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RELATIVE DEPRIVATION, INEQUALITY, AND MORTALITY

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ABSTRACT

I present a model of mortality and income that integrates the "gradient," the negative relationship between income and mortality, with the Wilkinson hypothesis, that income inequality poses a risk to health. Individual health is negatively affected by *relative deprivation* within a reference group, defined as the ratio to group mean income of the total "weight" of incomes of group members better-off than the individual. I argue that such a model is consistent with what we know about the way in which social status affects health, based on both animal and human models. The theory predicts: (a) within reference groups, which may be as large as whole populations, mortality declines with income, but at a decreasing rate; the mortality to income relationship is monotone decreasing and convex. (b) If the upper tail of the income distribution is Pareto then, among the rich, there will be a negative liriear relationship between the logarithm of the probability of death and the logarithm of income, whose slope is larger the larger is Pareto's constant, itself often interpreted as a measure of equality. (c) A mean-preserving increase in the spread of incomes raises the risk of mortality for everyone. Between reference groups (e.g. states or countries) mortality is independent of the level of average income, but depends on the gini coefficient of income inequality, as does actual aggregate mortality across US states. Individual data from the National Longitudinal Mortality Study show that the relative deprivation theory provides a good account of the mortality gradient within states, but actually fails to account for interstate correlation between mortality and income inequality. Further analysis of the aggregate data shows that the effect of income inequality is not robust to the inclusion of other controls, particularly the fraction of blacks in the population. The fraction black is positively associated with white (male) mortality in both the individual and aggregate data and, once the fraction black is controlled for, there is no effect of income inequality on either male or female mortality. No explanation is offered for why white mortality should be higher in states with a higher proportion of blacks in the population.

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1. Introduction

1.1 The gradient

There is a large literature in public health, stretching back more than 200 years, that documents "the gradient," a negative relationship between mortality and socioeconomic status; better-off people live longer; Adler et al (1993, 1994), Marmot (1994, 1999), Preston and Taubman (1994), Smith (1999) provide recent reviews. The gradient is large: in the US, Rogot, Sorlie, and Johnson (1992) estimate that a person whose family income was greater than $50,000 in 1980 had life-expectancy about 25 percent longer than a person whose family income was less than $5,000. Deaton and Paxson (1999) estimate that the regression of the log-odds of dying within a year of interview on the logarithm of (a relatively poor estimate of) income has a slope steeper than –0.5. In the public health and sociological literatures, "socioeconomic status" is usually taken as the fundamental causative variable in the gradient, and different measures—assets, occupation, education, or income—are treated as more or less interchangeable "markers" of socioeconomic status. In the smaller (and more skeptical) literature in economics, Fuchs (1993), Garber (1989), education is usually assigned the primary role, and emphasis is given to the reverse mechanism, from health to income, as well as to risky behaviors such as smoking and obesity that are more prevalent among poorer, less educated people. However, Deaton and Paxson (1999) show that the role of income on mortality is not much diminished by controlling for education, nor by attempting to eliminate feedback from health to income. Furthermore, the public health literature has demonstrated reasonably convincingly that neither reverse causality nor risky behaviors (nor differential access to medical care) can account for more than a fraction of the gradient, and takes the position that there is a direct causal link from social status to health status. Their position is

supported by experimental evidence from animal (and some human) studies, in which social status and exposure to disease can be manipulated, e.g. Cohen et al (1997), Cohen (1999), Shively et al (1994, 1997). Biological mechanisms underlying the gradient are currently under investigation, but the leading hypothesis is that mortality is linked to psychosocial stress associated with social position, Adler et al. (1993). While there clearly *are* forces running from health to income, this paper accepts the public health arguments, taking as its starting point that income is protective of health, and goes on to propose a specific form for the relationship.

1.2 Inequality as a health hazard?

More controversial than the existence of the gradient is Wilkinson's (1996) hypothesis, that inequality is itself a health hazard. Wilkinson argues that population health is determined by population income only at low levels of income, and that once a country passes through the epidemiological transition, it is not income but income inequality that is the fundamental determinant of population health. Within industrialized countries, individual income determines individual health while, between them, income inequality plays the same role for population health. The original evidence, still much cited, is presented in Wilkinson (1996, pp. 74–78) which documents a lack of correlation between life expectancy and GDP per head across OECD countries, together with impressively high cross-country correlations between life expectancy and the fraction of total income received by the poorest 70 percent of the population, both in levels and in first-differences from 1975–85. But these international correlations have not survived further analysis and data improvements, see Judge et al (1998), though recent evidence in Marmot and Bobak (2000) implicates inequality in mortality patterns in Eastern Europe.

More robust evidence on inequality and health comes from the US, where Kaplan et al (1996)

and Kennedy et al (1996a, b) demonstrated a correlation between age-adjusted mortality and

various measures of income inequality across thee U.S. states in 1990. Figure 1 illustrates; it

shows for the 50 states plus the District of Columbia in 1990 a scatter plot of the log-odds of age

adjusted mortality from all-causes for all persons (taken from compressed mortality files via the

CDC Wonder web site) against the variance of log household income per equivalent (calculated

on an individual basis from the 5 percent sample of the 1990 census; details of sources and

construction are given in Section 3.1 below.) Similar plots can be drawn for 1980, and for other

measures of inequality. In spite of the relationship between income and mortality in the

microeconomic data, there is no relationship between average income and mortality across the

states. It should be noted that I have followed Kaplan et al and Kennedy et al in using age-

adjusted mortality for all races. Because black mortality rates are higher than white mortality

rates, and because the more unequal states—which are largely in the South—also are those with a

higher fraction of blacks, the correlation between mortality and inequality, although still

significant, is weakened if calculated for white mortality alone. The correlation in Figure 1 is

0.6805, and the *t*-value on the associated regression is –6.5; if mortality is taken for whites alone,

the correlation is 0.4190, and the *t*–value –3.2, and if the variance of log income is replaced by

the variance of log income among whites, the correlation is only 0.2716 and the associated *t*-

value 2.0. I shall return to this interaction between inequality and race at the end of the paper.

Wilkinson's many writings on the effects of inequality on health are richly suggestive of

further investigation, but none provides a precise characterization. One line of argument is that

inequality works by aggregation. The relationship between mortality risk and income is nonlinear

at the individual level, so that when we compare average mortality across populations, the distribution of income will play a role. This version of the hypothesis has come to be labeled as a "statistical artefact," Gravelle (1996), a term that is unfortunate if only because, even if aggregation is the only cause of a link between inequality and mortality, a decrease in inequality will still effect a "real" decrease in mortality. Wolfson et al (1999) use the individual data to calibrate the size of the aggregation effect, and find that it is not large enough to explain the correlation, though note the different conclusion in Miller (2000). More fundamental roles for inequality include an association between inequality and a lack of social cohesion and trust, the difficulty of forming protective friendships and support networks in more unequal societies, and the negative effect of inequality on the ability to provide public goods that protect health, Kawachi, Kennedy, and Wilkinson (1999).

A principal aim of this paper is to propose a model in which the gradient and the inequality hypothesis are combined within a single framework that is consistent with the evidence to date and that is amenable to further statistical analysis.

2. Relative deprivation and mortality

2.1 Inequality and health in history

An intriguing account of why inequality might be bad for us comes from the literature on hunter-gatherers. It has been argued by many commentators, most notably by McKeown (1976), that health is maximized and mortality minimized when humans live and work under conditions that mimic those under which we evolved. For most of human existence, and a great deal of our evolution, humans lived as hunter gatherers. Such an existence involved much exercise in the

form of brisk walking, as well as a diet that is high in fibre and in cereals, low in meat and in fats, and from which sugar is almost entirely absent. Hunter gatherer bands are too small to permit the sustained existence of infectious diseases that require human hosts, and before agriculture and the domestication of animals, humans were likewise exempt from diseases that rely on animal reservoirs. Both infectious and chronic disease were at a minimum. Human minds, like human bodies, evolved during the hunter gatherer period, and according to one account, that of "Machiavellian intelligence," intelligence evolved to deal, not with mechanical tools, but with the social relationships and cooperation that were necessary to permit bands to come into being and to be successful as hunter gatherers, Jolly (1966), Humphrey (1976), Byrne and Whiten (1988). One successful social tool is thought to be an evolved preference for equality or fairness, and a century and a half of empirical literature on hunter-gatherers supports the notion that hunter-gatherer bands were strictly egalitarian, with punishments (up to and including death) for those who deviated from strict practices of equal sharing of food or who otherwise attempted to place themselves above the common level, Erdal and Whiten (1996). The inability to store the meat from occasional kills of large animals might plausibly make equitable sharing an effective tool for intertemporal smoothing. Only with the switch to agriculture did the conditions of production allow inequality to become institutionalized so that, although agriculture and later industrialization brought great increases in productivity, they also brought new risks of infectious and chronic disease, including disease from violating evolved needs for fairness and equity. Similar arguments for a strong preference for fairness can be made without necessarily supposing that humans are "hardwired" for equity, see Bowles and Gintis (1998) for a review.

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2.2 How might inequality affect health?

A useful way of thinking about inequality and health comes from research, not on humans, but on primates, where links between rank and health have been well documented, Sapolsky (1993). Inequality among primate groups does not mimic inequality among humans in early agricultural societies; in evolutionary terms, primate behavior is a model for human behavior prior to the hunter-gatherer phase. The continual use of physical violence to enforce rank among primates is more extreme than among even the most barbaric human groups. Nevertheless, Sapolsky's work among wild baboons provides a model of the biochemical pathways through which the enforcement of rank by superior over inferior animals can plausibly lead to disease. Inferior animals are repeatedly stressed by insults or aggression by superior animals. The biochemical system of stress response, although protective in the short run, loses its capacity to respond quickly and to readjust to normal if continually activated, and ultimately becomes permanently stimulated and a health hazard, Brunner and Marmot (1999). We also know, most notably from the Whitehall studies of British civil servants, that rank is protective against a wide range of human disease, particularly coronary heart disease and cancers, Marmot (1994).

Given the animal results, the degree to which low rank is harmful to an individual is likely to depend on the number of people of higher rank, because each such person is in a position to deliver the threats, insults, enforced obeisance, or ultimate violence that generate stress. Individuals who are insulted by those immediately above them, insult those immediately below them, generating a cascade of threats and violence through which low-ranked individuals feel the burden, not just of their immediate superiors, but of the whole hierarchy above them. As a result, we might suppose that the intensity of the threat from one person to someone below her depends

on the distance between the superior and the inferior individual. More powerful people can hurt you more. If we then take the leap of identifying rank with income—my purpose is to build an economic framework for mortality—ill health or the risk of death for each individual will depend on the sum of income differences between him and all the people superior to him. Such is the model explored in this paper.

2.3 A formulation

The basic hypothesis is that the risk of mortality, denoted m, is a linear function of (is equal up to choice of units of) the sum of income differences above that person within his or her reference group. This sum is normalized by average income within the reference group so that, at least for the moment, I am working with a theory of rank or relative standing, not one in which the average income of the group is itself protective. This will need to be extended below to allow for some role for *absolute* income, but for the moment I confine myself to the simpler version. Formally, I write

$$m(x) = a + \frac{b}{\mu} \int_x^{x^T} (y-x)\,dF(y) \tag{1}$$

where x is the income level under consideration, so that $m(x)$ is the probability of death for a person with income x, a and b (with b positive) are parameters that allow us to translate cumulated incomes into mortality risk, μ is mean income in the reference group, x^T is the highest income in the group, and $F(y)$ is the cumulative distribution function of group incomes.

The mortality equation can be rewritten in a number of useful ways. One is to note that

$$m(x) = a + b[1 - F(x)]\frac{\mu^+(x) - x}{\mu} \tag{2}$$

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where $\mu^+(x)$ is the average income of those whose incomes are higher than x. The mortality risk for an individual with income x is related to the fraction of the group whose income is greater than his multiplied by the difference between their average income and his. This gives simple expression to the idea that risk depends on rank—or at least its complement, the fraction of people above you—and on how much richer they are than you.

Figure 2 illustrates. It shows the cumulative distribution function, $F(x)$, the fraction of people whose incomes are less than x, for each value of x. For a person with income x, the contribution to risk of people whose incomes lie between y and $y + dy$ is the product of dF and $y - x$, which is the shaded area in the graph. The total weight of incomes above x is given by the sum of all such areas above x, which is the area ABC in the figure. This graphical presentation also makes it clear that this area is also the area under the curve $1 - F(x)$ from x to x^T, so that (1) can also be written in the form

$$m(x) = a + \frac{b}{\mu} \int_{x}^{x^T} [1 - F(y)] dy \qquad (3)$$

where $f(y)$ is the probability density function of y. (The result can also be obtained directly by integrating equation (1) by parts.)

The integral on the right hand side of (3) was introduced into the economics literature by Yitzhaki (1979) as a measure of relative deprivation in the sense of Runciman (1966); in our formulation, relative deprivation, measured in units of mean income, is the driving force behind mortality risk. Yitzhaki also proves a number of useful results about his measure of relative deprivation, which were further extended by Hey and Lambert (1980) and Berrebi and Silber

(1985), and on which I shall draw below. The "relative deprivation curve," was introduced by Kakwani (1984); it is the same concept that I use here (i.e. Yitzhaki's measure divided by mean income) but expressed, not as a function of income, but of rank in the income distribution.

The most important properties of the income to mortality curve are clear from inspection of Figure 2. First, mortality risk falls as income rises. The area ABC is smaller the higher is *x* and falls from a maximum of unity for the poorest person (if the income of the poorest person is zero) to its minimum value of zero for the richest person in the group. Second, the rate at which mortality falls with income is lower the higher is the level of income. Again, note from the figure that, as we raise *x*, the amount by which the area ABC shrinks is proportional to the distance between 1 and $F(x)$, a distance that becomes smaller as we move to higher incomes at the right. The mortality to income curve is therefore monotone decreasing and convex in income, properties that are readily verified by differentiation of (1) or (3). These properties correspond to the commonsense notion that increases in income have a greater effect on the health of the poor than on the health of the rich, although all have better health at higher income. It is worth noting that this result is only apparently inconsistent with the frequently repeated statement in the public health literature that there is a "linear" gradient between health and socioeconomic status. Since much of the literature that forms the basis for this statement uses ordinal measures of socioeconomic status (occupational status or education), no such conclusion can be drawn. What is usually *meant* is that higher rank improves health at *all* levels of socioeconomic status, not just at the bottom of the distribution among the poor—the top ranking mandarins in Whitehall have lower mortality than the civil servants just below them—which is entirely consistent with the model I am proposing here.

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2.4 Inequality and mortality

The relative deprivation model is therefore consistent with the gradient, at least in qualitative terms. What implications does it have for inequality and how does it integrate the gradient with effects of inequality on health? The first result, which comes from Yitzhaki's original paper, is about *average* health in each reference group. Given that equation (1) describes the risk of death for each member of the reference group, we can derive the average mortality for the group as a whole by averaging over both sides. Yitzhaki shows that the average of the integral is the gini coefficient of income inequality multiplied by mean income so that, for mortality,

$$\bar{m}_g \ = \ a + b\,G_g \qquad\qquad (4)$$

where the subscript g denotes a reference group, so that $\bar{m}_g$ is average mortality within the group, and G_g is the gini coefficient of income inequality for the group. For (reference group) aggregates of people, health is related, not to the level of income, but to income inequality. Yitzhaki's result follows directly from the definition of the gini coefficient, which is the average, relative to mean income, over all pairs of people in society of the absolute value of their difference in income. Since in the formulation here, mortality at income x depends on the absolute difference in income between x and all higher incomes, the averaging over x brings *all* the pairs into the calculation and delivers the gini coefficient. One reasonable question is why the gini measure plays such a special role here, and whether mortality might not be linked to other measures of inequality. Indeed Zerrebi and Silber (1985) have shown how alternative but related measures of deprivation lead to a range of familiar inequality indexes, and the formulation here could be generalized in that direction.

Since the aggregate inequality relation (4) is derived by aggregating equation (1), in which mortality is related to income, it might seem that the inequality effect on mortality is an aggregation effect, or a "statistical artefact." But there is more to it than that. Although the mortality curves (1) and (3) are indeed nonlinear in income, both the position and the shape of the curves depend on the level of income inequality, so that the model predicts, in a sense to be made precise below, a direct effect of inequality on health at the individual level. Indeed, note first Kakwani's (1984) result that the relative deprivation for a person with average income is the relative mean deviation (Pietra or Robin Hood) index of income inequality.

The most general result is about the effects of group income inequality on the *position* of the mortality to income relationship within the reference group. Using the result noted by Hey and Lambert (1980), a mean-preserving spread in the distribution of incomes will increase Yitzhaki's measure of relative deprivation, so that by the mortality equations (1) or (3), an increase in inequality will (weakly) raise mortality for everyone.

How increases in inequality change the position of the mortality income curve will depend in general on exactly how the more unequal incomes are distributed. Suppose that we have two income distributions $F_1(x)$ and $F_2(x),$ with identical means μ. If $F_2(x)$ is more equal than $F_1(x)$ in the sense of second-order stochastic dominance, mortality will be lower with distribution 2 than with distribution 1. The difference in the mortality curves is, from (3)

$$\Delta m_{12}(x) \equiv m_1(x) - m_2(x) = \frac{b}{\mu} \int_x^{x^T} [F_2(y) - F_1(y)] dy \qquad (5)$$

which, by the properties of second-order dominance discussed above, is positive. How this

reduction in mortality is distributed by income can be seen by differentiating (5) with respect to income x:

$$\frac{\partial \Delta m_{12}(x)}{\partial x} = \frac{b}{\mu}[F_1(x) - F_2(x)].$$ (6)

In the simple special case where the two distribution functions cross only once at y, say, then below y, $F_1(x)$ is above $F_2(x)$ so that the benefits of the mortality decline are increasing with income up to y with the opposite true above y. In consequence, the mortality benefits of the reduction in inequality are at their largest in the middle of the income distribution, and are less (although always still non-negative) for the poor or the rich in the tails of the distribution.

Much of the literature proposes a different effect, that the burden of inequality falls relatively heavily on the poor so that, when inequality increases, the mortality of the poor rises by more than that of the rich and the gradient steepens. The contrary result in (6) depends on defining rich and poor in terms of their income, not by their position in the income distribution, and different results are possible if we examine the effects of changing inequality holding constant, not income, but rank. To derive these results, define $p = F(x)$ as the rank (p for percentile) of person with income x, and rewrite the mortality curve (3) as a function of p,

$$\tilde{m}(p) = a + \frac{b}{\mu}\int_{F^{-1}(p)}^{y^T}[1 - F(y)]dy$$ (7)

which (apart from a and b) is Kakwani's (1984) relative deprivation curve. As Kakwani shows, the relative deprivation curve is linked to the Lorenz curve $L(p)$ through the identity

$$\tilde{m}(p) \equiv a + b[1 - L(p) - L'(p)(1 - p)],$$ (8)

where $L'(p)$ is the derivative of $L(p)$ with respect to p. Like $m(x)$, the relative deprivation

curve $m(p)$ is monotone decreasing, but it is *not* generally true that a mean preserving spread in

the income distribution must increase mortality at any given percentile rank p. However, we can

examine the effect of inequality on the mortality curve (7) by starting from the formula for its

slope, which is

$$\frac{\partial \tilde{m}(p)}{\partial p} = -b(1-p)\frac{1}{\mu f[F^{-1}(p)]}.$$ (9)

If (9) is differentiated with respect to some suitable measure of inequality and the result is

negative then, by the symmetry of the cross-partials, the effect of an increase in inequality on

mortality will be less for people of higher rank. For this to happen, the expression $f[F^{-1}(p)]$

must decrease as inequality increases. Once again, there is no general result. However, if

inequality increases by scaling up every person's distance from the mean, so that in the new

distribution, everyone is proportionally further from the mean, the condition will hold, and an

increase in inequality will steepen the gradient. (Demonstrations of these results are given in the

Appendix).

2.5 Illustrations

One useful illustration of the theory is the case where incomes have a Pareto distribution. This

distribution is often used to characterize the *upper tail* of the income distribution in practice, but

is not a good description of the distribution of income among the poor, see for example Cramer

(1966, Chapter 4.) The cdf of the Pareto distribution is

$$F(x) = 1 - \left(\frac{x}{x_0}\right)^{-\alpha}$$ (10)

where x_0 (greater than zero) is the smallest income in the population, and α is a parameter greater

than 1. A value for α of 2 is often found to provide a good fit to the upper tail of the income

distribution; and appropriate values can readily be estimated by examining the slope of the plot

of the logarithm of $1 - F(x)$ against the logarithm of x. The parameter α controls the speed with

which the distribution function converges to 1, so that a higher value of α corresponds to a

thinner upper tail of the income distribution, and in this sense to a more equal distribution of

income. For two Pareto distributions with the same mean, the one with the higher value of α has

the higher Lorenz curve.

Given a Pareto distribution of income, and noting that the mean is $\alpha x_0 / (\alpha - 1),$ the mortality

to income curve takes the form

$$m(x) \; = \; a + \frac{b}{\alpha} \left(\frac{x}{x_0} \right)^{-(\alpha - 1)} \tag{11}$$

If the intercept a is zero, so that mortality is simply relative deprivation up to scale, we have

$$\ln m(x) \; = \; \ln\left(\frac{b}{\alpha} \right) - (\alpha - 1)\ln\left(\frac{x}{x_0} \right) \tag{12}$$

and the logarithm of the probability of death is a decreasing linear function of income whose

slope and position depends on the inequality of income. Note that the Pareto distribution implies

that the effect of income on reducing mortality is larger the more equal is the income distribution.

The effect of changes in inequality, here represented by the parameter α, while holding the mean

$\alpha x_0 / (\alpha - 1)$ constant is

$$\frac{\partial \ln m(x)}{\partial \alpha} = -\ln\left(\frac{x}{x_0}\right) \tag{13}$$

As in the general case, decreases in inequality holding the mean constant, here represented by an increase in the Pareto parameter α, decrease mortality. In this special case, the reduction in mortality is (absolutely) larger for higher income people.

The Pareto distribution is not a good fit even to the upper tail of the income distribution in the US. Figure 3 illustrates the case of the lognormal distribution, and show relative deprivation as a function of rank in the income distribution for three lognormal distributions with the same log mean, and standard deviations of logs of 0.5, 0.6, and 0.7. Relative deprivation is fixed at zero for the person at the top of the distribution, and the effect on mortality of higher inequality becomes larger as we move towards the bottom. Eventually, however, the effect reverses, and ultimately, if the lowest income is close to zero, the three curves come together again for a relative deprivation of unity.

Figure 4 shows actual relative deprivation curves calculated using individual per equivalent incomes from the 5 percent sample of the 1990 census for selected US states. The assumption here is that each state is a reference group, and that people assess their standing and deprivation relative to other persons in their state. It is far from obvious that a state is a sensible reference group, and the assumption is used partly for illustration, and partly to support the exploration in the next section of whether the relative deprivation ideas might help explain the interstate patterns of mortality and inequality with which I began.

For better visibility of the different states, the curves show the logarithm of relative deprivation against income. (Note that the logarithmic scale also exaggerates the differences at

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the top of the distribution.) The District of Columbia has the highest relative deprivation. New York and California, with lower but still moderate income inequality, come next and are close to one another. Utah and Maine, low inequality states, are the two lowest curves shown. But note the position of Mississippi and Louisiana, two of the most unequal states, whose relative deprivation curves are closer to those of the equal states Maine and Utah than to California or New York. The ranking of deprivation curves works in this way because Mississippi and Louisiana are not only unequal, they are also poor; indeed, more generally in the US, poor states are more unequal. In consequence, any given *absolute* income is a higher *relative* income in Mississippi than in New York so that, on the assumption that the state is the relevant reference group, the relative deprivation associated with any income level is lower in Mississippi than in New York.

If we think of relative deprivation as affecting mortality, aggregate mortality will be higher in the high inequality states. Although the Mississippi curve is below the California curve, the mass of incomes in Mississippi is lower than in California, so that although the relative deprivation curve is lower in Mississippi than in California, its average relative deprivation (and thus mortality) is higher. Further, because deprivation is relative, average relative deprivation and the associated mortality are independent of the *level* of average state income. However, within each state, and conditional on income, mortality declines as income rises along the relative deprivation curve. Within states, and conditional on income, income inequality acts in a way that may at first seem paradoxical. Because the effect of income on mortality depends on the level of income relative to other incomes in the state, a given income level will be more protective in states where average income is lower. But across the states of the US, lower average incomes are associated

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with higher income inequality, so that a regression of mortality on income and income inequality using pooled data across states would show a *negative* (perverse) effect of inequality. Effectively, inequality is picking up the role of average state income, which is omitted from the regression. Clearly, this perverse effect could not be taken as evidence against the (assumed to be true) proposition that inequality is a health hazard. Although I have placed this argument in the context of state incomes and state income inequality, it applies to any context where relative deprivation is defined within any community or group, and where there is a negative correlation across communities between average income and income inequality. The effect of income inequality on mortality in micro regressions needs to be treated with some care.

Note finally that it would be possible to supplement the theory to include a role for individual incomes, or average state incomes. Just as relative deprivation may lead to mortality through psychosocial stress, absolute income may act independently so as to protect health.

3. Empirical evidence

3.1 Data and empirical strategy

The data come from four sources, the National Longitudinal Mortality Study (NLMS), national vital statistics from the Center for Disease Control, the March 1981 Current Population Survey (CPS), and the five percent samples from the 1980 and 1990 censuses. The NLMS, see Rogot, Sorlie, Johnson, and Schmitt (1992), is a continuing survey run by the Bureau of the Census in which respondents in the CPS are followed until death so that, in its fullest form, the NLMS contains a personal and household record from the CPS together with an indicator of whether the person is alive or dead at a given later date and, if the latter, the time from interview to death as

well as the information from the death certificate. The public use sample of the NLMS is a limited subset of these data. It contains information on more than 600,000 people in households responding to the CPS surveys of March 1979, April 1980, August 1980, December 1980, and March 1981, although the public use data do not tell us which household came from which survey. Around 43,000 of these people had died within the follow-up time of 3,288 days. Because most of the CPS interviews in the NLMS were not conducted in March, the total family income variable in the survey is not continuous, but is grouped into seven ranges; in 1980 dollars, these are (i) less than $5,000, (ii) $5,000–$9,999, (iii) $10,000–$14,999, (iv) $15,000–$19,999, (v) $20,000–$24,999, (vi) $25,000–$49,999, and (vii) $50,000 and over. The public use version of the NLMS does not contain state identifiers, though the Census Bureau kindly made special calculations for this paper, the results of which will be reported below.

I use the March 1981 CPS and the 1980 census to provide information on household income and household demographics that will supplement the data in the NLMS; note that I have no way of identifying the individuals in the CPS with the same individuals in the NLMS, so matching can only be done at some appropriate level of aggregation of which I give details below. Both 1980 and 1990 censuses, together with mortality data from the CDC, are used in the final subsection in an attempt to reconcile the results from the NLMS with the aggregate, state-level patterns of mortality and inequality with which I began.

My statistical procedures are conditioned by the nature of the NLMS data, particularly the grouping of income and the unavailability of state identifiers outside of the Census Bureau. Suppose that, over some follow up period, the probability that individual i dies, p_i, is written in the form:

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$$p_i = prob(\alpha + \beta a_i + \gamma' z_i + \epsilon_i \leq 0) \equiv prob(y_i \leq 0) \qquad (14)$$

where a_i is age, z_i is vector of relevant determinants (including relative deprivation), and ϵ_i is

idiosyncratic variation orthogonal to both a_i and z_i. The parameters α, $\beta < 0$, and γ are to be

estimated. The quantity y_i can be interpreted as a stock of health which, when negative, results in

death. Linearity in age is a special assumption that is not reasonable in general; however, I will

restrict my attention to people aged 25 to 85 at the time of interview, over which range the log

odds of mortality is approximately linear in age. This corresponds to (14) with ϵ logistically

distributed.

Individual deaths are observed from the NLMS, as are ages. However, we do not observe the

variables z_i, except in so far as we know which of seven family income groups apply to the

household in which the individual lives. To deal with this, I first use the NLMS to estimate the

probability of death as a function of age and of a set of dummy variables, one for each of the

family income classes. At the second stage, I use the CPS or the census to calculate averages of

the z variables, which can be regressed on the coefficients of the dummies to recover the

parameters of interest. Effectively, at the first stage I am using the NLMS to estimate for each sex

an age-adjusted mortality profile by income group. At the second stage, I attempt to explain those

profiles with data from the CPS and the census, averaged by NLMS income group.

To see how this works more formally, start by writing out y_i in full:

$$y_i = \alpha + \beta a_i + \gamma' z_i + \epsilon_i \qquad (15)$$

Let g_i denote the family income group to which i belongs, taking a value from 1 to 7. Take

expectations of (15) conditional on age and on g_i,

$$E(y_i | g_i = k, a_i) = \alpha + \beta a_i + \gamma' E(z_i | g_i = k, a_i) \tag{16}$$

where I have assumed that $E(\epsilon_i | g_i = k, a_i) = 0$. This assumption requires either that family

income itself is included in the vector z, or if not, that income has no effect on mortality

conditional on the variables included in z. Note that the expectation on the right hand side of (16)

can be calculated from CPS or census data for any variable included in those sources.

In principle, it would be possible to go forward on the basis of (16) alone. However, the

analysis is much simplified if I assume that the expectations of z_i are separable and linear in age,

so that I can write

$$E(z_i | g_i = k, a_i) = E(z_i | g_i = k) + \theta (a_i - E(a_i)) \tag{17}$$

for some vector of parameters θ. There is no general reason for (17) to hold, and the assumption

should be regarded as a convenient choice of functional form. If (17) is substituted into (16), we

can rewrite y_i in the form

$$y_i = (\alpha - \gamma'\theta E(a_i)) + (\beta + \gamma'\theta)a_i + \gamma' E(z_i | g_i = k) + \eta_i \tag{18}$$

where η_i is a new idiosyncratic term that is orthogonal to age and to $E(z_i | g_i = k)$. Equation (18)

can be written in a somewhat more convenient form by defining dummy variables δ_{ik} which are

1 if i belongs to family income group k, and 0 otherwise, so that

$$y_i = \tilde{\alpha} + \tilde{\beta} a_i + \sum_{k=1}^{7} \psi_k \delta_{ki} + \eta_i \tag{19}$$

where, by comparing (19) and (18), the coefficients on the dummy variables are

$$\psi_k = \gamma' E(z_i | g_i = k). \tag{20}$$

The parameters of equation (19) can be estimated (up to scale) from the NLMS, for example by a logit on age and income dummies, and the parameter estimates then regressed on the conditional expectations (20), calculated from the CPS or census, in order to recover the parameters γ. The procedure is reminiscent of two-sample instrumental variables estimation; here the instruments are grouping variables, and the efficiency of the estimation will depend on how much information remains in z once it has been projected on to the small number of income groups with which we have to work. Clearly, not much can be hoped for with only seven groups, but as will be seen later, we can do better by pooling data across the 50 states.

3.2 A national reference group?

It is useful to begin by showing what happens when we make the not unreasonable assumption that people take everyone else in the US as their reference group, so that relative deprivation is judged, not by weight of income above you in your local community, but in the country as a whole. The theory of Section 2 is silent as to the appropriate reference group, so that it makes sense to explore different definitions. The nation as a whole is one possibility because people are aware of other people's levels of living through national media. At the other extreme, people almost certainly compare themselves to their immediate geographical neighbors, with whom they live and work. Using the state as reference group is less plausible than either the nation or the locality, and I work at that level in Section 3.3 below to test whether the relative deprivation theory can help us understand the state-level facts on the gradient and on the effects of income inequality. Nevertheless, national and local measures of relative deprivation make more sense.

Looking at relative deprivation and mortality at the national level also provides a good

opportunity to see how the model works in a simple case. Table 1 shows the parameter estimates of equation (17) using a logit model for the probability of death, looking at whites only, for ages 25 through 85 at the time of interview, with death defined as occurring within 3,288 days of interview, and with the equations for males and females estimated separately. Figure 5 plots the parameter estimates for each income group, for males and females; these are shown as the circles, and labeled "actuals." The parameter estimates are plotted against the average of the logarithm of family income within each of the NLMS income groups; the data are taken from the March 1981 CPS, which reports total family income for 1980. Each person is assigned the logarithm of family income of the household to which he or she belongs. The averages shown here were computed for men; those for women differ only slightly.

Male mortality is higher than female mortality. For both sexes, the points fall from left to right; individuals with higher family income have a lower probability of death. As emphasized in the gradient literature, the effects of income are not confined to the poor, and the association of higher income with lower income extends all the way up of the income distribution so that, for example, the people whose family income is in the top 5 percent have lower mortality than those in the group immediately below. As is also generally found in the gradient literature, the slope is steeper for men than for women. The solid straight lines show the best linear fit to both curves. For both males and females, though more so for the latter, the straight line is a good approximation; the log odds of mortality is approximately linear in the logarithm of family income. This would be predicted by the relative deprivation theory if the distribution of income were Pareto, but because the Pareto distribution gives a poor fit, even at the top of the income distribution, and is much worse at the bottom, the approximate linearity cannot be taken as any

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evidence for the theory. A more appropriate evaluation is given by computing average relative

deprivation within each of the income groups, and fitting the estimated parameters to the result.

This calculation yields the broken lines in Figure 5. Although the straight lines are good

approximations, the relative deprivation measures do better, especially for males. For males, the

root mean square error falls from 0.036 to 0.022, and for females, from 0.033 to 0.031. With only

five degrees of freedom in each of these regressions, not too much should be made of the

improvement, but the finding is encouraging for the relative deprivation story.

3.3 Relative deprivation and mortality between and within the states

Although the states are not very plausible reference groups, we know that health is positively

related to income within states, and negatively to income inequality across states, so it is worth

exploring whether these facts can be explained by the relative deprivation account of mortality.

The NLMS public use file does not contain state identifiers, but the Census Bureau ran logit

regressions of the form (19) for each of the 50 states plus the District of Columbia for white

females and males separately. Three of these logits, for Nebraska and West Virginia for females,

and for the District of Columbia for males, had sample sizes too small or had too few deaths for

the estimation to converge, and I make no use of the unconverged parameter estimates in what

follows. The census calculations thus yield 350 estimates for men (50 states by seven income

groups) and 343 for women (49 states by seven income groups.) These then become the

dependent variables in pooled state by income group regressions.

The explanatory variables are the means by income group of relative deprivation and of the

logarithm of income. The CPS is too small to permit adequate calculation of these numbers by

state and sex, so I instead use the 5 percent (long-form) sample from the 1980 census. For each

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household, I calculate income per equivalent by dividing total income by the sum of the number of adults and half the number of children, and I assign the result to each individual in the household. For each state and income group, I then calculate mean log income per equivalent over all white males and white females (separately) in the income group. Relative deprivation is calculated from equation (2). There are two possible measures, one corresponding to a reference group only of other white people in the state, in which mean income per equivalent, the fraction of people with higher incomes, and their mean income per equivalent, refer only to other whites. The other is when the reference group is everyone in the state, irrespective of race. In the tables reported below, I show only the first of these; the results are almost identical using the second.

The results that follow are concerned with two questions: (a) is mortality related to relative deprivation within states as it was for the whole country, and does relative deprivation outperform a straightforward measure of income? (b) given that relative deprivation averages to the gini coefficient, does the dependence of mortality on relative deprivation explain the interstate relationship between mortality and the gini coefficient?

The regressions work as in the national case, with only a few modifications. Equation (19) is readily extended to

$$y_{is} = \tilde{\alpha} + \tilde{\beta} a_{is} + \sum_{k=1}^{7} \psi_{ks} \delta_{ki} + \eta_{is} \tag{21}$$

where s indexes the state to which individual i belongs. The logits from (21), run by the Census Bureau, give me estimates of the ψ_{ks}. Equation (20) is as before, with the addition of the state suffix, which I write for the specific case of relative deprivation as

$$\psi_{ks} = \gamma_0 + \gamma_1 r_{ks} + \epsilon_{ks} \tag{22}$$

where r_{ks} is the average relative deprivation in income group k in state s. Because I am interested

in whether the average of relative deprivation over groups within the state helps predict average

mortality in the state, this is not quite the regression that I need to run. Instead, the relative

deprivations in each income group need to be multiplied by the fraction of the population in the

state within the group before they will average to the gini coefficient. Define f_{ks} as the fraction of

the population (by sex) in income group k in state s, and multiply (22) through by f_{ks} to give

$$f_{ks}\Psi_{ks} = \gamma_0 f_{ks} + \gamma_1 r_{ks} f_{ks} + \epsilon_{ks} f_{ks} \tag{23}$$

which, with the addition of a constant term (which ought to be, and is, close to zero) is the

equation estimated on the pooled data. Of course, relative deprivation is sometimes replaced by

the mean of log income per equivalent, or supplemented by other variables.

Table 2 contains the results. In the top panel, least squares regression is applied to the pooled

data with weights given by the square root of the number of people in the NLMS logits. This

weight does not vary across income groups within the states and is chosen to capture the

differential precision of the logit estimates between small and large states. (These regressions are

almost identical if run without weights.) The t-values shown here are not corrected for possible

correlation across income groups within states; an attempt to use the robust (group) correction to

the variance generated implausibly small standard errors. The bottom panel shows random

effects pooled regressions; these do not use the weights, but do allow for correlated errors within

states, albeit in a restricted way. Fixed effects regressions, in which each state has its own

intercept, are not reported, but the parameter estimates are almost identical to the random effects

estimates. That the two sets of estimates are the same is tested using the Hausman tests reported

in the table; these never come close to rejecting the hypothesis.

The first column shows that relative deprivation is strongly correlated with mortality, both for females and males though, as in the national results, the effect for females is about half as large as the effect for males. The weighted least squares and random effects estimators are very close to one another. However, the R^2 statistics in the bottom panel show that, while relative deprivation explains a good deal of the variation in mortality within states, especially for men whose gradient is steeper, it explains essentially none of the variation across states. In these data, and as calculated, the state gini coefficient is not correlated with average mortality in the state. Much the same is true for income. The logarithm of income per equivalent also helps explain mortality (see the second columns in each panel), once again the effect is half as large for females as for males, and once again, the explanation works within, but not between states. Unlike the finding for the gini coefficient, this is no surprise because we know that mean income does not predict mean mortality across the states.

The third column in Table 2 enters both income and relative deprivation in an attempt to let the data choose between them. But the data cannot always do so; although always jointly significant, neither variable is always strongly preferred, though for males, the *t*-values are higher for relative deprivation than for income, particularly in the random effects model. For males there is again a replication of the national evidence in Figure 5, where relative deprivation fitted (male) mortality more closely than did income. Including both income and relative deprivation simultaneously does nothing to improve the prediction of mortality between the states.

What is most surprising (and disappointing) is the finding that the measure of relative deprivation does nothing to remedy the failure of income to explain the pattern of mortality

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across states. It is disappointing, because the relative deprivation theory seems to have little payoff in this context, though its performance using smaller, more plausible reference groups may be better than across states, as it is for the country as a whole. More important is that the result is a surprise because the correlation between state mortality and state income inequality is well-established, and there is no trace of it in these results. Understanding why is the topic of the final subsection.

3.4 On inequality and mortality across the states

How can the negative findings on relative deprivation be reconciled with the aggregate data from which we began? Looking at this requires going back to the aggregate data, but first consider the regressions from the NLMS shown in the final column of Table 2. In these, in an attempt to improve the between state performance, I have added the fraction of the state population that is black. For males, this fraction has a large effect on *white* male mortality. An increase of 0.13, one standard deviation and the difference between (say) New York or Texas and Georgia, would increase the log odds of white male mortality by 0.26, or the probability of death by 26 percent. The estimates show no significant parallel effect for women.

Note that, across the states of the US, income inequality is positively and to some extent mechanically correlated with fraction black. Where the fraction of blacks is high, and since black incomes are lower than white incomes, the gini coefficient is high when calculated over all races, but not particularly so when calculated over whites only. The interstate correlation between fraction black and the overall gini coefficient is 0.74, but with the gini coefficient over white incomes only 0.29. In this way, the fraction black is a mechanical contributor to overall income inequality, though not to white income inequality as used in Table 2.

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Before returning to the aggregate results, it should be noted that there is no reason to expect consistency between the NLMS and the comprehensive data from the vital statistics. First, the NLMS is a sample, albeit a large one, but death is an infrequent event, and the sample size in some of the states is barely adequate, even for all cause mortality. Even over follow up of nearly ten years, most states have less than two hundred deaths of each sex. Second, the NLMS is a longitudinal follow-up study of a population whose characteristics were observed once around 1980. The mortality data from the CDC relate to the whole population in a single year. In the NLMS, we are looking at the effects of income or income inequality at one moment on the subsequent mortality of the surveyed individuals. In the aggregate data, we are linking average income in the state to average mortality in the state. Depending on the time lags between income, income inequality and its consequences for mortality, the two comparisons are likely to give quite different answers. Third, the CDC data used here are age-adjusted by applying state and age-specific mortality rates to a standard population, whereas the NLMS data were age adjusted by allowing explicitly for age in the logits. Fourth, and finally, the CDC data I use are for mortality at all ages, including child and infant mortality. Although these data are thereby not comparable with the 25 to 85 age restriction used in my calculations with the NLMS (which was enforced by the age-adjustment procedure), I have chosen the comprehensive data to be comparable with the standard literature on inequality and mortality.

Even so, the population weighted averages of the ψ_{ks} coefficients that measure age-adjusted mortality in the regressions in Table 2 are correlated with the age-adjusted all-age log odds of mortality from the CDC in 1980 and 1990 with correlation coefficients 0.58 (1980) and 0.61 (1990) for men, but only 0.14 (1980) and 0.23 (1990) for women. It is not clear why the

correlation with men is so much stronger than that for women but, at least for the former, the correlations are high enough to make the comparison worthwhile. Some of the difference presumably comes from the variation induced by estimation of the logits, and some from the relatively small sample size of the NLMS. Table 13 of Rogot, Sorlie, Johnson and Schmitt (1992) provides (indirectly) age-adjusted mortality rates for females and males for a larger (and somewhat later, the CPS cohorts run through March 1985) version of the NLMS with 566,783 females and 532,565 males of all ages. The mortality rates for this sample are correlated with the CDC rates for 1980 and 1990 with correlation coefficients of 0.76 and 0.70 for men, and 0.66 and 0.46 for women.

Table 3 shows the results of analyzing the aggregate CDC data. The dependent variable is the log odds of age-adjusted (to the 1980 U.S. population), all-cause, all age mortality, pooled over the two years 1980 and 1990, while the right-hand side income and population figures are constructed as previously described from the 1980 and 1990 censuses. I have also included a dummy for 1980 to allow for general progress in mortality reduction; a positive coefficient indicates progress, a negative coefficient regress. As usual, the results for females in the left panel are an attenuated version of the results for males in the right panel, but the patterns are the same. The regressions in the first columns are chosen to be close to those reported in the public health literature and they show the standard result. The income variable (here the state average of the logarithm of income per equivalent) has little or no effect on mortality at the state level. By contrast, income inequality (here the gini of income per equivalent) is strongly associated with higher mortality.

The rest of the table investigates further the inequality result. In the second column, the

dependent variable is white mortality, not all race mortality as in the first column. Black mortality is typically higher than white mortality in the US, and the most unequal states are in the South, have a high fraction of black population, and have high income inequality. As a result, adding black and white mortality together over a set of states with variable shares of black population mechanically exaggerates the effect of inequality on mortality. When we look only at white mortality, the gini coefficient is still estimated to be a significant hazard, but the coefficient is considerably smaller. The third column switches to an inequality measure that is computed only over white households in the state, so that I am relating white mortality to white incomes and white income inequality, ignoring the presence and incomes of other races. The coefficients are smaller still, and are now barely significantly different from zero, and not so for women. It is the income inequality across households of all races that is correlated with white mortality, not the income inequality among whites themselves.

The final columns show the results of including the fraction black, as in the experiments with the NLMS in the final columns of Table 2. The coefficients for both males and females are significantly different from zero with the female coefficient half the size of the males. Compared with the NLMS results, the coefficients are much smaller (about a fifth the size for men) but apply to both sexes. White mortality, for both men and women, is higher in states where a larger fraction of the population is black. Once the fraction black is included in the regression, income inequality has no effect.

The obvious interpretation of these results is that the effect of inequality on health is spurious, reflecting a failure to control for race, or something that is correlated with race—though not income inequality. But such a bald interpretation ignores the fact that the results that include

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race raise as many questions as they answer, and clearly tell us nothing about mechanisms that might generate the result. Indeed, some of the discussions of why inequality affects health—lack of social cohesion, lack of trust, that heterogeneity of tastes reduces the ability to provide public goods—might provide starting points for a discussion of why white mortality is higher when whites live in states that are more racially mixed. Along related lines, Miller and Paxson (2000) show that mortality among *blacks* depends on black average incomes relative to white average incomes, so that black white income differences are a health hazard for blacks. Without development of a better theory for these effects, the results in Table 3 should not be taken at face value. Nevertheless, they are useful for two things. First, they help us reconcile the evidence from the NLMS with the aggregate data. The NLMS data analyzed here show no relationship between mortality and income inequality for either women or men, but show a role for race for men. (Neither inequality nor race significantly predicts the age-adjusted mortality rates in the fuller NLMS discussed above.) Second, they show that the now standard and frequently cited correlation across the US states between income inequality and mortality is not robust to controlling for the racial composition of the states.

4. Summary and conclusions

This paper has proposed that relative deprivation—defined in terms of the relative weight of all incomes of people who are better-off—should plausibly be linked to mortality. Such an explanation is capable in principle of integrating the gradient—that within reference groups, mortality is lower for higher income individuals—with the finding that, across groups, within group income inequality is positively associated with average group mortality. Such an account is

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most plausible for well-defined reference groups, perhaps the nation as a whole, or more likely

smaller groups based on neighborhood or employment. Nevertheless, the paper makes an attempt

to see whether the relative deprivation theory can help explain mortality within and between the

US states, even though states are not very plausible as reference groups. For men, relative

deprivation appears to predict mortality more closely than does income, both within states, and

for the US as a whole. In spite of this, average state relative deprivation—the gini coefficient—

fails to predict average state mortality in the data used here, which come from the National

Longitudinal Mortality Study. While this finding points to a failure of the theory at the state

level, it also points to an inconsistency between the sample data from the National Longitudinal

Mortality Study and the population data from the vital statistics. But further analysis of the vital

statistics shows that the effect of inequality on white mortality is not robust to controlling for the

fraction of the state's population who are black. A high fraction black is associated with higher

male mortality both in the NLMS data and in the vital statistics. Why this should be the case

remains an important topic of further research.

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6. Appendix

This Appendix justifies the two claims made in Section 2.4: (a) that the relative deprivation curve, in which relative deprivation is a function of rank p, does not necessarily move upwards in response to a mean-preserving increase in spread, (b) that it nevertheless does so for "simple" increases in variance.

(a) Figure A.1 illustrates the case of a mean preserving reduction in spread for which, at constant income x, mortality declines (as it must), but where, at constant rank p, morality increases. The curve OAL is the cdf of income, x is the reference income point, and p the corresponding rank. A mean reducing spread is represented by hollowing out the area ABC at the bottom of the distribution, and adding the equal-area segment DEJ around the point x, so that the new cdf is $OABCDEJL$. Relative deprivation is the area between the cdf and unity above x so that, after the shift, there is a reduction in relative deprivation at x by an amount equal to the shaded triangle KJH. At p by contrast, the reduction in deprivation represented by KHJ is offset by an increase in deprivation represented by the rectangle $EFGH$. Whenever this rectangle is larger than the triangle, there will be a net increase in relative deprivation at rank p. The cdf can be chosen to make the triangle KHJ arbitrary small (for example, by making it flat above x) without affecting the rectangle so that, in general, there is no guarantee that a mean reducing spread will decrease relative deprivation at a given rank.

(b) Suppose that t is a "standardized": variable with standard density $\theta(t)$ and cdf $\Theta(t)$. Income y is given by $\mu + \sigma t$. We show that, for fixed p, relative deprivation is non-decreasing in σ, and that the derivative is larger at lower p. Note that $F(y) = \Theta[(y-\mu)/\sigma]$, $f(y) = \sigma^{-1}\theta[(y-\mu)/\sigma]$,

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and $F^{-1}(p) = \mu + \sigma\,\Theta^{-1}(p)$. Hence substituting into (7)

$$\tilde{m}(p) = a + \frac{b}{\mu} \int_{\mu + \sigma\Theta^{-1}(p)}^{\infty} \left[1 - \Theta\left(\frac{y - \mu}{\sigma} \right) \right] dy. \tag{24}$$

Or, substituting t for y,

$$\tilde{m}(p) = a + \frac{b}{\mu}\sigma \int_{\Theta^{-1}(p)}^{\infty} 1 - \Theta(t)\, dt. \tag{25}$$

which is non-decreasing in σ. The second derivative is

$$\frac{\partial^2 \tilde{m}(p)}{\partial p\,\partial\sigma} = -\frac{b(1-p)}{\mu\,\theta\,[\Theta^{-1}(p)]} \tag{26}$$

which is nenon-positive, so that the relative deprivation of the poor increases more than that of

the rich when inequality increases.

Table 1: Logit estimates of the probability of death: NLMS

	Females		Males	
	Estimate	s. e.	Estimate	s. e.
Age	0.095	0.0009	0.093	0.0007
Income $5–10K (15.1%)	–0.110	0.0277	–0.210	0.0336
Income $10–15K (17.0%)	–0.229	0.0318	–0.407	0.0347
Income $15–20K (14.6%)	–0.226	0.0381	–0.583	0.0383
Income $20–25K (15.0%)	–0.363	0.0418	–0.699	0.0396
Income $25–50K (24.9%)	–0.407	0.0369	–0.810	0.0363
Income > $50K (5.0%)	–0.435	0.0635	–1.029	0.0559
Constant	–7.630	0.0649	–6.540	0.0576
Pseudo R^2	0.2586		0.2763	

Notes: White males and females from the public use sample of the NLMS: the variable being explained is the probability of death within 3,288 days of initial interview; there are 160,429 females of whom 14,134 died and 143,960 males of whom 17,722 died. The omitted income category is family income less than $5,000. All incomes are total income of the family in which the individual lives, and were converted to 1980 prices within the Census Bureau before being added to the public use data. The percentages shown in the first column are the fractions of the sample (men and women together) in the income groups; 8.6 percent of the sample are in the omitted income category.

Table 2: Pooled state and income group estimates of probabilities of death
(*t*-values in parentheses)

WEIGHTED LEAST SQUARES

	FEMALES				MALES			
Mean relative deprivation	0.698 (5.0)	–	0.640 (1.0)	0.491 (0.7)	1.418 (8.6)	–	1.221 (1.9)	0.911 (1.5)
Mean ln(y/e)	–	–0.227 (4.9)	–0.020 (0.1)	–0.070 (0.3)	–	–0.456 (8.3)	–0.067 (0.3)	–0.165 (0.8)
Fraction of pop. in group	–8.695 (104.7)	–6.395 (14.6)	–8.498 (4.0)	–8.016 (3.6)	–8.809 (122.4)	–3.472 (6.54)	–7.411 (3.5)	–6.596 (3.3)
Constant	–0.001 (0.1)	0.000 (0.0)	–0.001 (0.1)	–0.001 (0.1)	–0.009 (0.9)	–0.006 (0.6)	–0.009 (0.9)	–0.009 (0.9)
Fraction black	–	–	–	0.239 (0.9)	–		–	1.970 (6.6)

RANDOM EFFECTS, UNWEIGHTED

	FEMALES				MALES			
Mean relative deprivation	0.693 (8.2)	–	–0.135 (0.2)	–0.180 (0.3)	1.409 (14.2)	–	1.991 (3.6)	1.951 (3.7)
Mean ln(y/e)	–	–0.236 (8.4)	–0.280 (1.5)	–0.296 (1.5)	–	–0.458 (13.5)	0.198 (1.1)	0.185 (1.0)
Fraction of pop. in group	–8.730 (175.1)	–6.348 (24.0)	–5.896 (3.1)	–5.747 (2.9)	–8.101 (200.9)	–3.462 (10.6)	–10.11 (5.4)	–10.14 (5.7)
Constant	0.002 (0.2)	0.003 (0.2)	–0.003 (0.2)	0.003 (0.2)	–	–0.006 (0.6)	–0.009 (0.8)	–0.010 (0.9)
Fraction black	–	–	–	0.084 (0.3)	–	–	–	1.995 (5.7)
R^2 within	0.992	0.993	0.993	0.993	0.994	0.993	0.994	0.994
R^2 between	0.044	0.006	0.005	0.006	0.031	0.019	0.006	0.153
R^2 total	0.973	0.973	0.973	0.973	0.978	0.978	0.978	0.981
Hausman test	0.00	0.00	0.57	0.35	0.12	0.00	0.83	1.04

Notes: The dependent variables are the state by income group coefficients on logits of the probability of death for whites on age and income group dummies for each of the 50 states plus the District of Columbia. For females, Nebraska and West Virginia are excluded; for males, DC is excluded, all because of non-convergence of the logits. Death is death within 3,288 days of initial interview in the CPS. Relative deprivation, income per equivalent, and the gini coefficient are calculated from the 5 percent sample of the 1980 Census. For all three, the base concept is family income per equivalent, zero and negative incomes deleted, with adults (over 18) calculated as 1 and children (18 and under) counted as 0.5. Family income per equivalent is attributed to each individual, and the mean of log income per equivalent and the mean of relative deprivation are calculated over all white individuals in each income group. All variables in all regressions are multiplied by the fraction of the population in the relevant sex, state and income group; these fractions, the f_i in (23), are also added to the regression, see "Fraction of pop. in group."

Weighted least squares regressions were calculated by least squares with each observation in each state weighted by the square root of the number of males or females in the state in the NLMS. The random effects regressions are unweighted. The Hausman test tests the hypothesis that these random effects are identical to fixed effects estimates; the test statistic shown is distributed as χ^2 with degrees of freedom equal to the number of parameters in the relevant column.

Table 3: Mortality and inequality in the population across states

	FEMALES				MALES			
	All races	Whites			All races	Whites		
Mean ln(y/e)	0.005	0.019	0.012	–0.035	–0.099	–0.081	–0.102	–0.189
	(0.1)	(0.5)	(0.3)	(0.8)	(1.8)	(1.9)	(2.3)	(4.8)
Gini (y/e) 0	1.114	0.553	–	–0.005	1.684	1.135	–	0.027
	(3.7)	(2.3)		(0.0)	(4.7)	(4.4)		(0.1)
Gini (y/e) 1	–	–	0.392	–	–	–	0.635	–
			(1.4)				(2.0)	
Fraction black	–	–	–	0.239	–	–	–	0.476
				(2.9)				(6.2)
1980 dummy	–0.001	0.111	0.102	0.060	0.059	0.129	0.101	0.029
	(0.0)	(3.6)	(3.2)	(1.8)	(1.3)	(3.9)	(2.8)	(0.9)

Notes: The dependent variable is the log odds of age adjusted all-cause mortality taken from the CDC Wonder website. Data are pooled over 1980 and 1990, so that there are 102 observations: 50 states plus DC by two years. The population used for age adjustment is the US population in 1980 for both 1980 and 1990. The income per equivalent and gini coefficients are as described in previous tables and were calculated from the 5 percent (long form) samples of the 1980 and 1990 censuses. Gini (y/e) 0 refers to the gini coefficient of income per equivalent calculated over all individuals, while gini (y/e) 1 refers to whites only. In each panel, the first regression is for mortality over all races, and the remaining three are for whites only. All regressions are weighted by the square root of the relevant population size.
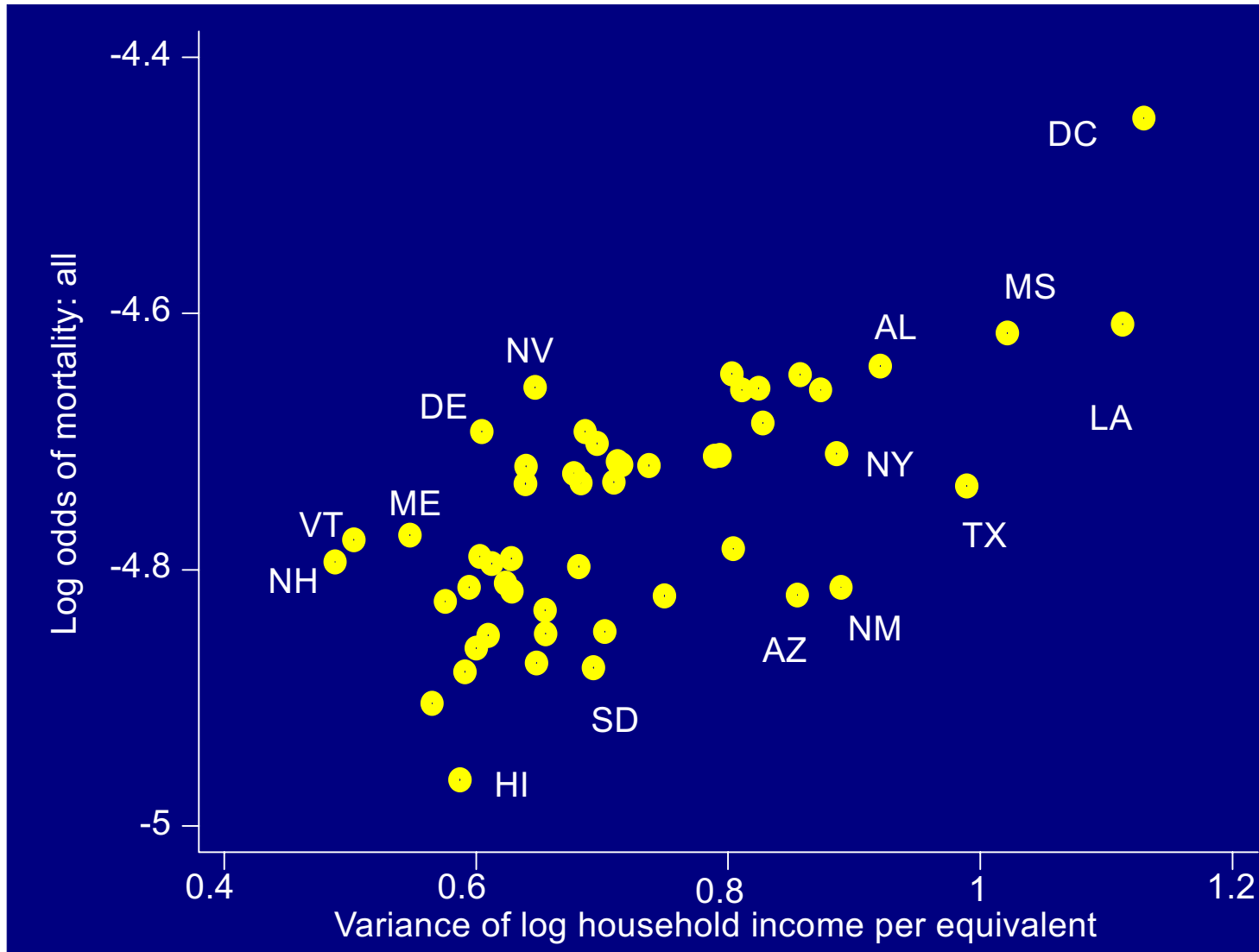
Figure 1: Mortality and income inequality across the 50 states and District of Columbia, 1990
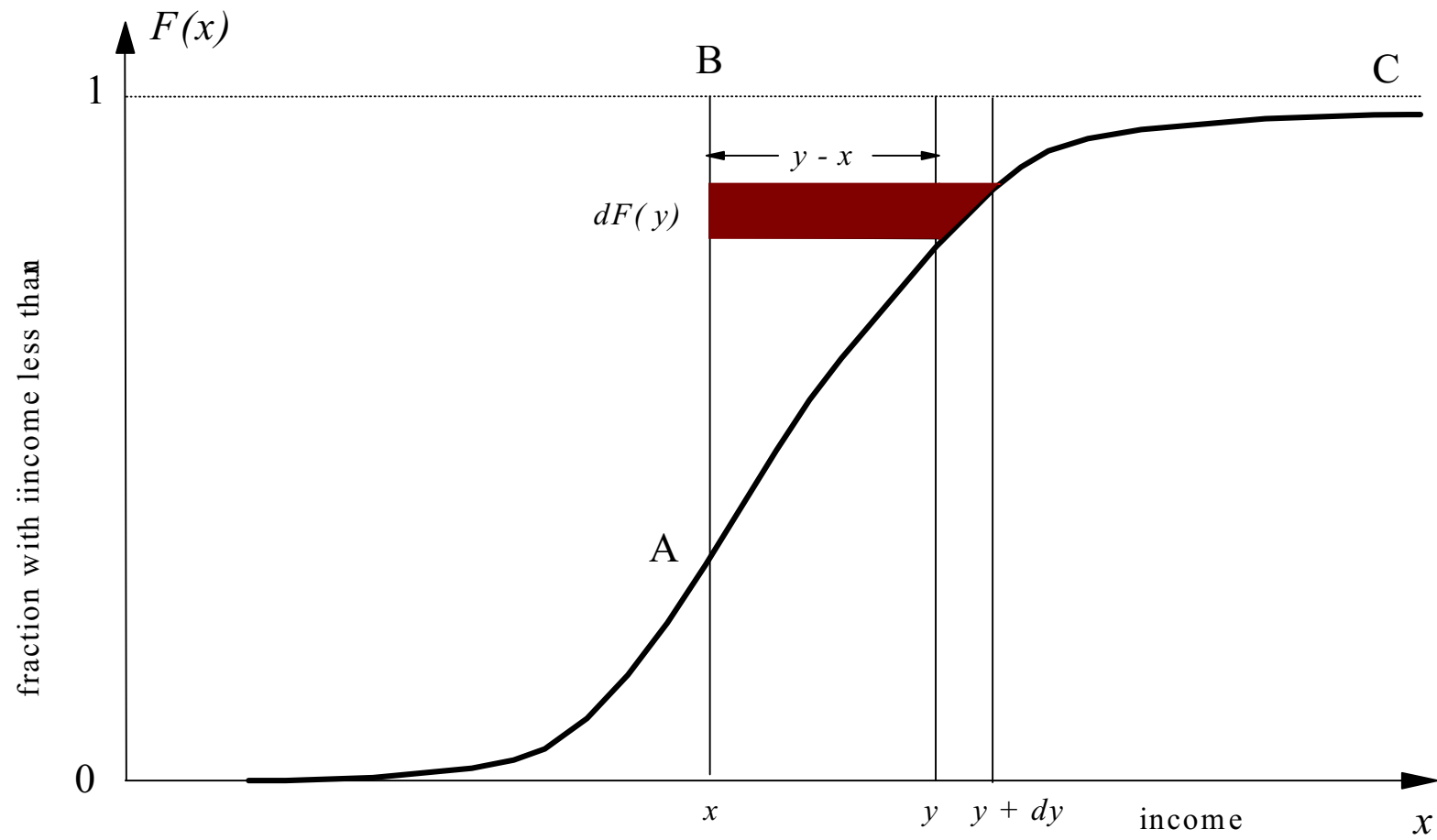
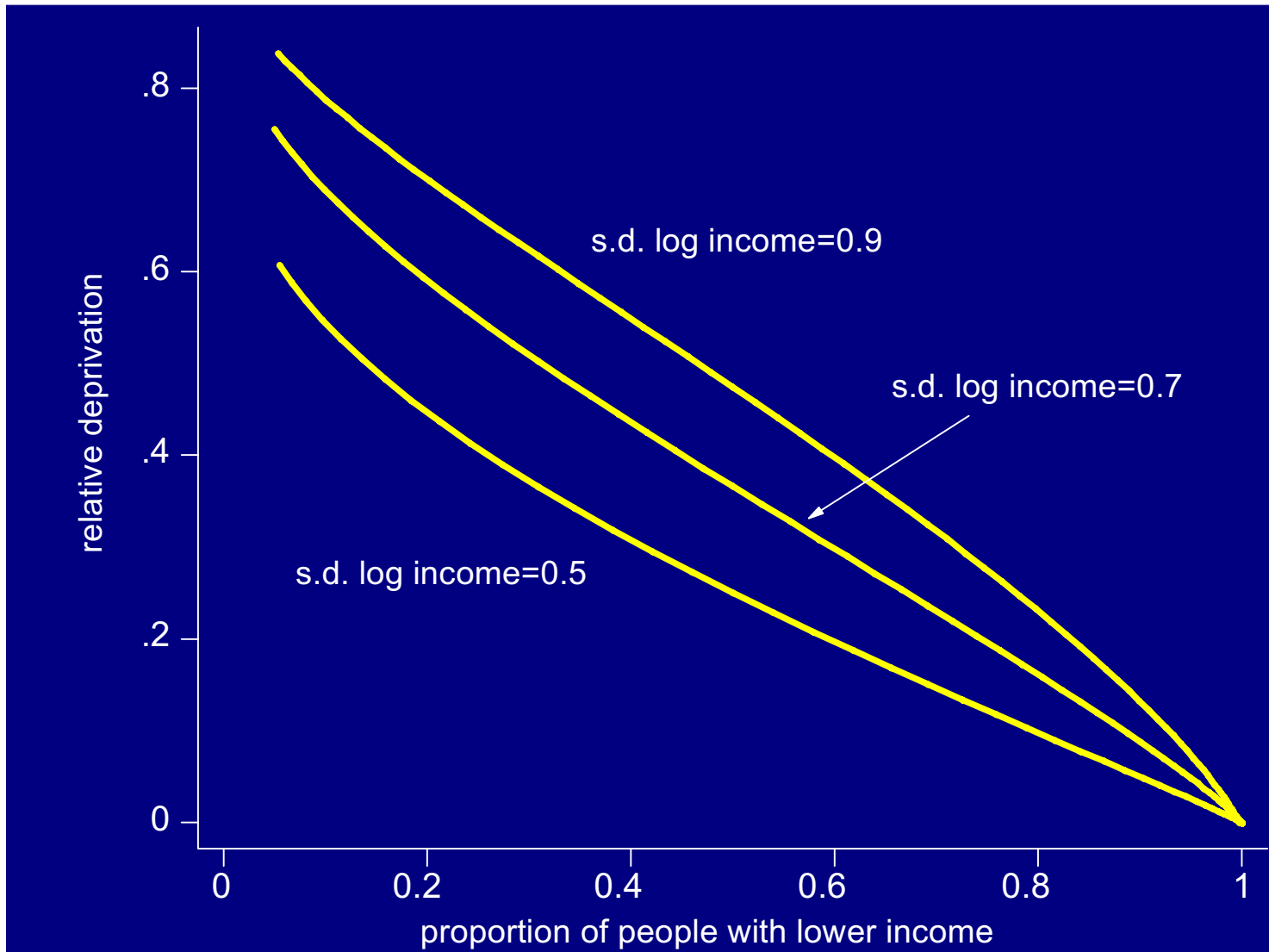Figure 2: Computing relative deprivation from the distribution of income

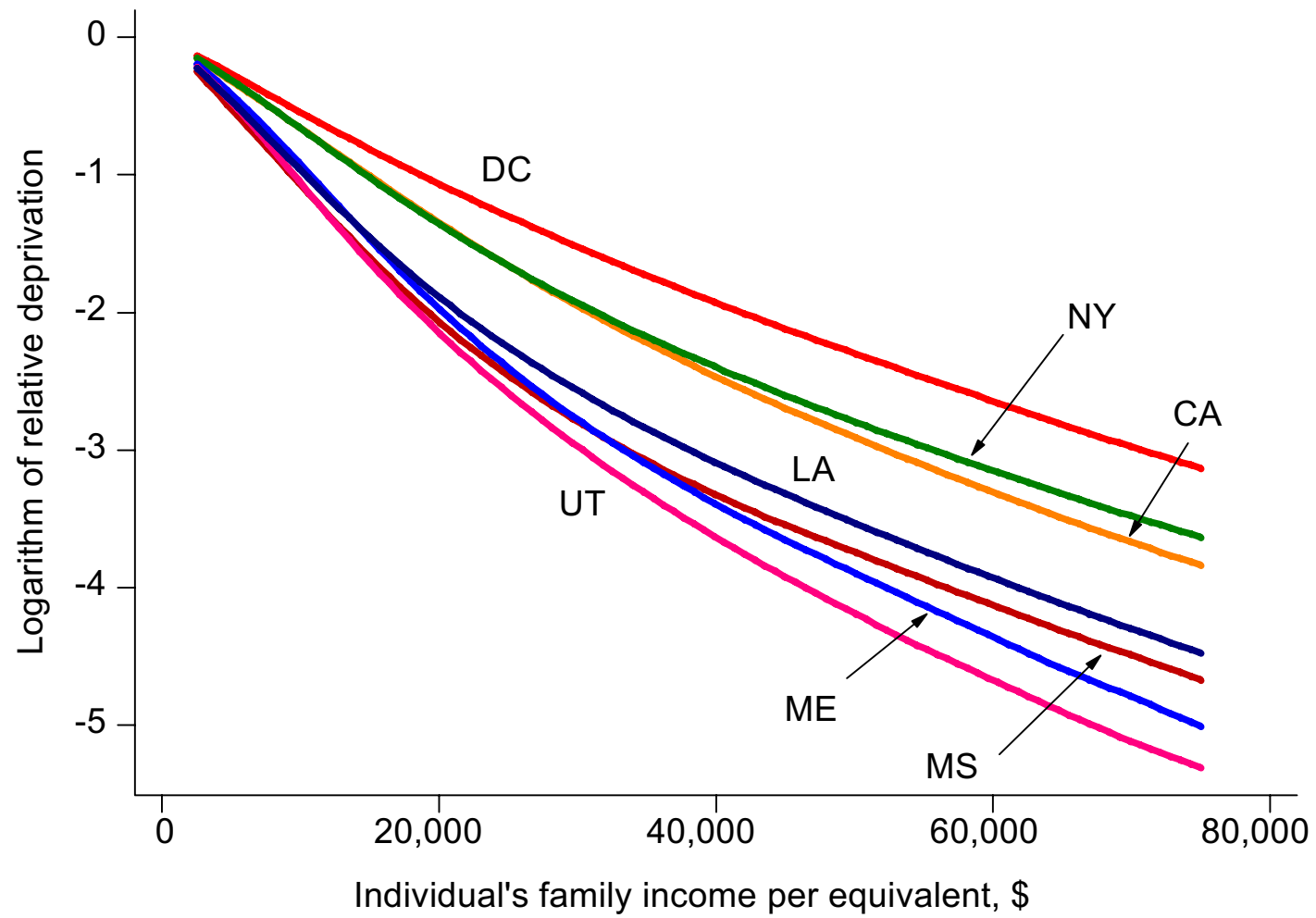**Figure 3**Figure 3: Illustrative relative deprivation curves for lognormal distributions

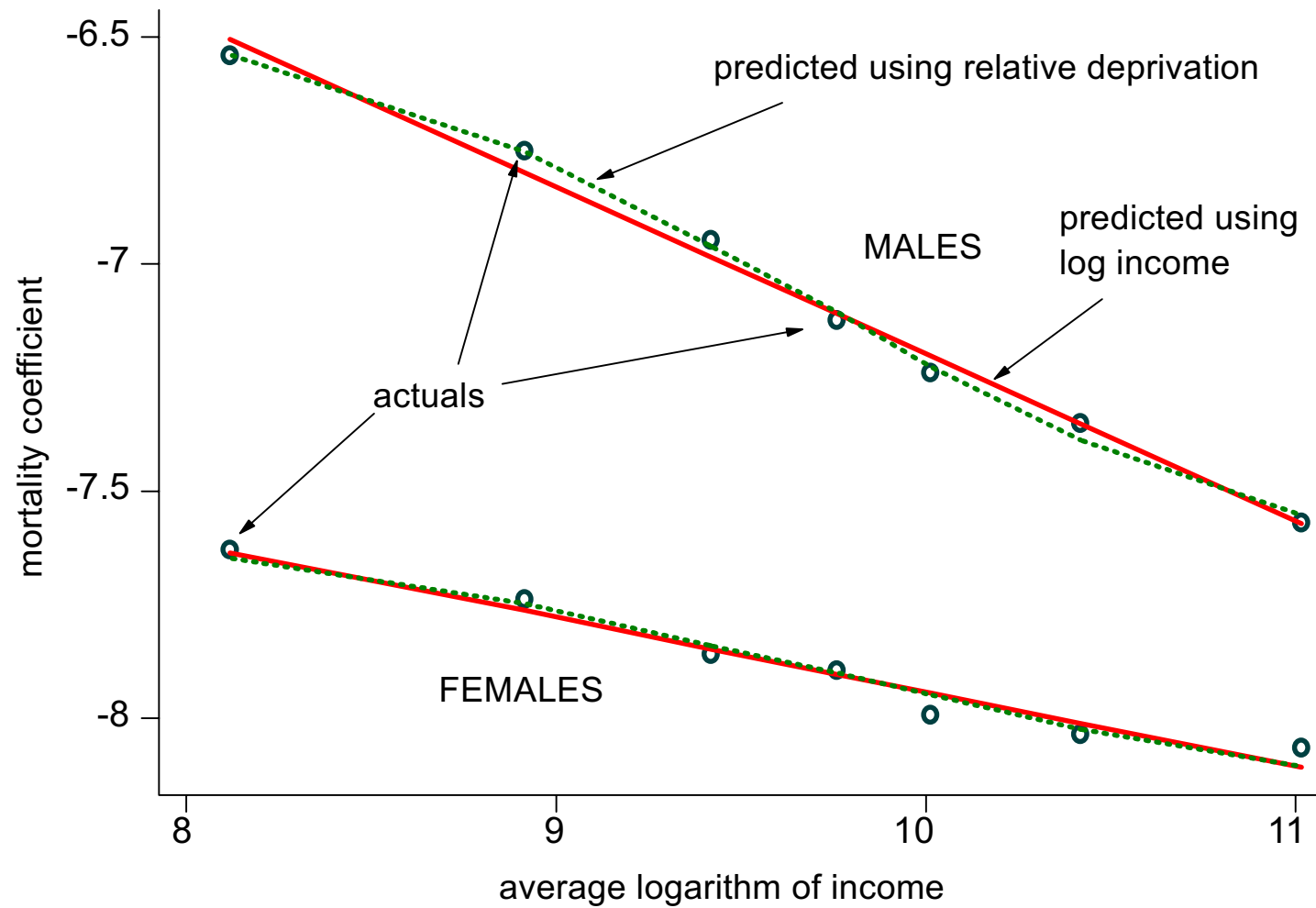Figure 4: Relative deprivation curves for selected US states, 1990

Figure 5: National age-adjusted mortality by income group in relation to income and relative deprivation
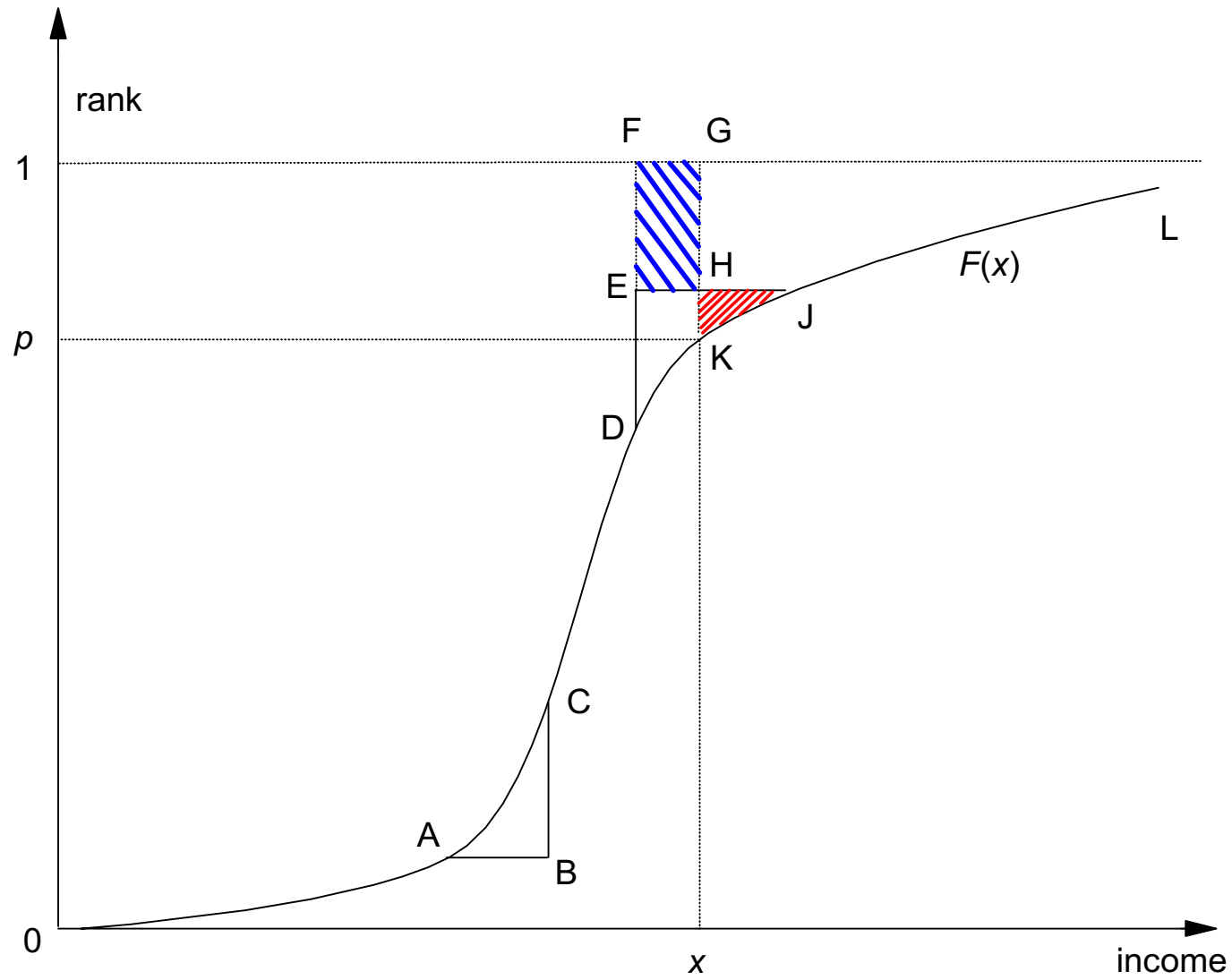
Figure A.1: A mean preserving reduction in spread and its effect on relative deprivation