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Gender-Based Health Disparities: A State-Level Study of the American Adult Population

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HEALTH

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EXECUTIVE SUMMARY

Many studies empirically investigate sex differences in health outcomes at national and international levels, but our understanding of gender-based health differences across U.S. states remains opaque.[1] What we do know is that the health of American women continues to improve, but progress has been uneven. While female life expectancy at birth has increased from 78.8 years in 1990 to 81.2 years in 2015,[2] these gains vary substantially across U.S. states. The range in life expectancy for both males and females across states is so large that it exceeds the range in life expectancy across similarly developed nations (7.4 years vs. 4.7 years).[3] Furthermore, some states show signs of worsening health for women. For example, the age-adjusted death rate for middle-aged non-Hispanic Caucasian women in southern states increased over the past two decades.[4] The public health data also point to a disproportionate increase in health inequality across states for women compared to men.

This study ranks and groups states based on how women fare relative to men in a composite health disparity index.[5] We believe this approach better serves our main goals, which are: (1) to provide an accurate snapshot of variation in gender-based health disparity across states, (2) to shed light on the racial dimension of gender-based health disparity, and (3) to engage state policymakers in a cooperative discussion. The results indicate that despite having a lower mortality rate and engaging less in risky health behaviors than men, women experience many physical and mental health inequalities across all states. Health disparities are most pronounced in self-rated physical health status and the prevalence of depression. The gender differences in health by race show that African American women compared to African American men have substantially different health disparities than those of Caucasian women and men. When we combine all races, gender-based health disparity shows a strong geographic pattern.

1 Peggy McDonough and Vivienne Walters, "Gender and Health: Reassessing Patterns and Explanations," *Social Science and Medicine*, 52 (2001): 547-559; Sally Macintyre, Kate Hunt, and Helen Sweeting, "Gender Differences in Health: Are Things Really as Simple as They Seem?," *Social Science and Medicine*, 42 (1996): 617-624; Anne Case and Christina Paxson, "Sex Differences in Morbidity and Mortality," Demography, 42 (2005): 189-214; Eileen Crimmins, Jung Ki Kim, and Aida Sole-Auro, "Gender Differences in Health: Results from SHARE, ELSA and HRS," *European Journal of Public Health*, 21 (2010): 81-91.

2 National Center for Health Statistics, National Vital Statistics System, "Mortality," 2015.

3 John Wilmoth, Carl Boe and Magali Barbieri, "Geographic Differences in Life Expectancy at Age 50 in the United States Compared with Other High-Income Countries," in *International Differences in Mortality at Older Ages: Dimensions and Sources*, eds. Eileen Crimmins, Samuel Preston, Barney Cohen (Washington DC: The National Academies Press, 2011), 333–366.

4 Andrew Gelman and Jonathan Auerbach, "Age-Aggregation Bias in Mortality Trends," *PNAS*, no. 7 (2016), 113.

5 A composite health disparity index is a single score that combines information from multiple health indicators.

Key Findings:

- States in the low-disparity group had better health indicators for both women and men. Similarly, states in the high-disparity group had worse health indicators for both women and men. These associations suggest that public health policies directed at improving the health of everyone may also reduce health disparity between men and women.
- Gender-based health disparity is largest in southern states and lowest in northeastern states.
- The variation in health disparity across states is larger among Caucasians than among African Americans.
- A strong positive association exists between physician availability and health disparity, possibly attributable to more and better preventive care.

Measuring health and comparing health of subpopulations poses significant conceptual and technical challenges. Most studies employ single or multiple proxies for health such as mortality rate and specific disease prevalence. In choosing which indicators to measure health outcomes, we follow the recommendation of the Committee on the State of the USA Health Indicators.[6] Namely, we consider the mortality, self-reported health status, chronic disease prevalence, mental health, and health-related behaviors (obesity, tobacco use, excessive alcohol consumption) categories. We restrict our chronic conditions to the following categories: pain (arthritis), respiratory conditions (COPD/emphysema, asthma), circulatory conditions (cardiovascular disease, hypertension, diabetes, kidney disease), cancers (skin and other types of cancer), and mental health (depression).

6 National Academy of Sciences: Institute of Medicine, "State of the USA Health Indicators," Letter Report, 2009.

No single indicator can accurately describe an individual's health. We use a Bayesian latent variable method to extract common information contained in each indicator based upon some prior knowledge of the relationships and construct a latent health-disparity index.[7] Essentially, this method combines multiple indicators into a single score by capturing common information in them. We recognize that each indicator is an imprecise measure of health disparity and, therefore, we also recognize that a statistically derived index from these indicators is also imprecise. Even if one state receives a better score than another, it does not necessarily imply that the health disparity is significantly greater, in a statistical sense, in that state. We solve this issue by clustering states into groups based on each state's health disparity score and the estimated uncertainty about the score. We use 30 different statistical criteria to determine the optimal number of groups, which helps to avoid the arbitrary inclusion or exclusion of any state.

7 A Bayesian analysis, in contrast to traditional statistical methods, is an approach to make sense of data by incorporating prior information into the decision-making process. For a detailed treatment, see Jeff Gill, *Bayesian Methods: A Social and Behavioral Sciences Approach 3rd Edition*, (Chapman & Hall/CRC), 2014.

INTRODUCTION

To have a better understanding of gender-based health differences and to implement policies that will reduce health disparities, we first must recognize that the distribution of various health conditions is driven by more than biological factors alone. Policymakers should focus on reducing systematic health differences between men and women that arise from inequitable distribution of resources, hindered access to health services, education, and other avoidable social and economic factors. The first step in developing effective policies is obtaining reasonable estimates of the problem.

This research study illustrates that health disparities experienced by American women significantly vary across states and by race. Our findings indicate that women tend to have higher prevalence of arthritis, asthma, respiratory disease, and kidney disease than men. The gender differences in health by race show that African American women compared to African American men have substantially different health disparities than those of Caucasian women and men. The data show that the difference in prevalence of various diseases between men and women is smaller for African Americans compared to Caucasians. A lower gender-based health disparity, however, does not mean that African American women enjoy better health than Caucasian women. In fact, African American women have worse health outcomes than Caucasian women. When we combine all races, gender-based health disparity shows strong geographic patterns. Namely, disparity is high in southern states and low in northeastern states. States in the low disparity group had better health indicators for both women and men. Similarly, states in the high disparity group had worse health indicators for both women and men. These associations suggest that public health policies directed at improving the health of everyone may also reduce health disparity between men and women. The uncertainty in the estimated disparity scores is large for all states, which suggests that relative standings of states must be interpreted with great caution.

Data

We utilize information from the Behavioral Risk Factor Surveillance System (BRFSS) survey conducted in 2015 and the Multiple Cause of Death Files, 1999-2014 from the Centers for Disease Control and Prevention (CDC) WONDER database.[8]

We follow the recommendation of the Committee on the State of the USA Health Indicators, established by the Institute of Medicine of the National Academy of Sciences, on which indicators should be included to measure health outcomes. Namely, we consider mortality, self-reported health status, chronic disease prevalence, mental health, health-related behaviors (obesity, tobacco use, excessive alcohol consumption) categories. We restrict our chronic conditions to the following categories: pain (arthritis), respiratory conditions (COPD/emphysema, asthma), circulatory conditions (cardiovascular disease, hypertension, diabetes, kidney disease), cancers (skin and other types of cancer), and mental health (depression). Chronic disease, health-related behaviors, mental health, and general health variables are drawn from the BRFSS 2015. Mortality data in 2014 by state, sex, and age are from the CDC's Multiple Cause of Death files. The variable definitions and summaries by state and sex are in Tables A-E (p. 11-19). We limit our analysis to the adult population (over 15 years old) in the U.S.

8 Centers for Disease Control, Behavioral Risk Factor Surveillance System, 2015, https://www.cdc.gov/brfss/annual_data/annual_2015.html; Centers for Disease Control, WONDER Database: Multiple Cause of Death Data, 2014, https://wonder.cdc.gov/mcd.html.

Table B (p. 12-13) reveals that differences in chronic disease prevalence do not consistently favor one gender. For example, men tend to have higher prevalence of cardiovascular disease, hypertension, and high cholesterol levels than women. In contrast, women tend to have higher prevalence of arthritis, asthma, respiratory disease, and kidney disease than men. Women consistently fare much worse than men in self-reported physical health status and mental health (Table D, p. 16-17). Men, on the other hand, have consistently higher rates of heavy drinking, smoking, and being overweight or obese (Table C, p. 14-15). Crude mortality rate differences between women and men across states show significant variability, ranging from 130 more male deaths per 100,000 population in New Mexico to 20 more female deaths per 100,000 population in Rhode Island (Table E, p. 18-19).

Table A. Description of variables used to calculate ranks and define clusters

Variables	Description
Demographics	
Sex	Respondent's sex; Variable has two values: Female and Male
Age	Respondent's age
Race	Respondent's race
Health Indicators	
Mortality	Crude mortality rate per 100,000
Self-reported General Physical Health	Respondent's self-reported physical health status; Variable has two values: Good or Excellent Health and Fair or Poor Health
Mental Health: Depression	Respondent's yes or no response to the question "Ever told you have a depressive disorder?"
Overweight or Obese	Calculated variable for adults who have a BMI >25
Alcohol Consumption	Calculated variable for heavy drinkers (>14 per week for men and >7 per week for women)
Tobacco Use	Calculated variable for adults who are current smokers
High Blood Pressure	Calculated variable for adults who have been told they have high blood pressure by a doctor
Diabetes	Respondent's yes or no response to the question "Ever told you have diabetes?"
Kidney Diseases	Respondent's yes or no response to the question "Ever told you have kidney disease?"
Chronic Obstructive Pulmonary Disease (COPD)	Respondent's yes or no response to the question "Ever told you had COPD/emphysema/chronic bronchitis?"
Heart: Coronary Heart Disease or Myocardial Infarction	Calculated variable for having CHD or MI
Cholesterol	Calculated variable for adults who have had their cholesterol checked and found it high
Asthma	Respondent's yes or no response to the question "Ever told you have asthma?"
Arthritis	Respondent's yes or no response to the question "Ever told you have arthritis?"
Skin Cancer	Respondent's yes or no response to the question "Ever told you had skin cancer?"
Other Types of Cancer	Respondent's yes or no response to the question "Ever told you had other types of cancer?"

Source: Demographics and morbidity variables are from the CDC's BRFSS 2015; Mortality variable is from the CDC's National Center for Health Statistics, CDC WONDER database (2014).

Table B. Prevalence of common morbidities in U.S. states by sex (2015)

State (by percent)	Skin Cancer		Other Cancer		Diabetes		Hypertension		Cardiovascular		Cholesterol		Arthritis		Asthma		COPD		Kidney	
	F	M	F	M	F	M	F	M	F	M	F	M	F	M	F	M	F	M	F	M
Alabama	7.4	9.2	8.7	5.8	15.5	12.9	40.7	40.1	7.4	9.1	41.2	43	37.1	29.1	17.6	13.5	12	9	2.9	2.6
Alaska	3.6	2.4	7.6	3.3	12.2	7.6	24.9	29.9	3.9	5.1	33.7	34.2	24.5	18.2	17.3	9.9	4.4	3.7	2.1	1.6
Arizona	7.8	8.5	8.6	5.6	12.7	9.8	28.6	33	4.8	7.7	36.6	38	27.7	19.4	17.9	13.4	7.3	5.5	4.3	3.2
Arkansas	5.8	7.4	8.9	4.9	14.8	11.3	38.3	40.4	7.9	9.3	40.4	42.4	33.4	25.9	17.8	14.4	11.4	8	3.8	2.5
California	5.1	5.1	7.5	4.4	12.8	10.7	26.9	30.1	4.3	5.4	32.8	35.7	22.4	15.7	14.8	10.8	4.5	3.6	2.5	2.2
Colorado	6.6	6.4	7.7	5.1	7.4	7.6	22.7	28.8	3.2	5.8	29.5	33.8	25.5	20	15.1	12.7	4.6	4.1	2.8	2.1
Connecticut	5.8	5.5	8.3	5.9	10.2	10.3	28.7	32.2	3.9	7.4	34.9	40.2	28.2	20.5	19.3	13.2	5.8	4.4	1.7	2.1
Delaware	6.7	7.9	8.8	5.4	14	12.2	33.2	35.9	6.3	8	36.9	41.5	31.9	23.9	18	10.5	8.6	5.5	3.1	3.8
District of Columbia	2.7	4.4	6.7	4.1	9.6	8.2	29.1	29.7	3.3	5.7	31.9	30.6	21.8	14.7	18.6	15.3	6.3	4.1	2.6	2.4
Florida	8.6	9.8	8.1	6.6	12.1	11.7	31.5	35.6	6.1	8.9	37.1	39	30.1	21.4	14.4	10.5	7.8	6	3.1	3
Georgia	5.9	6.7	8	5.2	13	11.3	34.6	37.9	5.6	7.9	35.6	37	28.8	20	16.3	12	7.5	6.3	3	2.9
Hawaii	4.4	4.7	7.6	4.3	10.1	8.7	29.7	34.2	3.3	5.7	35.3	37.4	20.2	17.6	19.1	14.4	4.4	4.3	3.6	2.6
Idaho	7.3	7.9	8	5.5	10.8	7.4	27.6	35	4.2	7.1	34.7	40.6	28.6	22	15.7	11.7	5.3	4.5	2.3	1.3
Illinois	4.7	4.6	7.2	5.4	10.8	10.8	29.2	32.5	4.2	8.1	34.6	37.5	27.7	18.7	15.3	11.8	5.8	5.7	2.6	2.6
Indiana	5.1	6	8	5.3	11.9	12.2	30.4	34.4	5.2	10.7	38.3	40.1	30.4	24.6	17.9	11.5	8.2	7.7	3.2	2.3
Iowa	6.3	6.5	8.5	5.4	9	9.7	28.8	32.4	4.4	7.7	35.7	36.6	29.3	22.3	13.7	10.6	6.1	5.3	2	1.8
Kansas	6	6.8	8.7	5.5	11.6	9.8	30.1	33.1	4.7	7.2	36.8	38	28	20.9	14.6	12.3	6.9	5.4	3.3	2.5
Kentucky	6.6	8.6	9.3	6.2	14	14.4	36.8	41.3	6.5	12.6	39.2	42.2	35.6	28.1	18.9	16.5	12.3	11.8	3.6	2.4
Louisiana	4.4	6.1	8.1	5.9	15.3	12.7	39	39.7	6.7	9.6	39.2	39.2	32.2	23.3	15.2	14	9	6	2.7	2.9
Maine	7.9	6.4	10.8	6.8	11.3	10.1	31.2	37.3	5.8	10.2	36	41.3	35.1	26.7	18.3	13	8.1	8.1	3	2.2
Maryland	4.7	5.2	6.8	6	11.7	10.9	31.6	33.6	4.6	7.1	34.4	37.7	27.7	19	16.9	10.6	6.5	5.7	2.6	2
Massachusetts	6.1	5.8	8.1	5.3	10.3	9.5	26.8	32.7	4.4	7.7	31.3	38.1	28.5	19.4	17.7	13.1	6.2	5.1	2.6	2.2
Michigan	5.9	6.2	8.1	5.8	10.7	11.5	32	34.3	5.7	8.9	37.7	38.7	34.5	25.2	17.2	14.2	8.5	6.8	3.8	3.1
Minnesota	5.7	5.7	7.9	5.3	9.6	8	24.3	28.4	4	6.4	30.8	34.1	24.8	18.2	13.5	8.7	4.7	4.3	2.3	1.8
Mississippi	6	6.2	8.5	5.2	15.6	15	42.5	42.2	7.3	9.7	38.9	38.6	32	24.9	12.4	12	9.1	6.4	3.3	2.4
Missouri	6.3	7.3	9.1	5.6	12.3	12.3	31.1	37.2	6.3	8.9	36.2	38	33.3	25.1	16.7	12.1	9.6	7	3.1	2.3

Source: CDC, Behavioral Risk Factor Surveillance System 2015

Table B. Prevalence of common morbidities in the U.S. states by sex (2015)

State (by percent)	Skin Cancer		Other Cancer		Diabetes		Hypertension		Cardiovascular		Cholesterol		Arthritis		Asthma		COPD		Kidney	
	F	M	F	M	F	M	F	M	F	M	F	M	F	M	F	M	F	M	F	M
Montana	7.1	8.2	9.6	6.2	8.3	8.2	25.8	32.4	4.5	6.6	30.6	35.8	29.2	24.4	15.1	10.3	6.9	4.5	2.3	2.6
Nebraska	5.6	6.4	8.5	5.2	10.2	9	27.2	32.6	4.3	7.5	33	37.5	27.1	19.7	13.4	10.7	6.1	4.8	2.5	2.2
Nevada	4.5	6.7	7.1	4.8	10.6	10.6	27.9	28.7	6	6.4	38.3	35	24.5	18.7	17.1	10.1	7.9	5.2	3.9	2.6
New Hampshire	6.6	6.8	9	6.2	9.1	8.7	26.8	31.7	3.9	7.6	33.6	37.9	29	24.1	17.6	12.7	7.9	5.3	2.6	2.7
New Jersey	5.1	4.5	7.2	4.3	10.3	9.9	29.1	32.7	4.3	7.1	32.7	38.5	26.8	18.8	13.3	9.8	5.2	4.7	2.1	2
New Mexico	4.8	6.3	7.5	4.6	13	11.3	29.2	30.9	5.3	6.3	30.9	38.2	26.3	22.7	17.2	12.8	6.8	5.3	3.4	2.5
New York	4.8	4.4	7.2	4.7	10.5	10.5	28.1	30.5	4.4	7.4	35.1	38.3	27.4	19	16.5	12.8	6.4	5	1.9	2.3
North Carolina	6.6	7.6	9	5.4	12.6	10.2	35.1	35.2	5.5	8.7	37.3	36.7	30	23.7	15.5	11.1	8.3	6.5	3	2.6
North Dakota	4.3	4.7	7.3	5.5	10.6	8.5	29.8	31	4.5	6.7	35.1	35	26.7	19.3	14.3	11.3	6	4.3	2.6	2
Ohio	6.1	6.1	7.7	5.7	12.3	11.4	31.1	37.8	5.4	8.7	35.6	37.8	32.3	24.3	17.1	10.8	8.9	6.9	3.1	3.2
Oklahoma	4.6	6.1	7.7	4.7	13.2	11.9	34.4	38	6.7	10.4	36.4	39.8	32.4	22.8	16.3	12.2	10	7.2	2.5	2.7
Oregon	7.8	8	9.6	5.9	11.2	12.2	27.8	32.4	4.2	7	35.3	38.3	30.9	22.5	20.5	15.3	6.5	4.6	3.5	2.7
Pennsylvania	5.7	6	9.6	6.3	12.1	10.8	30.2	35	5.5	8.8	33.9	38.8	33.6	24.7	17.5	12.3	8.1	5.8	2.4	2.9
Rhode Island	6.4	6.2	8.9	5.7	10.6	9.8	30.4	34.6	4.3	8.1	33.2	37.4	30.7	22.8	18.2	13.5	6.7	5.8	2.7	2.6
South Carolina	6.5	7.6	8.1	5.7	13	11.9	36.7	39	5.4	8.7	38.7	39	32.5	25.5	14.8	11.1	8.4	5.8	3.3	2.3
South Dakota	6.9	5.5	8.7	5.6	9.7	10.3	28.5	31.4	6.2	8	32.4	34.2	27.9	20.7	14.7	10.3	5.8	5.4	2.2	2.1
Tennessee	7	8.1	8.7	4.8	15	12.6	37	40	7.2	9.9	38.4	41.8	35.6	28.1	16.4	12.5	10.6	8.4	3.5	3.4
Texas	4.7	4	6.7	4.5	12.2	12.3	28.1	30.8	4.7	7.6	36.5	35.7	24.2	15.8	13.4	10.5	6.1	4.1	3.1	2.4
Utah	6.5	7.4	6.5	4.9	9.3	7.5	20.6	26.5	2.9	5	29.5	34.9	22.6	16.6	16.3	11.6	4	3.4	2.9	2.3
Vermont	7.2	6.7	8.4	5.1	8.7	9.2	25.6	33.3	4.7	8.4	30.5	37.9	29.9	23.9	19.4	12.8	6.1	6.2	3	2.1
Virginia	5.8	5.5	7.7	4.7	13.4	9.8	31.2	35.4	4.4	6.5	34.6	36.7	26.9	19.4	15.1	9.3	6.1	5.4	2.4	2.2
Washington	6.3	5.8	8.5	5.8	10.1	9	26.1	33.5	4.3	7.2	33.9	38.8	28.7	20.2	17.5	12	6.3	5.9	3.9	2.6
West Virginia	7	8.5	9.8	5.9	15.2	14.7	41.1	44.4	8.9	13.4	37.8	40.3	39.6	36.3	17.3	12.7	14.5	12.2	3.6	3.6
Wisconsin	4.9	5.1	8.1	4.9	8.5	9	28.9	30.2	4.6	7.8	35	37.2	29.1	20.2	15.5	10.4	5	4.4	2.8	1.5
Wyoming	6.7	7.3	9.8	5.9	8.4	9.6	26.3	33.3	4.5	7.7	32.7	37.4	29.1	22.7	15.3	11.7	7.1	7.4	3.3	2.4

Source: CDC, Behavioral Risk Factor Surveillance System 2015

Table C. Prevalence of overweight or obesity, heavy drinking, and tobacco use, by sex (2015)

State (by percent)	Overweight or Obese		Heavy Drinker		Current Smoker	
	Female	Male	Female	Male	Female	Male
Alabama	64.8	72.6	3.9	5.8	19.2	23.8
Alaska	61.3	72.1	10.9	6.5	18.5	19.6
Arizona	59.1	71.1	4.1	6.3	12	16.2
Arkansas	65.9	73	3.7	7.1	22.1	27.8
California	53.9	66.5	5.4	6.1	8.3	15.2
Colorado	48.2	64.4	6	5.7	14.2	17.1
Connecticut	53.7	69.6	5.8	6.4	10.9	16.3
Delaware	61.4	72.3	4.8	6	14.2	20.9
District of Columbia	51.8	57.1	11.8	6.1	16.1	15.8
Florida	57.9	70.1	6.1	6	14.3	17.4
Georgia	59.4	71.6	5.1	5.5	15.5	20
Hawaii	47.7	65.7	5.8	9.5	10.8	17.3
Idaho	57.9	71.9	4.6	6.1	13	14.6
Illinois	59.4	73.1	5.6	6.9	12.8	17.6
Indiana	60.4	72.5	4	6.7	19.3	21.9
Iowa	59	73.7	4.8	7.1	16.7	19.5
Kansas	61.1	74.5	4.1	6.2	16.1	19.3
Kentucky	61.7	72.5	3.8	8.1	25.5	26.4
Louisiana	65.5	73	6	7.3	19.3	24.7
Maine	61.5	71.5	7.8	8.4	18.1	21
Maryland	60.8	69.1	5.1	4.8	13.4	16.9
Massachusetts	50.6	69	7.1	7.2	11.9	16.4
Michigan	60.4	72	5.6	7.5	19.1	22.4
Minnesota	54.9	70.2	6.6	6.4	14.8	17.6
Mississippi	65.9	74.4	3.4	5.8	18.4	27

Source: CDC, Behavioral Risk Factor Surveillance System 2015

Table C. Prevalence of overweight or obesity, heavy drinking, and tobacco use, by sex (2015)

State (by percent)	Overweight or Obese		Heavy Drinker		Current Smoker	
	Female	Male	Female	Male	Female	Male
Missouri	59.7	72.7	4.4	8	21	23.6
Montana	51.9	69.2	7.1	8.3	18.5	19.3
Nebraska	60.2	73.4	4.6	7	15.8	18.4
Nevada	57.8	71.1	6	6.4	14.6	20.5
New Hampshire	54.7	72.2	6.6	6.3	15.4	16.5
New Jersey	55.7	71	4.9	4.7	11.5	15.7
New Mexico	59.5	69.4	3.6	5.4	16	19.1
New York	53.4	65.8	5.1	6	12.9	17.7
North Carolina	60.9	70.7	3.6	5.8	16.3	21.9
North Dakota	57.4	75.4	5.8	7.3	15.4	21.9
Ohio	61.5	71.4	5.2	7	20.2	23.1
Oklahoma	64.3	73.4	3.2	5.2	20.4	24
Oregon	57.6	71.1	7.2	7.3	16.3	17.9
Pennsylvania	60	72.4	4.6	6.7	16.6	19.8
Rhode Island	55.5	70	5.8	6.5	12.8	18.5
South Carolina	62.4	70	4.7	8.2	16.2	23.4
South Dakota	56.9	71.3	4	5.5	20.6	19.5
Tennessee	64.6	72.8	4.2	5.3	21.1	22.8
Texas	62.5	74.5	4.7	6.9	12.4	18.2
Utah	51.5	67.2	3	4.2	7	11.2
Vermont	53.1	66.3	7	8.4	14	18
Virginia	58.1	70	5.6	6.2	14.4	18.8
Washington	55.8	68.7	7	5.7	13.4	16.6
West Virginia	64.8	77.2	2.4	4.6	25.7	25.7
Wisconsin	58.8	72.7	7.7	8.8	14.9	19.8
Wyoming	57.7	72.1	5.6	6.7	17.5	20.6

Source: CDC, Behavioral Risk Factor Surveillance System 2015

Table D. Prevalence of poor physical and mental health (2015)

State (by percent)	Physical Health		Mental Health	
	Female	Male	Female	Male
Alabama	24.5	19.7	27.7	16.1
Alaska	13	14.2	20.7	11.8
Arizona	19.2	18.4	21.7	15.2
Arkansas	25	22.6	28.6	18
California	19.3	16.7	15.9	9.7
Colorado	14.5	13.3	23.7	14.9
Connecticut	15.1	14.8	21.4	13.4
Delaware	18.8	16.3	22	13.3
District of Columbia	14.9	8.7	21.7	13.9
Florida	19.2	17.6	20.3	12.5
Georgia	18.6	17.5	22.9	13.3
Hawaii	13.4	13.8	14.2	9
Idaho	15.2	14	25.7	13.6
Illinois	18.3	14.3	18.8	11.7
Indiana	18.5	19.1	25.9	14.7
Iowa	13	13.1	24.4	13.5
Kansas	16	15.4	25.2	13.6
Kentucky	24.3	20.1	23.4	13.8
Louisiana	23.2	20.6	24.5	15.4
Maine	15.9	16.3	30.3	17.3
Maryland	14.9	12.7	19.6	12.8
Massachusetts	15.1	14.1	25.1	16.3
Michigan	18.1	17.1	24.6	14.4
Minnesota	12.7	12.1	23.8	13.7
Mississippi	25.2	21.9	23.2	12.8
Missouri	18.7	16.9	28.4	14.7

Source: CDC, Behavioral Risk Factors Surveillance System (2015).

Table D. Prevalence of poor physical and mental health (2015)

State (by percent)	Physical Health		Mental Health	
	Female	Male	Female	Male
Montana	14.9	15.3	24.9	14.9
Nebraska	14.2	13.7	22.5	12.4
Nevada	20.4	14.8	21.5	11.7
New Hampshire	12.6	11.5	25.7	16
New Jersey	17.1	14.8	14.9	10.3
New Mexico	20.2	21.4	24.5	15.7
New York	17.2	16.4	18.6	12.6
North Carolina	21	17.3	23.2	13.9
North Dakota	14.8	13	25.4	12.5
Ohio	16.6	16.5	24.9	13.9
Oklahoma	22	21.5	28.4	16.7
Oregon	19	18.1	32.3	20.9
Pennsylvania	17.1	15.7	24.5	12
Rhode Island	14.6	17.9	23.8	18.5
South Carolina	18.3	17.6	23.7	14.8
South Dakota	15	12.3	21.4	10.9
Tennessee	21.1	21.1	25.5	16.6
Texas	20.1	18.6	19.9	12.1
Utah	12.5	12.4	26.9	14.7
Vermont	12.1	13	26.7	18.7
Virginia	16	14.3	20.2	10.9
Washington	15.3	14.5	26.8	16.5
West Virginia	26.6	25.2	28.7	17.2
Wisconsin	15	14.3	22	12.9
Wyoming	15.6	14.2	26.1	15.9

Source: CDC, Behavioral Risk Factors Surveillance System (2015).

Table E. Mortality by sex, crude rates per 100,000 (2014)

State	Female Mortality	Male Mortality	Difference
Alabama	991	1083	-92
Alaska	493	621	-128
Arizona	716	816	-101
Arkansas	981	1075	-94
California	612	656	-44
Colorado	644	671	-27
Connecticut	840	820	20
Delaware	842	926	-84
District of Columbia	691	745	-54
Florida	876	996	-120
Georgia	734	790	-56
Hawaii	721	795	-74
Idaho	750	793	-44
Illinois	811	824	-13
Indiana	908	940	-31
Iowa	947	932	15
Kansas	880	896	-16
Kentucky	975	1058	-83
Louisiana	897	993	-96
Maine	985	1047	-62
Maryland	747	789	-42
Massachusetts	815	822	-7
Michigan	929	967	-37
Minnesota	764	755	10
Mississippi	958	1087	-129
Missouri	938	987	-49

Source: CDC, National Center for Health Statistics, CDC WONDER Database.

Table E. Mortality by sex, crude rates per 100,000 (2014)

State	Female Mortality	Male Mortality	Difference
Montana	890	943	-52
Nebraska	842	857	-15
Nevada	689	845	-156
New Hampshire	859	877	-19
New Jersey	803	793	10
New Mexico	779	909	-130
New York	755	764	-9
North Carolina	833	885	-52
North Dakota	855	819	36
Ohio	973	1003	-31
Oklahoma	958	1027	-69
Oregon	833	888	-55
Pennsylvania	1002	1007	-6
Rhode Island	946	904	42
South Carolina	893	991	-98
South Dakota	863	896	-33
Tennessee	947	1029	-82
Texas	652	713	-61
Utah	560	576	-17
Vermont	902	893	9
Virginia	754	774	-20
Washington	720	756	-35
West Virginia	1148	1251	-103
Wisconsin	880	867	12
Wyoming	766	830	-64

Source: CDC, National Center for Health Statistics, CDC WONDER Database.

Methodology

The main goal of any composite index is twofold: (1) to summarize a large amount of information, and (2) to convey useful knowledge to end users. No ideal method exists that allows one to squeeze multiple measures into one, but the problem has a few feasible technical solutions. For example, most studies that provide rankings use weighted averages of multiple measures. Although the choice of weights varies, the underlying logic is the same: combine multiple measures by assigning to each a specific weight that corresponds to that measure's relative importance. Everyone who produces ranks must also decide how many measures to combine and how to allocate weights among these measures.

Our choice of measures was guided by a broad concept of health that encompasses physical, mental, and overall well-being as advocated by the World Health Organization (WHO). We also followed the recommendations of the Committee on the State of the USA Health Indicators. As is common to all research, the number of measures used in the analysis is limited by the availability of reliable and consistent data.[9] Our final data set consists of 16 indicators that cover chronic conditions, mortality, health-related behaviors, mental health, and a subjective evaluation of one's health.

Although we can observe disparity in mortality or disparity in kidney disease between men and women, neither can be thought of as an accurate depiction of gender-based health disparity. Each of these observed measures contains information about an unobserved health disparity, but each also contains different amount of other information or noise that may not be related to health disparity. If we were simply to calculate a weighted average of these quantities, we would still end up with a noisy summary.

9 Sarah Burgard and Patricia Chen, "Challenges of Health Measurement in Studies of Health Disparities," *Social Science and Medicine*, 106 (2014): 143-150.

In this report, we use a Bayesian latent variable method to remove noise and retain information that is common to all indicators.[10] This approach has several attractive features. First, we do not have to worry about picking the "best" weights, because we are no longer averaging these indicators. Instead, we are statistically extracting common information for each state from all 16 indicators. Second, it allows us to calculate uncertainty associated with our estimated health disparity index explicitly. For example, if every indicator places Vermont at the top, then there is no disagreement or uncertainty about Vermont's place. If Vermont placed 20th in kidney disease, third place in mortality and 49th in obesity, any guess of Vermont's position in the health disparity index will have a substantial uncertainty associated with it. Third, we can make a distinction between a numerical difference in the calculated health disparity index and a substantive difference in health disparity. Suppose Arizona receives the index score of 0.23 (rank 33) and Georgia receives the index score of 0.21 (rank 32). Numerically, Georgia appears to fare better than Arizona, since a bigger positive number implies a larger health disparity. If we also knew that there is 95 percent chance Arizona's score is between -0.3 and 0.7 and Georgia's score is between -0.4 and 0.65, we would conclude there is no meaningful difference in health disparity between Arizona and Georgia, and their scores are statistically indistinguishable from each other.

10 Ulrich Paquet, "Bayesian Inference for Latent Variable Models," Technical Report, Number 724, University of Cambridge Computer Laboratory, July 2008, https://www.cl.cam.ac.uk/techreports/UCAM-CL-TR-724.pdf; Cassandra Guarino, Greg Ridgeway, Marc Chun, and Richard Buddin, "A Bayesian latent variable model for institutional ranking," *Higher Education in Europe*, 30 (2005): 147-165; Christopher Claassen, "Measuring University Quality," *Scientometrics*, 104 (2015): 793-807; Kevin Quinn, "Bayesian factor analysis for mixed ordinal and continuous responses," *Political Analysis*, 12 (2004): 338-353.

An index is useful if it accurately depicts the problem and conveys knowledge that is simple to understand and easy to apply. Ranks alone provide an incomplete picture, but adding uncertainty estimates creates an unnecessary confusion to end users. We solve this issue by clustering states into groups based on each state's health disparity score and the estimated uncertainty about that score. We use 30 different statistical criteria to determine the optimal number of groups, which helps us avoid arbitrary inclusion or exclusion of states. We believe this approach better serves our main goals of providing an accurate snapshot of variation in gender-based health disparity across states, shedding light on the racial dimension of gender-based health disparity, and engaging state policy makers in a cooperative discussion.

11 See Kim Esbensen and Paul Geladi, "Principal Component Analysis," *Chemometrics and Intelligent Laboratory Systems*, 2 (1987): 37-52.

Summary of Analytical Steps

Step 1. Transform each health disparity indicator into its standardized form:

$$X_k = \frac{x_k - \overline{x_k}}{S_{x_k}}$$

where $\overline{x_k}$ is the arithmetic mean and S_{x_k} is the standard deviation of values on an indicator x_k, and k ranges from 1 to 16.

Step 2. Conduct a Principal Component analysis to check the single common factor assumption: Principal component analysis is a statistical procedure that uses information to transpose a group of observations of likely correlated variables into a group of linearly uncorrelated variables referred to as principal components. The number of original variables is equal to, or greater than, the number of principal components to which they are transformed.[11] In other words, it reduces the number of separate variables. Although we cannot be certain that any one of the 16 indicators measures health precisely, we assume that they all share a common information about health. The purpose of this step is to check the validity of that assumption indirectly.

Step 3. Carry out a Bayesian latent variable analysis using one latent factor: The structure of equations for each state has the following form:

$$Arthritis_i = \beta_1^1 \, \theta_i + \varepsilon_i^1, \qquad with \;\; \varepsilon_i^1 \sim N(0, \delta_1^2)$$

$$Asthma_i = \beta_1^2 \, \theta_i + \varepsilon_i^2, \qquad with \;\; \varepsilon_i^2 \sim N(0, \delta_2^2)$$

$$Mortality_i = \beta_1^{16} \, \theta_i + \varepsilon_i^{16}, \qquad with \;\; \varepsilon_i^9 \sim N(0, \delta_{16}^2)$$

where i denotes states, θ_i is the gender-based health disparity index score for state i, and denotes factor loading for the difference between women and men in the prevalence of arthritis. We estimate these equations using non-informative priors on factor loadings and a standard normal prior on the latent variable. We use 50,000 simulations for each subset of data.

Step 4. Calculate probability that a given state's health disparity score will be in the top 10 and the bottom 10 states: Use realizations from each of the 50,000 simulations.

Step 5. Conduct tests that statistically determine the optimal number of hierarchical clusters: Using the results in Step 4, use the 30 chosen criteria to determine the optimal size of hierarchical clusters.

Step 6. Assign each state to its corresponding group: Using the Ward method for hierarchical clustering and the size of clusters from Step 5, Ward's variance criterion minimizes the aggregate within-cluster variance. To apply this technique, at each step you find the pair of clusters, which results in a minimum rise in aggregate within-cluster variance after joining. This rise is a weighted squared gap between cluster centers.[12] Among many alternative approaches, Ward's hierarchical clustering algorithm has shown superior statistical properties.[13]

Step 7. Calculate and compare summary statistics for each group.

12 Fionn Murtagh, "A Survey of Recent Advances in Hierarchical Clustering Algorithms," *The Computer Journal, Oxford Academic,* 26(4) (1983): 354-359.

13 Laura Ferreira, David Hitchcock, "A Comparison of Hierarchical Methods for Clustering Functional Data," *Communications in Statistics-Simulation and Computation,* 38 (2009): 1925-1949.

Gender-Based Health Disparity Rankings and Clusters of States

In this section, we report our findings in a five-step approach. First, we show the estimates of latent gender-based health disparity scores for each state and its corresponding 95 percent credible interval. Second, we discuss outcomes of hierarchical cluster analysis. Third, we highlight final rankings and groupings. Fourth, we compare groups with respect to their median levels of 16 underlying indicators. We conclude the discussion by exploring the gender-based health disparity among blacks and whites separately.

The latent gender-based health disparity index scores based on 16 health indicators is shown in Figure 1 (p. 27). The horizontal axis shows latent scores for health disparity, where positive numbers indicate larger disparity in health for women and negative numbers indicate smaller disparity in health for women. The states are ordered in accordance with their median score, which is depicted as solid circles. The solid lines extending to the right and the left of median scores represent 95 percent credible intervals. In contrast to confidence intervals that are meaningful only in a repeated experiment sense, credible intervals have a more intuitive interpretation. They specify an interval which contains the true score with 95 percent probability.

Although there are differences in the position of solid circles (median scores), uncertainty associated with these median scores is large enough to make comparisons based on medians rather unconvincing. For example, Nevada has the highest median disparity score (1.68), and Alabama has the second highest median score (1.59), but their credibility intervals almost entirely overlap each other. On the other hand, Vermont has the lowest median disparity score (-1.53), and its credibility interval has substantially smaller overlap with Massachusetts' credible interval. These credibility intervals can inform us that with 95 percent certainty, we can say that gender-based health disparity in Ohio is better than in Arkansas because the right tail of Ohio's credible interval does not overlap with Arkansas's credible interval. Following this approach, we can immediately conclude that the amount of uncertainty associated with the true disparity score is large, and ordering states in accordance with a single number fails to depict the true differences accurately.

To provide a more informative summary, we created a hierarchical cluster analysis dendrogram of states based on posterior distributions (after transforming and combining) of latent gender-based health disparity scores. Figure 2 (p. 28) shows a tree diagram, where the vertical axis measures a posterior score based distance. There are three main branches, each with smaller branches. Often, analysts are left to make ad hoc decisions with respect to the size of groups. For example, we can choose three groups (three main branches) or six groups (secondary branches) or sixteen (tertiary branches). We determine the number of groups based on 30 statistical criteria. Over half of these tests indicated that the optimal number is three.

Table F (p. 26-27) shows the final rankings and optimal groupings of states. The second column indicates the group, the third shows estimated median value of the latent health disparity score, the fourth column shows the simple average of 16 indicators as our baseline score, and the fifth column shows what the ranks would be under the equally weighted index of 16 indicators. Comparing states in the high-disparity group with those in the low-disparity group, one immediately notices geographic patterns. Namely, most of the states in the high-disparity group are in the southern U.S., and those in the low-disparity group are mostly in the Northeast. We were concerned that we may have made an error in calculations when we observed the District of Columbia in the list of high disparity states. However, after checking the data and our codes, we were assured the results are robust. The prevalence of heavy drinking and tobacco use among women in the District of Columbia is higher than in most states. Also, the prevalence of hypertension and high cholesterol levels are substantially higher and are on par with or greater than the numbers reported for men.

Table G (p. 31) shows median prevalence of 15 health indicators and crude mortality rates across three groups. Almost all rows corresponding to a specific source of disparity indicate that the prevalence of disease, risky behavior, and mortality is worse in the high-disparity group and better in the low-disparity group. Furthermore, these results are consistent for both men and women, which suggests that gender-based health disparity diminishes as the overall population health improves.

Recent health research studies highlight sharp differences in health outcomes between blacks and whites in the U.S. To capture the racial dimension, we explored health disparity between men and women among African Americans and Caucasians separately. Our analysis of data sets, separated by race, indicate that the gender-based health disparity among Caucasians closely resembles the national trends, whereas differences in health between African American men and women show high dissimilarity to the national trends. We find that the variation in health disparity across states is larger among Caucasians than among African Americans. Although health outcomes for African Americans are worse than for Caucasians, the difference in health outcomes between African American men and women appears to be small. The gender-based health disparity among African Americans is lowest in Hawaii and Oregon and highest in New Mexico, Nevada, and Utah. Our results also illustrate that the estimates of disparity for both races come with large uncertainty bounds. Therefore, a reader must exercise great caution in interpreting the ranks presented in the appendix.

Figure 1. Latent gender-based health disparity scores with 95 percent uncertainty bounds

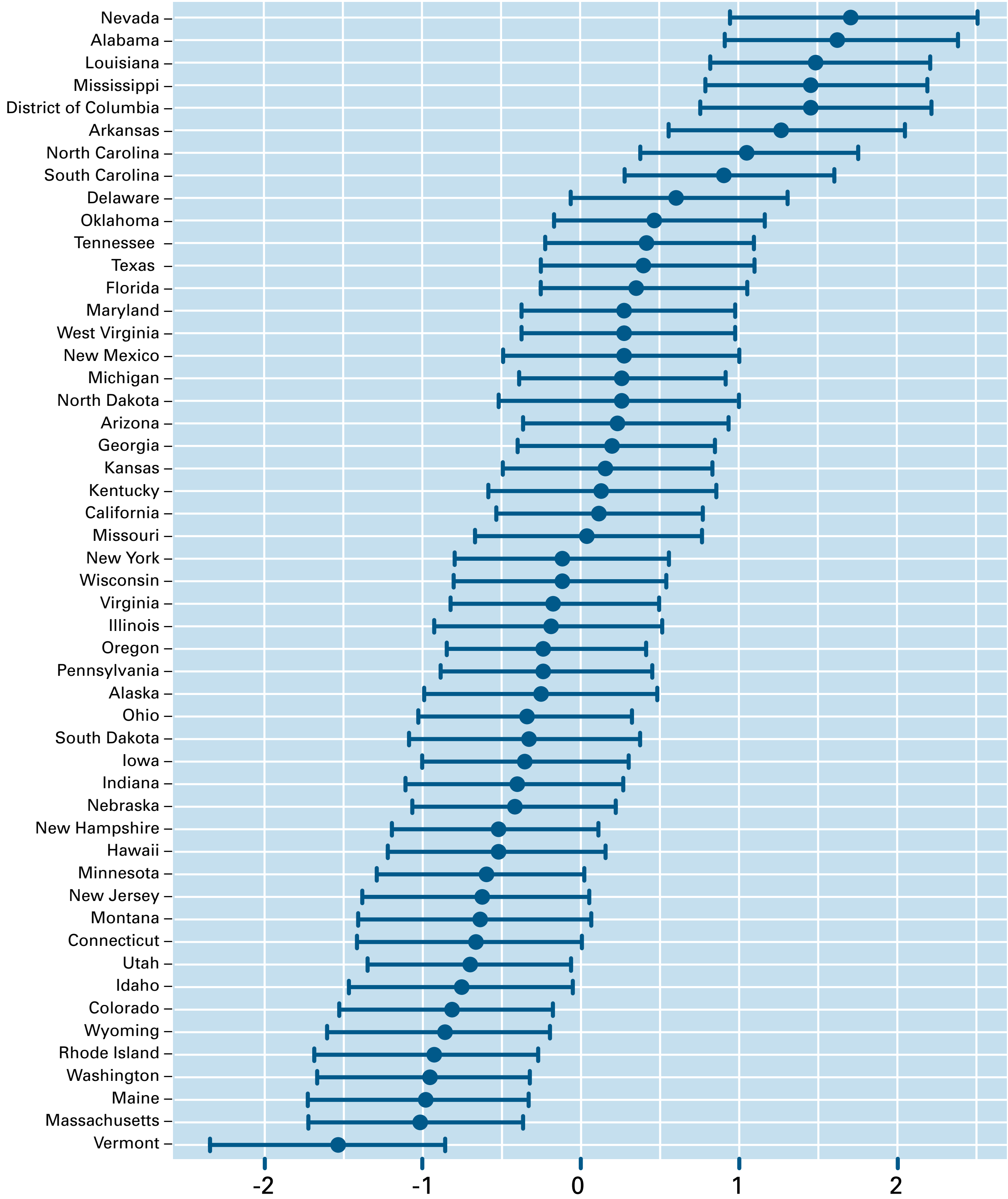


Figure 2. Hierarchical clusters of states

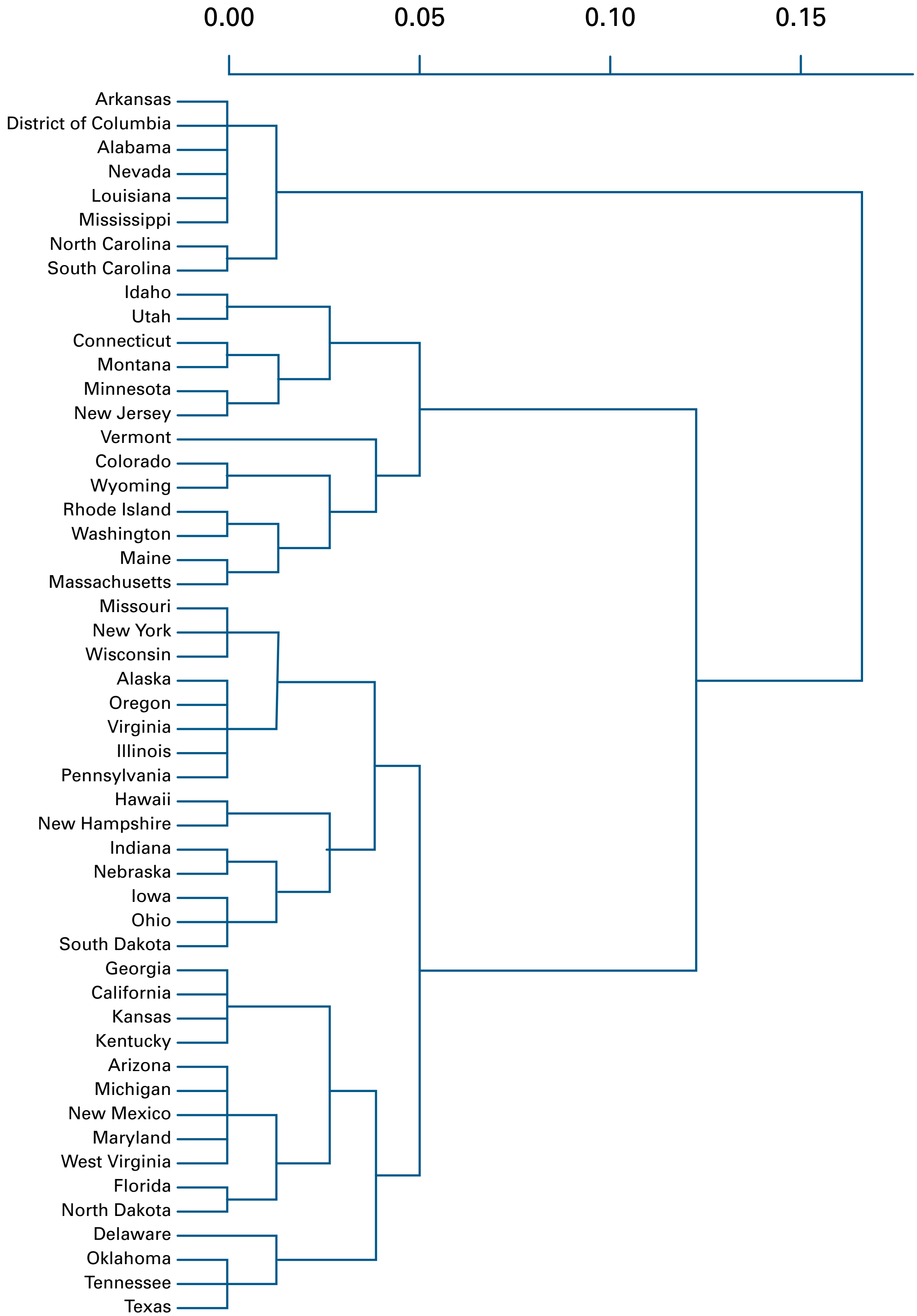


Table F. Gender-based health disparity ranks and clusters of states

State	Disparity Group	Latent Score	Final Rank	Baseline Score	Baseline Rank
Nevada	High	1.68	51	0.36	47
Alabama	High	1.59	50	0.47	48
Louisiana	High	1.49	49	0.05	29
Mississippi	High	1.47	48	0.1	33
District of Columbia	High	1.45	47	0.74	51
Arkansas	High	1.27	46	0.48	49
North Carolina	High	1.05	45	0.29	46
South Carolina	High	0.91	44	-0.12	21
Delaware	Average	0.61	43	0.11	34
Oklahoma	Average	0.47	42	0.02	26
Tennessee	Average	0.41	41	0.15	39
Texas	Average	0.4	40	-0.01	23
Florida	Average	0.35	39	-0.25	11
Maryland	Average	0.29	38	0.06	31
West Virginia	Average	0.27	37	-0.18	16
New Mexico	Average	0.27	36	-0.26	10
Michigan	Average	0.27	35	0.04	28
North Dakota	Average	0.26	34	0.16	40
Arizona	Average	0.24	33	0.02	27
Georgia	Average	0.21	32	0.07	32
Kansas	Average	0.16	31	0.12	35
Kentucky	Average	0.12	30	-0.37	2
California	Average	0.11	29	0	24
Missouri	Average	0.03	28	0.16	41
New York	Average	-0.11	27	-0.18	18
Wisconsin	Average	-0.11	26	0.17	42

Source: Author's calculations. Baseline scores and baseline ranks are results from weighting all dimensions of health disparity equally.

Table F. Gender-based health disparity ranks and clusters of states

State	Disparity Group	Latent Score	Final Rank	Baseline Score	Baseline Rank
Virginia	Average	-0.17	25	0.27	44
Illinois	Average	-0.18	24	-0.27	8
Oregon	Average	-0.23	23	0.23	43
Pennsylvania	Average	-0.24	22	0.14	37
Alaska	Average	-0.25	21	0.69	50
Ohio	Average	-0.33	20	0	25
South Dakota	Average	-0.33	19	0.27	45
Iowa	Average	-0.36	18	-0.15	19
Indiana	Average	-0.39	17	-0.22	13
Nebraska	Average	-0.42	16	-0.18	17
New Hampshire	Average	-0.52	15	-0.12	20
Hawaii	Average	-0.52	14	-0.61	1
Minnesota	Low	-0.6	13	0.05	30
New Jersey	Low	-0.62	12	-0.19	15
Montana	Low	-0.64	11	-0.32	6
Connecticut	Low	-0.66	10	-0.24	12
Utah	Low	-0.71	9	-0.27	9
Idaho	Low	-0.76	8	-0.06	22
Colorado	Low	-0.81	7	-0.31	7
Wyoming	Low	-0.86	6	-0.33	5
Rhode Island	Low	-0.93	5	-0.34	4
Washington	Low	-0.96	4	0.14	36
Maine	Low	-0.98	3	0.15	38
Massachusetts	Low	-1.02	2	-0.2	14
Vermont	Low	-1.53	1	-0.34	3

Source: Author's calculations. Baseline scores and baseline ranks are results from weighting all dimensions of health disparity equally.

Table G. Comparison of health indicators across groups (by percent)

Health Dimensions	High Disparity	Average Disparity	Low Disparity
Skin Cancer: Female	5.9	5.8	6.5
Skin Cancer: Male	7.1	6.2	6.4
Other Cancer: Female	8.3	8.1	8.3
Other Cancer: Male	5.3	5.4	5.5
Diabetes: Female	13.9	12.1	10.1
Diabetes: Male	11.6	10.9	9.2
High Blood Pressure: Female	37.5	29.9	26.3
High Blood Pressure: Male	39.4	33.4	32.7
Heart Problems: Female	6.4	4.8	4.3
Heart Problems: Male	8.9	7.8	7.2
Cholesterol: Female	38.8	35.5	32.7
Cholesterol: Male	38.8	37.9	37.9
Arthritis: Female	32.1	28.9	28.6
Arthritis: Male	24.3	21.2	20.5
Asthma: Female	16.3	16.6	16.3
COPD: Female	8.7	6.9	6.1
COPD: Male	6.2	5.4	4.7
Kidney Disease: Female	3.1	3	2.7
Kidney Disease: Male	2.5	2.5	2.2
Overweight/Obese: Female	63.6	59.6	54.9
Overweight/Obese: Male	71.8	72.2	69.6
Heavy Drinking: Female	4.3	4.9	6
Heavy Drinking: Male	6.2	6.4	6.4
Tobacco Use: Female	17.4	15.9	13.4
Tobacco Use: Male	23.6	19.5	17.1
General Health: Female	22.1	18.2	15.1
General Health: Male	18.7	16.4	14.2
Mental Health: Female	23.5	23.1	25.1
Mental Health: Male	14.4	13.3	14.9
Mortality: Female	894.8	856.6	802.7
Mortality: Male	991.7	891.85	819.8

Source: Author's calculations based on data from BRFSS 2015 and CDC WONDER Database 2014; The above values represent sample design adjusted prevalence; Mortality numbers represent crude rates per 100,000 population

Policy Implications of Gender-Based Health Disparity Rankings and Clusters of States

Although causal factors and effective policy solutions to a latent gender-based health inequality across states deserve a carefully designed, separate investigation, the results in this study provide several potentially important policy implications. First, we find that states where women have far worse health outcomes than men also tend to have lower overall population health outcomes and states where women fare better also tend to have better health outcomes for both men and women, which suggests that investment in overall public health may have an important role in reducing the gender-based health disparity. Second, our results indicate that differences in health disparity across states have a significant association with the differences in the available workforce in the health-care sector across states, captured by the doctors-to-patient ratio. Third, a geographic pattern of the gender-based health disparity appears to reflect socio-economic differences across states.

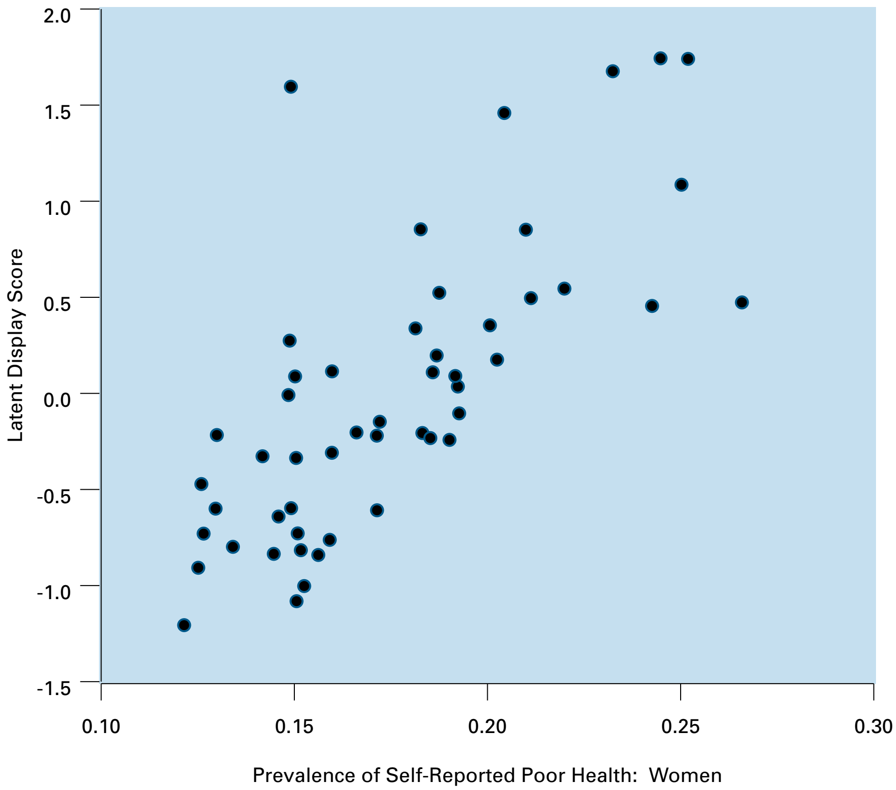
Overall Population Health and Gender Differences in Health

Nobody would be surprised to learn that women in a state with the highest overall population health ranking enjoy better health compared to women in most states. However, it is unclear how a state where women have better health outcomes than men would fare in the overall population health rankings. For example, we may have a state that has a very low population health ranking with men having far worse health outcomes than women. Alternatively, we may have a state with a high population health ranking with men and women enjoying similar health outcomes. The gender-based health disparity favors women in the first example and is worse for women in the second, despite the obvious advantage of the latter.

We were surprised to find that states with lower latent gender-based health disparity scores (favoring women) also tend to have better overall population health outcomes. Although this pattern is observed with all 16 indicators to a varying degree, we limit our illustration to the six indicators shown in Figures 3-5. States with low disparity scores (favoring women) are associated with lower prevalence of hypertension, self-reported poor health, heart disease, mortality rate, diabetes, and obesity for both men and women. To assess the robustness of our findings, we compared the estimated latent gender-based health disparity scores with the Milken Institute's State Chronic Disease Index.[14] Almost all our high-disparity states were in the bottom third of the index. These associations suggest that states may reduce the health gender-gap by improving their overall public health outcomes.

14 Ross DeVol, Armen Bedroussian, Anita Charuworn, Anusuya Chatterjee, Kyu Kim, Soojung Kim, and Kevin Klowden, "An Unhealthy America: The Economic Burden of Chronic Disease-Charting a New Course to Save Lives and Increase Productivity and Economic Growth," Milken Institute, 2007.

Figure 3(a). Latent disparity score vs. hypertension and self-reported poor health, by sex



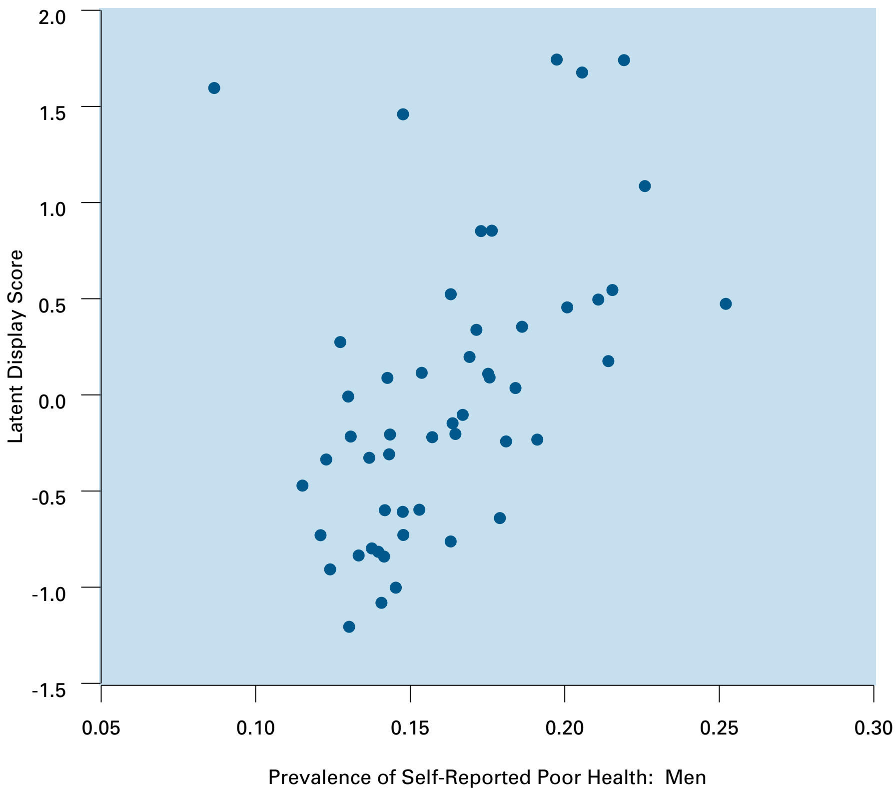


Figure 3(b). Latent disparity score vs. hypertension and self-reported poor health, by sex

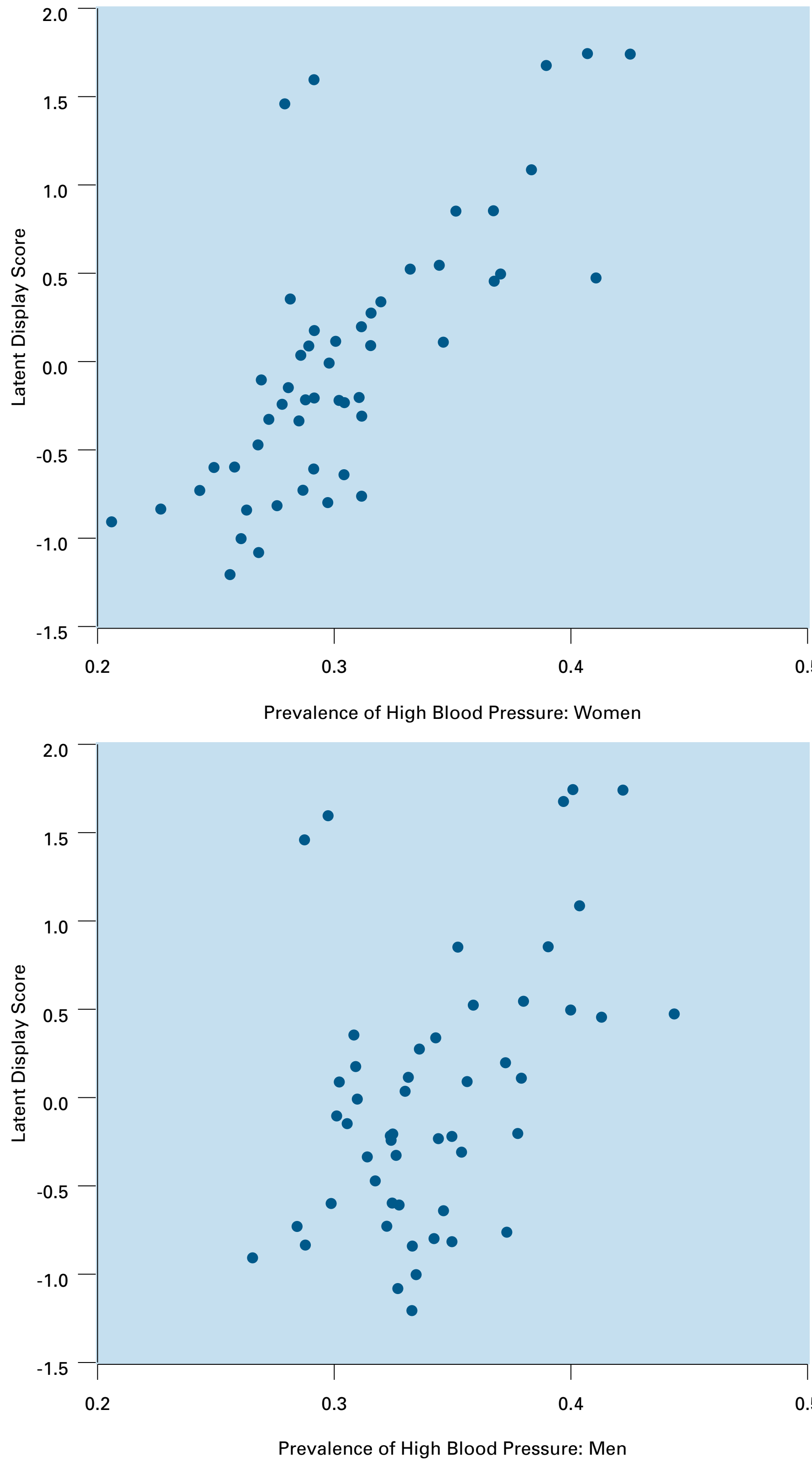


Figure 4(a). Latent disparity score vs. heart disease and mortality rate, by sex

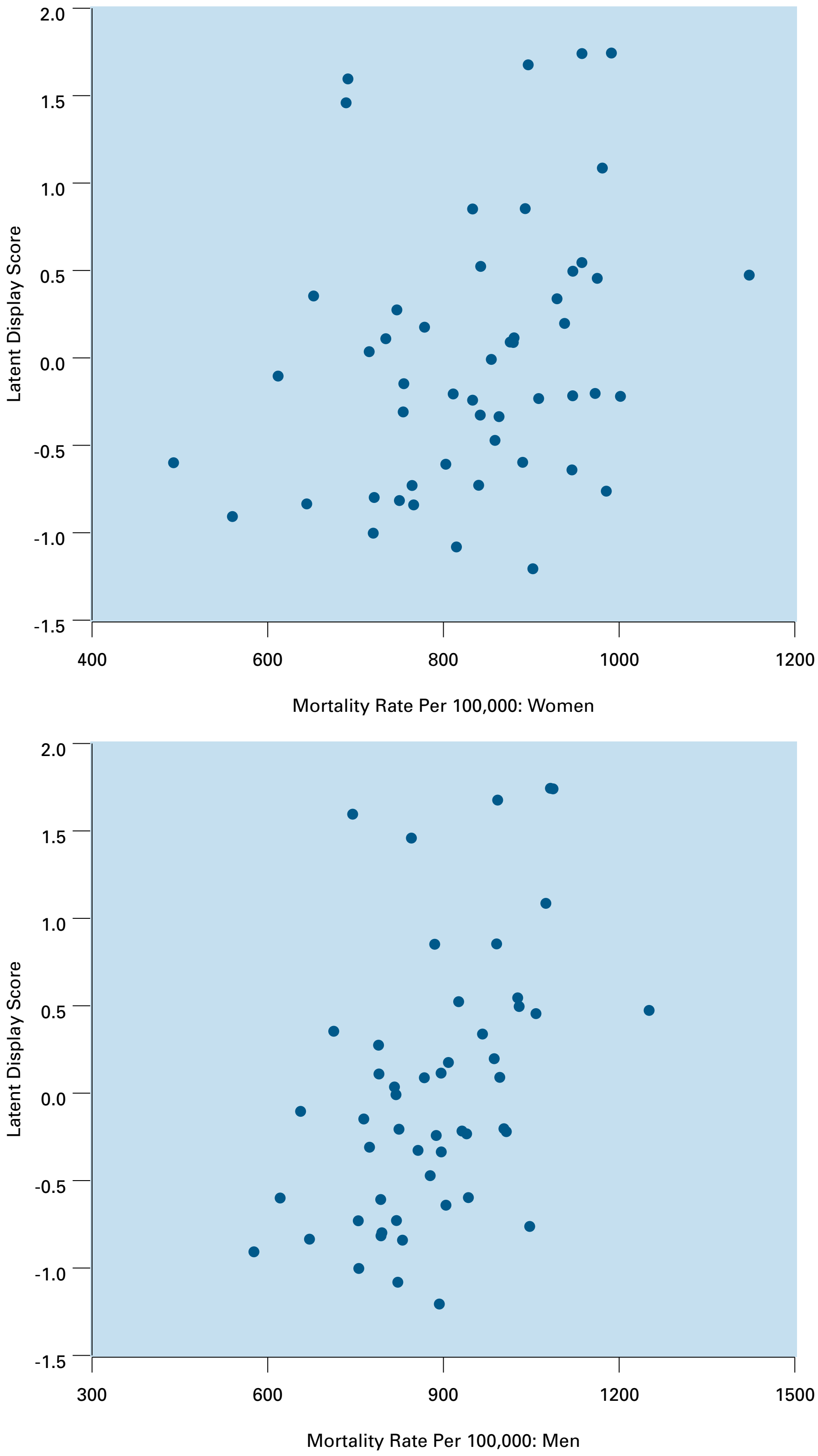
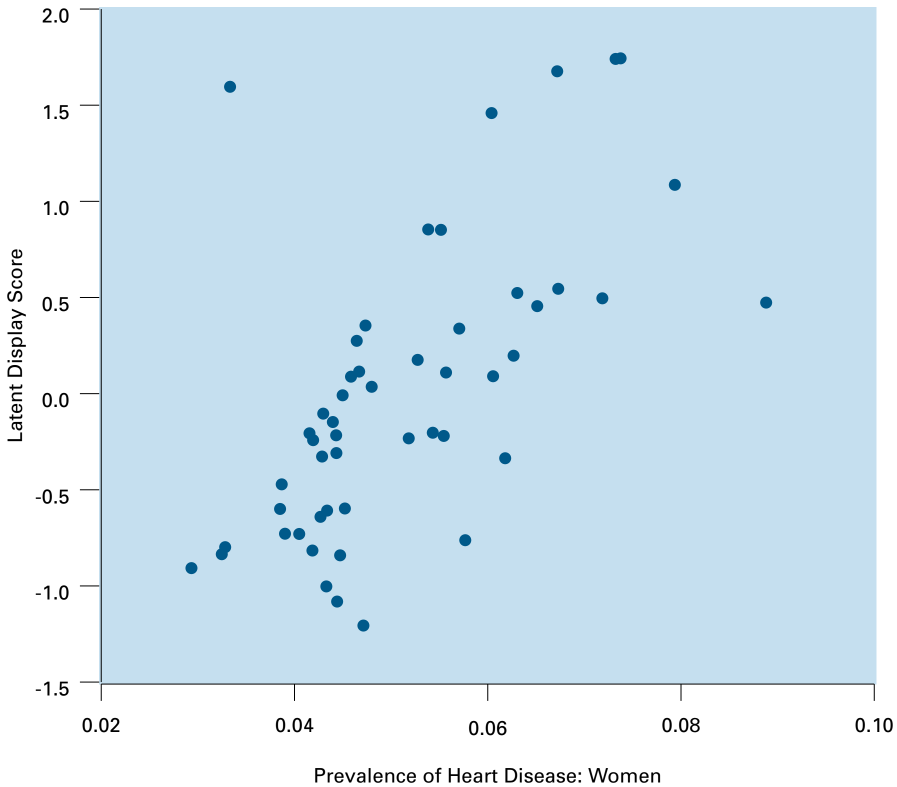


Figure 4(b). Latent disparity score vs. heart disease and mortality rate, by sex



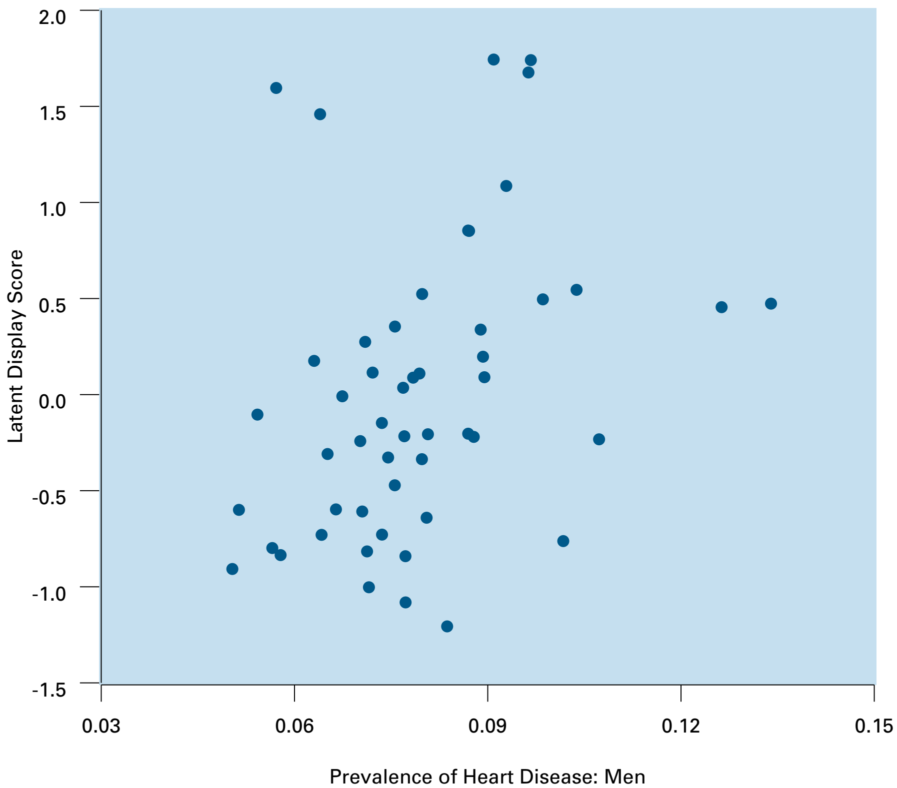
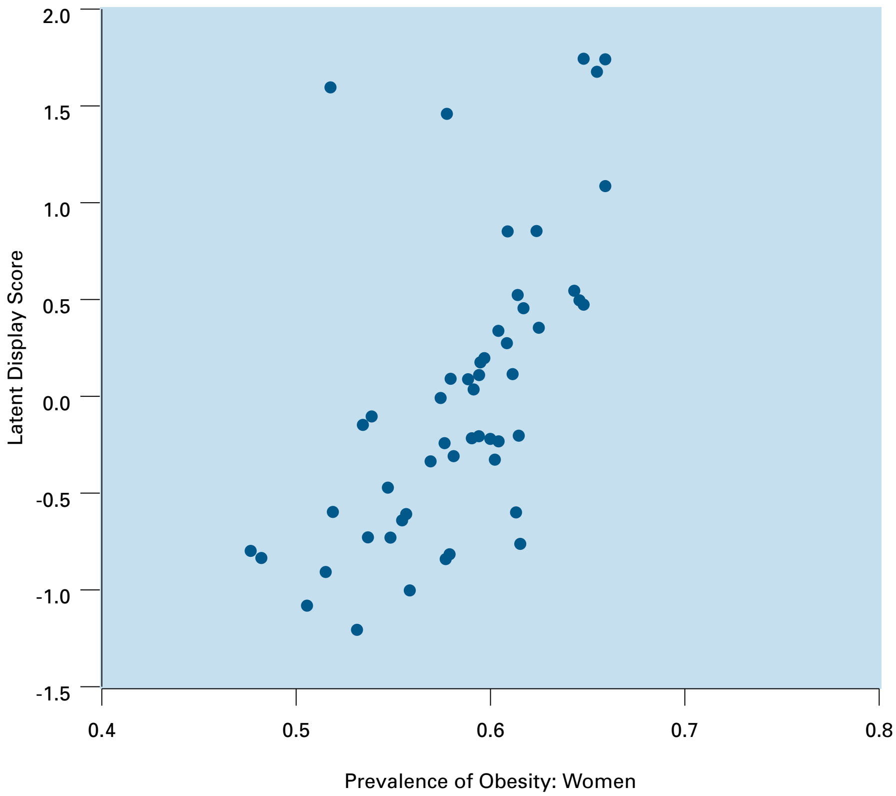


Figure 5(a). Latent disparity score vs. diabetes and obesity



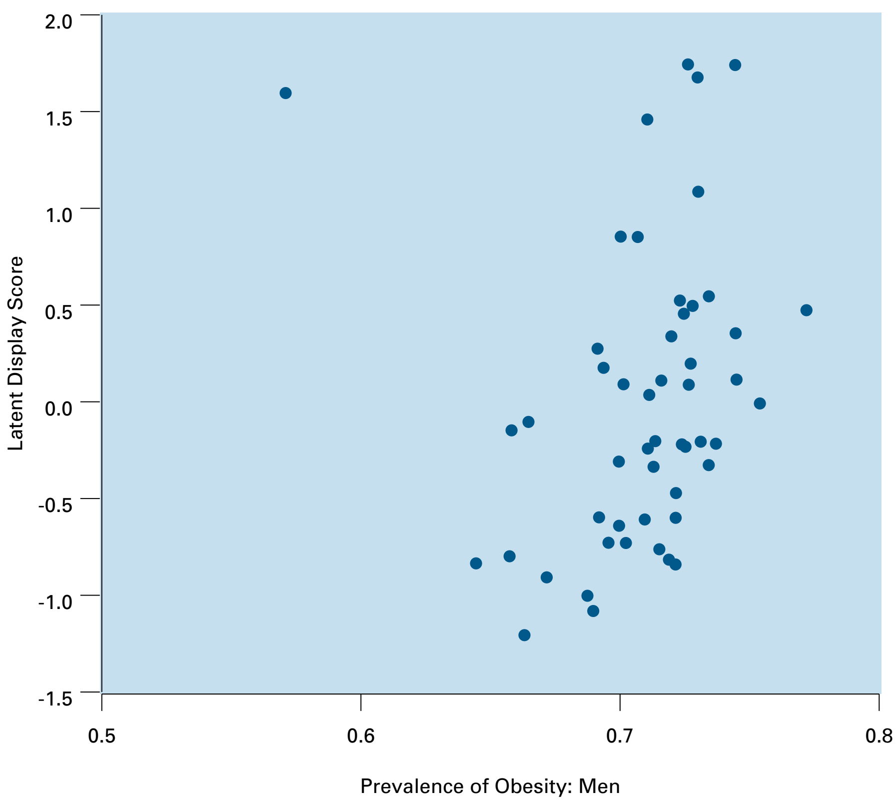
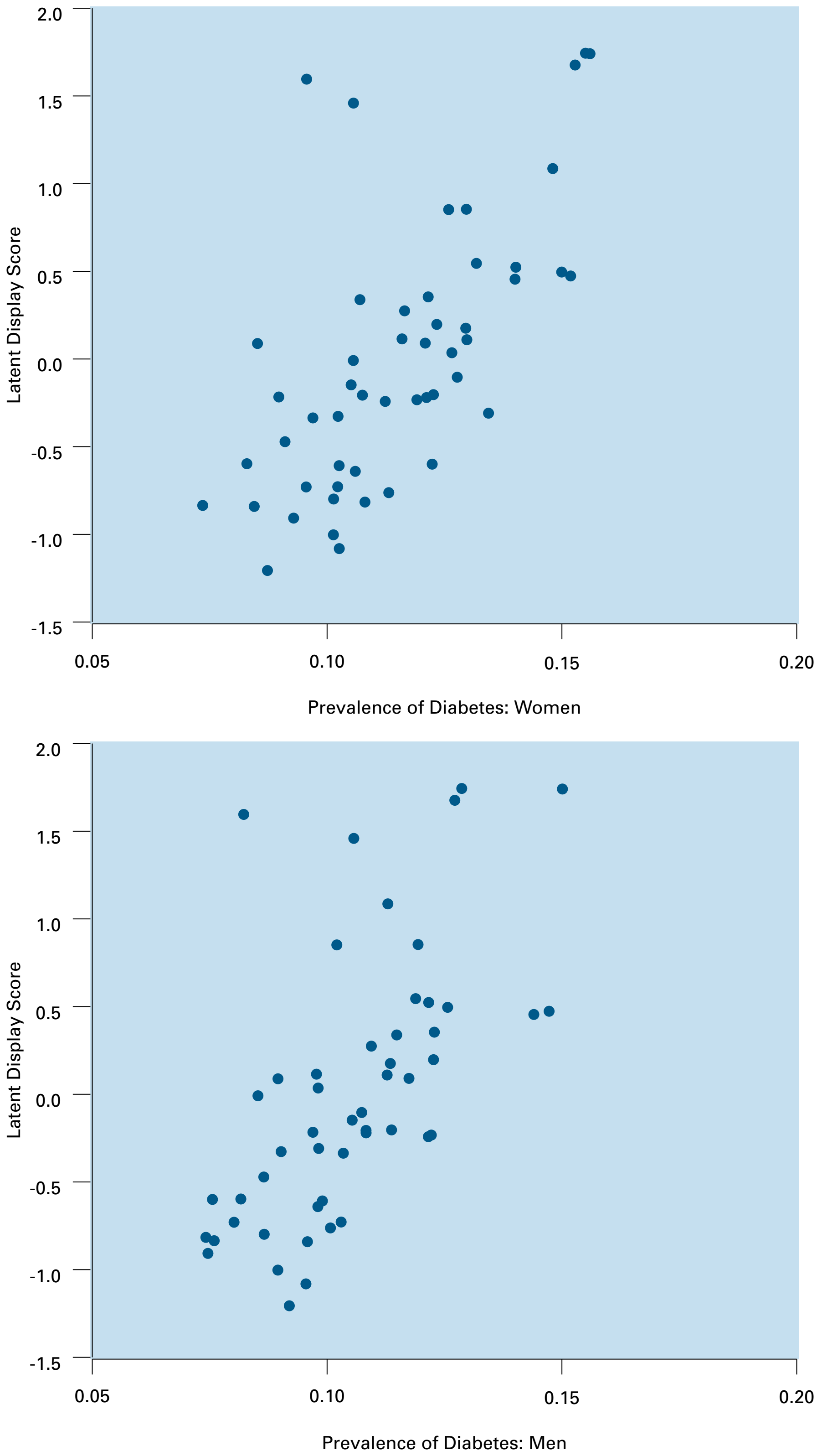


Figure 5(b). Latent disparity score vs. diabetes and obesity



Health-Care Resources and Gender Differences in Health

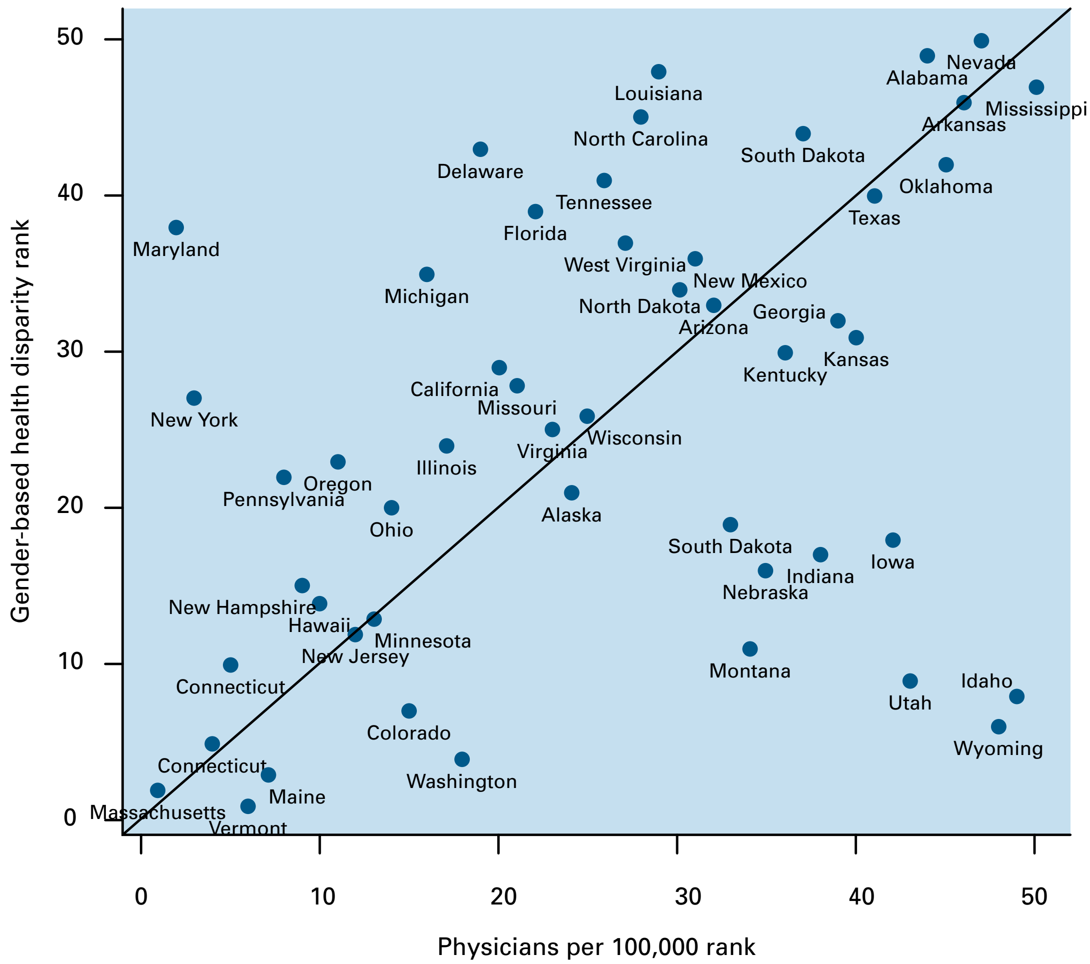
It has been long known that states with a higher doctors-to-residents ratio tend to have a larger number of medical facilities and more medical students, who often perform their residency in those states. The share of the health-care sector in these states' economies also tends to be larger. More health-care resources, in turn, help to ensure better public health in those communities. Our findings indicate that having more resources in health-care services may also influence the gender-based health disparity.

We took the data on the number of active physicians per 100,000 population from the 2015 State Physician Workforce Data Book published by the Association of American Medical Colleges and ranked states accordingly. We plotted these against our own ranking to see if there is any association between health-care resources and the gender-based health disparity (Figure 6, p. 41). There is a strong positive association between physician availability ranks and health disparity ranks. This suggests that greater physician availability permits more opportunities for preventative medical interventions such as behavior modification or early detection of a health condition. The association is far more pronounced at the top- and bottom-ranked states and is weaker in between, which is consistent with our own estimates of uncertainty for the latent gender-based health disparity scores. States in high-disparity and low-disparity groups are close to the diagonal line, which indicates that resource constraints are good predictors.

We carried out similar exercises using other health-care service resource indicators. For example, when we compared Employment Concentration scores by state from the Milken Institute's "America's Health Care Economy" report, we found that states with high gender-based health disparity also have lower employment in the health-care industry.[15] These bivariate associations suggest a potential link between availability of health-care resources and the gender-based health disparity.

15 Ross DeVol and Rob Koepp, "America's Health Care Economy," Milken Institute, 2003.

Figure 6. State rankings: Gender-based health disparity vs. physicians per 100,000



Socio-Economic Factors and Gender Differences in Health

A geographic pattern of the gender-based health disparity across states highlights underlying and possibly causal socio-economic factors. Recent health economics and epidemiological studies all point to a substantial geographic variation in health indicators. Mortality trends, for example, exhibit a strong income gradient.[16] The gap in life expectancy between the richest 1 percent and poorest 1 percent of Americans is estimated to be 14.6 years.[17] The same study also suggests that life expectancy at the bottom of income distribution has a positive association with a fraction of college graduates, government expenditures, and fraction of immigrants. A majority (51 percent) of state-level variation in high rates of cardiovascular disease (CVD) and mortality rates due to CVD were explained by socio-economic factors.[18] Furthermore, the study shows that state-level median household income, the tax rate on soda, the absence of farmer's markets to supply fresh produce, and access to convenience stores are strong predictors of CVD rates. A comprehensive study of 11 health indicators from five nationally representative surveys also shows that for almost all health indicators, the predictive strength of income and education variables has practical and statistical significance.[19] Our findings complement this well-documented but poorly understood phenomenon in the literature. Namely, our results show that a geographic variation in health inequality between men and women across states coincides with the pattern seen in the overall population health indicators and appears to reflect differences in income, education, and other socio-economic factors.

16 Janet Currie and Hannes Schwandt, "Inequality in Mortality Decreased Among the Young While Increasing for Older Adults, 1990-2010," *Demography*, 352 (2016): 708-711.

17 Raj Chetty, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron and David Cutler, "The Association Between Income and Life Expectancy in the United States, 2001-2014," *JAMA* (2016): E1-E17.

18 Samson Gebreab, Sharon Davis, Jurgen Symanzik, George Mensah, Gary Gibbons and Ana Diez-Roux, "Geographic Variations in Cardiovascular Health in the United States: Contribution of State- and Individual-Level Factors," *Journal of the American Heart Association* (2015): 1-12.

19 Paula Braveman, Catherine Cubbin, Susan Egerter, David Williams and Elsie Pamuk, "Socioeconomic Disparities in Health in the United States: What the Patterns Tell Us," *American Journal of Public Health*, S1 (100): S186-S196.

CONCLUSION

This study ranks and groups the U.S. states based on how women fare relative to men in a composite health disparity index. Our results show that states in the low-disparity group had better health indicators for both women and men. Similarly, states in the high-disparity group had worse health indicators for both women and men. Disparity ranks also show a strong linear association with the number of physicians per capita. These associations suggest state public health policies that have been successful at improving overall population health may have been successful at reducing gender-based health disparity as well.

Although a myriad of studies has been written on gender-based health inequality, ours offers several substantive contributions. First, our choices of indicators to measure health and health disparity is informed by the consensus opinion in the field. Often, studies that compare health of individuals across states use a large number of indicators ranging from health outputs (e.g., prevalence of diabetes) to health inputs (e.g., nurses per 100,000 population). We deliberately avoid mixing inputs and outputs. Instead, our choice of indicators for measuring health are based on health outcomes that experts in the field suggest as essential components of health. Second, we explicitly report uncertainty with our estimates of health disparity. To make the constructed index useful, we combine the scores and their uncertainty estimates and assign each state to its corresponding health disparity group. We are not aware of any other state-level indices of health or health inequality that report confidence intervals around their reported scores. Without these confidence intervals, calculated ranks create a false impression that the difference between the fifth and the sixth-ranked states is similar to the difference between the 27th and the 28th ranked states. In reality, it is possible that there is no real difference between the fifth and the sixth-ranked states, while the difference between the 27th and the 28th ranked states is extremely large. In that respect, our methodological approach provides an accurate characterization of how states compare to each other. Third, we investigate health disparity by race and show that rankings and groups of states differ for African Americans compared to Caucasians. Namely, we find that gender-based health disparity differences across states are substantially smaller among African Americans compared to Caucasians.

Despite the above-mentioned insights, our methodology is subject to several limitations. The results rely on a strong and untestable assumption that there is a single dimensional construct, a gender-based health disparity, which is partially contained in each of our 16 indicators. Although our indirect assessment through a principal component analysis confirmed the substantial weight of the first component, we cannot be certain, although the analysis strongly suggests that it captures our intended construct. Also, we were cautious in our choice of priors. In the analysis, we let the data dictate the relative importance of indicators. A more rigorous approach in the future studies may specify expert opinion informed priors with respect to ex-ante relative importance of indicators. We also recognize that the differences in health reflect differential biological exposure and vulnerability of women compared to men to various morbidities, health risks, and mortality. Combined with demographic adjustments, incorporating these factors may provide a different picture of gender-based health disparity across U.S. states. Nonetheless, the results reported in this study offer significant improvements and additional insights over the existing alternatives. We are confident that our transparent approach, which recognizes the proper role of uncertainty and model limitations, will encourage state-level policymakers to cooperate in seeking pragmatic solutions to gender-based health disparity challenges today and in the future.

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Rankings and Clusters by Gender and Race

Table H. Gender-based health disparity ranks and clusters of states: Caucasian population

State	Disparity Group	Latent Score	Final Rank	Baseline Score	Baseline Rank
Alabama	High	1.7	51	0.8	50
Arkansas	High	1.7	50	0.8	49
Louisiana	High	1.3	49	0.3	46
Nevada	High	1.1	48	0	26
Oklahoma	High	1.1	47	0.4	47
Mississippi	High	0.9	46	0.1	34
West Virginia	High	0.8	45	-0.1	22
Alaska	High	0.7	44	0.9	51
Missouri	High	0.6	43	0.2	41
Kentucky	High	0.6	42	-0.1	18
South Carolina	High	0.6	41	0	24
Tennessee	High	0.6	40	0.2	38
North Carolina	High	0.6	39	0.2	37
Oregon	High	0.5	38	0.3	45
Texas	High	0.5	37	0.4	48
Arizona	Average	0.4	36	0.2	39
Georgia	Average	0.3	35	0.3	43
California	Average	0.3	34	0.3	44
Delaware	Average	0.3	33	-0.3	10
Michigan	Average	0.2	32	0.1	33
Florida	Average	0.1	31	-0.4	6
Kansas	Average	0.1	30	0	23
Indiana	Average	0	29	-0.1	20
Maine	Average	0	28	0.2	36
New Mexico	Average	-0.1	27	-0.5	4
Pennsylvania	Average	-0.1	26	0	28

Source: Author's calculations.

Rankings and Clusters by Gender and Race

Table H. Gender-based health disparity ranks and clusters of states: Caucasian population

State	Disparity Group	Latent Score	Final Rank	Baseline Score	Baseline Rank
Wisconsin	Average	-0.1	25	0.1	35
Ohio	Average	-0.1	24	0.1	31
Wyoming	Average	-0.1	23	-0.2	16
Hawaii	Average	-0.2	22	0	27
South Dakota	Average	-0.2	21	0.2	40
Maryland	Average	-0.2	20	0.3	42
Montana	Average	-0.3	19	-0.3	9
Iowa	Average	-0.3	18	0	25
New Hampshire	Average	-0.3	17	-0.1	19
Idaho	Average	-0.4	16	-0.2	15
Nebraska	Average	-0.4	15	-0.3	12
Virginia	Average	-0.5	14	0	29
Washington	Average	-0.6	13	0	30
Utah	Average	-0.6	12	-0.3	11
Minnesota	Average	-0.6	11	-0.1	21
North Dakota	Average	-0.6	10	-0.2	17
District of Columbia	Average	-0.7	9	0.1	32
New York	Average	-0.8	8	-0.2	14
Colorado	Low	-0.9	7	-0.5	3
Vermont	Low	-1	6	-0.4	7
Connecticut	Low	-1	5	-0.4	8
Illinois	Low	-1.2	4	-0.6	1
Rhode Island	Low	-1.2	3	-0.3	13
Massachusetts	Low	-1.3	2	-0.5	5
New Jersey	Low	-1.4	1	-0.5	2

Source: Author's calculations.

Figure 7. Hierarchical clusters of states: Caucasian population

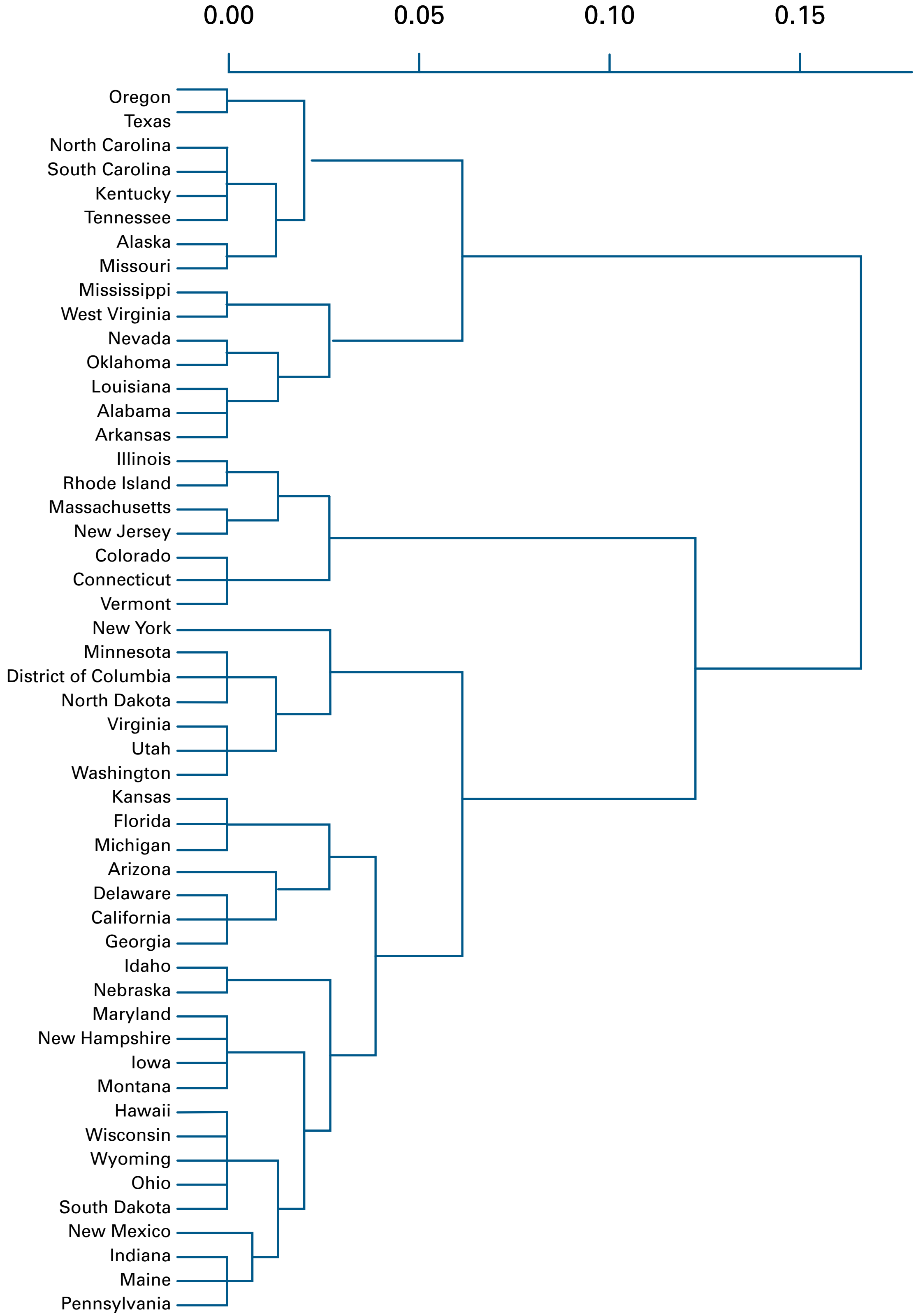

Figure 8. Gender-based health disparity scores and 95 percent uncertainty bounds, Caucasian population

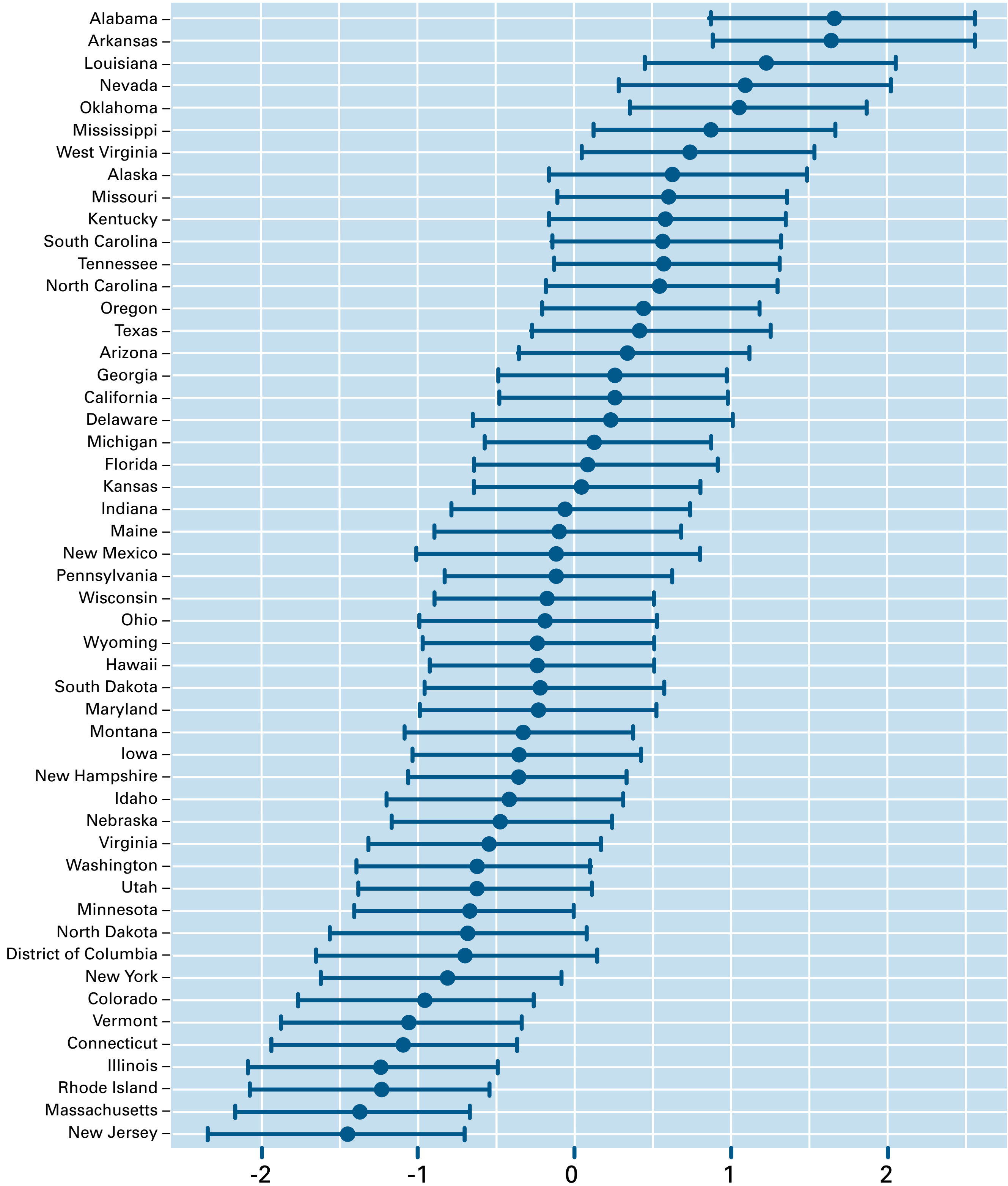

Table I. Comparison of health indicators across groups: Caucasian population (by percent)

Health Dimensions	High Disparity	Average Disparity	Low Disparity
Skin Cancer: Female	7.6	7.7	8.0
Skin Cancer: Male	9.5	8.0	7.2
Other Cancer: Female	10.2	9.4	8.9
Other Cancer: Male	5.7	6.2	6.3
Diabetes: Female	13.0	9.7	8.7
Diabetes: Male	11.8	9.5	9.5
High Blood Pressure: Female	35.5	30.1	29.4
High Blood Pressure: Male	39.0	34.5	33.5
Heart Disease: Female	6.8	5.0	4.4
Heart Disease: Male	10.7	7.9	8.5
Cholesterol: Female	38.7	35.8	33.1
Cholesterol: Male	40.9	39.1	38.9
Arthritis: Female	35.3	30.7	30.8
Arthritis: Male	27.1	23.1	22.8
Asthma: Female	16.2	16.1	18.1
Asthma: Male	12.0	11.3	13.2
COPD: Female	10.3	7.6	6.5
COPD: Male	7.6	6.1	5.9
Kidney Disease: Female	3.6	2.8	2.5
Kidney Disease: Male	2.4	2.3	2.3
Overweight/obese: Female	59.2	56.4	50.7
Overweight/obese: Male	73.5	71.9	70.4
Heavy Drinking: Female	4.3	6.0	6.8
Heavy Drinking: Male	7.2	6.9	7.5
Tobacco Use: Female	21.1	15.6	13.4
Tobacco Use: Male	22.4	17.5	17.0
General Health: Female	20.6	14.0	12.7
General Health: Male	17.3	13.5	12.5
Mental Health: Female	27.9	25.0	23.7
Mental Health: Male	15.9	14.1	15.5
Mortality: Female	994.8	890.0	924.9
Mortality: Male	1056.0	900.1	905.3

Source: Author's calculations. The above values represent sample design adjusted prevalence; mortality numbers represent crude rates per 100,000 population.

Table J. Gender-based health disparity ranks and clusters of states: African American population

State	Disparity Group	Latent Score	Final Rank	Baseline Score	Baseline Rank
New Mexico	High	1.2	43	1.1	43
Nevada	High	1.1	42	0.3	36
Utah	High	1	41	0.7	41
Washington	High	0.9	40	0.7	42
Kentucky	High	0.8	39	0.4	40
District of Columbia	High	0.6	38	0.3	39
Arkansas	High	0.5	37	-0.2	14
California	High	0.4	36	0.3	38
Illinois	Average	0.3	35	0	26
Michigan	Average	0.3	34	0.1	30
Florida	Average	0.3	33	0.2	34
Virginia	Average	0.2	32	0.3	37
Louisiana	Average	0.2	31	-0.2	10
Missouri	Average	0.2	30	0	20
Ohio	Average	0.2	29	-0.1	18
Mississippi	Average	0.1	28	-0.1	15
North Carolina	Average	0.1	27	0.1	29
Maryland	Average	0.1	26	-0.1	19
Nebraska	Average	0.1	25	-0.2	13
Massachusetts	Average	0.1	24	0	24
Alaska	Average	0.1	23	0.2	35
Alabama	Average	0	22	-0.1	17

Source: Author's calculations.

Table J. Gender-based health disparity ranks and clusters of states: African American population

State	Disparity Group	Latent Score	Final Rank	Baseline Score	Baseline Rank
Tennessee	Average	0	21	-0.2	11
Minnesota	Average	0	20	0	25
Pennsylvania	Average	0	19	-0.1	16
Delaware	Average	0	18	0.1	31
Oklahoma	Average	0	17	0.1	27
Connecticut	Average	0	16	0.1	28
South Carolina	Average	0	15	-0.3	7
Kansas	Average	0	14	0.2	33
Rhode Island	Average	-0.1	13	0	21
New York	Average	-0.1	12	0.1	32
New Jersey	Average	-0.1	11	0	22
Wisconsin	Average	-0.2	10	-0.3	5
Georgia	Average	-0.2	9	-0.2	9
Texas	Average	-0.3	8	-0.2	8
Arizona	Average	-0.3	7	-0.3	6
Indiana	Low	-0.5	6	-0.5	3
Colorado	Low	-0.6	5	0	23
West Virginia	Low	-0.8	4	-0.3	4
Iowa	Low	-0.9	3	-1	2
Oregon	Low	-2.3	2	-0.2	12
Hawaii	Low	-2.4	1	-1	1

Source: Author's calculations.

Figure 9. Gender-based health disparity scores and 95 percent uncertainty bounds, African American population

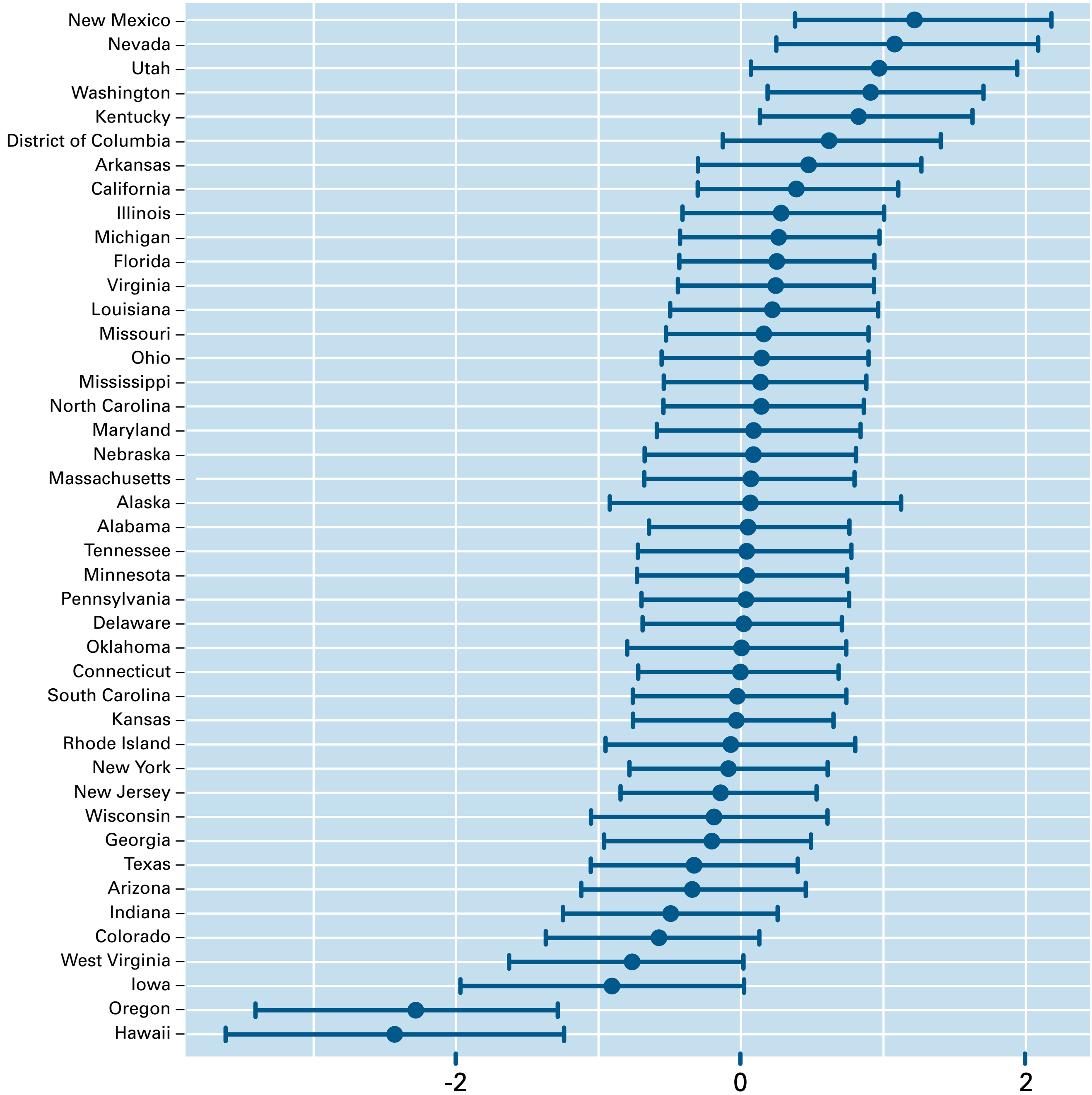

Figure 10. Hierarchical clusters of states, African American population

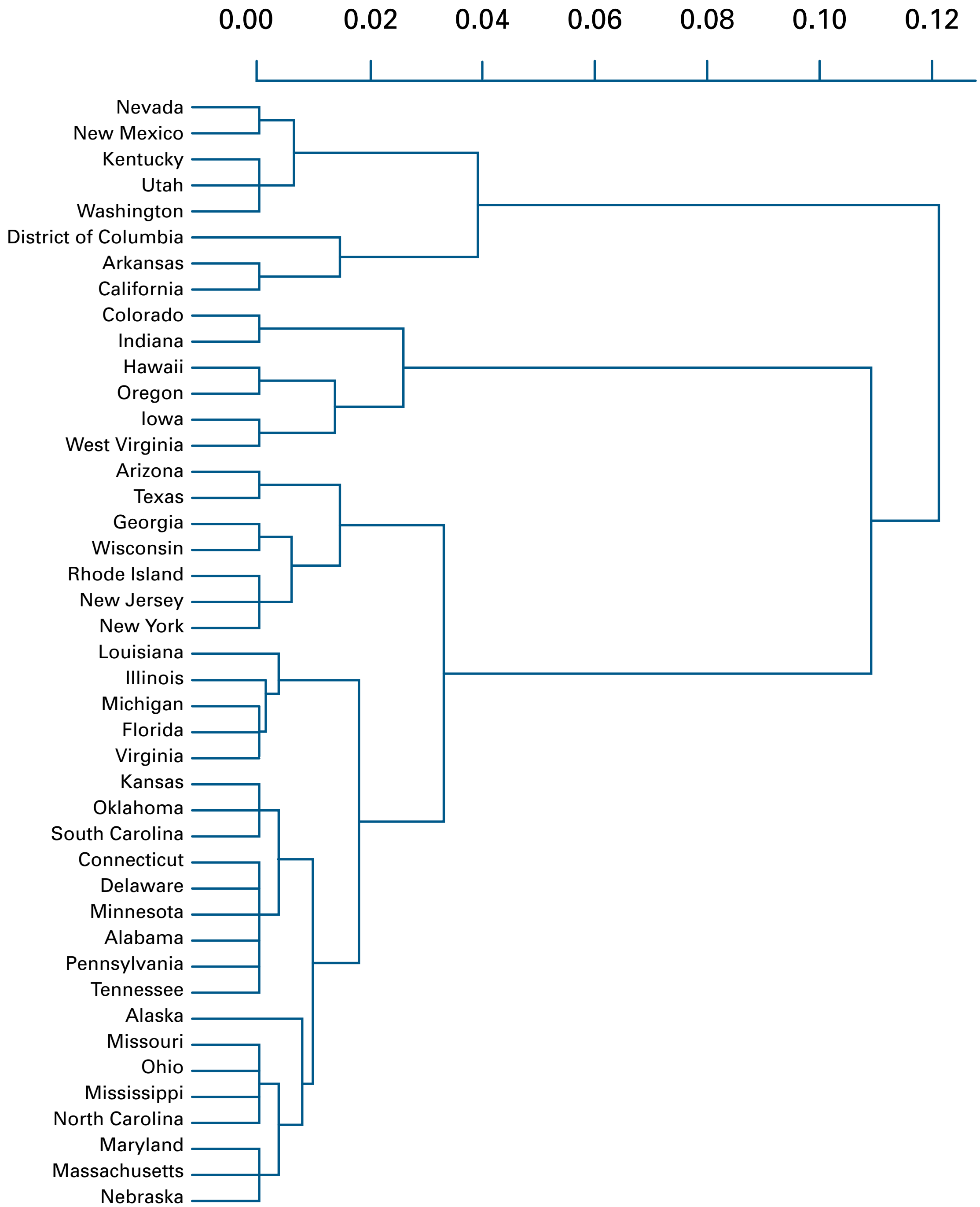

Table K. Comparison of health indicators across groups: African American population (by percent)

Health Dimensions	High Disparity	Average Disparity	Low Disparity
Skin Cancer: Female	0.0	0.3	0.0
Skin Cancer: Male	0.3	0.3	0.5
Other Cancer: Female	4.7	5.0	6.1
Other Cancer: Male	4.4	4.0	7.3
Diabetes: Female	16.5	16.5	10.1
Diabetes: Male	14.0	13.5	15.4
High Blood Pressure: Female	43.6	40.0	33.8
High Blood Pressure: Male	37.5	40.3	36.8
Heart Disease: Female	6.6	5.3	3.5
Heart Disease: Male	6.3	6.2	3.3
Cholesterol: Female	35.5	33.4	27.7
Cholesterol: Male	32.1	34.9	35.5
Arthritis: Female	26.7	28.0	24.5
Arthritis: Male	17.9	19.9	22.5
Asthma: Female	20.0	17.8	21.2
Asthma: Male	19.8	14.0	12.4
COPD: Female	9.2	6.0	3.1
COPD: Male	4.6	4.7	5.0
Kidney Disease: Female	3.5	2.4	2.1
Kidney Disease: Male	2.3	2.7	2.9
Overweight/obese: Female	74.1	73.3	67.6
Overweight/obese: Male	65.8	72.0	73.8
Heavy Drinking: Female	5.5	3.5	2.3
Heavy Drinking: Male	2.5	4.8	9.1
Tobacco Use: Female	24.5	15.6	20.0
Tobacco Use: Male	22.1	24.6	28.9
General Health: Female	25.4	22.7	19.5
General Health: Male	17.6	18.9	21.2
Mental Health: Female	20.8	17.7	19.3
Mental Health: Male	16.0	11.2	16.7
Mortality: Female	584.6	634.3	449.0
Mortality: Male	698.3	704.9	458.5

Source: Author's calculations.

Table L. Gender-based health disparity ranks and clusters of states, age-adjusted values

State	Disparity Group	Latent Score	Final Rank	Baseline Score	Baseline Rank
Alabama	High	1.74	51	0.33	46
Mississippi	High	1.74	50	-0.01	25
Louisiana	High	1.68	49	0.05	30
District of Columbia	High	1.6	48	0.58	49
Nevada	High	1.46	47	0.61	50
Arkansas	High	1.09	46	0.3	45
South Carolina	High	0.85	45	-0.08	19
North Carolina	High	0.85	44	0.22	43
Oklahoma	Average	0.55	43	-0.05	20
Delaware	Average	0.52	42	0.09	34
Tennessee	Average	0.5	41	0.16	39
West Virginia	Average	0.47	40	-0.01	27
Kentucky	Average	0.46	39	-0.44	3
Texas	Average	0.35	38	0.06	31
Michigan	Average	0.34	37	0.06	32
Maryland	Average	0.27	36	0.04	29
Missouri	Average	0.2	35	0.18	42
New Mexico	Average	0.18	34	-0.2	12
Kansas	Average	0.11	33	0.1	35
Georgia	Average	0.11	32	-0.05	22
Florida	Average	0.09	31	-0.05	21
Wisconsin	Average	0.09	30	0.17	41
Arizona	Average	0.04	29	0.17	40
North Dakota	Average	-0.01	28	-0.09	18
California	Average	-0.1	27	0.03	28
New York	Average	-0.15	26	-0.29	8

Source: Author's calculations. Baseline scores and baseline ranks are results from equally weighting all dimensions of health disparity.

Table L. Gender-based health disparity ranks and clusters of states, age-adjusted values

State	Disparity Group	Latent Score	Final Rank	Baseline Score	Baseline Rank
Ohio	Average	-0.2	25	-0.01	26
Illinois	Average	-0.21	24	-0.4	5
Iowa	Average	-0.22	23	-0.14	17
Pennsylvania	Average	-0.22	22	-0.03	24
Indiana	Average	-0.23	21	-0.2	13
Oregon	Average	-0.24	20	0.35	47
Virginia	Average	-0.31	19	0.24	44
Nebraska	Average	-0.33	18	-0.17	16
South Dakota	Average	-0.34	17	0.13	38
New Hampshire	Average	-0.47	16	-0.05	23
Montana	Low	-0.6	15	-0.19	14
Alaska	Low	-0.6	14	0.97	51
New Jersey	Low	-0.61	13	-0.22	11
Rhode Island	Low	-0.64	12	-0.55	2
Connecticut	Low	-0.73	11	-0.38	6
Minnesota	Low	-0.73	10	0.08	33
Maine	Low	-0.76	9	0.38	48
Hawaii	Low	-0.8	8	-0.55	1
Idaho	Low	-0.82	7	0.1	36
Colorado	Low	-0.84	6	-0.24	10
Wyoming	Low	-0.84	5	-0.24	9
Utah	Low	-0.91	4	-0.17	15
Washington	Low	-1	3	0.13	37
Massachusetts	Low	-1.08	2	-0.41	4
Vermont	Low	-1.21	1	-0.3	7

Source: Author's calculations. Baseline scores and baseline ranks are results from equally weighting all dimensions of health disparity

ABOUT THE AUTHOR

Dr. Ken Sagynbekov is a health economist at the Milken Institute. His research focuses primarily on applied microeconomic analysis of health with an emphasis on quantitative methods. Sagynbekov's work has been published in peer-reviewed academic journals and government reports. Before joining the Institute, he was a professor of economics at the University of Regina in Canada, where he led a team of researchers to find practical solutions to community safety issues and served as lead investigator in several large government-funded research projects. In addition to academia, Sagynbekov worked as an economic consultant in Central Asia with USAID's fiscal reform initiative. He earned his B.S. in finance from Clemson University and his M.A. and Ph.D. degrees in economics from the University of Mississippi. He works at the Institute's Santa Monica office.

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