Income Inequality in Rural Southeast Missouri

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Income inequality has been increasing in the United States since at least 1980. However, in a 34-county region of southeast Missouri, income inequality actually decreased from 1990 to 2000. As well, income inequality was less in the selected region as compared with the entire United States in 1999. A simple, single-equation regression model is used to identify the factors that influence income inequality in southeast Missouri. Five factors stand out as especially significant: the percent of the population under 18 years of age, the percent of the families that are female-headed, the female labor force participation rate, the level of income, and the percent of the population with a high school diploma (but no higher degree). Income inequality increases with income and the percent of female-headed families, whereas it decreases with increases in the other three factors.

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There is strong evidence that income inequality in the United States has been increasing since at least 1980 (see, for example, Levernier, 1996; Levernier, Partridge, and Rickman, 1995 and 1998a; Partridge, Rickman, and Levernier, 1996). In addition, there is considerable variation in income inequality at the regional level. For example, income inequality tends to be higher in nonmetropolitan areas than it is in metropolitan areas (Levernier, Partridge, and Rickman, 1998b). The causes of the observed regional variation have been studied by researchers for states (Levernier, Partridge, and Rickman, 1995; Partridge, Rickman, and Levernier, 1996), for counties (Levernier, Partridge, and Rickman, 1998a), and for urban areas (Garafalo and Fogarty, 1979).

Although some studies have considered the entire population of over 3,000 counties in the United States (for example, Levernier, Partridge, and Rickman, 1998a), this study considers income inequality in a small sample of 34 counties in southeast Missouri at two points in time: 1989 and 1999. We are concerned with identifying the causes for the variation in income inequality that exists in the 34 counties and for the changes that occur over the 10-year period. Studying a subset of the population of 3,000 U.S. counties allows us to determine whether the factors affecting income inequality in our small sample are similar to those in the entire population of counties. When the 3,000 counties are included in a single study, some of the unique characteristics of the many subregions in the United States are surely lost because of simple aggregation. Therefore, there is value in bringing the microscope to bear on a small region of the entire country. In addition, because income inequality changes over time, it is important to identify those factors that have a continuing effect on inequality as opposed to factors that have a more transitory effect.

Although the measurement of income inequality and the identification of the factors that influence inequality are interesting endeavors in their own right, the ultimate goal of a study such as this one must be to make policy prescriptions

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that emanate from the results. Persistent and increasing income inequality is likely to be deemed undesirable by many in society, though that can be a controversial statement. In fact, Kuznets (1955) was one of the first to point out that income inequality may increase initially as a region or country develops. That is, it may be normal or even necessary over a period of time for income inequality to increase as income progresses. This implies, perhaps, that attempts to reduce income inequality could be futile or even harmful. Nevertheless, economic policies that reduce inequality are likely to be favored over those that increase it. The results from this study are likely to be useful in crafting policies that promote greater income equality in southeast Missouri.

The organization of this paper is as follows. A review of income inequality in rural counties in southeast Missouri is given in the next section. The third section introduces the basic model that is used in this paper to identify the factors that affect the variation in income inequality in rural southeast Missouri. In this section, we also briefly review results from selected earlier studies. The fourth section outlines the results of the model for southeast Missouri. The final section offers a brief summary and conclusion.

INCOME INEQUALITY IN SOUTHEAST MISSOURI

The Gini coefficient, a simple measure of income inequality with a value that ranges from 0 (no inequality) to 1 (complete inequality), was used in this study as the measure of income inequality in a county. The U.S. Census Bureau (historical income inequality tables; www.census.gov/hhes/www/income/histinc/f04.html) reports that the Gini coefficient for the entire nation was equal to 0.401 in 1989 and 0.429 in 1999—evidence of rising income inequality in the United States.

Thirty-four rural counties in southeast Missouri comprise the sample. (See Figure 1 for a county map of the state of Missouri.) The 1990 U.S. Census (summary file 3; www.census.gov/main/www/cen2000.html) reports the total family income for a county as well as the number of families in 25 different income classes. The 2000 U.S. Census reports total income and number of families for 16 different income classes. Using the method of previous researchers, we assume that income level for each family is equal to the midpoint of its income class. For the highest, open-ended income class, we assume families are at the mean of the income class as reported by the U.S. Census Bureau.

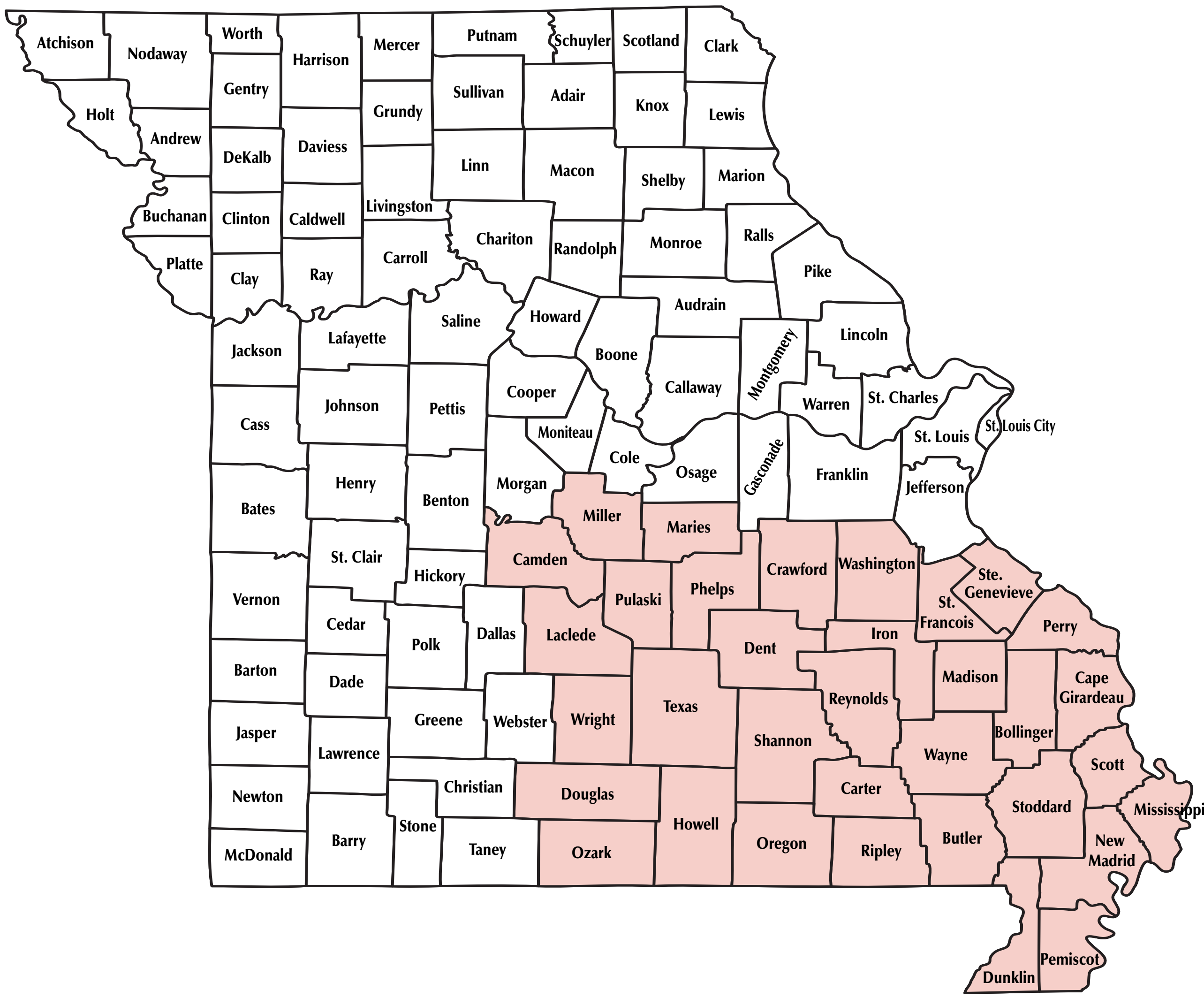
Maxwell (1990) explains the actual procedure for estimating the Gini coefficient based on income class data. We followed this procedure to arrive at the results in Table 1, which gives the Gini coefficient for each county in our study for 1989 and 1999. Note that the income collected in a decennial census is actually for the previous year; therefore, the Gini coefficients technically are for 1989 and 1999. Comparison data for the United States and for all of southeast Missouri are given in Table 1 as well. Note that the southeast Missouri data are not computed as the average of the 34 counties, but, rather, they are computed using the aggregate data for the entire region.

Two facts are readily apparent from the data in Table 1. First, income inequality in southeast Missouri is less than that in the entire United States in 1999. Second, income inequality actually fell in southeast Missouri in the 1990s, while it was rising in the United States. Income inequality fell in 19 of the 34 counties, rose in 14 counties, and remained unchanged in 1 county (Cape Girardeau). The Gini coefficient ranged from 0.3421 to 0.4815 in 1989. In 1999, the coefficient ranged from 0.3366 to 0.4809. One reason for the lower level of income inequality in southeast Missouri could be the lower overall rate of growth in the region relative to the rest of the country and relative to urbanized regions.

Although there are significant changes in levels and rankings from 1989 to 1999, the simple correlation coefficient between the two years is 0.69, which is highly significant at the 1 percent level. Counties in the Bootheel region of Missouri (such as Pemiscot, Dunklin, Mississippi, and New Madrid) have among the highest Gini coefficients. Counties just north of the Bootheel (Cape Girardeau, Ste. Genevieve, Perry, St. Francois,

Figure 1

Missouri Counties



and Bollinger) generally have lower Gini coefficients. Counties in the Ozarks region are more of a mixed bag, with some below the average (e.g., Laclede, Maries, and Miller) and others above the average (e.g., Wayne, Butler, Ripley, Douglas, and Howell). Therefore, it will be important in our empirical analysis to adjust for potential regional effects that might exist.

Table 1

Gini Coefficients

County	Gini 1989	Rank 1989	Gini 1999	Rank 1999
United States	0.4010		0.4290	
Southeast Missouri	0.4128		0.4097	
Bollinger	0.3816	28	0.3586	30
Butler	0.4306	8	0.4477	2
Camden	0.4097	13	0.4152	15
Cape Girardeau	0.3834	26	0.3834	26
Carter	0.3993	16	0.4207	13
Crawford	0.3819	27	0.3883	25
Dent	0.4360	7	0.3935	23
Douglas	0.4476	4	0.3956	21
Dunklin	0.4618	2	0.4262	10
Howell	0.4264	9	0.4127	16
Iron	0.3970	19	0.4303	5
Laclede	0.3695	31	0.3962	20
Madison	0.3808	30	0.3992	19
Maries	0.3897	22	0.3496	32
Miller	0.3809	29	0.3673	29
Mississippi	0.4458	5	0.4450	3
New Madrid	0.4424	6	0.4292	6
Oregon	0.4238	10	0.4256	11
Ozark	0.3889	23	0.4281	8
Pemiscot	0.4481	3	0.4809	1
Perry	0.3532	32	0.3455	33
Phelps	0.4064	14	0.3942	24
Pulaski	0.3421	34	0.3360	34
Reynolds	0.3954	20	0.3812	28
Ripley	0.4199	12	0.4170	14
St. Francois	0.3853	25	0.3816	27
Ste. Genevieve	0.3464	33	0.3524	31
Scott	0.3989	17	0.3951	22
Shannon	0.3949	21	0.4416	4
Stoddard	0.4224	11	0.4062	18
Texas	0.3977	18	0.4270	9
Washington	0.4002	15	0.4225	12
Wayne	0.4815	1	0.4290	7
Wright	0.3864	24	0.4064	17

NOTE: Spearman's rank correlation coefficient = 0.643 (t = 3.69).

MODEL AND LITERATURE REVIEW

The general approach to identifying the factors associated with income inequality is a simple model of the form:

$$INEQ = \mathrm{F}(DEMOG, LF, INDCOMP, HUMANK, GEOG),$$

where *INEQ* is some measure of income inequality in a region such as the Gini coefficient, *DEMOG* includes demographic variables, *LF* denotes variables related to conditions in the labor force, *GEOG* are variables that relate to regional effects, *INDCOMP* includes variables that measure the industrial composition of a region, and *HUMANK* are human capital variables. The various studies differ as to the exact variables that are included in each category and to the different categories that might be used. However, in all cases, economic theory is used to identify and to support the use of the individual variables that are included in the model.

The four demographic variables most often used are the percents of the dependent population that are under 18 (*UNDER18*) or over 64 years of age (*OVER64*) (two separate variables), the percent of African-Americans and/or other minorities (*BLACK*), and the percent of families that are headed by a female (*FEMALE*). Because of possible discrimination in the labor force, a greater proportion of African-Americans and/or other minorities in a region may lead to greater income inequality. This has generally been found to be true in previous studies (Persky and Tam, 1994; Levernier, 1996 and 1999; Partridge, Rickman, and Levernier, 1996). It is also expected that the greater the percent of the population that is dependent, the greater will be the degree of income inequality. People 65 years of age or older frequently have lower incomes. A greater proportion of this age group is likely to increase income inequality in a region. Similarly, the population under 18 usually receives little or no income, which could also contribute to income inequality. However, the actual research is mixed with respect to these variables. In some cases, just one group is found to be significant or has an unexpected sign.[1] Female-headed families are much more likely to be low income than are other families; therefore, as the percent of such families increases in a region, income inequality should increase. Most research finds this to be the case (see, for example, Levernier, Rickman, and Partridge, 1995 and 1998a).

Four types of variables fall into the labor force category. One variable relates to the labor force participation rate; here it is exclusively women (*FLFPR*). Women increased their participation in the labor force in record numbers starting in the 1970s, a trend that has continued through the 1990s. The entrance of women into the labor force will boost the earnings of the affected families and will contribute to reductions in income inequality if the women are from lower and middle class families. If women from upper middle income and upper income families enter the labor force, it is possible that increased labor force participation by women will increase income inequality. The overwhelming majority of studies find that income inequality falls when the labor force participation rate of women increases (Levernier, 1999; Levernier, Partridge, and Rickman, 1995 and 1998a). Instead of using the labor force participation rate for women only, some studies use the employment rate (Levernier, 1996) or the labor force participation rate for both sexes (Partridge, Rickman, and Levernier, 1996) with similar results. Our study includes only the female labor force participation rate.

A second labor force variable used in many studies is the percent of the population that is foreign born. Several studies find a positive and significant relationship between foreign born workers and income inequality (see, for example, Levernier, 1996). The theory is that foreign-born individuals frequently have lower skills or language impediments that reduce their income, thus contributing to income inequality. Because there are so few foreign born workers in the counties in our sample, this variable was not significant in any of the regressions and, therefore, is not included in our final regressions.

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[1] Levernier (1999), for example, found only the group under 18 to be positively related to income inequality; Levernier, Partridge, and Rickman (1998a) found that as the percent of the population over 64 increases, income inequality decreases in nonmetropolitan counties.

A third labor force variable relates to the conditions of the labor market in a region. Increases in employment (*EMPGROW*) in a region offer opportunities for unemployed individuals to increase their incomes, which should help to lower income inequality (see, for example, Levernier, Partridge, and Rickman, 1995; Levernier, 1999). Therefore, employment growth in the previous decade is included in the model as a measure of employment opportunities in the region.

The final labor force variable is the income of the region. The Kuznets (1955) hypothesis indicates that income inequality may increase as income in a region increases initially and then may decrease as income increases further. Therefore, a region's level of income inequality may be influenced by its present stage of economic development. Levernier, Partridge, and Rickman (1998a), for example, find a positive relationship between income level and income inequality for their sample of over 3,000 counties. Bishop, Formby, and Thistle (1992) also find a positive relationship for income. They use states in 1980 for their sample. However, Persky and Tam (1994) find a negative relationship between income and income inequality. So, because the relationship between income inequality and the level of income may not be linear, two models were tested here in addition to a simple linear model. One was a quadratic approach on the level of income. The empirical results did not support a quadratic approach. The second approach was to use the log form for income (*LINCOME*). This proved more satisfactory and was adopted for the final model.

Industrial composition variables relate to the type of industries that are found in a region. One hypothesis is that a large manufacturing sector offers relatively high-wage employment to less-educated workers, thereby contributing to a reduction in income inequality. Conversely, if employment in a region is concentrated in the retail and/or service sectors, this could lead to increases in income inequality. Another sector that could be of importance in determining income inequality is farm employment. Farm income is notoriously variable and frequently low; both of these facts could lead to greater income inequality in regions with a large farm sector. The ideal approach, perhaps, is that used by Levernier (1999) or Levernier, Partridge, and Rickman (1998a). They include the percent of employment in each major SIC (standard industrial classification) sector. However, because of restricted degrees of freedom in a small sample, we tested only two variables: the percent employed in the manufacturing sector (*MFG*) and the percent employed in the farm sector (*FARM*). We also tried, as an alternative measure, the percent of regional income for these two industries, but neither was significant.

Three human capital variables relating to education of the labor force have been used in various studies. Two variables relate to the level of education: the percent of the population (25 years of age or older) that has a bachelor's degree or higher (*COLLEGE*) and the percent of the population that has a high school diploma (but no college degree) (*HS*). The latter category includes individuals with some college and/or an associate's degree. Therefore, the excluded category is high school dropouts. It is difficult to say, a priori, how more college graduates in a region may affect income inequality. It is possible that more college graduates will increase income inequality. An increase in the population with high school diplomas is likely to decrease income inequality. Levernier, Partridge, and Rickman (1995), for example, find that increases in the percent of college graduates increase income inequality, whereas increases in the percent of those with a high school diploma decrease it. In addition to the level of education, several studies use the standard deviation of educational attainment (*EDUC*) in a region. The U.S.Census Bureau reports the number of individuals in a region in each education category: less than eighth grade education, high school dropout, high school diploma, etc. We take the standard deviation of these reported groups. It is generally found that a greater dispersion of educational attainment increases income inequality (Levernier, Partridge, and Rickman, 1998a).

In addition to the variables that have been discussed thus far, it is also likely that other factors that influence income inequality are unique to given regions. In addition, there may be omitted factors that are not measured by the variables

Table 2

Variable Statistics

Variable	Mean	Standard deviation	Maximum	Minimum
GINI (x100)	40.42	3.22	48.1	33.6
OVER64	16.21	2.44	21.1	6.7
UNDER18	25.98	1.95	30.9	20.2
BLACK	3.38	6.37	27.3	0.0
FEMALE	7.95	2.86	18.6	3.2
FLFPR	48.87	5.43	61.5	37.8
EMPGROW	16.62	14.12	52.8	–24.6
LINCOME	10.00	0.14	10.3	9.7
LPOP	9.83	0.61	11.1	8.6
MFG	16.64	7.98	34.1	1.7
FARM	11.83	7.08	31.2	2.5
COLLEGE	9.51	3.69	24.2	5.8
HS	54.79	6.62	66.3	42.1
EDUC	12.60	1.31	15.8	8.9

included within the model. It is important to control for these regional effects and omitted factors, usually through the use of dummy variables. In our model, we have five dummy variables that relate to regional effects. The state of Missouri is divided into regional planning areas, each served by a regional planning commission. Our 34 counties fall into six different regional planning areas. We use five dummy variables for the following planning commission areas: the Bootheel, Lake of the Ozarks, Meramec, Ozark Foothills, and South Central Ozarks. The excluded area is the Southeast Regional Planning area, which includes seven counties. (See Appendix A.) Although it might be preferable to include a dummy variable for each of the 34 counties individually (minus one to avoid perfect collinearity), limited degrees of freedom do not favor such an approach.[2] Counties in planning areas are likely to be fairly homogeneous, rendering a planning area approach tenable. One additional variable relating to geography is the population (*LPOP*) of the county. Income inequality may be affected by economies of scale or agglomeration economies, which can be approximated by the population of the county. Levernier, Partridge, and Rickman (1998a) found that the log of population was negatively related to income inequality in metropolitan counties, but it was insignificant in nonmetropolitan counties. Because our sample includes solely rural counties, it is possible that mere population size may not have any discernible effect on income inequality.

A final variable to be included in our model is a dummy variable representing time (TIME). The variable is equal to 1 for 1999 and 0 for 1989. This variable will capture any unique time-specific characteristics for the two time periods that are not captured by other regressors in the models.

EMPIRICAL RESULTS

Variable definitions are given in Appendix B, and variable statistics are given in Table 2. Ordinary least-squares regression was used with

[2] We did try a model that included dummy variables for each of the counties. The results were virtually the same, except that the high school variable was insignificant. As noted later, the results for the high school variable exhibit considerable instability and are to be interpreted with care. Only three of the county dummy variables were significant at the 10 percent level, and the adjusted R^2 was only marginally higher. We decided to report the model with the planning commission dummies because it allowed for greater degrees of freedom.

Table 3

Empirical Results

Variable	(1)	(2)	(3)
CONSTANT	*53.886 (1.75)	54.24 (1.54)	–16.985 (0.47)
OVER64	0.150 (0.87)	0.150 (0.86)	0.053 (0.33)
UNDER18	**–0.508 (2.21)	**–0.510 (2.09)	***–0.671 (3.03)
BLACK	–0.014 (0.15)	–0.014 (0.15)	–0.047 (0.52)
FEMALE	***0.874 (3.63)	***0.877 (3.20)	***0.948 (3.87)
FLFPR	***–0.378 (4.11)	***–0.377 (3.91)	***–0.298 (3.44)
EMPGROW	0.014 (0.77)	0.014 (0.76)	–0.003 (0.15)
LINCOME	–0.888 (0.29)	–0.925 (0.26)	**8.262 (2.15)
LPOP	**1.515 (2.56)	**1.511 (2.44)	0.584 (0.91)
MFG	0.060 (1.59)	0.060 (1.57)	0.027 (0.71)
FARM	**0.137 (2.32)	**0.137 (2.29)	0.039 (0.63)
HS	–0.019 (0.24)	–0.019 (0.21)	**–0.191 (2.01)
COLLEGE	0.066 (0.51)	0.066 (0.51)	–0.119 (0.94)
EDUC	0.03 (0.09)	0.033 (0.09)	0.044 (0.13)
TIME		–0.024 (0.02)	1.975 (1.62)
BOOTHEEL			1.301 (1.33)
LAKEOZ			***2.459 (2.83)
MERAMEC			**1.970 (2.38)
OZFOOT			**1.879 (2.12)
SCOZ			***4.612 (4.36)
R^2 (adjusted)	0.69	0.69	0.76
F-statistic	12.70	11.58	12.18

NOTE: Dependent variable: *GINI*; estimation: least-squares regression; number of observations: 68; numbers in parentheses are absolute values of *t*-tests; */**/*** indicate statistical significance at the 10/5/1 percent levels, respectively.

the Gini coefficient (multiplied by 100) as the dependent variable. Three regressions are reported in Table 3: Regression (1) excludes the time dummy and the regional dummy variables, regression (2) adds the time dummy, and regression (3) adds the regional dummy variables. The inclusion of the dummy variable for time has no effect on the regression. The variable *TIME* is negative and not significant in regression (2) but changes sign and approaches significance at the 10 percent level in regression (3).

The inclusion of the regional dummy variables does have a significant effect on the regression as two variables lose significance (*FARM*, *LPOP*) and two become significant (*LINCOME*, *HS*). Three variables are highly significant in all three regressions (*FEMALE*, *FLFPR*, *UNDER18*). The partial F for the inclusion of the regional dummy variable is 4.25, which is significant at the 1 percent level. This means the regional dummy variables should be included in the model. Therefore, our remarks will pertain mainly to regression (3) in Table 3.

All of the coefficients on the regional dummy variables are positive and four are significant at the 5 percent level. Apparently, income inequality increases as we move away from the seven counties served by the Southeast Missouri Regional Planning Commission. Beyond the regional dummy variables, five independent variables are significant at the 5 percent level or better: *FEMALE*, *LINCOME*, *FLFPR*, *UNDER18*, and *HS*. No other independent variable is significant at even the 20 percent level.

Similar to most other studies, this study shows a positive and highly significant relationship (better than 1 percent level) between income inequality and the percent of families that are headed by a female. The low level of income of such families, frequently due to low levels of human capital, acts to increase income inequality in a region. Note that the coefficient on *FEMALE* is very stable, exhibiting very little change as *TIME* and then the regional dummy variables are added to the model.

The coefficient on the log of average family income (*LINCOME*) is also positive and significant. This result is similar to several other studies that found that income inequality begins to rise with higher incomes (see, for example, Garafalo and Fogarty, 1979). Levernier, Partridge, and Rickman (1998b) suggest that as market rewards for high-tech employment increase relative to jobs requiring lesser skills, the existence of a bimodal distribution of income could lead to greater income inequality. However, one must be cautious making conclusions concerning income because the coefficient on the variable is significant only when the regional dummy variables are added, implying that a stability issue exists.

The coefficient of the percent of the population that is under 18 (*UNDER18*) is negative and significant, while that for the percent of the population over 64 (*OVER64*) is not significant. The relationship for *UNDER18* also exhibits considerable stability as additional variables are added to the regression, indicating that the relationship is robust. This result is contrary to that of Levernier (1999), who found a positive and significant relationship for metropolitan counties for the percent of the population under 18. Perhaps having children spurs greater labor force effort, which results in more income, particularly at lower and middle income levels.

The coefficient on the female labor force participation rate (*FLFPR*) is also negative and significant at the 1 percent level. In addition, the coefficient estimates exhibit considerable stability as additional variables are added to the regression. As women enter the labor force in southeast Missouri, incomes of lower and middle income families are likely to be most affected, resulting in greater income equality.

The education variables in the model (*COLLEGE*, *HS*, *EDUC*) are generally insignificant except for the percent of the population 25 years of age or older that has a high school diploma, but no college degree. The relationship for *HS* is negative, indicating that income inequality falls as more of a county's population has a high school diploma. Southeast Missouri includes many counties where the population has relatively low rates of high school completion. However, high school completion rates have increased substantially over the past 10 to 20 years, and this has clearly led to greater income equality. The insignificance of *COLLEGE* may partially be a reflection of the low levels of college completion in the region. Note that the coefficient on *HS* is small and insignificant in the absence of the regional dummy variables. There is some question concerning the stability of this estimate; therefore, one must again be cautious in making conclusions concerning this variable.

In the absence of regional effects, coefficients on both the percentage of employment in the farm sector and the log of population are positive and significant at the 5 percent level. However, the fact that they lose significance when regional dummy variables are added indicates these two variables are related to regional effects and likely are not significant as explanatory variables.

The failure of the proportion of minorities (*BLACK*) to reach significance is an indication that either labor force discrimination is low in southeast Missouri or that *BLACK* is highly correlated with other social variables that do attain significance (such as female-headed families). Further research is necessary to ascertain the role, if any, of this variable in income inequality in the study region.

CONCLUSION

Recently, Federal Reserve Chairman, Alan Greenspan, in an appearance at a Joint Economic Committee hearing responded to a question by

Congressman Jack Reed that the observed significant divergence in the fortunes of different groups in the labor market "is not the type of thing which a capitalist society…can really accept without addressing" (Grier, 2005). The results of this study give way to some definite policy conclusions to address inequality. Income inequality in southeast Missouri can be reduced if the trend toward increased labor force participation of women continues. Policies, such as improved access to child care, that allow women to enter the labor force in yet greater numbers will reduce inequality. In addition, improved child-care choices should also help boost the incomes of female-headed families, though for these families, insufficient human capital may also be part of the equation. Therefore, job training or even high school completion policies (such as general equivalency diploma [GED programs]) could help to improve the economic fortunes of female-headed families and help to reduce income inequality. The significance of the percent of the population with a high school diploma in our regressions indicates that more than just female-headed families would benefit from high school completion policies.

The significance of the dependent population under 18 years of age in reducing income inequality, as indicated, may be due to the greater incentive to labor effort that having children can provide to families. Once again, access to adequate child care can help families with dependent children increase their labor effort.

It is apparent that there are similar forces at work here with respect to the significant variables in our model. Many of these forces revolve around access to the labor market, something that can be increased with better access to child care. In a recent study of child care in 20 counties in southeast Missouri, Birk et al. (2005) detailed the economic impact of the industry in the region. It is a large sector with a significant impact, and, as the results of this study show, it no doubt contributes to the reduction in income inequality in southeast Missouri.

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APPENDIX A

COUNTIES

The counties included in the planning commissions are as follows:

Bootheel:	Dunklin, Mississippi, New Madrid, Pemiscot, Scott, Stoddard
Lake of the Ozarks:	Camden, Laclede, Miller, Pulaski
Meramec:	Crawford, Dent, Maries, Phelps, Washington
Ozark Foothills:	Butler, Carter, Reynolds, Ripley, Wayne
South Central Ozarks:	Douglas, Howell, Oregon, Ozark, Shannon, Texas, Wright
Southeast Missouri:	Bollinger, Cape Girardeau, Iron, Madison, Perry, Ste. Genevieve, St. Francois

APPENDIX B

LIST OF VARIABLES

GINI	Gini coefficient (multiplied by 100)
OVER64	Percent of population over 64 years of age
UNDER18	Percent of population under 18 years of age
BLACK	Percent of population that is African-American
FEMALE	Percent of female-headed families
FLFPR	Female labor force participation rate
EMPGROW	Employment growth rate in previous decade
LINCOME	Log of average family income, constant 1982-84 dollars
LPOP	Log of population
MFG	Percent of employment in the manufacturing sector
FARM	Percent of employment in the farm sector
COLLEGE	Percent of population 25 or older with at least a Bachelor's degree
HIGH	Percent of population 25 or older with a high school diploma but no college degree
EDUC	Standard deviation of educational attainment
TIME	Dummy variable equal to 1 in 2000 and 0 in 1990
BOOTHEEL	Dummy variable equal to 1 for counties in Bootheel planning region
LAKEOZ	Dummy variable equal to 1 for counties in Lake of the Ozarks region
MERAMEC	Dummy variable equal to 1 for counties in Meramec region
OZFOOT	Dummy variable equal to 1 for counties in Ozark Foothills region
SCOZ	Dummy variable equal to 1 for counties in South Central Ozark region