

Income Inequality and Health: What Have We Learned So Far?

S. V. Subramanian and Ichiro Kawachi

From the Department of Society, Human Development, and Health, Harvard School of Public Health, Boston, MA.

Received for publication November 3, 2003; accepted for publication December 19, 2003.

Abbreviation: OR, odds ratio.

INTRODUCTION

Many developed countries have experienced a sharp rise in income inequality during the past three decades, and the United States is no exception (1). For example, the average annual salary in America in inflation-adjusted 1998 dollars increased from \$32,522 in 1970 to \$35,864 in 1999, that is, a modest 10 percent increase over three decades. By contrast over the same period, the average annual compensation of the top 100 chief executive officers rose from \$1.3 million (or 39 times the pay of an average worker) to \$37.5 million (or more than 1,000 times the pay of an average worker) (2). Recent trends in *wealth* inequality have been equally noteworthy. The net worth of families in the top decile rose by 69 percent, to \$833,600 in 2001, from \$493,400 in 1998. By contrast over the same period, the net worth of families in the lowest fifth of income earners rose 24 percent, to \$7,900. The median accumulated wealth of families in the top 10 percent of the income distribution was 12 times that of lower-middle-income families through much of the 1990s, but in 2001, the median net worth of the top earners was about 22 times as great (3).

It is by now widely accepted that income poverty is a risk factor for premature mortality and increased morbidity (4). It should also be noted that there exists persuasive evidence indicating the reverse pathway, from poor health status to persistent poverty and poorer economic growth (5). In this review, however, we focus on the question: Does the unequal distribution of income in a society pose an additional hazard to the health of the individuals living in that society? Earlier ecologic studies, summarized elsewhere (6, 7), suggested an association between income inequality and poor health status. However, these studies have been criticized because of their inability to disentangle the effects of individual income (and income poverty) from the contextual effects of income inequality (6). In other words, an ecologic association between income inequality (e.g., measured by

the Gini coefficient of income distribution at the US state level) and poor health (e.g., measured by age-adjusted mortality rates within each state) may reflect either a *contextual* effect of income inequality on health, or a *compositional* effect of income-poor individuals residing in unequal states, or both. In attempts to overcome this methodological limitation of ecologic studies, researchers have published nearly two dozen multilevel studies of income inequality and health since 1997. Multilevel studies have the ability to simultaneously assess the associations of individual income and societal income inequality with individual health status.

In this paper, we review the published multilevel studies of income inequality and health. Although the published evidence so far is by no means conclusive about the relation between income distribution and population health, our aim is to draw attention to some emerging patterns in the accumulated findings and to suggest future directions for research in this topic. We start, however, by briefly rehearsing the conceptual basis for the relation between income inequality and health. Since the most common statistic that is used to measure income inequality is the Gini coefficient, we also outline a brief description of this measure.

THE MEASUREMENT OF INCOME INEQUALITY

Various measures are available to quantify the extent of income inequality within a given community or society. Of these, the Gini coefficient is frequently used. Algebraically, the Gini coefficient is defined as half of the arithmetic average of the absolute differences between all pairs of incomes in a population, the total then being normalized on mean income. If incomes in a population are distributed completely equally, the Gini value is 0, and if one person has all the income (the condition of maximum inequality), the Gini is 1.0. The Gini coefficient can also be illustrated

Correspondence to Dr. S. V. Subramanian, Department of Society, Human Development, and Health, Harvard School of Public Health, 677 Huntington Avenue, Kresge 7th Floor, Boston, MA 02115-6096 (e-mail: svsubram@hsph.harvard.edu).

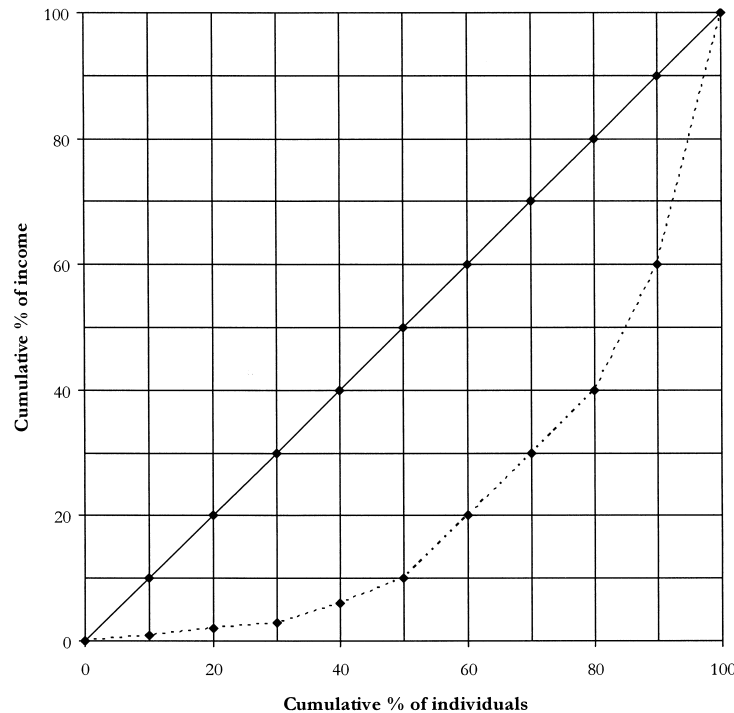


FIGURE 1. Lorenz curve.

through the use of a *Lorenz curve* (figure 1). On the horizontal axis (abscissa), the population (in this case, households) is sorted and ranked according to income, from the lowest decile group to the top decile group. The vertical axis (ordinate) then plots the proportion of the aggregate income within that community accruing to each group. Under conditions of perfect equality in the distribution of income (Gini = 0), each decile group would account for exactly 10 percent of the aggregate income, such that the Lorenz curve would follow the 45-degree line of equality. In reality, the Lorenz curve falls below the 45-degree line of equality, because the bottom groups in the income distribution earn considerably less than their equal shares. (In figure 1, it takes the bottom half of the households to account for just 10 percent of the aggregate income.) The degree to which the Lorenz curve departs from the 45-degree line of equality is a measure of income inequality. As it turns out, the Gini coefficient is the ratio of the area between the Lorenz curve and the 45-degree line of equality.

INCOME INEQUALITY AND HEALTH: THEORETICAL CONSIDERATIONS

It is widely acknowledged that *individual* income is a powerful determinant of *individual* health. It is also acknowledged that the relation between individual income and health status is concave, such that each additional dollar of income raises individual health by a decreasing amount. The concave relation between income and health has important implications for the aggregate-level relation between

income distribution and average health achievement, as noted by Rodgers (8).

As illustrated in figure 2, in a hypothetical society consisting of just two individuals, that is, a rich one (with income x_4) and a poor one (with income x_1), transferring a given amount of money (amount $x_4 - \text{amount } x_3$) from the rich to the poor will result in an improvement in the average health (from y_1 to y_2), because the improvement in the health of the poor person more than offsets the loss in health of the rich person. Indeed, it is possible that by transferring incomes from the relatively flat part of the income/health curve, there may be no loss in health for the wealthy.

Consequently, researchers have posited that an *aggregate* relation between the average health status of a society and the level of income inequality in a society could be observed *if* the individual-level relation between income and health (*within* society) is concave. That is, the *aggregate* relation between income inequality and health may be observed simply because of the underlying functional form of the individual income-health relation and assuming an x amount of transfer of money from the rich to the poor. Indeed, such a transfer also implies a reduction in the income inequality level in that particularly society and, as such, the society with the narrower distribution of income will have better average health status, all other things being equal (9). It is worth emphasizing that, if the relation between income and health at the individual level is linear (not concave), a transfer of income from the rich to the poor will reduce the level of income inequality but will not lead to improvements in the average health status of that society.

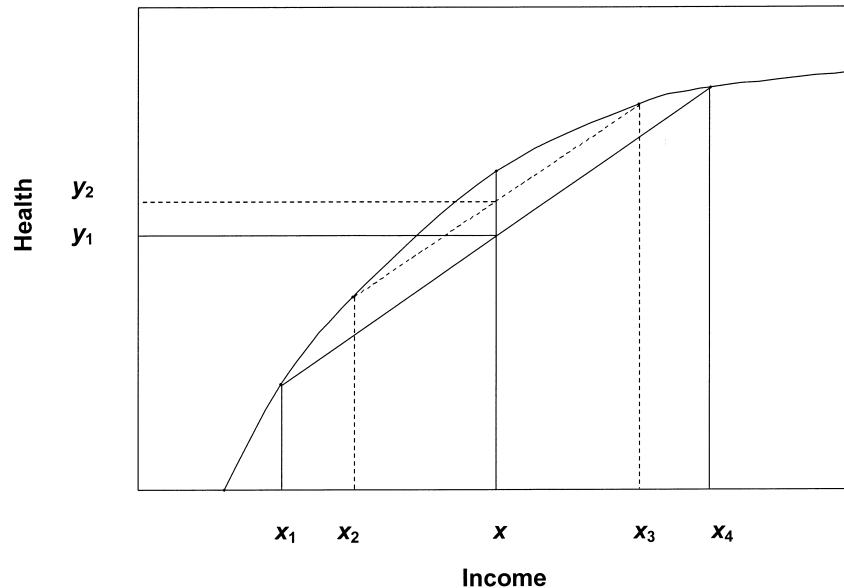


FIGURE 2. The individual-level relation between income and health.

Occasionally, this expected relation between income distribution and the average health status of a population (which is a direct function of the concave relation between individual income and health) has been described as a “statistical artifact” of the concave relation between individual income and health (10). The use of the term “artifact” is misleading here, because it suggests that the potential for improving the health of the poor through income redistribution is a statistical illusion. Indeed, there is nothing artifactual about improving the health of the poor and, hence, average population health through income and wealth redistribution. Moreover, the success of much philanthropy (e.g., donating money to provide vaccines to the world’s poor) rests on the validity of this assumption. Hence, throughout the rest of this review, we shall use the term “concavity effect” to describe the expected relation between income inequality and population *average* health status, when the shape of the association between individual income and health is concave.

In addition to the concavity effect just described, researchers have posited an additional contextual effect of income inequality on health (6). This is the hypothesis that the distribution of income in society, over and above individual incomes as well as societal average income, matters for population health such that individuals (regardless of their individual incomes) tend to have worse health in societies that are more unequal. Thus, income inequality per se may be damaging to the public’s health by causing a *downward shift* in the income/health curve. Throughout the rest of this review, we shall refer to the *independent contextual* income inequality effect as the “pollution effect” of income inequality on health.

The above distinctions, therefore, are *not* between the “effects of individual income” on health and the “effect of

income inequality” on health. Rather, they distinguish the “concavity-induced income inequality effect” from that related to the “income inequality as a societal effect.” Distinguishing the “concavity effect” of income inequality from the “pollution effect” of income inequality, meanwhile, requires multilevel data, with information gathered on both individual incomes and the extent of income inequality in the society within which the individual resides. The limitation of earlier studies (7) that utilized aggregate data to show a relation between income inequality and poor health status is that they were incapable of distinguishing between these two effects.

THE MULTILEVEL NATURE OF THE INCOME INEQUALITY HYPOTHESIS

The intrinsically multilevel nature of the income inequality hypothesis is illustrated by contrasting the individual-level and aggregate-level models. Using typical regression notations, we can specify the individual-level relation between income and health as follows:

$$y_i = \beta^*(x_i) + e_i, \quad (1)$$

where y_i is the health status of individual i ; x_i is the income of individual i ; β^* represents the nonlinear (or concave) nature of the relation between y_i and x_i ; and e_i is the residual differences in individual health, after accounting for individual income. Making the usual independent and identical distribution assumption that the residual individual-level differences follow a normal distribution with a mean of zero, have a constant variance, and are independent of one another, we can summarize the residual differences through a variance parameter, σ_e^2 . It may be noted that equation 1 will

also typically include an “intercept” parameter (associated with a constant) and, since it is not of interpretative significance, in this instance, we did not explicitly include this in our equations.

Meanwhile, the aggregate (societal) level relation between income inequality and health can be expressed in the following way:

$$y_j = \alpha(W_j) + u_j, \quad (2)$$

where y_j is the average health of a society j ; W_j is the income inequality in society j ; α estimates the relation between y_j and W_j ; and u_j is the residual differences in societal health, after accounting for societal level income inequality. Following the above independent and identical distribution assumptions, one can summarize these societal differences in a variance parameter, σ_u^2 .

Although equations 1 and 2 apparently allow us to test the “concavity effect” and the “pollution effect” respectively, they do so separately. By contrast, the “income inequality hypothesis” demands testing the two effects simultaneously in order to ascertain the independent (as well as the relative) importance of each of the two, and one way of expressing this would be

$$y_{ij} = \beta^*(x_{ij}) + \alpha(W_j) + u_j + e_{ij}, \quad (3)$$

where y_{ij} is the health status of individual i in society j ; x_{ij} is the income of individual i in society j (with β^* estimating the nonlinear (or concave) nature of the relation between y_{ij} and x_{ij} within a society); and W_j is the level of income inequality in society j (with α estimating the effect of societal income inequality on individual health) having taken account of the individual income-health relation. An important aspect of the specification in equation 3 is that variation in health status is seen to be coming from two sources, that is, individual (e_{ij}) and society (u_j), and the variation attributable to the level of individuals (σ_e^2) and to the level of societies (σ_u^2) is appropriately partitioned. Thus, underlying the combined model presented in equation 3 are two models: a “micro” model capturing the between-individual-within-society relation *nested* within a “macro” model specifying the between-society relation. Accordingly, explanatory variables of interest are also correctly specified according to their distinctive levels (e.g., income at the individual level and income inequality at the societal level). Typical single-level regression models are inadequate since they anticipate and model only a single source of variation (e.g., equations 1 and 2) and, as such, “multilevel regression models” (11) (also referred to as hierarchical (12), mixed and random-effects (13), covariance components (14), or random-coefficient regression (15) models) of the form specified in equation 3 are required to specify the income, income inequality, and health relation.

MULTILEVEL STUDIES OF INCOME INEQUALITY AND HEALTH: WHAT DOES THE EVIDENCE TELL US?

We summarize the published multilevel studies of income inequality and health in tables 1 and 2. We define “multilevel

studies” as those that utilize multilevel data in the form of an individual-level health outcome, a set of individual-level socioeconomic predictors (e.g., individual income), and an area-level income inequality measure (e.g., state income inequality). It must be noted that use of multilevel data has not always involved adopting an explicit multilevel analytical model of the form specified in equation 3. Indeed, as we show later, the majority of empirical work does not apply multilevel models to analyzing multilevel data. For comparability, the studies have been grouped according to those conducted within the United States (table 1) and those outside the United States (table 2). Our intent here is not to provide a detailed assessment of each study. Rather, we draw attention to six sets of patterns that emerge from the empirical findings.

First, in a comparison of tables 1 and 2, it is evident that the bulk of studies that suggest an association between income inequality and poor health have been conducted so far within the United States (16–25). However, even within the United States, several studies have not corroborated this association (26–30).

Second, studies conducted outside the United States have generally failed to find an association between income inequality and health (31–35). Interestingly, almost all the non-US countries listed in table 2 are considerably more egalitarian in their distribution of incomes compared with the United States, and they have stronger safety-net provisions. The Luxembourg Income Study provides a rigorous cross-national comparison of income distributions, using a summary measure called the *decile ratio*, which represents the ratio of the disposable income of the person at the 90th percentile of the distribution within each country to the income of the person at the 10th percentile (36): The higher the decile ratio, the greater the social distance between the top and bottom in society and the more unequal is the societal distribution of income. According to the Luxembourg Income Study, the decile ratios of the countries listed in table 2 were 2.78 in Sweden in 1992, 2.86 in Denmark in 1992, 3.46 in New Zealand in 1987/1988, 4.17 in Japan in 1992, and 4.67 in the United Kingdom in 1991 (36). The decile ratios in the United States were 5.78 in 1991 and 6.42 in 1994. The absence of an association between income distribution and health in the countries listed on table 2 may therefore reflect a threshold effect of inequality on poor health. When we turn to countries that are relatively more unequal than the United States (e.g., Chile (table 2)), we find some support for the relation (37).

Third, the geographic *scale* at which income inequality is assessed seems to matter. An examination of the US evidence overwhelmingly implicates the level of states (16, 19, 20, 22–25). The evidence at lower levels of aggregation, such as metropolitan areas (16), counties (26), and census tracts (20), is decidedly mixed. The more consistent association between state-level income inequality and health in the United States provides some clue about the pathways and mechanisms by which income distribution affects population health, an aspect that we shall return to later in this review. The state-level associations seem to suggest the importance of political mechanisms, such as the relation of economic disparities within each state to patterns of spending by state

TABLE 1. Published multilevel studies on the relation between income inequality and health within the United States

Authors, year (reference no.)	Data	Sample population	Method*	Outcome	Support for income inequality hypothesis
Fiscella and Franks, 1997 (26)	National Health and Nutrition Examination Survey (1971–1975)	14,407 adults from US counties (no. for counties not reported)	Single-level regression	Mortality	No
Daly et al., 1998 (27)	Panel Study of Income Dynamics (1980, 1990 cohorts)	About 6,500 adults from US states (no. for states not reported)	Single-level regression	Mortality	No
Kennedy et al., 1998 (19)	Behavioral Risk Factor Surveillance System (1993, 1994)	205,245 adults from 50 US states	Marginal models	Self-rated health	Yes
Soobader and LeClere, 1999 (20)	National Health Interview Survey (1989–1991)	9,637 White males from US counties and tracts (no. for counties and tracts not reported)	Marginal models	Self-rated health	Yes (at both county and tract levels)
Blakely et al., 2000 (17)	Current Population Survey (1995, 1997)	279,066 adults nested within 50 US states	Multilevel models	Self-rated health	Yes
Diez-Roux et al., 2000 (18)	Behavioral Risk Factor Surveillance System (1990)	81,557 adults nested within 50 US states	Multilevel models	Hypertension, smoking, sedentarism, body mass index	Yes
Kahn et al., 2000 (21)	National Maternal and Infant Health Survey (1991)	8,285 women from 50 US states	Marginal models	Depressive symptoms, self-rated health	Yes
Lochner et al., 2001 (22)	National Health Interview Survey–National Death Index-linked study (1987–1995)	546,888 adults from 50 US states	Marginal models	Mortality	Yes
Mellor and Milyo, 2002 (48)	Current Population Survey (1995–1999)	309,135 adults aged 25–74 years from US states and metropolitan areas (no. not reported)	Marginal models	Self-rated health	No
Subramanian et al., 2001 (23)	Behavioral Risk Factor Surveillance System (1993, 1994)	144,692 adults nested within 39 US states	Multilevel models	Self-rated health	Yes
Blakely et al., 2002 (16)	Current Population Survey (1995, 1997)	18,547 respondents and adults nested within 232 US metropolitan areas and 216 counties	Multilevel models	Self-rated health	No (at both metropolitan and county levels)
Sturm and Gresenz, 2002 (30)	“Healthcare for Communities” telephone survey (1997–1998)	8,235 adults from US metropolitan areas (no. for metropolitan areas not reported)	Marginal models	Self-reports of 17 common conditions (e.g., arthritis, depression)	No
Mellor and Milyo, 2003 (29)	Current Population Survey (1995–1999)	309,135 adults aged 25–74 years from US states	Marginal models	Self-rated health	No
Subramanian et al., 2003 (24)	Current Population Survey (1995, 1997)	90,000 adults aged ≥45 years nested within 50 US states nested within nine census divisions	Multilevel models	Self-rated health	Yes
Subramanian and Kawachi, 2003 (25)	Current Population Survey (1995, 1997)	201,221 adults nested within 50 US states	Multilevel models	Self-rated health	Yes

* The term “single-level regression” is used in a generic sense to represent models that ignore the nested structure of the data and thereby the clustering in the individual observations; as such, the functional form of the outcome—whether it is linear, binary, or count—is not relevant. The term “marginal models” is used to represent models that treat the nested structure of the data and the potential clustering in individual observations as a necessary nuisance and accordingly adjust the standard errors associated with the regression estimates. The term “multilevel models” is used to represent models that explicitly recognize the nested structure of the data in the data, and the potential clustering in individual observations is of substantive interest and hence modeled explicitly.

legislatures on social goods such as health care, education, and welfare. In other words, economic polarization leads to political polarization, as reflected by state variations in the generosity of benefits to the poor (38, 39).

If income inequality matters to health because of differences in political behavior (i.e., level of state effort on social spending), then this may constitute an additional reason why studies outside the United States have failed to corroborate an association between income distribution and health. As shown in table 2, studies outside the United States have been primar-

ily confined to smaller geographic scales (e.g., parishes within a single city (34)) at which one would not necessarily expect to find variations in political behavior or policy-making according to differences in income distribution.

Fourth, the US studies in table 1 show that the null studies were often based on smaller sample sizes and may have lacked statistical power to detect the effects of income inequality on health. For example, the only null study of state-level income inequality and mortality by Daly et al. (27) was based on a comparatively small sample of about

TABLE 2. Published multilevel studies on the relation between income inequality and health outside the United States

Authors, year (reference no.)	Data	Sample population	Method*	Outcome	Support for income inequality hypothesis
Gerdtham and Johannesson, 2001 (32)	Swedish Survey of Living Conditions (1997)	≥40,000 adults from municipalities in Sweden (no. for municipalities not reported)	Marginal models	Mortality	No
Jones et al., 2004 (33)	UK† Health and Lifestyle Survey (1997)	8,720 adults nested within 207 UK constituencies nested within 22 regions	Multilevel models	Mortality	No
Osler et al., 2002 (34)	Two cohort studies in Copenhagen, Denmark (1964–1992, 1976–1994)	25,728 adults from parishes within Copenhagen city (no. for parishes not reported)	Single-level regression	Mortality	No
Shibuya et al., 2002 (31)	Japanese Survey of Living Conditions of the People on Health and Welfare (1995)	80,899 adults from Japanese prefectures (no. for prefectures not reported)	Marginal models	Self-rated health	No
Blakely et al., 2003 (35)	New Zealand Census-Mortality Study	1,391,118 adults nested within regions within New Zealand (three alternatives, $n = 14$, $n = 35$, $n = 73$)	Multilevel models	All-cause and cause-specific mortality	No
Subramanian et al., 2003 (37)	2000 National Socioeconomic Characterization Survey, Chile	98,344 adults nested within 61,978 households nested within 285 Chilean communities nested within 13 regions	Multilevel models	Self-rated health	Yes

* The term “single-level regression” is used in a generic sense to represent models that ignore the nested structure of the data and thereby the clustering in the individual observations; as such, the functional form of the outcome—whether it is linear, binary, or count—is not relevant. The term “marginal models” is used to represent models that treat the nested structure of the data and the potential clustering in individual observations as a necessary nuisance and accordingly adjust the standard errors associated with the regression estimates. The term “multilevel models” is used to represent models that explicitly recognize the nested structure of the data in the data, and the potential clustering in individual observations is of substantive interest and hence modeled explicitly.

† UK, United Kingdom.

6,500, with 341 deaths in the first period and 375 deaths in the second period. Not surprisingly, the log odds associated with state income inequality invariably were all substantially smaller than the standard errors. Moreover, the fact that the magnitude of the income inequality effect (and in some cases the sign of the mortality-income inequality relation) changes between the two time periods necessitates a cautious interpretation of these results. By contrast, studies that found an association between state-level income inequality and mortality have tended to involve larger numbers. For example, Kennedy et al. (19) studied 205,245 subjects, Lochner et al. (22) studied 546,888 subjects, and Subramanian et al. studied 90,000 (24) and 201,221 (25) subjects.

Other null US studies carried out at levels of aggregation below the level of the state were similarly based on small sample sizes. For example, in the study by Fiscella and Franks (26), based on 14,407 adults in the National Health and Nutrition Examination Survey, the 95 percent confidence intervals around the mortality hazard ratio for county-level income inequality were quite wide (point estimate: 0.81, 95 percent confidence interval: 0.22, 2.92). Sturm and Gresenz (30) do not report the β coefficient or the standard error associated with the metropolitan or “economic area” income inequality predictor and report only the p value. While these studies may have lacked statistical power, we also hasten to add that the lack of an association between income inequality and health at levels below the US states may be attributable to a true absence of an association (a

finding corroborated in studies that were adequately powered, for instance, at the metropolitan area level (16)).

Fifth, with regard to the published multilevel studies in the United States, the state-level income inequality has been linked to a broad variety of health outcomes, ranging from mortality (22) and self-rated health (19, 21, 24, 25) to depressive symptoms (21), hypertension, smoking, body mass index, and sedentary behavior (18) (table 1). Therefore, the population health impacts of income inequality are potentially widespread, much like the impacts of income poverty on health outcomes.

Sixth, a final observation to make about the published multilevel studies concerns differences in methods of statistical analysis. As is evident from the tables, most studies have adopted what is referred to as “marginal” models (40, 41) compared with an explicit multilevel statistical model (11), which is closer to the specification outlined in equation 3. While marginal models are robust (42) when our interest is only in estimating the “fixed” (average) effect of an exposure (e.g., income inequality), there may be problems of inefficiency (43). Besides other general limitations (44), the key issue lies in the treatment of the clustering and heterogeneity in the outcome. Marginal models treat the variance structures (e.g., the variance that is explicitly attributable to states) as a nuisance while estimating the fixed effect for an exposure. From a multilevel statistical perspective, the failure to explicitly model the variance structure of the data (e.g., individuals nested within states) amounts to ignoring information about the variability that we are seeking to

explain through the fixed parameters of a statistical model. Of the 21 studies drawing upon multilevel data listed in the two tables, only eight studies (16–18, 24, 25, 33, 35, 37) appropriately recognize the true multilevel structure of the data while modeling the effect of income inequality on health.

INCOME INEQUALITY AND HEALTH: CURRENT DEBATES

Using the existing evidence, can we conclude that income inequality is a public health hazard? The answer to that question is far from settled (29, 45–48), and we now discuss the ongoing controversies in interpreting the empirical evidence. In particular, we focus on five sets of issues: confounding by individual income; confounding by educational attainment (and other individual socioeconomic correlates); confounding by racial composition; confounding by regional effects; and potential lag effects of income inequality on health.

Unfortunately, many of the ongoing debates and controversies cannot be resolved by careful reviews of the published studies alone. Strict comparisons across these studies are not possible, given differences in methods, model specifications, and the incomplete nature of information provided by study authors. Accordingly, we have attempted in the following section to provide tests for each controversial issue we have identified, using *comparable* data set, model specification, and modeling strategy. The data set we used was pooled from the Current Population Survey for the years 1995 and 1997 that was conducted by the US Bureau of Labor Statistics (49), which has a multilevel data structure of 201,221 adult individuals nested within the 50 US states.

The individual health outcome measure available in this data set is self-rated health, based on the single item: “Would you say your health in general is excellent, very good, good, fair, or poor?” Following previous studies (16, 19, 24, 25), the five categories were dichotomized with 0 for “excellent, very good, or good” and 1 for “fair or poor.” While self-rated health is not the same as mortality or clinically diagnosed morbidity measures, a review of 27 prospective studies in the United States and elsewhere has established that self-reported health is highly predictive of subsequent mortality, independent of other medical, behavioral, and/or psychosocial factors (50). Approximately 15 percent of the Current Population Survey sample population reported being in fair/poor health.

With respect to exposures, at the *individual level*, we included age (18–24 (reference), 25–44, 45–64, ≥65 years); sex (male (reference), female); race (White (reference), Black, others); marital status (married/partnered (reference), divorced/separated, widowed, single); education (≥16 (reference), 12–15, 8–11, 1–7 years); covered by health insurance (yes (reference), no); and equivalized household income (\$75,000 or more (reference), \$50,000–74,999, \$30,000–49,999, \$15,000–29,999, less than \$15,000). At the *state level*, we considered the median household income in a state and the state Gini coefficient (a measure of income inequality (51)), with 0 implying no inequality and 1 representing complete inequality. Both measures were derived from the 1989–1990 US Census (52, 53).

TABLE 3. Odds ratios and 95% confidence intervals for reporting fair/poor health (outcome) for a 5% change in US state Gini coefficient* under alternate specifications of the individual-level relation between income and self-rated fair/poor health†

	Alternate income specifications‡	OR§	95% CI§
Model 1	No individual income effect	1.32	1.19, 1.46
Model 2	Linear effect of income	1.31	1.18, 1.46
Model 3	Income transformed into log	1.30	1.17, 1.45
Model 4	Nonlinear with a second-order polynomial	1.31	1.17, 1.45
Model 5	Income as deciles	1.29	1.15, 1.43
Model 6	Income as quintiles	1.29	1.16, 1.44
Model 7	Income as categories¶	1.30	1.17, 1.45

* Gini coefficient, an income inequality indicator.

† Similar results have been reported elsewhere (58). However, since the objective here was to maintain uniformity across the different tests, the models were recalibrated for this review.

‡ All models additionally controlled for individual age, sex, marital status, race, years of education, covered by health insurance, and state median income.

§ OR, odds ratio; CI, confidence interval.

¶ The equivalized household income categories (\$) were as follows: ≥75,000 (reference); 50,000–74,999, 30,000–49,999, 15,000–29,999, <15,000.

As mentioned earlier, multilevel statistical techniques provide a technically robust framework to analyze the clustered nature of the outcome variable and are pertinent when predictor variables are measured simultaneously at different levels (11). The principles underlying multilevel modeling procedures have been extensively discussed elsewhere (54). The multilevel modeling of 201,221 individuals (at level 1) nested within 50 states (at level 2) was achieved through the multilevel binomial nonlinear logit link model using predictive/penalized quasi-likelihood procedure second-approximation procedures (55). Models were calibrated using the maximum likelihood procedure as implemented within MLwiN software version 1.10.006 (56) that utilizes the iterative generalized least-squares algorithm (11). We have previously reported some of the key results discussed in this section. However, given the minor changes in the data sample and model specification in those studies, we calibrated new models.

Confounding by individual income

Despite the fact that almost all of the studies listed in tables 1 and 2 controlled for individual income, skepticism has been expressed about whether the apparent association between income inequality and health could be due to misspecification of individual income and residual confounding (57). Using the Current Population Survey data, which include very detailed information on individual income, we tested the extent to which the relation between state-level income inequality and poor health in the United States is sensitive to alternative specifications of individual income (table 3) (58). The odds ratio of reporting poor health increases by 1.32 for every 5 percent increase in the state

TABLE 4. Change in the odds ratios and 95% confidence intervals for reporting fair/poor health (outcome) for a 5% change in US Gini coefficient* with a sequentially cumulative inclusion of different state and individual-level factors

Fixed part conditions	OR†	95% CI†
Baseline	1.57	1.39, 1.78
+ state median income	1.50	1.34, 1.67
+ individual age	1.53	1.37, 1.71
+ individual sex	1.52	1.36, 1.70
+ individual marital status	1.51	1.35, 1.69
+ individual race	1.42	1.27, 1.57
+ individual education	1.34	1.21, 1.48
+ individual/household equivalized income categories	1.30	1.17, 1.45
+ individual access to health insurance	1.30	1.17, 1.45

* Gini coefficient, an income inequality indicator.

† OR, odds ratio; CI, confidence interval.

Gini coefficient when no account is taken of the individual income-health relation (model 1). The odds ratio is 1.31 when a linear effect of individual income is assumed (model 2). Considering income in terms of transformed log yields an odds ratio of 1.30 (model 3), while a nonlinear specification in the form of a second-order polynomial yields an odds ratio of 1.31 (model 4). When income is specified as deciles and as quintiles, the estimated odds ratio is 1.29 (models 5 and 6). Using categories of income (model 7) yields an odds ratio of 1.30. Across the six different specifications of individual-level income, therefore, the differences in odds ratio for poor health associated with a 5 percent increase in the Gini coefficient were not substantial, suggesting that the relation between state income inequality and individual health is *independent* of the income-health relation at the individual level.

Confounding by educational attainment

Some observers have suggested that the relation between income inequality and poor health is confounded by differences in educational attainment (45, 59). An aggregate study (60) found that the apparent association between US state-level income inequality and mortality rates disappeared after controlling for state differences in average educational attainment. Previous *multilevel* studies, however, found that individual differences in educational attainment did not explain away the association between state income inequality and poor health status (24, 25, 61). In table 4, we show the extent to which the odds ratio of poor health in the Current Population Survey data is affected by introducing successive control variables at both the state and individual levels. The unconditional odds ratio of reporting poor health for a 5 percent increase in state income inequality is 1.57; conditioning this relation on the differential levels of state median income reduces the odds ratio to 1.50. Subsequently, introducing the individual demographic variables associated

with age, sex, and marital status does not attenuate the state income inequality effect (odds ratio (OR) = 1.51), but additionally accounting for individual race reduces the state income inequality effect (OR = 1.42). Including individual educational attainment attenuates the state income inequality effect somewhat (OR = 1.34), but nonetheless it remains statistically significant. Controlling for individual income further reduced the state income inequality effect (OR = 1.30), but additionally including availability of health insurance did not affect the association of state income inequality with poor self-rated health (OR = 1.30). These findings suggest that, while individual race, educational attainment, and income attenuate the baseline effect of state income inequality, they do not fully account for the observed association between self-rated poor health and state income inequality in the United States.

Confounding by racial composition

As the results in table 4 clearly demonstrate, accounting for racial composition—as measured through the individual clustering of racial groups—does not explain the state income inequality-health relation. However, it has been argued that the “proportion Black” in a state confounds the income inequality-health relation (47, 62). It may be noted that proportion Black is a state-level variable, as distinct from the individual-level clustering (within states) of Blacks, even though the two are in some ways related. We have demonstrated elsewhere that racial composition—whether measured as individual clustering of races within states or measured as proportion Black—does not account for the state income inequality-health relation (25, 58). While additionally including state proportion Black attenuates the effect of state income inequality (from an OR of 1.30 to 1.22), the effect estimate of the state proportion Black was itself not significant (table 5).

Confounding by regional effects

It is reasonable to anticipate that not only is there clustering of individuals within states but there also exists clustering of states within larger spatial units, namely, “regions.” Notwithstanding how one may identify the source of clustering of states, at least one previous empirical study used the census divisions (as fixed effects) to adjust for potential “regional confounding” (29). Doing so resulted in a much attenuated association between state-level income inequality and health. However, as argued before, if the clustering of states is something to be anticipated, it is arguably better to consider the regions as a third level in a multilevel model (24). Applying this three-level multilevel structure (individual nested within states nested within census divisions) to the Current Population Survey data (table 6), we found that the odds ratio of poor health associated with each 5 percent difference in state income inequality was attenuated from 1.30 (in the two-level model) to 1.18 (in the three-level model) but remained statistically significant.

TABLE 5. Change in the odds ratios and 95% confidence intervals for reporting fair/poor health (outcome) for a 5% change in US state Gini coefficient* and for a 5% change in proportion Black under alternative specifications of racial composition†

Alternative specifications of racial composition	OR‡	95% CI‡
State Gini (without state proportion Black)§	1.30	1.17, 1.45
State Gini (with state proportion Black)§	1.22	1.07, 1.39
State proportion Black (with state Gini)§	1.03	1.00, 1.06
State proportion Black (with state Gini, without individual Black)¶	1.04	1.01, 1.08

* Gini coefficient, an income inequality indicator.

† Similar results have been reported elsewhere (58). However, since the objective here was to maintain uniformity across the different tests, the models were recalibrated for this review.

‡ OR, odds ratio; CI, confidence interval.

§ Adjusted for individual age, sex, marital status, race, years of education, equivalized household income categories, covered by health insurance, and state median income.

¶ Adjusted for individual age, sex, marital status, years of education, equivalized household income categories, covered by health insurance, and state median income.

Lag effects of income inequality

Although almost all of the studies have measured state income inequality closest to the time when the outcome was also measured (typically around 1990), it is doubtful that income inequality has an instantaneous effect on population health (17). Accordingly, we examined the associations between state-level income inequality and poor health under different assumptions about lag periods. We evaluated the odds ratios of fair/poor health among respondents in the Current Population Survey in 1995/1997, according to the level of state income inequality measured in 1990, 1980, and 1970, that is, with 5-, 15-, and 25-year lag periods (table 7). We found the largest odds ratios of poor health for 1980 state income inequality (OR = 1.37), followed by 1990 (OR = 1.30) and 1970 (OR = 1.21). Consistent with a prior empir-

TABLE 6. Change in the odds ratios and 95% confidence intervals for reporting fair/poor health (outcome) for a 5% change in US state Gini coefficient* with and without accounting for the clustering of states†

Clustering structure	OR‡	95% CI‡
Individuals nested within states§	1.30	1.17, 1.45
Individuals nested within states within census divisions§	1.18	1.05, 1.31

* Gini coefficient, an income inequality indicator.

† Similar results have been reported elsewhere (58). However, since the objective here was to maintain uniformity across the different tests, the models were recalibrated for this review.

‡ OR, odds ratio; CI, confidence interval.

§ Models additionally controlled for individual age, sex, marital status, race, years of education, equivalized household income categories, covered by health insurance, and state median income.

TABLE 7. Change in the odds ratios and 95% confidence intervals for reporting fair/poor health (outcome) in 1995/1997 for a 5% change in US state Gini coefficient* measured in 1970, 1980, and 1990

Lag conditions for state income inequality	OR†	95% CI†
State income inequality, 1990‡	1.30	1.17, 1.45
State income inequality, 1980‡	1.37	1.16, 1.62
State income inequality, 1970‡	1.21	1.07, 1.35

* Gini coefficient, an income inequality indicator.

† OR, odds ratio; CI, confidence interval.

‡ Model additionally controlled for 1995/1997 individual age, sex, marital status, race, years of education, equivalized household income categories, covered by health insurance, and 1990, 1980, and 1970 state median income, respectively.

ical test (17), income inequality may therefore exert its strongest effects on health up to 15 years later. However, more tests would be required to see if a similar magnitude of effect is observed if we correlate 1970 state income inequality with 1985 health outcomes or 1990 state income inequality with 2005 health outcomes.

INCOME INEQUALITY AND HEALTH: AN AGENDA FOR FUTURE RESEARCH

Considerable effort and energy have been devoted so far to demonstrating a contextual effect of income inequality (or lack of it) on health. Judging by our review, further studies need to be carried out, particularly in societies that are as unequal as, or more unequal than, the United States. Several analytical challenges remain, including residual *ecologic confounding*, such as other aggregate factors that could potentially confound the relation of income inequality to health, and the problem of *endogeneity* (i.e., the presence of unobserved (and omitted) common cause variables at both the individual and aggregate levels or through reverse causation). Over and above these generic challenges of demonstrating a *causal* effect of income inequality on health, we highlight in this section a set of issues that promises to take the field forward in new directions.

Teasing out income inequality, relative income, and relative rank

So far, the multilevel studies have tested only for the contextual effects of "aggregate" income inequality, as measured by summary indicators, such as the Gini coefficient. However, as discussed by Wagstaff and Doorslaer (6), the relation between income inequality and health is also consistent with at least two other types of effects: 1) *relative income*, in which an individual's health depends on not only her own level of income but also the distance between her income and the incomes of others in society; and 2) *relative rank*, in which an individual's health depends on not only her own level of income but also the rank (or position) that level

of income confers in the social hierarchy. Distinguishing between these types of effects promises to yield rich insights into the mechanisms by which income matters for individual health. Indeed, some argue, on theoretical grounds, that any observed effect of absolute income on health already *incorporates* the effects of hierarchy (income rank) as well as relative income (63).

That said, with notable exceptions (64, 65), few researchers have attempted to test either of these hypotheses explicitly. In the case of the relative income hypothesis, the operationalization and measurement of “relative income” have proved problematic, because the choice of a relevant *reference group* against which individuals compare their own incomes is not obvious. Similarly, scant work has been undertaken on the relative rank hypothesis, owing to the difficulty of isolating a pure rank effect from the simultaneous effects of income (i.e., rank and income are highly collinear).

Testing “cross-level interactions”: who pays the price of income inequality?

Most multilevel studies on income inequality and health have not paid detailed attention to potential cross-level interactions, whereby state income inequality may affect the health of different population groups in different ways. It is noteworthy that few investigators have attempted to dissect the cross-level interactions between area-level inequality and the health of particular sociodemographic groups. That is, for whom is inequality most harmful, and why? Some evidence suggests that affluent individuals experience health benefits when they live in an area with high inequality (21, 23). Other studies suggest that income inequality is particularly detrimental to the health of poor or near-poor individuals (19, 22). More systematic work is required to unpack such interactions by key individual demographic and socioeconomic factors.

Pathways linking income inequality to health

Research on the potential pathways and mechanisms linking income inequality to health is still in its infancy. Three specific pathways have been conceptualized. The first posits a “*structural pathway*” between income inequality and health. For instance, it is likely that the relation between income inequality and residential segregation is causal, such that income inequality leads to spatial concentrations of race and poverty, which in turn influence individual health (66, 67). While American society is getting more, and not less, segregated (68) and getting more unequal (39), there is, however, little systematic empirical research that has explored the connections between the two and their influence on health. Second, the *social cohesion and collective social pathway* may mediate the multilevel relation between state income inequality and health (69). In recent times, the collective attribute of social relations has been conceptualized through the idea of “social capital” (70, 71). Again, a systematic multilevel investigation of how the state-level social capital may mediate the relation between state income inequality and health is currently lacking. Third, there is the

policy pathway, whereby the adverse influence of income inequality may operate through formulation and implementation of general social policies, as well as through health-related policies. A number of policy variables, such as primary health care indicators, welfare spending, child care, food assistance, vocational training, remedial training, health insurance, early childhood education, disability assistance, tax policy, and unemployment compensation, could mediate the relation between income inequality and health outcomes. The three pathways, moreover, need not be mutually exclusive. For example, social cohesion within a state may influence the pattern of state effort on social spending.

The importance of geographic scale

As revealed by our review, geographic scale (e.g., US states vs. counties) matters for the relation between income inequality and health. Future studies should recognize and anticipate, a priori, this level contingency between income inequality and health outcomes. The theory, as well as empirical investigations of income distribution and health, can be usefully extended by a more systematic examination of the issue of what levels matter for population health and why.

Need for longitudinal studies

Researchers need to recognize the limitations related to drawing inferences based on cross-sectional observational data. The availability of longitudinal observational data (e.g., repeated assessment of income inequality over time, in tandem with individual health outcomes) together with innovative application of multilevel structures (72) may provide a better handle on the *causal* nature of the relation between income inequality and health. In addition, more use could be made of quasi-experimental situations to evaluate causality in this area. Natural experiments, such as the recent rounds of tax cuts in the United States, may provide future opportunities to examine the impact of changes in income distribution on changes in population health outcomes.

Modeling choices and interpreting multilevel coefficients

Finally, issues related to modeling strategies and subsequent interpretation of the coefficients require careful consideration. One aspect of multilevel models that tends to be ignored is the random coefficients associated with areas (e.g., states), such as the variation in health that is attributable to states. Yet, it is the anticipated importance of the state-level random coefficient that often motivates researchers to consider state-level variables, such as income inequality, to explain this state-attributable variation in health. For instance, the extent of unconditional state-attributable variation in self-rated poor health, while statistically significant, is rather small (2 percent) (table 8). Individual demographic and socioeconomic markers account for about 35 percent of the unconditional state-attributable variation, reducing the residual variation to be explained by state-level variables to 1.4 percent. State median income accounts for

TABLE 8. Random parameter estimates of the between-state variation, % state-attributable variation, and % change in between-state variation with sequential introduction of predictors in the fixed part of a multilevel logistic model with self-rated fair/poor health as an outcome*

Fixed part conditions	Between-state variation	% state-attributable variation†	% change in between-state variation
Null	0.0721	2.14	
+ individual markers‡	0.0472	1.41	34.54
+ state median income§	0.0346	1.04	26.69
+ state Gini coefficient¶, #	0.0223	0.67	35.55

* All variance estimates were significant at less than the 0.0001 level.

† This coefficient refers to the % of variation that is attributable to states estimated from a two-level binomial logistic model when a variance component estimated at the state level is based on the “latent variable approach” method (73).

‡ Individual markers include age, sex, marital status, race, years of education, equivalized household income categories, and covered by health insurance.

§ The model additionally controlled for the individual markers.

¶ Gini coefficient, an income inequality indicator.

The model additionally controlled for the individual markers and state median income.

some 27 percent of the variation, and of the remaining variation (1 percent), state income inequality accounts for 35 percent of the variation. Thus, while state income inequality explains an impressive fraction of the state-attributable variation, it seems to be explaining a great deal of a rather small contextual variation. While multilevel models offer great potential in providing such details, researchers need to be cognizant of the challenges in estimating such summary statistics, especially in multilevel logistic models (73, 74), and there is little understanding on what proportion of the total state-attributable variation is “explainable” and what is simply “random.” Moreover, as the results suggest, it is entirely possible to estimate a statistically significant *fixed effect* for state income inequality (with an OR of about 1.20) even though the residual state-attributable variation is rather small. This can happen because of misspecification of the underlying variance structure and/or because, while there is “true” population variance due to sample size or issue related to sample representativeness (of contexts), it may not always be possible to estimate the “true” variation. These issues, nonetheless, raise important questions for interpreting context-attributable variation, in general.

The other methodological issue of relevance pertains to the choice of the modeling strategy. As we mentioned earlier, most studies do not explicitly estimate the state-attributable variation in their models. What difference does the choice of modeling strategy make to the point estimates of state income inequality? With the fixed part specification being kept constant across the different modeling strategies, the point estimates for state income inequality from a simple binary logistic model (one that ignores the state-attributable variation) and the marginal binary logistic model (one that

TABLE 9. Fixed estimates and standard errors, along with the change in odds ratios and their 95% confidence intervals, for reporting fair/poor health (outcome) for a 5% change in 1990 US state Gini coefficient* according to three modeling strategies†

Modeling approach	Estimate	SE‡	OR‡	95% CI‡
Single-level logistic model§	3.75	0.35	1.21	1.17, 1.25
Marginal logistic model¶	3.76	1.08	1.21	1.09, 1.34
Multilevel logistic model#	5.26	1.08	1.30	1.17, 1.45

* Gini coefficient, an income inequality indicator.

† All models controlled for 1995/1997 individual age, sex, marital status, race, years of education, equivalized household income categories, covered by health insurance, and 1990 state median income.

‡ SE, standard error; OR, odds ratio; CI, confidence interval.

§ In this modeling strategy, the potential clustering of individuals within states is ignored.

¶ In this modeling strategy, the potential clustering of individuals within states is considered a nuisance, and accordingly the standard errors are adjusted to reflect the “true” sample size based on the extent of clustering. We used SUDAAN 8.0.1 software (Research Triangle Institute, Research Triangle Park, North Carolina) to calibrate the marginal logistic model.

In this modeling strategy, the potential clustering of individuals within states is considered to be of substantive interest and therefore modeled. Accordingly, not only the standard errors are adjusted to reflect the “true” sample size based on the extent of clustering but also state-attributable variation is explicitly modeled and estimated. We used MLwiN 1.10.0006 software (Institute of Education, University of London, London, United Kingdom) to calibrate the multilevel logistic model.

adjusts for the state-attributable variation but does not model it explicitly) were similar ($\beta = 3.75$), with the associated standard errors being substantially underestimated in the simple binary logistic model (standard error, 0.35) (table 9). The point estimates for state income inequality from both these models, meanwhile, were *underestimated* when compared with the point estimate associated with state income inequality estimated from a two-level binary logistic model, with the state-attributable variance being explicitly modeled ($\beta = 5.26$) (table 9). The standard errors associated with the state income inequality point estimates from the marginal and two-level logistic models, meanwhile, are identical (standard error, 1.08).

One conclusion, in this instance, is that models that did not explicitly model the state-attributable variation underestimated the state income inequality effect with an odds ratio of 1.21 as compared with an odds ratio of 1.30 from a multilevel model. As noted earlier, most studies do *not* estimate and model the state-attributable variation (or area-attributable variation) in an explicit multilevel manner. Indeed, the rationale to use a multilevel, rather than a marginal, model is precisely when our focus is on the “area effects” rather than average population values, as is the case in marginal models. It should nonetheless be emphasized that area-attributable variation can be specified and modeled in both simple and complex ways (54), and here we have illustrated the simplest example of a multilevel model.

Meanwhile, it is well known that the interpretation of the β coefficients is different in a multilevel and a marginal model. For example, in a multilevel model, the β coefficient associated with state income inequality represents the change in the response probability of poor health for an individual in a *given state* and *conditional* on the unit change effected by the individual predictors *within each state*. Accordingly, there have been attempts to incorporate the “unit-specific” interpretation of the fixed β coefficients from a multilevel model (74). Meanwhile, in the marginal model, the β coefficient represents the *population* change in the individual response probability of poor health across *all* states for different levels of state income inequality and, as such, *averages* the effect across all states. As can be expected, this can lead to potential differences in the actual estimates between a multilevel and a marginal model. Future research, therefore, needs to carefully consider the choice of modeling strategy and specification on one hand and, on the other, to understand the precise conditions under which different modeling approaches produce different point estimates, thus enabling a truer interpretation of the state income inequality effects.

CONCLUSION

If recent national and global economic trends provide any indication, it is very likely that the subject matter of income inequality and its effects on population health will continue to be relevant for social epidemiology. We must emphasize that any discussion of inequality and health, in general, cannot be divorced from the fundamental question of “inequality of what?” (9, 75). Indeed, income-based inequality is, at best, simply one dimension that could be relevant to population health. Other axes of stratification (or hierarchy), such as the unequal distribution of wealth, political power, cultural assets, social assets, honorific status, human capital (to name a few), could also be important determinants of health outcomes (9). The aim in this review was, nevertheless, to focus on the literature that has investigated the empirical relation between income inequality and health. As our review suggests, the evidence implicating income disparities as a threat to public health is still far from complete. In this review, we highlighted what we have learned and what we still need to know. What is at stake is whether policy makers and the public health community ought to be concerned about the societal distribution of income in addition to the alleviation of income poverty through economic growth alone. As we have argued, the answer to that question depends on a combination of better data, more sophisticated analytical methods, and more rigorous application of theory and mechanisms connecting income inequality to public health.

ACKNOWLEDGMENTS

The authors thank Harvey Goldstein and Jim Ware for our exchanges with them with regard to comparisons of modeling strategies and Mah-J. Soobader and Stephen Gilman for their assistance with calibrating the marginal logistic model reported in this review.

REFERENCES

1. Subramanian SV, Kawachi I. Wage poverty, earned income inequality, and health. In: Heymann J, ed. *Global inequalities at work*. New York, NY: Oxford University Press, 2003:165–87.
2. Krugman P. For richer. *The New York Times Magazine* Oct 20, 2002:62–7.
3. Andrews EL. Economic inequality grew in 90’s boom, Fed reports. *New York Times* Jan 23, 2003:C1.
4. Marmot M. The influence of income on health: views of an epidemiologist. Does money really matter? Or is it a marker for something else? *Health Aff (Millwood)* 2002;21:31–46.
5. Subramanian SV, Belli P, Kawachi I. The macroeconomic determinants of health. *Annu Rev Public Health* 2002;23:287–302.
6. Wagstaff A, van Doorslaer E. Income inequality and health: what does the literature tell us? *Annu Rev Public Health* 2000; 21:543–67.
7. Kawachi I, Kennedy BP, Wilkinson RG. *The society and population health reader*. Vol 1. *Income inequality and health*. New York, NY: The New Press, 1999.
8. Rodgers GB. Income and inequality as determinants of mortality: an international cross-section analysis. *Popul Stud (Camb)* 1979;33:343–51.
9. Kawachi I. Income inequality and health. In: Berkman LF, Kawachi I, eds. *Social epidemiology*. New York, NY: Oxford University Press, 2000:76–94.
10. Gravelle H. How much of the relationship between population mortality and unequal distribution of income is a statistical artefact? *BMJ* 1998;316:382–5.
11. Goldstein H. *Multilevel statistical models*. 3rd ed. London, United Kingdom: Hodder Arnold, 2003.
12. Raudenbush S, Bryk A. *Hierarchical linear models: applications and data analysis methods*. Thousand Oaks, CA: Sage Publications, 2002.
13. Laird N, Ware JH. Random-effects models for longitudinal data. *Biometrics* 1982;38:963–74.
14. Dempster AP, Rubin DB, Tsutakawa RK. Estimation in covariance components models. *J Am Stat Assoc* 1981;76:341–53.
15. Longford N. *Random coefficient models*. Oxford, United Kingdom: Clarendon Press, 1993.
16. Blakely TA, Lochner K, Kawachi I. Metropolitan area income inequality and self rated health—a multilevel study. *Soc Sci Med* 2002;54:65–77.
17. Blakely TA, Kennedy BP, Glass R, et al. What is the lag time between income inequality and health status? *J Epidemiol Community Health* 2000;54:318–19.
18. Diez-Roux AV, Link BG, Northridge ME. A multilevel analysis of income inequality and cardiovascular disease risk factors. *Soc Sci Med* 2000;50:673–87.
19. Kennedy BP, Kawachi I, Glass R, et al. Income distribution, socioeconomic status and self-rated health: a US multilevel analysis. *BMJ* 1998;317:917–21.
20. Soobader MJ, LeClere F. Aggregation and the measurement of income inequality: effects on morbidity. *Soc Sci Med* 1999;48: 733–44.
21. Kahn RS, Wise PH, Kennedy BP, et al. State income inequality, household income, and maternal mental and physical health: cross sectional national survey. *BMJ* 2000;321:1311–15.
22. Lochner K, Pamuk ER, Makuc D, et al. State-level income inequality and individual mortality risk: a prospective multilevel study. *Am J Public Health* 2001;91:385–91.
23. Subramanian SV, Kawachi I, Kennedy BP. Does the state you live in make a difference? Multilevel analysis of self-rated health in the U.S. *Soc Sci Med* 2001;53:9–19.
24. Subramanian SV, Blakely T, Kawachi I. Income inequality as a

- public health concern: where do we stand? Commentary on "Is exposure to income inequality a public health concern?". *Health Serv Res* 2003;38:153–67.
25. Subramanian SV, Kawachi I. The association between state income inequality and worse health is not confounded by race. *Int J Epidemiol* 2003;32:1022–8.
 26. Fiscella K, Franks P. Poverty or income inequality as predictors of mortality: longitudinal cohort study. *BMJ* 1997;314:1724–8.
 27. Daly MC, Duncan GJ, Kaplan GA, et al. Macro-to-micro links in the relation between income inequality and mortality. *Milbank Q* 1998;76:315–39.
 28. Mellor JM, Milyo J. Reexamining the evidence of an ecological association between income inequality and health. *J Health Polit Policy Law* 2001;26:487–522.
 29. Mellor J, Milyo J. Is exposure to income inequality a public health concern? Lagged effects of income inequality on individual and population health. *Health Serv Res* 2003;38:137–51.
 30. Sturm R, Gresenz CR. Relations of income inequality and family income to chronic medical conditions and mental health disorders: national survey. *BMJ* 2002;324:20–3.
 31. Shibuya K, Hashimoto H, Yano E. Individual income, income distribution, and self rated health in Japan: cross sectional analysis of nationally representative sample. *BMJ* 2002;324:16–19.
 32. Gerdtham UG, Johannesson M. Income inequality and mortality. Malmö, Sweden: Department of Community Medicine, Malmö University Hospital, 2001.
 33. Jones K, Duncan C, Twigg L. Evaluating the absolute and relative income hypothesis in an exploratory analysis of deaths in the Health and Lifestyle Survey. In: Boyle P, Curtis S, Graham E, eds. *The geography of health inequalities in the developed world*. London, United Kingdom: Ashgate Press, 2004.
 34. Osler M, Prescott E, Gornbaek M, et al. Income inequality, individual income, and mortality in Danish adults: analysis of pooled data from two cohort studies. *BMJ* 2002;324:13–16.
 35. Blakely T, O'Dea D, Atkinson J. No association of income inequality with adult mortality within New Zealand. *J Epidemiol Community Health* 2003;57:279–84.
 36. Smeeding TM. U.S. income inequality in a cross-national perspective: why are we so different? In: Auerbach JA, Belous RS, eds. *The inequality paradox: growth of income disparity*. Washington, DC: National Policy Association, 1998:194–217.
 37. Subramanian SV, Degaldo I, Jadue L, et al. Income inequality and health: multilevel analysis of Chilean communities. *J Epidemiol Community Health* 2003;57:844–8.
 38. Krugman P. *The great unraveling: losing our way in the new century*. New York, NY: WW Norton & Company, 2003.
 39. Kawachi I, Kennedy BP. *The health of nations*. New York, NY: The New Press, 2003.
 40. Liang KY, Zeger SL, Qaqish B. Multivariate regression analyses for categorical data. *J R Stat Soc (B)* 1992;54:3–40.
 41. Zeger SL, Liang K, Albert P. Models for longitudinal data: a generalised estimating equation approach. *Biometrics* 1988;44:1049–60.
 42. Heagerty PJ, Zeger SL. Marginalized multilevel models and likelihood inference (with discussion). *Stat Sci* 2000;15:1–26.
 43. Goldstein H, Browne W, Rasbash J. Tutorial in biostatistics: multilevel modelling of medical data. *Stat Med* 2002;21:3291–315.
 44. Lindsey JK, Lambert P. On the appropriateness of marginal models for repeated measurements in clinical trials. *Stat Med* 1998;17:447–69.
 45. Lynch J, Davey Smith G. Commentary: income inequality and health: the end of the story? *Int J Epidemiol* 2002;31:549–51.
 46. Lynch J, Harper S, Davey Smith G. Commentary: plugging leaks and repelling boarders—where to next for the SS income inequality? *Int J Epidemiol* 2003;32:1029–36.
 47. Deaton A. Commentary: the convoluted story of international studies of inequality and health. *Int J Epidemiol* 2002;31:546–9.
 48. Mellor JM, Milyo J. Income inequality and individual health: evidence from the Current Population Survey. *J Hum Res* 2002;37:510–39.
 49. CPS utilities: data, documentation and extraction utilities for the US Bureau of the Census Current Population Surveys. Santa Monica, CA: Unicon Research Corporation, 1998.
 50. Idler EL, Benyamini Y. Self-rated health and mortality: a review of twenty-seven community studies. *J Health Soc Behav* 1997;38:21–37.
 51. Kawachi I, Kennedy BP. The relationship of income inequality to mortality: does the choice of indicator matter? *Soc Sci Med* 1997;45:1121–7.
 52. Historical income tables for states: table S4. Gini ratios by state: 1969, 1979, 1989. Washington, DC: Income Statistics Branch/Housing and Household Economic Statistics Division, US Census Bureau, 2000.
 53. Historical income tables for states: table S1. Median household income by state: 1969, 1979, 1989. Washington, DC: Income Statistics Branch/Housing and Household Economic Statistics Division, US Census Bureau, 2000.
 54. Subramanian SV, Jones K, Duncan C. Multilevel methods for public health research. In: Kawachi I, Berkman LF, eds. *Neighborhoods and health*. New York, NY: Oxford University Press, 2003:65–111.
 55. Goldstein H, Rasbash J. Improved approximations for multilevel models with binary responses. *J R Stat Soc (A)* 1996;159:505–13.
 56. Rasbash J, Browne W, Goldstein H, et al. *A user's guide to MLwiN, version 2.1*. London, United Kingdom: Multilevel Models Project, Institute of Education, University of London, 2000.
 57. Milyo J. Income distribution, socioeconomic status, and self-rated health in US. Authors ignored data in their study. (Letter). *BMJ* 1999;318:1417–18.
 58. Subramanian SV, Kawachi I. Response: In defence of the income inequality hypothesis. *Int J Epidemiol* 2003;32:1037–40.
 59. Pearce N, Davey Smith G. Is social capital the key to inequalities in health? *Am J Public Health* 2003;93:122–9.
 60. Muller A. Education, income inequality, and mortality: a multiple regression analysis. *BMJ* 2002;324:23–5.
 61. Blakely TA, Kawachi I. Education does not explain association between income inequality and health. (Letter). *BMJ* 2002;324:1336.
 62. Deaton A, Lubotsky D. Mortality, inequality and race in American cities and states. *Soc Sci Med* 2003;56:1139–53.
 63. Wilkinson RG. Income inequality, social cohesion, and health: clarifying the theory—a reply to Muntaner and Lynch. *Int J Health Serv* 1999;29:525–43.
 64. Aberg YM, Fritzell J, Lundberg O, et al. Exploring relative deprivation: is social comparison a mechanism in the relation between income and health? *Soc Sci Med* 2003;57:1463–73.
 65. Fritzell J, Lundberg O. Income distribution, income change and health: on the importance of absolute and relative income for health status in Sweden. Stockholm, Sweden: Swedish Institute for Social Research, 1995.
 66. Kawachi I. Income inequality and economic residential segregation. (Editorial). *J Epidemiol Community Health* 2002;56:165–6.
 67. Lobmayer P, Wilkinson RG. Inequality, residential segregation by income, and mortality in U.S. cities. *J Epidemiol Community Health* 2002;56:183–7.
 68. Massey D. The age of extremes: concentrated affluence and

- poverty in the twenty-first century. *Demography* 1996;33:395–412.
69. Kawachi I, Berkman LF. Social cohesion, social capital, and health. In: Berkman LF, Kawachi I, eds. *Social epidemiology*. New York, NY: Oxford University Press, 2000:174–90.
 70. Lochner K, Kawachi I, Kennedy BP. Social capital: a guide to its measurement. *Health Place* 1999;5:259–70.
 71. Subramanian SV, Lochner KA, Kawachi I. Neighborhood differences in social capital: compositional artifact or a contextual construct? *Health Place* 2003;9:33–44.
 72. Subramanian SV. The relevance of multilevel statistical models for identifying causal neighborhood effects. *Soc Sci Med* 2004; 58:1961–7.
 73. Goldstein H, Browne WJ, Rasbash J. Partitioning variation in multilevel models. *Understanding Stat* 2002;1:223–32.
 74. Larsen K, Petersen JH, Budtz-Jorgensen E, et al. Interpreting parameters in the logistic regression model with random effects. *Biometrics* 2000;56:909–14.
 75. Sen AK. *Inequality reexamined*. Cambridge, MA: Harvard University Press, 1992.