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CROSS-STATE VARIATION IN MEDICAID PROGRAMS AND FEMALE LABOR SUPPLY

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ABSTRACT

Although the Medicaid program is partially controlled by the federal government, there is considerable latitude in the ability of states to set eligibility requirements and the types of services available to recipients. This research examines the impact of different state Medicaid programs on the decision to enter the labor force and the number of hours worked by female heads of households. A pooled cross-section data set constructed from the 1988 through 1993 Current Population Survey March Supplements is used to test if different benefit levels across states impact labor supply behavior. This study adds to the existing Medicaid literature by incorporating new benefit measures and explicitly controlling for state random and fixed effects. OLS results support the prediction that Medicaid expenditures reduce labor supply, but controlling for state fixed or random effects alters the effect of both the AFDC and Medicaid programs on both the decision to participate as well as the number of hours worked of female heads of households. We also consider the effects of policy endogeneity on these estimates using instruments for state welfare generosity and find evidence that estimates of the effect of welfare on labor supply are sensitive to the failure to control for time-varying policy endogeneity.

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1. Introduction

The issue of the design and effects of government policies aimed at providing support for children is at the center of an ongoing national debate. Social scientists, policy makers, and the public at large have all focused their attention on the benefits and, perhaps even more so, the costs to society of this support network. These costs are perceived to take not just monetary forms but also to have adverse incentive effects in terms of work, out of wedlock births, divorce, etc.

Much of this debate has focused on the adverse effects of the cash components of welfare (Aid for Families with Dependent Children (AFDC) and Food Stamps), but recently other programs have become embroiled in this debate. As the costs of health care have risen, government provided Medicaid benefits have also come under increasing scrutiny. Medicaid expenditures are one of the fastest rising components of state budgets. State Medicaid spending more than doubled in real terms between 1980 and 1990, rising from $19.1 billion to $33.7 billion. Further, state Medicaid expenditures increased even more dramatically in the past few years rising about 19 percent in 1990-91 and 22.5 percent in 1991-92. Up until the mid 1980's, Medicaid coverage was primarily limited to recipients of AFDC and indigent senior citizens. Over the last ten years however, Medicaid coverage has been altered to include individuals with incomes above the AFDC maximum, primarily pregnant women or children whose parents have incomes at or slightly above the poverty line. Despite the fact that Medicaid is a federally mandated program, there is a large amount of latitude as to the number and types of individuals and services that each state can choose to cover. This state freedom implies that there are basically 51 different Medicaid programs in the United States, (Washington D.C. also participates in Medicaid). Because of this, there is a large variance in per-recipient Medicaid expenditures across states. In 1992, for example, annual per-recipient Medicaid expenditures for AFDC adults ranged from a high of $2,937 in Louisiana to a low of $575 in Mississippi.[1]

Recently, economists and other social scientists have used the cross-state variation in these programs as a form of "natural experiment" that allows them to access the effectiveness and adverse incentive effects of these programs. In this paper we use this approach to add to the literature on the effects of these programs on labor supply. First, we construct three new measures of the value of Medicaid benefits to adults, children, and families which vary across states and time. These alternate measure will allows us to test for the sensitivity of the conclusions from previous studies to the measure of Medicaid value used. Previous work on Medicaid and female labor supply has used measures of state level Medicaid spending which included spending on the elderly and disabled. Since these group accounts for a substantial share of all Medicaid expenditures, and they are not randomly distributed across states, this has the potential to bias the reported results. Second, because there is substantial variation across states in their labor market characteristics, demographic mixes, and other factors which are potentially correlated with both labor supply and benefit generosity, our analysis checks for the sensitivity of the results to the inclusion of state fixed and random effects. Estimates which control for these state specific factors yield substantially different implications for the impact of welfare or Medicaid on the work decision of women. Finally, given the evidence that cross-state variations in program design are not uncorrelated with labor market observables, we employ the instrumental variables technique developed in Besley and Case (1994) to control for potential policy endogeneity. The paper is organized as follows: Section II contains some institutional background on Medicaid. Section III is a review of previous work in this area. In Section IV we discuss the theoretical and empirical models. The data used in this paper and the results of our estimation are discussed in Section V. In Section VI conclusions and implications are drawn.

II. Institutional Background on Medicaid

Medicaid, enacted in 1965, was intended to provide health care insurance to low income individuals. Medicaid expenditures are paid for by both the federal government and the state governments. The program is essentially an open-ended-matching grant for the coverage of medical services for certain groups of individuals. The Medicaid eligibility criterion vary by state but the Categorically Needy (all AFDC recipients and their families) have historically been eligible for Medicaid in all states.[2] Those who leave AFDC because they no longer meet the income requirement, also continue to receive Medicaid for four months. Some states also allow individuals who do not meet the AFDC income requirements to quality through a Medically Needy program. The benefits received under this program are typically less than those for the Categorically Needy.[3] This programs is still means tested but the income and asset requirements are often higher than for AFDC.[4] Finally, changes in the Consolidated Omnibus Reconciliation Act (COBRA) in 1989 and 1990 mandated that states phase in an increase in their coverage so that by 1990 infants and pregnant women would be covered if their household income was up 133 % of the federal poverty level (FPL) and all children under 19 in households with income up to 100% of the FPL will be eligible by the year 2002. It also allowed states the option to provide coverage for pregnant women if their household income was up to 185% of the FPL. By 1993, 34 states had availed themselves of this option and 25 of them had increased coverage up to the maximum 185% of the FPL. Although the 1990 expansion only covered these women for pregnancy services, the net effect of these changes has been to expand the potential pool of families whose labor supply might be affected by Medicaid.

III. Previous Research

Studies on the effects of government transfer programs designed to provide assistance to low-income women and children are not new. There has been a voluminous literature on the incentive effects of AFDC and Food Stamps. Moffitt (1991) provides a detailed discussion of the effects on labor supply, female headship, and program participation. Most of these studies seem to find some adverse affect of program participation on female labor supply.

Recently, Blank (1989), Winkler (1991), Moffitt and Wolfe (1992), and Yelowitz (1995) have extended this literature to examine the impact of the Medicaid program on labor supply. Although Blank (1989), Winkler (1991), and Moffitt and Wolfe (1992) all find a negative effect on labor force participation, the size of the effect varies substantially across the studies. Further, Winkler and Blank fail to find any significant effect on welfare participation of changes in Medicaid generosity, while Moffitt and Wolfe find a significant effect. Yelowitz (1995) actually finds that relaxing the eligibility criterion increases labor supply. These differences may in part reflect differences in the measures of Medicaid used in each study. Because Medicaid is an in-kind benefit, the proper valuation for a family is problematic and the choice of appropriate specification or measure is not straight forward.

Winkler (1991) used state level Medicaid expenditures per recipient in her study. This measure does not allow for any individual heterogeneity in the valuation of the Medicaid insurance variable. Further, because she has only a single cross section she can not control for state specific effects that may be correlated with both the generosity of benefit and labor supply. Moffitt and Wolfe (1992) use a family specific health index to construct a measure of potential utilization of Medicaid coverage. The condition of an individual's health identifies the effects of Medicaid through the fact that those in poor health will place a higher value of Medicaid provided health service.[5] However, as Yelowitz (1995) notes, the coefficient on this variable may also capture two other effects of poor heath. First, poor health lowers the worker's marginal product and hence the wage an AFDC recipient could earn, potentially reducing labor supply.[6] Secondly, those in poor health will have a greater marginal disutility of work, or steeper indifference curves, again potentially reducing labor supply. Thus, the coefficient on this proxy could be capturing more than the direct effect of Medicaid. Finally, since Moffitt and Wolfe cannot identify state of residence in their data, they are not able to control for state-specific factors influencing benefits and labor supply.[7]

Yelowitz (1995) uses changes in state qualifying income requirements for families with young children following the legislative changes in the COBRAs of the 1980's and the Family Support Act (FSA) of 1988. Since states vary in their income eligibility thresholds, and in the timing of these eligibility changes, these rule changes provide a potentially exogenous source of variation in these programs within and across states. While this variable will capture the effect of variation in Medicaid on the extensive (eligibility) margin, it does not capture the effects of variation on the intensive (generosity or spending) margin. This distinction is theoretically important as the effect on labor supply of an expansion in benefit eligibility should lead to an increase in participation (although the effect on hours is ambiguous), while the latter would lead to a reduction in participation. Thus, the margin over which the effects of Medicaid operate in the Yelowitz (1993) is fundamentally different from the margin examined here or in the papers by Moffitt and Wolfe (1994) and Winkler (1991).[8] It should be noted that spending measures like those used in Winkler (1991) will capture increases in both the number of eligible recipients (take up rate) and in the generosity of this program. The total impact of this program on labor supply depends on induced variations on both margins. Further, since these changes in eligibility standards applied only to households with very young children or infants, they may not be highly correlated with cross-state and individual differences in the valuation of nonmaternity benefits which would affect the behavior of the majority of Medicaid recipients.[9]

IV. **Theoretical and Empirical Model**

Moffitt (1983), Blank (1989), Winkler (1991), and Yelowitz (1993) contain detailed discussions of the effects of welfare and Medicaid on the family budget constraint and labor supply. Following Moffitt (1983), let the utility function take the form U(H, Y, P) where H is hours, Y is disposable income, and P is an indicator of welfare participation. In the presence of welfare stigma effects, utility is increasing in income but decreasing in hours worked and participation. The budget constraint takes the form:

$$Y = WH\,(1-\tau_1 P) + N\,(1-\tau_1 P) + P\cdot G \qquad (1)$$

where W is net or after tax wages, N is nonlabor income, τ_1 is the AFDC implicit programmatic tax rate on earnings, and G is the sum of the value of AFDC and Medicaid benefits. Since

Medicaid is an in-kind benefit, this value should be the insurance value of the Medicaid expenditures rather than the cash value of the benefit. The labor supply function for the family that maximizes utility will be:

$$H = H\,(\,W(1-\tau_1\,P),\,N\,(1-\tau_1\,P) + P\cdot G) \tag{2}$$

We estimate a reduced form variant of this model where we consider labor supply on both the intensive and extensive margins. The decision to work can be expressed as follows:

$$LFP^{*}_{ist} = \beta_1\ X_{ist} + \beta_2\,BEN_{st} + \beta_3\,Med_{ist}\ + \epsilon_{1ist} \tag{3}$$

where $LFP_{ist} = 1$ if $LFP_{ist}^{*} \geq 0$; and $LFP_{ist} = 0$ otherwise. LFP_{ist}^{*} is a latent index of the gain in utility from participating in the market. LFP_{ist} is equal to 1 for workers. The vector X_{ist} includes measures such as age, and its square, years of education (and its square), years of education beyond high school, if a high school graduate (Edyrgt12), number of years of education below high school, if educational level is below a high school education (Edyrlt8), a dummy variable equal to one if the person was African-American (RACE), number of children (Kids), number of children under six (Kusix), nonlabor income (Nlabor) and dummies for divorced (Div) or separated (Sep). BEN is a vector of state welfare benefits levels and includes the state level maximum monthly values for a family of three on AFDC (AFDC), Food Stamps (FOOD) and a dummy variable MN which equals one if the state has a medically needy program. MED is a measure of real state level Medicaid spending. The error term ε_{ist} is normally distributed with mean zero and unit variance.

The probability that a woman will work can be written as:

$$\text{Prob}(\ LFP_{ist} = 1) = \text{Prob}\ (\ \epsilon_{1ist} \geq -\beta_1\ X_{ist} - \beta_2\ BEN_{st}\ - \beta_3\ Med_{ist}\ ) \qquad (4)$$
$$= 1 - \Phi(-\beta_1\ X_{ist} - \beta_2\ BEN_{st}\ - \beta_3\ Med_{ist}\ )$$

where Φ is the cumulative normal density function. Equation (4) was estimated as a probit model.

The second aspect of labor supply is the determination of the intensive variation or the number of hours worked. To estimate this model we follow Heckman (1980) and estimate a two-step model. The first stage equation uses the probit estimates of equation (4) to construct a sample selection correction, the inverse of the Mills ratio, λ_{ist}, which is then added to the hours equation:

$$H_{ist} = \delta_1\ X_{ist} + \delta_2\ BEN_{st} + \delta_3\ Med_{ist}\ +\ \delta_4\ \lambda_{\ ist} + \upsilon_{ist} \qquad (5)$$

where H_{ist} is annual hours worked for those that $H_{ist} > 0$ and the error term, υ_{ist} is normally distributed with zero mean and unit variance. As there are unlikely to be any variables affecting labor supply on the intensive margin that do not affect it on the extensive margin, our second stage equation is identified by the nonlinearity of the functional form.[10]

V. Data

The models in equations (3) and (4) were estimated using individual data drawn from the 1988-1993 March Supplement files of the Current Population Survey (CPS). In order to make the study comparable to earlier work, the sample was restricted to single females between the ages of 18 and 65 years old with at least one child under age 15. For the purposes of this study single-females were defined as those who were divorced, separated, or never married. The data set contained 21,229 observations. The state level AFDC and Medicaid data were drawn from various issues of the House Ways and Means Committee Green Book. The data set included forty-nine states and the District of Columbia.[11] All dollar values were deflated using the Consumer Price Index (CPI).

Because previous research suggests that estimates may be sensitive to the choice of Medicaid measure used, we tried a number of different measures. The Health Care Financing Administration (HCFA) provides state level Medicaid spending estimates for both AFDC adults and children. These measures subtract from state total Medicaid spending those amounts which go to the elderly, blind, and disabled populations. Since the focus of this paper is on the labor supply of women age 15-65, using Medicaid expenditures on non-targeted groups could give a misleading indication of cross-state variation in the generosity of benefits. This potential distortion is quite substantial as seen by the fact that real spending per AFDC recipient in 1992 was in \$575 in Mississippi but rises dramatically to \$1809 when the elderly and disabled are included. We check the sensitivity of previous results to their measure of Medicaid by using not only the average state expenditure per recipient (PRMCAID) construct of Winkler and Blank, but a measure of average Medicaid spending on AFDC adults (Medadult), children (Medchild), and a scaled family Medicaid (Medfam = Medadult + 3* Medchild) variable.[12]

Summary statistics for all the variables used in the analysis are presented in Table 1. About 68 percent of the female household heads in our sample work, and the average work week is almost 26 hours. About a third of the sample is on AFDC and the mean monthly benefit for recipients over this period was $262. The mean monthly value of state Medicaid expenditures per recipient (PRMCAID) was $92, while the mean value of family Medicaid benefits (Medfam) is $126. This suggests that on a cash expenditure basis, Medicaid health insurance for the average welfare family has a value of almost 50 percent of the value of the cash benefits received from the program. Clearly, this program represents a potentially important source of noncash income for recipients.

In Table 2 we present the results of estimating the probit employment (columns 1-4) and hours equations (columns 5-8) from equations (3) and (4), respectively using the different Medicaid variables discussed above. The estimated hours and employment equations yield results similar to those found in other studies with regards to the effects of our demographic variables. We find consistent evidence that higher AFDC spending reduces both employment and hours. Further, living in a state with a Medically Needy program (MN) reduces the likelihood of participating in the labor force and the average hours worked per week.

As found in Winkler (1991) and Moffitt and Wolfe (1992), Medicaid expenditures (PRMCAID) have a negative and significant effect on employment. Our results differ from Winkler, however, in that we also find a significant effect on hours. These results are remarkably robust to alternate constructs of the Medicaid variable. The economic significance of these variables can be seen in Table 3 where we calculate the marginal effects and elasticities for each of the Medicaid and AFDC variables. The economic importance of the AFDC and Medicaid variables seems roughly constant across the specifications. The magnitudes are such that a $26 increase in monthly AFDC benefits (about 10 percent) would reduce the labor force participation rate by about .6 percentage points (about 1 percent). This estimate is at the low end of the range of estimates of the impact of such a change in AFDC benefits found in Winkler (1990), where a 10 percent increase in AFDC reduced labor force participation between .8 and 1.5 percentage points. The effect of a 10 percent increase in monthly Medicaid spending would be to reduce labor force participation by about .36 percentage points. Thus, despite having a statistically significant effect, these results do not suggest that the magnitude of the impact of these welfare programs on labor force participation is large. We also find evidence that the estimated elasticities for hours are quite small. A 10 percent increase in monthly AFDC benefits or Medicaid expenditures would reduce hours worked by between .11 and .25 percent (between .04 and .10 hours per week). Thus, these pooled cross section results suggest a small but significant effect of both parts of the welfare program on both the intensive and extensive margins of labor supply.

Since work by Moffitt and others suggest that welfare effects on household formation differ for blacks (is larger), we also interacted these welfare measures with our racial indicator to see if there were differential labor supply effects.[13] Although controlling for observables black women tend to work less than whites, the adverse effects of AFDC and Medicaid on labor supply is limited to whites. While AFDC, and each of the Medicaid variables, are negative and significant for whites, the black interaction terms were strongly positive, significant, and large enough in magnitude to suggest that these programs have no adverse effect on labor supply. If anything these results suggest that Medicaid enhances labor force participation and hours worked for black women.[14]

The estimation approach used in these estimates exploits the cross-state variation in programmatic design to identify the effects on labor supply. As discussed in Moffitt (1994) and Hoynes (1995), states may differ in social or cultural norms or other unobserved factors which could be correlated with the level of their welfare benefits.[15] If these unobserved differences across states are correlated with both program generosity and labor supply, OLS estimates could be biased. If states that are wealthier have both more generous welfare benefits and lower labor supply, then our results might show a spurious inverse correlation between labor supply and benefits. The failure to control for unobserved state effects may significantly bias the estimated impact of state welfare programmatic variables on behavior. Moffitt (1994) and Hoynes (1995) found that including controls for state effects in a model of female headship reversed the positive effect of welfare found in OLS estimates.

Given this, we modeled this heterogeneity two ways to reflect the presence of either unobserved state random or fixed effects. In the random effects case, the estimated probit or OLS coefficients would be consistent, but inefficient as the standard errors on the group or state level variables will be too small. Amemiya (1978) and Borjas and Sueyoshi (1994) developed conceptually similar two-step estimators for random effects models for the OLS and probit specifications.

The first stage involves regressing the individual variables and a set of state specific intercepts on labor force participation or hours. In the second stage generalized least squares is used to regress the state specific intercepts on the state specific variables. These results from estimating our models using this two step process for employment (columns 1-4) and hours (columns 5-8) are reported in Table 4. Since the second stage errors may be non-spherical (heteroskedastic), we report White-corrected standard errors for the second stage model.

In the random effects specification, the welfare programmatic variables appear to have somewhat different impacts on the intensive and extensive margins. While AFDC and Food Stamps have an adverse (and significantly) affect on hours, they do not appear to be significantly related to labor force participation. Interestingly, the presence of a Medically Needy program now has a positive effect on both labor force participation and hours where the reverse was true in the OLS. There is no evidence that Medicaid expenditures adversely affect hours worked in these random effect specifications. Further, in only two of the four specifications do we find evidence that Medicaid adversely affects participation. The magnitude of point estimates of the effects of Medicaid on labor force participation are less than half those found in OLS estimates.

If state effects are fixed rather than random, then the error terms in our participation and hours models would be:

$$\epsilon_{ist} = d_s + \theta_{ist} \tag{6}$$

or

$$\upsilon_{ist} = d_s + \varsigma_{ist} \tag{7}$$

where d_s is a state fixed effect and the new error terms θ_{ist} and ς_{ist} are i.i.d. normal with zero mean and unit variance.

To test for time invariant factors that differ across states, we re-estimated our models including state fixed effects. These results are reported in Table 5 for employment (columns 2-5) and hours (columns 6-9). We can not reject the hypothesis that the state fixed effects matter in our model. For instance, the Chi-squared statistics for the inclusion of the state fixed effects in models 1 and 4 were 424.06 and 435.74, respectively, in the labor force participation equation. In models 1 and 4 for the hours equations the F-statistics were 2.96 and 3.01 respectively.[16]

Further, Hausman tests for each of our Medicaid models reject the random effects specification in favor of the fixed effects.[17]

When fixed effects were included in the hours equations, the coefficient on the Food Stamps policy variable reverses sign. Strikingly, once we control for state effects, the AFDC measure is no longer significant in the either the employment or hours equation, and its sign is actually reversed in many of the employment equations. The point estimates and elasticities (Table 3) of the impact of AFDC on hours are reduced by 19- 42 percent in the fixed effect specifications. This result suggests that state specific variation in unobserved factors which determine labor supply variation account for a substantial part of the previously estimated effect of AFDC on labor supply. Previous estimates that failed to incorporate this cross-state heterogeneity would seriously overestimate the disincentive effects of welfare and Medicaid on labor supply.

The estimates for the Medicaid variables now prove generally insignificant in the hours specifications, and in one case even switches sign. Similarly, once we control for state fixed effects, all the measures of Medicaid tend to lose their significance in the employment regressions. As seen in Table 3, the magnitude of the elasticities and marginal effects estimates in the hours and participation equations are consistently reduced and in many cases go from negative to positive. As with the AFDC variables, these results suggest that a significant amount of the previously estimated impact of welfare programs on labor supply is due to time invariant unobserved state effects.[18]

Finally, we explore a potential explanation for the source of the unobserved state effects. Besley and Case (1994) suggest that the inclusion of state effects may not remove unobserved heterogeneity bias from models using cross-state variation in polices to identify individual policy treatment effects. Moffitt (1994) suggests that the state level effects may reflect policy endogeneity arising from the political process when state program generosity reflects state economic performance. As Besley and Case (1994) suggest, failure to control for these time varying unobserved state specific factors may lead to bias in the type of cross-state "natural" experiment that we are attempting.

If policy endogeneity is a major concern, then the various measures of welfare generosity (AFDC, Medicaid, and Food Stamps) will be correlated with the error in the labor supply equation. The potential endogeneity of welfare benefits, Ben_{ist}, can be expressed as a function of the variables that determine labor supply, a set of other exogenous variables that are orthogonal to the error in the labor supply equations, Z_{st}, and an error term ϵ_{2ist} or:

$$Ben_{ist} = \beta_1 X_{ist} + \beta_2 Z_{st} + \epsilon_{2ist} \qquad (8)$$

Given the consistency in the direction of the effects of the individual components of welfare, and since the policy endogeneity with respect to each of the components of welfare is likely to have a common source, we follow Moffitt (1994) in aggregating the welfare measures into a composite dollar equivalent expenditures. The set of instruments, Z_{st}, that we use are three political variables that Besley and Case (1994) found to be exogenous in estimates of the effect of state specific disability programs on employment and earnings (percent of Democrats in the State House and Senate and whether the governor is a Democrat).

To insure that the qualitative nature of our previous results are not influenced by the aggregation of the three components of welfare into a composite, we first re-estimated our single equation models with and without fixed effects using the aggregate welfare constructs.[19] Those results are presented in Table 6. As can clearly be seen, all the welfare aggregates have a negative and statistically significant correlation with labor force participation and hours worked. Similarly, the addition of the state fixed effects dramatically reduces the estimated coefficients on the welfare variables, and we can not reject the null hypothesis that they affect both of our labor supply measures. Thus, the qualitative nature of our previous results are not sensitive to the use of an aggregate welfare measure.

In Table 7 we present the results of our instrumental variable estimation of the effects of welfare on labor supply. Given the discrete nature of the labor force participation variable, the instrumental variables (IV) estimation of the employment equation involves the estimation of the simultaneous log likelihood function for each woman where the likelihood function represents both the single equation probit model for participation and the linear least squares model of benefit generosity under the assumption that the errors in these two equations each are bivariate normal with mean zero and covariance Σ.[20]

As in the single equation models, the inclusion of fixed effects dramatically reduces the size and significance of the coefficients on the impact of the welfare variable on labor supply. While the effect of controlling for fixed unobserved state heterogeneity appears to reduce the estimated impact of the program variable, controlling for policy endogeneity appears to <u>increase</u> the estimate impact. The coefficients on the welfare measures in the IV employment equations (Table 7 column 2) with fixed effects are over 10 times bigger than the single equation results with fixed effects. Interestingly, the IV models with fixed effect yield parameter estimates only slightly smaller than the single equation models with no controls for state heterogeneity. While these coefficents are still not precisely estimated, they may suggest that magnitude of the bias in the single equation models that do not control for state heterogeneity is not as great as the fixed effects estimates would imply.

The effect of instrumenting for state heterogeneity appears to be even stronger in the hours equations. In contrast to the single equation results, we find that welfare still has a statistically significant adverse effect on hours in the fixed effect specification and that the fixed effects IV coefficients are even larger than the single equation estimates with no fixed effects. These results are supportive of the presence of policy endogeneity in the determination of state welfare benefits. These results suggest that unobserved political factors which generate more Democrats in state government tend to occur in states where employment is lower and welfare benefits are more generous. Of course, the increase in the magnitude of the IV coefficients is also consistent with the presence of measurement error (attenuation) bias in the welfare measures. Recall that the welfare measure should include Medicaid valuations for the individual (the insurance value) rather than the cash value measures used here. Thus, it seems plausible that measurement error causes an underestimate of the effect of these programs on labor supply.

To strengthen our confidence the IV results, we undertook two addition tests. First, Bound et al (1994) have shown that IV estimates may yield even more inconsistent estimates that OLS estimation if the correlation between the instrument and endogenous variable is weak. The results from estimating the first stage equation(8) with fixed state effects are presented in Table 8. They clearly indicate that the instruments are highly correlated with the endogenous welfare variable. The t-statistics for each of the instruments are quite large and indicate significance at the 5 percent level or better in all of the models, even the fixed effect ones. Secondly, since we have three instruments for our welfare measure we were able to performs tests of overidentifing restriction or that the political variables (instruments) do not belong in the labor supply equation. The results of the overidentification tests for the models with fixed effects are presented in Table 9.[21] In only one of the 8 estimated models do we fail to reject the hypothesis that these political variable have an independent effect on the labor supply behavior of single women. Taken as a whole these IV results suggest that the failure to control unobserved state policy endogeneity again leads to biased estimates. Our evidence suggests that fixed effect models will lead to underestimates of the effect of welfare on labor supply.

VI. **Summary and Conclusions**

In this paper we examine the effects of various elements of the government support network on labor supply. We exploit cross-state variation in the structure of these programs and control for state random and fixed effects that may have biased previous cross section estimates using state level benefit measures. Given the recent growth in both Medicaid spending and eligibility, we focus primarily on the Medicaid program.

Estimates of the effects of the Medicaid and other welfare programmatic variables were sensitive to the treatment of area or state effects. In models without controls for these effect, we found that all of the welfare variables had strong negative effects on employment, and, to a lesser degree, hours. The adverse effect of welfare on labor supply seems limited to whites in these models, despite the higher participation rate of blacks in these programs. In models with state fixed or random effects these variables were consistently found to have weaker or no significant adverse effect on employment and hours.

The role of policy endogeneity is explored through the uses of state level political variables as instruments for the welfare variables. These variables were found to be strongly correlated with within and across state variations in benefit levels, and to be orthogonal to the unobserved component of state welfare benefit generosity which is correlated with labor supply. The fact that the IV estimates are actually larger in the employment and fixed effect hours models is suggestive of the fact it is important to control for both unobserved fixed and time varying state specific effects when modeling the impact of these welfare programs on labor supply.

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ENDNOTES

1. Author's calculations based on data supplied by the Health Care Financing Administration.

2. SSI recipients may also be judged Categorically Needy and hence eligible for Medicaid. The 1990 Supreme Court decision in the Sullivan vs Zebly case broaden eligibility under SSI to include disabled children. The Congressional Research Service estimates that this increased the number of such children on Medicaid by 125,000. Given that these children account for less than 1 percent of the 14.3 million children receiving Medicaid in 1990, we follow Blank (1989) and exclude SSI recipients from consideration. See " Medicaid: Recent Trends in Beneficiaries and Spending" Report for Congress, U.S. Government Printing Office, Washington, D.C., 1992.

3. Thirty six states have adopted the Medically Needy program.

4. The Medically Needy income level can be set up to 133 percent of the AFDC maximum. It should be noted that seven (7) states actually set the threshold lower than the AFDC threshold.

5. In a paper on the effects of welfare on headship, Moffitt (1994) uses the sum of state expenditures per recipient on Medicaid, AFDC, and Food Stamps in a state as his measure of these programs.

6. Moffitt and Wolfe (1992) do include the actual wage net of estimated taxes for employed workers and a measure of the expected net wage for nonparticipants in their regression. The inclusion of these wage measures cuts their estimate of the adverse labor supply effect of Medicaid in half. It should be noted, however, that these wage measures do not fully control for this bias because poor health reduces the actual wage received below its potential, unobserved, value. Workers with identical observed wages, but differing in health status, may still have different labor supply behaviors because of differences in the size of this unobserved component. This unobserved gap will be positively correlated with the Medicaid valuation variable, but negatively correlated with labor supply, yielding an overestimate of the effect of Medicaid. For the nonparticipants, the expected net wage used in the Moffitt and Wolfe regression is estimated without controlling for the fact that this expected wage will vary with health status and hence be correlated with their Medicaid variable and labor supply.

7. It should be noted that Yelowitz (1995) also contains controls for state fixed effects.

8. Blank (1989) also looks at the effects of expanded eligibility through the creation of the Medically Needy program.

9. It should of course be noted that the converse holds true for our analysis. By ignoring cross state variation in the timing of changes in these eligibility criterion, we overlook changes in the expected value of Medicaid benefits that may be relevant for the labor supply decisions of pregnant women and those with small infants. These would be captured in our variables to some degree if they affect

average expenditures across states.

10. As a check on the sensitivity of our results to this assumption, we tried two alternate exclusion restrictions to gain identification. First, we followed Winkler (1991) and omitted kids under 6 from the second stage equation. Alternatively, we omitted the dummy variable for separated from the second stage equation. In both case we got results that are qualitatively similar to those reported in Tables 2 and 4. Because there seems to be no good theoretical rationale for these exclusion restricts we report the results without them. The alternate results are available from the authors upon request.

11. Arizona was excluded because it operates Medicaid as a demonstration project.

12. We also experimented with a family specific Medicaid measure that reflected the actual number of children in the household. The scaled variable was chosen to avoid potential endogeneity issues between household size and welfare benefits. It should be noted, however, that the qualitative nature of the results were not sensitive to the use of scaled as opposed to actual family size.

13. These results are available from the authors upon request.

14. It should be noted that these conclusions about the interaction of race and the Medicaid variables are not sensitive to the inclusion of the state fixed effects.

15. Given the fact that we only have pooled cross section data we are not able to examine bias introduced by unobserved individual effects that may be correlated with the policy variables. If selective migration induces a common taste for benefits and work then these individual effects could be correlated with the state and welfare effects. Hoynes (1995) presents evidence, however, that shows that controlling for state effects is sufficient to capture population heterogeneity across states.

16. The likelihood ratio test had a critical value of 67.22 in the Chi-square test at the 95 percent level and the F-test had a critical value of 1.34 at the 95 percent level.

17. The tests statistic for the specification using PRMCAID was 14.54 while it was 12.96 in the specification using Medfam which is well above the critical values for the Chi-squared test with 3 df.

18. Although our results are similar to Moffitt (1994) using CPS data over the period 1968-89, a concern might be that in the panel our results simply reflect the absence of sufficient within state variation in these benefits to generate statistically significant effects. As a crude check on this we regresses our welfare and Medicaid variables on state fixed effects to see how much of the variation in these variables would remain. The state effects explained between 57 and 77 percent of the variation in these measures suggesting that while cross state variation is an important component there is substantial variance in these measures left.

19. The results from using these aggregate measures and including Heckman corrections in the hours equations are also qualitatively similar to the disaggregated results. These results are available from the authors upon request.

20. See Evans, Oates, and Schwab (1992) for a derivation of this likelihood function. Thanks to William Evans for use of his SAS maximum likelihood estimation routine.

21. The over identification tests for the labor force participation equation are based 2SLS estimates where the second stage is a linear probability model.

TABLE 1

Summary Statistics and Variable Definitions

Variable	Mean	Standard Error
Dummy Variable for Worked Last Year (DWORK)	0.677	0.47
Monthly Average Per Recipient Medicaid Expenditure (PRMCAID)	88.92	36.71
Average Per AFDC Child Medicaid Expenditure (MEDCHILD1)	26.11	8.16
Average Per AFDC Adult Medicaid Expenditure (MEDADULT)	46.93	14.48
Family Specific Medicaid Expenditure = (MEDCHILD1 * KIDS) + MEDADULT	94.42	38.23
Scaled Family Medicaid Expenditure = MEDFAM= (MEDCHILD1 * 3) + MEDADULT	125.27	35.05
Age (AGE)	34.31	8.86
Age Squared (AGE^2)	1255.70	666.21
Years of Education (EDUC)	12.07	2.54
Years of Education Squared (EDUC^2)	152.10	56.94
Years of Education less than High School = 8 - EDUC, if EDUC < 8, 0 Otherwise (EDYRLT8)	0.1443	0.8065
Years of Education Beyond High School = EDUC - 12, if EDUC > 12, 0 Otherwise (EDYRGT12)	0.8497	1.415
Dummy Variable for Race = Black (RACE)	0.32	0.46
Number of Children Under Six Years Old (KUSIX)	0.62	0.80
Total Number of Children (KIDS)	1.82	1.04
Dummy Variable for Marital Status = Divorced (DIV)	0.44	0.49
Dummy Variable for Marital Status = Separated (SEP)	0.23	0.42
Dummy variable for AFDC Recipient (DAFDC)	0.33	0.47
Dummy Variable for Medicaid Recipient (DMCAID)	0.41	0.49
Dummy Variable for Food Stamp Recipient (DFOODS)	0.45	0.49
Non-Labor Income (NLABOR)	1314.38	2843.32
Maximum Monthly Food Stamp Allowance (FOOD)	137.88	22.78
Maximum Monthly AFDC Benefit (AFDC)	251.42	99.72
Average Hours Worked Per Week (HOURS)	25.88	19.20
Total Number of Observations: 21,229		

TABLE 2

Initial Regression Results of Probability of Working and Hours of Work

	Probit Model Regression Coefficients The Dependent Variable is DWORK				OLS Regression Coefficients Dependent Variable is Hours (Includes Heckman Correction)			
Variable	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Constant	-1.139 (2.46)*	-1.322 (2.88)***	-1.298 (2.80)***	-1.277 (2.77)***	17.96 (3.53)***	17.05 (3.29)***	16.97 (3.28)***	17.08 (3.31)***
Age	0.046 (6.27)***	0.045 (6.16)***	0.045 (6.16)***	0.0451 (6.18)***	0.689 (9.02)***	0.680 (8.94)***	0.678 (8.92)***	0.681 (8.94)***
Age²	-0.00063 (6.69)***	-0.00062 (6.63)***	-0.0006 (6.62)***	-0.00062 (6.64)***	-0.0084 (8.39)***	-0.0083 (8.31)***	-0.008 (8.29)***	-0.008 (8.31)***
EDUC	-0.0622 (.78)	-0.0499 (0.63)	-0.0487 (0.61)	-0.0538 (0.68)	-0.844 (1.38)	-0.789 (1.29)	-.719 (1.17)	-0.762 (1.24)
EDUC²	0.0148 (3.89)***	0.0142 (3.73)***	0.0142 (3.73)***	0.0144 (3.79)***	0.111 (3.94)***	0.108 (3.82)***	0.105 (3.71)***	0.107 (3.78)***
Race	-0.157 (6.99)***	-0.154 (6.86)***	-0.157 (6.99)***	-0.155 (6.89)***	-0.564 (2.51)**	-0.547 (2.44)**	-.575 (2.56)**	-.563 (2.51)**
Kusix	-0.209 (13.81)***	-0.212 (13.96)***	-0.210 (13.88)***	-0.211 (13.91)***	-0.9 87 (4.30)***	-0.992 (4.27)***	-.981 (4.24)***	-.986 (4.26)***
Kids	-0.169 (16.14)***	-0.168 (16.05)***	-0.168 (16.06)***	-0.168 (16.08)***	-0.997 (5.61)***	-0.982 (5.52)***	-.975 (5.47)***	-.981 (5.51)***
Div	0.384 (14.72)***	0.391 (14.98)***	0.389 (14.95)***	0.390 (14.95)***	2.184 (5.95)***	2.200 (5.90)***	2.186 (5.88)***	2.194 (5.90)***
Sep	0.133 (4.94)***	0.135 (5.02)***	0.134 (5.00)***	0.135 (5.03)***	0.365 (1.36)	0.370 (1.37)	.354 (1.31)	.363 (1.35)
Nlabor	-0.00003 (8.45)***	-0.00003 (8.27)***	-0.00003 (8.32)***	-0.00003 (8.30)***	-0.00034 (9.48)***	-0.00034 (9.39)***	-0.00034 (9.41)***	-0.00034 (9.41)***
Food	0.0018 (2.65)**	0.0025 (3.58)***	0.0024 (3.42)***	0.0025 (3.64)***	0.0096 (1.70)*	0.0142 (2.36)**	0.0119 (2.02)**	0.013 (2.21)**
AFDC	-0.00064 (3.99)***	-0.00061 (3.59)***	-0.00063 (3.82)***	-0.00056 (3.34)***	-0.0027 (1.95)*	-0.0024 (1.69)*	-0.0031 (2.24)**	-0.0027 (1.87)*
Edyrlt8	0.129 (2.66)**	0.138 (2.86)***	0.139 (2.88)***	0.136 (2.81)***	0.602 (1.30)	0.639 (1.37)	.679 (1.46)	.656 (1.41)***
Edyrgt12	-0.2059 (6.53)***	-0.201 (6.39)**	-0.202 (6.42)***	-0.204 (6.46)***	-1.61 (5.05)***	-1.57 (4.94)***	-1.54 (4.86)***	-1.56 (4.91)***
DNeedy	-0.081 (3.14)***	-0.0894 (3.48)***	-0.097 (3.76)***	-0.096 (3.74)***	-0.560 (2.78)**	-0.601 (2.95)***	-.614 (2.97)***	-.624 (3.02)***
Prmcaid	-0.00157 (5.59)***				-0.0108 (3.96)***			
Mills					6.40 (3.76)***	6.30 (3.67)***	6.25 (3.65)***	6.29 (3.68)***
Medadult		-0.0022 (3.05)***				-0.0153 (2.42)**		
Medchild			-0.0015 (3.58)***				-0.0054 (1.49)	
Medfam				-0.0012 (3.84)***				-0.0054 (2.05)**

Absolute Value of T-statistics in Parenthesis
* indicates significant at the 90% level
** indicates significant at the 95% level
*** indicates significant at the 99% level
Number of Observations (n) = 21,188

Number of Observations (n) = 14,525

TABLE 3

ECONOMIC IMPACT OF AFDC AND MEDICAID ON LABOR SUPPLY

	MARGINAL EFFECTS ON PARTICIPATION		ELASTICITY OF HOURS	
	NO FIXED EFFECTS	FIXED EFFECTS	NO FIXED EFFECTS	FIXED EFFECTS
WELFARE VARIABLES IN MODEL				
AFDC	-.00022	.000024	-.019	-.013
PRMCAID	-.00054	.000469	-.025	.012
AFDC	-.00024	-.000004	-.016	-.009
MEDADULT	-.00086	.00040	-.019	-.0004
AFDC	-.00022	.000059	-.021	-.013
MEDCHILD	-.00051	.000012	-.011	.014
AFDC	-.00019	.000045	-.018	-.015
MEDFAM	-.0004	.000062	-.018	-.013

Table 4
Second Stage OLS Regression Results
Dependent Variable is State Dummy Variable Coefficients

	Probit Model Regression Coefficients				OLS Regression Coefficients (Includes Heckman Correction)			
Variable	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Constant	-0.415 (3.31)***	-0.411 (3.32)***	-0.422 (3.90)***	-0.410 (3.71)***	.805 (1.07)	..868 (1.07)	1.15 (1.71)*	1.13 (1.55)*
AFDC	0.00012 (0.74)	0.00013 (0.88)	0.00021 (1.49)	0.00021 (1.46)	-0.0021 (2.05)**	-0.0022 (2.03)**	-0.0013 (1.44)	-0.0017 (1.77)
Food	0.00076 (1.57)	0.0008 (1.79)*	0.0010 (2.46)**	0.0010 (2.43)**	-0.0040 (1.53)	-0.0056 (2.11)**	-0.0034 (1.59)	-0.0042 (1.84)*
DNeedy	0.0515 (1.53)	0.050 (1.50)	0.044 (1.35)	0.045 (1.37)	0.462 (2.19)**	0.489 (2.28)**	0.441 (2.11)**	0.463 (2.19)**
PRMCAID	-0.00008 (0.44)				0.0025 (2.15)**			
Medadult		-0.0004 (0.81)				0.0072 (2.39)**		
Medchild			-0.000051 (2.51)**				-0.0015 (1.07)	
Medfam				-.00036 (2.15)**				0.00008 (0.07)

Absolute Value of T-statistics in Parenthesis
*** indicates significant at the 90% level**
**** indicates significant at the 95% level**
***** indicates significant at the 99% level**

TABLE 5
Regression Results of Probability of Working and Hours of Work
Including State Dummy Variables

	Probit Model Regression Coefficients The Dependent Variable is DWORK				OLS Regression Coefficients Dependent Variable is Hours (Includes Heckman Correction)			
Variable	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Constant	-1.62 (3.22)***	-1.43 (2.88)***	-1.42 (2.83)***	-1.44 (2.88)***	24.03 (4.73)***	24.73 (4.97)***	23.98 (4.79)***	24.25 (4.85)***
Age	0.050 (6.77)***	0.050 (6.76)***	0.05 (6.76)***	0.05 (6.76)***	0.624 (8.35)***	0.624 (8.35)***	0.622 (8.32)***	0.623 (8.33)***
Age^2	-0.00068 (7.18)***	-0.00068 (7.15)***	-0.00068 (7.16)***	-0.00068 (7.16)***	-0.0076 (7.74)***	-0.0076 (7.74)***	-0.0076 (7.71)***	-0.0076 (7.72)***
EDUC	0.0096 (0.12)	-0.0072 (0.09)	-0.011 (0.14)	-0.009 (0.11)	-0.825 (1.33)	-0.901 (1.46)	-.829 (1.34)	-.841 (1.36)
$EDUC^2$	0.011 (2.92)***	0.012 (3.15)***	0.0124 (3.20)***	0.012 (3.17)***	0.091 (3.18)***	0.094 (3.31)***	0.090 (3.18)***	0.091 (3.20)***
Race	-0.181 (7.35)***	-0.181 (7.35)***	-0.181 (7.34)***	-0.181 (7.34)***	-0.682 (2.91)***	-0.680 (2.90)***	-.681 (2.91)***	-.681 (2.91)***
Kusix	-0.206 (13.45)***	-0.206 (13.42)***	-0.206 (13.43)***	-0.206 (13.43)***	-0.652 (3.18)***	-0.649 (3.16)***	-.649 (3.16)***	-.648 (3.15)**
Kids	-0.173 (16.39)***	-0.173 (16.38)***	-0.173 (16.38)***	-0.173 (16.38)***	-0.720 (4.52)***	-0.719 (4.50)***	-.715 (4.48)***	-.716 (4.48)***
Div	0.372 (13.99)***	0.372 (14.00)***	0.372 (14.01)***	0.372 (14.01)***	1.60 (4.99)***	1.61 (4.98)***	1.60 (4.95)***	1.60 (4.95)***
Sep	0.126 (4.63)***	0.126 (4.62)***	0.126 (4.62)***	0.126 (4.62)***	0.084 (0.33)	0.084 (0.32)	.078 (.30)	.080 (.31)
Nlabor	-0.00003 (8.45)***	-0.00003 (8.55)***	-0.00003 (8.55)***	-0.00003 (8.54)***	-0.00031 (8.81)***	-0.00031 (8.82)***	-0.00031 (8.79)***	-0.00031 (8.80)***
Food	0.0007 (.67)	-0.0004 (0.35)	-0.0005 (0.46)	0.0005 (0.45)	-0.0129 (1.49)	-0.0134 (1.53)	-0.0132 (1.53)	-0.0138 (1.59)
AFDC	0.00007 (0.22)	0.00001 (0.03)	0.0002 (0.55)	-0.00013 (0.39)	-0.0019 (0.74)	-0.0014 (0.47)	-.0019 (0.74)	-0.0022 (0.87)
Edyrlt8	0.165 (3.35)***	0.155 (3.16)***	0.153 (3.12)***	0.154 (3.14)***	0.305 (0.67)	0.261 (0.58)	.298 (.66)	.291 (.65)
Edyrgt12	-0.180 (5.58)***	-0.187 (5.83)***	-0.189 (5.87)***	-0.188 (5.84)***	-1.18 (3.98)***	-1.21 (4.05)***	-1.17 (3.92)***	-1.18 (3.95)***
DNeedy	-0.125 (1.56)	-0.103 (1.29)	-0.099 (1.24)	-0.101 (1.26)	-0.725 (1.20)	-0.644 (1.07)	-.701 (1.17)	-.688 (1.14)
Mills					3.32 (2.28)**	3.30 (2.27)**	3.28 (2.26)**	3.29 (2.26)**
PRMCAID	0.0014 (2.41)**				0.0049 (1.04)			
Medadult		0.0011 (0.85)				-0.00030 (0.03)		
Medchild			-0.00004 (.06)				0.0067 (1.31)	
Medfam				-0.00018 (0.37)				-0.0038 (0.97)

Absolute Value of T-statistics in Parenthesis
* indicates significant at the 90% level
** indicates significant at the 95% level
*** indicates significant at the 99% level
Number of Observations (n) = 21,188

Number of Observations (n) = 14,525

TABLE 6
REGRESSION COEFFICIENTS
USING COMPOSITE WELFARE MEASURES
(HOURS MODEL EXCLUDES HECKMAN CORRECTION)

	DEPENDENT VARIABLE			
	EMPLOYMENT		HOURS	
WELFARE VARIABLE	NO FIXED EFFECTS	FIXED EFFECTS	NO FIXED EFFECTS	FIXED EFFECTS
WELFARE1	-.0021 (10.16)***	.00048 (1.15)	-.0052 (3.32)***	-.0015 (.46)
WELFARE2	-.0020 (10.00)***	.00029 (.71)	-.0048 (2.86)***	-.0024 (-.72)
WELFARE3	-.0021 (10.30)***	.00025 (.60)	-.0047 (2.83)***	-.0014 (.43)
WELFARE4	-.0020 (10.42)***	.00028 (.71)	-.0046 (-2.90)***	-.0012 (.38)

NOTES: * SIGNIFICANT AT 10 PERCENT LEVEL
** SIGNIFICANT AT 5 PERCENT LEVEL
*** SIGNIFICANT AT 1 PERCENT LEVEL

WELFARE1=AFDC+.70*FOOD+.368*PRMCAID
WELFARE2=AFDC+.70*FOOD+.368*MEDADULT
WELFARE3=AFDC+.70*FOOD+.368*MEDCHILD
WELFARE4=AFDC+.70*FOOD+.368* MEDFAM

TABLE 7
IV REGRESSION COEFFICIENTS
USING COMPOSITE WELFARE MEASURES
(HOURS MODEL EXCLUDES HECKMAN CORRECTION)

	DEPENDENT VARIABLE			
	EMPLOYMENT		HOURS	
WELFARE VARIABLE	NO FIXED EFFECTS	FIXED EFFECTS	NO FIXED EFFECTS	FIXED EFFECTS
WELFARE1	-.0014 (12.25)***	-.0387 (1.46)	-.0044 (1.39)	-.0462 (1.56)
WELFARE2	-.0015 (11.41)***	-.0011 (1.34)	-.0036 (1.00)	-.0537 (2.04)**
WELFARE3	-.0015 (11.60)***	-.0017 (1.70)*	-.0035 (1.02)	-.0618 (2.03)**
WELFARE4	-.0015 (12.09)***	-.0015 (1.56)	-.0044 (1.29)	-.0614 (2.00)**

NOTES: * SIGNIFICANT AT 10 PERCENT LEVEL
** SIGNIFICANT AT 5 PERCENT LEVEL
*** SIGNIFICANT AT 1 PERCENT LEVEL

WELFARE1=AFDC+.70*FOOD+.368*PRMCAID
WELFARE2=AFDC+.70*FOOD+.368*MEDADULT
WELFARE3=AFDC+.70*FOOD+.368*MEDCHILD
WELFARE4=AFDC+.70*FOOD+.368*MEDFAM

TABLE 8
FIRST STAGE OLS REGRESSION COEFFICIENTS
USING COMPOSITE WELFARE MEASURES

DEPENDENT VARIABLE

INSTRUMENT VARIABLE	WELFARE1	WELFARE2	WELFARE3	WELFARE4
PERCENT DEMOCRAT IN SENATE	572.24 (10.43)	58.54 (2.48)	-209.48 (5.21)	-180.85 (3.61)
PERCENT DEMOCRAT IN HOUSE	234.89 (3.46)	68.53 (2.35)	-323.08 (6.49)	-174.01 (2.81)
DEMOCRAT GOVERNOR	-68.54 (11.43)	34.40 (13.35)	-27.46 (6.25)	-8.89 (1.62)

NOTES: ALL MODELS INCLUDE STATE FIXED EFFECTS AND OTHER EXOGENOUS VARIABLES IN TABLE 2.

TABLE 9
OVER IDENTIFYING RESTRICTIONS TESTS
USING COMPOSITE WELFARE MEASURES
(HOURS MODEL EXCLUDES HECKMAN CORRECTION)

	DEPENDENT VARIABLE	
	EMPLOYMENT	HOURS
WELFARE VARIABLE		
WELFARE1	2.328*	1.89
WELFARE2	1.99	1.30
WELFARE3	1.62	1.29
WELFARE4	1.77	1.33

NOTES: ALL MODELS INCLUDED FIXED EFFECTS AND THE OTHER EXOGENOUS VARIABLES REPORTED IN TABLE 2. THE F- STATISTICS ARE F(3, 13813).

*** REJECT NULL THAT MODEL IS OVER IDENTIFIED AT 1 PERCENT LEVEL.
** REJECT NULL THAT MODEL IS OVER IDENTIFIED AT 5 PERCENT LEVEL.
* REJECT NULL THAT MODEL IS OVER IDENTIFIED AT 10 PERCENT LEVEL.

APPENDIX TABLE A
OLS REGRESSION COEFFICIENTS
DEPENDENT VARIABLE IS HOURS
(INCLUDES HECKMAN CORRECTION)

SPECIFICATIONS USING KIDS UNDER 6 FOR IDENTIFICATION

MEDICAID VARIABLE	WITHOUT FIXED EFFECTS	FIXED EFFECTS
PRMCAID	-.0115 (4.12)**	.0049 (1.04)
MEDADULT	-.0155 (2.46)**	-.00012 (.01)
MEDCHILD	-.006 (1.64)	.0067 (1.30)
MEDFAM	-.0058 (2.16)**	.0038 (.98)

SPECIFICATIONS USING SEPARATED FOR IDENTIFICATION

MEDICAID VARIABLE	WITHOUT FIXED EFFECTS	FIXED EFFECTS
PRMCAID	-.0106 (3.88)**	.0048 (1.02)
MEDADULT	-.0148 (2.35)**	-.0004 (.04)
MEDCHILD	-.0052 (1.42)	.0068 (1.38)
MEDFAM	-.0052 (1.97)**	.0038 (.98)

NOTES: * SIGNIFICANT AT 10 PERCENT LEVEL
** SIGNIFICANT AT 5 PERCENT LEVEL