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I. INTRODUCTION

Welfare caseloads have dropped dramatically in recent years, prompting many policy makers to declare an end to welfare as we have known it. The recent decline in caseloads has occurred concurrently with two distinct events. First, most states have restructured their welfare programs to place greater emphasis on getting welfare recipients into jobs. Second, the economy has exhibited strong employment growth with historically low unemployment rates throughout this period, providing unprecedented opportunities for welfare recipients to find employment. Determining the relative importance of these two effects in explaining past changes in welfare caseloads is essential in assessing their future trends. Two recent studies, one by Levine and Whitmore (written as a technical report of the Council of Economic Advisers, 1997) and the other by Ziliak et al. (1997), have found that economic conditions dominate in explaining caseload reductions, but they differ widely in the estimated size of the effect. The CEA attributes 40 percent of caseload decline to economic conditions measured by unemployment rates, while Ziliak et al. attribute 78 percent to unemployment rates. With economic conditions accounting for a substantial portion of the downward trend in welfare caseloads, the question confronting many policy makers is what might happen to the number of welfare cases when the inevitable downturn in the economy occurs. This question has far-reaching ramifications not only for those who turn to welfare programs for income support but also for the financing of state and federal welfare programs, for the funding of other programs that have benefitted from the reduction in welfare expenditures, and for the remaining income maintenance programs such as unemployment insurance and disability insurance.

Several studies have addressed the effect of business cycles on welfare caseloads. The approaches taken by these studies range from national-level time series analyses to state-level pooled cross section, time series studies. Some micro-level studies of individual welfare recipients, while not necessarily directly addressing the effect of business cycles on caseloads, are pertinent to this issue as well. Our proposed study relates most closely to four recent analyses that estimate the effect of economic conditions on welfare caseloads. These studies include Blank (1997), Levine and Whitmore (1997), Ziliak et al. (1997), and the Lewin Group (1997). The Lewin Group study is representative of the general methodology employed by these studies to estimate this relationship and simulate the effects on caseloads of various scenarios of business cycle trends. Specifically, they regress the number of caseloads (and other measures of program participation) on demographic, programmatic, and economic variables. By using pooled cross section, time series data, they control more fully for state and time effects than is possible with only time series data or cross sectional data. They find that changes in the unemployment rate have substantial effects on program participation and that these effects are more persistent than previously found.

Although these studies show the relationship between welfare caseloads and economic conditions, models such as these that use unemployment rates as the only measure of economic conditionsalone have been unable to explain the dramatic reduction in caseloads in recent years. Conversely, this same genre of models has also been unable to explain the large runup in caseloads during the latter part of the 1980s when the economic conditions were quite robust.

The purpose of this paper is to extend the current models to include additional measures of labor market conditions that may affect the variation in welfare caseloads. We believe the unemployment rate by itself may be a woefully incomplete measure of economic conditions affecting potential welfare recipients. The measures we develop are intended to reflect the availability of attractive jobs to welfare recipients. The paper is exploratory in that the variables we develop have not previously been used in the research literature that models welfare caseloads. Some of these variables have been used in the regional economics literature, but not as much in labor economics. Other variables we use are newly developed for this paper. The variables we use are all meant to measure aspects of the structure of local labor demand that might affect welfare recipients, and can reasonably be viewed as exogenous to welfare caseloads and to the labor supply behavior of potential welfare recipients. Thus, for example, we eschew variables that simply measure the economic status of potential welfare recipients, such as the unemployment rate of female household heads with lower levels of education. The economic status of potential welfare recipients is clearly endogenous in that it will be determined by unobserved welfare policies that affect welfare caseloads, and the economic status of potential welfare recipients is clearly affected by labor supply behavior as much as labor demand. Our focus is on labor demand factors affecting welfare caseloads.[1]

Specifically, in one set of models, we attempt to explain welfare caseloads at the state level by not only unemployment, but also state employment growth and three measures of the industrial mix of the state. State employment growth has been shown in the regional economics literature to have powerful effects on labor market outcomes, particularly for less-skilled groups

[1]Thus, we have not implemented the suggestion of our discussant, Joyce Zickler, that we use the wage and unemployment rates of various groups of low-skilled workers as explanatory variables. It might be useful to include such variables in a structural model, in which such variables are treated as endogenous, and other demand and supply shock variables that might affect these wage and unemployment rates are also included. Our focus here is on a simpler reduced form specification that focuses on labor demand factors affecting welfare caseloads.

(Bartik, 1991; Bartik, 1996; Blanchard and Katz, 1992). Some literature also suggests that local employment growth may also affect exit rates from welfare (Hoynes, 1997). One of the industrial mix measures, the average wage premium implied by the area's industry mix, has also been found in the regional economics literature to affect labor market outcomes (Bartik, 1993a, 1996). Finally, our work explaining state caseloads also includes two other industrial mix measures, one that measures the extent to which the state's industries are likely to hire only those with high school degrees, and the other measuring how likely the state's industries are to hire welfare recipients. These measures are new, but have some logical relationship to whether welfare recipients are likely to be able to find jobs.

In another set of models, at the metropolitan level, we go beyond net employment growth to examine how welfare caseloads are related to gross job flows. Studies, such as Davis and Haltiwanger (1992), have shown that the gross flows of employment change capture the dynamics of labor markets better than aggregate measures such as net employment change or unemployment rates. It may be the case that welfare recipients in labor markets with high job turnover have a difficult time finding and retaining jobs. We have access to a unique data set that contains estimates of the components of employment change at the metropolitan level. We examine the effects of gross job flows, and its components on welfare case loads for metropolitan areas during the early 1990s.

Our finding from both sets of models is that welfare caseloads are explained by not only unemployment but also many other aspects of the structure of local labor demand. At the national level, as we will see, the present paper is able to explain the runup in caseloads during the later 1980s as largely due to decreasing demand for less-skilled workers. On the other hand, the recent reductions in welfare caseloads cannot be explained by our labor demand indicators, and are most plausibly explained by a variety of welfare policies. This supports previous results using unemployment only. However, with an expanded set of labor demand indicators, the conclusion that welfare reform policies are lowering caseloads is strengthened. For prediction purposes, our results suggest an expanded set of economic variables that might improve prediction, whether at a national, state, or local level. Our results also suggest some policies that might help in a positive way to lower welfare caseloads, include measures to reduce the extent of job destruction or job instability in the labor market, and measures to improve the educational credentials of welfare recipients.

II. EXTENSION OF STATE-LEVEL ESTIMATES

Most studies, including Blank (1997), Levine and Whitmore (1997), Ziliak et al (1997), and Lewin (1997), use the total unemployment rate (TUR) to characterize labor market conditions. The TUR is intended to reflect the job vacancies for low-skill workers. However, the TUR has been a poor predictor of the number of caseloads during certain time periods. Consider Michigan's experience. If the TUR accurately reflected the job opportunities for low-skilled workers, one would have expected the rapid rundown in the state's total unemployment rate during the 1980s to be accompanied by a significant decline in ADC caseloads. As illustrated in figure 1, the caseloads remained stubbornly high during this period. Only after the waiver went into effect did the number of caseloads start to follow the decline in the unemployment rate that had already been falling for two years prior to the waiver.

As shown in table 1, a simple model of the monthly change in the log of cases regressed on unemployment rates of various lags shows that the unemployment rate does little to explain the differences in caseload. However, a dummy variable denoting the month in which Michigan was granted a waiver (August 1992) is statistically significantly related to ADC caseloads. The waiver affects the intercept of the regression, but does not affect the slope at any of the lags. This brief exercise is presented only to illustrate that at least for the state of Michigan, additional macro-economic variables must be introduced in order to explain caseload reduction.

Model Specification: Additional variables to reflect job opportunities for low-skilled workers

We add to the estimation several variables that will more fully reflect the labor demand conditions facing potential welfare recipients. Our first additional labor demand variable is the employment growth rate of the state. A higher state employment growth rate presumably implies more job vacancies, as well as fewer jobs being lost through business closings and contractions. It is arguable that job vacancies and job loss may be at least as important in determining welfare caseload growth as the percentage of the labor force that happens to be unemployed at a point in time.

In regional economics research, local employment growth has frequently been used to explain labor market outcomes of individuals in local labor markets (Bartik, 1991; Blanchard and Katz, 1992). This research suggests that local employment growth can plausibly be viewed as exogenous shocks to local labor demand in the short-run and medium-run, based on using instrumental variables that attempt to measure shifts in national demand for an area's export industries (Bartik, 1991; Blanchard and Katz, 1992). This is one advantage that employment growth has over the unemployment rate, which is plausibly as much due to labor supply behavior as labor demand behavior. Regional economics research shows that shocks to employment growth continue to affect labor force participation rates, wage rates, and per capita earnings in a local labor market for many years, while the effects of employment growth shocks on local unemployment rates tend to dissipate quickly (Bartik, 1993b). This suggests that employment growth measures aspects of local labor demand that will not be completely captured by local unemployment rates. In addition, the effects of employment growth appear to be greater for less skilled persons than for others (Bartik, 1996). This suggests that local employment growth may be particularly important in determining welfare caseloads. Some recent research suggests that local employment growth is more important in determining exit from welfare, and re-entry into welfare, than the local unemployment rate (Hoynes, 1997). Other recent research on the spatial mismatch hypothesis suggests that the employment growth rate in the suburbs vs. the city is more important than the level of employment in affecting the labor market outcomes of minorities, perhaps because job vacancies and job losses are particularly important to entry-level workers (Ihlanfeldt and Sjoquist, 1998).

The second local labor demand variable we add is the average wage premium implied by the area's industrial mix. We use the wage premia estimated by Krueger and Summers (1988) for each of 40 industries at the national level. The wage premium represents estimated industry effects from a wage regression that regresses wages (including fringe benefits) on worker characteristics, occupation dummies, and dummies for each industry. The resulting industry effects reflect the level of compensation that a worker in a specific industry receives that is different from what the market would dictate based on personal characteristics, including education and experience.[2] These industry wage premia, which do not vary over time, are multiplied for each state/year by the proportion of employment in each two-digit industry, and this product is then summed over all industries for that state/year cell to get the "average wage premium" variable that we use. Although the estimated wage premia are taken from a particular year, research papers by Krueger and Summers (1988) and Katz and Summers (1989) suggest that industry wage premia are remarkably stable over time. The average wage premium variable measures how much a typical worker could expect to get in higher wages than expected based on his/her personal characteristics, assuming that each industry in the state follows the pattern estimated by Krueger and Summers. If the wage premium entices welfare recipients into the labor force by exceeding their reservation wage, then states with higher wage premium would be expected to have fewer cases per capita. On the other hand, if a higher wage premium entices more higher skilled workers into the labor force as well, and employers use higher wage premia to be more selective about hiring and retaining workers, then a higher wage premium might damage job prospects for lower-skill workers, and thus increase welfare caseloads.

The average wage premium, or similar variables measuring whether an area has a high proportion of "good" jobs, has frequently been used to explain labor market outcomes in regional

[2]We extended Krueger and Summers (1988) results for private industries to cover the government sector in the following manner. These results were developed in a previous project that focused on the wages and employment of single mothers, so the data used were data on all single mothers from the March CPS from March 1983 to March 1995. We estimated wage equations using these data, regressing the log of the real wage on various worker characteristics, year dummies, state dummies, and industry dummies. We included dummies for all of Krueger and Summers' two-digit private industries, plus dummies for federal employment, and state and local employment. We regressed Krueger and Summers' estimated wage premium for each private industry on the estimated wage premium we obtained from the same industry. This regression was then used to predict a wage premium for the federal sector, and state and local employment, that is comparable to the private wage premium numbers generated by Krueger and Summers.

economics research. A number of studies have used the percentage of employment in manufacturing or some set of manufacturing industries, to explain local labor market outcomes (Borjas and Ramey, 1994; Bound and Holzer, 1993; Juhn, 1994; Karoly and Klerman, 1994). Research by Bartik suggests that the average wage premium variable dominates manufacturing related variables in explaining labor market outcomes (Bartik, 1996). All these studies show significant effects of some aspect of job quality on local labor market outcomes. Most of the studies suggest that local job quality has progressive effects, for example, helping less-educated workers more than more-educated workers (Borjas and Ramey, 1994; Bartik, 1993a, Bound and Holzer, 1993), and blacks more than whites (Bound and Holzer, 1993; Bartik, 1993a). However, Bartik (1996) finds that the wage premium variable tends to help more middle-income groups rather than low or high income groups. Several studies find that the wage premium or other local job quality variables tend to affect labor market outcomes for women as much as for men (Karoly and Klerman, 1994; Bartik, 1993a, 1996), which suggests that these variables will be relevant to welfare caseloads.

The other two measures of local labor demand are also based on the mix of industries in the state. Specifically, we include one variable measuring the educational requirements implied by the state's industry mix, and the percentage of welfare recipients employed implied by the state's industry mix. These two industry mix variables do not have the precedent of extensive previous use in research, but do seem logically related to labor demand for potential welfare recipients.

For the educational requirements variable, we calculated, for the nation as a whole, and for each year separately, the percentage of employment in each two-digit industry that was high school graduates, using data from the March CPS from March 1983 to March 1997. These data were then combined with data from each state and year on the proportion of employment in each two-digit industry, to calculate a variable measuring the proportion of employees in each state/year cell that would be high school graduates if each industry hired in a similar pattern as its national counterpart for that year. We regard this variable as a rough measure of the extent to which a state's demand is skewed by industrial composition toward higher education workers. This variable for a state relative to other states will increase if a state's industrial composition becomes more concentrated than the national average in industries that have a high percentage of employees with a high school education. Because the characteristics of industries for this variable are measured separately for each year, this variable will also increase relative to other states if a state's industrial composition stays the same, but the state's mix of industries happens to show a greater than average gain in percentage of employees with a high school education. The hypothesis is that welfare recipients may qualify for fewer jobs in states that have a higher than average concentration of jobs requiring high school degrees. As a result, we would expect this variable to be negatively correlated with caseloads.

The variable measuring whether a state's industries tend to employ welfare recipients is measured in a similar manner. The percentage of welfare recipients employed in each two-digit industry at the national level is calculated using March CPS data. However, for this variable we used only March 1996 data to define industry characteristics for all years. As will be seen in later analysis, we want to determine if our variables can explain recent national trends in caseloads, and we do not want this variable to be spuriously correlated with national trends in welfare caseloads. The March 1996 percentage employed who are welfare recipients in each industry are multiplied times the state's proportion of employment in that year in each respective two-digit industry to create a weighted variable for each state/year cell. This weighted variable tells us what proportion of employment would be welfare recipients in each state/year cell if each industry in that state and year had employed welfare recipients in the same proportion that its national counterpart did in 1996. Our first intuition was that this variable should be negatively correlated with caseloads, as one might expect that states whose industries tend to employ welfare recipients to be easier labor markets for welfare recipients to obtain jobs. A second explanation, and one that comports with the results, is that industries that hire a great many welfare recipients may also be the same industries with high turnover rates and other characteristics that *create* more welfare recipients, thus increasing welfare caseloads.

One obvious alternative to our industry mix variables is simply including variables for the proportion of state employment in each of the two-digit industries used in constructing these industry mix measures. We rejected this alternative because of our expectation, based on previous research projects, that such estimation would lead to hopeless problems with multicollinearity.[3] Even if multicollinearity were not a problem, there would be some serious problems with trying to interpret the large numbers of resulting coefficients on individual industries. Using these industry mix variables at least provides a manageable number of coefficients with some idea about what the underlying variables are measuring.

[3]Bartik experimented with using unrestricted variables for the proportion of employment in each two digit industry in the research leading to the studies reported in Bartik (1993a) and Bartik (1996). The basic problem is that nothing is significant when so many industry variables are included in the estimation.

Descriptive Statistics

To get a better sense of the nature of these local labor demand variables, we report a variety of descriptive statistics. Table 2 reports, for each of the three industry mix variables, the “top six” and “bottom six” industries in the calculations used to generate these indices. The pattern is what one would expect. The education variable tends to be high for various white collar dominated industries and low for various low-skilled manufacturing and service industries and agriculture. The welfare employment variable is high for various service-oriented industries and lower-skilled manufacturing. The wage premium variables are high for some high-wage manufacturing industries and other heavy industries, as well as more unionized industries, and lower for service oriented industries.

Table 3 presents means and standard deviations for all five of the local labor demand variables. In addition to presenting the ordinary standard deviation, we also report the standard deviation of the residuals from regressing these variables on a set of state and year dummies. Because the eventual estimation includes a complete set of state and year dummies, it is the variation in these variables after controlling for unobserved state and year effects that is really crucial. As the table shows, the variation in the three industry mix variables is dramatically reduced after controlling for state and year effects. This means that these variables show some pronounced national time trends and persistent patterns of variation across states.

Table 4 presents the correlation of the five labor demand variables, again after controlling for state and year effects. Although many of the correlations are statistically significant and of moderately large size, considerable independent variation in these five variables remains. For example, the largest absolute value of any correlation in the table is .554. The R-squared in regressing a variable on another variable will be the square of its correlation. Hence, the largest amount of variance that one variable explains of another is (.554) squared, or .307, less than one third of the variance.

The pattern of correlations is as one might expect. Employment growth and unemployment are strongly negatively correlated, although considerable independent variation remains. There are states in which unemployment remains low even though employment growth declines. The welfare variable is negatively correlated, as one would expect, with the educational requirements variable and the wage premium variable. States that have an increasing proportion of industries that employ welfare recipients also tend to have an increasing proportion of industries that pay poorly and have lower educational requirements. However, the variables are not close to perfectly correlated. Finally, the wage premium variable is positively correlated with employment growth and negatively correlated with the unemployment rate. This is consistent with previous research that finds, using causality tests, that trends in employment growth and the wage premium variable at the local level tend to mutually cause each other (Bartik, 1993a). This pattern of mutual causation is sensible. A state which gains higher wage industries will tend to experience some growth in labor demand from higher personal income. A state which experiences tightening labor markets may find it easier to attract higher wage premium industries, which may be less sensitive to the wage rate paid for labor.

Table 5 explores the spatial pattern of these local demand variables. The table reports, for 1996, the six states with the highest and lowest values of each variable. Unemployment tends to be low in rural states, but high in a diverse group of states with probably quite diverse economic problems. Employment growth tends to be high in some western and southern states, and low in diverse states. The spatial pattern of these two variables is far from perfectly matched; for example, California was 4th in unemployment in 1996 even though it was 12th in employment growth in 1996. The educational requirements variable tends to be high in northeastern states with many white collar industries, and low in southern and western states. The wage premium variable is high in heavily unionized manufacturing-dominated states, and low in states with a great deal of retail trade and service businesses. The welfare variable is high and low in a diverse collection of states that are difficult to summarize.

Figure 2 reports the national time trends in these labor demand variables. The unemployment rate and employment growth have the pattern one would expect, with employment growth trends seeming to lead unemployment rate trends slightly. The three industry mix variables show pronounced national time trends. The wage premium variable has dramatically declined over time as higher-paying manufacturing industries have declined. The welfare employment variable has increased as service oriented industries have increased. The educational requirements variable has increased as the proportion of educated workers employed has increased in many industries. Some additional work, not reported here, shows that the increase in the educational requirements variable is totally due to changes in the educational composition of individual industries, and not to changes in industry mix in favor of higher education industries. If the same industry variables are used for all years in calculating the educational requirements variable, the national time line is flat.

Results

Our models are extensions of those used by Blank (1997) and Levine and Whitmore (1997). The data used are pooled time-series cross section data at the annual level, for all 50 states (plus DC), for all years from 1984 to 1996. The dependent variable in our preferred models is the natural logarithm of AFDC cases per capita in each state/year cell. All regressions include a complete set of dummy variables for states and years, in order to control for unobserved fixed state characteristics that might affect caseloads, and unobserved national trends that might affect caseloads.[4] Specifications include various combinations of the five economic characteristics mentioned above: unemployment rates, employment growth, demand for high school graduates as predicted by industrial composition, demand for welfare recipients as predicted by industrial composition, and state wage premium as predicted by industrial composition. In addition, the preferred specifications include the log of the AFDC benefit level and whether or not the state has by that year received a waiver for welfare experimentation from the federal government.[5] Specifications differ in the dynamic specification describing the time pattern by which state economic characteristics affect welfare caseloads.

We began by estimating specifications that matched, as closely as possible given our data, the empirical models used by Levine and Whitmore, Blank, and some of the annual models used by Ziliak et al. These results are not fully reported here, but are available upon request. Specifically, we tried to match the specifications used by Levine and Whitmore (their table 2,

[4]State and year effects are in general strongly statistically significant. Therefore, we do not explore dropping these variables as this might lead to omitted variable bias.

[5]We use a rather simple specification of the waiver variable because our focus is on the effects of local labor demand conditions.

column 1), Blank (her table 2, column 1), and Ziliak et al (their table 4, column 4). For Blank's model, this involved switching the denominator of the dependent variable from total state population to the number of female household heads, with other relatives present, ages 16-44, with less than 16 years of education. It turns out that the choice of denominators does not significantly affect the coefficients on the economic variables that we focus on, so the remainder of this paper continues to focus on welfare caseloads per capita. In general, we are able to replicate their results fairly closely for the economic variable we have in common–the unemployment rate–despite some inevitable differences in the precise data used.

Our detailed presentation stresses three models (table 6). The first model is similar to Levine and Whitmore and Blank in simply having the *level* of the ln(caseloads per capita) as a dependent variable, without allowing for any lagged effects of caseloads. All five economic characteristics are included. In deciding on an optimal lag structure, we first tested from zero lags to two lags in unemployment in a model with only unemployment as a state economic characteristic. The optimal lag length in unemployment was then chosen based on the Akaike Information Criterion (AIC). We then added employment growth to this optimal model, and tested from zero lags to two lags in employment growth, choosing the optimal lag length in employment growth based on the AIC. Finally, we added the three industry composition variables to the regressors, and tested the optimal lag length (from zero to two lags) using the AIC, but restricting all three industry composition variables to have the same lag length. We include lags in all the local labor demand variables to allow for the possibility that wages, labor force participation rates, and other labor market outcomes that affect welfare caseloads will take some time to respond to labor demand shocks, and this response may change over time as the local labor market adjusts.[6]

Our second model adds in the lagged level of the ln(caseload per capita) as a regressor, inspired by Ziliak et al's findings that state welfare caseloads appear to be quite persistent from year to year. We also find great persistence, with a coefficient on the lagged dependent variable of 0.913 (standard error = .014; see table for more results). This second model does the same sequential testing procedure to separately determine the optimal lag length for each of the economic characteristics variables.

Finally, our third model drops the lagged dependent variable and uses the change in the ln(caseloads per capita) as a dependent variable. As noted by Ziliak et al, the coefficient close to one on the lagged caseload dependent variable suggests the possibility that the caseload variable is non-stationary. Research by Nickell (1981) suggests that coefficients on the lagged dependent variable in panels with short time series and fixed cross-sectional effects may be biased towards zero, so it is possible that the true coefficient on the lagged caseload variable is one. Again, the optimal lag length for the economic characteristics variables in this "changes" model are determined by sequential testing of various lag lengths. We should state that despite the possibility that the caseload variable is non-stationary, we regard the non-stationarity of the log of caseloads per capita as theoretically implausible. This implies that caseloads per capita are a random walk, with any random factor that happens to push caseloads up or down persisting indefinitely into the

[6] Note that the wage premium and welfare employment variables will vary quite a bit over time for a particular state even though the industry-specific measures used to construct these variables will not vary over time. These industry mix variables will vary as the industry mix changes over time for a particular state. As shown in the section on descriptive statistics, even though a great deal of variation in these industry mix variables is explained by fixed state effects and year effects, there remains much variation across time for a given state that differs from the national variation over time for the same variable.

future. It seems more plausible that caseloads are merely highly sluggish in adjusting to shocks, and that the true coefficient on lagged coefficients is less than one. Hence, we regard model II as the most intuitively plausible of the three models.

Table 6 shows the raw results for these three models. Before simulating the effects of the state economic variables, we wish to note several features of these models that already are apparent in this table. First, it is clear that much more than unemployment in a state's economic environment matters to caseloads. Employment growth and the three industrial composition variables also appear to be highly statistically significant in explaining state caseloads, and this occurs holding constant any fixed state characteristics, and national trends. Second, lags matter a great deal, with the lagged value of state economic characteristics in many cases mattering more than current characteristics in explaining caseloads. Third, in the case of employment growth, controlling for lagged caseloads makes a major difference in the estimated effects of this variable. Without controlling for lagged caseloads, employment growth is estimated to have positive effects on caseloads, while controlling for lagged caseloads, employment growth has negative effects on caseloads. One explanation of this pattern of results is that states that in the past have had recessions and employment declines, and as a result have high caseloads in the past, may tend on average to have higher employment growth as they recover from the downturn. The omission of lagged caseloads may bias the coefficient on employment growth because higher employment growth may proxy for poor growth and high caseloads in the past, and past caseloads tend to persist.

Table 7 simulates the effects of these economic variables. In all cases, what the table reports is the estimated effects of a 1 percent change in the economic variable four years after the shock, which helps make the effects more comparable between the static and more dynamic specifications. The number in parentheses at the top of the column for each variable is the standard deviation of each variable after controlling for state and year effects, that is, the standard deviation of the residual from regressing that state economic characteristics on state and year dummies. This number gives some sense of how much each economic variable varies independently over time for different states. As these numbers reveal, both the unemployment rate and employment growth show a similar percentage variation, while the high school graduate and wage premium variables vary only one-fifth as much, and the state welfare variable varies one-hundredth as much in percentage terms. In addition to reporting results for the state economic characteristics in our models I, II, and III, we report effects of unemployment in identical models that only include unemployment as a state economic characteristic. We also report effects of unemployment in three models similar to those estimated by Levine and Whitmore (1997), Blank (1997), and Ziliak et al (1997). The Levine and Whitmore model mainly differs in not including lags in the unemployment rate from our Model I with just unemployment. The Blank model mainly differs in having a different dependent variable, the log of caseloads per female headed household with relatives present. The Ziliak model uses as a dependent variable the "change" in log caseloads per capita, as in our model III, but also first differences all the other right hand side variables, including the unemployment rate.

The simulation results in table 7 also show a great sensitivity to the exact dynamic specification. For example, the effects of employment growth and the state economic characteristics vary greatly from Model I through Model III. Even if only the unemployment rate is included, the exact dynamics of the specification make a great deal of difference. Including lagged unemployment rates increases the estimated effects of unemployment on caseloads, as is evident from comparing a Levine-Whitmore style model (no lags in unemployment) to Model I with unemployment only. In addition, the Ziliak style model that first differences all variables shows a very small effect of unemployment, perhaps because in this model all effects of unemployment must occur immediately, and the changes in the unemployment rate variable on the right hand side cannot proxy for past lags in the level of unemployment.

In our preferred model, which is Model II, the effects of unemployment are considerably reduced, by more than half, when one adds employment growth and the three industrial composition effects to the specification. A permanent shock to employment growth of 1 percent has similar effects to a permanent shock to the unemployment rate of 1 percent, and the variation in these variables over time and states is fairly similar. A one standard deviation in the high school graduates variable or in the welfare recipient variable also yields roughly similar effects in magnitude to the employment growth or unemployment rate effects, while the effects of the wage premium are considerably smaller, and are statistically insignificant. The point estimates suggest, as one would expect, that faster employment growth lowers welfare rolls. A shift in industrial composition toward industries that tend to employ high school graduates also increases welfare rolls, while the point estimates suggest that an increase in high wage premium industries in an area tends to reduce welfare rolls. These effects are as expected. A surprising finding is that a shift in the industrial composition toward industries that tend to employ welfare recipients is estimated to increase welfare rolls. This finding appears to be somewhat sensitive to the specification. As mentioned above, perhaps this finding can be explained if industries that employ welfare recipients are also those that tend to have less stable jobs, which might contribute to increasing welfare rolls.

Welfare rolls might function as a type of substitute for unemployment insurance for some of these industries. We explore the effect of gross job flows on welfare caseloads in the next section.

A key policy issue is the effects of national or local recessions on welfare caseloads. Because our preferred specification, with other local labor demand variables, estimates a smaller coefficient on unemployment, does our preferred specification imply that a recession with high unemployment has less effect than is believed by other researchers? Our answer to this question is that the effect of a recession depends upon whether increases in unemployment are accompanied by similar changes in other local demand variables as have typically occurred in the past. One could argue that the specifications with only unemployment as a local demand variable already show the effects of unemployment, with other local labor demand variables allowed to endogenously adjust along with unemployment in whatever pattern of correlation has characterized the past joint behavior of these variables. In other words, one could view the specifications with only unemployment as a local demand variable as a "reduced form" version of the fuller specification.

To explore this point further, we estimated several auxiliary regressions in which each of the four labor demand variables, other than unemployment, are regressed on unemployment and a complete set of state and year dummies. These auxiliary regressions are used, along with the specification with five labor demand variables and a lagged dependent variable that we call "Full Model II", to simulate the effect on welfare caseloads after four years of a one point rise in the unemployment rate. As can be seen in Table 8, the effects of unemployment in this multi-equation simulation approximate that of Model II with only unemployment included. We then experiment with dropping, in turn, each one of the four auxiliary regressions, one at a time, from the multi-equation simulation. Dropping an auxiliary regression from the simulation implies that we are holding that variable constant, and not allowing it to change as it does on average when unemployment goes up. As the table makes clear, it is largely the employment growth variable that is generating the smaller coefficient on unemployment in Full Model II.

Therefore, the correct answer to the effects on caseloads of unemployment is that the results of previous authors are fine as long as employment growth increases as it has in the past when unemployment goes up. However, if we believe that in the nation, or in some particular state, unemployment may go up without the usual slowing of employment growth, then the effects of that unemployment rise on welfare caseloads will be smaller than some other researchers have predicted. Conversely, if the economy of the nation or some state will experience slower employment growth, but without a rise in unemployment, our model would lead us to predict a possibly significant rise in welfare caseloads. For example, one could imagine a state with economic problems that lead to slow employment growth or employment declines, but with sufficient out-migration and labor force dropouts that unemployment does not increase.

One key issue is whether the models estimated here, with additional labor demand variables, can explain the national trends in caseloads in the 1980s and 1990s. We explore this issue in two ways. First, we consider the year dummies estimated by the model. Figure 3 reports some of the year dummies estimated. (The 1996 dummy is the omitted dummy, so all year effects are relative to what occurs nationally on average in 1996). One of the graphs compares our preferred model, Full Model II, with an alternative model, Model II with only unemployment as a labor demand variables. Analyzing the year dummies here is somewhat complicated because these models include a lagged dependent variable; hence, if a year dummy is high relative to another year's dummy, this will push up caseloads in subsequent years as well. In any event, this graph indicates that with only unemployment as a labor demand variable, caseloads were pushed up by national year trends throughout the 1980s and early 1990s before some decline. With the other local labor demand variables, the year dummies have a fairly consistent effect throughout the 1980s before showing some decline in the early to mid-1990s. In the other graph in the figure, we consider the models without a lagged dependent variable, Full Model I and Model I with only unemployment. This comparison shows a more dramatic contrast. Model I with just unemployment shows a huge unexplained run-up in caseloads in the 1980s and early 1990s, whereas the full Model I shows, if anything, some unexplained decline in caseloads, particularly in the early 1990s.

Analyzing how different variables contribute to these national trends is complicated in our preferred specification, Full Model II, because of the presence of a lagged dependent variable. With a lagged dependent variable, caseloads at any point in time can be considered as a function of caseloads at any lagged past point in time, and trends in between that past time and the present in other variables, including the year dummies. It so happens that in 1984 and 1989, caseloads per capita were virtually the same, so in this case the rise in caseloads over some subsequent period is totally a function of all the other variables in the model. Table 9 uses this fortunate coincidence to consider whether the model can explain the rise in caseloads that occurred in the 1990s. Previous research by Blank suggested that economic variables cannot explain the rise in caseloads that occurred during this period. As the table shows, caseloads per capita rose in "ln percentage points" by 25.4 percent from 1989 to 1994. In model II, which includes only unemployment as a state economic characteristic, most of this increase is due to unexplained trends in the national time dummies over the 1989 to 1994 time period. But when other state economic characteristics are included, we actually find that unexplained time dummies show a drop in the caseload compared to what we would expect.

Panel B breaks down how national variables explain these differences in caseload during the previous five years. As shown in Panel B, most of the increase in caseloads from 1989 to 1994 appears to be explained by the increase in the "high school graduate demand" industrial mix variable. This variable increased from an average of 82.9 percent over the 1983-89 period to an average of 85.7 percent over the 1988-94 period, an increase of 2.8 percent.[7] The point estimates reported in table 7 suggest that each one percent increase in this variable is associated with about a 0.124 change in the ln(caseload per capita) variable, so an increase of 2.8 percent in this variable would be expected to increase the ln(caseload per capita) by more than 0.30 or over 30 "log" percentage points.

How much should we believe this finding? It should be recognized that this finding extrapolates the effects of relatively small differences in trends across states to relatively large changes over time for the nation. As shown in table 7, the standard deviation of this variable, controlling for state and year dummies, is only about one-fifth of 1 percent. It may be perilous to extrapolate estimated effects of differences across states of one-fifth of 1 percent to differences in the nation of 2 percent or more. On the other hand, the estimated effect is not inherently unreasonable. Welfare rolls are only 3 or 4 percent of the labor force in the United States. A change in welfare rolls of 30 percent is not a large percentage of the U.S. labor force. Changes in

[7]For each year, the value of this variable is calculated as a weighted mean over all 50 states and D.C., using 1996 state population as weights for all years. The averages reported here are simple averages of these averages for the previous 7 years, which are the years involved in these calculations given that the model includes two lags in the high school graduate variable.

the percentage of high school graduates demanded as a percentage of the workforce of 2 or 3 percent loom very large compared to welfare rolls.

IV. GROSS JOB FLOWS

As suggested in the results in the previous section, caseloads are influenced by components of net employment change, namely job creation and job destruction. In the previous section, we found an increase in caseloads in areas with a high concentration of industries that employ welfare recipients. One interpretation of this result is that jobs in these industries turnover more often and provide a less stable employment base for welfare recipients. Gross flows, the summation of job creation and job destruction, are typically used to measure job turnover. The purpose of this section is to take a closer look at the relationship between gross job flows and the number of caseloads to see if such information lends additional insight into the effect of labor market conditions on welfare caseloads.

Gross job flows are obtained by linking establishments longitudinally over a specific time period. The Census Bureau has embarked on a relatively new project to construct gross employment flows by linking all establishments, including the service sector which employs a large percentage of low-skill workers. Davis and Haltiwanger (1992) have linked manufacturing establishments using the Census Bureau's Longitudinal Data File (LRD), but manufacturing employs only a small percentage of low-skilled workers. Therefore, we requested that the Census Bureau create a special tabulation of the employment components for all metropolitan areas between 1989 and 1992. We use these data to examine the relationship between caseloads and labor market conditions across metropolitan areas.

Since the employment components span only the 1989-92 period, the analysis is basically a cross-sectional estimation. However, specification of a limited lag structure is possible, since caseload data for several years around the 1989-92 period are available. Furthermore, specification tests of the lagged structure using state-level data reported in the previous section reveals that either first-differencing the caseloads, or controlling for lagged caseloads, are plausible specifications. Additional analysis reveals that caseloads at the metropolitan level are also quite stable. Rank-order correlations of the caseloads for various time differences across metropolitan areas reveal that the ordering of MSAs according to the number of caseloads is persistent over time. The correlation for caseloads one year apart is about the same as the correlation for caseloads 6 years apart. The correlations average between 0.90 and 0.99.

These specifications are shown in table 10. Column A includes the change in caseloads per capita between 1990 and 1993 from as a dependent variable, whereas columns B and C use the 1993 level of caseloads per capita as a dependent variable and the 1990 level of caseloads is included as a control variable. These variables are regressed against various labor market characteristics, including gross job flows. Since gross flows are estimated for the 1989-92 period, this variable and the net employment change variable are in essence lagged one period. As can be seen in the table, using the change in caseloads per capita between 1990 and 1993 yields the same results as when the lagged dependent variable specification is used.

The persistence of caseloads per capita is evident in the large and highly statistically significant coefficient on the lagged dependent variable. The lagged unemployment rate variable is positive and statistically significant, while the contemporaneous unemployment variable is negative but not statistically significant. Taken together, the sum of the coefficients for these two lags are positive and statistically significant. Net employment change is relatively large and highly statistically significant. The negative coefficient suggests that areas with higher rates of net job growth have lower caseloads, as one would expect.

The gross job flow variable is also statistically significant and is positively correlated with caseloads per capita. Thus, areas with a high degree of job turnover have a larger percentage of the population on welfare, holding constant the area's unemployment rate and its rate of net job creation. This result is consistent with the finding in the previous section that areas with a more predominant mix of industries that employ welfare recipients will have higher caseloads, with the interpretation that employment in these industries is less stable. These estimates suggest that the dynamics of local labor markets that go beyond the typical measures of net employment change and unemployment rate are associated with changes in caseload. Unfortunately, longer time series of gross job flows are not available for all industries at any level of aggregation—national, state or metropolitan. It is not possible to estimate the contribution of gross job flows to the change in caseloads from the late 1980s to the present, as we did for the industry composition variables in the previous section.

We also entered the components of gross flows, job creation and job destruction, as separate variables in the model. Results in column D show that job destruction has a much larger effect than job creation on welfare caseloads. The coefficient on job destruction is statistically significantly different from zero, but the coefficient on job creation is not statistically significant. Areas with higher job destruction are associated with a faster growth in caseloads per capita. Employment growth was a key variable in explaining changes in welfare caseloads in the previous section. Obviously, employment growth is related to jobs created and destroyed. The results from this section suggest an asymmetry in jobs created and destroyed as they relate to welfare recipients. The jobs lost in an area are those that are more likely to be held by welfare recipients, while the jobs created may be those that are less likely to be filled by welfare recipients. The asymmetry does not necessarily occur across broad sectors with one sector experiencing primarily job gains while another experiences primarily job losses. On the contrary, most sectors experience relatively equal shares of job losses and job gains. Even manufacturing, which has suffered steady net job loss for the past two decades, experiences a large number of job gains. Rather, the asymmetry more than likely lies within the same, even narrow, sectors and is characterized by differences in accessibility and qualifications. This interpretation is supported by results from the previous section related to wage premium and high school qualifications.

A few states were granted waivers to include a work requirement before 1993. These states included Michigan, New Jersey, Oregon, Utah, and Vermont, according to Ziliak et al. (1997). We included a dummy variable for metropolitan areas in these states. As shown in column C, the growth in caseloads per capita was somewhat slower in metropolitan areas with waivers than in metropolitan areas without waivers.

V. CONCLUSION

Previous studies of the macro-economic determinants of welfare caseloads have had difficulty in explaining changes in welfare caseloads during the last decade or so using the simple macroeconomic measure of unemployment. Because welfare recipients will typically get entry-level jobs, employment variables that are closely related to job vacancies, such as employment growth, are also important in determining welfare caseloads, as we show empirically in this study. Recognizing that welfare recipients face more substantial barriers to employment than those who typically have more education and skills, we constructed several macro-economic variables that reflect the education requirement of industries and the predominance of low-skilled workers hired by various two-digit sectors. Estimates based on a data set of annual time series observations aggregated to the state level suggest that these variables help in explaining welfare caseloads. More specifically, areas with higher concentrations of industries that hire welfare recipients and demand workers with higher education levels have higher caseloads. Based on a separate set of metropolitan-based estimates, we also found that gross job flows are positively correlated with welfare caseloads, with job destruction dominating the effects. While the two sets of results come from different types of estimation and for areas with different levels of aggregation, the results suggest that skill levels required of industries and the dynamics of the local labor market, which go beyond the typical measures of unemployment rate, help to explain the anomalies in changes in welfare caseloads during the past decade. The findings underscore that welfare recipients have barriers to employment that are different from the rest of the labor force and thus variables that more closely reflect their circumstances should be considered in explaining welfare caseloads.

These findings are relevant to those attempting to predict caseloads at the national, state, or local level, in that it suggests that economic factors other than unemployment could be used to forecast welfare caseloads. In addition, the findings suggest that policies that can enhance net employment growth, reduce job volatility, and increase the educational credentials of welfare recipients may all help to reduce welfare caseloads.

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Table 1. Estimates of the Effect of Unemployment Rates on ADC Caseloads, Michigan, Monthly 1980-1998

Model	A		B	
	Coeff.	S. E.	Coeff.	S. E.
Constant	-.0120***	.0019	-.00007	.0027
Unemployment Rate	.00168	.0023	.0011	.0021
Unemployment Rate (t-1)	.00109	.0036	.0013	.0034
Unemployment Rate (t-2)	.00084	.0036	.0016	.0034
Unemployment Rate (t-3)	-.00511	.0036	-.0063*	.0034
Unemployment Rate (t-4)	.00028	.0036	.0017	.0034
Unemployment Rate (t-5)	.00140	.0036	-.0001	.0033
Unemployment Rate (t-6)	.00085	.0022	.0006	.0033
waiver*UR			.0065	.0097
waiver*UR (t-1)			-.0030	.0128
waiver*UR (t-2)			-.0127	.0141
waiver*UR (t-3)			.0097	.0143
waiver*UR (t-4)			-.0103	.0142
waiver*UR (t-5)			.0224	.0138
waiver*UR (t-6)			-.0078	.0098
waiver			-.0359***	.0057
R-square	.098		.335	

Source: State of Michigan, Department of Social Services, Family Independence Agency, Selected years.

Table 2. Top and Bottom Six Industries for the Three Industry Mix Variables

High School Graduates Variable		Welfare Recipient Variable		Wage Premium Variable	
Industry	**%**	**Industry**	**%**	**Industry**	**%**
Top six industries:					
Banking and other finance	98.1	Private household services	3.78	Petroleum products	61.9
Communications	96.4	Leather and leather products	3.56	Tobacco manufactures	52.7
Other professional services	96.3	Miscellaneous manufacturing	2.92	Public utilities	33.6
Public administration	96.3	Social services	2.65	Communications	29.3
Professional and photo equipment and watches	95.8	Personal services, excluding private household services	2.27	Railroad	26.8
Educational services	95.1	Retail trade	2.13	Transportation Equipment	26.7
Bottom six industries:					
Lumber and wood products	69.8	Not specified metal industries	0.0	Retail trade, other than eating and drinking places	-18.6
Textile mill products	69.1	Aircraft and parts	0.0	Personal services, excluding private household services	-19.4
Leather and leather products	66.7	Other transportation equipment	0.0	Education services	-21.6
Agriculture	63.4	Tobacco manufactures	0.0	Eating and drinking places	-21.9
Apparel and other textile products	62.4	Petroleum and coal products	0.0	Social services	-33.0
Private household services	48.4	Forestry and fisheries	0.0	Private household services	-51.7

Notes: The wage premium number for each industry is actually 100 times differential of each industry from all industry average for ln (wage). The high school graduates variable is % of industry's employees with high school degree as of 1996, from March 1997 CPS. The welfare recipient variable is the % of industry's employees who also receive welfare the previous year, from March 1996 CPS.

Table 3. Means and Standard Deviations of Five Local Demand Variables

	Mean	Standard Deviation	Adjusted Standard Deviation
Unemployment rate	6.85	2.03	1.08
Employment growth (%)	1.89	1.89	1.19
% High School Graduates	84.43	2.25	0.23
% Welfare Recipient	0.95	0.04	0.01
Wage premium	-1.35	1.26	.25

Notes: All means and standard deviations are weighted by the 1996 population of the state. Means and standard deviations are calculated based on data for 51 states (including D.C.) and 15 years (1982-96). The adjusted standard deviation is the weighted standard deviation of the residual from a preliminary regression of the variable on year and state dummies. This preliminary regression was also weighted.

Table 4. Correlations for Five Labor Demand Variables

	Employment Growth	High School Graduates Variable	Wage Premium Variable	Welfare Recipient Variable
Unemployment Rate	-0.538 (.0001)	0.091 (.0114)	-0.364 (.0001)	0.032 (.3837)
Employment Growth		-0.112 (.0019)	0.153 (.0001)	-0.003 (.8990)
High School Graduates Variable			0.283 (.0001)	-0.525 (.0001)
Wage Premium Variable				-0.554 (.0001)

Notes: These correlations are weighted correlations using 1996 population weights for all states. Correlations are for residuals from weighed regression of each of five variables on year and state dummies. Underlying observations are for 51 states (including D.C.) and 15 years (1982-96.) Number in parentheses is probability of correlation of this size occurring by chance if true correlation was zero.

Table 5. States with Highest and Lowest Values of Each Variable, 1996.

Rank	Unemployment Rate	Employment Growth Rate	High School Graduates Rate	Wage Premium Index	Welfare Recipients Rate
Top six states:					
1	Washington DC 8.7	Nevada 6.19	Washington DC 91.76	Indiana -.23	Nevada 1.25
2	West Virginia 7.6	Utah 4.58	New York 88.18	Michigan -.32	Rhode Island 1.06
3	Arkansas 7.5	Arizona 4.54	Massachusetts 87.97	Delaware -.64	Florida 1.05
4	California 7.5	Oregon 3.40	Connecticut 87.82	Ohio -.64	Montana 1.05
5	New Mexico 6.7	Colorado 3.06	New Jersey 87.82	Illinois -.80	Maine 1.03
6	Louisiana 6.6	Georgia 3.01	Maryland 87.73	Kansas -.92	New Hampshire 1.03
Bottom six states:					
46	Wisconsin 3.6	New Mexico .85	Massachusetts 85.79	Maine -3.53	Indiana .94
47	Iowa 3.3	New York .77	Idaho 85.78	Florida -3.84	Connecticut .93
48	Utah 3.2	Arkansas .67	Arizona 85.70	Montana -4.34	Washington .93
49	North Dakota 3.0	Rhode island .50	North Carolina 85.53	Washington DC -4.55	Kansas .91
50	South Dakota 2.9	Hawaii -.07	South Carolina 85.48	Hawaii -5.65	Arkansas .89
51	Nebraska 2.8	Washington DC -2.51	Nevada 84.77	Nevada -5.86	Washington DC .73

Notes: All numbers here are calculated in percentage terms. Wage premium index is 100 times (ln wage differential) for state predicted by its industrial mix. This number is negative for all states because original.

Table 6. Models of the Effect of Economic Variables on AFDC Caseloads

	Model I	Model II	Model III
Dependent Variable	Log(Caseload/ Population)	Log(Caseload/ Population)	Change in Log(Caseload/ Population
Variable:			
Lagged dependent variable	–	0.9129*** (0.0136)	–
Unemployment rate:			
Current	0.0218*** (0.0082)	0.0018 (0.0029)	-0.0001 (0.0030)
Lag 1	-0.0003 (0.0093)	0.0075*** (0.0026)	0.0005 (0.0034)
Lag 2	0.0431*** (0.0067)	–	0.0040* (0.0024)
Log of maximum AFDC benefit	0.5099*** (0.0842)	0.2005*** (0.0295)	0.1794*** (0.0302)
Any statewide waiver	-0.0945*** (0.0188)	0.0066 (0.0068)	0.0161** (0.0069)
Employment growth (change in log of employment):			
Current	1.2660*** (0.4806)	-0.2228 (0.1721)	-0.3988** (0.1766)
Lag 1	–	-0.5646*** (0.1736)	-0.7475*** (0.1802)
Lag 2	–	-0.3400** (0.1401)	0.4040*** (0.1454)
Percent of employment that will be high school graduates based on industry mix:			
Current	-0.0707 (0.0442)	0.0269* (0.0155)	0.0187 (0.0160)
Lag 1	0.0359 (0.0495)	0.0249 (0.0174)	0.0270 (0.0180)
Lag 2	0.0235 (0.0392)	-0.0269** (0.0137)	-0.0346** (0.0142)

Table 6. (Continued)

	Model I	Model II	Model III
Dependent Variable	**Log(Caseload/ Population)**	**Log(Caseload/ Population)**	**Change in Log(Caseload/ Population**
State wage premium (calculated as differential of average ln (wage) based on industry mix:			
Current	**0.1086**	**-0.0114**	**-0.0265**
	(0.0687)	**(0.00241)**	**(0.0248)**
Lag 1	**-0.0311**	**-0.0508**	**-0.0582***
	(0.0877)	**(0.0328)**	**(0.0339)**
Lag 2	**-0.1037***	**0.0615*****	**0.0910*****
	(0.0558)	**(0.0217)**	**(0.0225)**
Percent of employment that would be welfare recipients based on industry mix:			
Current	**2.6822****	**0.7886***	**0.5108**
	(1.3279)	**(0.4684)**	**(0.4826)**
Lag 1	**1.1941**	**-0.5080**	**-0.7093**
	(1.7426)	**(0.6470)**	**(0.6675)**
Lag 2	**0.4381**	**0.2957**	**0.4345**
	(1.2418)	**(0.4641)**	**(0.4815)**
Adjusted R-square	**0.9300**	**0.9915**	**0.7489**
Sample Size	**663**	**663**	**663**

Significance level: * = 1%; ** = 5%; * = 10%.**

***Notes*: Standard errors are in parentheses. All regressions use pooled time-series cross-section data of observations on state/year cells, with data on the dependent variable for all years from 1984 to 1996 (because of the two lags in some variables, data for 1982 and 1983 are also used), and for all 50 states plus the District of Columbia. All regressions are weighted by 1996 values for state population. All regressions, in addition to including variables for which coefficients are reported in table, include complete sets of state dummies and year dummies, to control for unobserved state or national influences on welfare receipt rates. Lag lengths for unemployment rate, employment growth, and three industrial mix variables are determined by choosing among lag lengths from zero to two based on Akaike Information Criterion, with constraint that lag length must be same for all three industry mix variables. F-tests reveal that for each group of current and lagged variables for a particular state economic climate variable (e.g., unemployment), the group is statistically significant at the five percent level in all cases except the unemployment variable for Model III, and the welfare variable for Model III.**

Table 7. Simulated Effects of State Economic Variables on Caseloads, Using a Variety of Models

	Unemployment (s.d. = 1.00)	Employment Growth (s.d. = 1.33)	High School Graduates Variable (s.d. = 0.22)	Wage Premium Variable (s.d. = 0.27)	Welfare Recipient Variable (s.d. = 0.01)
Full model I	**0.0646** **(12.93)**	**0.0127** **(2.63)**	**0.1301** **(5.85)**	**-0.0263** **(1.09)**	**4.3143** **(7.23)**
Full model II	**0.0337** **(3.73)**	**-0.0390** **(4.32)**	**0.1242** **(3.46)**	**-0.0596** **(1.41)**	**2.2924** **(2.61)**
Full model III	**0.0136** **(1.28)**	**-0.0620** **(5.91)**	**0.0710** **(2.18)**	**-0.0925** **(-1.72)**	**1.0205** **(0.95)**
Model I w/only unemployment	**0.0622** **(14.40)**				
Model II w/only unemployment	**0.0793** **(13.95)**				
Model III w/only unemployment	**0.0865** **(11.59)**				
Levine-Whitmore style model	**0.0421** **(9.23)** **[orig = 0.0473]**				
Blank style model	**0.0548** **(9.98)** **[orig = 0.038]**				
Ziliak, et al style model	**0.0080** **(2.80)** **[orig = 0.0066]**				

***Notes*: Pseudo *t*-statistics, equal to mean effect divided by standard deviation from 1000 Monte Carlo repetition of simulation, are reported in parentheses. All estimates report effect on ln (caseloads per/capita) after four years of 1% increase in variable in that column. Estimated standard deviation of residual, in percentage terms, of each variable, after regressing variable on set of year dummies and state dummies, is reported below that variable at top of columns. Nine models are considered, each of which takes up one row in table. Models I, II, and III are discussed in text. Models I, II and III with just unemployment are identical to their original counterparts, but drop other four state economic characteristic variables. Levine-Whitmore style model attempts to estimate model reported in Levine-Whitmore paper, Table 2, column 1. The original estimated effect in their paper is reported in brackets below our estimates of a similar style model. Blank style model attempts to estimate model similar to Blank, Table 2, column 1. Ziliak-style model attempts to estimate model similar to Ziliak, et al, Table 4, column 4. Again, for both Blank and Ziliak models, original estimates in author's paper are reported in brackets below estimates we obtained with a similar, but not identical model. For example, Blank model includes many more control variables than we included in Blank-style model, which may explain why she found slightly lower effects of unemployment.**

Table 8. Simulated Effects of 1% Increase in Unemployment on ln (caseload per/capita), Various Models

Model Used	Effect on ln (caseload per/capita)
Full Model II (from Table 7)	0.0337 (3.73)
Model II with only Unemployment (from Table 7)	0.0793 (13.95)
Full Model II, with auxiliary regressions	0.0649 (10.02)
Employment growth held constant	0.0424 (4.52)
High School graduates held constant	0.0618 (9.78)
Wage premium held constant	0.0601 (8.15)
Welfare Recipient variable held constant	0.0637 (10.01)

Notes: Pseudo t-statistics from 1000 Monte Carlo repetitions of simulations are in parentheses. There are four auxiliary regressions, regressing the four local demand variables (other than unemployment) on unemployment and year and state dummies. Full model II with auxiliary regressions uses these four additional equations to simulate effect of 1% increase in unemployment, with the four other demand variables allowed to change. Remaining models drop one of four auxiliary equations, thus implicitly holding that variable constant.

Table 9. Why Caseloads Increased from 1989 to 1994

Panel A: Difference Between 1989 and 1994 Caseloads and Time Effects	
Difference between ln(caseload/per capita), 1994 vs. 1989	**+ 0.254**
Difference explained by time dummies in previous five years, model with only unemployment included as state economic characteristic	**+ 0.275**
Difference explained by time dummies in previous five years, model with all five state economic characteristics included	**-0.096**

Panel B: Breakdown of contribution of different variables to 1994 minus 1989 difference in caseloads, model with all five state economic characteristics included	
Difference in caseload five years ago	**-0.004**
Welfare benefits	**-0.109**
Waivers	**0.003**
Unemployment rate	**-0.006**
Employment growth	**0.078**
Industry Composition: proportion of demand for high school graduates	**0.339**
Industry Composition: average wage premium	**0.020**
Industry Composition: proportion of demand for welfare recipients	**0.026**
Unobserved national time period effects over previous five years	**-0.096**
total change in ln(caseloads) to be explained	**0.254**

***Notes*: Calculations try to explain 1994 and 1989 caseloads as function of previous five year's variables, plus caseloads as of five years ago. As of five years ago (1989 for 1994, 1984 for 1989), caseloads per capita were virtually identical. These calculations simulate what happens to caseloads due to values of independent variables, allowing for lagged effects that occur due to including lags of some variables, and due to effects via lagged dependent variables. Because the model is linear, these effects should approximately add up.**

Table 10: The effects of economic conditions on the change in metropolitan caseloads, 1990-1993

Dependent variable: Column A: change in caseloads per capita 1990-1993
Columns B, C, D: caseloads per capita, 1993

	A	B	C	D
Log per capita income, 1990	-.0080**	-.0064**	-.0046	-.0046
	(.0032)	(.0031)	(.0030)	(.0031)
% poverty MSA 1990	-.00024*	-.00004	-.00006	-.00006
	(.00013)	(.00013)	(.00013)	(.00013)
Log max benefits 1990	.00079	.0018	.0004	.0004
	(.0043)	(.0041)	(.0040)	(.0040)
Log max benefits 1993	-.00058	-.0002	.0014	.0014
	(.0046)	(.0043)	(.0042)	(.0042)
Unemployment rate, 1990	.00054**	.00045*	.00065**	.00065**
	(.00028)	(.00026)	(.00027)	(.00027)
Unemployment rate, 1993	-.00035*	-.00017	-.00027	-.00027
	(.00021)	(.00020)	(.0002)	(.0003)
Gross flows, 1989-1992	.0263***	.0220***	.0203**	
	(.0043)	(.0043)	(.0042)	
Job gain, 1989-92				-.0074
				(.0058)
Job loss, 1989-92				.0480***
				(.0091)
% employment change 1989-92	-.0286***	-.0280***	-.0277***	
	(.0070)	(.0066)	(.0064)	
Waiver=1 (Since 1992)			-.0022**	-.0022**
			(.0008)	(.0008)
Caseload per capita 1990		.827***	.837***	.837***
		(.048)	(.0463)	(.0463)
Intercept	.066**	.044	.0264	.0264
	(.030)	(.029)	(.0291)	(.0291)
Adj. R-square	.282	.890	.896	.896

Note: Standard errors are below the coefficient estimates. (*,,***) denotes statistical significance at the 0.10, 0.05 and 0.01 confidence levels.**

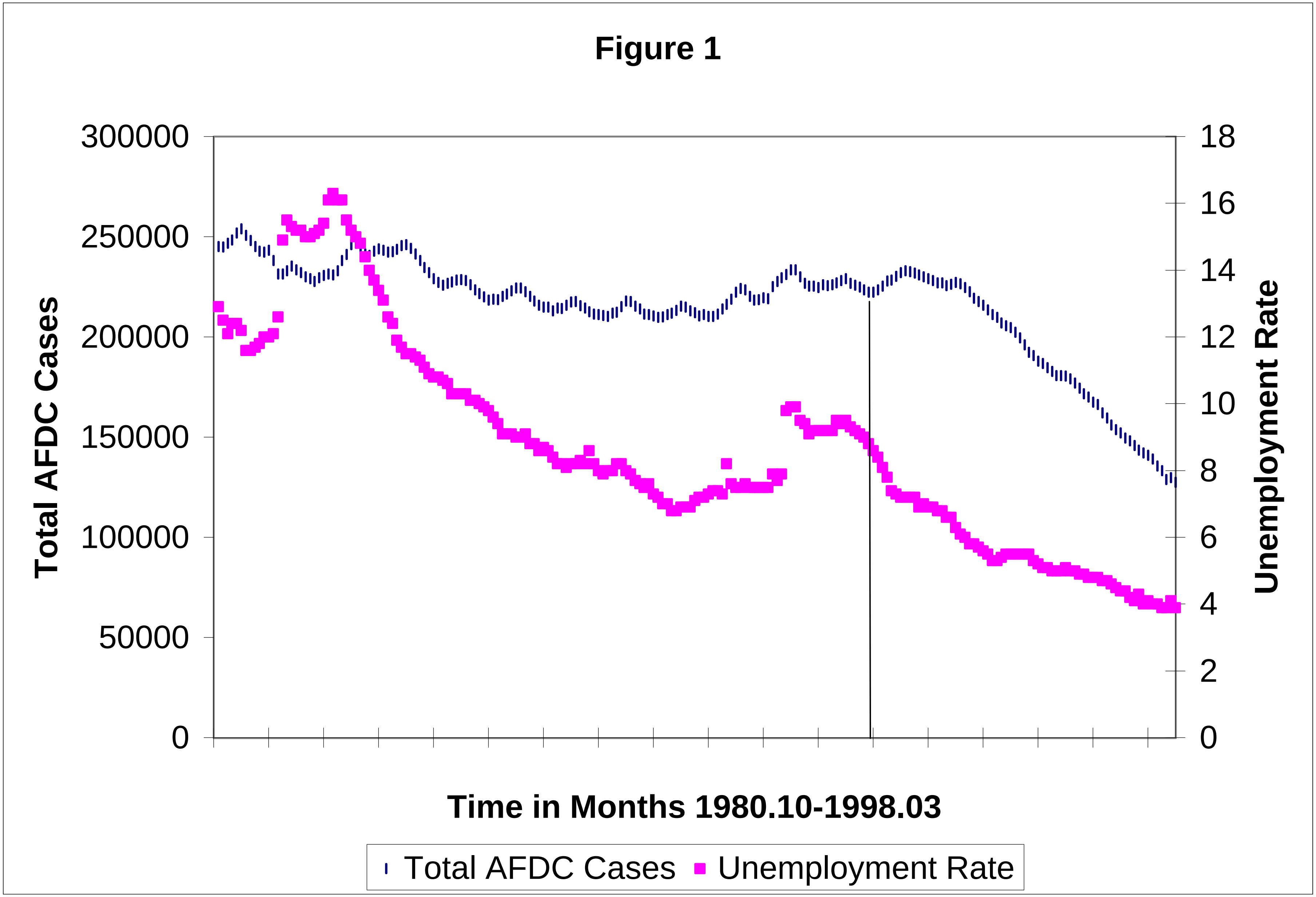
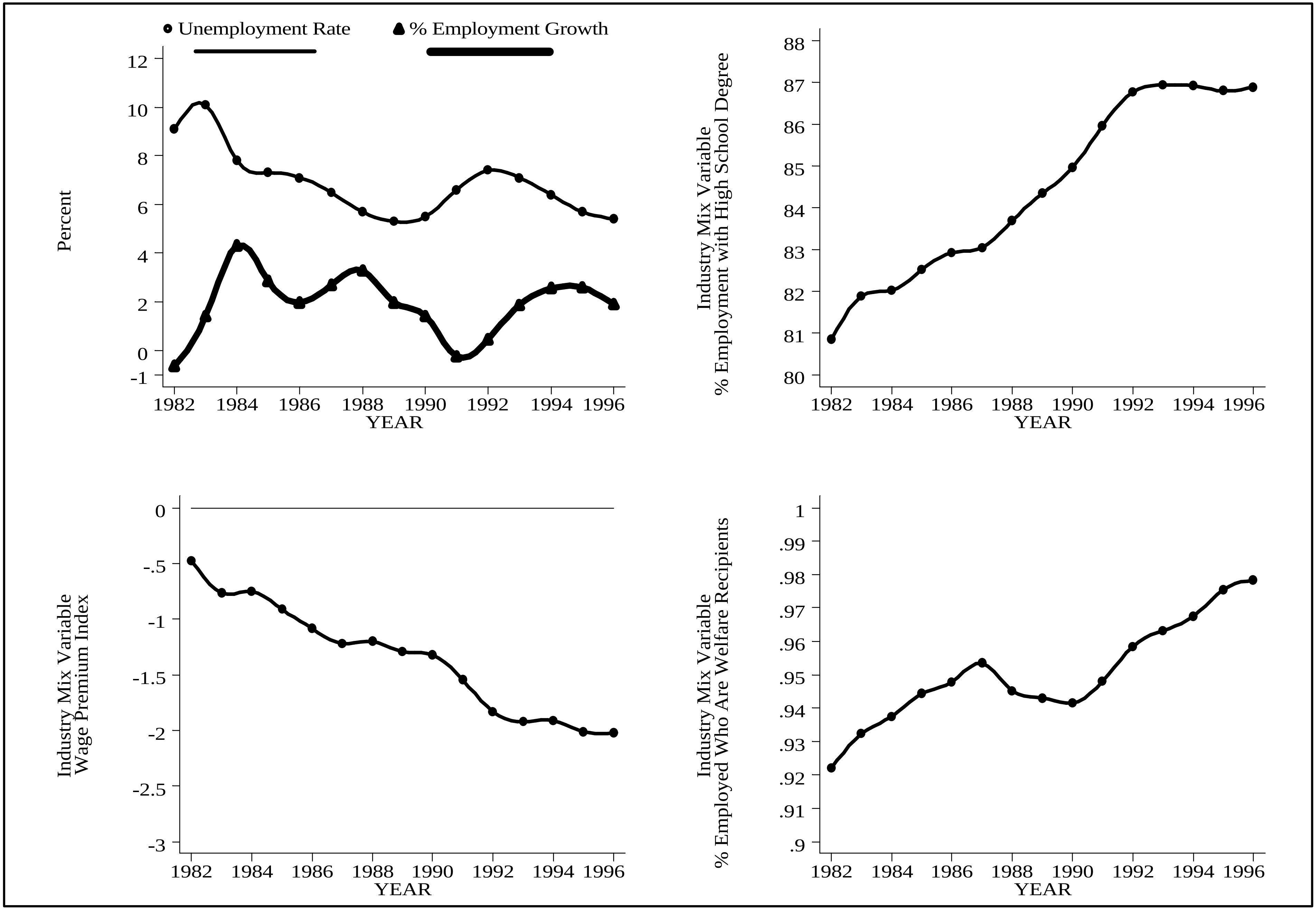


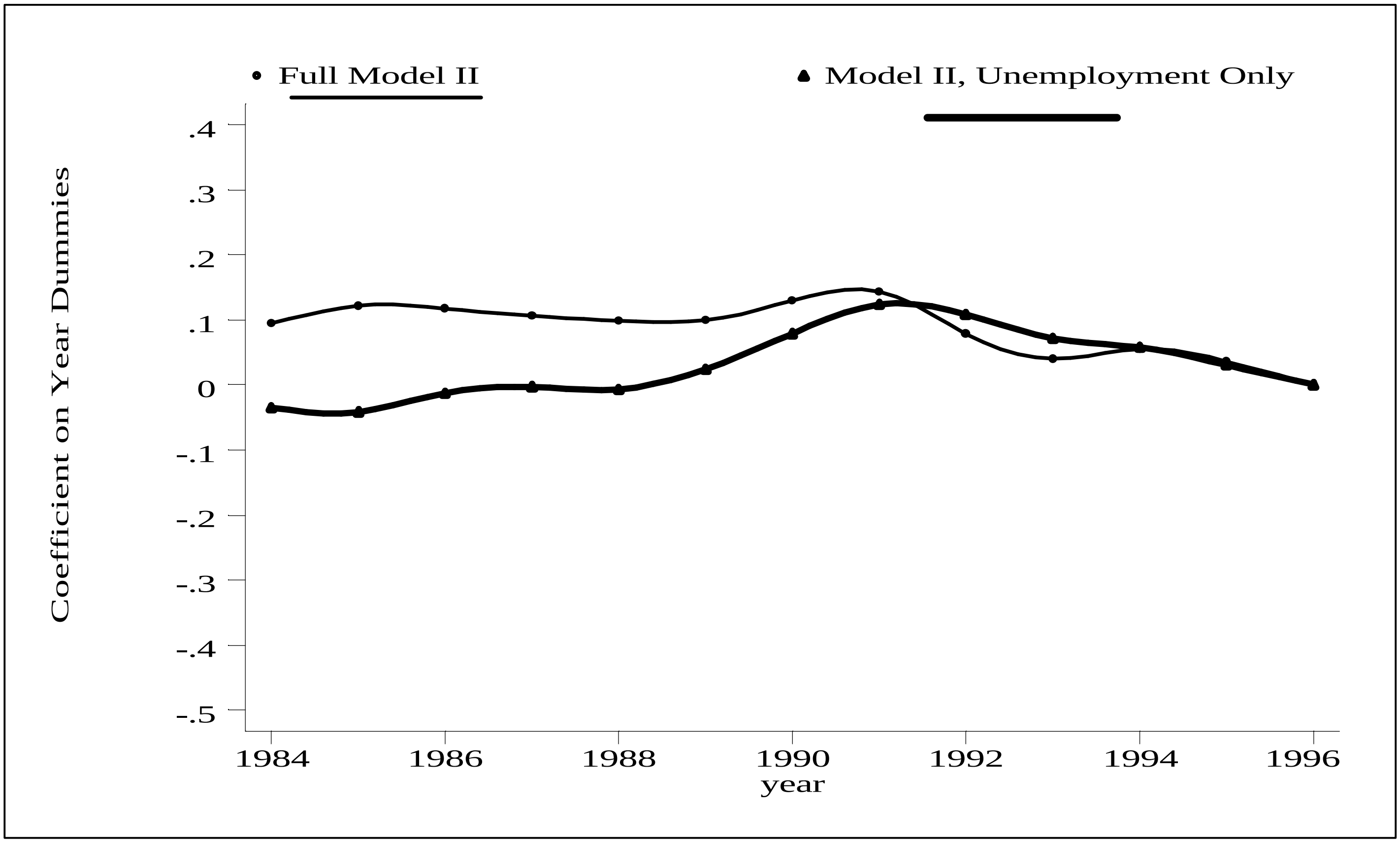
Figure 1
300000
250000
200000
150000
100000
50000
0
Total AFDC Cases
18
16
14
12
10
8
6
4
2
0
Unemployment Rate
Time in Months 1980.10-1998.03
Total AFDC Cases
Unemployment Rate

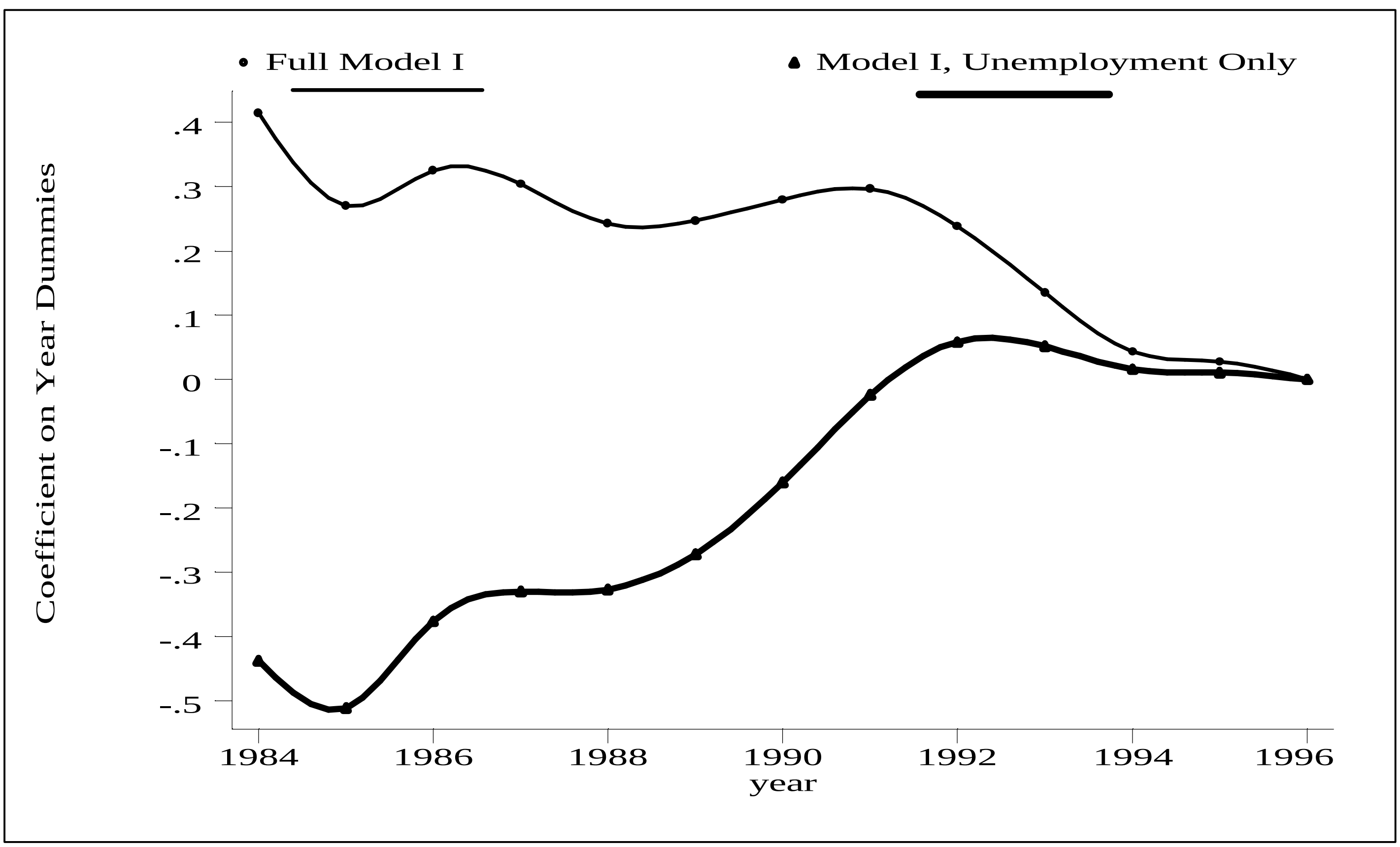
Figure 2. National Time Trends in Five Labor Demand Variables



Notes: All national averages are calculated using 1996 population weighted for each state. The three industry mix variables all predict a particular variable based on mix of industries and some industry characteristic.

Figure 3. Year Dummies from Various Models Explaining ln(caseload per capita)





Notes: Omitted dummy is 1996, so year dummy coefficient in that year is normalized to zero.