USING MATCHED BORDER COUNTIES FOR POLICY ANALYSIS:

THE EFFECTS OF ENTITLEMENT PROGRAMS ON FEMALE-HEADED HOUSEHOLDS AND FEMALE LABOR-FORCE PARTICIPATION

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The effects of entitlement programs on female-headed households and female labor-force participation have been the subject of study for decades. Although a majority of researchers have noted that there are negative effects associated with various forms of entitlement programs, there is some disagreement over the magnitude of the effects. One issue is the manner in which such studies are estimated econometrically. Many studies have used a state-level analysis to try and ascertain the effects of entitlement programs. However, analyzing the effects of entitlements programs at the state level can present problems. For example, as Levine and Zimmerman point out, "...states differ in their welfare generosity and a myriad of other characteristics" [1999, 397]. The fact that states differ in many different ways may bias estimates of the effects of welfare programs. In terms of geographic differences, Levine and Zimmerman note, "...if low benefit states have a nicer climate, then the flow of treatments out of the state would be reduced relative to the flow of treatments out of higher benefit states with a worse climate" [ibid.] Researchers have used many different techniques to control for differences across states that may bias the results. This paper offers another approach to that problem, by comparing the effects in counties on state borders with the effects in adjacent counties just across the state border.

The border county technique used here avoids many of the problems involved in trying to control for geographic factors in cross-sectional analyses of state policy. States differ in many ways, including climate, culture, and proximity to major markets, that could affect state economies. A common method of trying to control for such factors is to use variables such as regional dummies, variables for average temperature or rainfall, and so forth, but this method always runs the risk of omitting variables or

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misspecifying the nature of the geographic differences. This analysis looks at all counties on state borders within the 48 contiguous states, and compares those counties with the adjacent counties just across the state border. Because the counties border each other, differences due to geographic and locational factors should be minimized, and any differences between counties are more likely to be caused by differences in state policies. This paper examines the effects of Aid to Families with Dependent Children (AFDC) and the Food Stamp program on the share of female-headed households and female labor-force participation in 1990. While welfare programs have changed since then, a measure of the impact of those programs can still provide good policy guidance regarding the magnitude of the effects of transfer programs on the recipient population.

Much of the literature on the impact of welfare programs focuses on the labor market effects of AFDC payments. Garfinkel and Orr [1974] find that the AFDC program reduces the labor supply of mothers eligible for the program. In a widely-cited study, Levy [1979] argues that analysts should look at the impact on all female households, rather than just those who participate in the program, and finds that more generous AFDC benefits decrease hours worked. Bieker [1981], looking at the effect of AFDC in Delaware, finds that more generous benefits increased participation in the program and reduced labor-force participation. Danziger, Haveman, and Plotnick [1981] also find that AFDC payments affect labor supply negatively, but note several reasons why there may be ambiguities that make it difficult to estimate the magnitude of the effects. Moffitt [1986] examines the effect of changes in the structure of the program in 1981, and consistent with other studies, finds that the more benefits are reduced as a result of work income, the less income eligible women would earn. Cloutier and Loviscek [1989] find that local conditions, and especially the unemployment rate, can affect participation in the program. Consistent with other studies, Robins [1990a, 1990b] and Nord and Sheets [1990] both find that reduced benefit levels result in reduced participation rates in AFDC, using different methodologies and different data. Walters [1990] finds that because transfers can blunt the incentive to work, more generous AFDC payments can increase the measured poverty rate. Smith [1991] concludes that AFDC recipients tend to migrate from lower benefit states to higher benefit states. In contrast, Levine and Zimmerman [1999] find little evidence that there is widespread migration in response to welfare benefits. Moffitt [1992], in an extensive review of the literature, notes that AFDC reduces labor supply, that more generous benefits increase program participation, and that these programs increase the likelihood of single-parent households. Yelowitz [1995] finds that more generous Medicaid eligibility reduces AFDC participation, because more families can participate in Medicaid without being on AFDC. Chapman, Duncan, and Gray [1998], in contrast with most literature, finds that for people who earn income and are on AFDC, welfare payments do not appear to make individuals less likely to pursue work.

Using a number of different methodologies, the literature almost always finds that women respond to welfare benefits in the expected direction. They work less in response to more generous benefits, they migrate from states with less generous benefits to states with more generous benefits, and they are more likely to be single parents when being single helps them qualify for benefits. The results in this paper agree, finding that more generous AFDC benefits increase the incidence of households headed by single females, and reduce female labor-force participation rates.

In addition to supporting the existing literature, this paper contributes a new methodology for measuring the effects of welfare payments. This paper uses county-level data to examine female-headed households and female labor-force participation, but rather than simply using the county level observations as variables, this paper uses only counties that are on state borders, and matches each county's data with observations on adjacent counties across the state border. Thus, rather than simply looking at the female labor-force participation rate, for example, this paper uses the female labor-force participation rate in a county as a percentage of the female labor-force participation rates in adjacent counties across the state border as a dependent variable. This technique is a method for holding geographic factors constant without having to use geographic variables to capture effects from factors such as temperature, rainfall, religion, culture, or proximity to markets.

Other studies have used similar matching methodologies for this same reason. For example, Holmes [1998] looks at border counties to examine the effect of right-to-work laws on manufacturing employment, but Holmes did not directly compare each border county with only its neighbors, as is done here. In another frequently cited study, Card and Krueger [1994] empirically investigated the impact of minimum wage laws by comparing its effects on similar restaurants in New Jersey and eastern Pennsylvania, but their data was limited to those two locations. Fox [1986] uses matched metropolitan areas and finds that increases in the state and local sales tax rate reduces the level of retail activity for two of the three metropolitan areas studied. Isserman and Rephann [1995] compare counties within Appalachia with a "twin" county outside of Appalachia and determines that between 1969 and 1991, the counties of Appalachia grew faster than their control group "twins". Bronars and Lott [1998] examine concealed-weapons laws by looking at differences along state borders and conclude that concealed handguns deter criminals.

While those studies typically look at one or a few local areas and compare them with areas that are otherwise similar (Bronars and Lott is an exception), this study looks at every border county in the contiguous 48 states and compares them directly with the county or counties they touch in adjacent states. This minimizes any differences caused by geography and allows a much cleaner comparison of differences in state policies. Thus, the paper not only contributes information about the impact of entitlement programs on various measures of female economic performance, but also demonstrates a methodology that can be applied to other state policy issues.

THE SAMPLE AND MATCHING TECHNIQUE

The sample used in this analysis consists of all counties in the 48 contiguous United States that border other states. There are 1,129 border counties, but some of these counties border two states (for example, Houston County, Alabama, which borders both Georgia and Florida), and in those cases, the counties are included in the data set twice to allow comparisons between both border states. This increases the sample size to a total of 1,319 border matches. A simple cross-sectional analysis would use the county observations as variables, but this analysis calculates variables in a county as a percentage of the same variable in the adjacent county or counties across the state border, and uses those variables in the regression analysis. For example, the first dependent variable is the percentage of households headed by females, with children under 18, and with no husband. For this analysis, the percentage of female-headed households in county i is matched with the percentage of female-headed households in counties j, which are all counties in the adjacent state that touch county i, to produce the matched value for female-headed households, FHH_i, following the formula:

$$FHH_i = county_i / [(1/n)\sum_{j=1}^{n} county_j], \tag{1}$$

where $county_i$ is the percentage of female-headed households on one side of the policy border and $county_j$ is the percentage of female-headed households in all counties in the bordering state that touch county i. Observations calculated in this way are referred to as matched values, and all of the dependent variables in the regressions in Tables 2 and 3 are matched in this way.

In Columbus County, North Carolina, for example, female-headed households with children under 18 make up 7.26 percent of all households. In Horry County, South Carolina, which is adjacent to Columbus County and across the state border, female-headed households with children account for 6.34 percent of households. Substituting into the above formula, the matched value for female-headed households with children in Columbus County is 7.26/6.34 = 1.15. Horry County borders not only Columbus County, but also Brunswick County, North Carolina, where female-headed households with children are 5.33 percent of total households, so the matched value for Horry County is 6.34/((7.26+5.33)/2) = 1.01. The only South Carolina County that Brunswick County borders is Horry, so its matched value for female-headed households with children is 5.33/6.34 = 0.84. These matched values are interpreted as the value of the county's observation as a percentage of those it matches. So, for example, female-headed households are 115 percent as common in Columbus County as the counties it borders across the state line, while female-headed households are only 84 percent as common in Brunswick County as its matched county across the state border. This example shows the difference between the matched values and the raw data, and shows why when matched values are computed by taking the ratio of a county's value to those counties across the state border, the mean of the matched values will be close to one.

The independent variables are county-level observations that are matched in a similar manner, with the exception of the AFDC variables that are state-level variables, because AFDC is a state-level program. For example, Alabama in 1990 had a maximum AFDC benefit of \$118, while Georgia's maximum benefit was \$273 and Florida's was \$294. Houston County, Alabama, is in the southeast corner of the state, and borders Early and Seminole Counties in Georgia, and Jackson County in Florida. Using the formula above, Houston County's matched AFDC variable for the Georgia counties is \$118/\$273 = 0.43, and is \$118/294 = 0.40 when matched with Jackson County in Florida. The Georgia counties have a matched value of 2.31 with Houston

TABLE 1
Descriptive Statistics for Matched Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Maximum AFDC Grant	1319	1.055593	.3690484	−.4013605	2.491525
Combined Maximum AFDC Grant and Food Stamp Payment	1319	1.01023	.1558533	.6622596	1.509982
Population Density	1319	1.834492	4.065052	.0072796	69.47491
Median Age	1319	1.005504	.1005166	.5817175	1.858536
Average Tax Rate	1319	1.160981	.7235867	.1447513	6.739441
Local Per Capita Government Expenditures	1319	1.058822	.4213561	.1135225	4.292745
Average Wage	1319	1.012442	.2060185	.528004	2.079219
Urban Population Percentage	1319	.9302944	1.207961	0	11.51613
Percentage of Population that are High School Graduates	1319	1.007947	.1148659	.5894608	1.566164
Unemployment Rate	1319	1.06397	.4949885	.1681416	5.272727
Manufacturing Employment Percentage	1319	1.168202	1.033369	.035633	19.29774
Percentage of Females not in Labor Force	1319	1.008099	.1351905	.5623674	1.89082
Percentage of Female-Headed Households	1319	1.036887	.4073312	0	5.160462

County, Alabama, using the same formula, and the Jackson County, Florida, has a value of 2.49. The matched observations tend to have means close to one, because numerators and denominators tend to be about the same size, and when they are substantially different, as with the Alabama-Georgia and Alabama-Florida example just given, a larger numerator for one county becomes a larger denominator for the adjacent county across the state border, making the average close to one.

Table 1 shows descriptive statistics of the matched variables that are used in the regression analysis that follows. The means are close to one, as the Table shows.[1] The variables used in the regression analysis that follows are not the raw observations themselves, but rather are those observations as a percentage of the same variable in the adjacent county or counties across the state border. By calculating the data this way, each county is being compared directly with adjacent counties, reducing the likelihood that geographic factors were improperly accounted for in the analysis.

THE IMPACT OF AFDC ON FEMALE-HEADED HOUSEHOLDS

Table 2 presents results of two regressions examining the impact of AFDC payments on the number of female heads of households with no husband present and with children between the ages of 0 and 17 as a percentage of total households. As described in the previous section, the unit of observation is the county, and the dependent variable and all independent variables are matched against adjacent counties in the bordering state. All the variables are county-level observations except for the AFDC and food stamp variables, which are determined at the state level.[2] In the first

TABLE 2
Effect of Combined AFDC and Food Stamp Payments and the Effect of Maximum AFDC Grant on Female-Headed Households (*t*-statistics in parentheses)

Independent Variable	Dependent Variable: Female Heads, No Husband Children 0-17 as a percentage of Total Households	Dependent Variable: Female Heads, No Husband Children 0-17 as a percentage of Total Households
Constant	2.170960	2.337587
	(11.34)[a]	(12.64)[a]
Combined Maximum AFDC Grant	0.302970	
and Food Stamp Payment 1990	(5.35)[a]	
Maximum AFDC Grant 1990		0.125748
		(5.33)[a]
Average Tax Rate	−0.015855	−0.016532
	(−1.01)	(−1.05)
Percentage of Population that are High School	−0.487886	−0.483223
Graduates 1990	(−4.97)[a]	(−4.91)[a]
Manufacturing Employment	−0.020191	−0.019845
percentage 1990	(−2.18)[b]	(−2.15)[b]
Average Wage per Job	0.148867	0.143836
per Week	(2.56)[b]	(2.48)[b]
Median Age 1990	−1.407881	−1.407167
	(−9.45)[a]	(−9.43)[a]
Population Density 1990	0.012821	0.012773
	(2.66)[a]	(2.65)[a]
Local Per Capita	0.054540	0.058925
Government Expenditures	(1.96)[c]	(2.13)[b]
Unemployment Rate	0.221634	0.223680
Percentage 1990	(5.08)[a]	(5.13)[a]
Urban Population	0.044550	0.044583
Percentage 1990	(5.11)[a]	(5.12)[a]
Number of Observations	1319	1319
F-Stat	61.46[a]	61.40[a]
$\bar{R}^2$	.3144	.3143

a. Denotes significance at the 1 percent level, b. Denotes significance at the 5 percent level. c. Denotes significance at the 10 percent level.

regression, the independent variable measuring welfare generosity is the combined maximum benefit from both AFDC and food stamps, and in the second regression only the maximum AFDC benefit is used.[3]

Additional independent variables, included to hold other differences across states constant, are the average tax rate, which is state and local taxes as a percentage of state income, the percentage of the population that has graduated from high school, the percentage of the population employed in manufacturing, the average wage per job per week in the county,[4] the median age of the county's population, the county's population density, local per capita government expenditures, the county's unemployment rate, and the percentage of a county's population that lives in an urban area. As described earlier, these variables are matched against the county-level observations of the bordering state. The reason these variables are included is to try to adjust for factors that might affect the percentage of female-headed households in a county, but because of the matching technique used in the regressions, many factors that vary among counties, such as climate, culture, proximity to markets, and so forth, are accounted for, making this matching technique a desirable method for focusing in on the effects of state policies. By comparing adjacent counties, the most significant difference between the two will often be the state in which the county is located.

The non-AFDC independent variables are all significant, with the exception of the average tax rate. These other variables were included because they often appear in the literature on the effect of welfare, and it is interesting to look at the signs of some of them. The higher the percentage of a state's population who are high school graduates, the lower the incidence of female-headed households. The data do not show what percentage of female-headed households are due to divorce or death, versus unwed mothers, so this may indicate that more education reduces out-of-wedlock births, lessens the incidence of divorce or death of a spouse, or some combination. More manufacturing employment also lowers female-headed households, whereas a higher average wage raises the percentage of female-headed households. This may indicate that greater income-earning opportunities provide more financial resources to support a family. A higher state median age lowers the percentage of female-headed households. Higher state population density and a higher percentage of population in urban areas increases the incidence of female-headed households, as does a higher unemployment rate. Higher per capita government expenditures also increases the incidence of female-headed households, perhaps because government expenditures can substitute for income earned by a spouse, either indirectly by providing public goods or directly through transfer programs.

Holding these factors constant, and accounting for geographically-related factors by the county matching technique, the welfare variables are significant at the one percent level of confidence and positive, showing that more generous welfare benefits increase the percentage of households that are headed by females with no husband, and with children under 18 years old. This is true whether one measures the generosity of combined AFDC and food stamp benefits, which is done in the first regression, or whether one looks at AFDC payments alone, as is done in the second regression. Evaluating the effect of the program by looking at the means of the variables, the magnitude of the coefficient in the first regression indicates that if the combined AFDC and food stamp payment increases by 10 percent, the mean percentage of female-headed households would increase by about 2.95 percent.[5] Looking at AFDC payments alone, a 10 percent increase in the maximum benefit level leads to a 1.28 percent increase in female-headed households.[6]

THE EFFECT OF AFDC ON FEMALE LABOR-FORCE PARTICIPATION

Table 3 shows regression results using the same type of model as in the previous section, but this time using a measure of female labor-force participation (females

TABLE 3
Effect of Combined AFDC and Food Stamp Payments and the Effect of Maximum AFDC Grant on Female Labor Force
(*t*-statistics in parentheses)

Independent Variable	Dependent Variable: Females 16+, Not in Labor Force as a percentage of Female Population	Females 16+, Not in Labor Force as a percentage of Female Population
Constant	0.708322	0.762706
	(11.42)[a]	(12.47)[a]
Combined Maximum AFDC Grant and Food Stamp Payment 1990	0.098650	
	(4.88)[a]	
Maximum AFDC Grant 1990		0.040781
		(4.97)[a]
Average Tax Rate	−0.014082	−0.014297
	(−2.85)[a]	(−2.89)[a]
Percentage of Population that are High School Graduates 1990	−0.407206	−0.405631
	(−10.83)[a]	(−10.78)[a]
Manufacturing Employment Percentage 1990	0.010530	0.010639
	(2.66)[a]	(2.70)[a]
Average Wage per Job per Week	−0.034532	−0.036200
	(−1.96)[b]	(−2.05)[b]
Median Age 1990	0.605482	0.605689
	(15.58)[a]	(15.55)[a]
Population Density 1990	0.000293	0.000278
	(0.42)	(0.40)
Local Per Capita Government Expenditures	0.004207	0.005666
	(0.49)	(0.67)
Unemployment Rate Percentage 1990	0.035430	0.036106
	(4.38)[a]	(4.46)[a]
Urban Population Percentage 1990	−0.002079	−0.002072
	(−1.00)	(−0.99)
Number of Observations	1319	1319
F-Stat	96.99[a]	96.88[a]
$\bar{R}^2$	.4213	.4211

a. Denotes significance at the 1 percent level, b. Denotes significance at the 5 percent level.

aged 16 and over not in the labor force as a percentage of the total population of females 16 years old and older) as the dependent variable. The variables are matched in the same way as were the previous regression variables on female-headed households. Again, the non-welfare independent variables tend to be statistically significant, with the exception of population density, urban population, and local government expenditures.

Higher taxes reduce the percentage of females not in the labor force, and therefore increase female labor-force participation. One would expect taxes to discourage work, so the sign is unexpected, but perhaps it is proxying for government expenditures, which is insignificant in these regressions. Note that in the previous table, both the tax and government expenditures variables had the same signs as in Table 3, but expenditures was significant while the tax rate was not. A greater percentage of high school graduates decreases the percentage of females not in the labor force, so education, measured this way, increases female labor-force participation. A greater percentage of manufacturing employment increases the percentage of females not in the labor force, and a higher average wage reduces the percentage of females not in the labor force, which is consistent with the idea that lower wages lead to more two-earner households (and also, as Table 2 showed, more female-headed households). A higher median age leads to lower female labor-force participation, as does a higher unemployment rate.

The welfare variables show a highly significant relationship between both measures of the generosity of benefits and female labor-force participation. The coefficient estimate in the first regression indicates that an increase in the combined AFDC and food stamp payment of 10 percent would lead to a one percent increase in the percentage of females 16 and over not in the labor force. The second regression, where AFDC benefits are examined alone, indicates that a 10 percent increase in benefits will increase the percentage of females not in the labor force by about 0.43 percent.

AN ANALYSIS OF SUBSAMPLES

The border county matching technique used in this paper uses data from each county twice or more. Data are used once in the numerator of that county's own observation and then again in the denominator of the county or counties across the state border. If counties exactly matched up across state borders, the data for one county would be the reciprocal of the data from the matched county across the border. Exact matches across state borders are rare: only 34 counties (17 pairs of counties) exactly match each other, so by including all counties, new information is added to the data set, and it seems reasonable to undertake the analysis using every border county. Still, it may be that county observations are similar enough that the observations are almost duplicated, which could inflate the significance levels of the coefficients. There is no test or technique to estimate the degree to which significance levels might be inflated, so it might be reasonable to undertake the analysis in a way that eliminates the paired counties. That is done in Tables 4 and 5.

The data set is partitioned into two sets according to the value of the independent variable of interest: either the AFDC variable or the combined AFDC and food stamp variable. Recall that because of the matching technique, the variable means are close to one. The AFDC mean is 1.06 and the combined variable mean is 1.01. The data set is partitioned so that all counties where the variable of interest is greater than one are placed in one subsample and counties where the variable is less than one are placed in another. The same regressions reported in Tables 2 and 3 are then run again on both subsamples. Table 4 reports the results for the regressions that use female-headed households as the dependent variable and Table 5 reports the results when female labor-force participation is the dependent variable. The sample sizes are smaller, so the t-statistics are lower, but the adjusted R^2s are about the same and most coefficients that are statistically significant in the entire sample re-

TABLE 4
Effect of Combined AFDC and Food Stamp Payments and the Effect of Maximum AFDC Grant on Female-Headed Households with Restricted Sample (*t*-statistics in parentheses)

Independent Variable	Dependent Variable Female Heads, No Husband, Children 0-17 as a Percentage of Total Households			
Restricted Sample	AFDC > 1	AFDC < 1	Combined > 1	Combined < 1
Constant	2.751274	1.927363	2.631491	0.350273
	(9.84)[a]	(9.54)[a]	(8.49)[a]	(7.29)[a]
Combined Maximum AFDC Grant and Food Stamp Payment 1990			0.254242	0.560745
			(2.07)[b]	(3.81)[a]
Maximum AFDC Grant 1990	0.106374	0.314523		
	(2.57)[b]	(4.08)[a]		
Average Tax Rate	−0.027832	−0.011694	−0.026788	−0.015508
	(−1.38)	(−0.529)	(−1.31)	(−0.698)
Percentage of Population that are High School Graduates 1990	−0.628116	−0.375652	−0.631681	−0.354876
	(−4.31)[a]	(−2.85)[b]	(−4.35)[a]	(−2.67)[b]
Manufacturing Employment percentage 1990	−0.023430	−0.006857	−0.023551	−0.005961
	(−2.34)[b]	(−0.319)	(−2.36)[b]	(−0.275)
Average Wage per Job per Week	0.210641	0.108360	0.209290	0.097569
	(2.30)[b]	(1.57)	(2.29)[b]	(1.40)
Median Age 1990	−1.750746	−1.200303	−1.764899	−1.195131
	(−7.32)[a]	(−8.34)[a]	(−7.35)[a]	(−8.24)[a]
Population Density 1990	0.011208	0.014914	0.011034	0.015389
	(1.92)[c]	(2.17)[b]	(1.91)[c]	(2.23)[b]
Local Per Capita Government Expenditures	0.045216	0.089418	0.042267	0.090658
	(1.23)	(2.07)[b]	(1.15)	(2.06)[b]
Unemployment Rate Percentage 1990	0.280086	0.166643	0.275994	0.161338
	(3.73)[a]	(5.73)[a]	(3.64)[a]	(5.57)[a]
Urban Population Percentage 1990	0.055776	0.035633	0.056813	0.032471
	(3.88)[a]	(3.39)[a]	(3.87)[a]	(2.84)[b]
Number of Observations	644	666	639	652
F-Stat	35.84[a]	26.70[a]	35.40[a]	24.87[a]
$\bar{R}^2$	0.351	0.279	0.350	0.268

a. Denotes significance at the 1 percent level, b. Denotes significance at the 5 percent level. c. Denotes significance at the 10 percent level.

main significant, and with the same signs, in both subsamples. Qualitatively the results from the full sample and from the subsamples do not differ much.

Looking at Table 4, the signs remain the same for all variables as they are in Table 2 that run those regressions with the full sample. The average tax rate remains insignificant, as in Table 2. Most of the other variables remain statistically significant at least the 10 percent level, but manufacturing employment is insignificant for the <1 subsample while local per capita government expenditures becomes insignificant in the >1 subsample. The coefficient on the AFDC variable is .106 in the >1 subsample but much larger at .315 in the <1 subsample, and close to the .303 value in the full

TABLE 5
Effect of Combined AFDC and Food Stamp Payments and the Effect of Maximum AFDC Grant on Female Labor Force with Restricted Sample (*t*-statistics in parentheses)

Independent Variable	Dependent Variable Female 16+, Not in Labor Force as a Percentage of Female Population			
Restricted Sample	AFDC > 1	AFDC < 1	Combined > 1	Combined < 1
Constant	0.645740	0.810257	0.546954	0.773394
	(7.18)[a]	(10.06)[a]	(5.36)[a]	(8.90)[a]
Combined Maximum AFDC Grant and Food Stamp Payment 1990			0.147583	0.083051
			(3.44)[a]	(1.35)
Maximum AFDC Grant 1990	0.045276	0.039325		
	(3.21)[b]	(1.34)		
Average Tax Rate	−0.011448	−0.016231	−0.012032	−0.015518
	(−1.54)	(−2.35)[b]	(−1.61)	(−2.21)[b]
Percentage of Population that are High School Graduates 1990	−0.334667	−0.450988	−0.332552	−0.451711
	(−6.62)[a]	(−9.03)[a]	(−6.59)[a]	(−8.97)[a]
Manufacturing Employment Percentage 1990	0.007458	0.018880	0.007434	0.018342
	(1.89)*	(1.98)[b]	(1.88)[c]	(1.89)[c]
Average Wage per Job per Week	−0.074471	0.005621	−0.074823	0.005743
	(−3.08)[b]	(0.231)	(−3.10)[b]	(0.234)
Median Age 1990	0.656432	0.576196	0.648843	0.573419
	(11.24)[a]	(11.95)[a]	(11.18)[a]	(11.70)[a]
Population Density 1990	0.001289	−0.000596	0.001318	−0.000600
	(1.08)	(−0.811)	(1.11)	(−0.833)
Local Per Capita Government Expenditures	0.005068	0.005138	0.003861	0.003793
	(0.474)	(0.358)	(0.366)	(0.259)
Unemployment Rate Percentage 1990	0.056977	0.020476	0.056424	0.020595
	(4.51)[a]	(1.90)[c]	(4.49)[a]	(1.89)[c]
Urban Population Percentage 1990	0.000972	−0.004529	0.000438	−0.006054
	(0.316)	(−1.54)	(0.141)	(−1.99)[b]
Number of Observations	644	666	639	652
F-Stat	51.33[a]	47.23[a]	51.42[a]	46.41[a]
$\bar{R}^2$	0.439	0.410	0.441	0.411

a. Denotes significance at the 1 percent level, b. Denotes significance at the 5 percent level. c. Denotes significance at the 10 percent level.

sample. The combined coefficient is .254 in the >1 subsample and .561 in the <1 subsample, while the full sample coefficient is .303. The coefficient in the full sample is closer to the >1 subsample for AFDC, but closer to the <1 subsample for combined AFDC plus food stamps.

Table 5, which has female labor-force participation as the dependent variable, also has results qualitatively the same as for the full sample. Independent variables that are significant in the full sample are significant in the subsamples. Average tax rate is significant only in the <1 subsample and average wage variables are significant in only the >1 subsample. The signs of the significant variables remain the same in the subsamples as in the full sample. The independent variables of primary interest–AFDC and AFDC plus food stamps–are significant in the >1 subsample, with magnitudes slightly higher than in the full sample, but are not statistically significant in the <1 subsample. This could be interpreted as suggesting that above-average payments have an effect of reducing female labor-force participation at the margin, but below-average payments have little effect at the margin. Note also that because welfare variables in the >1 sample are highly significant, with t-statistics of 3.21 and 3.44, while the <1 sample has t-statistics of 1.35 and 1.34, the two subsamples do contain different information from a statistical standpoint, so combining them adds information and does not merely duplicate the results.

To the degree that the data in matched counties duplicate each other, the matching technique could inflate the significance levels of the coefficient estimates. Few counties have exactly reciprocal data, however, and the differences in the results of the two subsamples suggest that additional information is added by using both rather than just one. The results are qualitatively similar for the full sample and both subsamples, but an examination of all of the results suggests that there is not a problem with the full sample results.[7]

CONCLUSION

The literature on the impact of welfare programs consistently shows that the incentives implied by these programs have effects on potential recipients. This paper supports that conclusion by showing that an increase in the generosity of Aid to Families with Dependent Children increased the incidence of female-headed households and reduced female labor-force participation in 1990, but the magnitude of the estimates here are smaller than is generally found in the literature. Danziger, Haveman and Plotnick state in their widely-cited review, "[a]ll but one find statistically significant negative impacts, but the coefficient estimates vary widely" [1981, 993]. Included in their review of the literature is a table of various elasticity estimates that measure the effect of the AFDC guarantee on such dependent variables as the female employment rate, female labor-force participation, and hours worked by females. The elasticity estimates of the employment rate with respect to the income guarantee ranges from –0.7 to –0.76, while the elasticity of hours worked with respect to the income guarantee ranges from –0.9 to –1.11. The only paper reviewed by the authors concerning the elasticity estimate of participation with respect to the income guarantee places that estimate at –1.14.[8] Although elasticity estimates are not directly comparable across studies where the dependent variable differs, our elasticity estimates do indicate that the income guarantee increases the incidence of female-headed households and also increases female labor force non-participation, which is consistent with the observations made by Danziger, Haveman and Plotnick [1981], but with magnitudes of -0.3 to -0.04. The smaller elasticity measures obtained here could be the result of the county matching technique that holds constant things that may be unaccounted for in other studies.

In 1996 the AFDC program was replaced by Temporary Aid to Needy Families (TANF), which is intended to require recipients to work in exchange for time-limited assistance. States design their own programs, and a considerable amount of flexibility is allowed, including the flexibility of states to exclude some recipients from the work requirement and the flexibility to for some recipients to exceed the time limits. In the booming economy of the late 1990s welfare caseloads fell substantially. As this paper is being written, the economy has slowed in 2001-2002, which may provide a better indicator of the effectiveness of TANF. Meanwhile, this study may be useful both for showing the impact of welfare programs in general, and to provide a benchmark to evaluate the reforms of the 1990s.

These results are of interest not only because of the conclusions they draw but also because of the methodology used to generate them. In contrast to a straightforward cross-sectional analysis, where every observation is compared with every other observation, this paper used counties that were on state borders as the unit of analysis, and expressed its dependent variables as a fraction of the same variable for the county or counties on the other side of the state border. Therefore, rather than simply looking at female labor-force participation in a county, each county's female labor-force participation was expressed as a percentage of the female labor-force participation in the adjacent county or counties just across the state border. By expressing the variables in this way, each county is being compared directly with cross-state counties touching that county. This means that geographically-related factors such as weather, culture, religion, and proximity to major markets should be accounted for by this border county matching technique. It is possible to try to use dummy variables to try to control for geographic factors such as this, but by making the comparison between counties that are geographically contiguous, such factors should be almost completely controlled for by the border county matching technique.

This border county matching technique is similar to that used in other studies, but by directly matching counties to their neighbors across state borders, it holds geographic factors constant in a way that similar studies, such as Holmes [1998] do not. By using every border county in the 48 contiguous United States as a unit of observation, it offers a comprehensiveness that goes beyond simply pairing up similar areas to examine a policy difference. This same technique could be used to compare other state policies, so this study offers not only some additional insight on the effects of welfare programs on female-headed households and female labor-force participation, but also a methodology that could be applied more generally.

NOTES

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1. The mean for population density is the furthest from 1, because the matched observations are skewed. The minimum is close to zero, as the table shows, and the maximum is 69.5.
2. Note, however, that the AFDC and food stamp variables are not the same for each county in the state, because they are matched to the counties they border in the adjacent state. The example given in the text above shows that Alabama counties bordering Florida have different AFDC values than Alabama counties bordering Georgia, even though the maximum AFDC benefit is the same state-wide.
3. The data for both the maximum AFDC grant and the maximum combined AFDC grant and Food Stamp payment are found in Overview of Entitlement Programs, 1990 Green Book: Background

Material and Data on Programs Within the Jurisdiction of the Committee on Ways and Means, Committee on Ways and Means, U.S. House of Representatives, Washington, D.C., 1990, 553-55.

4. The figures for average wage per job per week are available from the Bureau of Economic Analysis (http://www.bea.doc.gov/bea/regional/reis/).
5. The elasticities were calculated from within STATA,which reports the elasticities at the variable means.
6. To get an idea of the magnitudes, the range of AFDC payments across states in 1990 varied from a low of $118 in Alabama to a high of $703 in New York.
7. To the extent that information is duplicated in the two subsamples, the t-statistics in the full sample will be inflated, but there is no test that can adjust for whatever information is duplicated. The appropriate *t*-statistics will be somewhere between those in the full sample and those in the subsamples, but because the results in the subsamples are significant at conventional levels, even the low boundaries for the t-statistics preserve the qualitative results of the paper.
8. Moffitt [1992) does a review, but states that "the literature on the labor supply effects of AFDC is of moderate size, consisting of approximately 10 studies over the past 20 years." As a result, Moffitt relies on the overview of Danziger, Haveman, and Plotnick [1981) for empirical estimates. Because there have been few recent studies, that is yet another reason to take a new look at the impact of AFDC.

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