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The Determinants of the Distribution of Mortality in United States Counties

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ABSTRACT

The purpose of this study is to determine the significant factors that affect the distribution of mortality by county in the United States, by using mortality data from the Multiple Cause of Death File of the National Center for Health Statistics from 1985 to 1994. These data are used to calculate distributions of mortality for men and women in each county by year. Gin coefficients are determined and used in a multiple regression model to ascertain the determinants of the distribution of mortality within counties. State and year effects are identified for the entire period, but the availability of data on the independent variables in the model is limited to census years. Hence, the complete model of determinants of the distribution of mortality is tested for 1990. Previous studies of the determinants of life expectancy, mortality, and the distribution of life expectancy suggest a number of variables that should be included in a model of the determinants of mortality at the county level. The level of education attained, mean income, poverty rate, unemployment rate, household size, population density, urbanization, and racial composition are among the variables that are expected to be important determinants of the distribution of mortality in United States counties. State effects and year effects are identified through the use of appropriate dummy variables.

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The Determinants of the Distribution of Mortality in United States Counties

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Abstract

The purpose of this study is to determine the significant factors that affect the distribution of mortality by county in the United States, by using mortality data from the Multiple Cause of Death File of the National Center for Health Statistics from 1985 to 1994. These data are used to calculate distributions of mortality for men and women in each county by year. Gin coefficients are determined and used in a multiple regression model to ascertain the determinants of the distribution of mortality within counties. State and year effects are identified for the entire period, but the availability of data on the independent variables in the model is limited to census years. Hence, the complete model of determinants of the distribution of mortality is tested for 1990. Previous studies of the determinants of life expectancy, mortality, and the distribution of life expectancy suggest a number of variables that should be included in a model of the determinants of mortality at the county level. The level of education attained, mean income, poverty rate, unemployment rate, household size, population density, urbanization, and racial composition are among the variables that are expected to be important determinants of the distribution of mortality in United States counties. State effects and year effects are identified through the use of appropriate dummy variables.

Economic and social equity has been a primary concern of policy-makers in the United States for many decades. This concern has resulted in legislation at federal, state, and local levels designed to affect income distribution and access to public services. It is natural that society's interest in equity should eventually extend to the ultimate human inequality: the distribution of life spans. The purpose of this study is to identify the significant factors that affect the distribution of mortality (age at death) by county in the United States. Because mortality is something that affects all people very personally, the results of this study may be of interest not only to economic demographers, health economists, public health officials, state and local government officials and other public policy-makers, but also, perhaps, to the public at large. Section I discusses briefly the genesis of the present study from previous research on mortality and life expectancy. Section II provides a description of the regression models designed to help identify determinants of the distribution of mortality at the county level, and discusses the data and methodology used in the study. Section III contains a summary of the regression results and a discussion of the findings. The final section lists conclusions and suggestions for future research.

I. Genesis

Although there have been a number of previous studies examining the determinants of life expectancy and mortality, almost all of the research has focused on small samples and/or models containing few explanatory variables. To our knowledge, there have been no large-scale studies to date investigating the factors affecting the distribution of mortality. In fact, examination of the distribution of mortality has been limited to a single study by Israelsen, Israelsen and Israelsen (2005a), which identifies the distribution of mortality in U.S. counties for males and females and provides a ranking by county of relative inequality in those distributions, as measured by the Gini coefficient. That study does not attempt to explain differences in county mortality distributions, but does provide some interesting information, including the fact that, on average, the distribution of mortality is 30% less equal for men than for women in U.S. counties. Table 1 identifies the U.S. counties with the lowest and highest Gini coefficients. Figures 1 and 2 are U.S. county maps on which counties are shaded from white to black according to the size of the mortality Gini coefficient. Lighter areas represent counties with more equal distributions of mortality, and darker area represent counties with less equal distributions. Other research on mortality includes Franzini, Ribble, and Spears (2001), who analyzed income factors on mortality in Texas counties, controlling for ethnicity, education, and access to health care. They found that in counties with a population over 150,000, mortality increased with income inequality, and in counties containing fewer than 150,000 the opposite was true. Hurt, Ronsmans, and Thomas (2006) found that there is a negative relationship between number of births and female mortality. Other studies have looked at mortality in different contexts, including the impact of the collapse of the Soviet Union on mortality rates in Russia (Brainerd

Table 1. U.S. counties with the lowest and highest mortality Gini coefficients.

Counties with the lowest Gini coefficients

Males		Females	
County	**Gini**	**County**	**Gini**
McPherson, NE	0.0205	Thomas, NE	0.0368
Roberts, TX	0.0463	Camas, ID	0.0370
Kenedy, TX	0.0484	Jones, SD	0.0386
Slope, ND	0.0500	Loup, NE	0.0419
Wheeler, OR	0.0526	Roberts, TX	0.0454
Sully, SD	0.0538	Logan, NE	0.0475
Rock, NE	0.0636	Wallace, KS	0.0513
Grant, NE	0.0643	Billings, ND	0.0546
Oliver, ND	0.0666	McMullen, TX	0.0553
Puite, UT	0.0668	Oldham, TX	0.0555
Logan, NE	0.0705	Greeley, KS	0.0560
Billings, ND	0.0717	Logan, ND	0.0561
Mineral, CO	0.0732	Rich, UT	0.0568
Prairie, MT	0.0734	Sheridan, KS	0.0571
Kent, TX	0.0750	Wibaux, MT	0.0582
Hayes, NE	0.0760	Cheyenne, CO	0.0583
Logan, ND	0.0762	Kent, TX	0.0583
Keya Paha, NE	0.0773	Harding, SD	0.0598

Counties with the highest Gini coefficients

Males		Females	
County	**Gini**	**County**	**Gini**
Wade Hampton, AK	0.2978	Wade Hampton, AK	0.2956
Dillingham, AK	0.2891	North Slope, AK	0.2496
Nome, AK	0.2888	Apache, AZ	0.2325
Bethel, AK	0.2847	Pitkin, CO	0.2309
Chattahoochee, GA	0.2816	Bethel, AK	0.2256

North Slope, AK	0.2786	Shannon, SD	0.2233
Yukon-Koyukuk, AK	0.2694	Corson, SD	0.2222
Apache, AZ	0.2692	Todd, SD	0.2198
Prince of Wales-Outer Ketchikan, AK	0.2582	Dillingham, AK	0.2194
Pitkin, CO	0.2582	Kenai Peninsula, AK	0.2162
McKinley, NM	0.2540	Nome, AK	0.2152
Summit, CO	0.2498	Eagle, CO	0.2115
Garfield, MT	0.2447	Fairbanks North Star, AK	0.2103
Sioux, ND	0.2428	Clear Creek, CO	0.2085
Todd, SD	0.2426	Alpine, CA	0.2063
Kodiak Island, AK	0.2412	Yukon-Koyukuk, AK	0.2057
Eagle, CO	0.2374	Briscoe, TX	0.2044
Shannon, SD	0.2335	McKinley, NM	0.2032
Coconino, AZ	0.2325	Sioux, ND	0.2028
San Juan, UT	0.2291	Matanuska-Susitna, AK	0.1952

Source: Israelsen, Israelsen, and Israelsen (2005a)

Figure 1.

Mortality Gini Coefficient for Females by County (1988)

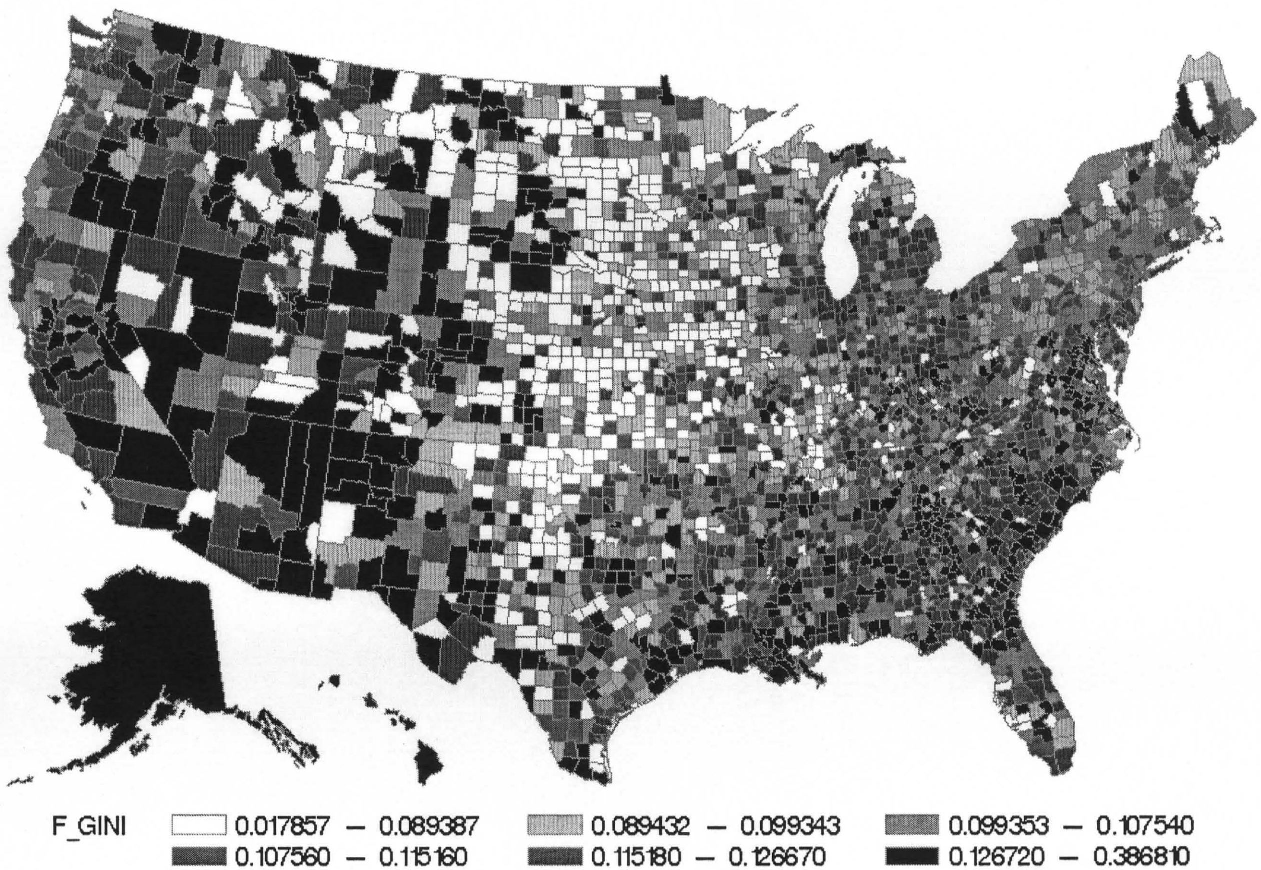
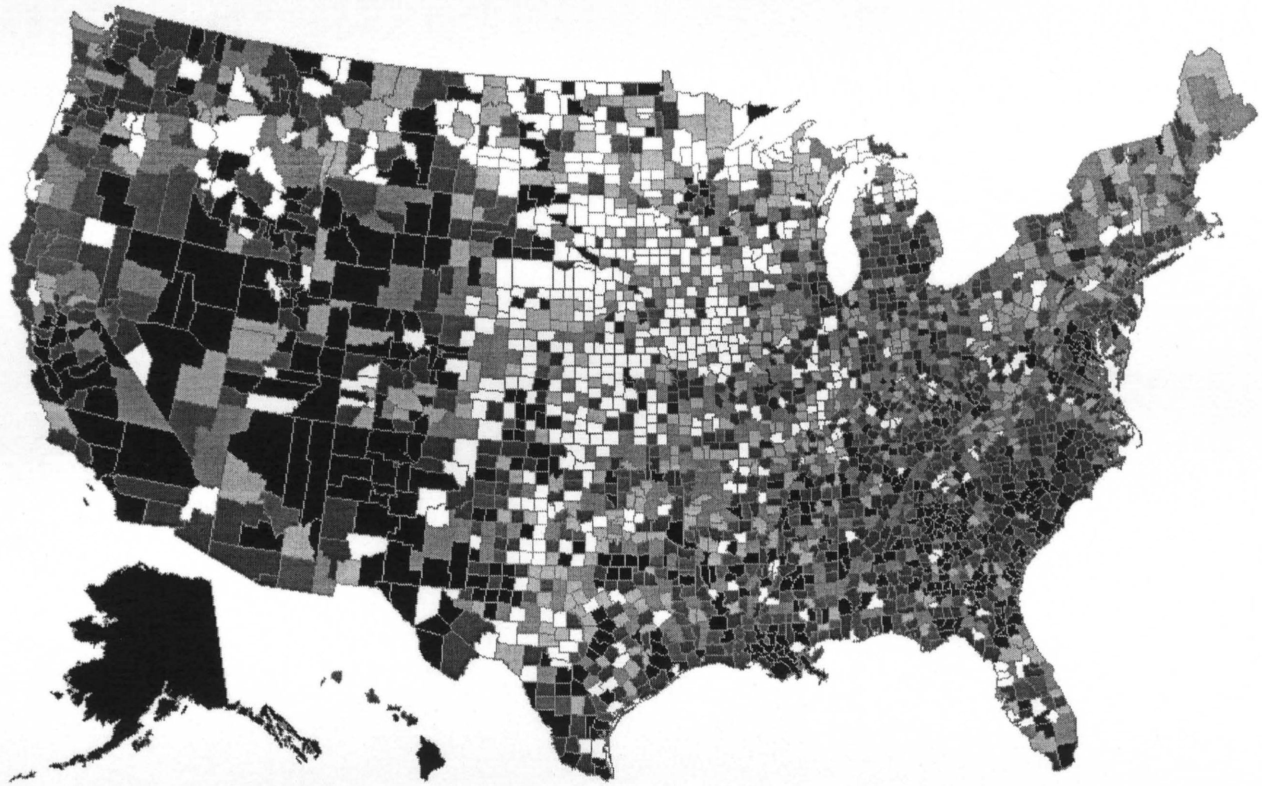


Figure 2.

Mortality Gini Coefficient for Males by County (1988)



M_GINI
0.013514 – 0.109400
0.109410 – 0.121760
0.121770 – 0.131010
0.131080 – 0.141360
0.141450 – 0.154460
0.154490 – 0.446670

and Cutler, 2005) and mortality as a factor in population changes (Guillot, 2005). The current study is the first to examine determinants of the distribution of mortality by county.

Because of the relationship between mortality and life expectancy, several studies done on life expectancy are also of interest. Two studies that come close to the topic discussed in this paper are by Israelsen, Israelsen and Israelsen (2001, 2002). Their 2001 paper examines the determinants of life expectancy by county for all United States counties, and their 2002 paper looks specifically at determinants life expectancy in Mountain States counties. These studies identify significant factors affecting life expectancy, including educational attainment, percent of the population speaking a language other than English at home, percent of the population foreign-born, income, and income squared. These factors all have a positive effect on life expectancy, as does the percent of the population whose ancestry is Northern European. The percent of the population that is black and the percent that is American Indian, Eskimo, and Aleut are negatively related to life expectancy. Other variables that have a negative effect on life expectancy are violent crime rates, population density, latitude, and elevation. It is important to note that many of these factors affect only one sex, or affect them to varying degrees or with different levels of statistical significance.

Another pertinent study done by Israelsen, Israelsen, and Israelsen (2005b) calculates the distribution of life expectancy by U.S. state, and identifies determinants of relative inequality in those distributions, as measured by the Gini coefficient. They find that relative inequality in the distributions of poverty rate, urbanization, education, percent white, and age within states are important determinants of relative inequality in the distribution of life expectancy. There have been numerous other studies on life expectancy, but, as with mortality, these generally utilize relatively small samples or look at relatively few factors affecting life expectancy, such as race (Ewbank, D.C. (1987), Geronimus et al (1996), Harvard (1998), Manton et al (1987), McGehee (1994)).

II. Models and Data

Variables and data sources. The primary purpose of this study is to identify the determinants of the distribution of mortality by U.S. county. In particular, we are interested in explaining differences in relative inequality in mortality distributions among counties. These differences are relatively large, as seen in Table 1, with Gini coefficients ranging from .021 to .298 for males (a factor of 14), and from .037 to .296 for females (a factor of 8). There are also relatively large differences in mortality inequality between males and females, as evidenced by average county mortality Gini coefficients, which are .108 for females and .132 for males. The Gini coefficients are calculated from mortality data taken from the Multiple Cause of Death File of the National Center for Health Statistics. Because of privacy concerns, the National Center for Health Statistics stopped making individual death data for "small" counties available after 1988. Hence, the female and male mortality Gini coefficients that are used as dependent variables in our models are calculated for that year.[1] Independent variables used in the models were chosen based on a survey of the literature in related areas, specifically work done by Israelsen, Israelsen, and Israelsen on the determinants of life expectancy. These variables fall in several categories—economic (real per capita income, average mortgage payment, poverty rate, and unemployment rate), social (crime index, violent crime rate, mean household size, percent of households married, percent of population with 12 years of education completed, and physicians per 100,000 people), demographic (percent foreign born, percent speaking a language other than English at home, percent urban, percent rural farm, population density, average age, and percent by race and ancestry), and geographic/environmental (latitude, longitude, elevation, insolation, temperature, precipitation, humidity, and an amenity index). The independent variable names and descriptions are given in Table 2. Data for population, urban population, rural farm population, households, poverty, educational attainment, language, foreign born, ancestry, race, age, latitude, longitude, and physicians are taken from the U.S. Bureau of the Census. Income data are taken from the U.S. Bureau of Economic Analysis. Unemployment data are taken from the U.S. Bureau of Labor Statistics. Mortgage payment data are taken from Housing and Urban Development. Crime data are taken from the U.S. Federal Bureau of Investigation. Elevation data are taken from the U.S. Geological Survey. Insolation rates are taken from NASA. Amenity data are taken from U.S. Department of Agriculture. Weather data are taken from the Area Resource File. Pollution data are taken from the Environmental Protection Agency.

Table 2. Variable names and descriptions

Variable Name	Variable Description
State abbreviations	dummy variables for counties in the particular state
MARRIED	percent of the county households in which a married couple resides
HHSIZE	mean household size
MORTGAGE	average household monthly mortgage payment
REAL_PCINC	per capita income *(average monthly U.S. rent/average rent in county)
POVERTY	percent of the county population below the poverty level
URBAN	percent of the county population living in an urban area
RURAL_FARM	percent of the county population living on a rural farm
FOREIGN_BORN	percent of the county population born in a foreign country
LANGUAGE	percent of persons 5 years and older speaking a language other than English at home
UNEMPLOYMENT	civilian labor force unemployment rate
CRIME_INDEX	crime rate index
VIOLCRIME	violent crimes per 100 people
EDUC	percent of persons 25 years or older who have completed at least 12 years of education
POP_SQ_MI	persons per square mile
BLACK	percent of the population reporting primary race as black
NEUR	percent of the population reporting Northern European (English, Scotch, Scotch-Irish, Welsh, Swedish, Norwegian, Dutch, Danish, or German) as primary ancestry
HISP	percent of the population reporting Hispanic (Mexican, Puerto Rican, or Cuban) as primary ancestry
AMINESAL	percent of the population reporting primary race as American Indian, Eskimo, or Aleut
ASIAN	percent of the population reporting Asian (Chinese, Filipino, Japanese, Asian Indian, Korean, or Vietnamese) as primary race
IRISH	percent of the population reporting Irish as primary ancestry
BLACK:WH	absolute value of the percent of the population reporting primary race as white minus percent of the population reporting primary race as black
NEUR:WH	absolute value of the percent of the population reporting primary race as white minus percent of the population reporting Northern European (English, Scotch, Scotch-Irish, Welsh, Swedish, Norwegian, Dutch, Danish, or German) as primary ancestry
HISP:WH	absolute value of the percent of the population reporting primary race as white minus percent of the population reporting Hispanic (Mexican, Puerto Rican, or Cuban) as primary ancestry
AMINESAL:WH	absolute value of the percent of the population reporting primary race as white minus percent of the population reporting primary race as American Indian, Eskimo, or Aleut
ASIAN:WH	absolute value of the percent of the population reporting primary race as white minus percent of the population reporting Asian (Chinese, Filipino, Japanese, Asian Indian, Korean, or Vietnamese) as primary race
IRISH:WH	absolute value of the percent of the population reporting primary race as white minus percent of the population reporting Irish as primary ancestry
POLL_PM10	average micrograms per square meter of particulate matter that is less than 10 micrometers in diameter over a 24 hour period.

INTPTLAT	latitude of the geographical center of the county
INTPTLNG	longitude of the geographical center of the county
INSOL	average annual solar insolation, measured in kilowatt hours per square meter per day
AMENITY	scale constructed by combing six measures (warm winter, winter sun, temperate summer, low summer humidity, topographic variation, and water area)
TEMPJAN	average temperature in January
TEMPJUL	average temperature in July
TEMPANN	average annual temperature
PRECIPJAN	average precipitation in January
PRECIPJUL	average precipitation in July
PRECIPANN	average annual precipitation
HUMIDJAN	average humidity in January
HUMIDJUL	average humidity in July
ELEVATION	elevation of the county seat
PHYSICIANS_100K	physicians per 100,000 people
AGE	average age of the population

Expected signs. Because Gini coefficients are influenced by changes over the entire range of the distribution of mortality, expectations for the signs of the impacts of independent variables on mortality Gini coefficients are not easily formed. Nevertheless, information from previous mortality and life expectancy studies can allow us to reason about the direction of impact of several independent variables on the relative inequality in mortality distributions. For example, we know that female life expectancy is inversely related to household size and that the number of births aversely affects female mortality. We also know that these effects are not the same for every female; hence, it is expected that the coefficient for HHSIZE will be positive in the female mortality Gini regressions. We might also expect that the MARRIED variable coefficient will be negative, based on the positive effect marriage has on life expectancy, especially for males, and on the fact that children growing up in a two-parent home also have longer life expectancies than those growing up in other circumstances. If most households were headed by married couples, we might reasonably conclude that a higher percentage of married households would reduce mortality Gini coefficients. However, because less than half of households are married, the impact could very well be in the opposite direction. The coefficient of the POVERTY variable is expected to be positive, i.e., the greater is the percentage of families living in poverty, a condition that reduces life expectancy in the U.S., the greater will be the mortality Gini coefficient. Because individuals living in poverty normally make up a relatively small minority of a county population in which the majority live considerably longer, increasing to some extent the fraction living in poverty would likely increase relative inequality as measured by the Gini coefficient. Higher values of CRIME_INDEX and VIOLCRIME are expected to increase mortality Gini coefficients. If more people die at a younger age due to crime, or if stress in high-crime neighborhoods has a detrimental effect on expected age at death, inequality in the mortality distribution will likely become larger.

The race, ancestry, and ethnicity variables have been studied in other works. Findings have indicated that, relative to overall white life expectancy, people of Irish ancestry have shorter life expectancies, as do blacks, American Indians, Eskimos and Aleuts, *ceteris paribus*. In addition, people of Northern European ancestry have life expectancies that are longer than those of other whites. Because the life expectancies are so different between each of these ancestry and racial groups and whites, and because the majority of most counties' populations are white, it would seem that there would be a positive relationship between these variables and mortality Gini coefficients. It is expected that this relationship will be more evident in models utilizing the percent-whites-minus-the-percent-of-the-other-race/ancestry-variables than in those utilizing the actual race and ancestry variables.

There are few expectations for the environmental factors included in this study. Based on the Israelsen, Israelsen and Israelsen life expectancy studies, the pollution variable, POLL_PM10, is expected to affect women more than it does men. The sign of the pollution coefficient for female mortality inequality regressions is expected to be positive, for the same reasoning used with the MARRIAGE variable. Life expectancy studies indicate that females are more adversely affected by pollution than are males, particularly by small particle pollution.[2] Because the effect of pollution is not uniform among females, it would be reasonable to expect that higher levels of pollution would lead to a greater degree of inequality in female mortality. There are no prior expectations as to the signs of the other variables in this study.

Models. Four regression models were created and tested for females and for males. The four models differ in two respects: (1) the inclusion of state dummy variables, and (2) the form of the race/ancestry variables. Models 1 and 2 include state dummy variables, whereas models 3 and 4 exclude state dummy variables. State dummy variables are used in the first two models to pick up any state effects—such as differences in the pace of life—that might not be captured by other variables in the models. Because such effects might, indeed be accounted for by other variables, and because of likely multicollinearity between state dummy variables and other independent variables in the models, models 3 and 4 exclude the dummy variables. As an alternative method of accounting for the large observed differences in life expectancy between whites and other races/ancestries, models 2 and 4 replace race/ancestry variables with variables representing the absolute values of the percent of the population white minus the percent of the population of that race/ancestry.

III. Results

In this study, statistical significance tests are theoretically somewhat problematic. Because the study utilizes the entire population of data on mortality for 1988, there is no statistical inference involved in evaluating the results. Since hypothesis tests of model goodness-of-fit and independent variable coefficients are based on sampling from a population, F-tests and t-tests are irrelevant, strictly speaking. However, we can justify the use of such tests if we imagine that our population data for 1988 is an unbiased sample of a larger population of data for years previous to and after 1988. Based on this artifice, we have summarized regression results for each of the four models, for both males and females, in Table 3. The table lists all of the independent variables in each model, with the sign of the estimated coefficients and the level of statistical significance. It is clear from the table that the models for both females and males are robust to specification changes, as there are almost no sign reversals for statistically significant coefficients across models, and the level of statistical significance is also very consistent across models. The models are more effective in explaining relative inequality in male mortality than in female mortality. In each model specification, the R^2 values are larger for the male mortality Gini models than for the female models, ranging from .400 to .433 for male Gini regressions and from .325 to .366 for female Gini regressions. Adjusted R^2 values have a similar range, from .393 to .417, and from .317 to .348 for male and female regressions, respectively. Contrary to our expectations, the models utilizing the actual race/ancestry variables yield higher goodness-of-fit statistics than do those utilizing the percent difference specification for race/ancestry.

Table 3. Signs (sn) and statistical significance (sg) of independent variables for all regressions.

	Model 1F		Model 1M		Model 2F		Model 2M		Model 1aF		Model 1aM		Model 2aF		Model 2aM	
Variable	Sn	Sg	Sn	Sg	Sn	Sg	Sn	Sg	Sn	Sg	Sn	Sg	Sn	Sg	Sn	Sg
MARRIED	+	***	+		+	***	+		+	***	+		+	***	+	**
HHSIZE	+	***	+	***	+	***	+	***	+	***	+	***	+	***	+	**
MORTGAGE	+	***	+	***	+	***	+	***	+	***	+	***	+	***	+	**
REAL_PCINC	-	*	-		-	*	-		-	*	-		-		-	
POVERTY	-		-	***	-		-	**	-		-	***	-		-	*
URBAN	-		-	***	-		-	***	-		-	***	-		-	***
RURAL_FARM	-	***	-	***	-	***	-	***	-	***	-	***	-	***	-	***
FOREIGN_BORN	-		+		-	**	-		-		+		-	***	-	
LANGUAGE	-		-		+		+		-		-		+		+	
UNEMPLOYMEN	+		+		+		+		+	*	+		+		+	
CRIME_INDEXPC	+	**	+	***	+	***	+	***	+	***	-	***	+	***	+	***
VIOLCRIMPC	-		-		-		-		-		+		-		+	
EDUC1	-	*	-	**	-		-	**	-		-	**	-		-	*
POP_SQ_MI	+		+	**	+		+	***	+		+	***	+		+	**
BLACK	+	***	+						+	***	+					
NEUR	-	***	-	***					-	***	-	***				
HISP	-		-						-		-					
AMINESAL	+	***	+	***					+	***	+	***				
ASIAN	+		+						-		-	**				
IRISH	-	*	-						-		-					
BLACK:WH					+	*	+						+	**	+	
NEUR:WH					+	***	+	***					+	***	+	***
HISP:WH					+	***	+	**					+	***	+	**
AMINESAL:WH					-	***	-						-	***	-	
ASIAN:WH					-	***	-	**					-	***	-	**
IRISH:WH					+		+						-		-	
POLL_PM10	+		-		+		-		+		-		+		+	
INTPTLAT	-		-	***	-		-		-		-	***	+		-	
INTPTLNG	+		-		+		-		-		-	***	-		-	
INSOL	-		-		-		-		-	**	-	***	-		+	*
AMENITY	+		+		+		+		+		-		+		+	
TEMPJAN	-		-		-		-		-		-	*	-		-	***
TEMPJUL	-		+		-		+		-		-		-		-	***
TEMPANN	+		-		+		-		+		+		+		+	***
PRECIPJAN	+		+		-		-		+	***	+	***	+	*	+	*
PRECIPJUL	+	**	+		+	**	+		+	***	+	***	+	***	+	**
PRECIPANN	-		+		+		-		-	***	-	*	-	**	-	
HUMIDJAN	+		-		+		-		+		+		+		-	*
HUMIDJUL	-	***	+		-	***	+		-	**	+		-	***	+	
ELEVATION	+		+	*	+		+	**	+		+	***	+	**	+	***
PHYSICIAN/100K	-		+		-		+		-		+		-		+	
AGE	-	***	-	***	-	***	-	***	-	***	-	***	-	***	-	***
AZ	+		-		+		-									
AR	+		-		+		-									

CA	+		-		+		-									
CO	+		-		+		-									
CT	-	*	-		-		-									
DE	+		+		+		+									
DC	+		+		+		+									
FL	+		+		+	*	+	*								
GA	+		+		+		+									
HI	-		-	**	-		-	***								
ID	-		-		-		-									
IL	-		-		-		+									
IN	-		+		+		+									
IA	-		-		-		-									
KS	-		-		-		-									
KY	+		+		+		+									
LA	-		+		-		+									
ME	-		-		+		+									
MD	-		-		-		-									
MA	-	*	-	**	-		-	*								
MI	-		-		-		-									
MN	-	*	-		-		-									
MS	-		-		-		-	*								
MO	-		+		+		+									
MT	-		+		-		+									
NE	-		-		-		-									
NV	+		-		+		-									
NH	-		-	*	-		-									
NJ	-	**	-	**	-	**	-	**								
NM	+		-		+		-									
NY	-	*	-	*	-	*	-	*								
NC	+		-		+		-									
ND	-		-		-		-									
OH	-		+		+		+									
OK	-	***	-		-	**	-									
OR	+		+		+		+									
PA	-		-		-		-									
RI	-		-	**	-		-	**								
SC	+		+		+		+									
SD	-		-		+		+									
TN	-		+		+		+	*								
TX	-		-		-		-									
UT	-	***	-	**	-	***	-	**								
VT	-		-		-		-									
VA	-		-		-		-									
WA	+		+		+		+									
WV	+		+		+		+									
WI	-		-	**	-		-	*								
WY	+		+		+		+									

*** = statistically significant at .01
** = statistically significant at .05
* = statistically significant at .10

Thirteen state dummy variables are statistically significant in one or more of the regressions, all with negative coefficients. Hence, counties in those states have lower mortality Gini coefficients than one would expect given the impact of the other independent variables in the model, relative to Alabama, which is the control state. Alaska is excluded from the regressions because the pollution variable is not available for Alaska.

Economic variables. Among the economic variables, average mortgage payment stands out as the most consistent determinant of relative mortality inequality. The MORTGAGE coefficient is positive and statistically significant for both men and women in each model. MORTGAGE is used as a cost of living indicator, so the results imply that as the cost of living rises in an area, relative inequality in the distribution of mortality increases. The estimated coefficients for REAL_PCINC are negative for all regressions, but are statistically significant only in three of the female Gini mortality specifications. The inference here is that increases in county per capita income reduce relative mortality inequality, especially for women. The estimated POVERTY coefficients are negative in all regressions, contrary to our expectations, but would be statistically significant only in the regressions for male mortality inequality. Hence, it is suggested that increases in poverty rates in a county, *ceteris paribus*, reduce relative mortality inequality, at least for males. In contrast, the estimated coefficients for UNEMPLOYMENT are positive in each of the models, but statistically significant only in one female mortality regression.

Social variables. Among the social variables, MARRIED and HHSIZE coefficients are positive in every case. In addition, the estimated coefficients for HHSIZE are statistically significant in all regressions. The estimated coefficients for MARRIED are statistically significant in all female mortality regressions, but in only one male mortality regression. It appears, then, that increases in the percentage of married households and average family size in a county have a positive impact on the degree of mortality inequality—particularly for female mortality in the case of increases in married households. The crime and violent crime variables are highly multicollinear, hence it is difficult to separate the effects of the two on mortality inequality. Nevertheless, coefficients for CRIME_INDEXPC are statistically significant in all regressions, with a positive sign in all but one (female) regression. The sign reversal is likely due to the collinearity problem, as VIOLCRIME has coefficients opposite signs to those of the general crime index in all but one case. None of the violent crime coefficients are statistically significant. The impact of educational attainment is consistent throughout the regressions, with negative estimated coefficients for EDUC1 in all cases. The coefficients are statistically significant for all male mortality regressions, and for one female mortality regression. The implication of this finding is that an increase in the percentage of the county population with at least 12 years of education leads to a reduction in county mortality inequality, especially for men. The estimated coefficients for PHYSICIAN/100K are negative for female mortality inequality and positive for male mortality inequality in every case, but none are statistically significant.

Demographic variables. The estimated coefficients for URBAN and RURAL_FARM were negative in every regression. The coefficients for both variables were statistically significant in all of the male mortality regressions, but only the RURAL_FARM coefficients were significant in female mortality regressions. Apparently, increases in the percentage of the population not living in suburbs or rural non-farm areas of a county cause the distribution of mortality to become more equal. FOREIGN_BORN and LANGUAGE coefficients show no clear pattern, perhaps as a result of the obvious collinearity in the two variables. On the other hand, population density does have an identifiable impact on mortality inequality, particularly for males. The sign of POP_SQ_MI coefficients is positive for all regressions, and the estimated coefficients are statistically significant for all male mortality specifications. Apparently, population crowding increases mortality Gini coefficients. The alternative race/ancestry variables yield very different results in the models. The percentage race/ancestry specification gives the results expected by the authors, with positive BLACK and AMINESAL coefficients and negative NEUR coefficients in all regressions. The estimated coefficients for AMINESAL and NEUR are statistically significant in all model specifications for both male and female mortality, and the estimated coefficients for BLACK are statistically significant in the four male mortality regressions. The inference here is that increases in the percentage of blacks, American Indians, Eskimos, and Aleuts in a county results in increases in relative mortality inequality, while increases in the percentage of the population of Northern European ancestry results in decreases in relative mortality inequality. The alternative specification of the variables, the absolute value of the difference between the percent of the race/ancestry group relative to the percentage white population yields coefficients that are generally significant in the various regressions, but with a sign pattern that differs in some respects from that found from using the actual race/ancestry percentage variables. In this specification of race/ancestry, the signs of the coefficients of BLACK:WH, NEUR:WH, and HISP:WH are positive, while the signs of AMINESAL:WH and ASIAN:WH coefficients are negative. The signs of NEUR:WH and AMINESAL:WH are unexpected, indicating that something more complex than anticipated exists in the relationship between those variables and mortality Gini coefficients. The construction of the variables, themselves, may be the explanation. For example, among Americans who report ancestry, the largest categories reported as primary ancestry are Northern European countries, with Germany ranking first. Since the majority of Americans are white, and the majority of whites have Northern European ancestry, counties with high percentages of Northern European ancestry will also have high percentages of whites, and the absolute size of the differences in those percentages will be low, leading to small values of NEUR:WH in the counties that are dominated by Northern European ancestry. If those counties also have relatively low mortality Gini coefficients, as we hypothesize, then the estimated coefficient for NEUR:WH will be positive, as we observe. The other seemingly puzzling result is the negative estimated coefficient for AMINESAL:WH. Since American Indians (and natives in Alaska) are heavily concentrated in relatively few counties, often on reservations, and since in those counties the AMINESAL population is very large relative to that of whites, the AMINESAL:WH variable will also be very large. If the homogeneity of the population leads to a more concentrated distribution of mortality, the estimated coefficient for AMINESAL:WH will be negative, as we observe. Finally, the estimated AGE coefficients are negative and statistically significant in all regressions. A higher average age in a county is associated with a lower degree of relative mortality inequality. In this regard, it is interesting that the relationship between mean age and the distribution of age at death is analogous to that between mean income and the distribution of income.

Geographic and environmental variables. Because of multicollinearity among geographical, environmental, and state dummy variables, the impact of individual variables is difficult to identify in many cases. Nevertheless, some patterns are clear. For example, pollution seems to increase relative mortality inequality for females and reduce it for males, though the coefficients are generally not significant. Higher temperatures in January tend to reduce mortality inequality, although most estimated coefficients are not statistically significant. The alternating patterns of signs and general absence of statistical significance of the coefficients for TEMPJAN, TEMPJUL, and TEMPANN are classical symptoms of the multicollinearity that exists among those variables and the geographic variables. Precipitation variables for January and July seem to be better predictors of relative inequality in age at death, particularly in the regressions without state dummy variables. The estimated coefficients are positive and statistically significant in all of those regressions. However, the contrasting signs of the PRECIPANN variable again signal the multicollinearity problem. The humidity variables are also quite interesting, with alternating patterns of signs between male and female mortality regressions, and between July and January. Most interesting are the HUMIDJUL coefficients, which are negative and significant in all of the female mortality inequality regressions and are positive but not significant in all of the male mortality inequality regressions. The last of the geographic variables, ELEVATION, has positive estimated coefficients for all regression equations and the coefficients are statistically significant in all the male mortality Gini coefficient regressions. With regard to the general problem of multicollinearity among the geographic and environmental variables, it is instructive that many of these variables show more predictable patterns and greater statistical significance in the models that do not include state dummy variables.

IV. Conclusions

This study has identified economic, social, demographic, geographic, and environmental determinants of relative mortality inequality in United States counties. It is proposed to extend the study by updating it to include data from 2000. It is hoped that the findings of this and future such studies will be of use to interested economists and to public policy-makers who are interested in social equity.

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Endnotes

1. The majority of counties are "small" by the National Center for Health Statistics criterion, and conducting the study using only large counties would give biased results. However, the NCHS has provided the authors order statistics for small counties for years after 1988. It is possible to estimate distribution characteristics from order statistics using flexible distribution functions, such as the McDonald distribution (GB2). This procedure can be tested for bias, and if found to be unbiased, will allow us to extend the analysis to years beyond 1988.

2. In this regard, it is interesting that recent studies reportedly show evidence that females are more susceptible than males to lung cancer caused by second-hand smoke, and that the females who develop lung cancer this way are more likely than males to develop a more serious type of lung cancer.

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