The Effect of PRWORA on Welfare Caseloads in Pennsylvania:

Fixed Effects Versus Random Effects Models

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Abstract

This paper uses administrative data from various government agencies from 1990-2002 to test the impact of the 1996 welfare reform on caseload numbers in Pennsylvania counties. The results of fixed and random effects models are compared. Though both models suggest that PRWORA had a significant effect on welfare caseloads, the fixed effects model assumes that this effect was constant across counties, does not allow a test of individual county slopes, and does not allow a test of specific, measured county level fixed effects. The random effects model allows the effect of PRWORA to differ by county and also allows for the direct test of fixed county level variables. In particular, I test whether the effect of PRWORA differed in urban and rural counties, and find small differences in the impact of PRWORA across counties. However, I find no evidence to suggest that systematic differences in the effect of TANF exist between rural and urban counties in Pennsylvania.

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The late 1980s and early 1990s were marked by a steep rise in welfare caseloads throughout America. In response to these trends, during his first State of the Union Address, President Clinton promised to "end welfare as we know it" (Executive Office of the President, 1993). As part of this promise, he proposed that the government strengthen families and provide welfare recipients with the skills necessary to move them off of welfare and into the labor force. The president kept his promise of reform by signing the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) in 1996. The bill overhauled the welfare system and replaced the existing program, Aid to Families with Dependent Children (AFDC), with a new program, Temporary Assistance for Needy Families (TANF). As implemented, TANF contains several strict regulations that require welfare recipients to either work or attend job training in order to continue receiving government assistance. Moreover, the bill places limits on the amount of time participants can receive welfare benefits, and contains several initiatives aimed directly at reducing teen and non-marital births as a means of fighting rising welfare caseloads and persistent welfare dependence (Sawhill, 2002).

The 1996 welfare reforms appear to have had an immediate and significant impact on welfare caseloads (Haskins, 2001). Between 1996 and 1998, total welfare caseloads fell by 33%, and it is estimated that roughly 1/3 of this decline is a direct result of the 1996 legislation (CEA, 1999). However, the Council of Economic Advisors (CEA) notes that the effects of TANF were not uniform across states. Percent declines in welfare caseloads between 1996 and 1998 ranged from 83% in Idaho, to 4% in Nebraska. Though differences in state policies account for a large fraction of the discrepancies between states (Blank, 2001), they do not tell the complete story, as the effects TANF were not necessarily uniform within states either. Several reports based on within state data suggest that TANF had a differential effect on rural and urban counties (Whitener, Weber, & Duncan, 2001; Henry, Lewis, Reinschmiedt, & Lewis, 2001; Lee, Harvey, & Neustrom, 2002). Taken together, these state and county differences suggest that the effects of public policy on welfare caseloads are moderated by differences in other local and regional variables.

Several authors have used administrative panel data in order to assess the variables that contribute to the rise and fall of welfare caseloads. The most common model is a time-series cross-sectional fixed effects design (CEA, 1999). Though this model provides an adequate test of the effects of macro-level variables, it assumes that the effects of welfare reform are constant across geographic units. However, this assumption is not always plausible. Though fixed effects models may account for individual differences between geographic units, for the most part they merely control for individual characteristics with dummy variables and do not allow researchers to model and define the effects of stable, between-unit variations (Snijders & Bosker, 1999). However, random effects models—also known as mixed models or random coefficient models—do allow researchers to test the effects of specific, stable, unit-level variables. Both fixed effects and random effects models have advantages and disadvantages, and the appropriateness of each model depends on the research questions being asked. This paper uses administrative data from various government agencies from 1990-2002 to test the impact of the 1996 welfare reform on caseload numbers in Pennsylvania counties. Moreover, by comparing the results of fixed and random effects models I also examine whether the 1996 welfare reform had a differential effect on rural and urban counties within the state of Pennsylvania.

Background

Within-State Caseload Analysis

Most studies examining the changes in welfare caseloads involve panel studies across states and years. However, there are several advantages to performing a within state analysis. Though average state welfare usage is related to the overall strength of the state economy, local economic conditions have a more direct influence on welfare participation rates (Henry, Reinschmiedt, Lewis, & Hudson, 2002). State level aggregation tends to mask the effects of local economic conditions, whereas county level analysis is more sensitive to the influence of local variation in economic trends. The same argument can be made for other variables measuring within state variation. For example, a large national study performed by the Government Accountability Office (GAO, 2004) found that on average, across the nation, rural and urban areas experienced the same average percentage decline in welfare caseloads after the implementation of TANF. However, in a review of recent literature, Whitener, Weber, and Duncan (2001) report that when analyses are confined to rural and urban differences within the same state, rural and urban differences in the effect of TANF on welfare caseloads emerge.

Within state analysis also controls for large variations in welfare policies between states. Blank (2001) reports that state welfare eligibility requirements are one of the most robust predictors of state welfare caseloads. Therefore, much of the between state variation in welfare caseloads is often attributable to differences in state policies. The passage of PRWORA in 1996 gave considerable autonomy to states by providing block grants and inviting state legislators to creatively implement welfare policies (Sawhill, 2002). If anything, now there exists greater between-state variation in welfare policy than existed in the past. It is possible, therefore, that the impact of state level rural and urban differences are confounded by state level differences in welfare policy and implementation. If one assumes that welfare policies within a single state should differ little between counties, then a within state analysis eliminates this confound.

Differences between Rural and Urban Populations

There are several reasons for predicting that TANF would have a differential effect on rural and urban areas. Pickering (2000) argues that several major tenets of PRWORA failed to consider the realities of economic conditions and family life in rural America; and instead more closely represent the characteristics of connected metropolitan areas. In general, rural populations are more likely to receive public assistance than urban populations (Parisi et al., 2003). Moreover, high unemployment is found disproportionately in rural areas, and rural households have the greatest likelihood of being in poverty, even after controlling for local labor markets and other local economic conditions (Brown & Hirschl, 1995; Lee et al., 2002; Weber & Duncan, 2000; Gibbs, 2002; Lichter & Jensen, 2001; RUPRI, 1999). In addition, rural wages tend to be lower than urban wages, and the working poor in rural areas are much more likely to be in poverty when compared to their urban counterparts (Findeis et al., 2001; Gibbs, 2002).

Rural economies also tend to be more fragile than those found in urban areas. Many rural economies are based on a single industry, and are often harder hit by a downturn in the economy (Findeis et al., 2001). Moreover, even when macro-level economic conditions improve, rural labor markets tend to lag behind metro markets (Gibbs, 2001).

In addition to facing more severe economic circumstances, rural residents often face spatial barriers that make it difficult to meet the work requirements and residency requirements outlined in TANF (Taylor, 2001; Pickering, 2000; Snyder & McLaughlin, 2004). Moreover, rural areas often lack the infrastructure for providing residents with solid employment (Weber & Duncan, 2000). In addition, rural residents often face greater barriers to securing steady work, as access to quality childcare and public transportation are often limited in rural areas (Brasher, Broyles, Jacobs, & Volk, 2002; Whitener, Weber, & Duncan, 2001).

Rural isolation not only affects individual residents, it also can have an impact on the operations of state programs. In Louisiana, Lee et al. (2002) found that the effectiveness of many state policy goals was a function of geographic isolation. Shortly after the implementation of TANF, researchers reported only small differences in overall TANF use between metro and non-metro parishes. However, they found that the state's ability to reduce individual parish caseload numbers was a function of the parish's relation to metro areas. The farther rural parishes were from large cities, the more difficult it was to reduce welfare caseloads (See also Whitener, Weber, & Duncan, 2001).

Rural and urban populations also demonstrate differences in fertility and marital trends, which are associated with welfare participation. Rural residents tend to marry earlier than their urban counterparts (Heaton et al., 1989; McLaughlin, Lichter & Johnston, 1993; Meyers & Hastings, 1995). Moreover, delayed marriage among urban populations leads to a higher proportion of non-marital births among urban groups (Haveman, Wolfe, & Pence, 2001). On the other hand, the likelihood of living in poverty is still the greatest for female headed families living in nonmetro areas (Snyder & McLaughlin, 2004). Taken together, these variables suggest that the 1996 welfare reform may have had a differential effect on rural and urban areas, and therefore, it may be important to model these differences when assessing factors that contribute to welfare decline.

The results of studies tracking rural and urban differences in the effects of the 1996 welfare reform on caseload numbers are mixed (Kaplan, 1998). National studies tend to find no differences between rural and urban areas (GOA, 2004); however, rural and urban differences tend to emerge in within state analyses (Whitener, Weber, & Duncan, 2001). Though the GOA (1994) reports that nationally there were no urban and rural differences in caseload declines after the implementation of TANF, if within state differences did exist, it was more common for caseloads in rural areas to decline more than caseloads in urban areas. However, detailed studies from Louisiana (Lee et al., 2002), Mississippi and South Carolina (Henry et al., 2002), and Minnesota (Gennetian, Redcross, & Miller, 2002), suggest that state level welfare reforms are more successful in urban areas than in rural areas.

Pennsylvania is an ideal state for assessing rural and urban differences in the effects of the 1996 welfare reform for many reasons. The majority of previous within state analysis have been conducted in the South and the Midwest regions of the United States, while Pennsylvania is located in the Northeast, a region that has not received much attention. Pennsylvania is a large state. According to the 2000 U.S. Census, Pennsylvania is the sixth largest state in the union, and has a population of more than 12 million people (U.S. Census Bureau, 2004). Moreover, Pennsylvania has both a large urban population (located primarily in Philadelphia and Pittsburg) and a large rural population (located primarily in the central and northern areas of the state). In addition, Pennsylvania's 67 counties are fairly evenly divided between urban and rural classifications (32 and 35 respectively), thus allowing for a large number of observations of both rural and urban counties.

Fixed Effects Models

A common model for determining the rise or fall in welfare caseloads is a time-series—cross-sectional fixed effects design. These models typically involve predicting state welfare participation rates or caseloads by gathering state level administrative panel data on various independent variables and then adding state and year fixed effects as controls into a regression model. A good example of the cross-sectional regression approach was outlined by the Council of Economic Advisors (CEA, 1997), and their model has been followed by several other researchers (Blank, 2001; Lee, Harvey, & Neustrom, 2002; Henry et al., 2001). The basic model is as follows:

$$C_{sy} = \beta_0 + \beta_1 D_{sy} + \beta_2 G_{sy} + \beta_3 Z_{sy} + \nu_s + \rho_y + trend*\nu_s + \varepsilon_{sy} \quad (1)$$

The dependent variable, $C_{sy,}$ is typically a measure of welfare caseloads for each state in a particular year (the subscripts s and y stand for state and year, respectively, throughout the model). D represents a vector of demographic variables such as the proportion of non-marital births, or the percent of the population that is African American for a given county in a given year. G represents a vector of variables that describe specific policies that are in effect in a particular state within a given year such as family caps or work sanctions. Z represents a vector of economic variables thought to influence welfare caseloads such as average state wages or state unemployment rates. The two vectors ν_s and ρ_y represent state and year fixed effects respectively, and ε_{cy} represents an independently and identically distributed random error term. State specific time trends ($trend*\nu_s$) are also often included in the model, and the data are typically weighted by state population.

There are several advantages to analyzing time-series—cross-sectional data with a fixed effects approach. First, the use of fixed effects is an effective way to control for unmeasured, time-invariant, individual differences, as well as unit-invariant differences between time points (Allison, 1994; Worral & Pratt, 2004). The fixed effects usually consist of dummy codes for each state (minus one) and each year (minus one). These controls tend to reduce bias due to missing or unmeasured third variables. For example, in a given time period, states with high non-marital birth rates may also have high welfare uptake rates. However, both variables may be driven by a third, unmeasured and time-invariant variable such as persistent poverty. Models that fail to account for this third variable would tend to bias the effect of non-marital childbearing on welfare participation. In addition, it is possible that all units in the model could experience an event in the same year that greatly affects the relationship between two variables. For example, a sudden, sharp downturn in the national economy may bias the log-term relationship between unemployment and welfare participation. A fixed effects approach controls for these other variables, thus producing unbiased estimates.

Not only does controlling for individual unit and time effects produce unbiased estimates, it also allows researchers to generalize the results across units and time (Worral & Pratt, 2004). This is especially advantageous for institutions like the federal government. Because most laws enacted by the U.S. Congress apply to the entire nation, it would be important to asses to overall impact of federal legislation, while controlling for state specific variation. Because these models control for individual state and time differences, they provide an unbiased measure of the general relationships between outcomes and predictors at the national level.

Despite these advantages, there are a few drawbacks to using fixed effects models. First, depending on the number of units and time points, the number of dummy codes can become somewhat cumbersome—especially if unit specific time trends are included in the model (Allison, 1994). Second, these models assume that the error structure, ε_{sy}, is independent for all *s* and *y,* and this is not always appropriate given that observations are often nested within units. With regard to welfare, caseload totals one year are likely to be highly correlated with caseloads numbers from the previous year. Third, these models assume that the relationships between variables are uniform across time and units (Snijders & Bosker, 1999). Though the fixed effects indicate differences in the intercepts of states, all states are assumed to have the same slopes, and this assumption may not allows be appropriate. It is possible that the 1996 welfare legislation had a differential effect on specific states due to variation between the states on unmeasured stable characteristics. However, any stable differences in state characteristics are linearly dependent with the dummy codes for the state fixed effects, and therefore difficult to analyze.

Random Effects Models

When using time series-cross sectional data, in order to test the effect of unit level stable characteristics, such as rural and urban differences, it may be more appropriate to use a random effects or random coefficients model (Snijders & Bosker, 1999). These models are similar to the fixed effects models outlined above, except they allow for unit level differences in slopes between the outcome and the predictor variables. The basic specification is as follows (Raudenbush & Bryk, 2002; Snijders & Bosker, 1999):

$$C_{sy} = \beta_{0s} + \beta_{1s}D_{sy} + \beta_{2s}G_{sy} + \beta_{3s}Z_{sy} + \varepsilon_{sy} \qquad (2)$$

Again, the dependent variable, $C_{sy,}$ is a measure of welfare caseloads for each state in a particular year (the subscripts s and y stand for state and year, respectively, throughout the model). D represents a vector of demographic variables, G represents a vector of policy variables, and Z represents a vector of economic variables thought to influence welfare caseloads. The state and year fixed effects dummy codes from equation (1) are removed, however, because any unit specific deviations from the estimated parameters in equation (2) are accounted for by the introduction of a random component (Singer & Willet, 2003). This model can be viewed as a two level model with observations (Level -1) nested within states (Level-2). In this model, each β is thought to be state specific, because it contains a state specific element. For example, individual state differences in the intercept, β_{0s}, may be modeled by the following equation:

$$\beta_{0s} = \gamma_{00} + U_{0s}$$

In this instance, γ_{00} represents the mean intercept for all states, and U_{0s} represents the variance of state specific deviations from this intercept. ε_{sy} and U_{0s} are assumed to be independent from one another. Due to the complex structure of these models, they are typically estimated using maximum likelihood procedures (ML), and when all units have the same number of observations, ML provides the most efficient and unbiased estimates (Singer, & Willet, 2003). The advantage of a random effects model is that individual state differences and the influence of level-2 predictor variables can be included in the model without being linearly dependent with one another as in the fixed effects model (Snijders & Bosker, 1999).

For the current study, I intend to examine the effects of the 1996 welfare reform on welfare caseload numbers in the state of Pennsylvania. More specifically, I examine whether the 1996 welfare reform had a differential effect on rural and urban counties within Pennsylvania, comparing the results of both fixed effects models and random effects models.

Hypotheses

H1: The effect of TANF on welfare caseloads will differ between rural and metro counties. More specifically, the impact of PRWORA on welfare caseloads will be stronger in metro counties, leading to greater declines in caseloads in metro counties than in rural counties.

Data

All data for this study were received from various federal and state agencies in the spring of 2004 (see Table 1). Most of the data come from yearly summary reports for all 67 Pennsylvania counties for all years between 1990 to 2002 (in some cases calendar year reports are used, in other instances fiscal year reports are used).

Welfare Measures

Data on welfare budgets and expenditures were received from the Office of Income Maintenance (OIM), within the Pennsylvania Department of Public Welfare. The OIM produces yearly summary reports tracking welfare caseloads and expenditures for each of the state's 67 counties. These reports include the number of persons eligible for cash assistance, the number of budgets eligible for cash assistance, the total expenditures for cash assistance, and the percent of the population that is eligible for and currently receiving benefits. Data for this analysis come from county annual reports for fiscal years 1990-2002. Following the convention of Blank (2001) and the CEA (1997), welfare participation rates for each county are put in the same metric by dividing the total number of households receiving cash assistance by the county population, and then taking the log of this calculated variable.

Demographic Measures

Previous research suggests that single motherhood is associated with increased rates of welfare receipt (Blank, 2001; Foster, Jones & Hoffman, 1998; Causes of Poverty, 1996; McLanahan, 1994; Wertheimer & Moore, 1998). In order to control for the effect of single mothers on welfare caseloads I calculate the share of non-marital births within each county. The Bureau of Health Statistics and Research within the Pennsylvania Department of Health records the mother's age, race, and marital status for all live births within the state of Pennsylvania. Data for this analysis come from yearly summary reports of all Pennsylvania counties from 1990-2002[1]. For the current analysis, raw frequency counts have been converted into birth ratios. More specifically, for each county I calculated the ratio of married births to all births in order to put all of the counties in the same metric.

In order to measure whether a county is rural or urban, I adapted the 2003 rural-urban

[1] These data were provided by the Bureau of Health Statistics and Research, Pennsylvania Department of Health. The Department specifically disclaims responsibility for any analyses, interpretations or conclusions

continuum codes provided by the Economic Research Service within the US Department of Agriculture (ERS, 2004). This variable indicates how rural or urban a county is based on population and location. The original scale is a 9 point ordinal measure. Due to the nature of Pennsylvania counties, I collapsed a few of the categories, to form a 7 point ordinal measure (for a more detailed explanation of the new coding system, please see Table 2 in the appendix). The lower numbers refer to urban counties, and the higher numbers represent more rural counties. These particular codes are based on the 2000 census. In the analysis, I treat this variable as time-invariant, despite the fact that county designations may be modified over time due to changes in population and development. However, the codes are updated with each new census, and between the 1990 and the 2000 censuses the coding scheme was changed, making direct comparisons between the two code years difficult. Despite the changes, however, the 1993 codes and the 2003 codes are highly correlated (r = .91). Moreover, had the same codes been used for both censuses, almost every county in Pennsylvania would have received the same designation, and at most counties would have moved one designation. Therefore, the codes are more or less time-invariant for the years involved in the current study, and this variable provides a rough measure of the urban and rural nature of the counties during the years of interest.

Estimates of the population for each county for the years 1990-2002 were obtained from the U.S. Census Bureau website (www.cenus.gov/).

Economic Measures

Previous research suggests that welfare caseloads are largely influenced by local economic conditions (Gibbs, 2001; Moffit, 2001; CEA, 1999), and therefore, a few key economic controls will be included in the analysis. The average yearly unemployment rate for each county was provided by the Pennsylvania Bureau of Labor Statistics yearly summary reports. Average yearly wage per job were obtained from the Bureau of Economic Analysis within the U.S. Department of Commerce. The average wage per job for each year was converted to 2002 dollars using the Consumer Price Index (CPI-U) provided by the Bureau of Labor Statistics (www.bls.gov/). In addition, due to the skewed distributions of both these variables, the log of each variable is used in the analysis.

Fixed Effects Models

The basic analytic strategy for the first part of the study is based on equation (1) and outlined by the CEA (1997). However, instead of state data, the following fixed effects models are based on county data and policy variables are excluded:

$$C_{cy} = \beta_0 + \beta_1 F_{cy} + \beta_2 Z_{cy} + \nu_c + \rho_y + \text{trend}^*\nu_c + \varepsilon_{cy} \qquad (3)$$

The dependent variable is equal to the log of the total number of welfare households divided by the population in a given county for a particular year (The subscripts c and y stand for country and year, respectively, throughout this model). F represents the proportion of non-marital births. Z represents a vector of economic variables thought to influence welfare caseloads, including unemployment rates and average wages. The two vectors ν_c and ρ_y represent county and year fixed effects respectively and trend*ν_c represents county specific linear and quadratic trends. ε_{cy} represents an independently and identically distributed random error term, and the data are weighted by population. Because the county and year fixed effects and county specific time trends tend to inflate measures of R^2, the root mean squared error will be used to determine improvements in the predictive powers of the various models.

The results of the fixed effects models are outlined in Table 3. I begin by specifying a simple model relating only the key predictor variables (non-marital births, unemployment, and wages) to the county welfare caseloads. In model 1 all variables are significantly related to welfare caseloads, consistent with the findings of previous research. Model 2 adds the county and year fixed effects, and is similar to the model specified by the CEA (1997). The addition of these county and year controls improves the predictive power of the model significantly, as evidenced by a decrease in the root mean squared error (RMSE) from 87.143 to 21.770. However, with this tighter specification only the economic variables are significant predictors of welfare caseloads.

Model 3 adds the county specific linear and quadratic time trends. Worrall and Pratt (2004) argue that these unit specific trend variables control for any unit specific deviations from the general trends due to unmeasured or unaccounted variables. However, as with the county fixed effects, adding theses variables merely controls for any such deviations, and does not try to explain them. With this tight specification, only unemployment rates significantly predict welfare caseloads. This model is a better predictor of welfare caseloads (a decrease in the RMSE of 11.316); however, it also comes at the inclusion of 132 additional predictor variables.

The results of Model 3 suggest that the model may be over specified. Figure 1 contains a plot of the county welfare caseloads by year. Caseloads for all counties from 1990-2002 appear to follow the same general curve and the trajectories seem to vary only in their intercepts. This suggests that the county fixed effects (individual county intercepts) and the year fixed effects (the mean for each year) account for the vast majority of variation in welfare caseloads. To test this hypothesis, I ran the analysis with only the state and year fixed effects and they explained 98.2% of the variance in county welfare caseloads (Model 4; R^2 = .982; RMSE = 22.170). Next, I performed the analysis with the county and year fixed effects and the county specific time trends included in the model and these controls accounted for 99.6% of the variance in county welfare caseloads (Model 5; R^2=.996; RMSE = 10.494). All three time varying predictors in

Model 1 were significantly related to welfare caseloads ($p<.001$), however, when non-marital births, unemployment rates and wages are added to the model containing the fixed effects and county specific time trends, it leads to a reduction in the RMSE of only .050. This suggests that I have modeled changes in county welfare caseloads with a high level of precision, however, with the exception of unemployment rates, I am unable to explain what is causing caseloads to rise or fall. Given that model 1 explains much of the variance in welfare caseloads with only three predictors ($R^2 = .719$), even if these three coefficient estimates are biased upwards, it suggests that that the 210 dummy coded control variables are capturing between and within county differences in unemployment, average wages, and non-marital births. However, at this point, with models 3, 4, and 5, I can only conclude that unmeasured county characteristics and universal year to year changes are driving the rise and fall of welfare caseloads, thus highlighting one of the drawbacks of an over specified fixed effects model.

In order to understand what the fixed effects are controlling, it is often helpful to examine a plot of county welfare caseloads over time. The uniform pattern of county caseloads over time in Figure 1 suggests that it may be possible to model the effects of TANF as a function of time. However, all counties experienced TANF at the same time, and therefore, the year fixed effects are linearly dependent with any variable indicating the introduction of TANF. There are at least two methods for dealing with this. The first is to examine a plot of the year fixed effects (Blank, 2001). The year fixed effects represent any changes in the mean county welfare case loads for a given year that are not explained by any other predictor variables or covariates included in the model (Worrall & Pratt, 2004). Figure 2 contains a plot of the coefficients for the year fixed effects from Model 2 in Table 3. After controlling for non-marital births, unemployment rates, and wages, the average county caseload numbers appear to decline steeply after 1996. Though this visual analysis does not prove that this decline is due entirely to TANF, the introduction of TANF is one of the unmeasured variables represented by the year fixed effects. Had I included more time varying covariates in the model, I would be more confident in attributing the drop in caseloads to TANF; however, this quick visual inspection does suggest that TANF may have played a significant role in caseload reductions.

Allison (1994) recommends a more quantitative method for modeling change over time with panel data, making it possible to estimate the overall effects of an event. Because all counties in Pennsylvania experienced TANF at the same, any coding scheme indicating years when TANF was in place will be linearly dependent with the year fixed effects. In order to account for this, Allison argues that one can drop the year fixed effects and specifically model the effects of time. A simple adaptation of the fixed effects model in equation (3) that models time may look something like:

$$C_{cy} = \beta_0 + \beta_1 F_{cy} + \beta_2 Z_{cy} + \beta_3 X_y + \nu_c + \text{trend}{*}\nu_c + \varepsilon_{cy} \qquad (4)$$

The dependent variable, the time varying covariates, the county fixed effects, the county specific trends, and the error term are the same as in equation (3). However, the year fixed effects are replaced by a Variable X_y that indicates the whether or not the 1996 welfare reform was in place ($X_y = 0$ for the years 1990-1996; $X_y = 1$ for the years 1997-2002). The results of this analysis are included in the column for Model 6 in Table 3. This model predicts welfare caseloads in a manner comparable to that of the full model specified by Model 3 (difference in RMSE = 5.064). However, model 6 is much easier to interpret. The results of Model 6 suggest that after accounting for key demographic and economic covariates, and state specific time trends, the implementation of TANF led to an average county caseload reduction of 23% during the 1990s. These results are similar to those found by the CEA (1999). Moreover, in Model 6 all of the time varying predictor variables are significantly associated with welfare caseloads ($p. < .001$) in a fashion that corroborates previous research. Increases in non-marital births and unemployment rates are positively associated with welfare caseloads, whereas an increase in average wages is negatively associated with growth in welfare caseloads.

Model 6 contains the fixed county effects as well as the county specific time trends, and is therefore, the most conservative estimate of the impact of TANF implementation on welfare caseloads in Pennsylvania. In model 7 the county specific time trends are removed, and it is estimated that TANF led to an average county caseload decline of approximately 41%. In model 8, only the time-varying covariates are included and it is estimated that county caseloads declined by an average of 45% after the implementation of TANF. The actual effect of TANF probably lies somewhere between the conservative estimate in Model 6, and the most liberal estimate in Model 8.

In general, the fixed effects models are very useful for determining the overall effects of TANF implementation on welfare caseloads in Pennsylvania. However, these models assume that the effects of TANF are universal across counties. Moreover, because the county fixed effects are linearly dependent with any measured stable county differences, the impact of the fixed county differences cannot be modeled. In this analysis, the fixed county effects do not allow me to model rural and urban differences between counties. Though it may seem possible to drop the county fixed effects dummy codes, and instead include the rural and urban codes as predictors in the model, the estimates of these coefficients are biased because they do not account for the fact that repeated measures are taken from each county (Snijders & Bosker, 1999). However, random effects models overcome these drawbacks and allow for an unbiased test of rural and urban differences in county welfare caseloads as well as rural and urban differences in the effect of TANF on those caseloads.

Random Effects Models

The basic analytic strategy for the random effects models is based on equation (2); however, instead of state data, the following random effects models are based on county data:

$$C_{cy} = \beta_{0c} + \beta_{1c}D_{cy} + \beta_{2c}Z_{cy} + \varepsilon_{cy} \qquad (5)$$

All random effects models were estimated using HLM (Raudenbush, Bryk, Cheong, & Congdon, 2001) in order to examine the if rural and urban differences between counties account for any variation in county welfare caseloads or any variation in the effect of the 1996 welfare reform on the decline in caseload numbers. The interclass correlation from the intercept only model was .56. This value suggests that over 50% of the variance in welfare caseloads between 1990 and 2002 occurs between counties. In the following series of models I attempt to explain this variation with a measure of the rural and urban nature of each county.

I begin by running a simple model to determine if, after controlling for key time varying predictor variables, there is a significant difference between counties in average welfare caseloads. I assume that the effect of unemployment, non-marital births, and average wages is the same across counties, and therefore, the only random element occurs in the estimate of the intercept. The model specification is:

$$C_{cy} = \beta_{0c} + \beta_{1}\text{Unemployment} + \beta_{2}\text{Wages} + \beta_{3}\text{Non-marital} + \varepsilon_{cy} \qquad (6)$$

$$\beta_{0c} = \gamma_{00} + U_{0c}$$

In this case, β_{0c} represents a county specific average of welfare caseloads composed of two parts. γ_{00} represents the sample average, and U_{0c} represents the individual county deviation from the sample average. The results of this analysis are found in the column for Model 9 in Table 4. In this simple model, as expected, all three of the key covariates are significant predictors of welfare caseloads ($p. <.001$). In addition, there appears to be significant variance between counties in average welfare caseloads ($Var(U_{0c}) = .050$, $p. <.001$). After transforming the results to a more interpretable metric, these data suggest that from 1990 to 2002, an average of 6.97 households per 1000 persons in Pennsylvania were receiving cash assistance welfare payments. However, after accounting for individual county differences in non-marital births, average wages, and unemployment rates, 95% of Pennsylvania counties, fall between 2.48 and 19.54 households per 1000 persons receiving cash assistance. These data suggest that there are significant between county differences in the proportion of the population receiving cash assistance.

Next, I tested if any of the between county differences in welfare caseloads could be explained by rural and urban differences between the counties. The specification for this model is the same as in equation (6), except the rural code is now used to predict each counties' intercept, or average welfare usage:

$$\beta_{0c} = \gamma_{00} + \gamma_{01}Rural + U_{0c}$$

In this case, β_{0c} represents a county specific average of welfare caseloads composed of three parts. γ_{00} represents the sample average, γ_{01} represents the effects of county rural designation on the county average, and U_{0c} represents the individual county deviation from the sample average after accounting for the rural designation. The results of this model are reported in the column for Model 10 in Table 4. The rural and urban code, as a level-2 predictor, does not significantly explain any of the between county variation in average welfare caseloads ($\gamma_{01} = -.004$; $p. > .75$).

Though county rural and urban differences do not explain any of the observed differences in mean county welfare caseloads from 1990 to 2002, I wanted to test whether the 1996 welfare reform had a differential effect on rural and urban counties. First, I set up a model similar to the fixed effects model in equation (4), which adds the variable X_y, a measure of years in which TANF had been implemented. However, I also included a random coefficient that allows for individual county deviation from the main TANF effect. The exact specification for this model is as follows:

$$C_{cy} = \beta_{0c} + \beta_1 \text{Unemployment} + \beta_2 \text{Wages} + \beta_3 \text{Non-marital} + \beta_{3c} X_y + \varepsilon_{cy} \qquad (7)$$

$$\beta_{0c} = \gamma_{00} + U_{0c}$$

$$\beta_{3c} = \gamma_{30} + U_{3c}$$

In this case, β_{0c} represents a county specific average of welfare caseloads from 1990-1996 that is composed of two parts. γ_{00} represents the sample average from 1990-1996, and U_{0c} represents the individual county deviation from the sample average for that time span. β_{3c} represents a county specific change in average of welfare caseloads between the time before TANF(1990-1996) and after TANF (1997-2002) that is composed of two parts. γ_{30} represents the overall average change in welfare caseloads after the passage of TANF, and U_{3c} represents the individual county deviation from the sample average change for that time span. The results of this analysis are found in Table 4, in the column for model 11, and suggest that the implementation of the 1996 welfare reform significantly reduced welfare caseloads in Pennsylvania. County welfare caseloads fell by an average of 43%, consistent with the fixed effects models. Moreover, there is significant variation between the counties in the effect of welfare reform (Var (U_{3c}) = .007, $p. <.001$).

The results of model 11 suggest that from 1990 to 1996 an average of 9.04 households per 1000 persons in Pennsylvania were receiving cash assistance welfare payments. However, the average for 95% of Pennsylvania counties lies between 3.28 and 24.89 households per 1000 persons. Likewise, from 1997 to 2002 on average of 5.15 households per 1000 persons in Pennsylvania were receiving cash assistance welfare payments. However, the average for 95% of Pennsylvania counties lies between 3.52 and 7.55 households per 1000 persons.

In order to test if any of the variance between counties in the effect of TANF is a result of rural and urban differences between the counties, I added a county level predictor to the estimate of the effect of TANF in equation 7. The model is the same as in equation (6), except that the coefficient for the effect of TANF now consists of three components:

$$\beta_{3c} = \gamma_{30} + \gamma_{31}\text{Rural} + U_{3c}$$

In this model, β_{3c} represents a county specific change in average welfare caseloads between the years prior to the implementation of TANF, and the years after TANF, composed of three parts. γ_{30} represents the sample average, γ_{31} represents the effects of county rural designation on the county average, and U_{3c} represents the individual county deviation from the sample average after accounting for the rural designation. The results of this analysis are displayed in Table 4 in the column for Model 12. The data suggest that the rural and urban code, as a level-2 predictor, does not significantly explain any of the between county variation in the effect of TANF on changes in average welfare caseloads (γ_{31} = -.004; p. > .35).

There were many reasons to hypothesize that TANF would have a more powerful impact on caseload reductions in metro counties; however, these results suggest that there was no difference in caseload reductions between rural and metro counties in Pennsylvania. One explanation for the null findings may be found in the nature of the coding scheme. These codes are ordinal in nature and are fairly specifically defined by the population and location of each county (ERS, 2004). It is possible that a seven unit classifications scheme is too specific to capture rural and urban differences. For example, there may be little difference in moving from a metro county of 1,001,000 persons (code 1) to a metro county of 800,000 people (code 2). However, moving from an urban county of 225,000 people (code 3) to a rural county of 25,000 people (code 4) may lead to more drastic changes in local conditions. To test this hypothesis, I reanalyzed the final model using a dichotomous metro or nonmetro county designation (model 13 in table 4), but this new variable did not change the results in any significant way. It is also possible that the county designations are too broad, as counties may be composed of both rural and urban areas, and that these within the county differences may be masked by county level designations.

The most probable explanation, however, for the failure of the rural codes to predict differences between counties in the effect of TANF implementation may simply be the fact that there were few between county differences. Figure 1 contains a plot of county welfare caseloads over time. Almost all of the counties appear to follow the same general path. It appears that there are variations between counties in the height of their individual curves; however, the counties appear to follow the same general trajectory. Figure 3 displays a similar plot of county welfare caseloads over time, except that the counties are grouped by their rural urban continuum codes, and a vertical line is added to represent the passage of TANF in 1996. Again, differences in the heights of the curves emerge; however, there is no systematic explanation behind these height differences. For example, the top trajectory represents counties with a rural code of 1, while the bottom curve represents counties with a rural code of 2. The similarity of the curves in this plot suggests that the effect of TANF was fairly uniform across rural and urban counties. When a dichotomous metro and nonmetro designation is used, the two curves are nearly identical and overlay one another (figure not shown). Taken together, these results provide strong evidence that the implementation of TANF was fairly uniform across counties in Pennsylvania.

Discussion

I intended to replicate the results of previous studies indicating that the implementation of TANF had a strong impact on welfare caseload numbers during the 1990s (Haskins, 2001; CEA, 1999), and wanted to further examine rural and urban differences. Using the same fixed effects models that others had employed with state data (Blank, 2001; CEA 1999), I obtained nearly identical results with county data, finding that TANF explained roughly 1/3 of the recent declines in welfare caseloads in Pennsylvania. Though these results are not surprising, it is possible that they may overestimate the relationship between welfare reform and caseloads in Pennsylvania. This is because I have only included three key time-varying predictor variables. Moreover, though I control for county specific time trends in the fixed effects models, it is possible that other important covariates mediate the relationship between welfare caseloads and welfare reform. Other key county variables related to welfare caseloads worth examining might include female headship rates (Snyder & McLaughlin, 2004), welfare benefit levels (Moffit, 2001; Blank, 2001; CEA, 1999), teen birth rates (Wertheimer & Moore, 1998), proportions of elderly residents and immigrants (Blank, 2001), and changes in the wages of the lowest earners (CEA, 1999). However, the inclusion of county specific time trends in the fixed effects model should account for much of the variation due to these unmeasured variables (Worral & Pratt, 2004). Moreover, even if every one of these variables had a significant effect, it is doubtful that these effects would erase the overall effect of TANF.

Based on the results of previous studies, I was confident that TANF would have a significant effect on welfare caseloads. However, I was more interested in determining if this effect was uniform across all counties. In order to test this hypothesis, I argued in favor of using random effects models in order to test the impact of fixed county characteristics. In particular, I was interested in examining whether rural and urban differences between counties explain any of the between county differences in the effect of the 1996 welfare reform. I hypothesized that TANF would lead to greater reductions in welfare caseloads in the more metro counties (e.g. those near Philadelphia and Pittsburgh) when compared to the more rural counties (e.g. those in the central and northern regions of the state). The random effects models suggest that TANF did have a strong overall effect on welfare caseloads in the 1990s. Moreover, the results suggest that there was significant variation in the effects of TANF on welfare caseloads between specific counties. However, rural and urban differences between counties did not explain any of these observed differences.

The results of this study conflict with the results of within state analyses performed in Louisiana (Lee et al., 2002), and Mississippi and South Carolina (Henry et al., 2001). In these previous studies it was found that reductions in welfare caseloads were larger in more urban counties when compared to more rural counties. However, differences between the states may explain the conflicting results. Whitener, Weber, and Duncan (2001) discuss the hardships faced by counties the ERS has designated as "persistently poor counties"—counties where at least 20% of the population has lived below the poverty line since 1960. Though the 1996 welfare reforms reduced caseload numbers in most of these counties, the declines were not as great as the declines in other counties within the same states. The majority of the persistently poor counties are located in the rural south, and several of them are found in Louisiana, Mississippi, and South Carolina. However, no "persistently poor" counties are located within Pennsylvania. In addition, rural counties in Pennsylvania do not tend to be as isolated from metro areas as other rural counties. Only 7 of Pennsylvania's 67 counties are not adjacent to a metro county. It is possible, therefore, that the rural poor in Pennsylvania do not face the spatial barriers and employment barriers experienced by the rural poor in other states (Pickering, 2000; Whitener, Weber & Duncan, 2001).

Another purpose of the study was to demonstrate the utility of using random effects models to examine the effects of an event with time-series cross-sectional data. Both the fixed and random effects models provide similar results. In this case, both models demonstrated that TANF had a strong impact on caseload numbers between 1990 and 2002. Moreover, both models are able to account for the independent effects of stable county characteristics. However, the fixed effects models merely control for these county level differences, whereas the random effects models allow one to test the effects of these variables, assuming they have been measured (Snijders & Bosker, 1999).

Snijders and Bosker (1999) argue that when choosing between the two models, it is best to consider what type of questions one hopes to measure. If you are interested in the overall effect of an event across units, it is best to use a fixed effects design, because the tight specifications of the model control for any unmeasured unit and time effects. For example, the 1996 welfare reform allowed the states a large degree of autonomy in implementing TANF, and—with a few exceptions—the federal government set fairly broad parameters under which TANF was to be executed (Sawhill, 2002). Moreover, not all states implemented TANF at the same time. Theses two factors taken together lead to great variation between states in the implementation of TANF, all of which the federal government had little control over. Therefore, in order to assess the impact of federal legislation, it makes sense for the CEA to use a fixed effects model that controls for state variations, and provides a measure of the overall impact of the federal components of the legislation.

On the other hand, within a state, policy makers assessing the impact of state legislation may be more interested in variations between jurisdictions in the effects of state reforms. Moreover, they may be particularly interested in understanding any specific county variations that may lead to differences in the effectiveness of state level reforms. If assessing the impact of stable, unit-level variables is the primary goal, than a random effects model may be better suited for these research questions (Snijders & Bosker, 1999). In this example, we tested if TANF had a differential effect on welfare caseloads in rural and urban counties. Though we found that the effect of TANF was not uniform across counties in Pennsylvania, any observed county differences were not a result of urban and rural differences between the counties.

Where might researchers go from here? After controlling for unemployment, average wages and non-marital births, the differences between counties in the effectiveness of TANF are significant. In the random effects model, the average county deviation from the main effects of TANF was significant. Though I was unable to explain any of these county deviations by rural and urban differences, these deviations may be of special interest to politicians, local leaders, and social service workers. Random effects models may allow them to better understand the source of these individual county differences; and therefore, tailor local policies to meet these needs. Instead of controlling for individual county differences, if researchers have several measures of stable characteristics that separate counties, they may be able to parse the variation controlled for in fixed effects models into useable information that can be modeled, and not just statistically controlled. In addition, random effects models could also be used to model individual county variation on a number of other county level outcome variables such as food stamp receipt, Medicaid participation, crime rates, poverty rates, or average educational attainment.

In this analysis, the random effects were limited to overall measures of individual county differences in welfare caseloads and the effects of TANF on welfare declines. However, the random effects can also be used to test if the effects of covariates are uniform across counties. For example, in the current data, unemployment rates had a fairly robust impact on county welfare caseloads. Based on the results from Model 9, if the average unemployment rate in Pennsylvania grew from 6% to 7%, the average county welfare participation would grow from 6.45 households per 1000 persons to 7.57 households per 1000 persons. However, this assumes that the effect of unemployment on welfare caseloads is uniform across counties. It is possible the average effect of unemployment differs across counties due to rural and urban differences or variation in some other stable county characteristic. For example, residents of rural counties are more likely to rely on kin for economic assistance (Hofferth & Iceland, 1998), and therefore, in the event of an economic downturn, a change in unemployment may be more likely to affect the welfare utilization of urban populations. Such a hypothesis could easily be tested using a random effects approach.

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Table 1
Description of Data Used in the Analysis

Source	Data	Type	Years Avail.
Demographic Measures			
U.S. Census Bureau	Estimated mid-year county population	Total Persons	1990-2002
Bureau of Health Statistics and Research (Pennsylvania Department of Health)	Total births by age	Frequency Counts	1990-2002
	Total births by marital status	Frequency Counts	1990-2002
Economic Research Service (U.S. Department of Agriculture)	County rural urban continuum codes	Ordinal coding scheme ranging from 1 to 9	2003
Economic Measures			
Pennsylvania Bureau of Labor Statistics	Unemployment rate	Yearly average	1990-2002
Bureau of Economic Analysis (U.S. Department of Commerce)	Average wage per job	Yearly Average	1990-2002
Welfare Measures*			
Office of Income Maintenance (Pennsylvania Department of Public Welfare)	Persons/Budgets eligible for cash assistance, foodstamps, and medical assistance	Average monthly frequency counts	1990-2002
	Percent of the population that is currently receiving cash assistance**, foodstamps, and medical assistance	Yearly average	1990-2002

*Reports based on fiscal years
**Original figure not available for 1994, calculated using average monthly total divided by estimated population

Table 2
ERS Rural Urban Continuum Code Conversions

Code	Description	Frequency
	2003 Codes	
	Metro counties:	
1	Counties in metro areas of 1 million population or more	13
2	Counties in metro areas of 250,000 to 1 million population	14
3	Counties in metro areas of fewer than 250,000 population	5
	Nonmetro counties:	
4	Urban population of 20,000 or more, adjacent to a metro area	14
5	Urban population of 20,000 or more, not adjacent to a metro area	0
6	Urban population of 2,500 to 19,999, adjacent to a metro area	12
7	Urban population of 2,500 to 19,999, not adjacent to a metro area	5
8	Completely rural or less than 2,500 urban population, adjacent to a metro area	2
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area	2
	Total	67
	Adjusted 2003 Codes	
	Metro counties:	
1	Counties in metro areas of 1 million population or more	13
2	Counties in metro areas of 250,000 to 1 million population	14
3	Counties in metro areas of fewer than 250,000 population	5
	Nonmetro counties:	
4	Urban population of 20,000 or more	14
5	Urban population of 2,500 to 19,999, adjacent to a metro area	12
6	Urban population of 2,500 to 19,999, not adjacent to a metro area	5
7	Completely rural or less than 2,500 urban population	4
	Total	67
	Dichotomous Codes	
1	Metro counties	32
0	Nonmetro counties	35
	Total	67

Table 3
Fixed Effects Estimates of the Determinants of Total County Welfare Caseloads.
Dependent variable = log(Average yearly cash assistance households/Population)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Proportion non-marital births	1.548**	0.105	0.025			0.669**	-.381	2.034**
	(0.009)	(0.127)	(0.090)			(0.115)	(.136)	(.049)
Log (unemployment rate)	1.250**	0.311**	0.101*			0.389**	.392**	.515**
	(0.062)	(0.056)	0.036)			(0.023)	(.041)	(.050)
Log (average wage)	0.685**	0.437*	0.226			-2.532**	-2.058**	.374**
	(0.115)	(0.198)	(0.256)			(0.242)	(.234)	(.081)
TANF (0= pre-TANF; 1= post-TANF)						-0.112**	-.232**	-.343**
						(0.006)	(.010)	(.011)
County effects	no	yes	yes	yes	yes	yes	yes	no
Year effects	no	yes	yes	yes	yes	no	no	no
County specific time trends	no	no	yes	no	yes	yes	no	no
Root mean squared error	87.143	21.770	10.454	22.170	10.494	15.818	31.324	60.573
Adj-R^2	.719	.982	.996	.982	.996	.991	.964	.864
Predictors in model	3	81	213	78	210	202	70	4
Observations	871	871	871	871	871	871	871	871

Standard errors are in parentheses. All regressions based on data for 67 counties from 1990-2002.
** Significant at p.<01; * Significant at p.<05

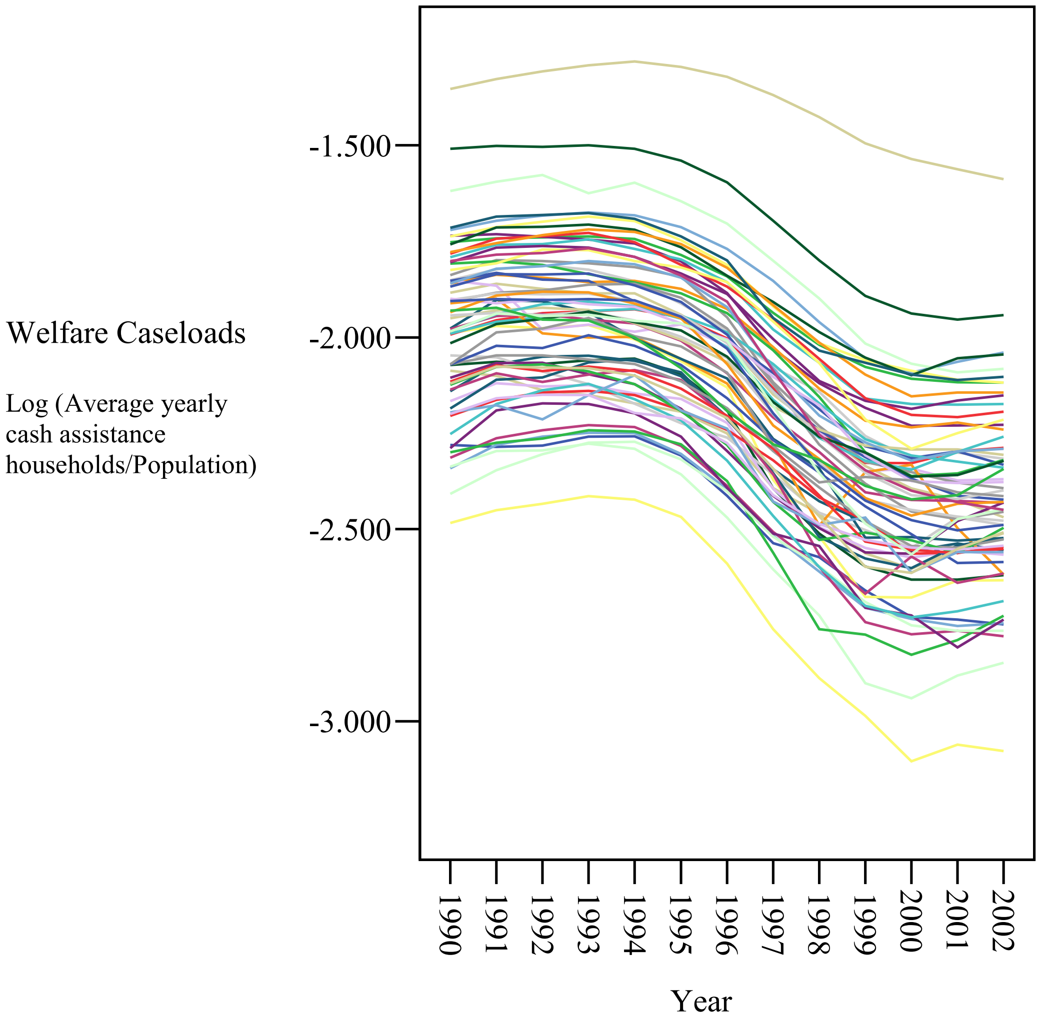

Figure 1
County Welfare Caseloads by Year

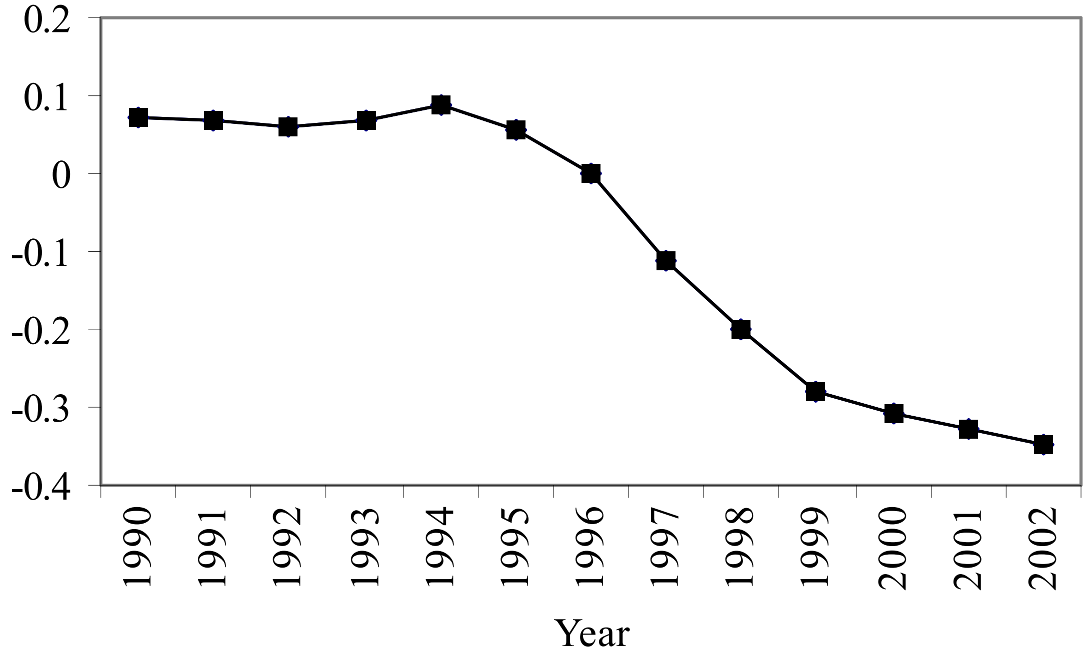

Figure 2
Year Fixed Effects for Total Caseloads Regression

Table 4
Random Effects Estimates of the Determinants of Total County Welfare Caseloads. Dependent variable = log(Average yearly cash assistance households/Population)

	Model 9	Model 10	Model 11	Model 12	Model 13
Fixed Effects					
Intercept	-2.157*** (0.027)	-2.157*** (0.027)	-2.044*** (0.027)	-2.043*** (0.027)	-2.044*** (0.038)
Proportion non-marital births	-1.346*** (0.292)	-1.346*** (0.292)	-0.126 (0.187)	-0.127 (0.188)	-0.127 (0.188)
Log (unemployment rate)	0.835*** (0.094)	0.835*** (0.094)	0.356*** (0.044)	0.357*** (0.044)	0.356*** (0.044)
Log (average wage)	-5.412*** (0.558)	-5.412*** (0.558)	-3.980*** (0.410)	-3.98*** (0.412)	-3.98*** (0.410)
Rural Urban Code x Intercept		-0.004 (0.016)		-.001 (.016)	.003 (.055)
TANF (0= pre-TANF; 1= post-TANF)			-0.244*** (0.012)	-0.246*** (0.008)	-0.255*** (0.008)
Rural Urban Code x TANF				-0.007 (0.008)	0.020 (0.022)
Variance Components					
Residual Variance	0.009	0.009	0.003	0.003	0.003
Intercept Variance	0.050***	0.051***	0.048***	0.048***	0.049***
TANF variance			0.007***	0.007***	0.007***
Observations	871	871	871	871	871

Standard errors are in parentheses. All regressions based on data for 67 counties from 1990-2002.
***Significant at p.<001

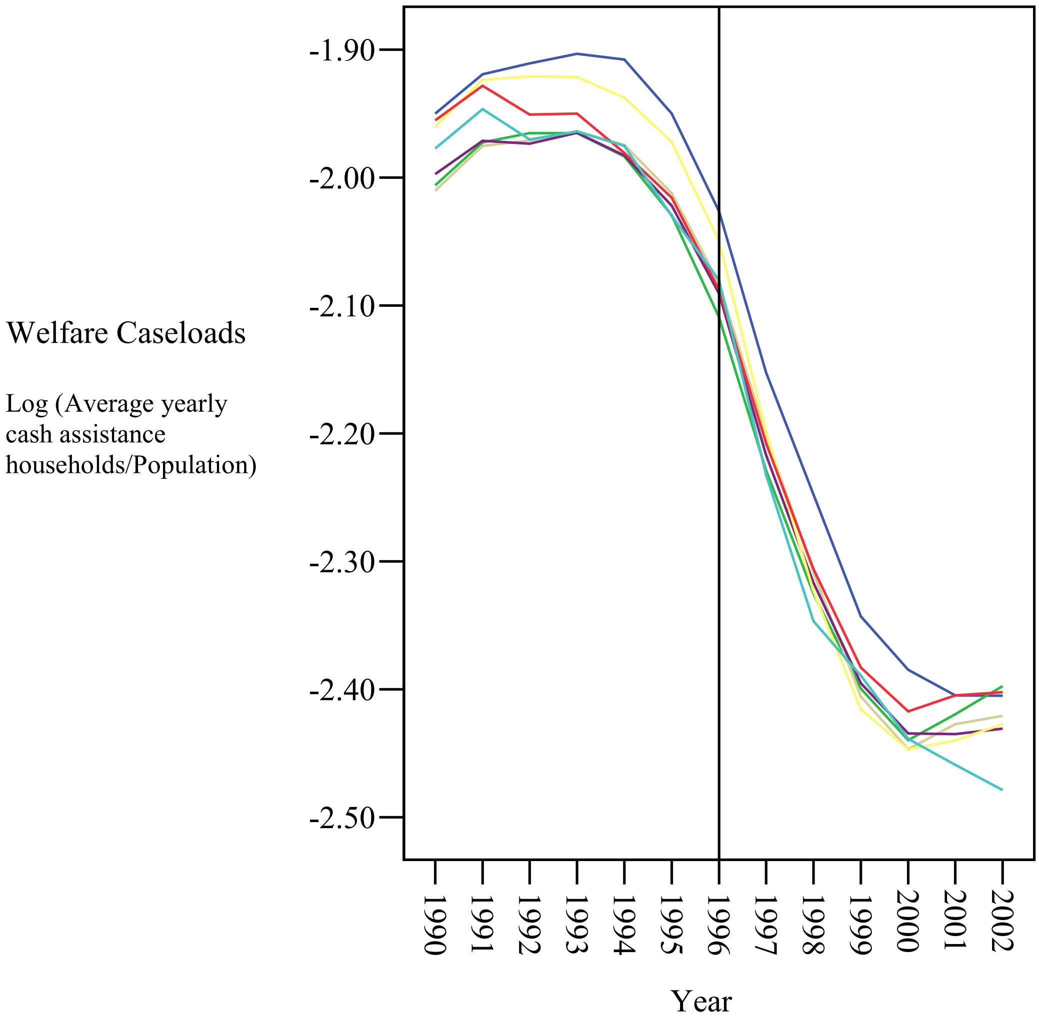

Figure 3
County Welfare Caseloads by Year- Means for Rural Urban Codes