Contributions of Health Care to Longevity: A Review of 4 Estimation Methods

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ABSTRACT

PURPOSE Health care expenditures and biomedical research funding are often justified by the belief that modern health care powerfully improves life expectancy in wealthy countries. We examined 4 different methods of estimating the effect of health care on health outcomes.

METHODS We reviewed the contributions of medical care to health outcomes using 4 methods: (1) analyses by McGinnis and Schroeder, (2) Wennberg and colleagues' studies of small area variation, (3) Park and colleagues' analysis of County Health Rankings and Roadmaps, and (4) the RAND Health Insurance Experiment.

RESULTS The 4 methods, using different data sets, produced estimates ranging from 0% to 17% of premature mortality attributable to deficiencies in health care access or delivery. Estimates of the effect of behavioral factors ranged from 16% to 65%.

CONCLUSIONS The results converge to suggest that restricted access to medical care accounts for about 10% of premature death or other undesirable health outcomes. Health care has modest effects on the extension of US life expectancy, while behavioral and social determinants may have larger effects.

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INTRODUCTION

It is often argued that improvements in population health,[1,2] and life expectancy in particular,[3] are best pursued via investments in medical services. Over the last few decades evidence has accumulated, showing that more powerful determinants of health and life expectancy lie elsewhere.[4] Making high-yield investments to extend life expectancy requires an understanding of the relative contributions of health care and other determinants of health[5] to health outcomes.

It is estimated that a lack of access to medical care accounts for only about 10% of premature deaths.[6] The methodology underlying these estimates, however, remains obscure. In this article we review 4 different estimates of the contributions of health care to premature mortality and other health outcomes.

METHODS

Using Google Scholar, we searched for articles about the relationship between medical care and life expectancy. In addition, we considered reports from the National Academy of Medicine[7] that reviewed estimates of the contributions of health care to health outcomes. Two articles with high citation rates were identified. McGinnis and Foege[8] has been cited nearly 4,000 times, and their estimates were updated in 2004.[9] And a report by Schroeder,[6] that built on their method, has been cited over 800 times. We reviewed articles that cited these 2 milestone works to identify other attempts to produce similar estimates that had achieved high citation rates.

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The RAND Health Insurance Experiment summary[10] emerged as a frequent reference (cited over 1,500 times) for the limited effects of medical care on longevity. Estimates based on small area variation studies were developed by Wennberg and collegues,[11] while Park and collegues[12] relied on comparisons of US counties.

For each of the 4 methods, we summarize estimates provided by the authors. Kreiger persuasively argued that various determinants of health should not be expected to add up to 100%.[13] In our review, we excluded estimates that were derived by subtracting the percentages attributable to other determinants from 100%. A summary of the data sources and analysis methods for the 4 approaches is provided in Table 1, and a description of each is provided below.

McGinnis and Schroeder

In an article cited over 800 times, Schroeder[6] argued that 40% of premature deaths can be attributed to behavior patterns, 15% to social circumstances, 10% to medical care, and 5% to environmental exposure. The remaining 30% was attributed to genetic predispositions. Schroeder's estimates[6] were based on a 1993 article by McGinnis and Foege[8] and 2002 article by McGinnis, Williams-Russo, and Knickman.[14] They explored information about the presence or absence of factors associated with premature mortality for the leading causes of death. As an example, for motor vehicle crashes that resulted in a fatality, they looked for evidence that the driver had a blood alcohol level high enough to cause impairment. Factors considered in their analysis ranged from health habits to preventable infectious diseases, and any toxic exposures. For each leading cause of death, McGinnis and Foege[8] calculated a population-attributable fraction associated with risk for the fatal disease. For lung cancer, they estimated that cigarette smoking accounted for 80% to 90% of premature deaths from lung cancer and that smoking could shorten life expectancy by about a decade. When population-attributable fractions were calculated for each of the major diseases, they summed the proportion of all deaths attributable to underlying behaviors or exposures. To accommodate for uncorrected overlap, the estimated total for each cause of death was the sum of the lower bounds of available estimates, not the midpoints. McGinnis/Schroeder refer to these conservative estimates as the true underlying causes of death.[6,8]

McGinnis and Foege[8] noted that cigarette smoking was the most important underlying cause of death, accounting for 400,000 premature US deaths each year. Diet and physical activity patterns accounted for another 300,000 premature deaths, while alcohol overuse was associated with over 100,000 early deaths. Also on the list of the top 10 underlying causes of death were those related to firearms, risky sexual behavior, motor vehicle crashes, and illicit drug use.

Several authors reference the McGinnis/Schroeder articles[6,8] for the 10% estimate of premature death attributable to poor access to quality medical care. In an *Annual Review of Public Health* report by Lee and Paxman,[15] 20% of premature deaths were attributed to genetic factors, 20% to socioeconomic factors, and 10% to inadequacies of medical care. They assumed the remaining 50% was attributed to behavior patterns. Lee and Paxman[15] cite the McGinnis and Foege[8] analysis as the basis for their estimates, but we excluded their analysis because the crucial estimate for behavior patterns was obtained by subtraction from 100%. Other reports reference an article by McGinnis, Williams-Russo, and Knickman,[14] which provides

Table 1. Summary of the Data Sources and Analysis Methods

Study	Population	Data Source	Analysis Method
McGinnis,[8] Schroeder[6]	US population	US Vital Statistics	Examined PAF for a range of risk factors associated with defined causes of death. Summed PAF for each determinant across various causes of death
Wennberg[11]	US Medicare recipients aged ≥65 years enrolled in Parts A and B in 2007	Medicare claims. Deaths among Medicare recipients in 2007	Evaluated variation in use of health care and age, sex, and race adjusted mortality across 306 HRRs. Applied regression with adjustments for medical diagnoses, poverty, and a behavioral index
Park[12]	US population aggregated at the county level	2010-2013 County Health Rankings and Roadmaps database included 2,996 (95%) of US counties	LGCM used to estimate health outcome, which was a combination of morbidity and mortality. Four factors (behaviors, clinical care, social/economic, and physical environment) used to explain health outcomes with statistical adjustment for yearly variation and state specific characteristics
Newhouse[10]	2,750 families including 7,700 individuals aged <65 years randomly assigned to different levels of cost sharing[a] and followed 3-5 years	Health surveys and physical examinations administered at the beginning and end of the study	Comparisons of experimental groups for self-reported outcomes. Similar comparisons for clinical diagnoses, including hypertension, vision, dental health, and serious symptoms

HRR = hospital referral region; LGCM = latent growth curve modeling; PAF = population attributable fraction; US = United States.

[a] Levels of cost sharing were 0% (free medical care), 25%, 50%, or 95%.

the same numbers. That article similarly does not show how the numbers were derived, but cites a Centers for Disease Control and Prevention analysis suggesting that about 10% to 15% of premature mortality could be avoided through access to higher quality health care. The McGinnis and Foege[8] article does not include an original assessment of the contributions of medical care to premature death. Lack of reliable medical care is mentioned in a section of the article that cites a report from the Carter Center suggesting that 7% of premature deaths before age 65 may be attributable to lack of access to primary care.[16] Unfortunately, the Carter Center publication does not provide the information necessary to replicate the calculations.

Wennberg and Colleagues

Another line of evidence comes from research on variations in health care use. Wennberg and colleagues studied the wide variations in health care costs for Medicare recipients across 306 hospital service areas in the United States.[11] The investigators used Medicare claims data to estimate which factors account for the variations in cost and in mortality, using (1) a medical diagnoses index based on the Centers for Medicare and Medicaid Services Hierarchical Condition Clusters Index; (2) a poverty index based on the proportion of the population aged 65 years and older that had total household incomes below the federal poverty line; and (3) a behavioral health index based on the number of people with hip fractures, obesity, self-reported health problems, smoking, and strokes.

In small area variation studies, the best predictors of mortality are typically the basic demographic factors: age, sex, and race. It is not a surprise to demographers that communities with a higher proportion of older people or men have higher death rates. Black race is also a predictor of shorter life expectancy.[17] Because these relationships are well known, analysts often consider them nuisance variables and the analyses are reported with adjustments for age, sex, and race.

The index of medical diagnoses was a strong predictor of medical care costs, but explained only about 5% of the variation in mortality adjusted for age, sex, and race. Conversely, the behavioral index was a much better predictor, explaining 65% of the variation in mortality. In other words, knowing the diagnoses of people in a geographic region does not tell us a lot about death rates. Further, some communities spend much more on medical care than others. With or without adjustment for the disease burden, communities that receive more medical care do not have longer life expectancies. Other factors, such as the proportion of people in the region who are obese, smoke cigarettes, and self-report health problems, are much better predictors of mortality rates.[18]

Park and Colleagues

Using a completely different methodology, Park and colleagues[12] set out to evaluate the relative contributions of several factors to health outcomes. The 2010-2013 County Health Rankings and Roadmaps database provided information from 2,996 of the 3,141 counties in the United States, which was used with latent growth curve modeling (LGCM) to estimate the contributions of factors to the variability of selected health outcomes. The outcomes included premature mortality and morbidity assessed through self-reported poor physical health days, self-reported poor mental health days, and low birthweight. The index gave equal weight to mortality and morbidity. The predictor variables included health behaviors (tobacco use, diet and exercise, alcohol use, sexual activity), clinical care (access to care, quality of care), social and economic factors (education, employment income, family and social support, community safety), and physical environment (air quality and building environment). The County Health Rankings and Roadmaps database included detailed information on each of these characteristics. For example, in each county, education was classified as high school graduation, some college, or college degree. For physical environment, air quality was estimated by air pollution ozone days, air pollution particulate matter days, and daily air particulate matter. A measure of drinking water quality was also included. The analysis was done sequentially for the years 2010 through 2013. We concentrated on overall estimates obtained from the average across years. The LGCM analyses were adjusted for proportions of African American and Hispanic residents in each county, and for the percentage of each county that was rural. Further, the model adjusts for estimated measurement error attributable to yearly variations and to state-specific characteristics.

The adjusted multilevel LGCM model was used to estimate the relative contributions of each factor to the aggregate health outcomes. The unit of analysis was county. The estimates suggested that health behaviors accounted for 28.9% of the variation in health outcomes, social and economic factors for 45.6%, health care for 17.2%, and physical environment for 8.3%.

In her critique of the method, Kreiger[13] noted that the LGCM model accounted for only 54% of the within-state variation in health outcomes. The common variance explained was then divided into the 4 categories to obtain estimates that sum to 100%. She argued that the estimates should be multiplied by 0.54. To get to 100%, an unexplained category representing 46% of the variation should be added. Following Kreiger's suggestion, we offer low estimates for each category that were obtained by multiplying the original estimate by 0.54.

Newhouse and the Insurance Experiment Group

An additional approach is represented by the RAND Health Insurance Experiment.[10] The experiment, conducted in the 1970s, randomly assigned families to health insurance plans that varied in required copayments.[19] At one end of the continuum was a plan that had no cost sharing. Those assigned to this plan received health care without any out-of-pocket expenses (free care). At the other end of the continuum was a plan that required out-of-pocket expenditures until a high annual deductible of $1,000 was met.[20] The 2 other groups had intermediate levels of cost sharing, with copayments of 25% or 50% with the same deductible.[20]

Variation in cost sharing had a substantial impact on the use of health care services. Those in the high-deductible group had about 40% fewer visits to doctors compared to those who received medical care without copayments. In addition, they were 23% less likely to be admitted to the hospital and had costs that were 31% lower than those with free care. These results suggest that manipulation of out-of-pocket expenditures has substantial effects on the utilization of health care. For our purposes, the manipulation of health insurance benefits created an experimental comparison of the effects of having more or less health care.

The effect of variability in health services received on health outcomes was less clear. Overall, assignment to different levels of cost sharing did not have substantial effects on health outcomes. An early article suggested that variation in health care had no effect on health status.[11] A later analysis showed that less health care resulted in damaged health for some vulnerable populations. For example, hypertension was less well-controlled among those in the high-cost sharing plan, resulting in an approximate 10% increase in the probability of death.[21]

On the basis of the RAND Health Insurance Experiment and subsequent analyses, we use a range of 0% to 10% assessment for the effects of health care on longevity. A summary of the estimates derived from the 4 methods is offered in Table 2.

DISCUSSION

We estimated the effect of health care on premature death using 4 methods. The estimates converge around Schroeder's conclusion[6] that health care accounts for between 5% and 15% of the variation in premature death. The various methods were consistent in showing that social and behavioral factors account for a much higher percentage of the variation in premature mortality than health care does. For example, the McGinnis/Schroeder method[6,8] estimates that social circumstances account for about 15% of the variance in early mortality. The Wennberg method[11] estimates that social circumstances account for 29% of variability, and the Park model[12] estimates that social effects account for 46%. Similarly, the McGinnis/Schroeder method[6,8] estimates that behavior patterns account for 40% of the variability in early mortality, the Wennberg method[11] estimates 65%, and the Park method[12] estimates 29%. In sum, these methods indicate that social and behavioral factors account for substantially more of the variability in premature mortality than health care does.

Each of the 4 methods considered the percentage of premature deaths or poor health outcomes to be attributable to various factors. The methods reported here differ from regression models, which estimate the amount of variance attributable to various factors, although regression model estimates sometimes suggest similar conclusions. For example, we obtained information on the costs of health care as a proportion of the 2017 gross domestic product for countries reporting data to the Organization for Economic Cooperation and Development (OECD), and we used OECD data on life expectancy. In wealthy countries, there is an approximately linear relationship between health care expenditure and longevity. The coefficient of determination (R^2) for this relationship is 0.12, suggesting that about 12% of the variation in life expectancy can be explained by variation in health care expenditure. The estimate varies depending on which OECD countries are included in the analysis. For high-income countries, there is a negative relationship, primarily driven by the United States as an outlier with relatively high cost and low life expectancy. It might be argued that 10% is a common result in analysis of messy data. Percentage of variation explained is estimated from the coefficient of determination, which is the correlation squared. Correlations of 0.32 account for about 10% of the variation.

Table 2. Summary of Estimates from 4 Methods

Study	Social Circumstances	Behavior Patterns	Medical Care
McGinnis,[8] Schroeder[6]	15	40	7-10
Wennberg[11]	29[a]	65[b]	5-17[c]
Park[12]	25-46[d]	16-29[d]	7-17[d]
Newhouse[10]	NE	NE	0-10

LGCM = latent growth curve modeling; NE = not estimated.

[a] Includes 19% based on poverty index + 10% from age, race, sex adjustment.

[b] Based on a population health index that includes obesity, smoking status, and self-reported poor physical health days/month.

[c] Low estimated from Hierarchical Condition Cluster (HCC); high estimated from HCC adjusted for demographic variables.

[d] Low estimates based on Krieger's suggestion that reported numbers should be adjusted by the percentage of variance in outcomes accounted for LCGM by the model.[13] This was accomplished by multiplying each estimate by 54%.

We must emphasize that the 4 methods we reviewed are very different from one another. They use different outcome measures, analytic techniques, and data sets. One important concern in our comparison is that the 4 approaches differ in what was measured (Table 1). Some of the methods use attributable risk models and describe how much of current life expectancy, or a proxy for it, can be attributed to each determinant. A problem with attributable risks, as reported by McGinnis and Foege,[8] is that they cannot simply be summed. To address this problem, the McGinnis and Foege method[8] used death, rather than premature mortality, as the numerator, but the denominator remained undefined. Other models estimate the contribution of each factor for increasing life expectancy. While we observed that each approach converges on somewhat the same result, we are unable to explain why this should be the case.

Another concern is that the 4 methods used different measures of health, medical care, and social determinants. As a result, estimates for health behaviors and for social factors may be based on different underlying variables. Further, behaviors and social determinants are highly correlated, so their relative importance may differ while their combined effects may be similar. The inclusion of genetics in the McGinnis/Shroeder model[6,8] suggests immutable components are also included; this differs from other models that seek to identify opportunities for intervention. The subject populations for the various studies also differ. The Wennberg[11] data set, for example, focused on the elderly population (Medicare data) while other studies considered a wider range of ages. Although the Medicare population is important, it completely ignores infant mortality, which is a likely source of health care-associated variation.

An important article by Kreiger cautioned that causes of health should not be expected to sum to 100%.[13] Different determinants of health might combine independently or synergistically to more than 100%. In part, this is because the determinants of health are often highly correlated. When the population-attributable fraction is determined independently for each risk factor, it is likely that the sum will exceed 100% because the overlap between pairs of determinants is double counted. In the Schroeder analysis, deaths were attributed to health care (10%), behavioral factors (40%), social circumstances (15%), and environmental exposures (5%).[6] The remaining 30% was ascribed to genetic predispositions. We deemphasize the estimate that genetic factors contributed 30% to premature mortality because that value was obtained by subtracting the other influences from 100%.

Krieger's critique[13] of the County Health Rankings and Roadmaps effort[12] emphasized that the method was not independent of other analyses. For example, in addition to the original analysis of county data, the county rankings relied on judgments from experts and on weights from other analyses, including the McGinnis report.[8] It might be argued that the estimates converge, at least in part, because the analyses are not independent. The methods used by Wennberg[11] and in the RAND Health Insurance Experiment,[10] however, appear to be completely independent of the McGinnis/Shroeder[6,8] and Park[12] approaches.

Several lines of evidence suggest that income and poor health habits are associated with poor access to medical care.[22,23] As a result, the population-attributable fraction for medical care should be inflated. In other words, the estimate that 10% of premature mortality is attributable to medical care is more likely to be an overestimate rather than an underestimate. In order to avoid the assumption that determinants sum to 100%, we report population-attributable fractions for independent risk factors. We avoided interpretation of percentages that were obtained by subtracting the other determinants from 100%.

Our search for methods for estimating contributions of various determinants to premature mortality is not likely to have been exhaustive. Other attempts to estimate the effects of medical treatment have also suggested modest benefits. Bunker, Frazier, and Mosteller[24] estimated the effects of curative and preventive interventions on life expectancy, and found that some treatments produce substantial benefit for individuals. For example, successful treatment of women with cervical cancer could add 21 years to the life expectancy of a particular patient. The condition affects about 13,000 women annually, therefore the estimated gain in total US population life expectancy for treatment of cervical cancer is only 1 week. Similarly, successful treatment of colorectal cancer could add 12 years of life to as many as 155,000 adults. But on a population-wide basis, it contributes only about 1 week to average life expectancy. Likewise, treatments for appendicitis, pneumonia, and influenza, although successful for many individuals, on average have a negligible effect on population life expectancy. Only a few conditions have large effects on population health. In particular, ischemic heart disease treatment might add 6 to 8 months of life expectancy to the overall population. The larger population effect is related to prevalence. Successful prevention or treatment of heart disease could add an average of 14 years of life to as many as 6 million people. Similarly, prevention or treatment of hypertension, which in the Bunker et al[24] analysis affected 58 million people, would add about 10 years of life for affected individuals, resulting in a population gain of 4 months. Overall, Bunker et al[24] argued that medical care had only small effects

on population life expectancy, even though it can have large effects on individuals.

CONCLUSIONS

The suggestion that health care services account for only a small percentage of the variation in national life expectancy has important implications. Both personal and institutional health care expenditures are justified by confidence that health care spending enhances longevity and other indices of population health. Efforts to model the value of health care spending often assume that 100% of the variation in health outcomes is attributable to health care services. Even the most sophisticated models assume that 50% of the variation in population health is attributable to health care.[1,2,25] Our analyses reaffirm the belief that health care is 1 component of a larger set of influences on health outcomes. An intervention associated with 10% of the variation in life expectancy in wealthy countries such as the United States is a worthy investment. The evidence that we examined suggests that a more diversified portfolio of national investments in health care services would generate a higher yield in the United States and other wealthy countries. For example, the United States is an outlier in expenditure on health care, but is closer to the center of the distribution of wealthy counties on the combination of medical and other nonmedical human capital spending. Wealthy OECD countries spend on average about $2 on nonmedical social services for each $1 spent on medical care. In contrast, US expenditure is about $0.55 for nonmedical social services for each $1 spent on medical care.[26] The recently enacted Chronic Care Act allowing Medicare Advantage plans to cover interventions beyond traditionally defined health care is a step in the right direction. Due to a longer duration of health benefit, extending similar coverage policies to pregnant women and children enrolled in Medicaid, may generate even higher yields.

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