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Identifying characteristics of high-poverty counties in the United States with high well-being: an observational cross-sectional study

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ABSTRACT

Objective To identify county characteristics associated with high versus low well-being among high-poverty counties.

Design Observational cross-sectional study at the county level to investigate the associations of 29 county characteristics with the odds of a high-poverty county reporting population well-being in the top quintile versus the bottom quintile of well-being in the USA. County characteristics representing key determinants of health were drawn from the Robert Wood Johnson Foundation County Health Rankings and Roadmaps population health model.

Setting Counties in the USA that are in the highest quartile of poverty rate.

Main outcome measure Gallup-Sharecare Well-being Index, a comprehensive population-level measure of physical, mental and social health. Counties were classified as having a well-being index score in the top or bottom 20% of all counties in the USA.

Results Among 770 high-poverty counties, 72 were categorised as having high well-being and 311 as having low well-being. The high-well-being counties had a mean well-being score of 71.8 with a SD of 2.3, while the low-well-being counties had a mean well-being score of 60.2 with a SD of 2.8. Among the six domains of well-being, basic access, which includes access to housing and healthcare, and life evaluation, which includes life satisfaction and optimism, differed the most between high-being and low-well-being counties. Among 29 county characteristics tested, six were independently and significantly associated with high well-being (p<0.05). These were lower rates of preventable hospital stays, higher supply of primary care physicians, lower prevalence of smoking, lower physical inactivity, higher percentage of some college education and higher percentage of heavy drinkers.

Conclusions Among 770 high-poverty counties, approximately 9% outperformed expectations, reporting a collective well-being score in the top 20% of all counties in the USA. High-poverty counties reporting high well-being differed from high-poverty counties reporting low well-being in several characteristics.

Strengths and limitations of this study

► In this study of high-poverty counties in the USA, we used a unique and validated measure of population well-being, the Gallup-Sharecare Well-being Index.

► We described high-poverty counties with high and low well-being using 29 characteristics from the Robert Wood Johnson Foundation County Health Rankings and Roadmaps, a well-established model of population health.

► As this was a cross-sectional study, we were unable to assess whether or not improving these characteristics would actually improve well-being in high-poverty counties.

► Our study examined associations by county, due to lack of well-being data at the city or neighbourhood level, and both poverty and well-being are likely to be heterogeneous at the county level.

INTRODUCTION

Poverty is negatively associated with physical, mental and social health.[1–14] In particular, studies have linked poverty with higher rates of obesity and greater incidence of coronary artery disease, as well as lower levels of life satisfaction and social capital.[1 5 9–12] Though it is essential to decrease rates of poverty in the USA, there is also a need to mitigate its adverse health consequences through policies and programmes focused on high-poverty populations.[15]

One approach to understanding how to reduce the consequences of poverty is to study populations with high rates of poverty that report high levels of physical, mental and social health, together defined as high well-being.[16] Well-being includes both the absence of disease, and also a sense of opportunity, happiness and lack of stress. It reflects the ability to afford food, housing and healthcare, to live in a safe neighbourhood and to

work in a trusting, respectful environment.[16–19] As poverty is negatively associated with many aspects of well-being, if high-poverty populations report high well-being, these populations have outperformed expectations.[1–8 20] By exploring the characteristics of high-poverty populations with high well-being and comparing them to high-poverty populations with low well-being, we may identify potential targets for well-being improvement efforts.

Accordingly, we sought to identify the community characteristics most strongly associated with high versus low well-being among counties with high rates of poverty. We conducted this analysis using county-level estimates of well-being from the Gallup-Sharecare Well-Being Index, a survey that comprehensively evaluates well-being across the nation.[17] We compared the characteristics of high-poverty counties with high and low well-being, relative to the distribution of all counties, using data from the Robert Wood Johnson Foundation (RWJF) County Health Rankings and Roadmaps (CHRR), which includes a robust portfolio of factors describing counties in the USA.[17 21 22]

METHODS

We conducted an observational cross-sectional positive-deviance study of high-poverty counties or county equivalents (eg, parishes and boroughs) to determine which domains of the Gallup-Sharecare Well-Being Index differed the most between high-well-being and low-well-being counties, and to identify the county characteristics that were most strongly associated with high versus low well-being.

Data sources and measures

County-level poverty prevalence was measured by 2010 county-level percent of persons in poverty from the Area Health Resources Files (AHRF) of the Health Resources and Services Administration. These estimates are from the Bureau of Census' Small Area Income Poverty Estimates files for 2010 and are constructed from statistical models which include data from federal income tax returns, participation in the Food Stamp programme, and the previous census.[23]

Well-being data were obtained from the 2010–2012 Gallup-Sharecare Well-Being Index, a national survey that comprehensively measures subjective well-being.[17] The Gallup-Sharecare Well-Being Index has been validated as a measure of population well-being by Gallup and prior studies have linked it with life expectancy, employee productivity, healthcare utilisation and spending, and voting patterns.[17 19 24–27]

Data were collected in a national telephone survey of individuals age 18 and older from all 50 states and the District of Columbia; approximately 1000 telephone (landline and cell) surveys were conducted each day during the fielding period.[17] Six well-being domains, as well as population demographics, were evaluated with 55 survey questions. 'Physical health' assesses the burden of chronic disease and recent illness. 'Emotional health'
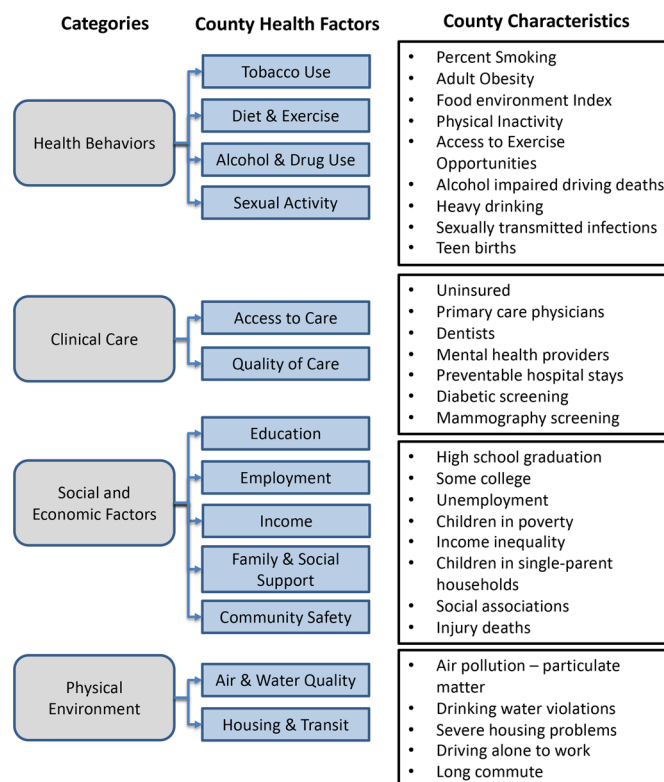

Figure 1 County characteristics, organised into categories, adapted from the 2014 RWJF County Health Rankings and Roadmaps (CHRR). All measures obtained from 2014 RWJF CHRR except for percent smoking and percent heavy drinkers (from the Institute for Health Metrics and Evaluation) and income inequality and social associations (from 2015 RWJF CHRR).

measures daily emotions and the presence or absence of depression. 'Healthy behaviours' assess the prevalence of smoking, exercising and eating fruit and vegetables. 'Life evaluation' measures life satisfaction and optimism about the future. 'Basic access' includes perception of safety and access to housing and healthcare. 'Work environment' assesses job satisfaction, trust and respect in the workplace and, unlike the other domains, is collected only from the subset of respondents who report being employed. Each domain is represented on a scale of 0–100. The composite well-being score is an unweighted mean of all six domains.[17]

In order to describe the demographics of survey respondents and their counties of residence, we used 2013 rural–urban continuum codes from AHRF as well as region of the USA and annual household income of respondents from the Gallup-Sharecare Well-Being Index. Data on county-level characteristics were obtained from the 2014 RWJF CHRR, a well-established population health model.[21] In this model, county factors that influence the health of a county are organised into four categories: clinical care, social and economic factors, health behaviours and physical environment. Each factor is represented by 1–4 county characteristics (figure 1). Data for four county characteristics—excessive drinking,

inadequate social support, tobacco use and violent crime rates—were not comparable across states or missing for many counties.[21][22] Tobacco use and excessive drinking were replaced with 2011 estimates of mean smoking prevalence and percent heavy drinkers, respectively, from the Institute for Health Metrics and Evaluation.[28–30] Heavy drinking was defined as the consumption, on average, of more than one drink per day for women or two drinks per day for men in the past 30 days.[29] Inadequate social support was replaced with the number of social associations from the 2015 RWJF CHRR.[31] We were unable to find an alternative data source for violent crime rates, so this variable was excluded. Finally, we included income inequality, measured as a Gini coefficient, in the list of characteristics, because this county characteristic was added to the CHRR in 2015, and because income disparities within a community may affect well-being.[31][32] These data were also obtained from the 2015 RWJF CHRR.[31] The 29 characteristics used in our study were categorised into tertiles based on each characteristic's distribution across our sample of high-poverty counties.

Statistical analysis

We first examined the distribution of poverty rates and well-being across counties in the USA. We determined that defining high-poverty counties as those where the percent of persons in poverty was in the top 25% of all counties in the USA would allow for adequate sample sizes of high-well-being and low-well-being counties. These high-poverty counties are characterised by at least 20.2% of individuals living in poverty. Among these high-poverty counties, we defined high-well-being counties as those with a well-being score in the top 20% of all counties in the USA and low-well-being counties as those with a well-being score in the bottom 20% of all counties in the USA. We summarised well-being as well as respondent and county characteristics for these two groups of counties. We also calculated Cohen's D standardised differences for each of the six domain scores to determine which domains differed the most between high-well-being and low-well-being counties.

We then used a multi-step procedure to identify which of the 29 community characteristics from the RWJF CHRR model of population health differed the most between high-well-being and low-well-being counties. Since we expected that many county characteristics would be correlated within and across categories, we used an approach similar to that previously utilised in other studies to reduce many related factors to a smaller representative set.[33][34] First, we estimated a series of bivariate logistic regression models, one for each characteristic in figure 1. The outcome of each model was whether the high-poverty county was classified as high versus low well-being. To account for differing precision of the well-being estimates, each county-level observation was weighted by the number of survey respondents. To account for correlation of observations within each state, we used generalised estimating equations models, and to account

for missing values of independent variables, we used multiple imputation.[35][36] For each model, we calculated R^2 as the squared correlation between predicted and observed values, as well as the C-statistic.[37] From the bivariate results, we retained characteristics significantly associated with the county composite well-being score ($p<0.05$) and those that explained a meaningful amount of variance in the outcome ($R^2>0.05$). Among the characteristics retained, we assessed for multicollinearity within each category of characteristics using variance decomposition, eliminating the characteristic with smallest variance decomposition component when the singular value was greater than 20.[38] We estimated a model for each category of characteristics including only those characteristics retained from the prior steps. In two final models, we included all variables independently significant ($p<0.05$) in their respective category models. The first of these models included only these variables; in order to assess any impact of differential respondent income, the second included the percent of respondents in each income category. For each logistic regression model, we report the C-statistic and R^2 as defined above.

Analyses were performed using Stata V.15.1.

Patient and public involvement

No patients or the public were involved in the planning and design of this study.

RESULTS

Well-being data were available for 3091 counties in the USA. Among these counties, 770 met our definition of being 'high-poverty', with percent of persons in poverty in the top quartile of all counties in the USA.

Among all 3091 counties, well-being scores ranged from 35.6 to 87.1 (mean 66.5, SD 4.2). When the sample was limited to high-poverty counties, well-being scores ranged from 46.2 to 81.3, with a mean score of 64.3 and SD of 4.3. In comparison, the mean well-being score for all other counties in the USA was 67.2 and the SD was 3.9 (see online supplemental figure 1).

Among high-poverty counties, 72 had a composite well-being score in the top 20% of all counties in the USA and were classified as 'high-well-being' and 311 had a composite well-being score in the bottom 20% of all counties in the USA and were classified as 'low-well-being'. High-well-being counties had a mean well-being score of 71.8 with a SD of 2.3, while low-well-being counties had a mean well-being score of 60.2 with a SD of 2.8 (table 1). The majority of counties in both the high-well-being and low-well-being groups were urban and the distributions of urban and rural counties in these two groups were not significantly different from each other. The majority of both high-well-being and low-well-being counties were located in the South, but typically in different regions within the South, with the largest percentage of high-well-being counties located in the South Atlantic region and the largest percentage of low-well-being counties located

Table 1 Geography and demographics of all high-poverty counties, and of high-poverty counties with high and low well-being

Variable	Value	All high-poverty counties	Low-well-being counties	High-well-being counties	P value
N		770 (100)	311 (100)	72 (100)	
Urban/rural status, N (%)	Urban	595 (77.3)	215 (69.1)	44 (61.1)	0.19
	Rural	175 (22.7)	96 (30.9)	28 (38.9)	
Region of the USA, N (%)	New England	1 (0.1)	0 (0.0)	0 (0.0)	<0.001
	Mid Atlantic	5 (0.6)	0 (0.0)	0 (0.0)	
	East North Central	36 (4.7)	11 (3.5)	3 (4.2)	
	West North Central	49 (6.4)	22 (7.1)	13 (18.1)	
	South Atlantic	216 (28.1)	86 (27.7)	23 (31.9)	
	East South Central	201 (26.1)	110 (35.4)	7 (9.7)	
	West South Central	183 (23.8)	65 (20.9)	14 (19.4)	
	Mountain	50 (6.5)	13 (4.2)	9 (12.5)	
	Pacific	29 (3.8)	4 (1.3)	3 (4.2)	
Income of respondents Mean (SD)	%>120k	5.8 (3.6)	4.9 (3.4)	6.3 (5.3)	0.005
	% 60k–120k	14.7 (5.7)	12.7 (5.1)	18.2 (7.8)	<0.001
	% 36k–60k	18.6 (6.1)	18.4 (6.4)	19.6 (8.0)	0.185
	%12k–36k	29.6 (7.3)	31.6 (7.2)	25.7 (8.7)	<0.001
	%<12k	12.6 (6.0)	14.1 (6.0)	9.7 (6.0)	<0.001
	% Unknown	18.7 (6.8)	18.2 (6.1)	20.5 (13.0)	0.031
Well-being score Mean (SD)		64.3 (4.3)	60.2 (2.8)	71.8 (2.3)	<0.001

in the East South Central region (table 1; figure 2; online supplemental table 1). Finally, the incomes of survey respondents were slightly higher in high-well-being counties compared with those in low-well-being counties and a joint test of differences in all income groups was significant (p<0.001) (table 1).

When the six domains of well-being were compared between high-well-being and low-well-being counties, the largest standardised differences were for the basic access and life evaluation domain scores. Compared with domain scores in low-well-being counties, basic access and life evaluation domain scores in high-well-being counties were 2.56 and 2.51 SD higher, respectively (table 2).

In bivariate analyses, among the 29 community characteristics tested, 21 were significantly associated with high versus low well-being (p<0.05) (see online supplemental table 2). Among these 21 characteristics, 10 explained greater than 5% of the variation in well-being. These characteristics were primary care physicians, mental health providers, preventable hospital stays, some college, injury deaths, smoking, obesity, physical inactivity, heavy drinking and long commute. These 10 characteristics were retained and used to estimate a model for each category. The health behaviours category model explained the greatest amount of variance (R^2: 0.24; C-statistic: 0.81) and the physical environment model explained

High poverty counties
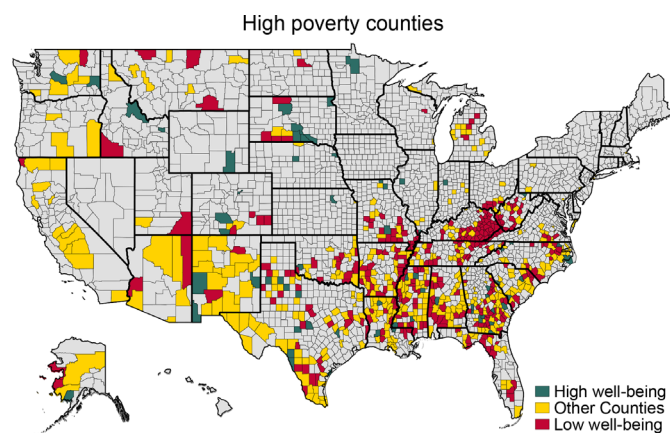
Figure 2 Map of high-poverty counties with high well-being and low well-being. Source: Gallup-Sharecare Well-Being Index.

- High well-being
- Other Counties
- Low well-being

Table 2 Standardised differences in domain scores when comparing high-well-being and low-well-being counties among all high-poverty counties (all significant at p<0.001)

Domain	Standardised difference (95% CI)
Basic access	2.56 (2.25 to 2.87)
Life evaluation	2.51 (2.20 to 2.82)
Physical health	2.46 (2.15 to 2.77)
Emotional health	1.71 (1.43 to 1.99)
Healthy behaviours	1.51 (1.23 to 1.78)
Work environment	1.25 (0.97 to 1.52)

Table 3 Category-specific models: ORs describe odds of a county having high versus low well-being

Variable		OR	95% CI	Wald P value
Health behaviours				
R^2: 0.243	**C: 0.812**	**N: 383**		
Percent smoking	Tertile 1	Ref		<0.001
	Tertile 2	0.03	0.01 to 0.10	
	Tertile 3	0.02	0.01 to 0.06	
Adult obesity	Tertile 1	Ref		0.241
	Tertile 2	0.71	0.35 to 1.43	
	Tertile 3	0.31	0.08 to 1.21	
Percent heavy drinkers	Tertile 1	Ref		<0.001
	Tertile 2	7.23	2.20 to 23.83	
	Tertile 3	10.54	3.36 to 33.06	
Physical inactivity	Tertile 1	Ref		0.002
	Tertile 2	0.26	0.12 to 0.56	
	Tertile 3	0.65	0.16 to 2.69	
Clinical care				
R^2: 0.177	**C: 0.775**	**N: 383**		
Primary care physicians	Tertile 1	Ref		<0.001
	Tertile 2	1.12	0.28 to 4.44	
	Tertile 3	4.58	1.79 to 11.77	
Mental health providers	Tertile 1	Ref		0.096
	Tertile 2	1.93	0.61 to 6.07	
	Tertile 3	3.97	1.14 to 13.80	
Preventable hosp. stays	Tertile 1	Ref		<0.001
	Tertile 2	0.18	0.06 to 0.56	
	Tertile 3	0.03	0.01 to 0.13	
Social and economic factors				
R^2: 0.163	**C: 0.765**	**N: 383**		
Some college	Tertile 1	Ref		<0.001
	Tertile 2	1.36	0.41 to 4.50	
	Tertile 3	16.55	5.16 to 53.05	
Injury deaths	Tertile 1	Ref		<0.001
	Tertile 2	0.24	0.05 to 1.11	
	Tertile 3	0.06	0.02 to 0.13	
Physical environment				
R^2: 0.050	**C: 0.663**	**N: 383**		
Long commute-driving alone	Tertile 1	Ref		<0.001
	Tertile 2	0.34	0.07 to 1.56	
	Tertile 3	0.06	0.02 to 0.14	

the least amount of variance (R^2: 0.05; C-statistic: 0.66) (table 3). Eight characteristics were significant in their respective category models with a p value<0.05, and these eight characteristics were included in the final combined model (table 4).

In the final combined model, six characteristics remained significantly associated (p<0.05) with high versus low well-being: lower rates of preventable hospital stays, higher supply of primary care physicians, lower prevalence of smoking, lower physical inactivity, higher percentage of heavy drinkers and higher percentage of residents with some college education. In the final model, the R^2 value was 0.30 and the C-statistic was 0.83. After adjusting for respondent-level income, three factors remained significantly associated with higher well-being: heavy drinking, smoking and primary care physician density. In this final adjusted model, the R^2 was 0.34 and the C-statistic was 0.84 (table 4).

DISCUSSION

In this study of 770 high-poverty counties, approximately 9% achieved high well-being despite economic disadvantage. These counties shared distinctive characteristics, including lower rates of preventable hospital stays, higher supply of primary care physicians, lower prevalence of smoking, lower physical inactivity, higher percentage of some college education and paradoxically a higher percentage of heavy drinkers.

Recently, our team identified 12 county characteristics explaining over two-thirds of the variation in well-being across all counties in the USA.[39] As we found in this study, characteristics in clinical care and social and economic categories were significantly associated with higher well-being, suggesting that access to high-quality healthcare and affordable education may be especially important to well-being, both in all counties and in this sample of high-poverty counties.

Higher supply of primary care physicians and lower rates of preventable hospital stays were both significantly associated with high versus low well-being. These findings are consistent with prior research showing better health outcomes among populations served by primary care-based health systems.[40 41] For example, a 2005 study showed that a higher supply of primary care providers at the county level was associated with lower total and heart disease mortality rates, even after controlling for socioeconomic and demographic characteristics.[42] In addition, in our recent study of all counties in the USA, we found a significant negative association between rates of preventable hospital stays and individual-level resident well-being.[39] Lower preventable hospital stays may reflect greater access and quality of care in the outpatient setting, better insurance coverage and stronger partnerships between a hospital and its surrounding community; factors that may be especially important to the well-being of high-poverty populations.[21 43–47]

We were surprised to find that heavy drinking was associated with high versus low well-being, given that excessive drinking has previously been linked with multiple adverse health outcomes.[29 48 49] It is important to note, however, that excessive drinking is inconsistently defined in the literature. In our study, heavy drinking was defined

Table 4 Final multivariable models, unadjusted and adjusted for income of respondents. ORs describe odds of a county having high versus low well-being

Variable		Final multivariable model, unadjusted R²: 0.300, C-statistic: 0.829			Final multivariable model adjusted for income of respondents R²: 0.341, C-statistic: 0.843		
		OR	95% CI	Wald P value	OR	95% CI	Wald P Value
Percent smoking	Tertile 1	Ref		<0.001	Ref		<0.001
	Tertile 2 vs 1	0.04	0.01 to 0.12		0.07	0.03 to 0.17	
	Tertile 3 vs 1	0.05	0.01 to 0.19		0.06	0.01 to 0.31	
	Tertile 3 vs 2	1.12	0.20 to 6.44		0.91	0.17 to 4.75	
Percent heavy drinkers	Tertile 1	Ref		<0.001	Ref		<0.001
	Tertile 2 vs 1	6.33	2.66 to 15.06		5.58	2.44 to 12.80	
	Tertile 3 vs 1	6.39	2.01 to 20.36		4.74	1.67 to 13.50	
	Tertile 3 vs 2	1.01	0.46 to 2.20		0.85	0.36 to 1.99	
Physical inactivity	Tertile 1	Ref		0.042	Ref		0.120
	Tertile 2 vs 1	0.28	0.10 to 0.80		0.41	0.14 to 1.22	
	Tertile 3 vs 1	0.88	0.28 to 2.75		1.08	0.35 to 3.36	
	Tertile 3 vs 2	3.14	0.96 to 10.23		2.64	0.95 to 7.35	
Primary care physicians	Tertile 1	Ref		<0.001	Ref		0.021
	Tertile 2 vs 1	0.53	0.11 to 2.53		0.51	0.12 to 2.19	
	Tertile 3 vs 1	3.11	1.53 to 6.32		2.05	1.05 to 4.00	
	Tertile 3 vs 2	5.83	1.49 to 22.87		4.06	1.03 to 16.05	
Preventable hospital stays	Tertile 1	Ref		0.046	Ref		0.282
	Tertile 2 vs 1	0.35	0.10 to 1.15		0.52	0.15 to 1.81	
	Tertile 3 vs 1	0.30	0.10 to 0.90		0.42	0.14 to 1.32	
	Tertile 3 vs 2	0.86	0.21 to 3.56		0.81	0.20 to 3.23	
Some college	Tertile 1	Ref		0.007	Ref		0.157
	Tertile 2 vs 1	0.94	0.12 to 7.05		0.63	0.09 to 4.51	
	Tertile 3 vs 1	2.72	0.40 to 18.42		1.61	0.24 to 10.89	
	Tertile 3 vs 2	2.91	1.45 to 5.82		2.54	0.98 to 6.59	
Injury deaths	Tertile 1	Ref		0.067	Ref		0.164
	Tertile 2 vs 1	0.44	0.16 to 1.22		0.64	0.24 to 1.69	
	Tertile 3 vs 1	0.31	0.11 to 0.86		0.44	0.18 to 1.06	
	Tertile 3 vs 2	0.69	0.24 to 2.00		0.68	0.22 to 2.13	
Long commute	Tertile 1	Ref		0.433	Ref		0.773
	Tertile 2 vs 1	1.34	0.56 to 3.20		0.93	0.33 to 2.58	
	Tertile 3 vs 1	2.35	0.64 to 8.56		1.53	0.36 to 6.43	
	Tertile 3 vs 2	1.75	0.59 to 5.17		1.65	0.42 to 6.53	

as greater than one drink per day for women and greater than two drinks per day for men,[30] but others have used higher thresholds.[48 49] It is possible that heavy drinking as defined among our sample served as a signal for one or more unmeasured confounders. Additional exploration into this relationship would be required to understand true targets for well-being improvement.

Lower rates of smoking and higher levels of some college education were significantly associated with high versus low well-being. The percentage of some college education includes the percentage of individuals with an associate's, bachelor's, graduate or professional degree, as well as those who completed some postsecondary education but did not attain a degree.[22 50] Smoking and postsecondary education were highlighted in a 2016 analysis of the geographic variation in life expectancy among low-income populations. Authors found that life expectancy in low-income areas was negatively correlated with rates of smoking and positively correlated with the fraction of college graduates.[51] There are many reasons why measures of smoking prevalence and postsecondary education may help to explain both variation in life

expectancy and variation in well-being among high-poverty populations. Potential harms of smoking include both adverse health consequences to smokers themselves, and also to those exposed to secondhand smoke, while potential benefits of postsecondary education include access to more employment opportunities, as well as better health outcomes among both educated individuals and their children.[52–56]

Finally, higher rates of physical activity were associated with high versus low well-being, consistent with prior work linking physical activity with mental and physical health.[57 58] For example, in a recent report from the Appalachian Regional Commission, RWJF, and the Foundation for a Healthy Kentucky, both physical activity and smoking were shown to explain variation in health outcomes among Appalachian counties.[59] Our results suggest that efforts to encourage exercise, such as improving neighbourhood walkability and allowing for greater access to parks and recreation facilities may be especially impactful in high-poverty counties.[7]

Measures of community safety, family and social support were not significant in our final model. This finding was unexpected, as prior work has suggested that community violence and lower social capital, including trust and cohesion between neighbours, mediate the relationship between poverty and poor health outcomes.[1] We used only one measure of community safety: 'injury death rate', because the other measure 'violent crime rates', was incomparable across counties, and we were unable to find an alternative data source. In addition, though we were able to utilise both 'children in single-parent households' and 'social associations' to represent family and social support, these measures may not adequately capture aspects of social capital that have the strongest influence on well-being. If other measures of social capital and community violence had been available at the county level, these characteristics may have helped to explain variation in well-being across high-poverty counties.

Although our sample was limited to counties in the highest quartile of poverty, the income of respondents varied, with respondents in high-well-being counties reporting higher incomes than respondents in low-well-being counties (table 1). Similarly, we found that the percent of children in poverty, a measure of county-level income, was significantly and negatively associated with well-being (see online supplemental table 2). Therefore, differences in income partly explained differences in well-being across these high-poverty counties. However, although the bivariate association between percent children in poverty and well-being was significant, this variable explained less than 5% of variance in well-being (see online supplemental table 2). We found that other county characteristics more fully explained differences in well-being among these high-poverty counties. Similarly, even after controlling for differences in individual income, three factors remained significantly associated with high versus low well-being: heavy drinking, smoking and primary care physician density, confirming that

individual income does not fully account for variation in well-being among high-poverty counties. The associations of physical inactivity, preventable hospital stays and some college with well-being became insignificant, suggesting that income may be the underlying confounder in the relationships of these factors with well-being.

Among the six domains of well-being, we found that the 'basic access' and 'life evaluation' scores were most different between high-well-being and low-well-being counties, suggesting that efforts focused on these domains may be especially impactful in high-poverty counties. These domains may be related to the community characteristics we identified in this study. For example, perception of neighbourhood safety, a component of the basic access domain, has previously been negatively associated with the prevalence of smoking.[60] Similarly, percentage of college graduates at the county level has been associated with average life satifaction, a component of the life evaluation domain.[5] Future work should explore the relationships between these community characteristics and each of the well-being domains, as these analyses may provide additional insights into predictors of well-being in the setting of economic disadvantage.

This study has several limitations. First, as this was a cross-sectional study, we are unable to assess whether or not improving these characteristics would actually improve well-being in high-poverty counties. It is possible that other unmeasured factors explain the relationships we found between these community characteristics and well-being, and which represent the true targets for well-being improvement efforts. For example, the positive association between some college and well-being may reflect other characteristics of high-well-being counties such as access to affordable community colleges or state universities, parenting styles and cultural beliefs that promote higher education, or sufficient employment opportunities for individuals with postsecondary education. A mixed-methods approach incorporating qualitative analyses may be useful in further exploring the relationships between the characteristics identified in our study and the well-being of high-poverty counties. Second, though the Gallup-Sharecare Well-Being Index is a national survey that uses stratified random sampling, design weights were not available at the county level; however, though this may limit inferences about the well-being of any individual county, it does not affect inferences about associations among counties. Finally, our study examined associations by county, due to lack of well-being data at the city or neighbourhood level, and both poverty and well-being are likely to be heterogeneous at the county level. However, counties are important units for policy action and represent municipalities for which there are a number of key metrics available.

As poverty is negatively associated with many aspects of well-being, it is essential to reduce the burden of poverty affecting many counties in the USA.[1–8 13 14] Though poverty eradication remains an essential priority, our findings suggest that targeting certain county characteristics may

mitigate the negative influence of poverty on well-being. Specifically, efforts to improve access to high-quality primary care and affordable postsecondary education, increase taxes on tobacco, reduce barriers to tobacco cessation treatment and improve neighbourhood walkability may be especially impactful among high-poverty populations, an idea worth testing.[7 42 47 54 55]

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