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Issue: *The Biology of Disadvantage***Evaluating the evidence base: Policies and interventions to address socioeconomic status gradients in health^a**William H. Dow,¹ Robert F. Schoeni,² Nancy E. Adler,³ and Judith Stewart³¹Division of Health Policy and Management, School of Public Health, University of California, Berkeley, CA, USA. ²Institute for Social Research, University of Michigan, Ann Arbor, MI, USA. ³Department of Psychiatry, University of California, San Francisco, CA, USA

Address for correspondence: William H. Dow, Division of Health Policy and Management, School of Public Health, University of California, Berkeley, 239 University Hall, Berkeley, CA 94720-7360. wdow@berkeley.edu

This chapter discusses the current evidence base for policies that could address socioeconomic status (SES) health gradients in the United States. The present volume has documented an enormous amount of research on the linkages between SES and health, but there are still relatively few studies that rigorously establish the effectiveness of particular policies or interventions in reducing those gradients. Given the difficulty in developing randomized evidence for many types of interventions related to social determinants of health, we argue for conducting policy analysis from a Bayesian perspective. This Bayesian approach combines information on best available theory and evidence regarding probable health benefits and costs of an intervention, providing a framework that also incorporates the probable costs of inaction. The second half of the chapter adopts a ladder metaphor to classify policies and interventions that could reduce SES gradients in population health. Using this framework, we consider the evidence base for various types of policies, focusing primarily on the social determinants of health, under the rubric that “all policy is health policy.” We conclude by discussing promising strategies for future strengthening of the evidence base for policy, including the role of health impact assessment.

Keywords: socioeconomic status; health policy; health disparities

Introduction

This volume has documented an enormous amount of research on the linkages between socioeconomic status (SES) and health. SES and health exhibit strong relationships throughout time and place, and across many dimensions of SES and health. In terms of political science theories of policy stages, the research community has clearly established that a striking and highly troubling phenomenon exists. As discussed in the Dow and Rehkopf chapter, these SES gradients in health are worse in the United States than in many other settings and have been worsening in recent decades. These gradients have been recognized by researchers for many years, and in some settings have risen onto the agenda of policy makers, though much more so in Europe and Canada than in the United States. Once publicly acknowledged by agenda setters as a problem, selecting effective

policies and interventions requires a deeper body of evidence to point to the most promising approaches for causally ameliorating the gradients.

Research advances highlighted in this volume contribute to this policy formulation effort by elucidating specific biological pathways by which SES “gets under the skin” and influences health outcomes. This helps establish where there are plausible causal pathways running from SES to health, helps guide development of appropriately targeted interventions, and suggests outcomes to measure for purposes of evaluating intervention effects. Despite this wealth of new research, however, the evidence base includes few studies that rigorously establish the effectiveness of particular policies or interventions based on strong experimental or quasi-experimental causal designs. Indeed, relatively few out of the thousands of SES health gradient studies are even able to convincingly tease out

what portion of that observed relationship reflects causal pathways from SES to health, as opposed to the adverse SES effects of ill health, or third variable explanations. Nevertheless, many in the field believe that there is now a strong case in favor of public policies targeting the social determinants of health. How do we reconcile the paucity of strong causal evidence with this strong support for policy intervention?^a

The next section of this chapter presents a cost-benefit framework useful for addressing this tension as we move from evidence to policy, and argues that in place of using statistical significance of randomized trials as the paramount guide to policy, a Bayesian policy analysis approach provides a more appropriate framework for guiding decisions in this arena. If the weight of theory and evidence suggests that SES is likely to have substantial causal effects on population health, then even in the absence of strong causal evidence, the Bayesian approach in many cases may favor proactive policies and interventions.

The latter half of the chapter uses a ladder metaphor to illustrate a framework for classify-

^aThe tension about what policy implications are supported by the existing evidence base has at times been presented as tension between disciplines. Economists are sometimes characterized as overly dismissive of observational studies and hence reluctant to draw firm policy conclusions about social determinants. Some social epidemiologists have in turn been thought to allow personal preferences for redistribution to color their interpretation of the strength of the evidence regarding the extent to which redistribution would lead to improved population health. Our extended interactions at multidisciplinary meetings of the MacArthur Network on SES and Health have suggested that these stereotypes are often unfair. It is certainly likely that historically prevailing attitudes within disciplinary traditions shape people's predispositions when initially engaging with this topic. While each discipline has its own set of theoretical priors, prevailing attitudes, and preferred methodological approaches, when engaged with the full spectrum of evidence arising out of the many perspectives represented in this volume, we have found that many of the supposed disciplinary blinders recede. This experience (see chapter by Adler and Stewart in this volume on the network process) reaffirms the importance of cross-fertilization of ideas, approaches, and results across disciplinary silos in improving our ability to move from research to informative policy debates.

ing various types of policies and interventions that could reduce SES gradients in population health. Using this framework, we consider the evidence base for various types of policies, focusing primarily on the social determinants of health, under the rubric that "all policy is health policy." We conclude by discussing promising strategies for strengthening the evidence base for policy.

A framework for moving from evidence to policy

Classical randomized trial approach to evidence-based decisions

Across many disciplinary traditions, the randomized trial has been considered to yield the strongest (most internally valid) level of evidence. The Evidence-Based Medicine movement and its precursors have for many years emphasized randomized studies as providing the highest possible level of evidence. To be recommended for adoption under this approach, a treatment should ideally be shown in a randomized trial to yield positive health benefits at the 5% significance level. Recent reviews have discussed application of these concepts to the related area of Evidence-Based Public Health.^{1,2} A key difficulty highlighted is that while some public health interventions are amenable to randomized study, many population-level social determinant interventions have to date not been feasible to study using randomization designs. If randomized evidence was required for policy decisions, then this would remove many population-based interventions from consideration, in favor of more individualized interventions that are more amenable to randomization, such as medical care.³ However, other researchers have argued that the lack of randomized trial results should not imply lack of action; decisions still must be made, and should use the best *available* evidence.⁴ In fact, many health policies and interventions are based on evidence that is relatively weak or sometimes missing altogether. While the evidence base in both medicine and public health is growing, it is still relatively limited. A majority of medical practices have weak to no formal evaluation.⁵ Within public health, a recent study found that more than 40% of programs lack an evidence base.⁶ Thus while it is of course desirable to have the strongest evidence possible, it would be a counterproductive double standard to insist on

randomized evidence before backing any policies or interventions relating to the social determinants of health.

Potts *et al.* went further than this, arguing that where nonexperimental evidence is strongly suggestive, it would be unethical *not* to act.⁷ They approvingly cite Smith and Pell's satirical essay that provocatively argues that because randomized trials have not proven the efficacy of parachutes, they should not be used until a randomized, placebo-controlled parachute trial has been conducted.⁸ Extensive commentary in letters submitted to the journal in response criticized Potts *et al.*, however, on two key counts. First, there was concern about possible cherry picking of the nonexperimental evidence in support of some favored approach. Indeed, Ioannidis warns that nonrandomized studies may systematically produce larger results than randomized ones, presumably due to data mining (possibly inadvertent) and publication bias problems, and that "claimed research findings may often be simply accurate measures of the prevailing bias" in a field.^{9,10} Randomized trials do not wholly avoid this problem, however, as their design and framing may reflect underlying assumptions and they often produce conflicting results. Concern about publication bias and data mining highlights the importance of critical, comprehensive, and balanced literature reviews; however, it should not preclude the use of nonexperimental evidence when it is the best available for policy. A second critique of the Potts *et al.* approach is potentially more serious: that the health field is replete with examples of poorly tested and now discontinued practices and interventions that have turned out to be useless or even harmful on net after further study. However, such cases are not the norm, and this critique ignores the many medical practices that have turned out to indeed be beneficial despite lack of early rigorous testing. What these concerns highlight is the importance of having a framework for prospectively using the best available information to choose which interventions are expected to have net benefits that are greater than net costs.

Decision science and Bayesian policy analysis

Here, we turn to the field of Decision Science, an area of study devoted to making optimal use of evidence for decision making, based on the tools of cost-effectiveness, cost-utility, and cost-benefit

analysis.¹¹ A considerable portion of this field has focused on decisions about clinical medicine, but similar conceptual principles apply to nonmedical health policies. Among the most important conceptual differences between decision analysis and the traditional focus on randomized trials is that unlike classical statistics, decision analysis does not focus solely on 5% significance levels to determine whether an intervention is recommended. Cost-benefit analysis (the conceptually most appropriate but most challenging decision science method in practice), is guided instead by an analysis of whether, after appropriately considering all of the benefits and costs of a policy or intervention, and their estimated uncertainty, the expected benefits outweigh the expected costs.

Consider an intervention that would increase health by ΔH units over the status quo, at an incremental cost of ΔC . To reflect uncertainty about our estimates, the future time path of benefits, and the value of health, we will represent the health improvement as having a present discounted (i.e., as valued today) expected value of $EV[\Delta H]$. Similarly, represent the present discounted expected value of intervention costs as $EV[\Delta C]$. The benefit-cost decision rule would be to recommend this intervention for populations where: $EV[\Delta H] > EV[\Delta C]$. Note that proponents of an intervention often argue that the "cost of inaction" (maintaining the status quo) must be considered as well. This cost of inaction is already incorporated into the decision rule, as it typically refers to the value of the foregone health improvement, $EV[\Delta H]$, which would not be obtained if the intervention were not to be adopted. But it is useful to state in both manners, as a reminder to focus not just on the costs of the intervention $EV[\Delta C]$, but to instead compare which of these amounts is larger. More precisely, the net "cost of inaction" can be defined as $EV[\Delta H] - EV[\Delta C]$; that is, the net surplus to society that would be foregone if the intervention were not adopted.

Actual estimation of the full $EV[\Delta H]$ and $EV[\Delta C]$ is of course complex, but focusing here on this simple relation is instructive for thinking about common features of policies and interventions discussed in the latter half of the chapter. Consider what is included in the cost calculation $EV[\Delta C]$. As the cost-effectiveness literature has emphasized, this should capture any incremental change in direct and indirect costs, both now and in the future, as

compared to what costs would have been in the absence of the intervention. Whose costs are included will depend on whether the analysis is from the perspective of an individual, family, or some larger population group. A typical population health analysis might take the perspective of the nation, thus include both personal and public budgetary costs of everyone in the nation. From this perspective, any unintended efficiency loss caused by the intervention should also be taken into account. For interventions with public budgetary costs (including many key social determinants discussed below), an important efficiency loss to take into account would be the “marginal cost of public funds”;¹² that is, the welfare loss from reduced work effort caused by raising taxes. Raising \$1 of budget revenue may cost the economy \$1.15 for a relatively nondistortionary tax, or it could cost substantially more for other types of taxes that have bigger negative impacts on behavior. It would also be appropriate to include among the costs any other losses induced by the program, such as negative work incentives induced by means-testing programs; in practice, however, such costs are rarely estimated and thus are left to be considered more qualitatively alongside the numeric benefit–cost result.

Calculation of benefits $EV[\Delta H]$ also requires careful consideration. Many health investments may not pay off for many years, while costs are incurred upfront, thus benefits may be less striking after appropriately discounting. For example, if an early childhood program improves chronic disease outcomes by one unit when the child reaches age 50, then discounting at 3% annually yields a present value of that improvement equal to less than one-fourth of a unit. At the same time, when considering health benefits of nonhealth policies, it is important to take into account the value of nonhealth benefits as well. For example, Dow and Schoeni¹³ calculated the $EV[\Delta H]$ of health improvements from investing in college education so as to raise the health of less educated Americans up to the level of college-educated Americans; the health benefit was roughly one trillion dollars, but the wage benefit of education would likely be valued at more than double this amount. This finding, that the health value of nonhealth policy may be somewhat smaller than the nonhealth value, may be common when examining policies targeted at the social determinants of health. To accomplish a full analysis across different

types of outcomes, it is necessary to use a common economic value metric. It is tempting to cite the health benefits only in health units, such as reduced asthma cases or increased quality-adjusted life years (QALYs), but comparing the full costs and benefits of such policies will require going the next step and placing a dollar value on health (e.g., the commonly used value of \$100,000 per QALY). Valuing both health and nonhealth benefits is likely to result in more favorable assessments of the benefits of such policies.

What about the many sources of uncertainty in decision science analyses? Best practice in decision science modeling involves extensive sensitivity analysis. One type of sensitivity is with respect to modeling decisions and assumptions, such as the value of a QALY. A second type of sensitivity is with respect to statistical uncertainty surrounding the value of parameter inputs, such as the estimated effectiveness of an intervention on health. Stochastic decision analysis techniques have been developed from either a classical frequentist perspective, using traditional confidence intervals from a randomized trial, or alternatively from a Bayesian perspective using a prior distribution influenced by both confidence intervals and potentially subjective factors, such as strength of study design as well as theoretical priors. While one could insist on only using classical statistical inference from randomized trials when conducting decision analyses, such approaches are in the minority; a Bayesian-like choice of sensitivity thresholds has long been employed, and formal Bayesian practices are now emerging as well.^{14–16}

In fact, Claxton goes one step further, arguing for a full Bayesian-theoretic decision approach in which decisions are based only on whether mean net benefit is positive ($EV[\Delta H] > EV[\Delta C]$), regardless of confidence intervals (surrounding, for example, the estimate of the health effect ΔH).¹⁷ When a policy decision must be made, he argues that the best available estimates should be used and acted upon, without favoring one outcome over another based solely on arbitrary significance level choices. Claxton, Neumann, Araki, and Weinstein (2001) provide an example in which relying on a classical approach insisting on 5% significance levels would result in an unduly conservative decision to withhold an Alzheimer’s treatment, and thus would result in net harm to the population.¹⁸ It is

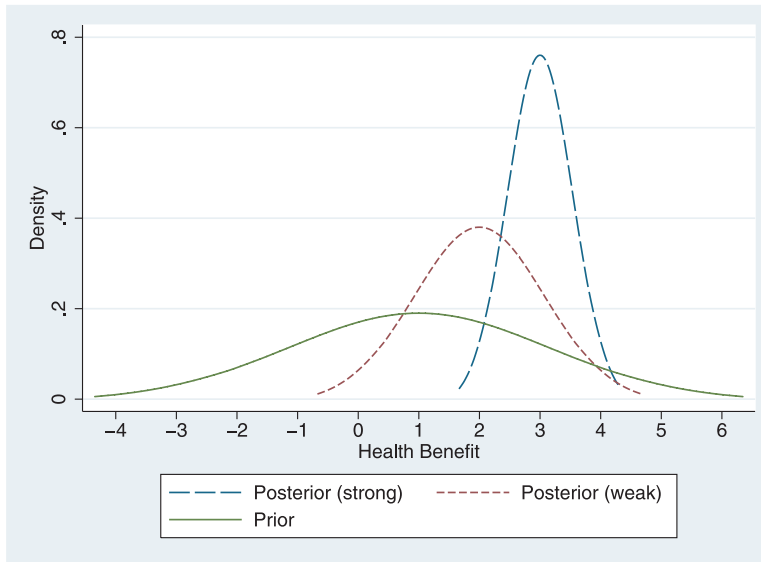


Figure 1. Illustrative Bayesian distributions of health improvements from interventions.

important to note though that this does not imply that confidence intervals and quality of evidence are irrelevant—on the contrary, in a Bayesian analysis the quality of evidence is likely to factor even more importantly than in a classical statistical paradigm.

In a Bayesian policy analysis, an analyst begins with theoretical arguments and evidence from related areas to form a *prior distribution* (i.e., prior to bringing to bear direct evidence on the policy) of the likely net empirical effect of the policy (on ΔH and ΔC). Although we discuss this prior distribution in formal statistical terms, it is of course common that these priors are held quite informally (by both researchers and policy makers). In a situation in which the analyst has a relatively diffuse prior, acknowledging, for example, the theoretical potential that the intervention has some chance of either helping or harming health, then before considering the weight of evidence, the analyst's prior is likely to be that a costly intervention would not yield net benefit. This situation is illustrated in the left-most distribution of Figure 1, which depicts a probability density function of the likelihood that the net health effects of an intervention would take on various values. The prior distribution of Figure 1 shows a mean estimated net health benefit that is positive (size one unit), but with considerable uncertainty. As new evidence develops, the analyst uses this new knowledge to

update this prior distribution, resulting in a new “posterior distribution” (reflecting the original theoretical information plus the new empirical evidence) of the net health benefits. If a strong randomized trial were conducted that precisely estimated large benefits, of say a magnitude four units net health improvement in the Figure 1 example, then the posterior distribution of ΔH might become quite tight and pulled close to that estimate. This is illustrated by the right-most (strong) posterior distribution in Figure 1, which results in an updated mean effect of three units. If the costs are less than three units, then the Bayesian analysis might accord well with the classical analysis. But if instead only a small observational study is available, even if it estimated the same effect size of four units, the prior distribution would not be moved as far to the right. Instead, the prior distribution may only weakly move to the right, as in the posterior distribution in the middle of Figure 1, which depicts an updated mean of two units. In this case, depending on the net cost, the Bayesian analysis may or may not yield an estimate that $EV[\Delta H] > EV[\Delta C]$. If the net cost were greater than two units then the Bayesian analysis would accord with a classical perspective, but if costs were below two units then even in the absence of a strong randomized trial the Bayesian analysis would support the policy proposal. Thus in Bayesian policy analysis, the validity

and precision of estimated ΔH only indirectly affects the policy recommendation, rather than dominating it. Instead of solely focusing on the statistical significance of randomized trial evidence, the Bayesian policy analysis is better able to incorporate both theoretical priors and weaker types of evidence, as well as the crucial information on intervention costs.

Finally, Claxton points out that this same Bayesian method of indirectly incorporating study quality and confidence intervals may be used to derive the value of producing additional research on ΔH , by estimating how likely different types of new evidence would be to substantially move the posterior distribution. Thus the Bayesian approach has the further benefit of helping guide efficient investment into future research agendas.

We next turn to considering types of policies and interventions that could reduce socioeconomic disparities in health. Many of these have characteristics discussed above. They generally lack evidence from randomized trials, while having varying degrees of observational evidence, as well as varying levels of theoretical agreement regarding likely orders of magnitude and direction of effects. The feasibility of conducting various types of decision analysis will also vary across these interventions. As of yet there are no formal Bayesian policy analyses to report, and given the nature of the political processes in which the evidence must be used, formal Bayesian analyses are unlikely to gain widespread use in considering these policies beyond the research community. But the conceptual framework of Bayesian policy analysis is crucial to apply even if informally: combining all available information from theory, randomized trials, and observational studies will provide a stronger basis for choosing those policies and interventions with the highest expected positive social benefit after accounting for full social costs.

A taxonomy of policies and interventions to reduce socioeconomic status gradients in health

A society can attempt to reduce SES–health gradients in many different ways. Here, we use the metaphor of the ladder (referred to elsewhere in the volume) to classify different types of policy options. Assume that the ladder reflects the SES distribution in a society, from low SES (bottom of the ladder) to high

(top of the ladder), with the 10 rungs of the ladder indicating the SES level of the 10 SES deciles. In Figure 2A, the 10 connected data points can be thought of as a curved SES ladder superimposed on a graph showing health on the vertical axis as a function of SES on the horizontal axis. The figure depicts the health gradient as nonlinear, diminishing with SES but still upward sloping even between the highest two rungs.

As we discuss each policy domain, we refer to current evidence on the impact of such policies on health; in some cases the evidence has already been examined in this volume (e.g., income and education in the Kawachi chapter). As Brownson *et al.* discuss,^{1,2} however, there are now a variety of organizations that provide public health evidence summaries, such as the Centers for Disease Control and Prevention’s (CDC’s) *Guide to Community Preventive Services*,¹⁹ and we do not duplicate those summaries here. For many of the types of policy examples mentioned below, however, there are no evidence summaries.

In fact, for some of these nonhealth social policies, the health implications remain relatively unexplored (e.g., effects of school quality). For some types of nonhealth policies, this is not surprising because nonhealth analysts have not appreciated the potential impacts on health, and health outcomes are not their central concern. This is unfortunate though both for those interested in health impacts and those interested just in social and economic impacts. Those interested in social and economic outcomes are estimating incomplete cost–benefit analysis by ignoring potential health benefits (or costs) of the policies. From the perspective of health researchers, ignoring these effects is unfortunate because in cases (such as, perhaps education) the health benefit of these nonhealth policies may in the long run swamp the health effects of more targeted health policies.

We also note that the decision analysis for whether to support such policies is dramatically more difficult for these nonhealth policies, as evidenced by the already difficult debates surrounding, for example, welfare reform. We do not attempt here to balance the health and other benefits against the larger sets of costs involved; we simply highlight the areas in which there may be substantial gradient-reducing health benefits. A substantial task lies ahead for researchers to tackle such issues in depth.

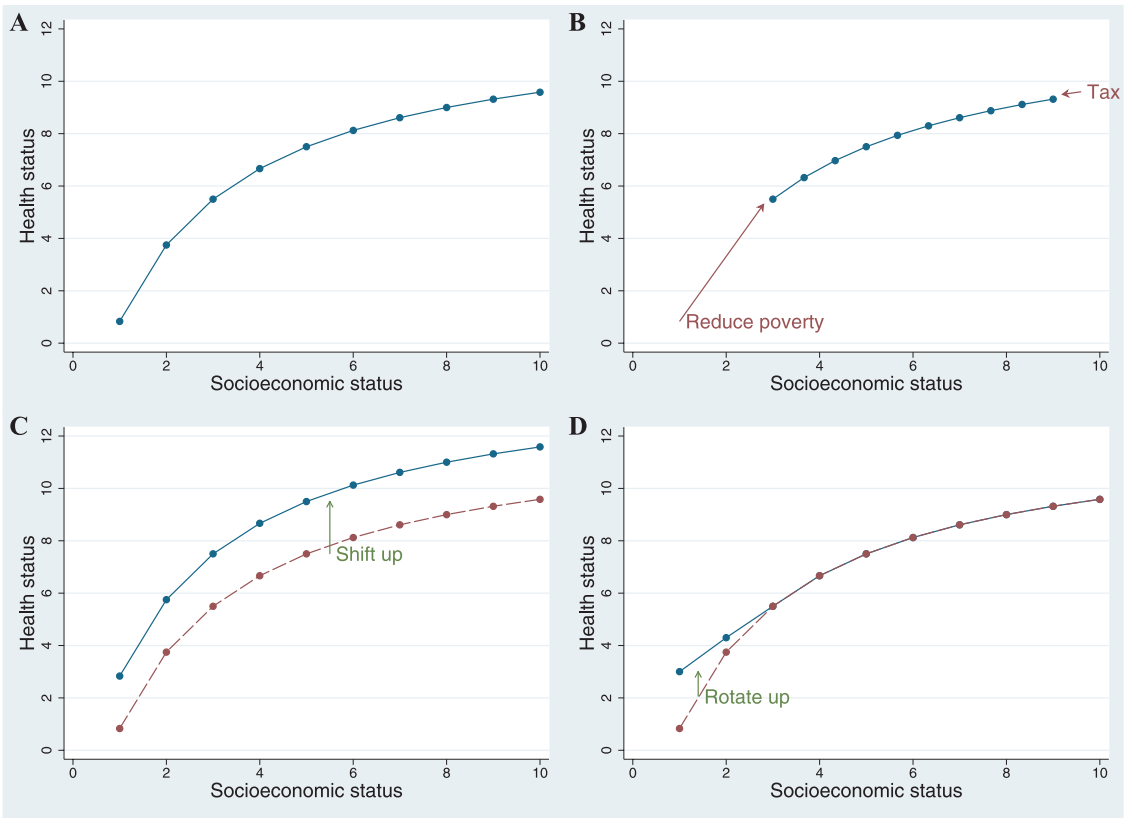


Figure 2. (A) Depiction of typical current ladder relationship between SES and health. (B) Shrinking the gradient through redistribution. (C) Investing in population-wide social determinants of health. (D) Reducing the gradient by targeting risks and improving buffers among the lowest SES groups.

A further general difficulty of the evidence base is that where some evidence is available, these studies often speak only to possible effects of the general construct under consideration (e.g., income) with little evaluation of specific interventions needed to influence the construct (e.g., earned-income tax credits vs. cash welfare). But as Kawachi, Adler, and Dow discuss in this volume, the specific mode of transmission may well effect both the magnitude as well as possibly even the sign of the health implications. Berkman²⁰ has argued that in order to refine proposed interventions it will be essential to better understand the social and institutional contexts and how they interact with individuals’ characteristics to produce very different health impacts in different settings. She further argues for a deeper understanding of the etiologic period during which individuals are most sensitive to intervention. As

discussed elsewhere in the volume, a great deal of research has suggested that prenatal and early childhood periods may be particularly important. It has been further argued that from a cost–benefit perspective investing in early life may yield much greater returns than investing in interventions during adulthood.²¹

The time dimension also deserves special attention in terms of the time needed for an intervention to have the expected effects. Many low-SES individuals have been in low SES settings for years, and their families and associated social networks may have been in low SES conditions for generations. Although the evidence is overwhelming that higher SES individuals have better health outcomes than low SES individuals, it is not a simple task to move an individual from one SES milieu to another. Income support policies can raise an individual’s

income dimension of SES, but raising income without intervening on the many other dimensions of that person's SES (such as wealth, education, social capital, neighborhood, etc.) may have only limited benefits. In fact, increasing the dissonance between SES dimensions may even be harmful. Such a concern is consistent with the Moving to Opportunity finding about a random low-income housing voucher allowing a move from a poor to a nonpoor neighborhood: in that study, male youths had worse physical health outcomes and engaged in more risky behaviors after their move.²² Similarly, unexpected negative health findings from positive income shocks were discussed in Kawachi, Adler, and Dow. It may be that the benefits of moving to a higher income level will not be seen until the next generation. This perspective is also consistent with fetal programming and epigenetic research discussed earlier in the volume. Poverty researchers have of course been attempting for decades to discover feasible poverty reduction policies within the United States, thus we face with humility the task of identifying appropriate poverty-reducing strategies that improve health. It is to this set of policies that we next turn as we begin the ladder-based health policy taxonomy.

Raising SES of the lowest SES groups

The left-hand arrow in Figure 2B illustrates the effect on the gradient of policies that improve the economic status of low SES populations, such as reducing poverty. By moving low SES individuals in a society up along the curve toward the right, gradients are reduced. Raising their SES leads to a tighter distribution of income in society, thus there is less scope for SES disparities in health. Graphically, this is illustrated as compressing the bottom of the ladder toward the middle, which shortens the distance between the rungs (SES deciles) on the ladder.

Examples

In the short run, programs that provide additional income to the family may assist the family in climbing up the ladder. These include transfer programs, such as Temporary Assistance for Needy Families, Supplemental Security Income, Supplemental Nutrition Assistance Program, and Special Supplemental Nutrition Program for Women, Infants, and Children; tax policy, such as the Earned Income Tax

Credit; and minimum wage legislation. The health outcome consequences of these policies have not been extensively investigated; see Herd, House, and Schoeni for a recent review of the health effects of income transfer programs.²³ Although many analysts have a strong prior expectation that these should improve health, the empirical literature has generated conflicting results as discussed by Kawachi, Adler, and Dow. For example, evidence suggests that some types of income may improve child health outcomes²⁴ while simultaneously raising adult obesity.²⁵ Studies on the impact of increasing income on health have thus far been relatively short run, however, leaving open the question of whether sustained intervention over decades may yield more unambiguously beneficial health results.

When considering interventions that may raise SES over the course of generations, a more commonly considered type of intervention is education. Several recent literature reviews of this topic offer compelling quasi-experimental evidence on health effects.^{26,27} Heckman has specifically argued for the importance of investing in early education, though there is little evidence to guide us regarding long-term health benefits; Muennig *et al.* report null effects of the Perry Preschool Project on health, but the confidence intervals are large due to the small sample size.²⁸ Equally vexing is the challenge in determining what dimension of education should be given higher priority. Muennig and Woolf have quantified health benefits versus costs of smaller class size, finding that reducing class sizes in kindergarten through grade 3 appears to be a cost-effective way to improve health (QALYs), but many more such studies will be needed before the literature could hope to provide evidence-based recommendations.²⁹ Given the strong disagreements about the direct educational effects of various types of educational interventions, we again should have humility as we attempt to glean the most productive educational investments in terms of health outcomes.

Redistribution away from highest SES

Along with raising the bottom of the ladder, one could develop policies that would shorten the top. Those could be coupled, since one method of financing poverty reduction is increasing taxes for high SES individuals. As depicted in the right-hand arrow of Figure 2B, this would have the further effect

of moving the right tail of the SES distribution toward the mean, thus again reducing scope for SES-related health gradients but also lowering health of the most advantaged. More generally, with the type of nonlinear ladder depicted here characterized by diminishing marginal health productivity of SES, redistribution from high SES to low SES will reduce SES health disparities and increase total health in the population. Graphically, this is illustrated as shortening the top of the ladder, bringing those at upper SES levels closer toward the mean.

Examples

Raising top marginal tax rates, and regulating executive pay, are two examples of such redistribution. We are not aware of any evidence regarding direct health consequences of these policies. It is plausible that reducing the super wealthy could have spillover health effects due to lower inequality, though as discussed in the Kawachi, Adler, and Dow chapter, the evidence is weak on this point.

Reducing population-wide risk exposures

By reducing population-wide risk exposures, lower SES individuals often experience disproportionate benefits due to their higher vulnerability and lower incomes. Graphically, such population-wide investments are depicted in Figure 2C as raising the entire ladder equally, though in some cases we could expect a larger rise for the low SES due to their greater risk. It should be noted, however, that some population-wide policies may differentially benefit those higher on the ladder. To the extent that achieving health benefits requires corollary action on the part of individuals, those higher on the ladder may be better equipped to take advantage of the intervention or policy. For example, smoking rates have dropped in relation to a variety of policies, but the drop has been sharper among those with more income and more education.

Examples

Policies with population-wide consequences include clean air legislation, antidiscrimination policies, gas taxes, and tobacco taxes. *A priori* these could be expected to have larger impacts on lower SES individuals. For example, Chay and Greenstone have found that reduced air pollution disproportionately lowered infant mortality among disadvantaged populations.³⁰

Targeted exposure reduction among low SES

Gradients exist in part due to higher risk exposures among the low SES. If those exposures can be reduced, this would rotate up the left portion of the ladder, thus reducing part of the negative health consequences of low SES (Fig. 2D).

Examples

The workplace is one promising arena for prevention to help reduce exposures to both occupational illnesses as well as toxic stress, as discussed by Clougherty, Souza, and Cullen in this volume. Another arena with much current active research is that of neighborhoods. Interventions have been proposed for improving low-income neighborhoods by increased policing, expanding parks and recreational opportunities, reducing liquor store licensing, encouraging green grocers, etc. CDC's *Guide to Community Preventive Services* discusses evidence reviews of some dimensions of these interventions. In general, the evidence is not yet sufficient to recommend intervention according to classical statistical criteria. This is an area in which many people have strong theoretical priors about the likely benefits of community intervention, thus many local policy makers are ahead of the classical statistical evidence currently, perhaps implicitly using Bayesian policy analysis criteria to justify intervening before the evidence base is built.

Buffering negative health consequences of low SES

As discussed above, low SES individuals may have fewer coping resources for buffering the adverse effects of shocks. Providing buffers can again result in the left portion of the ladder rotating up in Figure 2D, thus reducing the health gradient across the population.

Examples

A variety of buffers have been proposed to help protect low SES individuals from the negative health consequences of their higher exposure risks, including universal health insurance, paid sick leave policies, workplace control and autonomy, and social support interventions. Health insurance is perhaps the most important of these, as well as the most studied, and the one with the largest welfare impact.³¹ Another area that has been studied extensively, is social support; there have even been recent

randomized trials, although they have been largely negative thus far, which is something of a caution regarding the challenges in constructing actual intervention programs to fit our hypothesized pathways.²⁰

Strengthening the social safety net

The left tail of Figure 2A partly comprises individuals who in previous periods were higher on the ladder but subsequently experienced negative shocks, sometimes beyond their control, such as recession-driven involuntary unemployment. Policies that strengthen the social safety net can prevent individuals from experiencing precipitous drops down the SES ladder. Over time, this can result in fewer individuals at the lower end of the ladder, thus having the same net effect as policies that raise the lower part of the SES distribution as depicted in Figure 2B.

Examples

Unemployment insurance and job training programs are crucial examples of safety net policies. But while the health consequences of unemployment have been extensively studied and discussed elsewhere in this volume, there is in fact little evidence regarding the extent to which particular features of unemployment insurance may or may not protect health.

Conclusion

Moving forward, there is great scope for generating additional relevant analysis of specific policies and interventions to inform future agenda setting. To the extent that existing policies can be evaluated using strong designs with perhaps quasi-experimental methods, this should by all means be encouraged.

The evaluation of policies in nonhealth sectors, including those that we have discussed in this paper, may be facilitated by the use of “health impact assessments (HIAs).” HIAs are similar to EIAs, environmental impact assessments. HIAs evaluate the effects of a given policy on health of the affected population while EIAs focus primarily on the impact on the physical environment. HIAs are currently being used primarily in Europe. However, there is growing interest in and application of them in the United States³² where they have largely been applied to municipal policies thus far. For example,

HIAs have estimated the health impact on the residents of San Francisco of a city ordinance requiring a living wage rather than a minimum wage,³³ and the health impact on the Inupiat populations in Alaska’s North Slope of the development of oil fields.³⁴ The methodology could potentially be used for state or federal policy as well. At whatever level HIAs are done, they will require an evidence base to inform the evaluation of health effects. There are some early efforts to undertake to acquire and systematize such information.³⁵ However, this is a formidable task and much work remains to be done.

As the Health Impact Assessment field matures, practitioners as well as researchers will likely be contributing substantially to our evidence base. Their work would be further enhanced by closer attention to the principles of cost–benefit and cost-effectiveness analysis, which have been refined in recent decades for related studies. It would also benefit the field to develop a body to serve as an information clearing house of completed studies on social determinants, to identify ongoing efforts, and help match relevant interventions with potential researchers.

While additional research is needed, we believe there is ample existing evidence to support our priors that social and economic factors have a first-order effect on improving population health. The research literature has firmly established many times over the existence of socioeconomic gradients in health, and a great deal of research suggests that these are often due to causal effects of socioeconomic factors on health. For many policies, these benefits to health augment well-established benefits in social and economic outcomes such as labor market earnings and income. Moreover, we have argued that lack of randomized trials should not in and of itself preclude investments in reducing health gradients. In settings outside the United States, agenda setters have successfully promoted social determinants policies despite the equivocal evidence. Recently, the Robert Wood Johnson Foundation’s Commission for a Healthier America released a set of recommendations agreed upon by their bipartisan commission as having evidence sufficient for policy recommendation, including a focus on early childhood education.³⁶ The commission, however, did not take on the issue of poverty reduction as a strategy for improving health and reducing gradients. A future effort to focus on ways to improve

health by reducing child poverty could yield meaningful progress in the policy realm.

The challenge in translating this evidence into policy is in identifying specific policy levers that could in fact substantially improve health and pass the cost-benefit test. Our reading of the evidence is that if socioeconomic disparities in U.S. population health are to be substantially improved by the next generation, investing in all manner of education is broadly speaking one of the most promising approaches. Supplementing this with income support policies, particularly surrounding pregnancy and early childhood, could also have substantial benefits according to our understanding of the current literature. Current national efforts to reduce uninsurance could rectify some important dimensions of current gradients, but preparing for a future national debate over expanded educational attainment should be a high priority for health policy researchers interested in the social determinants of population health.

Conflicts of interest

The authors declare no conflicts of interest.

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