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**Instrumental Variable Estimates
of the Labor Market Spillover Effects
of Welfare Reform**

Upjohn Institute Staff Working Paper No. 02-078

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Abstract

By increasing the labor supply of welfare recipients, welfare reform may reduce wages and increase unemployment among other less-educated groups. These “spillover effects” are difficult to estimate because welfare caseloads decrease in response to improvements in the economy, which leads caseload reductions to be associated with improvements in labor market outcomes. This paper corrects for the endogeneity of caseloads by using instruments that reflect policy. The estimates suggest that welfare reform has significant spillover effects: welfare reform reduces employment of male high school dropouts, and reduces wages of single mothers and male high school dropouts.

INTRODUCTION

The welfare reforms of the 1990s likely increased the U.S. labor supply of lower-education single mothers by more than one million persons (Bartik 1998; Bartik 2000). An important unsettled issue is the effect of welfare reform on wages and employment of persons who do not receive welfare, that is, welfare reform's "spillover effects." These spillover effects have been infrequently estimated. Most of these estimates rely on indirect evidence from more general labor market models. Other estimates inadequately deal with statistical problems due to the endogenous response of welfare caseloads to economic conditions.

In this paper, I estimate models that pool time-series and cross-section data from the Current Population Survey on the state-year cell means of wages, employment, and other labor market outcomes for various demographic groups. These labor market outcomes are dependent variables that are related to control variables and the state's welfare caseload.

A key contribution of this paper is that the endogeneity of caseloads is corrected for with a rich set of instrumental variables. The econometric problem in estimating the causal effects of declines in welfare caseloads on labor market outcomes is that welfare caseloads are endogenously determined by the state's economy. A stronger state economy will reduce welfare caseloads and improve labor market outcomes, leading to the appearance that caseload declines cause labor market outcomes to improve. But I seek to estimate causal effects on labor market outcomes of caseload declines due to welfare reforms. To do so, I treat state welfare caseloads as endogenous and use ten instrumental variables that reflect state welfare reform policies.

The resulting estimates indicate significant spillover effects of welfare policies. Among other effects, welfare reforms reduce the wages of male high school dropouts.

The next section of this paper presents theoretical discussion of welfare reform effects and a review of previous research. I then go on to discuss this paper's model, data, and estimation techniques, and present the results.

WELFARE REFORM'S SPILLOVER EFFECTS: THEORY AND PREVIOUS RESEARCH

The main emphasis of recent welfare reform in the United States has been to make it more difficult for persons to get on—or stay on—welfare. This wave of welfare reform began in 1993 when the Clinton administration gave many states far-reaching waivers from federal welfare rules. Most of these waivers allowed states to be tougher in standards for welfare eligibility or requiring work. The 1996 federal welfare reform act that set up the Temporary Assistance for Needy Families (TANF) program gave all states much greater freedom to carry out restrictive welfare reform policies. TANF also set minimum standards requiring each state to increase work among welfare recipients or reduce welfare caseloads.

The most obvious labor market effect of welfare reform has been the resulting increase in the labor supply of single mothers. As Figure 1 shows, since 1993 the precipitous decline in welfare caseloads has been accompanied by a dramatic increase in labor force participation rates of single mothers, compared to other females with modest education.

To begin the discussion of the likely effects of this labor supply shock, I consider a simple labor market model. This model illustrates why it is difficult to come up with convincing theoretical predictions of welfare reform spillovers.

The model considered is a partial equilibrium model of the low-wage labor market, and assumes involuntary unemployment. The model includes a labor supply equation that expresses the labor supply of low-wage workers as a function of their wage and their unemployment rate, the labor demand for such workers as a function of their wage and unemployment rate, and a “wage curve” that expresses wages as a function of the unemployment rate. Unemployment is a realistic assumption for the low-wage labor market. A wage curve can be rationalized by “efficiency wage” models in which employers find it profit-maximizing to pay above-market-clearing wages (Blanchflower and Oswald 1994). Above-market-clearing wages may increase profits by increasing worker morale, as well as increasing the opportunity cost of being fired, reducing quits, and making hiring easier.¹

This model can be solved for the percentage change in employment and wages in the low-wage labor market due to an increase in labor supply, such as might be brought about by welfare reform. Table 1 performs this exercise under various assumptions about the model’s structural elasticities. (The model equations and solutions are presented in this table’s notes.) The new workers entering the low-wage labor market reduce the wages of all the workers in this market. The increase in employment is less than the number of new workers entering the labor market, with the difference indicating displacement of some of the original workers from employment. As Table 1 shows, the magnitude of these wage and displacement effects depends upon the structural elasticities.

¹For those who don’t like wage curve models and/or involuntary unemployment, the unemployment rate can be held fixed by assuming an infinite elasticity of wages with respect to unemployment in the wage curve. This fixed unemployment will then be some frictional or structural amount determined by the flow of information in the labor market and the matching of workers and jobs.

This theoretical analysis suffers from several problems. First, we have not reached a consensus about the structural elasticities of labor supply and labor demand. There is disagreement over whether unemployment and a wage curve should be included in such analyses, and wide disagreement over the elasticity of labor demand with respect to wages in the low-wage labor market. The immigration literature, which finds that increased immigration in a local labor market has slight effects on local wages, has been interpreted as implying that the demand for low-wage labor is quite sensitive to the wage (Johnson 1998; Borjas, Freeman, and Katz 1997). The minimum wage literature, which finds modest negative effects of the minimum wage on employment, has been interpreted as implying small elasticities of demand for low-wage workers (Bartik 2000, 2001; Katz 1998).

Second, it is not clear how to define the low-wage labor market. Which education levels are part of the low-wage labor market? Are low-wage men and women part of the same labor market? Whether an increase of one million persons in labor supply is a large or small percentage increase depends upon how large one defines the relevant labor market.

Third, this partial equilibrium labor market omits spillover effects on types of labor that are substitutes or complements for low-wage labor. Such effects can be calculated by specifying a general equilibrium labor market model, as has been done, for example, in Bartik (2000), (adopting a model originally used by Johnson [1998]), but we know little about the cross-elasticities of labor demand for different labor types, which are crucial in determining such models' results. As Hamermesh states in his authoritative review, "Knowledge of the extent of substitution among various groups of workers is not well developed" (Hamermesh 1993, p. 136).

Finally, welfare reform may have more complex effects than simply increasing the labor supply of welfare recipients or persons who would have received welfare but for the reform. Welfare reform could affect the labor supply of single mothers who would not have been on welfare even without welfare reform, but who had some chance of being on welfare in the future. These women may increase their labor supply behavior because of a reduced “safety net.” Welfare reform could also alter the wage curve by making some individuals more reluctant to quit and more eager to take jobs, both of which will lower wages for a given unemployment rate. Welfare reform could also reduce the bargaining power of labor versus businesses, which could lower the wage for a given unemployment rate. The increased labor supply of ex-welfare recipients who receive low wages may decrease the wages that most workers consider fair, which will also affect the wage curve. Publicity about welfare reform may increase the interest of some employers in hiring ex-welfare recipients.

The few previous studies of the spillover effects of welfare reform are summarized in Table 2. I have adjusted the effects predicted by these studies to a labor supply increase due to welfare reform of 1.4 million persons, based on the review of the literature in Bartik (1998, 2000). Some studies (Mishel and Schmitt 1995; Holzer 1996; Bernstein 1997, The Lewin Group 2001) focus on welfare reform’s effects on a low-wage labor market using partial equilibrium models, with demand and supply parameters derived from previous research, and the scope of the low-wage labor market derived by intuition, which results in larger negative effects of welfare reform on wages if the labor market affected by welfare reform is assumed to be of modest size.

Enchautegui (2001) estimates labor demand by estimating cross section equations in which factor shares for labor types in an MSA from the 1990 Census are estimated as a function of the

quantities of each labor type in the MSA. She finds that welfare reform will have large negative effects on wages of welfare recipients, other less-educated women, and male high school dropouts.

Lerman and Ratcliffe (2001) find no correlation between increases in the labor supply of single mothers in different cities and wage trends of single mothers and other less-educated groups in these cities. The limitation of this analysis is that increases in the labor supply of single mothers will endogenously respond to improvements in city labor market conditions.

Lubotsky (2000) examines the effects of Michigan's abolition in 1991 of its general assistance program, which exogenously increased the labor supply of general assistance recipients in Michigan compared to other states. Lubotsky does a quasi-experimental analysis of "differences in differences in differences," in which trends in Michigan versus other states for potentially affected groups are compared to trends in Michigan versus other states for other groups. Lubotsky's point estimates suggest that the abolition of general assistance may have reduced wages of female high school dropouts but not male high school dropouts. Estimated effects are generally not statistically significant, however, and are sensitive to the specification.

Bartik (2000) considers several models of how welfare reform affects wages and employment. Bartik's first model is a general equilibrium model derived from Johnson (1998). Welfare reform's effects on the wages of less-educated women vary from a decline of 1 percent to a decline of 15 percent. Welfare reform decreases wages by 1 percent if different types of labor are readily substitutable, and welfare recipients are assumed to be part of the relatively large labor market of "high school graduate equivalent" women. Welfare reform decreases wages by 15 percent if a separate

labor market is assumed for female high school dropouts, and substitutability between this group and other labor market groups is limited.

Bartik's second model is a wage curve model with five labor market groups, with single mothers as one group, and more and less-educated men and women comprising the other four groups. The labor supply, labor demand, and wage curve equations of the model are estimated using pooled time-series cross-section data on state-year cells. Welfare reform is analyzed as an increase in labor supply, particularly for single mothers. The model predicts that welfare reform will cause wage declines of two percent for single mothers and wage declines almost as great for other groups, as the model suggests strong relationships among the wages of different groups. However, because relative wages don't change much and the model estimates modest responses of relative labor demand to relative wages, welfare reform has large effects on the unemployment rate of single mothers, pushing unemployment rates of this group up in some years by over 4 rate points. The validity of this model depends upon whether welfare reform can be modeled as only increasing labor supply, rather than shocking other equations.

Bartik's third model is a reduced form model using data on the same five groups from 1979 to 1997. In the model, labor market outcomes for groups for a state/year cell are directly estimated as a function of state welfare caseloads. The instrumental variable used is whether the federal government gave the state a waiver from federal rules during that year, with all states assumed to have a waiver in 1997 (after TANF was adopted in 1996). The estimates suggest that welfare reform has large negative effects on the wages of single mothers. No significant effects on unemployment are found, but the point estimates suggests welfare reform may increase unemployment of less-educated men and lower

unemployment of single mothers. A limitation of this study is that it relies on just one instrumental variable which is a zero-one dummy.

MODEL, DATA, ESTIMATION AND SIMULATION TECHNIQUES

The model equations are estimated using data in which each observation is on a state/year cell, and the estimation uses pooled data for all states and years from 1984 to 2000. The dependent variable is a mean labor market outcome for a group in a state/year cell. Separate equations are estimated for each dependent variable and group. The dependent variables considered are wages, unemployment rates, employment to population ratios, and labor force participation rates. The groups considered include single mothers, and other women and men divided by education level. The key independent variables of interest are current and lagged values of a state's average welfare caseload per capita. Current caseload per capita is treated as endogenous, because a state's labor market outcomes may affect the caseload. Instrumental variable estimation (two-stage least squares) is used to correct for this endogeneity. The instruments measure exogenous policy variables that shift the welfare caseload independently of the economy. The equations also include lagged dependent variables, dummy variables to control for state and year fixed effects, and current and lagged values of a variable controlling for shifts in labor demand due to national demand for the state's industry mix.

The equations estimated can be written as

$$Y_{jgst} = B_{jg0} + B_{jgw}(L)(WCPC)_{st} + B_{jgy}(L)Y_{jgst-1} + B_{jgd}(L)D_{st} + F_{jgs} + F_{jgt} + e_{jgst},$$

where Y_{jgst} is labor market outcome j for group g in state s , during year t , where labor market outcomes include wages, unemployment rates, employment/population ratios, and labor force

participation rates. Groups include all persons ages 20–64, and these are divided into seven sub-groups which include single moms, women who are not single moms divided into three educational categories: high school dropouts, high school graduates who have not graduated from college, and college graduates; and men who are divided into these same three education categories. $WCPC_{st}$ is the average monthly welfare caseload per capita in state s during year t . Y_{jgst-1} is the one-year lag of the dependent variable. D_{st} is the ratio of predicted employment in state s and year t to employment in state s and year t during a base year (1984), with the prediction derived by assuming that the state's industries grew at their national average between the base year and year t . F_{jgs} and F_{jgt} indicate that each equation includes dummies for state and year fixed effects. The B represents estimated coefficients, and the “ jg ” subscripts indicate the differing coefficients for each of the 32 equations estimated (four outcomes times eight groups). The $B(L)$ notation indicates that a number of lags in the variable to the right are included in the estimation, with each lag having a freely estimated coefficient (lag length determination is discussed below).

In the estimation, the current $WCPC_{st}$ variable is treated as endogenous, whereas lags in this variable are treated as exogenous. A set of instruments is used to estimate each equation separately by 2SLS, with the instruments proxying for changes in caseloads that are independent of the economy and caused by policy. The instruments are discussed further below.

What are these equations estimating? The equations are not structural labor supply or demand equations. Instead, they should be interpreted as reduced form equations that express outcomes as a function of exogenous policy shocks to welfare caseloads. As discussed in section 2, the labor market has many labor supply, labor demand, and wage curve equations that determine each group's wages,

employment, and labor force. These variables help determine welfare caseloads, but caseloads are also determined by policies, independent of variables that shock the labor market. These reduced form equations examine shifts in labor market outcomes associated with non-labor market related shifts in welfare caseloads.

What is the rationale for this specification? The inclusion of lagged *WCPC* and *Y* allows complex dynamics in how welfare caseloads affect labor market outcomes. We expect dynamic behavior because elasticities of labor supply, demand, and wage curves vary over time. The lagged caseload is also included because the caseload determinants literature suggests that state welfare caseloads are highly persistent (Figlio and Ziliak 1999; Bartik and Eberts 1999; Klerman and Haider 2001). Predictions of caseloads are more accurate if the lagged caseload is a predictor, and the inclusion of the lagged caseload changes the effects of policy variables on welfare caseloads (Moffitt 2002). Therefore, it is desirable to include the lagged caseload in the first- stage equation used to predict the current caseload. If the lagged caseload is used in the first-stage equation, however, it cannot be validly excluded from the second-stage equations explaining labor market outcomes. Once the lagged caseload is included, should it be treated as endogenous? If it is endogenous, the lagged caseload cannot be used to predict current caseload in the first-stage estimation, making this first-stage estimation less accurate. In addition, instruments would be needed that differentially affect current caseload versus lagged caseload, and such instruments are difficult to find. The lagged caseload will be endogenous if no lagged dependent variables are included, as the lagged caseload will be correlated with lagged outcome variables that are correlated with current economic outcomes. If lagged dependent variables are included in the estimation, however, it is more plausible that the lagged

caseload will be uncorrelated with the current residual—i.e., exogenous. The lagged caseload could be viewed as predetermined, and by controlling for lagged dependent variables, the specification controls for the lagged outcomes that most strongly affect the dependent variable.

The “industry mix” demand prediction partially controls for the shifts in labor demand that lead to reverse causation from labor market outcomes to caseloads. We do not want to control for overall employment growth (as it might be affected by welfare reforms), but state employment growth is affected by interactions between the state’s “industry mix” and national growth by industry. This “industry mix” or “share” prediction has been shown to proxy for shifts in national demand for the state’s “export base”: goods or services in which the state specializes that are traded among states (Bartik 1991, Appendix 4.2).

Year dummies allow for national forces that affect all states’ labor market outcomes, such as national economic cycles or growth trends. State dummies control for fixed characteristics of states that might affect labor market outcomes, such as amenities that attract people or business.

Data on Dependent and Right-hand Side Variables

Data on the dependent variables come from the Outgoing Rotation Group (ORG) of the U.S. Current Population Survey. The dependent variables used are the mean ln (real wage), unemployment rate, employment-to-population ratio, and labor force participation rate, all of which are measured in unit-free percentage terms. The means calculated are weighted means using appropriate ORG weights. The unemployment, labor force participation, and employment- to-population ratio variables are standard. The wage is defined as usual weekly earnings divided by usual weekly hours and there is

some editing of individual wage observations before calculating means to eliminate outliers that result from misreporting.²

The sample used to calculate means was restricted to 20–64 year olds to ensure that the data reflects most full-time labor market activity, but avoids the main time periods for retirement and schooling. A single mother is defined as an unmarried female whose child lives in the same household. The first year in the CPS-ORG in which mother-child relationships can be identified was 1984, so this is the first year used in estimation. The education groupings (high school dropout, high school grad, college grad) were chosen to maintain a reasonable sample size for each group for each state-year cell, yet maximize similarity among individuals within a group. Persons with some college were grouped with persons with only a high school degree because wage trends for the “some college” group are more similar to the “high school degree only” group than to the “college graduate” group (Bartik 2000). The sample size for each of these eight groups is adequate for calculating state-year cell means. The minimum sample size used to calculate labor force participation and employment-to-population ratios across all eight groups is 46 persons. Of the state-year cell means for the labor force and employment variables, 99 percent have a sample size of 75 persons or greater, and 95 percent have a sample size of 106 or greater. (The sample size is somewhat lower for the unemployment and wage variables, as these are only calculated for labor force participants or the employed.)

Table 3 shows national means for some variables. Men and persons with more education work more and have higher wages. The single mother group is more similar to male high school dropouts in

²Outliers are defined as real wage rate (1999 dollars) less than \$2.00 per hour, or more than \$250 per hour, or usual weekly hours less than 10 and real wage more than \$100 per hour. No adjustments are made for the top-coding of usual weekly earnings in the CPS, which is controlled for in part by year and state dummies.

labor market outcomes than single mothers are to female high school dropouts. Also, the labor force participation rate and employment-to-population ratio for single mothers increased significantly from 1993 to 2000. Real wages went up during the 1993 to 2000 economic boom for all groups, but went up the most for the more educated. Unemployment rates went down for all groups and employment-to-population ratios went up, but by greater amounts in absolute value for low-education groups. These trends are consistent with other analyses of the 1990s (Mishel, Bernstein, and Schmitt 2000).

The groupings are designed so that the single mother group comprises a clear majority of the welfare caseload. As a result, only for the single mother group might the estimates be significantly distorted by “compositional effects.” Compositional effects occur if persons in a group who leave welfare and join the labor force have significantly different wages or unemployment rates from others in the group. If this occurs, the group’s mean wages and unemployment rates will be altered by welfare reform, even if there are no spillover effects of welfare reform on persons in the group who did not recently leave welfare. Spillover effects on a group’s labor market outcomes would be proportional to the reduction in caseloads relative to the size of the group. Compositional effects would be proportional to the reduction in caseloads of members of that group relative to the size of the group. Therefore, the importance of compositional effects in altering estimated spillover effects for a group is proportional to that group’s share of the caseload. Sixty to seventy percent of the welfare caseload lies within the single mother group.³ The share of the welfare caseload in other groups is never more than

³It might be surprising that in 2000 only 60 percent of the adults ages 20–64 who are on welfare are single mothers. Welfare status is measured as of a typical month the previous year, whereas marital status and presence of an “own minor child” is measured as of the March interview. Some of those who are married or who do not have a minor child as of March would have been a single mother while receiving welfare the preceding year. Eighteen percent of TANF adult recipients are married (U.S. Department of Health and Human Services 2000, Table 10:13).

17 percent, and for the male groups is always less than 10 percent. Compositional effects will be further considered in analyzing the results.

Welfare caseload data comes primarily from the U.S. Department of Health and Human Services. Annual average monthly caseloads are calculated from the original monthly data, per capita caseloads were calculated by dividing by the state's mid-year population.⁴ Such scaling is needed because the labor market effects of welfare caseloads should depend on the size of the caseload relative to the state's labor market.

The "industry mix" demand prediction variable uses two-digit industry employment data for each state in 1984, the first year used in estimation.⁵ The employment level for each state as of year t is predicted assuming that each two-digit industry grew at its national average from 1984 to t , and then the resulting predictions are scaled so that each state equals one in 1984. The resulting equation for creating this variable is

$$D_{st} = \sum_i (E_{s84i}/E_{s84})(E_{nti}/E_{n84i}),$$

where E_{s84i} is state employment in 1984 in industry i , E_{s84} is total state employment in 1984, E_{nti} is national employment in year t in industry i , and E_{n84i} is national employment in 1984 in industry i .

Nine percent of TANF children are living with a head of household who is not their parent, such as their grandparent (U.S. DHHS, Table 10:26).

⁴Some editing was done where a state's data exhibited large monthly jumps. Some states are inconsistent in what categories of welfare cases, particularly TANF cases, are reported to DHHS. Adjustments were done by finding months in which data series overlapped, then doing percentage adjustments so that all months were adjusted to the most comprehensively defined welfare case.

⁵These two-digit data were used in previous studies of mine, and were originally derived from ES-202 data from the U.S. Department of Labor. Data suppression was overcome by interpolation and extrapolation. Bartik (1993) provides details.

Instrumental Variable Estimation

Instrumental variable estimation of the model is needed because the welfare caseload is endogenous. The caseload is endogenous because it depends on the economy: the caseload will decrease if labor market outcomes improve for single mothers. This reverse causation leads to a statistical association between caseload declines and better labor market outcomes for single mothers, and, because labor market outcomes are positively correlated across groups, better outcomes for other groups. On the other hand, by increasing the labor force of single mothers, welfare-reform-induced caseload declines may worsen wages and unemployment for single mothers and other competing groups. (Reform-induced caseload declines will be similar to economically-induced caseload declines in being associated with increased labor force participation and employment of single mothers, but the size of these effects may be greater for reform-induced caseload declines.) The observed association between labor market outcomes and welfare caseloads depends upon what shocks dominate the data.

The solution to this estimation problem is to correct for the endogeneity of the current caseload variable using instrumental variables. These instruments reflect shocks to the welfare caseload that are associated with policy, and are independent of the economy. I use ten instrumental variables, which fall into five types. First, I include a variable indicating whether the state had been granted a statewide “waiver” from federal welfare rules. Starting in 1997, after TANF, all states are considered to have waivers. The waiver data were originally obtained from Phil Levine (Levine and Whitmore 1998).⁶

⁶For all state/year cells without a waiver, which includes all states prior to 1993, the waiver variable is zero.

Second, I include three TANF spending variables. TANF switched the federal funding of welfare from a matching grant to a fixed grant. Prior to TANF, the matching percentage depended on state income. I assume that this matching percentage is captured mostly by state and year dummies. After TANF, states received a federal welfare grant fixed in nominal dollars and based on the highest amounts received by the state from the federal government for some previous years under the old welfare system. States were required to maintain 75 percent of their previous state welfare spending. Finally, 17 states received supplemental welfare grants starting in 1998, with the supplement going to states with above-average population growth and a low level of federal welfare grants. All three of these variables were specified in real per capita terms and used as instruments (Committee on Ways and Means 2000, Tables 7-1 and 7-2).⁷ Greater funds could lead to less pressure to reduce caseloads, or on the other hand, they may enable states to devote more resources to support services that reduce caseloads.

Third, there are three political instrumental variables: dummy variables for whether a Republican is governor, whether Republicans control both houses of the state legislature, and whether Democrats control both houses. The ideologies and constituencies of the two parties suggest that Republican control would reduce caseloads. Although a downturn in the state's economy may lead to a switch in party control, the state's level of economic activity is not obviously correlated with party control.

⁷For all years prior to 1997, the TANF spending variables are zero for all states, as fixed grants were not used to fund welfare prior to TANF.

Fourth, two instrumental variables reflect the TANF sanctions policy. States can reduce caseloads by sanctioning welfare recipients for violating a welfare rule, for example missing an appointment with a caseworker. I use two sanctions variables taken from a paper by Pavetti and Bloom (2001), which are dummy variables for “moderate” sanctions and “stringent” sanctions. Stringent sanctions are those that either cut off the entire family immediately from TANF payments, or else gradually cut off the entire family from TANF payments but immediately cut off all food stamp and Medicaid benefits (25 states have these sanctions policies). Moderate sanctions are gradual full family sanctions but no sanction of food stamps or Medicaid, or a partial sanction on TANF benefits with a 100 percent sanction on food stamps (13 states). All other sanction policies are considered lenient. These sanctions dummies are only allowed to have a value of one from 1997 to 2000; all states are assumed to lack sanctions prior to 1997.

Finally, an instrumental variable is constructed that estimates the probability of being on welfare in a state/year cell, controlling for the individual’s earnings and non-welfare income, and other individual characteristics. This variable was derived by estimating a model using a sample from the March Current Population Survey (March 1977 to March 2001) of 16–64 year old single mother heads of households.⁸ Using this sample, I estimated a logit model of the probability of the single mother receiving welfare during the preceding year. This was estimated as a function of sets of dummy variables for the single mother’s characteristics: education, race, mother’s age, age of youngest child, number of children, family wage and salary income, other income than wage or salary and welfare, and

⁸The longer sample period than for the CPS-ORG was used, first, because comparable data were available for a longer period in the March CPS than in the CPS-ORG, second, because a longer time period allows greater precision, and third, because I will use these predictions for other projects.

the state/year cell.⁹ After estimating this model, I calculated the probability of being on welfare for each single mother in the March 2001 sample if they had lived in one particular state/year cell, and then calculated the mean of this hypothetical probability over the March 2001 sample. That is, the coefficient on a particular state-year dummy was substituted for the coefficient for the individual's actual state and year. The resulting calculated probabilities for each state-year cell show the probability of single mothers being on welfare in that state and year, holding constant the characteristics of single mothers by setting them to the values observed in the March 2001 sample. This calculation holds constant many economic influences on caseloads by holding the level and distribution of earnings and nonwelfare income among single mothers constant.¹⁰

In this sample, the unadjusted national average percentage of single mothers on welfare declines from 30.3 percent for 1993 to 10.2 percent in 2000. The adjusted percentage predicted to be on welfare, using the estimated coefficients and the national sample's characteristics in March 2001, declines from 19.4 percent in 1993 to 10.1 percent in 2000.¹¹ These figures suggest that of a total decline in the percentage on welfare of 20.1 percent (30.3–10.2), at least 9.3 percentage points (19.4–10.1)—or 46 percent—is due to policy.¹²

⁹Appendix 1, available from the author, reports coefficient estimates for the logit estimation.

¹⁰David Ellwood has independently done similar calculations (Ellwood 2001).

¹¹Note that the predicted percentage on welfare is not precisely equal to the actual for 2000, which occurs because the estimation procedure is nonlinear.

¹²Such calculations may understate the effects of welfare reform because reform increases single mothers' earnings. However, to create a valid instrument, it is critical to identify caseload declines that are clearly due to policy, rather than to encompass all policy-induced caseload declines.

Another Estimation Problem: Serial Correlation and Lag Length

As is well known, serial correlation in the equation residual will lead to biased estimates if the equation includes a lagged dependent variable, as this lagged dependent variable will then be correlated with the current residual. Corrections that are usually made for such serial correlation use further lags in exogenous right-hand side variables as instruments under the assumption that the original lag length is correct. This assumption seems questionable. Instead, I assume that any serial correlation reflects a misspecification, in that the equation omits some variables that are serially correlated. The solution for this misspecification is to include these omitted variables. The most obvious omitted variables to add to the specification are further lags in the right-hand variables.¹³

Therefore, in choosing an optimal lag length, I add lags if this is needed to eliminate serial correlation; I also add lags if these lags add significant explanatory power. The selection procedure begins with a general model, restricts it to a narrower model, and then gradually extends that narrower model. First, I estimate all equations with eight lags in all right-hand side variables, which eliminates all serial correlation from the residuals for all groups and all variables.¹⁴ For each dependent variable and group in this eight-lag specification, I did a series of F -tests, each a test of the significance of all lags from m lags to eight lags, with m varying from two to eight. I chose as my initial starting point for subsequent investigation for that dependent variable and group the minimum lag length q , for which all

¹³The standard tests for serial correlation with lagged dependent variables add a lagged residual to the original equation and test its significance (Davidson and MacKinnon 1993, pp. 358, 370). This, essentially, is asking if one more lag in all right hand side variables is significant.

¹⁴All serial correlation tests are the Gauss-Newton regression tests described by Davidson and MacKinnon (1993, p. 370).

lag lengths from $q+1$ through eight are insignificant at the 1 percent level using an F -test. I reestimated the model with the full sample available using a lag length of q and tested for serial correlation. If the serial correlation test was insignificant at the 5 percent level at lag length q for that group and dependent variable, I reestimated this same model at lag length $q+1$ and tested for the statistical significance of the added lag. If the added lag was insignificant at the 5 percent level, I decided that lag length q was the optimal model. Alternatively, if either there was significant serial correlation at lag q , or lag $q+1$ was statistically significant, then the entire procedure was repeated at lag $q+1$. This process continued until an optimal lag length was chosen for each group and dependent variable. At this optimal lag length, by construction there is no serial correlation and the next lag is statistically insignificant (except for the few cases in which the optimum is eight lags).¹⁵ Table 4 shows the optimal lag lengths: of 32 equations, 6 have a lag length of one, 16 of two or less, 20 of three or less, and only 3 are at the maximum lag length of eight.

Simulations

I use the model's estimates to simulate the effects of the welfare reform-induced reductions in caseloads that have occurred since 1993. To calculate the welfare-reform induced declines in the national caseload, I used Blank's estimates (Blank 2001, Table 2, column 1) of the influence of the

¹⁵An alternative estimation procedure would use the Akaike Information Criterion (AIC) or Schwartz's Bayesian Criterion (SBC) to choose an optimal lag length. However, either AIC or SBC would need supplementation with some addition of lags to eliminate serial correlation.

unemployment rate on the welfare caseload per capita.¹⁶ I calculated the changes in the caseload that have occurred since 1993 due to changes in national unemployment and the remaining change in the caseload is assumed to be due to welfare reform.

Interpreting these simulations as the effects of “national” welfare reform requires some heroic assumptions. The model is estimated using pooled time-series cross-section observations on state-year cells, with year effects held constant. The simulation effects represent the impact in a typical state of implementing the percentage caseload reductions of national welfare reform, with all other states’ policies held constant. If all states were to change their welfare reform policies, we would expect national year effects to change.

How will these national year effects change? If all states change their welfare policies, this reduces the incentives of labor and capital to move. Labor and capital mobility will cause welfare reform’s effects on wages and unemployment to be reduced in size. On this basis, a nationwide caseload reduction would have greater labor market effects than a similar percentage reduction in caseloads in one state. But in addition, national welfare reform policies will have greater macro/general equilibrium effects. National welfare reform might change national wages enough to have price effects, reducing real wage effects. These price and wage changes might lead to changes in Federal Reserve policy. A national labor supply increase due to lower welfare caseloads will increase national income

¹⁶I chose Blank’s model because it is well-known and uses a dependent variable that is identical to my caseload variable (caseload per capita). I used her sparse model because it forces all the economic variables to enter via the unemployment variable, which is the only one of Blank’s economic variables that I can easily measure for each year.

and, hence, increase labor demand, causing some of welfare reform's detrimental labor market effects to be reduced in size.

This paper's simulation effects of "national" welfare reform only represent national effects if the mobility effects of welfare reform in just one state, and the general equilibrium/macro effects of national welfare reform, have effects on labor market outcomes that on net are small. This is certainly possible. Low-education workers are less mobile than other workers, and are only one part of the labor market, reducing the influence of welfare reform on capital mobility. General equilibrium effects of changes in this one part of the labor market could be modest.

RESULTS

In this section, I consider, first, the validity of the instruments. I then summarize the implications of the main results, and examine the overall effects of welfare reform.

Instruments

Although the instruments make sense theoretically, whether they correct for the biases in OLS estimation in practice depends upon the instruments' explanatory power. Instrumental variable estimation in finite samples is biased towards the OLS estimates. The bias of Two Stage Least Squares (2SLS) relative to OLS is approximately equal to one over the F -statistic on the instruments in the first stage equation predicting the endogenous variable (Bound, Jaeger, and Baker 1995).

Table 5 reports the F -statistics on the instruments from the first stage of two-stage least squares. Twenty of the 32 first-stage equations have an F -statistic of between 2.5 and 3.5. The bias in two-stage least squares estimation will be 30 to 40 percent of the bias in OLS estimates.

Another issue is the question regarding which instruments do the best job predicting welfare caseloads, and whether or not their estimated effect on caseloads is reasonable.¹⁷ The first-stage results suggest that the adjusted probability of single mothers being on welfare, adjusted for the earnings distribution of single mothers, has statistically significant positive effects on the welfare caseload. A Republican governor reduces caseloads by a statistically significant amount, whereas Democratic control of both houses of the state legislature has positive effects on caseloads that are marginally statistically significant. Both moderate and stringent TANF sanctions have similar negative effects on caseload, although these effects are only of marginal statistical significance. Basic TANF grants per capita have negative effects that are marginally statistically significant. These negative effects may occur because these particular states have greater resources to provide support services for welfare-to-work programs under TANF, or because their pre-TANF welfare policies deviated more from what the state's political system desired. Overall, the effects of the different instruments on welfare caseloads seem consistent with expectations.

¹⁷Appendix 2, available from the author, reports typical first-stage coefficients for the ten instruments.

2SLS and OLS Estimates

To summarize the results, Table 6 focuses on the short-run and long-run effects of welfare caseloads, as estimated by both OLS and 2SLS.¹⁸ The short-run effect of caseloads can be immediately derived from the coefficient on the current caseload variable. The long-run effect on caseloads is the sum of the coefficients on the caseload variables, divided by one minus the sum of the coefficients on the lagged dependent variable.¹⁹ To make these short-run and long-run effects “unit-free,” the units are rescaled so the effects represent 100 times the change in the dependent variable for a change in caseload per capita of 0.000192, which is 1 percent of the national caseload per capita in 1993. Because the dependent variables are calculated so that 0.01 can be considered a 1 percent change, the resulting effects can be interpreted as short-run and long-run “elasticities.”

The OLS results in Table 6 are consistent with the notion that OLS estimates are biased because the economy affects caseloads. The OLS estimates suggest that welfare caseload declines are associated with improvements in labor market outcomes for less-educated groups, reducing unemployment in both the short-run and long-run, and increasing wages, employment- to-population ratios, and labor force participation rates in the long-run. The strength of these estimated beneficial “effects” of caseload decline for many less-educated groups suggests that the OLS-estimated coefficients actually reflect a reverse causation, with a strong state economy boosting labor market outcomes, which reduces caseloads.

¹⁸Appendix 3 to this paper, available from the author, reports the raw coefficient estimates for 2SLS for all variables except the state and year dummies.

¹⁹This assumes that the long-run equilibrium is stable. This is not explicitly tested, but simulations over a ten-year period suggest that the long-run equilibrium is stable for all 32 equations estimated by 2SLS.

The 2SLS coefficients are quite different, and are consistent with a more reasonable explanation of how reform-induced declines in welfare caseloads might affect labor market outcomes. The 2SLS estimates suggest that welfare reform causes significant short-run and long-run increases in the labor force participation rate of single mothers. This increase results in some short-run displacement from employment of male high school dropouts, whose employment-to-population ratio drops. The labor supply shock due to welfare reform also results in some significant short-run reductions of wages, concentrated on single mothers and male high school dropouts. Over time, welfare reform's effects on single mothers' labor force participation is reduced, perhaps because single mothers respond to their lower wages. The lower wages persist for male high school dropouts but wages increase for some more-educated groups, such as female high school graduates, male high school graduates, and male college graduates. This may reflect some long-run increase in demand for these groups' labor as complements to the greater supply of labor by single mothers.

The magnitude of the estimated effects cannot be explained by compositional effects. Consider the labor force participation effects for single mothers: in a typical month in 1993, 25.3 percent of this group received welfare (see Table 3). A 1 percent decline in the caseload would reduce the percentage of the single mother group on welfare by 0.253 percent. Even if this increased the labor force participation rate for these persons from zero to one, the estimated elasticity due to this effect alone would be -0.253 . The actual estimated short-run elasticity in Table 6 is -0.625 , which is about two-and-a-half times as great. This suggests that reform-induced caseload declines cause some single mothers who would not have received welfare, but might have been at risk of needing welfare in the future, to enter the labor market. The labor supply shock from welfare reform is considerably greater

than would be predicted by just looking at the change in caseloads and the relative labor force participation of recipients and non-recipients.

Reasonable calculations suggest that compositional effects could explain, at most, half of the elasticity of wages for single mothers reported in Table 6.²⁰ The rest must be due to spillover effects of welfare reform in reducing the wages of single mothers who were already in the labor force. If compositional effects cannot explain the wage effects for single mothers, they are even less likely to explain effects for other groups, such as male high school dropouts, that comprise a much smaller share of the welfare caseload. Most of the effects reported in Table 6 represent spillover effects of welfare reform on individuals who would not have been on welfare.

Finally, the magnitude of the effects of welfare reform on overall wages is difficult to explain by labor supply and demand elasticities. The short-run effects imply that a 1 percent decline in the welfare caseload will boost overall employment by 0.05 percent and reduce overall wages by 0.27 percent.²¹

Suppose that labor supply is completely inelastic with respect to wages. Then the relevant short-run

²⁰Data from the March 1994 CPS suggests that in March of 1994, single mothers who were on welfare the previous year had a $\ln(\text{real wage})$ that was lower by 0.49 than those not on welfare the previous year. The unemployment rate of this ex-welfare recipient group in March 1994 was 36.7 percent. Suppose that: 1) the true labor force shock of a 1 percent decline in welfare rolls is an increase in the labor force participation rate of 0.625 rate points; 2) this additional labor force earned $\ln(\text{wages})$ that were lower than average wages for single mothers by 0.49; and 3) the unemployment rate of these new labor force entrants is 36.7 percent. Then the new labor force entrants would increase the employment-to-population ratio of single mothers by 0.396 rate points ($0.396 = 0.625(1 - 0.367)$). The 1993 employment-to-population ratio of single mothers was 60.6 percent. If this additional employment had a $\ln(\text{wage})$ lower by 0.49 than the average single mother, then average $\ln(\text{wages})$ of single mothers would decline by $(-0.49)[0.396 / (0.396 + 60.6)] = -0.00318$. This corresponds to an elasticity of $\ln(\text{wage})$ with respect to $\ln(\text{caseload})$ of 0.318, which is less than half of the 0.827 in Table 6.

²¹The 0.05 percent boost in employment can be derived in several ways. First, the point estimates suggest that labor force participation will increase by 0.04 rate points. With an overall labor force participation rate of 0.789 in 1993, this is an increase in both the labor force and employment, of 0.05 percent. Also, just looking at single mothers by themselves, the increase in their labor force participation due to a 1 percent decline in the caseload is 0.625 rate points. But this group is only 6.4 percent of the population in 1993. The increase of single mothers in the labor force will increase the overall labor force participation by 0.064 times 0.625, resulting in an increase of 0.04 rate points.

demand elasticity is the factor price elasticity for overall labor, which demonstrates how the wage employers are willing to pay for overall labor varies with the quantity of labor—holding capital constant, but allowing output to increase with increased labor supply. Hamermesh's (1993) review of the labor demand literature suggests that a plausible factor price elasticity for overall labor is ≈ 0.3 , which implies that the percentage wage decline due to an overall labor supply increase is less than one-third of the percentage labor supply increase.²² Instead, the wage decline is five times the percentage increase in labor supply. The effects on overall wages suggest that welfare reform may have effects on wage norms that are not fully captured by simple labor supply and demand models.

Welfare Reform Effects

I used the 2SLS estimates to simulate the effects of welfare reform on labor market outcomes. As discussed in section 3, these simulations show the effects of a state adopting reforms that reduce caseloads by similar percentages to the national caseload's decline due to welfare reform. These simulations only show the national effects of welfare reform if mobility effects and general equilibrium effects do not cause significant biases from state-specific welfare reform to national welfare reform.

Table 7 reports estimated effects of welfare reform on welfare caseloads per capita, the labor force participation rate of single mothers, overall wages, and the wages of male high school dropouts,

²²This factor price elasticity of ≈ 0.3 is consistent with an output-constant elasticity of demand for labor of ≈ 0.3 . Hamermesh (1993) shows that the output-constant elasticity of demand for overall labor is $\approx (1-s)/SUB$, and the factor price elasticity is $\approx (1-s)/(1/SUB)$, where s is the factor share of labor and SUB is the elasticity of substitution between labor and capital. Research suggests that SUB is close to 1, and s is close to 0.7. The difference in slope of these two different demand curves is attributable to what is held constant (output or capital) moving along a locus of equilibrium combinations of wages and employment.

for each year from 1994 to 2000.²³ Figure 2 uses the estimated welfare reform effects on single mothers to show the actual trends in labor force participation rates of single mothers (1984 to 2000), and the trends that the simulation predicts would have occurred without welfare reform. The simulation suggests that without welfare reform, the labor force participation rates of single mothers would have shown much more modest increases.

Figure 3 uses the estimated welfare reform effects on overall wages to project what wage trends would have been without welfare reform, compared to what actually occurred. The results suggest that without welfare reform, overall real wages in the U.S. during the 1990s boom would have begun to increase sooner than they actually did. This assumes that Federal Reserve policy would not have been altered significantly if this had occurred. More pronounced real wage effects of the 1990s boom may have led to a different Federal Reserve policy and macro outcomes.

Figure 4 uses the estimated welfare reform effects on overall wages and male high school dropout wages to calculate how welfare reform affected trends in the wage differential. Male dropout wages decreased relative to overall wages throughout the 1984 to 2000 time period, but at a slower rate during the late 1990s. The simulations suggest that without welfare reform, this wage differential might have narrowed during the late 1990s boom.

This study's estimates of welfare reform's effects on the wages of male high school dropouts seem comparable to previous estimates of the maximum negative wage effects on disadvantaged groups

²³Appendix 4, available from the author, reports the full set of results for all groups, all dependent variables, and all years from 1994 to 2000.

(Table 2). However, the overall wage effects of welfare reform are considerably greater than one would expect based on previous studies.²⁴

CONCLUSION

This paper's results suggest that there are significant labor market spillover effects of welfare reform. In the short-run, welfare reform-induced declines in caseloads and increases in the labor force participation of single mothers may cause employment losses for less-educated males. Welfare reform also has some negative effects on real wages, particularly in the short-run. In the long-run, more educated groups gain wage boosts due to welfare reform.

These displacement and wage losses are significant spillover costs of welfare reform. On the other hand, the moderating effect of welfare reform on overall wage trends may have allowed macro policy to be more expansionary in the late 1990s, increasing the boom's duration.

These results strengthen the case for adopting policies to offset the negative spillover effects of welfare reform. The adverse wage trends of less-educated groups such as male high school dropouts are, in part, a consequence of welfare reform. If policymakers have contributed to the cause of these trends, there is greater political onus on them to alleviate them. Possible responses include expanding post-market wage subsidies to low income workers such as the Earned Income Tax Credit. In

²⁴Table 2 normalizes previous studies to a labor supply increase of 1.4 million. This is irrelevant to the current model because this model allows the caseload decline to have endogenously determined effects on labor supply. This model's assumed decline in caseloads due to welfare reform is somewhat less than in the scenarios used in the paper (Bartik 1998) that yielded the 1.4 million labor supply figure. In the current paper, welfare reform is assumed to have lowered caseloads since 1993 by 47 percent. In Bartik (1998), the reform-induced caseload decline, which yielded the 1.4 million labor supply increase, was 54 percent. On the other hand, the estimated labor force participation increase for all 20–64 year olds as of 2000 is 0.0179, on a 2000 population base of 161 million. This is a labor supply increase of 2.9 million, which is about twice the 1.4 million normalized figure.

addition, policymakers could consider ways to increase private and public labor demand for disadvantaged workers (Bartik 2001).

The results suggest that the magnitude of spillover effects should be explored for many labor market policies. Significant spillover effects might also occur due to job training and education policies.

Finally, researchers should continue to explore spillover effects by finding plausible quasi-experiments with some exogenous variation in policies, and we should also continue to develop a better understanding of wage determinants. This study suggests that the spillover effects of labor market policies go beyond what would be predicted by simple supply and demand models.

REFERENCES

- Bartik, Timothy J. 2001. *Jobs for the Poor: Can Labor Demand Policies Help?* New York, New York and Kalamazoo, Michigan: Russell Sage Foundation and W. E. Upjohn Institute for Employment Research.
- . 2000. “Displacement and Wage Effects of Welfare Reform.” In *Finding Jobs: Work and Welfare Reform*, David E. Card and Rebecca M. Blank, eds. New York: Russell Sage Foundation, pp. 72–122.
- . 1998. “The Labor Supply Effects of Welfare Reform.” W.E. Upjohn Institute for Employment Research staff working paper 98-053, available at <http://www.upjohninst.org>.
- . 1993. *Economic Development and Black Economic Success*. Upjohn Institute Technical Report 93-001, Kalamazoo, Michigan: W.E. Upjohn Institute for Employment Research.
- . 1991. *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, Michigan: W.E. Upjohn Institute for Employment Research.
- Bartik, Timothy J. and Randall W. Eberts. 1999. “Examining the Effect of Industry Trends and Structure on Welfare Caseloads.” In *Economic Conditions and Welfare Reform*, Sheldon H. Danziger, ed. Kalamazoo, Michigan: W.E. Upjohn Institute for Employment Research, pp. 119–157.
- Bernstein, Jared. 1997. “Welfare Reform and the Low-Wage Labor Market: Employment, Wages, and Wage Policies.” Technical paper 226, Washington, D.C.: Economic Policy Institute.
- Blanchflower, David G., and Andrew J. Oswald. 1994. *The Wage Curve*. Cambridge, Massachusetts: MIT Press.
- Blank, Rebecca M. 2001. “What Causes Public Assistance Caseloads to Grow?” *Journal of Human Resources* 36(1): 85–118.
- Borjas, George J., Richard B. Freeman, and Lawrence F. Katz. 1997. “How Much Do Immigration and Trade Affect Labor Market Outcomes?” *Brookings Papers on Economic Activity* 1: 1–90.
- Bound, John, David A. Jaeger, and Regina M. Baker. 1995. “Problems with Instrumental Variables Estimation When the Correlation between the Instruments and the Endogenous Explanatory Variable is Weak.” *Journal of the American Statistical Association*, 90(430): 443–450.

- Davidson, Russell, and James G. MacKinnon. 1993. *Estimation and Inference in Econometrics*. New York: Oxford University Press.
- Ellwood, David T. 2001. "The Impact of the Earned Income Tax Credit and Social Policy Reforms on Work, Marriage, and Living Arrangements." In *Making Work Pay: The Earned Income Tax Credit and Its Impact on America's Families*, Bruce D. Meyer and Douglas Holtz-Eakin, eds. New York: Russell Sage Foundation, pp. 116–165.
- Enchautegui, Maria E. 2001. "Will Welfare Reform Hurt Low-Skilled Workers?" Assessing the New Federalism discussion paper 01-01. Washington, D.C.: The Urban Institute.
- Figlio, David N., and James P. Ziliak. 1999. "Welfare Reform, the Business Cycle, and the Decline in AFDC Caseloads." In *Economic Conditions and Welfare Reform*, Sheldon H. Danziger, ed. Kalamazoo, Michigan: W.E. Upjohn Institute for Employment Research, pp. 17–48.
- Hamermesh, Daniel S. 1993. *Labor Demand*. Princeton: Princeton University Press.
- Holzer, Harry J. 1996. "Employer Demand, AFDC Recipients, and Labor Market Policy." Discussion paper 1115-96, Madison, Wisconsin: Institute for Research on Poverty.
- Johnson, George E. 1998. "The Impact of Immigration on Income Distribution Among Minorities." In *Help or Hindrance: The Economic Implications of Immigration for African Americans*, Daniel Hamermesh and Frank D. Bean, eds. New York: Russell Sage Foundation, pp. 17–50.
- Katz, Lawrence F. 1998. "Wage Subsidies for the Disadvantaged." In *Generating Jobs: How to Increase Demand for Less-Skilled Workers*, Richard B. Freeman and Peter Gottschalk, eds. New York: Russell Sage Foundation, pp. 21–53.
- Klerman, Jacob, and Steven Haider. 2001. "A Stock-Flow Analysis of the Welfare Caseload." Discussion paper, RAND, Santa Monica, California.
- Lerman, Robert I., and Caroline Ratcliffe. 2001. "Are Single Mothers Finding Jobs Without Displacing Other Workers?" *Monthly Labor Review* 124(7): 3–12.
- Levine, Philip B., and Diana M. Whitmore. 1998. "The Impact of Welfare Reform on the AFDC Caseload." *National Tax Association Proceedings–1997*. Washington, D.C.: National Tax Association.
- The Lewin Group. 2001. *How Well Have Rural and Small Metropolitan Labor Markets Absorbed Welfare Recipients?* Washington, D.C.: U.S. Department of Health and Human Services.

- Lubotsky, Darren. 2000. "The Labor Market Effects of Welfare Reform." Working paper, University of California, Berkeley, California.
- Mishel, Lawrence, Jared Bernstein, and John Schmitt. 2001. *The State of Working America, 2000–2001*. Ithaca, New York: ILR Press.
- Mishel, Lawrence, and John Schmitt. 1995. "Cutting Wages by Cutting Welfare: The Impact of Reform on the Low-Wage Labor Market." Briefing paper 58, Economic Policy Institute, Washington, D.C.
- Moffitt, Robert A. 2002. "The Temporary Assistance for Needy Families Program." Working paper 8749, National Bureau of Economic Research, Cambridge, Massachusetts.
- Pavetti, LaDonna and Dan Bloom. 2001. "State Sanctions and Time Limits." In *The New World of Welfare*, Rebecca M. Blank and Ron Haskins, eds. Washington, D.C.: Brookings Institution Press, pp. 245–269.
- U.S. Department of Health and Human Services. 2000. "Temporary Assistance for Needy Families (TANF) Program." Washington, D.C.: Administration for Children and Families.
- U.S. House of Representatives, Committee on Ways and Means. 2000. *2000 Green Book; Background Material and Data on Programs within the Jurisdiction of the Committee on Ways and Means*. Washington, D.C.: U.S. Government Printing Office.

Table 1 Displacement and Wage Elasticities for Less-Educated Workers in Response to an Increase in the Labor Supply of Less-Educated Workers

Scenario	Assumptions about Demand and Supply Behavior	Displacement Elasticity	Wage Elasticity
Baseline	Elasticity of demand with respect to wage of ! 0.5, elasticity of demand with respect to unemployment of 1.5, elasticity of wages with respect to unemployment of (! 0.6).	0.50	! 0.16
Short run	Same as baseline, but elasticity of demand with respect to unemployment of 0.75.	0.64	! 0.21
Greater response of demand to unemployment	Same as baseline, but elasticity of demand with respect to unemployment of 3.0.	0.36	! 0.12
Greater response of wages to unemployment	Same as baseline, but elasticity of wages with respect to unemployment of (! 2.0).	0.49	! 0.41
Greater response of labor demand to wages	Same as baseline, but elasticity of labor demand with respect to wages of (! 1.5).	0.43	! 0.14
Long-run effects with unemployment returning to frictional level	Same as baseline, but elasticity of wages with respect to unemployment of (! 1,000).	0.44	! 1.11
Long-run market-clearing model with high elasticity of demand	Same as long-run model, but elasticity of labor demand with respect to wages of (! 1.5).	0.21	! 0.53

SOURCE: Author's calculations, derived from Table A1.1 of Bartik (2001), pp. 308–309.

NOTE: The model has four equations: labor supply is $L^s = L^s(W, U)$; labor demand is $L^d = L^d(W, U)$; the wage curve is $W = W(U)$; the unemployment rate is defined by $L^s(1 - U) = L^d$; W is the wage rate and U is the unemployment rate. We add a proportionate shock to the quantity supplied. Totally differentiating this model, we get the following elasticities of wages and employment with respect to a proportionate shock to labor supply: $\epsilon_w = (1 - U)/(F + G)$; $\epsilon_E = G/(F + G)$, where $F = [(1/1 - U)(1/g) + e + a(1/g)]$ and $G = [h! b(1/g)]$, and g is the percentage change in wages for a one-point increase in the unemployment rate, e is the elasticity of labor supply with respect to wages, a is the percentage change in labor supply due to a one-point increase in the unemployment rate, h is the elasticity of labor demand with respect to wages, and b is the percentage change in labor demand due to a one-point increase in the unemployment rate. The displacement of less-educated workers by the new labor market entrants is equal to one minus the employment elasticity. The assumed parameters in the baseline and other scenarios are justified in Appendix 1 in Bartik (2001). All simulations assume unemployment of eight percent, elasticity of labor supply with respect to wage of 0.4, and elasticity of labor supply with respect to a one-point change in unemployment of ! 0.5.

Table 2 Summary of Previous Research on Spillover Effects of Welfare Reform

Study	Study's assumptions and groups considered	Wage effect for group for supply shock of 1.4 million	Displacement effects
Mishel and Schmitt (1995)	Labor demand elasticity of ! 0.3, labor supply elasticity of 0. Group analyzed is bottom 30% of wage distribution.	! 15%	0.00
Holzer (1996)	Labor demand elasticity of ! 0.3, labor supply elasticity of 0.4. Groups analyzed are high school dropouts and bottom quintile of high school grads.	! 5 to ! 7%	0.57
Bernstein (1997)	Labor demand elasticity of ! 0.3, labor supply elasticity of 0.4. Group analyzed is female high school grads or less, ages 16 to 35.	! 8%	0.57
Lewin Group (2001)	Labor demand elasticity of ! 0.3, labor supply elasticity of 0.4. Group analyzed is 47 million low-skill workers.	! 5%	0.60
Enchautegui (2001)	Estimates factor price elasticities. Labor supply elasticities set to zero. 8 groups: men and women with three education groups, immigrants, welfare workers.	! 12% for welfare recipients, ! 2.5% for male high school dropouts, ! 9% for female high school dropouts	0.00
Lerman and Ratcliffe (2001)	Estimates correlation between percent growth in labor force of single mothers and wages of various low-wage or low-education workers in 20 MSAs.	No significant effects	No significant effects
Lubotsky (2000)	Comparison of female and male high school dropouts and other groups in Michigan and other states, before and after Michigan's 1991 abolition of General Assistance.	! 16% for female high school dropouts, but statistically insignificant. Zero for other groups	0.3 to 0.6 for female high school dropouts
Bartik (2000), first estimates	General equilibrium model with CES production of aggregate labor, with intragroup elasticities of substitution of 1.5 or 0.5. Zero labor supply elasticity. Men and women, divided into high school vs. college equivalents, or high school dropouts vs. others.	High/low substitution and female HSE: (! 1%/! 3%); High/low substitution and female HSD (! 5%/! 15%)	0.00
Bartik (2000), second estimates	Estimated wage curve model with demand, supply, and wage curve estimates for five groups, divided by gender and college graduation, and single mothers as 5 th group.	! 2% for single mothers, ! 1% for overall wages	0.2 for single mothers in long-run
Bartik (2000), third estimates	Estimated cross-section time-series model, using annual data on states, of effects of exogenous declines in caseloads rolls on wages and unemployment of five groups: single mothers, and males and females divided by college graduation.	! 18% to ! 21% for single mothers, no other statistically significant effects	Insignificant

NOTE: Displacement effects is loss of jobs of persons other than persons added to labor supply, as proportion of jobs obtained by labor force entrants.

Table 3 National Weighted Means for Key Variables

Variable	Year	Single mothers	Female high school dropouts	Female high school grads (not college grads)	Female college grads	Male high school dropouts	Male high school grads (not college grads)	Male college grads	All 7 groups (all ages 20–64)
Real wage (2000 \$)	1993	11.53	8.20	11.48	18.00	10.80	14.46	22.86	14.61
	2000	12.29	8.28	12.26	20.35	10.98	15.73	25.65	16.19
ln (real wage)	1993	2.316	2.027	2.331	2.772	2.272	2.550	2.995	2.530
	2000	2.366	2.038	2.385	2.860	2.282	2.618	3.084	2.606
Unemployment rate	1993	11.8	10.6	5.3	3.1	11.9	6.9	3.1	6.2
	2000	6.9	7.8	3.3	1.8	6.3	3.6	1.7	3.5
Employment/ population ratio	1993	0.606	0.390	0.677	0.797	0.667	0.823	0.907	0.740
	2000	0.747	0.431	0.696	0.787	0.717	0.835	0.913	0.769
Labor force participation rate	1993	0.688	0.436	0.715	0.822	0.758	0.884	0.936	0.789
	2000	0.803	0.468	0.720	0.801	0.765	0.866	0.928	0.797
Welfare receipt rate (monthly)	1993	0.253	0.041	0.009	0.001	0.013	0.004	0.001	0.023
	2000	0.074	0.016	0.004	0.001	0.005	0.002	0.000	0.007
Percent of monthly welfare caseload	1993	70.2	9.5	11.0	0.3	3.9	4.8	0.3	100.0
	2000	59.6	10.1	16.2	1.0	3.5	8.8	0.7	100.0
Welfare caseload per capita	1993								0.0192
	2000								0.0081
Proportion of population	1993	6.4	5.4	29.3	10.1	6.7	30.1	12.1	100.0
	2000	6.2	4.7	28.0	12.3	5.8	29.8	13.2	100.0

NOTE: Data on welfare receipt and percent of monthly caseload derived from March 1994 and March 2001 Current Population Survey. Monthly welfare receipt rate and caseload based on proportion of months in previous year on public assistance for those who received AFDC or TANF. Welfare caseload per capita derived from DHHS caseload figures and Census population numbers. All other data come from 1993 and 2000 Outgoing Rotation Group of Current Population Survey.

Table 4 Optimal Lag Length for each Dependent Variable and Group

	Overall	Single mothers	Female high school dropouts	Female high school graduates (not college grad)	Female college graduates	Male high school dropouts	Male high school graduates (not college grad)	Male college graduates
ln(wage)	2	2	2	1	2	2	1	1
Unemployment rate	5	2	8	8	4	6	7	8
Employment-to-population ratio	2	7	4	3	5	2	2	4
Labor force participation rate	1	7	1	3	3	2	3	1

NOTE: See text for description of selection of optimal lag length.

Table 5 F-Statistics on 10 Instrumental Variables in First-Stage Prediction of Current Welfare Caseload Variable for Each Dependent Variable and Group

Variable	All	Single mothers	Female high school dropouts	Female high school grads (not college grads)	Female college graduates	Male high school dropouts	Male high school grads (not college grads)	Male college grads
Wage	2.70	2.64	3.12	6.66	3.07	2.87	6.39	7.61
Unemployment rate	3.29	3.28	1.78	2.40	2.80	3.19	2.28	1.81
Employment-to-population ratio	3.39	2.16	2.72	2.68	2.91	3.18	3.38	2.80
Labor force participation rate	7.35	2.02	7.42	2.79	2.69	2.88	2.64	7.19

NOTE: All *F*-statistics are statistically significant at 0.05 level except for unemployment rate, male college grads (probability = 0.0574), and unemployment rate, female high school dropouts (pr = 0.0620). All other *F*-statistics are also statistically significant at 0.01 level except for labor force participation rate, single mothers (pr = 0.0301), and employment rate, single mothers (pr = 0.0196).

Table 6 Short-Run and Long-Run Elasticities of Labor Market Outcomes with Respect to Welfare Caseloads (Standard errors in parentheses; t-ratios in brackets)

Group	2SLS		OLS	
	Short-Run Effect	Long-Run Effect	Short-Run Effect	Long-Run Effect
Dependent variable: Log of Wage				
All	0.2693 (0.1079) [2.50]	0.0436 (0.0523) [0.83]	! 0.0249 (0.0178) [! 1.40]	! 0.0912 (0.0249) [! 3.66]
Single Moms	0.8270 (0.3116) [2.65]	0.1063 (0.0715) [1.49]	0.0088 (0.0515) [0.17]	! 0.0721 (0.0336) [! 2.15]
Female High School Dropouts	0.1099 (0.2609) [0.42]	! 0.0939 (0.0524) [! 1.80]	! 0.0134 (0.0544) [! 0.25]	! 0.1159 (0.0267) [! 4.33]
Female High School Graduates	0.1170 (0.0689) [1.70]	! 0.0639 (0.0223) [! 2.87]	! 0.0026 (0.0193) [! 0.13]	! 0.0855 (0.0206) [! 4.15]
Female College or More	0.3656 (0.1955) [1.87]	0.0213 (0.0567) [0.38]	! 0.0066 (0.0380) [! 0.17]	! 0.0749 (0.0275) [! 2.72]
Male High School Dropouts	1.2059 (0.3578) [3.37]	0.1781 (0.0800) [2.23]	0.0722 (0.0576) [1.25]	! 0.0520 (0.0347) [! 1.50]
Male High School Graduates	0.1969 (0.0797) [2.47]	! 0.0689 (0.0217) [! 3.18]	! 0.0102 (0.0212) [! 0.48]	! 0.1004 (0.0201) [! 5.00]
Male College or More	0.2019 (0.1020) [1.98]	! 0.0543 (0.0226) [! 2.40]	0.0596 (0.0308) [1.94]	! 0.0705 (0.0206) [! 3.43]
Dependent variable: Unemployment Rate				
All	0.0067 (0.0290) [0.23]	0.0097 (0.0101) [0.96]	0.0246 (0.0070) [3.52]	0.0150 (0.0055) [2.74]
Single Moms	! 0.2858 (0.1561) [! 1.83]	0.0145 (0.0346) [0.42]	0.1130 (0.0298) [3.79]	0.0884 (0.0145) [6.09]
Female High School Dropouts	! 0.1152 (0.1995) [! 0.58]	0.0209 (0.0314) [0.67]	0.0028 (0.0426) [0.07]	0.0363 (0.0176) [2.07]
Female High School Graduates	! 0.0643 (0.0421) [! 1.53]	! 0.0123 (0.0111) [! 1.11]	0.0030 (0.0099) [0.30]	0.0014 (0.0060) [0.24]

Table 6 (Continued)

Group	2SLS		OLS	
	Short-Run Effect	Long-Run Effect	Short-Run Effect	Long-Run Effect
Female College or More	! 0.0049 (0.0534) [! 0.09]	0.0008 (0.0102) [0.08]	0.0095 (0.0115) [0.83]	0.0033 (0.0049) [0.67]
Male High School Dropouts	! 0.1689 (0.1514) [! 1.12]	0.0101 (0.0344) [0.29]	0.0368 (0.0370) [0.99]	0.0502 (0.0185) [2.71]
Male High School Graduates	0.1091 (0.0545) [2.00]	0.0259 (0.0136) [1.90]	0.0411 (0.0120) [3.43]	0.0109 (0.0078) [1.41]
Male College or More	! 0.0128 (0.0458) [! 0.28]	0.0026 (0.0078) [0.33]	0.0140 (0.0098) [1.42]	0.0065 (0.0043) [1.52]
Dependent variable: Employment Population Ratio				
All	! 0.0344 (0.0484) [! 0.71]	! 0.0317 (0.0190) [! 1.67]	! 0.0445 (0.0105) [! 4.23]	! 0.0351 (0.0096) [! 3.67]
Single Moms	! 0.3715 (0.2171) [! 1.71]	! 0.1810 (0.0524) [! 3.45]	! 0.1497 (0.0469) [! 3.20]	! 0.1323 (0.0292) [! 4.53]
Female High School Dropouts	! 0.1324 (0.2347) [! 0.56]	! 0.0975 (0.0596) [! 1.64]	0.0082 (0.0495) [0.17]	! 0.0652 (0.0283) [! 2.30]
Female High School Graduates	! 0.0253 (0.0888) [! 0.29]	! 0.0291 (0.0350) [! 0.83]	! 0.0084 (0.0179) [! 0.47]	! 0.0234 (0.0186) [! 1.26]
Female College or More	! 0.1848 (0.1194) [! 1.55]	! 0.0433 (0.0343) [! 1.26]	0.0031 (0.0262) [0.12]	0.0031 (0.0167) [0.18]
Male High School Dropouts	0.4791 (0.2124) [2.26]	0.0319 (0.0530) [0.60]	0.0019 (0.0410) [0.05]	! 0.0716 (0.0247) [! 2.90]
Male High School Graduates	0.0011 (0.0748) [0.01]	! 0.0073 (0.0252) [! 0.29]	! 0.0738 (0.0160) [! 4.61]	! 0.0288 (0.0123) [! 2.35]
Male College or More	! 0.0201 (0.0870) [! 0.23]	! 0.0161 (0.0232) [! 0.69]	! 0.0221 (0.0187) [! 1.18]	! 0.0166 (0.0111) [! 1.49]
Dependent variable: LFP Rate				
All	! 0.0443 (0.0252) [! 1.76]	! 0.0400 (0.0075) [! 5.30]	! 0.0297 (0.0076) [! 3.91]	! 0.0379 (0.0067) [! 5.65]

Table 6 (Continued)

Group	2SLS		OLS	
	Short-Run Effect	Long-Run Effect	Short-Run Effect	Long-Run Effect
Single Moms	! 0.6248 (0.2324) [! 2.69]	! 0.1997 (0.0516) [! 3.87]	! 0.1139 (0.0433) [! 2.63]	! 0.0912 (0.0287) [! 3.18]
Female High School Dropouts	! 0.1139 (0.1234) [! 0.92]	! 0.0377 (0.0246) [! 1.53]	0.0295 (0.0370) [0.80]	! 0.0240 (0.0215) [! 1.12]
Female High School Graduates	! 0.0826 (0.0826) [! 1.00]	! 0.0554 (0.0332) [! 1.67]	! 0.0022 (0.0167) [! 0.13]	! 0.0278 (0.0168) [! 1.66]
Female College or More	! 0.2010 (0.1207) [! 1.67]	! 0.0650 (0.0284) [! 2.29]	0.0053 (0.0230) [0.23]	! 0.0218 (0.0138) [! 1.59]
Male High School Dropouts	0.3131 (0.1803) [1.74]	0.0091 (0.0418) [0.22]	0.0450 (0.0348) [1.29]	! 0.0471 (0.0208) [! 2.26]
Male High School Graduates	0.1152 (0.0735) [1.57]	0.0046 (0.0180) [0.26]	! 0.0215 (0.0137) [! 1.57]	! 0.0253 (0.0090) [! 2.81]
Male College or More	! 0.0071 (0.0417) [! 0.17]	! 0.0105 (0.0089) [! 1.18]	! 0.0111 (0.0124) [! 0.89]	! 0.0109 (0.0079) [! 1.39]

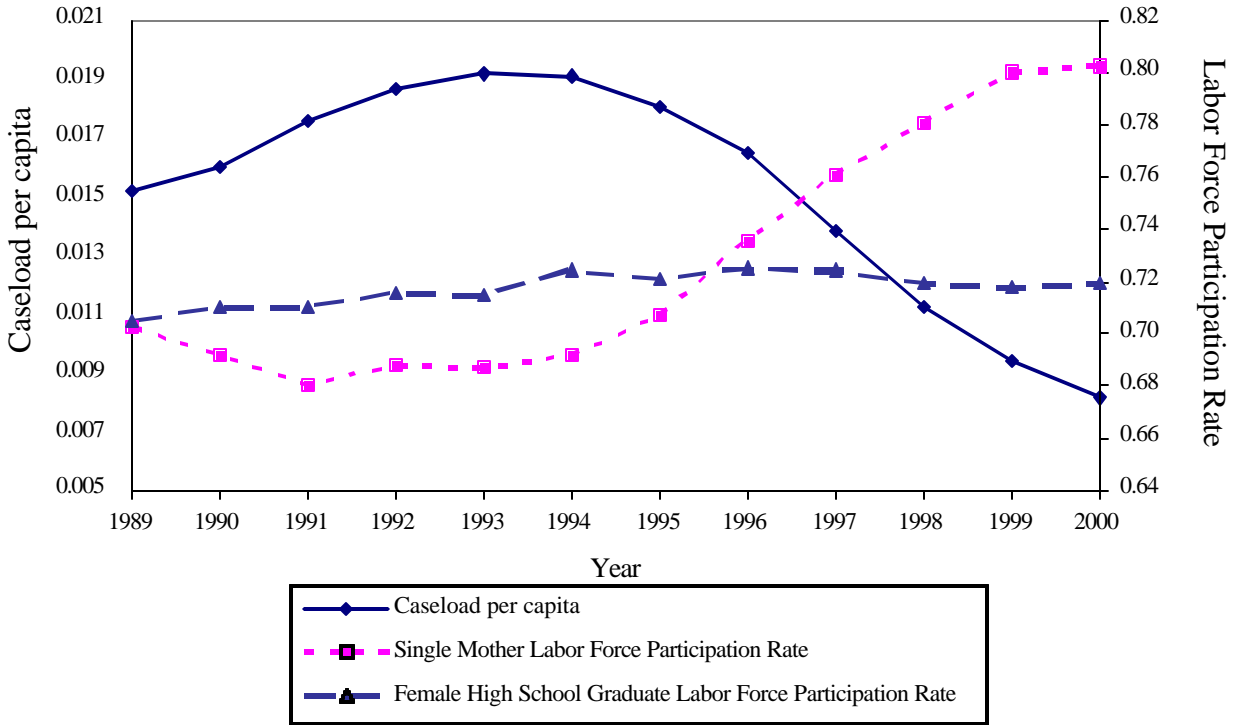
NOTE: These effects are 100 times the change in the labor market outcome which results from increase in welfare caseload per capita of 0.000192, which is change of 1 percent of average national level in 1993. Therefore, these effects are in elasticity terms: the number of rate points or ln points for a one-point change in caseloads.

Table 7 Selected Effects of “Welfare Reform” on Labor Market Outcomes
 (“Standard errors” in parentheses; “t-ratios” in brackets)

Variable	1994	1995	1996	1997	1998	1999	2000
Cumulative decline in welfare caseloads due to “reform” (%)	! 2	! 4	! 8	! 20	! 33	! 40	! 47
Effect on labor force participation rate, single mothers	0.0156 (0.0057) [2.73]	0.0137 (0.0045) [3.05]	0.0292 (0.0099) [2.95]	0.0831 (0.0279) [2.98]	0.1037 (0.0332) [3.12]	0.0858 (0.0257) [3.34]	0.0763 (0.0215) [3.55]
Effect on overall ln(real wage)	! 0.0066 (0.0026) [! 2.49]	! 0.0051 (0.0022) [! 2.28]	! 0.0115 (0.0051) [! 2.24]	! 0.0341 (0.0147) [! 2.33]	! 0.0400 (0.0184) [! 2.17]	! 0.0322 (0.0178) [! 1.81]	! 0.0287 (0.0191) [! 1.51]
Effect on ln(real wage) of male high school dropouts	! 0.0295 (0.0088) [! 3.36]	! 0.0111 (0.0043) [! 2.56]	! 0.0404 (0.0133) [! 3.04]	! 0.1314 (0.0410) [! 3.21]	! 0.1170 (0.0405) [! 2.89]	! 0.0665 (0.0309) [! 2.15]	! 0.0683 (0.0331) [! 2.06]

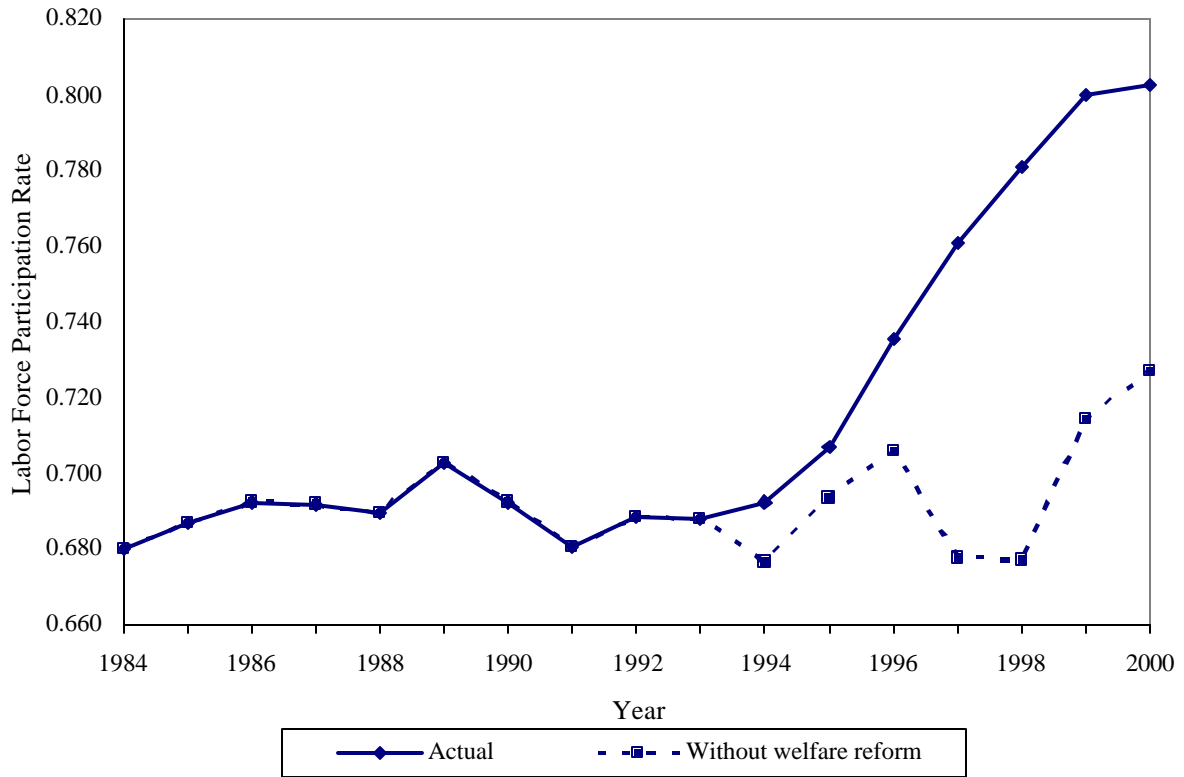
NOTE: Figures in table are based upon estimates of 2SLS model. The simulation uses assumed shock to welfare caseloads due to welfare reform, based upon Blank (2001) as described in text. The reform-induced decline in the caseload, as a percent of the 1993 level, is reported in the first row. The simulation takes 1000 random draws from variance-covariance matrix of 2SLS estimates. The number in parentheses is the standard deviation of the effect across the 1000 simulations. The number in brackets is the ratio of the mean effect to this standard deviation, the equivalent of a *t*-statistic. Explicit calculation of the 95% confidence interval indicates that the “*t*-statistics” do properly indicate statistical significance.

Figure 1 Recent Trends in Welfare Caseloads and Labor Force Participation of Single Mothers and Female High School Graduates



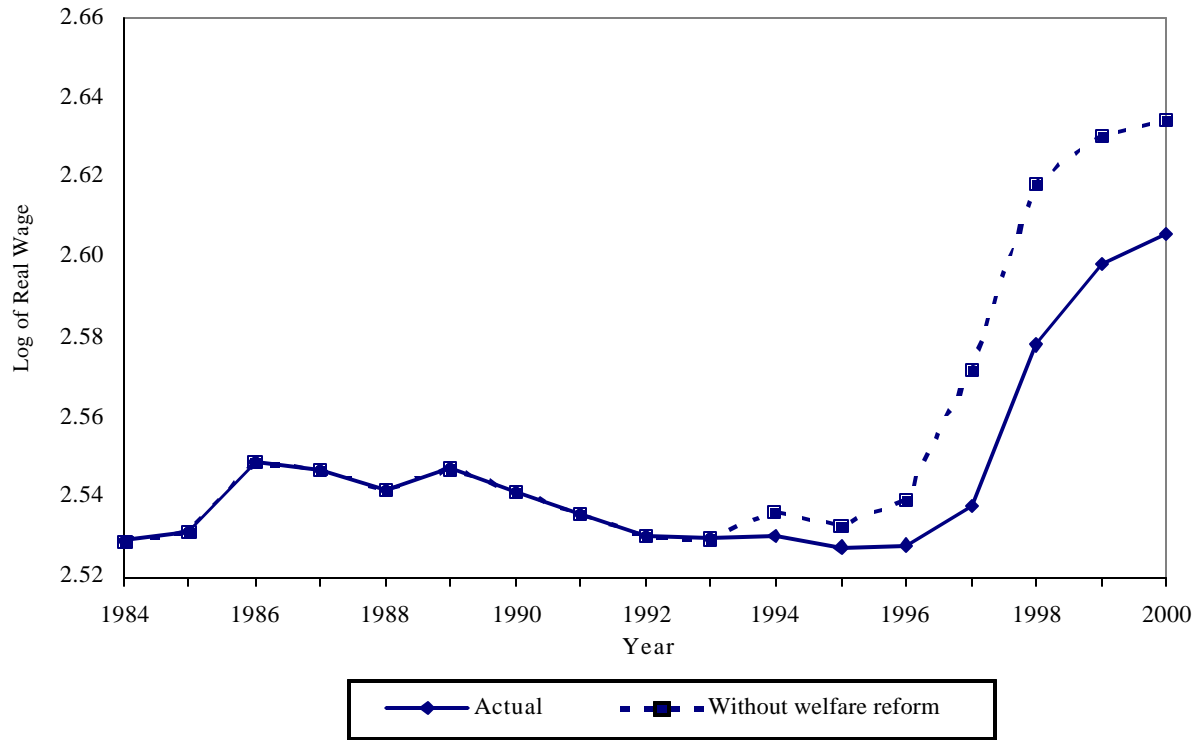
NOTE: Chart shows national average monthly AFDC/TANF caseload per capita for each year from 1989 to 2000, and labor force participation rates for single mothers, ages 20–64, and labor force participation rates for female high school graduates ages 20–64 who are not single mothers and not college graduates. Caseload data come from U.S. Department of Health and Human Services, population data from Census Bureau, and labor force participation data are calculated by the author from the Outgoing Rotation Group of the U.S. Current Population Survey. For these years, percentage of single mothers who are high school graduates but not college graduates is between 64% and 71%.

Figure 2 Labor Force Participation Trends for Single Mothers, with and without Post-1993 Welfare Reform



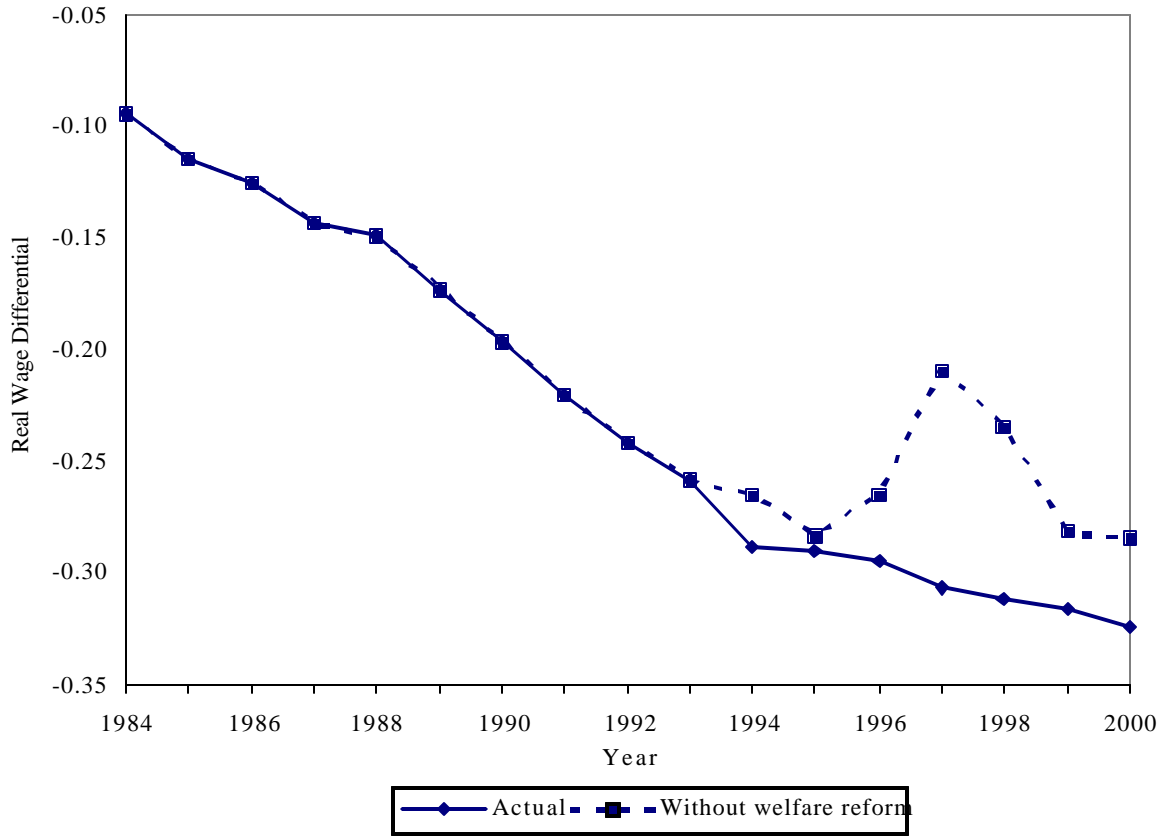
NOTE: Actual line shows actually observed labor force participation rates for single mothers, 1984 to 2000, calculated by the author from the CPS Outgoing Rotation Group. The “without welfare reform” line subtracts out the “effects” of welfare reform that are reported in Table 7.

Figure 3 Trends in ln(Real Wage) for All Groups, with and without Post-1993 Welfare Reform



NOTE: Number reported is national mean for ln(real wage) for all 20–64 year olds. Actual line shows observed mean from CPS-ORG. The “without welfare reform” subtracts out the negative effect of welfare reform on wages that is reported in Table 7.

Figure 4 Trends in Real Wage Differential, Male High School Dropouts vs. All Workers, with and without Post-1993 Welfare Reform



NOTE: Number measured on vertical axis is $\ln(\text{real wage of male high school dropouts})$ minus $\ln(\text{real wage of all 20–64 year olds})$. The actual line reports author’s calculations from the CPS-ORG. The “without welfare reform line” subtracts out the effects of welfare reform on wages as reported in Table 7.

Appendix 1 Logit Estimates

Explanatory Variables (All zero-one dummies)	Parameter Estimate	Standard Error	<i>P</i> Value
High School Dropout	1.056	0.057	<0.0001
High School Graduate	0.750	0.056	<0.0001
Some College	0.763	0.058	<0.0001
Black	0.606	0.021	<0.0001
Hispanic	0.178	0.029	<0.0001
Other Race	0.006	0.057	0.9126
Age: 20–24	0.970	0.041	<0.0001
Age: 25–34	0.882	0.043	<0.0001
Age: 35–44	0.698	0.047	<0.0001
Age: 45–54	0.723	0.054	<0.0001
Age: 55–64	0.309	0.070	<0.0001
Age of Youngest Child: 1	0.239	0.035	<0.0001
Age of Youngest Child: 2	0.284	0.037	<0.0001
Age of Youngest Child: 3	0.263	0.039	<0.0001
Age of Youngest Child: 4	0.265	0.041	<0.0001
Age of Youngest Child: 5–8	0.170	0.034	<0.0001
Age of Youngest Child: 9–12	0.114	0.038	0.0028
Age of Youngest Child: 13–19	0.001	0.042	0.9732
Number of Children in the Family: 2	0.481	0.021	<0.0001
Number of Children in the Family: 3	0.810	0.027	<0.0001
Number of Children in the Family: 4 or more	1.264	0.034	<0.0001
Family Wages and Salary: \$1–\$2,500	! 0.273	0.026	<0.0001
Family Wages and Salary: \$2,501–\$5,000	! 0.696	0.031	<0.0001
Family Wages and Salary: \$5,001–\$7,500	! 1.158	0.034	<0.0001
Family Wages and Salary: \$7,501–\$10,000	! 1.718	0.038	<0.0001
Family Wages and Salary: \$10,001–\$20,000	! 2.708	0.028	<0.0001
Family Wages and Salary: more than \$20,000	! 3.961	0.040	<0.0001
Family Non-Wage, Non-Welfare Income: \$1–\$2,500	! 0.163	0.022	<0.0001
Family Non-Wage, Non-Welfare Income: \$2,501–\$5,000	! 0.704	0.031	<0.0001
Family Non-Wage, Non-Welfare Income: \$5,001–\$7,500	! 0.751	0.032	<0.0001
Family Non-Wage, Non-Welfare Income: \$7,501–\$10,000	! 1.471	0.048	<0.0001
Family Non-Wage, Non-Welfare Income: \$10,001–\$20,000	! 2.128	0.045	<0.0001
Family Non-Wage, Non-Welfare Income: more than \$20,000	! 3.306	0.087	<0.0001

NOTE: All data used in this estimation come from March Current Population Surveys, 1977–2001. The data used is on 127,500 distinct individuals. Each individual in the sample is a female head of household who is ages 16–64, and has a child in the household who is 19 or fewer years old. The dependent variable is a 0-1 dummy with a value of 1 if the single mother received AFDC or TANF during any month of the preceding calendar year. This is estimated using a logit model as a function of a number of the single mother’s characteristics. These characteristics are measured by sets of dummy variables. The omitted dummies are: college graduate; white, non-Hispanic; mom’s age is 16–19; age of youngest child <1; one child in family; family wage and salary income of 0; family non-wage and non-welfare income of 0. The income variables are measured for the preceding year. The education, own-age, age of youngest child, and number of children variables are measured as of the March interview. The estimation includes a complete set of dummies for each state-year cell.

Appendix 2 First Stage Estimated Coefficients for the Instrumental Variables, Single Mothers Group, Corresponding to Second-Stage Equation with ln(Wage) Dependent Variable

Instrumental Variable	Estimated Coefficient	Standard Error	<i>t</i> Ratio
Adjusted probability of single mothers being on welfare,	0.00128	0.00060438	2.12
Statewide waiver	! 0.00006387	0.00014106	! 0.45
Moderate TANF sanctions	! 0.00028003	0.00017871	! 1.57
Stringent TANF sanctions	! 0.00024408	0.00016262	! 1.5
Basic TANF federal grants per capita, in 2000\$! 0.01067	0.00683	! 1.56
Required state “maintenance-of-effort” spending on needy children, per capita, in 2000\$	0.00253	0.00877	0.29
Supplemental TANF federal grants per capita, in 2000\$	0.04732	0.0497	0.95
Republican governor	! 0.00013755	0.00006786	! 2.03
Republicans control both houses of state legislature	! 0.00008581	0.00011099	! 0.77
Democrats control both houses of state legislature	0.00015749	0.00010802	1.46

NOTE: Each of 32 second-stage equations has its own first-stage estimates. However, the first stage results are all qualitatively similar. The dependent variable in this first stage is state welfare caseloads per capita. In addition to the 10 instruments, the first-stage estimation includes all the exogenous right-hand side variables of the second-stage including: lags in the caseload per capita; lags in the dependent variable (here, the ln(wage) for single mothers); current and lagged predicted employment demand; year and state dummies.

Appendix 3 2SLS Coefficient Estimates
(Standard errors in parentheses; *t*-ratios in brackets)

	All	Single Moms	Female High School Dropouts	Female High School Graduates	Female College or More	Male High School Dropouts	Male High School Graduates	Male College or More
Dependent Variable: Log of Wage								
Current caseload per capita	14.02738 (5.6177) [2.5]	43.07516 (16.2311) [2.65]	5.72238 (13.59) [0.42]	6.091705 (3.5773) [1.7]	19.04242 (10.1812) [1.87]	62.80967 (18.6366) [3.37]	10.25344 (4.1496) [2.47]	10.51444 (5.3123) [1.98]
1 st lag caseload per capita	! 21.0712 (7.9451) [! 2.65]	! 61.1535 (22.8757) [! 2.67]	! 6.708 (19.1982) [! 0.35]	! 7.55915 (3.407) [! 2.22]	! 25.574 (14.3964) [! 1.78]	! 95.406 (26.3473) [! 3.62]	! 12.0906 (3.9656) [! 3.05]	! 12.4322 (5.0212) [! 2.48]
2 nd lag caseload per capita	7.789359 (3.2245) [2.42]	21.90948 (9.2843) [2.36]	! 3.1776 (7.8686) [! 0.4]		7.179392 (5.9287) [1.21]	39.38669 (10.7826) [3.65]		
1 st lag log of wage	0.658538 (0.0517) [12.73]	0.213071 (0.0516) [4.13]	0.172887 (0.0398) [4.35]	0.559366 (0.0348) [16.09]	0.319711 (0.0393) [8.14]	0.274737 (0.0516) [5.33]	0.488319 (0.0379) [12.9]	0.321868 (0.039) [8.24]
2 nd lag log of wage	0.013379 (0.0454) [0.29]	0.095259 (0.0449) [2.12]	! 0.02391 (0.0396) [! 0.6]		0.097076 (0.0375) [2.59]	! 0.00684 (0.0483) [! 0.14]		
Current predicted employment growth	! 0.4008 (0.3188) [! 1.26]	! 1.00261 (0.8947) [! 1.12]	! 1.52142 (0.8129) [! 1.87]	! 0.63007 (0.3654) [! 1.72]	0.217096 (0.6119) [0.35]	! 0.67951 (1.0725) [! 0.63]	0.033122 (0.4205) [0.08]	! 0.68435 (0.5783) [! 1.18]
1 st lag predicted employment growth	1.04036 (0.5439) [1.91]	3.077234 (1.535) [2.0]	2.299549 (1.3877) [1.66]	0.541754 (0.38) [1.43]	! 0.34769 (1.0415) [! 0.33]	3.863678 (1.859) [2.08]	! 0.08875 (0.4374) [! 0.2]	0.603817 (0.6014) [1.0]
2 nd lag predicted employment growth	! 0.81004 (0.4065) [! 1.99]	! 2.63813 (1.161) [! 2.27]	! 1.04457 (1.0314) [! 1.01]		! 0.06886 (0.7731) [! 0.09]	! 4.00579 (1.3955) [! 2.87]		
Dependent Variable: Unemployment Rate								
Current caseload per capita	0.350204 (1.5094) [0.23]	! 14.8849 (8.1291) [! 1.83]	! 6.0004 (10.3899) [! 0.58]	! 3.34791 (2.1931) [! 1.53]	! 0.25516 (2.7811) [! 0.09]	! 8.79796 (7.8869) [! 1.12]	5.682114 (2.8405) [2.0]	! 0.66635 (2.383) [! 0.28]
1 st lag caseload per capita	0.78414 (1.9899) [0.39]	26.09344 (11.4295) [2.28]	6.498855 (12.7616) [0.51]	5.05777 (2.7163) [1.86]	1.879394 (3.7701) [0.5]	14.79441 (10.1732) [1.45]	! 6.10424 (3.533) [! 1.73]	2.062759 (2.9263) [0.7]
2 nd lag caseload per capita	! 0.4282 (1.0569) [! 0.41]	! 10.5962 (4.7486) [! 2.23]	! 3.95674 (6.2973) [! 0.63]	! 2.92228 (1.4067) [! 2.08]	! 2.45219 (1.9193) [! 1.28]	! 5.12251 (5.4908) [! 0.93]	3.740219 (1.857) [2.01]	! 1.04508 (1.4654) [! 0.71]
3 rd lag caseload per capita	! 1.14304 (0.8165) [! 1.4]		! 0.9087 (5.3048) [! 0.17]	0.389709 (1.2137) [0.32]	1.522629 (1.3104) [1.16]	! 0.93502 (4.3702) [! 0.21]	! 3.46033 (1.4654) [! 2.36]	! 0.5117 (1.2286) [! 0.42]
4 th lag caseload per capita	2.037774 (0.8617) [2.36]		9.542271 (6.4475) [1.48]	2.603585 (1.449) [1.8]	! 0.64253 (0.953) [! 0.67]	3.990556 (5.0821) [0.79]	3.077922 (1.7545) [1.75]	0.723215 (1.502) [0.48]

Appendix 3 (Continued)

	All	Single Moms	Female High School Dropouts	Female High School Graduates	Female College or More	Male High School Dropouts	Male High School Graduates	Male College or More
5 th lag caseload per capita	! 1.20212 (0.513) [! 2.34]		! 1.78332 (6.2681) [! 0.28]	! 2.69155 (1.5041) [! 1.79]		! 3.67368 (4.9116) [! 0.75]	! 0.72798 (1.7443) [! 0.42]	0.167007 (1.4461) [0.12]
6 th lag caseload per capita			! 9.05294 (6.9201) [! 1.31]	! 0.50171 (1.6229) [! 0.31]		0.496077 (2.8818) [0.17]	0.40655 (1.6913) [0.24]	! 0.91045 (1.5886) [! 0.57]
7 th lag caseload per capita			9.288072 (6.481) [1.43]	2.15499 (1.514) [1.42]			! 0.8108 (1.0134) [! 0.8]	1.831764 (1.5042) [1.22]
8 th lag caseload per capita			! 1.04307 (3.7165) [! 0.28]	! 1.75474 (0.8817) [! 1.99]				! 1.34864 (0.8707) [! 1.55]
1 st lag unemployment rate	0.390453 (0.0429) [9.11]	0.158041 (0.0449) [3.52]	! 0.12558 (0.0522) [! 2.4]	0.016183 (0.0561) [0.29]	! 0.00912 (0.0398) [! 0.23]	0.125122 (0.0481) [2.6]	0.149792 (0.0503) [2.98]	! 0.06303 (0.049) [! 1.29]
2 nd lag unemployment rate	0.036525 (0.0442) [0.83]	0.030748 (0.04) [0.77]	! 0.20909 (0.0524) [! 3.99]	! 0.03501 (0.0534) [! 0.66]	! 0.05257 (0.0391) [! 1.34]	! 0.02998 (0.0471) [! 0.64]	! 0.10386 (0.0524) [! 1.98]	! 0.10896 (0.051) [! 2.14]
3 rd lag unemployment rate	! 0.05176 (0.0448) [! 1.15]		! 0.14044 (0.0543) [! 2.59]	! 0.02292 (0.0496) [! 0.46]	! 0.08465 (0.039) [! 2.17]	! 0.12174 (0.0475) [! 2.57]	! 0.00983 (0.0505) [! 0.19]	! 0.12251 (0.0478) [! 2.57]
4 th lag unemployment rate	0.000932 (0.0463) [0.02]		! 0.14354 (0.0567) [! 2.53]	! 0.11335 (0.0519) [! 2.19]	! 0.09428 (0.0378) [! 2.5]	! 0.05546 (0.0482) [! 1.15]	! 0.05529 (0.0473) [! 1.17]	! 0.17899 (0.0528) [! 3.39]
5 th lag unemployment rate	! 0.16717 (0.0367) [! 4.55]		! 0.15966 (0.0586) [! 2.72]	! 0.07488 (0.048) [! 1.56]		! 0.1577 (0.0489) [! 3.23]	! 0.13364 (0.0473) [! 2.83]	! 0.21131 (0.0458) [! 4.61]
6 th lag unemployment rate			! 0.26048 (0.0591) [! 4.41]	! 0.06881 (0.0494) [! 1.39]		! 0.18587 (0.0489) [! 3.8]	! 0.06516 (0.0463) [! 1.41]	! 0.20666 (0.0472) [! 4.38]
7 th lag unemployment rate			! 0.11865 (0.06) [! 1.98]	! 0.16148 (0.0465) [! 3.48]			! 0.11942 (0.0408) [! 2.92]	! 0.129 (0.0469) [! 2.75]
8 th lag unemployment rate			! 0.21288 (0.0599) [! 3.55]	! 0.1162 (0.0464) [! 2.5]				! 0.20414 (0.0476) [! 4.29]
Current predicted employment growth	! 0.02529 (0.1263) [! 0.2]	! 0.39533 (0.4945) [! 0.8]	1.37959 (1.0845) [1.27]	! 0.01256 (0.2603) [! 0.05]	! 0.0026 (0.1871) [! 0.01]	1.087209 (0.6915) [1.57]	! 0.65751 (0.2431) [! 2.7]	! 0.57884 (0.2512) [! 2.3]
1 st lag predicted employment growth	! 0.12232 (0.2136) [! 0.57]	! 0.06323 (0.8455) [! 0.07]	! 2.24343 (1.9492) [! 1.15]	! 0.57074 (0.4594) [! 1.24]	0.041154 (0.3259) [0.13]	! 2.03944 (1.2861) [! 1.59]	0.77464 (0.4504) [1.72]	0.595115 (0.4562) [1.3]

Appendix 3 (Continued)

	All	Single Moms	Female High School Dropouts	Female High School Graduates	Female College or More	Male High School Dropouts	Male High School Graduates	Male College or More
2 nd lag	0.109493	0.689968	0.217598	0.581442	0.022469	! 0.42073	! 0.39027	! 0.25748
predicted	(0.2157)	(0.625)	(1.7651)	(0.426)	(0.3538)	(1.3245)	(0.4661)	(0.413)
employment growth	[0.51]	[1.1]	[0.12]	[1.36]	[0.06]	[! 0.32]	[! 0.84]	[! 0.62]
3 rd lag	0.220335		0.225082	! 0.16055	! 0.29809	0.837064	1.090341	0.095672
predicted	(0.206)		(1.5561)	(0.3808)	(0.3006)	(1.164)	(0.4164)	(0.3608)
employment growth	[1.07]		[0.14]	[! 0.42]	[! 0.99]	[0.72]	[2.62]	[0.27]
4 th lag	! 0.267		0.274543	0.344015	0.27407	0.285358	! 1.0866	0.092327
predicted	(0.1818)		(1.4072)	(0.3424)	(0.1792)	(1.1132)	(0.3688)	(0.3232)
employment growth	[! 1.47]		[0.2]	[1.0]	[1.53]	[0.26]	[! 2.95]	[0.29]
5 th lag	0.137146		1.247118	! 0.18711		! 0.42515	0.107433	0.242959
predicted	(0.1103)		(1.2638)	(0.305)		(0.9777)	(0.3647)	(0.2888)
employment growth	[1.24]		[0.99]	[! 0.61]		[! 0.43]	[0.29]	[0.84]
6 th lag			! 0.79997	0.202379		0.823029	! 0.01556	! 0.47406
predicted			(1.2767)	(0.3069)		(0.5973)	(0.3298)	(0.2925)
employment growth			[! 0.63]	[0.66]		[1.38]	[! 0.05]	[! 1.62]
7 th lag			0.218619	0.005522			0.232048	0.145297
predicted			(1.1387)	(0.2752)			(0.2032)	(0.2604)
employment growth			[0.19]	[0.02]			[1.14]	[0.56]
8 th lag			0.06829	! 0.01736				0.174428
predicted			(0.7032)	(0.1697)				(0.1629)
employment growth			[0.1]	[! 0.1]				[1.07]
Dependent Variable: Employment Rate								
Current	! 1.78887	! 19.3465	! 6.89775	! 1.31959	! 9.62486	24.95274	0.054673	! 1.04883
caseload per capita	(2.5199)	(11.3048)	(12.2258)	(4.6253)	(6.2174)	(11.065)	(3.8952)	(4.532)
	[! 0.71]	[! 1.71]	[! 0.56]	[! 0.29]	[! 1.55]	[2.26]	[0.01]	[! 0.23]
1 st lag	! 0.02733	18.79884	7.751932	0.17385	11.27993	! 42.0241	! 3.10689	0.108975
caseload per capita	(3.5181)	(14.09)	(16.5433)	(6.4178)	(8.1969)	(15.645)	(5.4725)	(6.0972)
	[! 0.01]	[1.33]	[0.47]	[0.03]	[1.38]	[! 2.69]	[! 0.57]	[0.02]
2 nd lag	1.048321	! 7.29532	! 0.12688	! 1.54215	! 0.94696	18.22265	2.848692	0.792912
caseload per capita	(1.4815)	(7.2812)	(8.38)	(2.7979)	(4.2496)	(6.4536)	(2.279)	(3.1081)
	[0.71]	[! 1.0]	[! 0.02]	[! 0.55]	[! 0.22]	[2.82]	[1.25]	[0.26]
3 rd lag		4.01905	0.933271	1.976875	! 0.5502			! 1.16628
caseload per capita		(5.704)	(5.6924)	(1.0132)	(3.2732)			(2.1242)
		[0.7]	[0.16]	[1.95]	[! 0.17]			[! 0.55]
4 th lag		! 10.1731	! 6.3963		! 6.43728			0.562788
caseload per capita		(6.9053)	(4.1859)		(3.4007)			(1.5432)
		[! 1.47]	[! 1.53]		[! 1.89]			[0.36]
5 th lag		6.759592			4.148552			
caseload per capita		(6.7316)			(1.9512)			
		[1.0]			[2.13]			
6 th lag		! 3.62502						
caseload per capita		(6.6525)						
		[! 0.54]						

Appendix 3 (Continued)

	All	Single Moms	Female High School Dropouts	Female High School Graduates	Female College or More	Male High School Dropouts	Male High School Graduates	Male College or More
7 th lag caseload per capita		! 2.78985 (3.8677) [! 0.72]						
1 st lag employment rate	0.621324 (0.0381) [16.3]	0.256027 (0.0496) [5.16]	0.198996 (0.0432) [4.61]	0.38677 (0.0393) [9.85]	0.270647 (0.0453) [5.98]	0.372347 (0.0437) [8.53]	0.504615 (0.038) [13.28]	0.281034 (0.0429) [6.54]
2 nd lag employment rate	! 0.08719 (0.0377) [! 2.31]	! 0.12517 (0.0525) [! 2.39]	0.013316 (0.0442) [0.3]	0.065487 (0.0424) [1.54]	! 0.09311 (0.0474) [! 1.97]	! 0.06617 (0.0441) [! 1.5]	! 0.0439 (0.0378) [! 1.16]	! 0.01733 (0.0429) [! 0.4]
3 rd lag employment rate		! 0.11734 (0.0549) [! 2.14]	! 0.04831 (0.0463) [! 1.04]	0.079164 (0.0413) [1.92]	! 0.04738 (0.0473) [! 1.0]			! 0.03465 (0.0433) [! 0.8]
4 th lag employment rate		! 0.1097 (0.0531) [! 2.06]	! 0.09681 (0.0482) [! 2.01]		0.003171 (0.0471) [0.07]			! 0.12304 (0.0436) [! 2.82]
5 th lag employment rate		! 0.0715 (0.0538) [! 1.33]			! 0.07723 (0.0441) [! 1.75]			
6 th lag employment rate		! 0.09645 (0.0526) [! 1.84]						
7 th lag employment rate		! 0.1843 (0.0535) [! 3.45]						
Current predicted employment growth	0.200821 (0.1562) [1.29]	! 1.72533 (0.9398) [! 1.84]	! 0.18182 (0.8107) [! 0.22]	! 0.03283 (0.3015) [! 0.11]	! 0.4783 (0.4899) [! 0.98]	0.056582 (0.6654) [0.09]	0.792425 (0.2406) [3.29]	0.276742 (0.3044) [0.91]
1 st lag predicted employment growth	! 0.12049 (0.2634) [! 0.46]	1.340355 (1.7502) [0.77]	0.275893 (1.4187) [0.19]	0.185026 (0.5167) [0.36]	0.151138 (0.8363) [0.18]	1.912579 (1.1402) [1.68]	! 0.77557 (0.4092) [! 1.9]	0.114111 (0.5281) [0.22]
2 nd lag predicted employment growth	! 0.12651 (0.1946) [! 0.65]	1.511757 (1.7869) [0.85]	! 0.24569 (1.5407) [! 0.16]	! 0.20926 (0.5194) [! 0.4]	0.495069 (0.8482) [0.58]	! 1.88889 (0.849) [! 2.22]	! 0.06702 (0.3005) [! 0.22]	! 0.66271 (0.5757) [! 1.15]
3 rd lag predicted employment growth		! 2.1157 (1.5941) [! 1.33]	1.039824 (1.3037) [0.8]	0.022862 (0.2746) [0.08]	! 0.01574 (0.8005) [! 0.02]			0.17249 (0.4888) [0.35]
4 th lag predicted employment growth		1.93588 (1.4059) [1.38]	! 0.70636 (0.7778) [! 0.91]		! 0.88229 (0.6979) [! 1.26]			0.067828 (0.2902) [0.23]
5 th lag predicted employment growth		! 1.03294 (1.3781) [! 0.75]			0.769641 (0.4197) [1.83]			

Appendix 3 (Continued)

	All	Single Moms	Female High School Dropouts	Female High School Graduates	Female College or More	Male High School Dropouts	Male High School Graduates	Male College or More
6 th lag predicted employment growth		0.701893 (1.2241) [0.57]						
7 th lag predicted employment growth		! 0.47065 (0.7534) [! 0.62]						
Dependent Variable: Labor Force Participation Rate								
Current caseload per capita	! 2.30454 (1.3129) [! 1.76]	! 32.5417 (12.1039) [! 2.69]	! 5.93177 (6.4261) [! 0.92]	! 4.30097 (4.3036) [! 1.0]	! 10.468 (6.2843) [! 1.67]	16.30556 (9.3932) [1.74]	5.997362 (3.8286) [1.57]	! 0.36837 (2.1717) [! 0.17]
1 st lag caseload per capita	1.269103 (1.2323) [1.03]	34.6266 (15.1272) [2.29]	4.456594 (6.0293) [0.74]	5.566259 (5.9751) [0.93]	13.14127 (8.6882) [1.51]	! 25.0813 (13.2428) [! 1.89]	! 8.93545 (5.3185) [! 1.68]	! 0.01008 (2.0294) [0.0]
2 nd lag caseload per capita		! 12.3553 (7.7281) [! 1.6]		! 4.85726 (2.619) [! 1.85]	! 2.80105 (3.7579) [! 0.75]	9.112863 (5.3941) [1.69]	2.823758 (2.3075) [1.22]	
3 rd lag caseload per capita		4.081055 (5.9644) [0.68]		2.255983 (0.961) [2.35]	! 2.54501 (1.3696) [! 1.86]		0.293114 (0.8308) [0.35]	
4 th lag caseload per capita		! 4.68022 (7.1489) [! 0.65]						
5 th lag caseload per capita		3.2927 (6.9702) [0.47]						
6 th lag caseload per capita		! 7.40798 (6.8974) [! 1.07]						
7 th lag caseload per capita		! 0.20813 (4.0382) [! 0.05]						
1 st lag labor force participation rate	0.502638 (0.0315) [15.95]	0.306537 (0.0569) [5.38]	0.247804 (0.0373) [6.64]	0.401216 (0.0401) [10.01]	0.279869 (0.0428) [6.54]	0.376408 (0.0412) [9.13]	0.404227 (0.043) [9.4]	0.306753 (0.0361) [8.5]
2 nd lag labor force participation rate		! 0.16203 (0.0617) [! 2.63]		0.054328 (0.0434) [1.25]	! 0.06593 (0.0436) [! 1.51]	! 0.08982 (0.0423) [! 2.13]	! 0.02571 (0.047) [! 0.55]	
3 rd lag labor force participation rate		! 0.0856 (0.0627) [! 1.37]		0.081077 (0.0425) [1.91]	! 0.00321 (0.0417) [! 0.08]		! 0.12074 (0.0458) [! 2.64]	
4 th lag labor force participation rate		! 0.11296 (0.0598) [! 1.89]						

Appendix 3 (Continued)

	All	Single Moms	Female High School Dropouts	Female High School Graduates	Female College or More	Male High School Dropouts	Male High School Graduates	Male College or More
5 th lag		! 0.16975						
labor force		(0.0642)						
participation rate		[! 2.64]						
6 th lag		! 0.05839						
labor force		(0.0587)						
participation rate		[! 1.0]						
7 th lag		! 0.17847						
labor force		(0.0593)						
participation rate		[! 3.01]						
Current	! 0.08474	! 0.5402	! 0.18737	! 0.15749	! 0.41782	! 0.10748	0.28917	0.2846
predicted	(0.1465)	(0.9719)	(0.7168)	(0.2858)	(0.412)	(0.5409)	(0.2489)	(0.2414)
employment growth	[! 0.58]	[! 0.56]	[! 0.26]	[! 0.55]	[! 1.01]	[! 0.2]	[1.16]	[1.18]
1 st lag	0.09334	! 0.5948	0.336007	! 0.03	0.19481	1.277336	! 0.02572	! 0.32084
predicted	(0.1523)	(1.8134)	(0.7449)	(0.4892)	(0.7006)	(0.9218)	(0.4238)	(0.251)
employment growth	[0.61]	[! 0.33]	[0.45]	[! 0.06]	[0.28]	[1.39]	[! 0.06]	[! 1.28]
2 nd lag		1.314402		0.364823	0.557685	! 0.99079	0.090371	
predicted		(1.8553)		(0.4912)	(0.7061)	(0.6939)	(0.4277)	
employment growth		[0.71]		[0.74]	[0.79]	[! 1.43]	[0.21]	
3 rd lag		! 1.84101		! 0.15264	! 0.31339		! 0.37632	
predicted		(1.6587)		(0.2606)	(0.3736)		(0.2258)	
employment growth		[! 1.11]		[! 0.59]	[! 0.84]		[! 1.67]	
4 th lag		1.810017						
predicted		(1.4712)						
employment growth		[1.23]						
5 th lag		1.118225						
predicted		(1.4446)						
employment growth		[0.77]						
6 th lag		! 1.63865						
predicted		(1.2766)						
employment growth		[! 1.28]						
7 th lag		0.727995						
predicted		(0.7872)						
employment growth		[0.92]						

NOTE: This table presents most of the relevant raw coefficient estimates, standard errors, and t-statistics from 2SLS estimation for all eight groups and all four types of dependent variables. These are the original coefficient estimates, and are not adjusted to elasticity form. The rate dependent variables are all measured as rates that vary in the zero to one range. All estimating equations also include year and state dummies.

Appendix 4 Simulated Effects of Welfare Reform on Various Labor Market Outcomes
 (“Standard errors” in parentheses; “*t*-ratios” in brackets)

Year	All	Single Moms	Female High School Dropouts	Female High School Graduate	Female College or More	Male High School Dropouts	Male High School Graduate	Male College or More
Log of Wage								
1994	! 0.0066 (0.0026) [! 2.49]	! 0.0202 (0.0077) [! 2.65]	! 0.0027 (0.0064) [! 0.42]	! 0.0028 (0.0017) [! 1.63]	! 0.0090 (0.0048) [! 1.86]	! 0.0295 (0.0088) [! 3.36]	! 0.0047 (0.0020) [! 2.40]	! 0.0048 (0.0025) [! 1.91]
1995	! 0.0051 (0.0022) [! 2.28]	! 0.0083 (0.0032) [! 2.56]	! 0.0016 (0.0028) [! 0.57]	! 0.0026 (0.0021) [! 1.23]	! 0.0054 (0.0027) [! 1.97]	! 0.0111 (0.0043) [! 2.56]	! 0.0043 (0.0022) [! 1.94]	! 0.0036 (0.0025) [! 1.44]
1996	! 0.0115 (0.0051) [! 2.24]	! 0.0303 (0.0119) [! 2.54]	! 0.0019 (0.0092) [! 0.21]	! 0.0044 (0.0038) [! 1.14]	! 0.0143 (0.0080) [! 1.79]	! 0.0404 (0.0133) [! 3.04]	! 0.0077 (0.0042) [! 1.85]	! 0.0068 (0.0048) [! 1.41]
1997	! 0.0341 (0.0147) [! 2.33]	! 0.0920 (0.0353) [! 2.61]	! 0.0089 (0.0293) [! 0.30]	! 0.0131 (0.0103) [! 1.27]	! 0.0429 (0.0236) [! 1.82]	! 0.1314 (0.0410) [! 3.21]	! 0.0230 (0.0115) [! 2.01]	! 0.0217 (0.0138) [! 1.57]
1998	! 0.0400 (0.0184) [! 2.17]	! 0.0860 (0.0338) [! 2.54]	! 0.0058 (0.0276) [! 0.21]	! 0.0152 (0.0148) [! 1.03]	! 0.0451 (0.0252) [! 1.79]	! 0.1170 (0.0405) [! 2.89]	! 0.0272 (0.0158) [! 1.71]	! 0.0230 (0.0179) [! 1.28]
1999	! 0.0322 (0.0178) [! 1.81]	! 0.0576 (0.0270) [! 2.13]	0.0095 (0.0193) [0.49]	! 0.0074 (0.0147) [! 0.51]	! 0.0317 (0.0215) [! 1.48]	! 0.0665 (0.0309) [! 2.15]	! 0.0156 (0.0151) [! 1.04]	! 0.0095 (0.0158) [! 0.60]
2000	! 0.0287 (0.0191) [! 1.51]	! 0.0559 (0.0297) [! 1.88]	0.0234 (0.0210) [1.11]	0.0017 (0.0138) [0.13]	! 0.0260 (0.0229) [! 1.13]	! 0.0683 (0.0331) [! 2.06]	! 0.0027 (0.0137) [! 0.19]	0.0024 (0.0139) [0.18]
Unemployment Rate								
1994	! 0.0001 (0.0007) [! 0.19]	0.0070 (0.0038) [1.82]	0.0030 (0.0051) [0.58]	0.0016 (0.0011) [1.49]	0.0002 (0.0013) [0.16]	0.0044 (0.0037) [1.18]	! 0.0026 (0.0013) [! 1.93]	0.0004 (0.0012) [0.30]
1995	! 0.0007 (0.0006) [! 1.18]	0.0003 (0.0018) [0.18]	0.0012 (0.0019) [0.64]	0.0002 (0.0006) [0.43]	! 0.0007 (0.0005) [! 1.38]	0.0006 (0.0022) [0.25]	! 0.0018 (0.0008) [! 2.26]	! 0.0005 (0.0005) [! 0.92]
1996	! 0.0011 (0.0014) [! 0.79]	0.0071 (0.0058) [1.23]	0.0053 (0.0074) [0.71]	0.0025 (0.0018) [1.35]	0.0002 (0.0019) [0.12]	0.0044 (0.0063) [0.71]	! 0.0053 (0.0022) [! 2.38]	0.0000 (0.0018) [! 0.01]
1997	! 0.0019 (0.0038) [! 0.50]	0.0257 (0.0179) [1.44]	0.0154 (0.0215) [0.72]	0.0071 (0.0050) [1.43]	! 0.0003 (0.0054) [! 0.05]	0.0164 (0.0174) [0.94]	! 0.0133 (0.0064) [! 2.09]	0.0007 (0.0051) [0.13]
1998	! 0.0050 (0.0046) [! 1.08]	0.0133 (0.0175) [0.76]	0.0114 (0.0197) [0.58]	0.0043 (0.0053) [0.82]	! 0.0023 (0.0049) [! 0.46]	0.0078 (0.0189) [0.42]	! 0.0166 (0.0070) [! 2.37]	! 0.0018 (0.0050) [! 0.36]

Appendix 4 (Continued)

Year	All	Single Moms	Female High School Dropouts	Female High School Graduate	Female College or More	Male High School Dropouts	Male High School Graduate	Male College or More
1999	! 0.0067 (0.0043) [! 1.57]	! 0.0042 (0.0133) [! 0.32]	0.0097 (0.0124) [0.78]	0.0038 (0.0044) [0.86]	! 0.0017 (0.0035) [! 0.48]	! 0.0041 (0.0150) [! 0.27]	! 0.0160 (0.0054) [! 2.93]	! 0.0031 (0.0035) [! 0.89]
2000	! 0.0063 (0.0041) [! 1.54]	! 0.0056 (0.0143) [! 0.39]	0.0140 (0.0117) [1.19]	0.0046 (0.0043) [1.07]	! 0.0013 (0.0031) [! 0.41]	! 0.0080 (0.0134) [! 0.59]	! 0.0149 (0.0054) [! 2.78]	! 0.0016 (0.0032) [! 0.50]
Employment/POP Ratio								
1994	0.0008 (0.0012) [0.71]	0.0094 (0.0053) [1.76]	0.0036 (0.0056) [0.64]	0.0007 (0.0021) [0.35]	0.0046 (0.0030) [1.53]	! 0.0117 (0.0052) [! 2.25]	0.0000 (0.0018) [! 0.02]	0.0006 (0.0021) [0.30]
1995	0.0019 (0.0011) [1.80]	0.0086 (0.0038) [2.25]	0.0024 (0.0031) [0.78]	0.0012 (0.0015) [0.84]	0.0034 (0.0020) [1.72]	! 0.0037 (0.0034) [! 1.09]	0.0014 (0.0014) [0.99]	0.0009 (0.0013) [0.70]
1996	0.0032 (0.0022) [1.46]	0.0189 (0.0092) [2.05]	0.0054 (0.0094) [0.58]	0.0032 (0.0037) [0.87]	0.0066 (0.0050) [1.32]	! 0.0136 (0.0081) [! 1.67]	0.0017 (0.0032) [0.51]	0.0015 (0.0036) [0.43]
1997	0.0076 (0.0065) [1.18]	0.0512 (0.0257) [1.99]	0.0162 (0.0261) [0.62]	0.0068 (0.0111) [0.62]	0.0215 (0.0144) [1.50]	! 0.0487 (0.0256) [! 1.90]	0.0029 (0.0096) [0.31]	0.0046 (0.0100) [0.46]
1998	0.0136 (0.0082) [1.67]	0.0689 (0.0300) [2.30]	0.0194 (0.0276) [0.70]	0.0113 (0.0126) [0.90]	0.0265 (0.0161) [1.64]	! 0.0385 (0.0280) [! 1.37]	0.0083 (0.0114) [0.73]	0.0069 (0.0110) [0.62]
1999	0.0172 (0.0075) [2.29]	0.0635 (0.0241) [2.64]	0.0132 (0.0227) [0.58]	0.0167 (0.0112) [1.50]	0.0157 (0.0128) [1.22]	! 0.0101 (0.0214) [! 0.47]	0.0117 (0.0099) [1.18]	0.0074 (0.0093) [0.80]
2000	0.0180 (0.0075) [2.40]	0.0600 (0.0206) [2.91]	0.0095 (0.0201) [0.47]	0.0197 (0.0123) [1.60]	0.0116 (0.0116) [1.00]	! 0.0065 (0.0212) [! 0.31]	0.0108 (0.0100) [1.08]	0.0084 (0.0082) [1.03]
LFP Rate								
1994	0.0011 (0.0006) [1.81]	0.0156 (0.0057) [2.73]	0.0030 (0.0030) [0.98]	0.0021 (0.0020) [1.08]	0.0051 (0.0029) [1.76]	! 0.0077 (0.0044) [! 1.73]	! 0.0027 (0.0018) [! 1.54]	0.0002 (0.0010) [0.23]
1995	0.0018 (0.0008) [2.33]	0.0137 (0.0045) [3.05]	0.0033 (0.0029) [1.13]	0.0016 (0.0014) [1.12]	0.0033 (0.0017) [1.95]	! 0.0035 (0.0028) [! 1.27]	! 0.0015 (0.0012) [! 1.19]	0.0004 (0.0011) [0.38]
1996	0.0034 (0.0014) [2.42]	0.0292 (0.0099) [2.95]	0.0064 (0.0057) [1.13]	0.0052 (0.0034) [1.52]	0.0074 (0.0043) [1.74]	! 0.0096 (0.0067) [! 1.42]	! 0.0037 (0.0029) [! 1.25]	0.0008 (0.0020) [0.38]

Appendix 4 (Continued)

Year	All	Single Moms	Female High School Dropouts	Female High School Graduate	Female College or More	Male High School Dropouts	Male High School Graduate	Male College or More
1997	0.0085 (0.0038) [2.25]	0.0831 (0.0279) [2.98]	0.0178 (0.0164) [1.08]	0.0132 (0.0104) [1.27]	0.0251 (0.0138) [1.81]	! 0.0332 (0.0214) [! 1.55]	! 0.0118 (0.0086) [! 1.37]	0.0019 (0.0057) [0.33]
1998	0.0136 (0.0053) [2.54]	0.1037 (0.0332) [3.12]	0.0246 (0.0210) [1.17]	0.0168 (0.0119) [1.41]	0.0272 (0.0143) [1.91]	! 0.0299 (0.0230) [! 1.30]	! 0.0115 (0.0098) [! 1.17]	0.0031 (0.0075) [0.42]
1999	0.0163 (0.0053) [3.09]	0.0858 (0.0257) [3.34]	0.0238 (0.0180) [1.32]	0.0210 (0.0106) [1.98]	0.0185 (0.0102) [1.81]	! 0.0112 (0.0168) [! 0.67]	! 0.0051 (0.0078) [! 0.65]	0.0039 (0.0066) [0.59]
2000	0.0179 (0.0049) [3.67]	0.0763 (0.0215) [3.55]	0.0226 (0.0157) [1.44]	0.0261 (0.0117) [2.23]	0.0194 (0.0106) [1.83]	! 0.0055 (0.0166) [! 0.33]	! 0.0016 (0.0071) [! 0.23]	0.0044 (0.0058) [0.77]

NOTE: These estimates combine the 2SLS estimates with an assumed shock to caseloads due to welfare reform. The numbers reported are the mean effects from 1,000 simulations, with each simulation based on one random draw from the distribution of 2SLS parameter estimates. The “standard errors” are the standard deviation of the effects from these 1,000 simulations. The “t-statistics” are the ratios of these mean effects to the standard deviations.