INCOME INEQUALITY AND SECTOR SHIFT IN PENNSYLVANIA COUNTIES

Martina Vidovic, Bloomsburg University of Pennsylvania
Peter Bohling, Bloomsburg University of Pennsylvania

ABSTRACT

This paper examines the impact of sector shift toward the reliance on the service sector for employment on income inequality in the state of Pennsylvania after accounting for other relevant factors identified in the existing literature to be associated with income inequality. Our results indicate that Pennsylvania counties which are associated with greater percent of employment in the service sector have significantly higher income inequality while counties with higher percent of population employed in manufacturing have lower income inequality. The results are robust to several different measures of income inequality.

INTRODUCTION

Over the last few decades, social scientists have become increasingly interested in income inequality in the United States. The economic expansion of the 1980s and 1990s has not been shared equally by all segments of population. Although, average incomes have been increasing for everyone, so has the inequality in distribution of income with the top 20 percent of households receiving increasingly disproportionate amount of aggregate household income. For example, the Census Bureau shows that in 1980, the lowest 20 percent of households received 4.3 percent of aggregate household income, while the top 20 percent received 43.7 percent of total household income. However, by 1990 the share of income received by the bottom 20 percent fell to 3.9 percent and then further to 3.5 percent in 2001, while the share of income received by the top 20 percent of households increased to 46.6 percent in 1990 and to 50.1 percent by 2001. Between 1980 and 1990, the share of income received by the lowest fifth declined by 9.3 percent and by 7.7 percent between 1990 and 2000, while the share of income received by the highest fifth increased on average by 6.5 percent over the same two decades.

Simon Kuznets (1955) developed a theory on how income inequality and economic development are related within a nation. He suggested a "bell-shaped" relationship (known as the inverted U-hypothesis) between income inequality and per capita income as a measure of economic development. According to Kuznets' hypothesis, income inequality increases in the early stages of economic development (income growth) but declines in the later stages after certain income threshold has been reached. In the early stages of economic development, inequality increases as increasing population growth hurts the poor and most of the wealth is concentrated in the hands of a few entrepreneurial households. In the later stages of growth, the emergence of social and economic institutions improves the position of low income households leading to a slowdown in income growth at the top of the income distribution, and ultimately to a decline in income inequality. Norman Cloutier (1997) developed a theory that inverts the Kuznets hypothesis right side up. He argued that initially, rise in manufacturing sector will increase average incomes and reduce inequality while later, the decline in manufacturing and an increase in service sector will lead to a greater differentiation between workers in skill levels and an increase in inequality. Since 1980s, there has been an upswing in inequality in distribution of income and at the same time the shares of employment in the manufacturing sector have been decreasing while the service sector has been growing.

This paper examines the impact of sector shift toward the reliance on the service sector for employment on income inequality in the state of Pennsylvania after accounting for other relevant factors identified in the existing literature. Manufacturing still accounts for a larger share of employment in Pennsylvania than in the nation. Over time however, industrial structure has followed the national trend of a greater reliance on the service sector for employment and a lesser reliance on manufacturing. In 1990, slightly over 23% of the labor force in Pennsylvania was working in manufacturing and about 65% in service. In 2000, manufacturing employment was less than 20% while service sector employment increased to 71%. Our results indicate that Pennsylvania counties associated with greater percent of employment in the service sector have significantly higher income inequality while counties with higher percent of population employed in manufacturing have lower income inequality.

MEASURES OF INCOME INEQUALITY

To examine income distribution in the 67 counties in Pennsylvania, we use data on family income from the 2000 Census Summary Tape File STF3C.[1] Census reports income in categories, and we base the income distributions on the number of families that fall in each income category. We assume that each family earns the midpoint point of each income interval, except for the open-ended "$200,000 or more" category where we use an adjustment based on fitting a Pareto distribution (see Klein, 1962:150-154, or Parker and Fenwick, 1983) to determine the average income earned by this category.

We employ three measures of income inequality which include the coefficient of variation (CV), the Gini coefficient and the Atkinson Deprivation Index. The Gini coefficient derives from the Lorenz curve which plots the relationship between the cumulative income shares against the cumulative population shares ranked by income from the lowest to the highest. The Gini coefficient is then calculated as a ratio of the area between the actual income distribution (Lorenz curve) and the diagonal line representing perfect equality to the total area below the diagonal. The value of the coefficient ranges from a maximum of 1 representing total inequality to 0 representing perfect equality. If one person in the population received all income, the Gini coefficient would be 1. However, if each percentile of the income distribution received the equivalent share of total income, the Gini coefficient would be zero. We calculate the value of the Gini coefficient using the following formula:

$$G = 1 - \sum_{i=1}^{n} f_i (p_i + p_{i-1})$$

where G is the Gini coefficient, f_i is the proportion of families in income category i and p_i is the proportion of total income received by families in income category i and all lower income categories.

The Atkinson Index is one of the few inequality measures that incorporate the social welfare function. The Atkinson's Index, A, is given by

$$A = 1 - y_\varepsilon / \mu$$

where, μ is the mean income in the county and y_ε is the equity-sensitive average income defined as the level of per capita income which if enjoyed by everyone would make total welfare exactly equal to the total welfare generated by the actual income distribution (Atkinson, 1970). For example, a value of $A = .3$, indicates that if incomes were equally distributed, only 70% of the existing total society's income is needed to achieve the same level of social welfare. The equity-sensitive average income (y_ε) is given by the expression

$$y_\varepsilon = \left[\sum^{n} p_i y_i^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}$$

where p_i is the proportion of families in the ith income category, y_i is the average income in the ith interval, ε is a parameter that reflects society's aversion toward inequality and n is the total number of income groups. The inequality aversion parameter ε can range from zero to infinity. As ε increases from zero, more weight is attached to income transfers at the lower end of the distribution and less weight to the transfers at the top. The larger the parameter, the greater is the society's aversion toward inequality. Common values of ε used in research are 0.5 and 2. For any income distribution, the value of A is between 0 and 1. Lower values of the Atkinson index indicate more equal income distribution with y_ε closer to μ.

Most of the research on inequality focuses on the Gini coefficient despite some of its weaknesses. For example, economies with similar incomes and Gini coefficients can have different income distributions as Lorenz curves can have different shapes and still yield the same Gini coefficients. The same limitation exists when Lorenz curves intersect as economies are compared (Allison, 1978).

The Gini coefficient is more sensitive to the changes in income of the middle classes than to that of the extremes (Allison, 1978). Braun (1987) concludes that this explains why Gini ratios show stability of income inequality in the United States over long periods of time.

The Gini coefficient, like other inequality coefficients is influenced by the method used to compute it. Often, Gini ratio is calculated using the Census income categories with an adjustment based on a Pareto curve for the open-ended category. Pareto curve adjustment is not always done, and the

[1] Inequality measures used in this study are based on gross income and are not adjusted for Federal and State taxes, subsidies (e.g. food stamps), family size or composition.

number of income categories reported differs from one Census year to another which makes comparisons over time inconsistent. Gini coefficient will be lower as the number of income categories is reduced (Sale, 1974).

As a result of these criticisms, entropy measures (for example Atkinson and Theil indices) can be used in conjunction with the Gini coefficient. These other measures are not without their own criticism. For example, Theil index is also sensitive to the income in the middle part of distribution and since it is derived from the Lorenz curve, it faces the problem of intersecting Lorenz curves and sensitivity to changes in the number of income groups used to compute it. Allison (1978) points out that the coefficient of variation is most sensitive to the inequality of extreme income, and as such not as useful as other measure.

Table 1 compares scores and rankings of the four measures of income inequality among the 67 counties in Pennsylvania. Atkinson (1955), in his study of Kuznet's income data, found the rankings between Gini coefficient and his measure to be more similar when the aversion parameter ε is less than 1.0 than when ε is 2.0. For the county data in this study, 21 out of 67 rankings are exactly the same comparing Gini and the Atkinson index with $\varepsilon = 0.5$, and only 10 are the same comparing Gini and the Atkinson index with $\varepsilon = 2.0$. If we consider rankings that only differ for up to two places, 20 out of 67 rankings compare between the Gini and Atkinson with $\varepsilon = 2.0$, and 46 out of 67 rankings compare between the Gini and Atkinson index with $\varepsilon = 0.5$.

The correlations among the four inequality measures shown in Table 2 are high and statistically significant at 1% level. The strongest correlation of 0.9916 is between the Gini and the Atkinson index with $\varepsilon = 0.5$, while the lowest correlation of 0.6152 is between the coefficient of variation and the Atkinson index with $\varepsilon = 2$.

Table 2
Correlations Among Measures of Income Inequality

	Gini	**Coefficient of variation**	**ε=2 Atkinson**
Coefficient of variation	0.8406[a]		
Atkinson ε=2	0.9103[a]	0.6152[a]	
Atkinson ε=0.5	0.9916[a]	0.8710[a]	0.9078[a]

Note: [a] indicates statistically significant at 1% level

SOURCES OF INCOME INEQUALITY

Our main hypothesis is that income inequality in Pennsylvania is directly related to the sector shift from manufacturing to service. To test this, we include percent population employed in manufacturing (MANUF) and percent population employed in service (SERVICE) sector. Since wages in the service sector tend to be, on average, lower than in the manufacturing sector, and the difference between workers in terms of skill is stronger in the service sector, we expect to see that income inequality is positively related to service sector employment and negatively related to employment in manufacturing. We further control for other important variables found to be associated with income inequality in the existing literature.

The Kuznets curve suggests a negative relationship between income inequality and the level of economic development. We use median family income (MEDINC) to represent economic development in a county (as it is closest to the measure of income per capita) and expect to see an inverse relationship between median family income and income inequality. Furthermore, Kuznets suggested that inequality will be greater in urban areas where social conditions are more diverse than in rural area. We measure the degree of urbanization by population density (POPDEN) and expect to find a positive relationship between population density (urbanization) and income inequality.

Kuznets (1955) also argued that a natural increase in population as measured by the difference between birth rate and death rate tends to increase income inequality as it increases the supply of unskilled labor. Today, most developed economies (including US counties) are at the stage where large declines in birth rate exceed the continued decline in death rate leading to an increase in life expectancy but a smaller population growth than in the past. We expect a positive (although very small) effect of rate of natural increase (POPINCR) on income inequality.

Additional explanation for the inverted-U pattern that Kuznets (1995) offered is reflected in the distribution of population within the agricultural and non-agricultural sectors of a developing economy. Kuznets argued that inequality is lower in the agricultural sector than in the non-agricultural sector. To capture the size of the agricultural sector, we include percent farm population (FARMPOP). We expect that the size of the agricultural sector will be negatively related to inequality.

The level of education tends to be highly correlated with the level of income however, some researches argue (see for example Jacobs (1985)) that the distribution of education in an economy may be related to distribution of income. We follow Nielson and Anderson (1997) and measure the distribution of education as educational heterogeneity based on the Thiel's entropy formula:

$$EDUC = \sum_{i=1}^{3} p_i \ln\left(\frac{1}{p_i}\right)$$

where p_1, p_2 and p_3 are the proportions of adult population (ages 25 and older) without high school degree, with high school degree only, and with a four year college degree only, respectively. Higher value of this variable indicates more even distribution of the adult population among the three categories of educational attainment. We expect this variable to be positively related with income inequality.

Additional factors that may have led to the rise in inequality in family income and earnings that started in the early 1970s include the changing role of women and the change in the socio-economic status of the elderly population (see Nielsen and Alderson, 1997). There has been an increase in labor force participation by women (FEMALELF) coupled with an increase in the number of female headed households (FEMALEHEAD). Insofar as women tend to be paid less than men and more often work part-time, in addition to an increase in the number of female headed households which often earn below the average level if income, this trend tends to increase the proportion of low income earners in a distribution. Therefore, we expect to find a direct relationship between percent females in labor force and percent female headed households and income inequality. Since early 1970s, elderly families have moved upward in the income distribution from the bottom to the middle. The increases in income coupled with improvements in health care have led to an increase in the number of elderly families over time. For example, in Pennsylvania, the average percent of population older than 65 has increased by 1 percent between 1990 and 2000 Census years. Therefore, we expect a negative relationship between income inequality and percent population older than 65 (AGE65).

In addition, Wood (1994) argued that competition from countries with relatively cheap low skill labor have led to a reduced demand for unskilled labor in industrialized countries and to a greater difference in wages between skilled and unskilled workers. As the gap between relative wages of skilled and unskilled workers widens, the income inequality will widen as well and we expect to find a positive relationship between income inequality and percent population that is unemployed (UNEMPL) in a county. The definitions of the variables used in this study along with sources of the data are presented in Table 3.

The summary statistics (see Table 4) reveal that the income inequality of Pennsylvania counties is similarly dispersed around the mean when measured by the Gini coefficient and the Atkinson index with inequality aversion parameter of 0.5. Larger dispersion around the mean exists when the aversion parameter used in calculating the Atkinson index is 2.

Table 4
Summary Statistics of Inequality Measures and Socioeconomic Variables

Variable	Mean	Standard Deviation
GINI	0.3629	0.0198
CV	0.7545	0.0606
ATKINSON, ε = 2	0.4571	0.0331
ATKINSON, ε = 0.5	0.1145	0.0120
MEDINC	44806.81	8426.99
FARMPOP	1.4746	1.2879
POPDEN	453.16	1415.00
POPINCR	0.3567	3.0387
EDUC	0.9021	0.0343
AGE65	16.1866	2.2653
MANUF	19.6448	6.8294
SERVICE	71.0537	7.4811
UNEMPL	3.3209	0.7739
FEMALELF	53.5702	4.0826
FEMALEHEAD	13.8179	3.8630

On average, in Pennsylvania counties, 16.2 percent of population is older than 65 years of age, 19.6 percent of labor force is employed in manufacturing while 71 percent is employed in the service sector. Almost one half of females are in labor force and 14 percent of all family households are female headed households.

Pearson correlation coefficients show a positive and statistically significant association between the percent population employed in the service sector and all measures of income inequality and negative and significant correlation between the percent population employed in manufacturing and income inequality. Strong positive correlation also exists between income inequality and percent unemployed, percent female headed households, population density, and educational dispersion, while a negative correlation exists between income inequality and percent females in labor force, and income inequality and population increase. The Pearson correlation coefficients are presented in Table 5.

Table 5
Correlations of Income Inequality with Socioeconomic Variables

	Inequality Measures			
Socio-economic Variables	**Gini**	**CV**	**Atkinson ε=0.5**	**Atkinson ε=2**
MEDINC	-0.1520	-0.3686	0.0307	-0.2092 [c]
FARMPOP	-0.1626	0.1322	-0.3581 [a]	-0.1399
MANUF	-0.5168 [a]	-0.2735 [b]	-0.5755 [a]	-0.4831 [a]
SERVICE	0.5207 [a]	0.2480 [b]	0.6248 [a]	0.4888 [a]
UNEMPL	0.5730 [a]	0.4291 [a]	0.5034 [a]	0.5803 [a]
FEMLF	-0.3202 [a]	-0.4022 [a]	-0.1827	-0.3456 [a]
FEMHEAD	0.6046 [a]	0.3685 [a]	0.7338 [a]	0.6418 [a]
POPDEN	0.4820 [a]	0.2489 [b]	0.5923 [a]	0.5130 [a]
POPINCR	-0.2635 [b]	-0.2630 [b]	-0.0709	-0.2401 [c]
AGE65	0.1398	0.2260 [c]	-0.0182	0.1418
EDUC	0.2614 [b]	0.0410	0.4127 [a]	0.2348 [c]

Note: [a] indicates statistically significant at 1% level; [b] indicates statistically significant at 5% level; [c] indicates statistically significant at 10% level.

DISCUSSION OF RESULTS

We estimate liner regression models with the four measures of income inequality as dependent variables. We take a natural log of median family income and population density. For each dependent variable we estimate three models. Model 1 includes only the Kuznets original variables while Models 2 and 3 add all the other socioeconomic variables. We do not include percent population employed in manufacturing and percent employed in service in the same model since they are highly negatively correlated but rather estimate two separate models (Model 2 versus Model 3). The results can be compared between models for each dependent variable and between measures of the dependent variable for each model. Tables 6 through 9 show the results.

Table 6
Regression Results where Dependent Variable is Gini Coefficient, 2000

Variable	Model 1	Model 2	Model 3
MEDINC (LN)	-0.0710 [a]	0.0389	0.0386
	(0.0165)	(0.0269)	(0.0265)
FARMPOP	0.0012	0.0063 [a]	0.0073 [a]
	(0.0017)	(0.0017)	(0.0017)
POPDEN (LN)	0.0095 [a]	-6.81E-05	-0.0009
	(0.0024)	(0.0033)	(0.0033)
POPINCR	-0.0021 [a]	-0.0014	-0.0013
	(0.0008)	(0.0009)	(0.0009)
EDUC	0.2121 [b]	0.1603 [b]	0.1557 [b]
	(0.0888)	(0.0699)	(0.0687)
AGE65	-	-0.0007	-0.0008
	-	(0.0012)	(0.001)
MANUF	-	-0.0007 [b]	-
	-	(0.0003)	-
SERVICE	-	-	0.0008 [a]
	-	-	(0.0003)
UNEMPL	-	0.0079 [a]	0.0073 [a]
	-	(0.0028)	(0.0027)
FEMALELF	-	-0.0022 [a]	-0.0023 [a]
	-	(0.0007)	(0.0007)
FEMALEHEAD	-	0.0026 [a]	0.0026 [a]
	-	(0.0009)	(0.0009)
INTERCEPT	0.8820 [a]	-0.1281	-0.1826
	(0.1614)	(0.2637)	(0.2596)
N	67	67	67
R^2	0.4996	0.7252	0.7343
Adjusted R^2	0.4586	0.6762	0.6868

Note: Standard deviation in parentheses. [a] indicates statistically significant at 1% level; [b] indicates statistically significant at 5% level; [c] indicates statistically significant at 10% level

Table 7
Regression Results where Dependent Variable is Coefficient of Variation, 2000

Variable	Model 1	Model 2	Model 3
MEDINC (LN)	-0.2519 [a]	-0.1064	-0.1111
	(0.0526)	(0.1085)	(0.1061)
FARMPOP	0.0133 [b]	0.0200 [a]	0.0228 [a]
	(0.0055)	(0.0069)	(0.0069)
POPDEN (LN)	0.0277 [a]	0.0202	0.0146
	(0.0076)	(0.0132)	(0.0132)
POPINCR	-0.0045 [c]	-0.0013	-0.0006
	(0.0024)	(0.0035)	(0.0034)
EDUC	0.4668	0.4157	0.4099
	(0.2829)	(0.2817)	(0.2752)
AGE65	-	0.0015	0.0025
	-	(0.0047)	(0.0045)
MANUF	-	-0.0012	-
	-	(0.0012)	-
SERVICE	-	-	0.0024 [c]
	-	-	(0.0013)
UNEMPL	-	0.01722	0.0144
	-	(0.0113)	(0.0111)
FEMALELF	-	-0.0042	-0.0039
	-	(0.0029)	(0.0028)
FEMALEHEAD	-	0.0005	0.0001
	-	(0.0036)	(0.0035)
INTERCEPT	2.8702 [a]	1.5438	.4085
	(0.5142)	(1.0626)	(1.0400)
N	67	67	67
R^2	0.4553	0.5212	0.542
Adjusted R^2	0.407	0.4357	0.4603

Note: Standard deviation in parentheses. [a] indicates statistically significant at 1% level; [b] indicates statistically significant at 5% level; [c] indicates statistically significant at 10% level

Table 8
Regression Results where Dependent Variable is Atkinson Index, $\varepsilon = 2$, 2000

Variable	Model 1	Model 2	Model 3
MEDINC (LN)	-0.1159 [a]	0.0932 [b]	0.0937 [b]
	(0.0262)	(0.0381)	(0.0383)
FARMPOP	-0.003	0.0062 [b]	0.0073 [a]
	(0.0028)	(0.0024)	(0.0025)
POPDEN (LN)	0.0171 [a]	-0.0020	-0.0023
	(0.0038)	(0.0046)	(0.0048)
POPINCR	-0.0013	-0.001	-0.0012
	(0.0012)	(0.0013)	(0.0012)
EDUC	0.3139 [b]	0.2169 [b]	0.2098 [b]
	(0.1409)	(0.0989)	(0.0995)
AGE65	-	-0.0030 [c]	-0.0034 [b]
	-	(0.0016)	(0.0016)
MANUF	-	-0.0009 [b]	-
	-	(0.0004)	-
SERVICE	-	-	0.0009 [b]
	-	-	(0.0005)
UNEMPL	-	0.0085 [b]	0.0085 [b]
	-	(0.0039)	(0.0039)
FEMALELF	-	-0.0045 [a]	-0.0048 [a]
	-	(0.0010)	(0.0010)
FEMALEHEAD	-	0.0059 [a]	0.0058 [a]
	-	(0.0013)	(0.0013)
INTERCEPT	1.3329 [a]	-0.5341	-0.6019
	(0.2562)	(0.3733)	(0.3758)
N	67	67	67
R^2	0.5468	0.8019	0.7997
Adjusted R^2	0.5097	0.7665	0.7639

Note: Standard deviation in parentheses. [a] indicates statistically significant at 1% level; [b] indicates statistically significant at 5% level; [c] indicates statistically significant at 10% level

Table 9
Regression Results where Dependent Variable is Atkinson Index, $\varepsilon = 0.5$, 2000

Variable	Model 1	Model 2	Model 3
MEDINC (LN)	-0.0509 [a]	0.0147	0.0144
	(0.0096)	(0.0158)	(0.0155)
FARMPOP	0.00007	0.0037 [a]	0.0042 [a]
	(0.0010)	(0.0010)	(0.0010)
POPDEN (LN)	0.0063 [a]	0.0004	-6.2E-05
	(0.0014)	(0.0019)	(0.0019)
POPINCR	-0.0009 [b]	-0.0006	-0.0006
	(0.0004)	(0.0005)	(0.0005)
EDUC	0.1192 [b]	0.0880 [b]	0.0866 [b]
	(0.0515)	(0.0410)	(0.0403)
AGE65	-	-0.0005	-0.0005
	-	(0.0007)	(0.0006)
MANUF	-	-0.0003 [b]	-
	-	(0.0002)	-
SERVICE	-	-	0.0005 [b]
	-	-	(0.0002)
UNEMPL	-	0.0043 [b]	0.0040 [b]
	-	(0.0016)	(0.0016)
FEMALELF	-	-0.0013 [a]	-0.0014 [a]
	-	(0.0004)	(0.0004)
FEMALEHEAD	-	0.0016 [a]	0.0016 [a]
	-	(0.0005)	(0.0005)
INTERCEPT	0.5196 [a]	-0.0807	-0.1094
	(0.0937)	(0.1547)	(0.1523)
N	67	67	67
R^2	0.5391	0.743	0.7499
Adjusted R^2	0.5014	0.6951	0.7052

Note: Standard deviation in parentheses. [a] indicates statistically significant at 1% level; [b] indicates statistically significant at 5% level; [c] indicates statistically significant at 10% level

For each dependent variable, the explanatory power of the model increases (measured by R square) as we include additional socioeconomic variables to those in Model 1. In all base models (Model 1), we find a statistically significant and negative relationship between median family income and income inequality, and positive and significant relationship between income inequality and population density as well as with educational dispersion. These results are as anticipated.

We find support for our main hypothesis that income inequality increases with the size of the service sector but decreases with the size of the manufacturing sector. The coefficient on percent labor force employed in manufacturing is negative and significant and the coefficient on percent labor force employed in service is positive and significant when the dependent variable is Gini coefficient or the Atkinson index. When the dependent variable is the coefficient of variation, only the coefficient on percent employed in the service sector is statistically significant at a 10 percent level.

Across all tables except Table 7, we find that income inequality is positively related to dispersion of population across a county, percent population that is unemployed and percent female headed households. All of these coefficients have the expected signs. However, we find that income inequality is lower in counties with a higher proportion of females in labor force and higher in counties with a greater percent of farm population which is contrary to our expectation. A similar conclusion was also reached by Nielson and Alderson (1997) who analyzed income inequality across all counties in the United States for Census years 1970, 1980 and 1990.

The coefficient on percent population older than 65 years of age is negative and statistically significant only when the dependent variable is the Atkinson index and the aversion parameter is 2. Thus, we find limited support that income inequality decreases with an increase in elderly population.

CONCLUSIONS

Income inequality in the United States and in Pennsylvania alone has been increasing in past three decades. This paper examines the relationship between income inequality in Pennsylvania counties using various measures of income inequality and socioeconomic data for the year 2000. The results indicate that an increase in income inequality is positively related to shift in employment from the manufacturing sector to the service sector even after accounting for many other socioeconomic characteristics of a county. The results are robust across different measures of income inequality. The highest similarity in findings exists between the Gini coefficient as a measure of income inequality and the Atkinson index reflecting a low level of aversion to inequality by a society.

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Martina Vidovic is an assistant professor of economics at Bloomsburg University of Pennsylvania. She received her Ph.D. in Economics from State University of New York, Binghamton. Her research interests are in environmental economics, public economics and applied micro-economic analysis.

Peter Bohling is a professor of economics at Bloomsburg University of Pennsylvania. He received his Ph.D. in Economics from the University of Massachusetts, Amherst. His research interests are in statistics, public economics, and applied micro-economic analysis.

Table 1
Family Income Inequality and Relative Rankings in Pennsylvania Counties, 2000

County	Gini	Coefficient of Variation	ε=2.0 Atkinson	ε=0.5 Atkinson
Elk	0.3137(1)	0.6252(1)	0.3828(1)	0.0874(1)
Adams	0.3211(2)	0.6308(2)	0.3956(2)	0.0904(2)
Cameron	0.3252(3)	0.6518(3)	0.4039(3)	0.0933(3)
Perry	0.3295(4)	0.6798(5)	0.4119(4)	0.0964(4)
York	0.3364(5)	0.6873(7)	0.4219(9)	0.0994(5)
Fulton	0.3392(6)	0.6937(8)	0.4243(10)	0.1012(9)
Carbon	0.3397(7)	0.6980(10)	0.4196(8)	0.1010(7)
Franklin	0.3401(8)	0.7063(16)	0.4170(7)	0.1011(8)
Pike	0.3416(9)	0.6767(4)	0.4254(11)	0.1007(6)
Warren	0.3420(10)	0.7096(17)	0.4138(5)	0.1019(10)
Lancaster	0.3438(11)	0.7042(15)	0.4365(17)	0.1034(11)
Juniata	0.3466(12)	0.7608(36)	0.4156(6)	0.1058(16)
Huntingdon	0.3473(13)	0.7178(21)	0.4355(16)	0.1057(15)
Lebanon	0.3482(14)	0.7232(23)	0.4328(13)	0.1056(14)
Beaver	0.3487(15)	0.7006(13)	0.4555(33)	0.1068(17)
Cumberland	0.3492(16)	0.7103(19)	0.4271(12)	0.1045(13)
Somerset	0.3494(17)	0.7303(25)	0.4344(14)	0.1072(8)
Bucks	0.3499(18)	0.6809(6)	0.4492(26)	0.1044(12)
Monroe	0.3523(19)	0.6959(9)	0.4590(36)	0.1078(9)
Northumberland	0.3530(20)	0.7519(30)	0.4422(20)	0.1098(22)
Northampton	0.3545(21)	0.7033(14)	0.4643(43)	0.1089(21)
Schuylkill	0.3555(22)	0.7627(37)	0.4407(9)	0.1110(24)
Berks	0.3556(23)	0.7139(20)	0.4697(49)	0.1103(23)
Forest	0.3556(24)	0.6987(11)	0.4443(22)	0.1089(20)
Mifflin	0.3559(25)	0.7648(40)	0.4470(24)	0.1117(26)
Wyoming	0.3591(26)	0.7096(18)	0.4591(38)	0.1111(25)
Bedford	0.3596(27)	0.8103(60)	0.4354(15)	0.1141(33)
Clearfield	0.3611(28)	0.7464(27)	0.4446(23)	0.1125(29)
Armstrong	0.3611(29)	0.7526(31)	0.4539(32)	0.1135(30)
Butler	0.3612(30)	0.7181(22)	0.4686(48)	0.1123(28)
Jefferson	0.3621(31)	0.7812(52)	0.4383(8)	0.1137(31)
Columbia	0.3628(32)	0.7761(48)	0.4441(2)	0.1141(34)
Chester	0.3636(33)	0.7002(12)	0.4757(55)	0.1118(27)
Tioga	0.3638(34)	0.7554(33)	0.4480(25)	0.1140(32)
McKean	0.3643(35)	0.7722(43)	0.4609(40)	0.1162(38)
Susquehanna	0.3663(36)	0.7635(38)	0.4538(30)	0.1158(36)
Potter	0.3667(37)	0.7691(42)	0.4527(28)	0.1163(39)
Lawrence	0.3674(38)	0.7439(26)	0.4751(54)	0.1171(41)
Venango	0.3676(39)	0.7787(51)	0.4721(50)	0.1186(46)
Crawford	0.3676(40)	0.7567(34)	0.4595(39)	0.1161(37)
Mercer	0.3685(41)	0.7741(46)	0.4679(47)	0.1180(43)
Centre	0.3687(42)	0.7518(29)	0.4675(46)	0.1165(40)
Union	0.3693(43)	0.8084(59)	0.4538(31)	0.1185(45)
Montgomery	0.3694(44)	0.7280(24)	0.4671(44)	0.1148(35)

Blair	0.3698(45)	0.7780(50)	0.4675(45)	0.1189(47)
Erie	0.3701(46)	0.7754(47)	0.4749(53)	0.1192(48)
Lycoming	0.3702(47)	0.7912(53)	0.4533(29)	0.1181(44)
Bradford	0.3708(48)	0.7737(44)	0.4727(51)	0.1193(49)
Westmoreland	0.3709(49)	0.7643(39)	0.4619(42)	0.1176(42)
Clarion	0.3722(50)	0.7764(49)	0.4801(58)	0.1208(52)
Clinton	0.3730(51)	0.8008(57)	0.4612(41)	0.1204(50)
Wayne	0.3742(52)	0.8169(62)	0.4574(35)	0.1213(55)
Luzerne	0.3746(53)	0.7739(45)	0.4762(56)	0.1209(53)
Lehigh	0.3754(54)	0.7498(28)	0.4930(61)	0.1207(51)
Montour	0.3778(55)	0.7998(56)	0.4503(27)	0.1209(54)
Indiana	0.3784(56)	0.7943(54)	0.4762(57)	0.1232(56)
Dauphin	0.3792(57)	0.7689(41)	0.5063(62)	0.1244(57)
Washington	0.3811(58)	0.7994(55)	0.4815(59)	0.1246(58)
Delaware	0.3820(59)	0.7591(35)	0.5141(64)	0.1248(59)
Greene	0.3837(60)	0.7554(32)	0.5128(63)	0.1277(62)
Snyder	0.3838(61)	0.9585(67)	0.4590(37)	0.1318(64)
Lackawanna	0.3847(62)	0.8158(61)	0.4835(60)	0.1270(61)
Cambria	0.3871(63)	0.9137(66)	0.4744(52)	0.1317(63)
Sullivan	0.3882(64)	0.8012(58)	0.4556(34)	0.1254(60)
Fayette	0.4068(65)	0.8787(65)	0.5237(65)	0.1425(66)
Allegheny	0.4076(66)	0.8517(64)	0.5374(66)	0.1418(65)
Philadelphia	0.4312(67)	0.8815(67)	0.5875(67)	0.1601(67)

Table 3
Variable Definitions and Sources

Variable and Source	Definition
US Census 2000	
Median family income (MEDINC)	Median family income
Population density (POPDEN)	Population per square mile (population / land area)
% unemployed (UNEMPL)	Percent civilian labor force (16+) that is unemployed
% manufacturing (MANUF)	(Population employed in manufacturing / total population)*100
% service (SERVICE)	(Population employed in wholesale, retail trade, service industry / total pop)*100
Educational heterogeneity (EDUC)	Theil's entropy formula (groups include: proportion of population 25 + with no high school degree, high school degree only and bachelor's degree)
% female headed household (FEMHEAD)	(Number of female headed family households / number of family households)*100
% females in labor force (FEMLF)	(Females 16 + in labor force / total females 16+)*100
% population 65 years and older (AGE65)	(Population 65+ / total population)*100
City and County Book 2000	
Population increase (POPINCR)	Birth rate – death rate (1997 values used for 2000)
REIS CD 2000	
% farm population (FARMPOP)	Percent farm population