# Relative Contributions of a Set of Health Factors to Selected Health Outcomes

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Although many researchers agree that multiple determinants impact health, there is no consensus regarding the magnitude of the relative contributions of individual health factors to health outcomes. This study presents a method to empirically estimate the relative contributions of health behaviors, clinical care, social and economic factors, and the physical environment to health outcomes using nationally representative county-level data and statistical approaches that account for potential sources of bias. The analyses for this study were conducted in 2014. Data were from the 2010–2013 County Health Rankings & Roadmaps. Data covered 2,996 of 3,141 U.S. counties. Ordinary least squares modeling was used as a baseline model. Multilevel latent growth curve modeling was used to estimate the relative contributions of health factors to health outcomes while accounting for measurement errors and state-specific characteristics. Almost half of the variance of health outcomes was due to state-level variation rather than county-level variation. When adjusted for measurement errors and state-level variation using multilevel latent growth curve modeling, the relative contribution of clinical care decreased and that of social and economic factors increased compared with the baseline model. This study presents how potential sources of bias affected the estimates of the relative contributions of a set of modifiable health factors to health outcomes at the county level. Further verification of these approaches with other data sources could lead to a better understanding of the impact of specific health determinants to health outcomes, and will provide useful information on policy interventions.

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## Introduction

The population health perspective has provided a comprehensive framework that emphasizes not only medical care but also health behaviors, socioeconomic factors, and physical environmental factors as important determinants of health.[1–6] Various attempts have been made to assess the relative impact of each determinant on health outcomes at the population level. These efforts have included expert and public opinion,[5,7–9] econometric analyses, and comparative assessment.[10–12] Namely, two national ranking models have combined population health models and available measures to draw attention to the multiple determinants of health. These models, and the weights associated with their specific measures, are widely used by researchers, policymakers, and the general public.[13,14] Yet, there is still no consensus regarding the magnitude of the relative contributions of health factors to health outcomes because of a lack of empirical support for the models.[8] Research approaches that provide empirically testable estimates for the relative contributions are required.

Increased availability of multiple years' worth of data for a wide variety of measures and advances in analytic approaches have created an opportunity to empirically examine the relative impacts among various health factors and health outcomes. These approaches provide researchers with the ability to carefully consider potential threats to validity, such as measurement error and nested characteristics, when using observational and ecological data. Therefore, the purpose of this study was to improve empirical estimates for relative contributions by accounting for potential sources of bias using county-level data. The authors' hypothesis is that estimates from the baseline model will be gradually improved by minimizing the impacts from measurement errors and then state-specific characteristics, among other sources of bias.

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## Methods

### Study Sample

Data were from the 2010–2013 County Health Rankings & Roadmaps (The Rankings). The Rankings project is designed to facilitate and promote community health improvement and is conducted by the University of Wisconsin Population Health Institute in collaboration with the Robert Wood Johnson Foundation.[14] Based on a model of population health, the Rankings measure the health of nearly all of the 3,143 counties and county equivalents in the U.S. using county-level measures capturing modifiable characteristics, and rank them from healthiest to least healthy within each state. The study sample consisted of 2,996 counties that were ranked all 4 years. This study was considered exempt from oversight by the University of Wisconsin IRB as data were at the county level and no individual private information was used.

## Statistical Analysis

Models examined in this study used composite scores (e.g., health behaviors composite score for 2013) instead of individual measures (e.g., adult smoking and adult obesity) for two reasons. First, the definitions and data sources of several individual measures varied by year (Figure 1). Second, model fit, which was poor while using individual measures, was moderate when using composite scores. Composite scores of health outcomes, health behaviors, clinical care, social and economic factors, and the physical environment were derived as a weighted sum of standardized measure values for each year.[14] Weights for constructs were adjusted for the inverse of the total weight for each construct. Therefore, composite scores still account for the variation of the reliability for each measure, but they were no longer confined by the Rankings weight scheme at the construct level.

$$\text{Composite Score of Construct} = \left(\sum \omega_i \cdot \frac{\text{County Value}_i - \text{Average}_i}{SD_i}\right) \Big/ \sum \omega_i,$$

where $i$=measure; $SD_i$=$SD$ of each measure; and $\omega_i$=weight for each measure used in the Rankings.

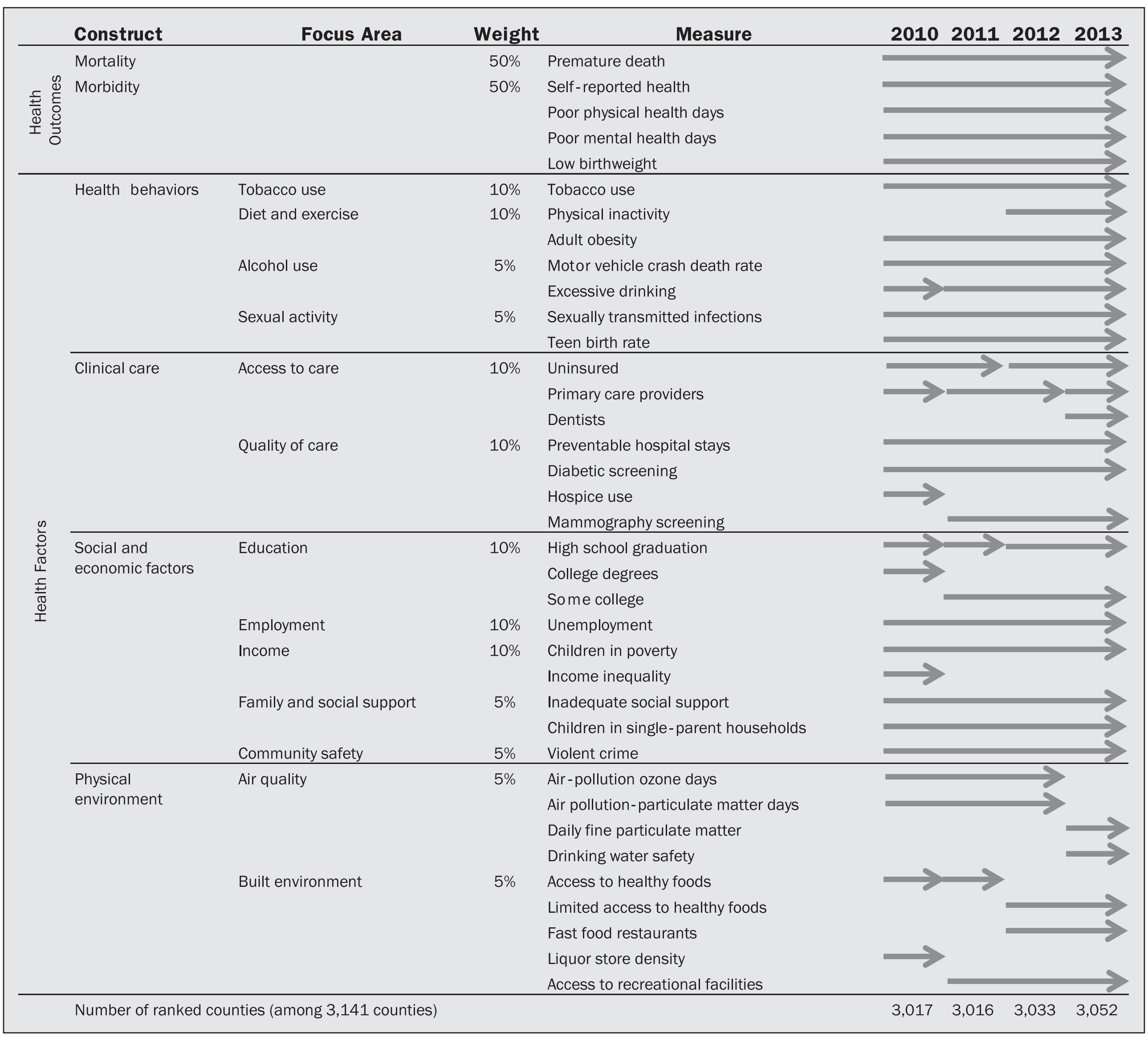


**Figure 1.** Measures used in the 2010–2013 County Health Rankings & Roadmaps.
*Note*: Years of available data are represented by arrows. Broken arrows represent substantial changes in the data source or calculation of the measure that would affect year to year comparisons. Data and details are available at www.countyhealthrankings.org.

Baseline estimates for the relative contributions of health factors to health outcomes without any adjustment were derived using pooled ordinary least squares (OLS). The estimates from OLS modeling were crude (i.e., baseline estimates) because OLS modeling per se is incapable of directly addressing measurement error[15] or nested characteristics (e.g., state-specific characteristics).[16] The potential impact of measurement errors and state-specific characteristics on the estimates of the relative contributions of health factors to health outcomes was examined by comparing baseline estimates from OLS to estimates derived using structural equation modeling (SEM) and hierarchical linear modeling (HLM). SEM, which is capable of simultaneously assessing construct validity and reliability in the estimation of the contribution of each unique health factor to health outcomes,[15] was used to detect measurement error, while HLM, which is an extension of OLS modeling that takes into account the nested characteristics of counties within states,[16] was used to detect the impacts of state-specific characteristics.

After identifying the impact of measurement error and state-specific characteristics, the authors improved upon the estimates from SEM and HLM by using latent growth curve modeling (LGCM) and multilevel LGCM. LGCM, as an extension of SEM, allows researchers to address growth trajectories during the study period using both intercept and slope latent constructs.[17] The structural association between latent constructs for health factors and health outcomes was estimated while parameterizing the yearly variations as slopes for adjustment purposes. This study's estimates from LGCM and multilevel LGCM, therefore, represent the contributions of each health factor to health outcomes at the middle of the study period (e.g., the intercept estimates for June 2011) after adjusting for the yearly variations of each construct (e.g., the slope estimates for each construct during a study period). Multilevel LGCM additionally incorporated hierarchical aspects of analyses (e.g., counties are nested within states)[15,18] to adjust for potential state-specific characteristics. Covariance among latent constructs was parameterized in the analyses to adjust for the potential correlation among these constructs.

The relative contributions were calculated using standardized coefficients representing the proportion of the total variance of each health factor.[19,20] Model fit statistics and cut off criteria[15,21,22] were presented. Intraclass correlation coefficients (ICCs) from multilevel LGCM were presented to show the amount of variation in health outcomes due to unobserved state-specific characteristics on health outcomes. The potential measurement errors indicating how well latent constructs from multilevel LGCM summarize each composite score over years were presented as residual variances of observed composite scores to the underlying latent variables. All analyses were adjusted for county characteristics, including population size, sex and age distribution, proportion of African American and Hispanics, and the percentage of the population living in a rural setting. The analyses for this study were conducted in 2014. Data management and statistical analyses were performed in SAS, version 9.3, and Mplus, version 7.1.

## Results

Table 1 summarizes the estimated relative contributions of health factors to health outcomes from OLS, HLM, and SEM. The OLS estimates for relative contributions of health factors to health outcomes were 26.5% for health behaviors, 32.5% for clinical care, 36.5% for social and economic factors, and 4.5% for physical environment. When adjusting for potential state-specific characteristics using HLM, there were considerable changes in the relative contributions as compared with those in OLS, resulting in estimates of 31.6%, 14.9%, 47.3%, and 6.2%, respectively. The relative impact of clinical care decreased 17.6% points (from 32.5% to 14.9%), whereas that of health behaviors increased 5.1% points (from 26.5% to 31.6%) and social and economic factors increased 10.8% points (from 36.5% to 47.3%) as compared with the baseline OLS model.

The authors also found that considerable yearly variations of estimated relative contributions existed. In HLM, for example, the estimated relative contributions of health behaviors ranged from 30.0% in 2011 to 35.4% in 2012 and those of clinical care ranged from 9.3% in 2010 to 20.0% in 2012. However, when accounting for these yearly variations as measurement errors using SEM, the estimated relative contributions were 24.1% for health behaviors, 31.4% for clinical care, 39.3% for social and economic factors, and 5.2% for physical environment, respectively, which were similar to those from OLS.

The authors further developed LGCM to adjust for yearly variations, and then multilevel LGCM to additionally account for state-specific characteristics (Table 2). The estimated relative contributions from LGCM were similar to those from OLS or SEM, and those from multilevel LGCM were similar to those from HLM (Tables 1, 2). Furthermore, the revision of the model from LGCM to multilevel LGCM greatly improved the model fit, although the fit statistics of LGCM and multilevel LGCM were not strong overall. When measurement errors (i.e., yearly variations) and state-specific characteristics were adjusted for using multilevel LGCM, the relative contributions of the four health factors were estimated as 28.9% for health behaviors, 17.2% for clinical care, 45.6% for social and economic factors, and 8.3% for physical environment.

Table 3 also supports the finding that significant variation in estimates was due to state-specific characteristics. Almost half of the variance of health outcomes using multilevel LGCM was due to state-level variation rather than county-level variation (ICC=0.48–0.49). ICCs for health behaviors, clinical care, and social and economic factors ranged from 0.41 to 0.54, indicating considerable influence of state-specific characteristics. State-level variation was smaller in the physical environment (ICC=0.19–0.41) than the other health factors, but still substantial in magnitude. Table 3 also summarizes residual variances that quantify the degree of measurement errors in composite scores for each latent construct. Measurement errors in the physical environment

**Table 1.** Estimated Relative Contributions of Health Factors on Health Outcomes Using OLS, HLM, and SEM

| | Overall | | 2010 | | 2011 | | 2012 | | 2013 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Est. (SE)** | **RC, %** | **Est. (SE)** | **RC, %** | **Est. (SE)** | **RC, %** | **Est. (SE)** | **RC, %** | **Est. (SE)** | **RC, %** |
| Baseline model using OLS | | | | | | | | | | |
| Health behaviors | 0.67 (0.03) | 26.5 | 0.68 (0.04) | 28.1 | 0.55 (0.03) | 23.9 | 0.71 (0.03) | 30.3 | 0.74 (0.03) | 28.7 |
| Clinical care | 0.81 (0.03) | 32.5 | 0.74 (0.04) | 30.3 | 0.67 (0.03) | 29.1 | 0.76 (0.03) | 32.4 | 0.74 (0.03) | 28.9 |
| Social and economic factors | 0.92 (0.03) | 36.5 | 1.00 (0.04) | 40.9 | 1.08 (0.03) | 46.9 | 0.78 (0.03) | 33.6 | 0.77 (0.03) | 30.1 |
| Physical environment | 0.11 (0.04) | 4.5 | 0.02 (0.03) | 0.7 | 0.00 (0.03) | 0.0 | 0.09 (0.03) | 3.7 | 0.32 (0.04) | 12.3 |
| Adjusted models for state-specific characteristics using HLM | | | | | | | | | | |
| Health behaviors | 0.71 (0.04) | 31.6 | 0.66 (0.04) | 31.5 | 0.62 (0.04) | 30.0 | 0.75 (0.04) | 35.4 | 0.75 (0.04) | 32.7 |
| Clinical care | 0.34 (0.04) | 14.9 | 0.20 (0.04) | 9.3 | 0.23 (0.04) | 11.1 | 0.43 (0.04) | 20.0 | 0.41 (0.04) | 18.0 |
| Social and economic factors | 1.07 (0.04) | 47.3 | 1.21 (0.04) | 57.4 | 1.16 (0.04) | 56.2 | 0.87 (0.04) | 40.7 | 0.90 (0.04) | 39.0 |
| Physical environment | 0.14 (0.04) | 6.2 | 0.04 (0.03) | 1.8 | 0.06 (0.03) | 2.7 | 0.08 (0.03) | 3.9 | 0.24 (0.04) | 10.3 |
| Adjusted models for potential measurement errors (i.e., yearly variations) using SEM | | | | | | | | | | |
| Health behaviors | 0.26 (0.01) | 24.1 | | | | | | | | |
| Clinical care | 0.33 (0.02) | 31.4 | | | | | | | | |
| Social and economic factors | 0.42 (0.02) | 39.3 | | | | | | | | |
| Physical environment | 0.06 (0.02) | 5.2 | | | | | | | | |

*Note:* The estimates are based on the standardized composite scores for health outcomes and health factors for each year. Population size, sex, and age distribution; proportion of African American and Hispanic; and percentage of rural area were controlled for.
HLM, hierarchical linear model; OLS, ordinary least square; RC, relative contribution; SEM, structural equation model.

**Table 2.** Estimated Relative Contributions of Health Factors on Health Outcomes Using OLS, LGCM, and Multilevel LGCM

| | OLS Model | | LGCM | | Multilevel LGCM | |
|---|---|---|---|---|---|---|
| | **Est. (SE)** | **RC, %** | **Est. (SE)** | **RC, %** | **Est. (SE)** | **RC, %** |
| Health behaviors | 0.67 (0.03)* | 26.5 | 0.25 (0.01)* | 24.9 | 0.27 (0.03)* | 28.9 |
| Clinical care | 0.81 (0.03)* | 32.5 | 0.31 (0.01)* | 30.6 | 0.16 (0.03)* | 17.2 |
| Social and economic factors | 0.92 (0.03)* | 36.5 | 0.35 (0.01)* | 34.8 | 0.43 (0.03)* | 45.6 |
| Physical environment | 0.11 (0.04)* | 4.5 | 0.10 (0.02)* | 9.7 | 0.08 (0.02)* | 8.3 |
| Model fit (cut off) | | | | | | |
| $\chi^2$ ($p \geq 0.05$ is preferred) | n.a. | | 8,200.5* | | 6,056.8* | |
| AIC (smaller is preferred) | 6,681.4 | | 90,811.6 | | 82,984.1 | |
| RMSEA ($<$0.10 is preferred) | n.a. | | 0.10 | | 0.07 | |
| CFI ($\geq$0.95 is preferred) | n.a. | | 0.93 | | 0.93 | |
| SRMSR ($<$0.08 is preferred) | | | | | | |
| Within | n.a. | | 0.12 | | 0.11 | |
| Between | n.a. | | n.a. | | 0.18 | |

*Note:* The estimates are based on the standardized composite scores for health outcomes and health factors for each year. Slopes were parameterized in both LGCM and multilevel LGCM to adjust for the yearly variations; estimates for the slopes were suppressed in the table. Population size, sex, and age distribution; proportion of African American and Hispanic; and percentage of rural area were controlled for. Cut off criteria came from Kline (2011) and Kenny (2014).

AIC, Akaike information criterion; CFI, Bentler comparative fit index; LGCM, latent growth curve model; n.a., not applicable; OLS, ordinary least squares; RC, relative contributions; RMSEA, root mean square error of approximation; SRMSR, standardized root mean square residual.

*$p < 0.001$.

**Table 3.** Assessment of the Potential State-Level Effect and Measurement Errors Using Multilevel Latent Growth Curve Model

| | Year | Intraclass correlation | Residual variance (SE) |
|---|---|---|---|
| Health outcomes | 2010 | 0.49 | 0.02 (0.00) |
| | 2011 | 0.48 | 0.02 (0.00) |
| | 2012 | 0.49 | 0.02 (0.00) |
| | 2013 | 0.49 | 0.08 (0.01) |
| Health behaviors | 2010 | 0.54 | 0.02 (0.00) |
| | 2011 | 0.53 | 0.03 (0.00) |
| | 2012 | 0.51 | 0.03 (0.00) |
| | 2013 | 0.50 | 0.02 (0.01) |
| Clinical care | 2010 | 0.41 | 0.09 (0.01) |
| | 2011 | 0.52 | 0.06 (0.01) |
| | 2012 | 0.50 | 0.05 (0.00) |
| | 2013 | 0.54 | 0.04 (0.01) |
| Social and economic factors | 2010 | 0.43 | 0.03 (0.00) |
| | 2011 | 0.46 | 0.03 (0.00) |
| | 2012 | 0.47 | 0.02 (0.00) |
| | 2013 | 0.46 | 0.01 (0.00) |
| Physical environment | 2010 | 0.23 | 0.24 (0.07) |
| | 2011 | 0.19 | 0.39 (0.07) |
| | 2012 | 0.25 | 0.38 (0.07) |
| | 2013 | 0.41 | 0.24 (0.03) |

composite scores (ranging from 24% to 39%) were relatively larger than those in other composite scores (ranging from 1% to 9%).

## Discussion

This study examined how various analytic approaches that account for different sources of bias in ecological and observational studies provide different estimates for the relative contributions of health factors to health outcomes. The modeling strategy in the context of this goal was to compare a set of alternative models accounting for measurement errors and state-specific characteristics to an unadjusted baseline model while estimating the relative contributions of health factors to health outcomes.

### Potential Sources of Bias in Observational and Ecological Studies

More valid estimates for the relative contributions can be obtained by minimizing the impacts of potential sources of bias, which include sampling error, measurement error, and confounding.[22] The authors gradually improved these estimates from the baseline model by minimizing the impacts from measurement errors and then state-specific characteristics among other sources of bias.

It is not uncommon for observational and ecological data to be subject to measurement error, so analytic approaches should account for it whenever possible. In both LGCM and multilevel LGCM, the structural associations were derived from latent variables inferred from a set of observed variables after accounting for measurement error,[23] whereas those in OLS modeling were derived with an assumption that all measures in the models were measured without measurement error.[15] This study found that the estimates for relative contributions were not that different between OLS and LGCM, which suggested that the impact of measurement errors indicated as yearly variations may not be considerable in the estimation of relative contributions of health factors in the data set. In general, measurement error may produce a wider CI but may not influence point estimates in regression models as long as these errors are non-differential to the outcomes (e.g., measurement error in health behaviors are not dependent to the health outcomes status).[22]

Omitted variable bias is one of the biggest threats to validity in observational studies.[24] This study focused on the omission of state-specific characteristics, which are often ignored despite the existence of a nested relationship between counties and states. State-specific characteristics can be better understood as characteristics that are relatively homogeneous within, but differ across, states. These characteristics may include differences in healthcare delivery systems and regulations, such as Medicaid eligibility and coverage; U.S. Department of Agriculture's Special Supplemental Nutrition Program for Women, Infants, and Children benefit distributions[25]; or differences in the patterns of health factors and health outcomes among states.[26–29] They may also include unmeasured state characteristics that produce state-level disparities in population health but are not captured by the set of measures used in the analysis.

Unfortunately, state-specific characteristics are multifaceted and difficult to capture by one set of measures. Therefore, multilevel approaches were used to obtain adjusted estimates for the effect of state-specific characteristics during analyses. The authors found that the estimates of the relative contributions were considerably different between LGCM and multilevel LGCM, and almost half of health outcomes could be explained by state-specific characteristics. The largest difference was found in the decreased contribution of clinical care and the increased contribution of social and economic factors. This indicated that health behaviors and social and economic factors may be more influential to the variation of health outcomes within each state, whereas clinical care may be more influential to the variation of health outcomes between states.

### The Relative Contributions of Health Factors to Health Outcomes

The relative contributions of health factors to health outcomes have been estimated in several ways. For example, McGinnis et al.[7] reviewed the literature and estimated the relative effects on early deaths of genetic predispositions (30%); social circumstances (15%); environmental exposures (5%); behavioral patterns (40%); and shortfalls in medical care (10%). Based on expert advice, the state-level America's Health Rankings follows an apportionment of behaviors (33%); community and environment (30%); policy (17%); and clinical care (20%) among determinants that account for 75% of overall health rankings.[13] The County Health Rankings & Roadmaps use a model where health behaviors, clinical care, social and economic factors, and the physical environment contribute 30%, 20%, 40%, and 10%, respectively, to county-level health outcomes that include measures of mortality and morbidity.[14] The present adjusted estimates for relative contributions were similar to the weight scheme currently used by the Rankings: the estimated contribution of health behaviors was 28.9%, that of clinical care was 17.2%, that of social and economic factors was 45.6%, and that of the physical environment was 8.3%.

### Cautions in Interpretation

It should be emphasized that the estimated relative contributions in this study may be unique to the Rankings model and data, and may change in magnitude depending on the model or data sources used in the analyses. The authors relied solely on the Rankings model and data because they are currently the most complete, annually updated source of widely available data on public health measures for every county in the U.S., and the approaches presented in this study were not tested in a different set of population health models or alternative data sets. Therefore, further validation of estimates and approaches is needed by examining alternative models and data sources with more years of data to better understand the relative contributions of health factors to health outcomes.

It is also important to note that, in the real world, the cost and effects of interventions to make the same magnitude of change in each health factor may differ from one another. In the present estimates, for example, the change of 1 SD in health behaviors has a larger impact than that of a 1 SD change in clinical care (28.9% vs 17.2%), but the efforts or costs of that change in health behaviors may not be the same as those for clinical care. Lastly, interpretation should be limited to the county level, as any inference at the individual level may introduce ecological fallacy.

### Limitations

This study should be considered in light of several limitations. First, using composite scores instead of individual measures requires sophisticated validation processes. The quality of the composite indicator is dependent on the quality of individual measures, and a composite indicator that compiles several measures into a single index measuring the underlying construct should capture complex and multidimensional characteristics of constructs without losing relevant information.[19] Moreover, slopes estimates in LGCM and multilevel LGCM were only used for adjustment purposes for the yearly variations, rather than for interpretive purposes, as this study only covers 4 years of data. Improvement of availability and quality of data in individual measures will ameliorate this limitation.

Second, there are some limitations stemming from the limited availability and quality of data that can be used in empirical studies. Temporality issues may emerge when working with the data that are currently available. There is limited availability of high-quality data that explain current health outcomes. At the same time, future health outcome data, which are explained by the current health factors measures, are also unavailable. Temporality issues may be more severe given the limited availability of reliable data. In the Rankings data, for example, some measures for each year may overlap to some extent, health factor measures may reflect later time periods than those of the health outcomes, and measures might be aggregated for multiple years. In addition, the degree of availability and quality of measures may vary. For example, measures for the physical environment are difficult to define and capture completely with high quality and reliability for each year for all counties.

Lastly, omitted variable bias due to factors other than state-specific characteristics may still exist if factors associated with both health factors and health outcomes were not included in the model, and the direction of bias of each contribution would be unknown.[24] In addition, potential sampling errors may exist. Among 3,141 counties in the U.S., 2,996 counties ranked all 4 years were used in the study, and excluded counties were generally small counties without reliable health outcome measures. If this selection is differential to the association between specific health factors and health outcomes, the estimates may be biased.

Although these limitations pose threats to the validity of the present estimates for the relative contributions of health factors to health outcomes, the authors expect the effects of these limitations will gradually be mitigated with rigorous applications of appropriate analytic approaches that can minimize their impact, as well as with the addition of new measures and more years of reliable data.

## Conclusions

The findings of this study suggest that statistical approaches that can account for measurement error and nested characteristics should be used when estimating the relative contributions of health factors to health outcomes using observational or ecologic data. Further verification of these approaches with other data sources could lead to a better understanding of the impact of health determinants on health outcomes and may provide useful information for researchers, public health officials, and community leaders looking to prioritize and optimize allocations of limited resources for the advancement of population health.

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