I. Estimating Missing Values for *Poverty Rate*

Our method for estimating poverty in the states is straightforward. Let

$NOPOOR{:}REGN_{j,t}$ = number of poor individuals in region j for year t;
$SHRPOOR{:}STATE_{i,j,t}$ = state i's share of $NOPOOR{:}REGN_{j,t}$ for year t; and
$NOPOOR{:}STATE_{i,j,t}$ = number of poor individuals in state i for year t;

Algebraically,

$$NOPOOR{:}STATE_{i,j,t} = NOPOOR{:}REGN_{j,t} * SHRPOOR{:}STATE_{i,j,t}. \quad [1.0]$$

Equation [1.0] is our operational definition of poverty in each of the fifty states at time t. To employ this definition, we need to establish and obtain annual data on $NOPOOR{:}REGN_{j,t}$ and $SHRPOOR{:}STATE_{i,j,t}$ for 1960-1990.

Estimating Poverty in Regions, 1960-1990

Poverty in the United States: 1992 (Bureau of the Census, Current Population Reports, Series P60, No. 185) lists the number of poor in the Northeast, Midwest, South, and West in 1959 and 1969-1990.[1] We use these data, with certain modifications. The Census Bureau only gives estimates for the South in 1970;

[1] The Northeast includes Connecticut, Massachusetts, Maine, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. The Midwest consists of Iowa, Illinois, Indiana, Kansas, Michigan, Minnesota, Missouri, North Dakota, Nebraska, Ohio, South Dakota, and Wisconsin. The South has Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia. Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming make up the West.

estimates from the other three regions are not reported. We interpolated regional shares of poverty from 1969 and 1971 for the Northeast, Midwest, and West. Then we multiplied the interpolated shares by the overall number of poor in the U.S. to arrive at estimates of the number of poor in each region for 1970.

No regional estimates are published for the years 1960-1968. We therefore had to construct the missing data. The construction proceeded in two stages. In the first stage, we converted data published in the *Social Security Bulletin* on poor families and unrelated individuals to $NOPOOR{:}REGN_{j,t}$, using the original definition of poverty for 1963, 1964, and 1966. In the second stage, the estimates for each region were adjusted to reflect a revised definition of poverty, one that uses the CPI as an index of inflation instead of changes in the USDA Economy Food Plan and reduces the gap between poverty thresholds for farm and non-farm families. This insures consistency in measurement over time, since published data for later years are based on the revised definition of poverty.

Regional estimates for 1960-62, 1965, and 1967-68 are linear interpolations over the shortest interval for which constructed or published numbers were available. The method of interpolation is the same used for 1970. Details are available upon request from XXXXX.

Estimating Poverty Shares in the States, 1960-1990

To estimate $SHRPOOR{:}STATE_{i,j,t}$, we assume that a state's share of its region's poor population is determined by its share of the region's "at-risk" population and personal income. People who earn little or no income comprise the at-risk population. This includes children under the age of eighteen and senior citizens who are at least sixty-five years old. Between the young and the old is a middle-aged group of people who are generally not at risk, except when they are unemployed.

Thus,

$$
\begin{aligned}
[2.0]\quad SHRPOOR{:}STATE_{i,j,t} \quad = \quad & a_i \\
& + b_1 * SHRYR017{:}STATE_{i,j,t} \\
& + b_2 * SHRNOWORK{:}STATE_{i,j,t} \\
& + b_3 * SHRYR65{+}{:}STATE_{i,j,t} \\
& + b_4 * SHRINCOME{:}STATE_{i,j,t} \\
& + b_5\, SHRYR017{:}STATE_{i,j,t} * SHRINCOME{:}STATE_{i,j,t} \\
& + b_6\, SHRNOWORK{:}STATE_{i,j,t} * SHRINCOME{:}STATE_{i,j,t} \\
& + b_7\, SHRYR65{+}{:}STATE_{i,j,t} * SHRINCOME{:}STATE_{i,j,t}
\end{aligned}
$$

where

a_i	=	state i's background share of poverty in year t;
$SHRYR017{:}STATE_{i,j,t}$	=	state i's share of region j's children under 18 in year t;
$SHRYR65{+}{:}STATE_{i,j,t}$	=	state i's share of region j's population over 64 in year t;[2]

[2] The number of unemployed adults equals the total number of residents aged 18-64 multiplied by the unemployment rate. In effect, this assumes that a state's workforce is composed of all people in this age group, and that the unemployment rate for this workforce is the same as it is for the civilian labor force, a smaller group that consists of people who have or are looking for work.

Age breakdowns of states' resident population as of July 1 are available on an annual basis in Current Population Reports, Series P-25, various numbers. Average annual unemployment rates for the civilian labor force in each state are from *Statistics on Manpower: A Supplement to the Manpower Report to the President* (annual, 1959-1966) and *Employment and Training Report to the President* (annual, 1967-1990).

$SHRNOWORK:STATE_{i,j,t}$ = state i's share of region j's unemployed 18-64 in year t;
$SHRINCOME:STATE_{i,j,t}$ = state i's share of region j's aggregate income in year t.[3]

In this formulation, income share interacts with each of the three at-risk population shares in determining poverty shares. In particular, b_1, b_2, and b_3 measure the effects of a state's share of its region's young population, its share of the region's unemployed population, and its share of the region's elderly population, respectively, in the (hypothetical) situation where a state's share of the region's income is zero. We expect b_1, b_2 and b_3 to exceed zero since increases in a state's share of its region's young, elderly, and unemployed populations should prompt increases in a state's poverty share when income share is fixed at any level. On the other hand, we predict $b_4<0$ because any increase in a state's share of its region's income should lead to a reduction in its poverty share when the state's shares of at-risk populations are fixed at any value.

The impact of income share on poverty share depends on the demographic characteristics of a state, however. Senior citizens differ from the young and unemployed in two respects. The elderly are better organized and have more political clout than other at-risk populations. They are also seen as more deserving of public assistance than the able-bodied poor (including the unemployed and the parents of needy children.) Thus, if a state's shares of its region's young and unemployed populations are held constant while its share of the elderly population grows, the proportion of its at-risk population that is viewed sympathetically by voters and politicians will increase. Similarly, if a state's share of its region's elderly population is held constant while its shares of the young and unemployed populations rise, the proportion of its at-risk population that is powerful and deemed worthy of public support will decrease.

When the proportion of a state's at-risk population that is powerful and deserving of support increases, so will does state policy makers' willingness to invest resources in public assistance. This willingness magnifies the negative impact of income share on poverty share. That is, b_7 should be negative, indicating that when a state's share of its region's unemployed and young populations remain fixed while its share of the region's elderly population grows, policymakers are more inclined to pursue redistributive policies. Such policies include Medicaid, which in conjunction with Medicare prevents many senior citizens from slipping into poverty when their health fails.

In contrast, when the proportion of a state's at-risk population that is powerful and seen to be deserving of sympathy decreases, policy makers' will be less willing support public assistance programs, e.g., Aid to Families with Dependent Children. Some family incomes will be raised above the poverty line by AFDC benefits, but in most states the benefits are too low to bring about a substantial reduction in poverty. Thus, b_5 should be positive, indicating that when a state's shares of the region's elderly and unemployed populations remain constant while its share of the region's young population increases, the negative impact of income share on poverty share will be weaker than we might expect on the basis of b_4 alone.

By similar reasoning, b_6 should exceed 0. When a state's shares of its region's elderly and young populations remain constant while its share of the region's unemployed population grows, the impact of income share on poverty share will be diminished. Like the young and their parents, the unemployed are generally not viewed sympathetically by the public, so policy makers will not favor them with insurance benefits that lift incomes above the poverty line.

[3] Aggregate personal income is the sum of all personal income in a state. Personal income is the sum of wages and salaries, other labor income, proprietors' income (adjusted for inventory valuation and capital consumption), rental income adjusted for capital consumption, dividend income, interest income, and income from transfer payments to persons, less personal contributions for social insurance. See *Local Area Personal Income, 1969-92* (U.S. Department of Commerce, Bureau of Economic Analysis: 1994).

*Estimating Equation 2.0***.** We used the preceding model to analyze data from the Censuses of 1960, 1970, 1980, and 1990. In addition to compiling basic demographic information, the Censuses counted the number of poor people in each state and region in 1969, 1979, and 1989, using the revised definition of poverty. For 1959, "Poverty in 1959-1960 by County and State" (Supplement 1 to *Dimensions of Poverty in 1965*, OEO, December, 1965) tabulates the number of poor in each of the fifty states, retroactively employing the original definition of poverty (which was of course not promulgated until 1964). After adjusting these numbers to conform to the revised definition of poverty we computed regional sums, and calculated SHRPOOR: $\text{STATE}_{i,j,t.}$

Having obtained comparable data for 1959, 1969, 1979, and 1989 we regressed SHRPOOR:$\text{STATE}_{i,j,t}$ on the explanatory variables listed in equation 2.0. We assumed the model was invariant over time, pooling the 200 observations. Because the dependent variable has a restricted range, we incorporated White's correction for heteroskedasticity in estimates of the standard errors for coefficients. The results of this regression are summarized in Tables 1 and 2.

Table 1: OLS Regression Results

Criterion	Estimate
N (50x4: 1959,1969,1979,1989)	200
Mean of SHRPOOR:STATE	0.080000
R-squared	0.996856
Adjusted R-squared	0.995625
F(56,143)	809.759113
Standard error of regression	0.006440
Regression sum of squares	1.880392
Residual sum of squares	0.005930

Obviously, the fit is excellent. Table 1 shows that our model explains more than ninety-nine percent of the observed variation in the dependent variable. And the signs of the estimated coefficients are all consistent with our predictions, according to Table 2.

There is no reason to question our decision to pool the data over time and across regions. In all four regions the residuals from the regression reported in Table 1 center around zero, and while the range of residuals is slightly larger in the Midwest than it is for the other regions, the difference is negligible. Similarly, the residuals center around zero in each of the four years under investigation, and the range of residuals is the same except for one large negative value in 1959 and one large positive residual in 1989.

Constructing Estimated State Poverty Shares. Using the regression estimates from Table 2, along with values for the independent variables in equation 2.0, we computed estimates of state shares of regional poverty (SHRPOOR:$\text{STATE}_{i,j,t}$) for all years between 1960 and 1990, inclusive.

Table 2 : OLS Estimates, Corrected for Heteroskedasticity

Variable	*Estimate*	*s.e.*	*t-ratio*	*p-value*
SHRYR017:STATE	1.419	0.233	6.085	0.000
SHRYR65+:STATE	0.580	0.190	3.054	0.003
SHRNOWORK:STATE	0.034	0.101	0.332	0.740
SHRINCOME:STATE	-0.803	0.225	-3.561	0.001
SHRYR017:STATE*SHRINCOME:STATE	0.815	0.755	1.079	0.282
SHRYR65+:STATE*SHRINCOME:STATE	-2.268	0.662	-3.428	0.001
SHRNOWORK:STATE*SHRINCOME:STATE	0.510	0.441	1.155	0.250
(State Effects Omitted)				

Computing and Validating State Poverty Estimates: 1960-1990

With values for NOPOOR:REGN$_{j,t}$ and SHRPOOR:STATE$_{i,j,t}$ in hand, we can use equation 1.0 to calculate NOPOOR:STATE$_{i,j,t}$ for each state and year from 1960-1990. There are three benchmarks for evaluating the quality of these estimates of the number of poor in each state. The Census counted poor people in each state for 1959, 1969, 1979, and 1989. The Survey of Income and Education, which was conducted in 1976, estimated the number of poor in each state in 1975. And the March edition of the Current Population Survey provided annual estimates of poverty by state for 1980-1990, inclusive.

If our method is sound, the estimates of NOPOOR:STATE$_{i,j,t}$ should closely approximate observed values in the benchmark years. That is, regressions of observed on estimated values should yield high R-squares, near-zero values for constant coefficients, and slope coefficients very close to one. These results would indicate a close correspondence between the true (or at least known) values and our constructions.[4] Table 3 summarizes the regression for the years in question. The fit is excellent in every respect:

Table 3: OLS Estimates, Known No. of Poor on Estimated No. of Poor

	Year	**Constant**		**Slope**		**Fit**	
No. of Poor		*a*	*s.e.*	*b*	*s.e.*	*Adj. R2*	**SEE**
Census	1959	12453.396	13219.920	0.984	0.013	0.992	62113.062
Census	1969	7581.892	4458.174	0.990	0.006	0.998	21810.372
Census	1979	-10512.190	5593.686	1.017	0.007	0.998	28071.250
Census	1989	-8568.548	9331.865	1.009	0.010	0.995	48998.980
	Pooled	-158.354	4340.781	0.999	0.005	0.995	43546.142
SIE	1975	-31252.663	9590.818	1.006	0.014	0.991	46498.447
CPS	1980	-44526.166	16734.149	1.017	0.020	0.982	81116.843
CPS	1981	-56411.313	15227.003	1.030	0.016	0.988	74034.204
CPS	1982	-40933.808	17115.841	1.002	0.017	0.986	83936.136
CPS	1983	-49024.842	15822.577	1.010	0.015	0.989	78324.454
CPS	1984	-58737.538	17193.552	1.026	0.017	0.986	85215.310
CPS	1985	-70911.153	20349.514	1.045	0.021	0.981	100792.369
CPS	1986	-31328.309	13477.545	0.989	0.014	0.990	67688.137
CPS	987	-50904.440	15622.640	1.019	0.016	0.988	78778.286
CPS	1988	-65191.151	17171.294	1.040	0.018	0.986	87482.787
CPS	1989	-45545.647	9875.471	1.011	0.010	0.995	50602.826
CPS	1990	-46678.407	20255.227	1.005	0.019	0.982	104413.623
	Pooled	-50548.356	4919.132	1.017	0.005	0.987	81630.180

[4] CPS estimates of the number of poor people in each state are based on surveys, and are therefore affected by sampling errors. The size of these errors varies from state to state and time to time. A longer version of this document, which is available from XXXXX, explores these errors and their implications in greater detail. Here it is sufficient to note that difference between our estimates and benchmark values may stem from flaws in the latter, as well as the former.

The R-squares are very high in every year, and the slope coefficient is always close to one (although it is little higher in 1981, 1985, and 1988). For 1980-1990 the estimated constants are significantly different from zero. However, these estimates depend on the scale of measurement. The relative intercept, which is the estimated constant divided by the mean of the dependent variable, is a scale-free alternative. For every year listed in Table 3, the relative intercept is less than .11 in absolute value. Since the relative intercept is really the parameter of interest, these small values are confirming evidence that our measures track the CPS values very well indeed.

Based on the results presented in Table 3, we have considerable confidence in our measure of poverty. It tracks other state-level indicators very well. Moreover, our measure does an excellent job of reproducing regional estimates of poverty, which are available for every year in the period under investigation. This is evident in the following table, which aggregates our estimate of state poverty to the regional level and compares the result to published values derived from the Current Population Survey.

Table 4: Ratio of Observed to Estimated No. of Poor, by Region

Year	*Northeast*	*Midwest*	*South*	*West*	*Ave.*	*Min.*	*Max.*
1960	0.9759	0.9504	0.9241	0.9477	0.9495	0.9241	0.9759
1961	0.9779	0.9493	0.9248	0.9468	0.9497	0.9248	0.9779
1962	0.9787	0.9498	0.9251	0.9484	0.9505	0.9251	0.9787
1963	0.9784	0.9504	0.9243	0.9475	0.9501	0.9243	0.9784
1964	0.9789	0.9519	0.9252	0.9466	0.9507	0.9252	0.9789
1965	0.9748	0.9522	0.9254	0.9388	0.9478	0.9254	0.9748
1966	0.9689	0.9513	0.9267	0.9414	0.9471	0.9267	0.9689
1967	0.9736	0.9503	0.9297	0.9452	0.9497	0.9297	0.9736
1968	0.9779	0.9508	0.9305	0.9518	0.9528	0.9305	0.9779
1969	0.9774	0.9517	0.9309	0.9541	0.9535	0.9309	0.9774
1970	0.9745	0.9470	0.9283	0.9410	0.9477	0.9283	0.9745
1971	0.9712	0.9460	0.9286	0.9284	0.9436	0.9284	0.9712
1972	0.9678	0.9442	0.9290	0.9340	0.9437	0.9290	0.9678
1973	0.9704	0.9462	0.9304	0.9291	0.9440	0.9291	0.9704
1974	0.9680	0.9458	0.9309	0.9275	0.9431	0.9275	0.9680
1975	0.9688	0.9440	0.9333	0.9287	0.9437	0.9287	0.9688
1976	0.9600	0.9438	0.9311	0.9326	0.9419	0.9311	0.9600
1977	0.9581	0.9446	0.9332	0.9318	0.9420	0.9318	0.9581
1978	0.9528	0.9441	0.9335	0.9250	0.9388	0.9250	0.9528
1979	0.9528	0.9450	0.9361	0.9329	0.9417	0.9329	0.9528
1980	0.9528	0.9454	0.9381	0.9402	0.9441	0.9381	0.9528
1981	0.9523	0.9466	0.9420	0.9356	0.9441	0.9356	0.9523
1982	0.9539	0.9465	0.9416	0.9299	0.9430	0.9299	0.9539
1983	0.9485	0.9469	0.9412	0.9257	0.9406	0.9257	0.9485
1984	0.9433	0.9469	0.9426	0.9232	0.9390	0.9232	0.9469
1985	0.9424	0.9479	0.9400	0.9293	0.9399	0.9293	0.9479
1986	0.9382	0.9486	0.9378	0.9380	0.9406	0.9378	0.9486
1987	0.9399	0.9494	0.9381	0.9424	0.9425	0.9381	0.9494
1988	0.9415	0.9483	0.9396	0.9321	0.9404	0.9321	0.9483
1989	0.9390	0.9497	0.9392	0.9201	0.9370	0.9201	0.9497
1990	0.9501	0.9498	0.9393	0.9008	0.9350	0.9008	0.9501

Avg.	0.9616	0.9479	0.9329	0.9354
Min.	0.9382	0.9438	0.9241	0.9008
Max.	0.9789	0.9522	0.9426	0.9541

If our state-level estimates of poverty were all accurate, the interior entries in Table 4 would all be one. That is, the sum of poverty in the states comprising a region should be the same as the number of poor people in the region as estimated by the CPS. Allowing for measurement error, this is generally true. Over time, the average ratio for the Northeast is .96, and for the Midwest it is .95. The averages for the South and Midwest are only a little lower, at .93 and .94, respectively.

II. Estimating Missing Values for *Out of Wedlock Births*

We first define OWL#_MISS as the number of out of wedlock births in each state year (Source: *Vital Statistics of the United States, 19XX*.) Data are fully available for the following states for years 1960-90:

> AL, DE, FL, IL, IN, IA, KS, KY, LA, MN, MS, MO, NJ, NC, ND, OR, PA, RI, SC, TN, UT, VA, WA, WV, and WY

Data are missing for one or more years for each of the remaining 23 states:

> AZ, AR, CA, CO, CT, GA, ID, ME, MD, MA, MI, MT, NE, NV, NH, NM, NY, OH, OK, SD, TX, VT, WI

Data on the number of out of wedlock births at the national level were collected for each year 1960-90 (Source: *Vital Statistics of the United States, 19XX*). This variable is labeled OWL_NAT.

For five states we interpolate or track (see Appendix) one to three contiguous missing or "erroneous" observations and treat them as observed (giving us a total of 30 states with "observed" data for all years). These states are:

State	Year(s)	Reason	Method
ME	1961	Missing	Linear Interpolation
MI	1978-79	Missing	Linear Interpolation
SD	1963-64	"Erroneous Filing"	Linear Interpolation
TX	1977-79	Missing	Track Oklahoma
WI	1961	"Erroneous Classification"	Linear Interpolation

These estimated values are combined with observed values to create OWL#_INT**.**

We estimate missing observations in the remaining states using one of two methods:

(A) The regression approach

For eight states with no more than eleven missing observations, we estimate missing observations using a regression procedure in which Y = OWL#_INT, X1 = OWL_NAT, X2 = state population, and for which there are at least three other X variables. We include one X variable for each neighboring state for which there are complete data for 1960-90. If there are not three neighboring states for which data are available, we supplement the states up to the level of three by first choosing the nearest state with the same political culture (based on Elazar's classification) for which data are available (distance measured from capital to capital). In all regressions except OH and NV (which have two shift years) we restrict OWL#_INT to its observed value in its shift year. For each state included in the regressions, we supplement observed values with predicted values creating a complete series for each state. The specific states for which this technique was used, along with the regression results, are summarized below.

State	Neighbor X's	Pol Culture X's	R-squared
AZ	UT	NC, LA	.9953
AR	KY,LA,MS,MO,TN		.9957
CO	KS, UT, WY		.9934
NE	IA, KS, MO,SD,WY		.9973
NV	OR,UT	IL	.9625
NH	ME	IA, KS	.9941
OH	IN,KY,PA,WV		.9993
OK	KS,MO	KY	.9971

(B) The target tracking approach (see Appendix for details)

For ten remaining states with 18-20 missing observations, we decided that regression estimation was not a reasonable strategy. For these states, we first determined which other states might exhibit similar trends in OWL#_INT, based on the same criteria for selecting regressors in the regression approach above. Then for each of these ten states, we estimated missing observations by assuming that the rate of change in these states was equal to the rate of change in the "similar" states, where the rate of change for the similar states was computed as a population-weighted average. Observed and estimated values were combined for these ten states to create a complete yearly series. The relevant information regarding this estimation is summarized below:

State	Neighbor X's	Pol Culture X's
CA	OR	WA, KS
CT	RI	WY, NJ
GA	AL,FL,NC,SC,TN	
ID	OR,UT,WA,WY	
MD	DE,NJ,PA,VA,WV	
MA	RI,ME	WY
MT	ND,SD,WY	
NM		IA, KS, SD
NY	NJ,PA	RI
VT		MN, WI, ND

We created a final series, labeled OWL#_EST by supplementing missing observations in OWL#_INT with observations estimated using one of the two estimation techniques summarized above. We then created our final series, which we use in our analysis of state poverty rates, as:

Out of Wedlock Births = OWL#_EST / State Population.

III. Measuring *Unskilled Wage*

We first collected data for RETPAY, defined as the taxable payroll (in $1000's) for the retail trade sector during the first quarter of the year, and for RETAIL#, defined as the number of employees in the retail trade sector in the mid-March pay period (Source for both RETPAY and RETAIL#: Bureau of the Census, *Country Business Patterns 19xx.*) Data are unavailable for all states for both RETPAY and RETAIL# for the following years: 1960-61, and 1963. A new variable, RETWAGE, was created that is equal to the average monthly gross pay (in dollars) received by an employee in the retail trade industry:

RETWAGE = [(RETPAY / 3) / RETAIL#] * 1000

Note that as with RETPAY and RETAIL#, RETWAGE is missing in years 1960, 1961 and 1963.

We also collected data for MANWAGE, defined as the average hourly wage for employees in the manufacturing sector. These data were collected for years 1959-65 only, and were available for all states (Source: Bureau of Labor Statistics, *Employment, Hours and Earnings, States and Areas, 19xx-19xx.*).

The RETWAGE series was supplemented by estimates of missing values for years 1960-61 and 1963 that were calculated by assuming that RETWAGE and MANWAGE followed identical trends for the periods 1959-62 and 1962-64. As an example, for data missing in 1963, retail wages were estimated by the following formula:

RW63 = RW62 + {[(MW63-MW62) / (MW64-MW62)] * (RW64-RW62)}

The final RETWAGE series, supplemented by these estimates of missing values, was used as the ***Unskilled Wage*** variable.

IV. Measuring *Cash Benefit* and *Total Welf Benefit*

Two welfare benefit variables are included in our analysis of state poverty rates – ***Cash Benefit*** and ***Total Welf Benefit***. Below, we describe data sources for these variables and strategies used to estimate missing values.

Cash Benefit

Cash Benefit is measured as the maximum monthly AFDC benefit for a family of four (1 adult and 3 children) with no income. We rely on AFDC benefit data reported in Berry, Fording and Hanson (2003). The primary source of the AFDC data is an electronic data file provided by Health and Human Services, which provides consistently timed observations for all states. The reporting date is July 1, 19xx. In some states, these data are modified in order to maintain a consistent basis for reporting data from 1960-1974, or to take ancillary grants into account. The best example of the latter is Oregon, which added to the basic AFDC grant a "minimum wage supplement" that was paid to all families with no earned income. A good example of the former is Virginia, which used information on Group III areas within the state, instead of the more commonly reported Group II areas.

Berry, Fording and Hanson rely on the maximum payment for a family of four in the high cost area of most states except Connecticut (Region A), Michigan (Wayne County), and New York (New York City). Although the treatment of these states differs from that of other states insofar as it substitutes the heaviest caseload area for the high cost area, this allows greater consistency in reporting for these states over time.

Total Welf Benefit

We measure ***Total Welf Benefit*** as the sum of two quantities: (1) the combined AFDC and Food Stamp guarantee for a family of four (one adult, three children), and (2) the average Medicaid expenditure for an AFDC family of four (one adult, three children).

Combined AFDC/Food Stamp Benefits

For purposes of our analysis, a state was coded as having a Food Stamp program if more than half the counties in a state offered the program. Accordingly, no states in our analysis are coded as having a Food Stamp program prior to 1967. After 1974, the Food Stamp program was universal and thus Food Stamp benefits were included in the calculation of ***Total Welf Benefit*** in all states.

The Food Stamp bonus is defined as the monthly value of Food Stamps to which a family of four is entitled in a state, assuming it has no income other than the maximum AFDC payment. The sum of the AFDC Benefit and the bonus is the combined AFDC and Food Stamp guarantee for a family of four.

Data on Food Stamp allotments were provided by Russell Hanson, Indiana University, who relied on the following sources:

> 1969: *Poverty, Malnutrition, and Federal Food Assistance Programs: A Statistical Summary*, Select Committee on Nutrition and Human Needs, U.S. Senate, 91st Congress, First Session, September, 1969, p. 18. These figures were adjusted for inflation to arrive at estimates for 1967 and 1968.
>
> 1971-1985: *The Food Stamp Program: History, Description, Issues and Options.* Committee on Agriculture, Nutrition, and Forestry. U.S. Senate, 99th Congress, 1st Session. Washington, DC: GPO, 1985, pp. 164-65.
>
> 1986-1990: *The Green Book*, 1993, p. 1265.
>
> 1970-1990: various issues of the *Federal Register*, which publishes the allotments once per year.

Medicaid

The average monthly Medicaid expenditure for an AFDC family of four (one adult, three children) is from Welfare Benefits Database, Robert Moffit, Department of Economics, Johns Hopkins University (http://www.econ.jhu.edu/People/Moffitt/DataSets.html). These data are unavailable prior to 1975. However, states began implementing the Medicaid program as early as 1966. To estimate values for earlier years (1966-74), we assume that the change in Medicaid expenditures for AFDC families in each state followed the same trajectory as national level data for the average Medicaid expenditure per Medicaid recipient over the 1966-75 period (Source: HCFA Division of Medicaid Statistics, unpublished data). These national level data are available only after 1968, so we estimate 1966-67 values by assuming that the rate of change in each state in 1966 and 1967 was identical to the change in the national CPI for medical services.

V. Regression Results for Version of Equation 2 with a Squared Term for *Cash Benefit* Added

[These results are referenced on page 15 of the manuscript (footnote 18).]

Independent Variable	(1)	(2)
Poverty$_{t-1}$	.720**	.704**
	(.030)	(.030)
Cash Benefit	.0016	-.0010
	(.0012)	(.0012)
Cash Benefit^{2}	- 1.52e-06*	-1.37e-06 *
	(6.39e-07)	(6.32e-07)
Total Welf Benefit (with Medicaid)/ Unskilled Wage	1.318*	---
	(.472)	
Total Welf Benefit (w/out Medicaid)/ Unskilled Wage	---	1.982*
		(.782)
Soc Sec Recipients	-.279**	-.275**
	(.055)	(.054)
Income	-.0002**	-.0002**
	(.00003)	(.00004)
Unemployment	.176**	.175**
	(.048)	(.047)
Relative Unemployment	-.797**	-.777**
	(.266)	(.260)
Unskilled Wage	-.003**	-.003**
	(.001)	(.001)
Relative Wage	5.132**	4.846**
	(.714)	(.753)
Manuf Jobs	-.099	-.098
	(.053)	(.053)
Out of Wedlock Births	.367**	.370**
	(.130)	(.129)
$\mathbf{R^2}$	.983	.983
N	1431	1431

**$p < .01$, two-tailed
*$p < .05$, two-tailed

Note: Column entries are unstandardized slope estimates, with panel corrected standard errors (PCSE) in parentheses. All models were estimated with the inclusion of unit effects (i.e., state dummies). All estimates were generated by STATA 8.0, using the XTPCSE procedure.

Appendix

The Target Tracking Estimation Procedure

Using the target tracking procedure, we estimate missing values of a variable, X, that has been observed for state S in year t1 and then later in year t2 (but not in between). Estimates are based on the trajectory of a variable, to be called TARGET, which has been observed in years t1, t2, and all years in between. Let

DIFFX = X(t2) - X(t1) [i.e., the change in X over the period between t1 and t2],

and let

DIFFTAR = TARGET(t2) - TARGET(t1) [i.e., the change in TARGET over the same period]

Assuming DIFFX and DIFFTAR have the same sign (both positive or both negative), for each year t later than t1 but earlier than t2, calculate:

RELTAR(t) = TARGET(t) - TARGET(t1).

Then, calculate the size of RELTAR relative to DIFFTAR:

FACTOR(t) = RELTAR(t) / DIFFTAR

Finally, estimate a value of X, labeled XNEW by multiplying DIFFX by FACTOR and adding the product to the initial value of X:

XNEW(t) = [(FACTOR(t))(DIFFX)] + X(t1).