TECHNICAL REPORT:
PRODUCING THE BEHAVIORAL HEALTH INDEX

Center on Society and Health
Virginia Commonwealth University
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BACKGROUND

Behavioral health and developmental disability services in Virginia are provided by 40 Community Services Boards (CSBs), which are administered by the Virginia Department of Behavioral Health and Developmental Services (DBHDS). The CSBs act as an important public safety net provider for Medicaid beneficiaries and indigent populations. Each CSB is composed of one or more municipalities (cities or counties) (Table 1). Although some CSBs obtain revenue from local funders and other sources, all CSBs are dependent to some degree on state funding. For some years, VDBHDS has apportioned CSB funding based largely on historical allocations and the size of local populations served by CSBs. The need for a more sophisticated approach to funding the CSBs has long been recognized. In 1987, DBHDS implemented a formula-based funding allocation method developed by Koch[1], but it was abandoned a decade ago. The need for an improved funding formula was recently revisited by the General Assembly, which commissioned a report on the subject by the Joint Legislative Audit and Review Commission.[2] Other states have also experimented with a variety of methodologies to prioritize resource allocation.

Table 1. Virginia Community Service Boards

Community Service Boards	Localities
Alexandria	Alexandria City
Alleghany Highlands	Alleghany Covington City
Arlington	Arlington
Blue Ridge	Botetourt Craig Roanoke Roanoke City Salem City
Chesapeake	Chesapeake City
Chesterfield	Chesterfield
Colonial	James City York Poquoson City Williamsburg City
Crossroads	Amelia Buckingham Charlotte Cumberland Lunenburg Nottoway Prince Edward
Cumberland Mountain	Buchanan Russell Tazewell
Danville-Pittslyvania	Pittsylvania Danville City
Dickenson	Dickenson
District 19	Dinwiddie Greensville Prince George Surry Sussex Colonial Heights City Emporia City Hopewell City Petersburg City
Eastern Shore	Accomack Northampton
Fairfax-Falls Church	Fairfax Fairfax City Falls Church City
Goochland-Powhatan	Goochland Powhatan
Hampton-Newport News	Hampton City Newport News City
Hanover	Hanover
Harrisonburg-Rockingham	Rockingham Harrisonburg City
Henrico	Charles City Henrico New Kent
Highlands	Washington Bristol City
Horizon	Amherst Appomattox Bedford Campbell Bedford City Lynchburg City

[1] Koch JR. A funding system for community mental health services. *Administration and Policy in Mental Health and Mental Health Services Research*. 1992;20(2):101-15.

[2] Joint Legislative Audit and Review Commission. *CSB Funding: A Report to the Governor and General Assembly*. JLARC Report 520. Richmond, VA: Joint Legislative Audit and Review Commission, 2019.

Loudoun	Loudoun
Middle Peninsula-Northern Neck	Essex Gloucester King and Queen King William Lancaster Mathews Middlesex Northumberland Richmond Westmoreland
Mount Rogers	Bland Carroll Grayson Smyth Wythe Galax City
New River Valley	Floyd Giles Montgomery Pulaski Radford City
Norfolk	Norfolk City
Northwestern	Clarke Frederick Page Shenandoah Warren Winchester City
Piedmont	Franklin Henry Patrick Martinsville City
Planning District 1	Lee Scott Wise Norton City

Portsmouth	Portsmouth City
Prince William	Prince William Manassas City Manassas Park City
Rappahannock Area	Caroline King George Spotsylvania Stafford Fredericksburg City
Rappahannock-Rapidan	Culpeper Fauquier Madison Orange Rappahannock
Region Ten	Albermarle Fluvanna Greene Louisa Nelson Charlottesville City
Richmond	Richmond City
Rockbridge Area	Bath Rockbridge Buena Vista City Lexington City
Southside	Brunswick Halifax Mecklenburg
Valley	Augusta Highland Staunton City Waynesboro
Virginia Beach	Virginia Beach City
Western Tidewater	Isle of Wright Southampton Franklin City Suffolk City

In late 2018, Dr Hughes Melton, then Commissioner of DBHDS, engaged the Center on Society and Health at Virginia Commonwealth University to develop a risk-based methodology for resource allocation that considered factors beyond population counts. The request was inspired by the Health Opportunity Index, developed in 2012 by the Virginia Department of Health, which assigned a score to counties, health districts, and legislative districts based on 13 indicators that were predictive of health outcomes, and the Healthy Places Index, a similar tool developed by CSH that relied on a more complex statistical approach. DBHDS expressed interest in a short-term project, focused on developing an expedient proxy that could be implemented within a period of months, and a longer-term effort to develop a more sophisticated methodology and more extensive behavioral health data sources.

CSH researchers began by studying the methods other states have used, with special attention given to the two-phase approach taken by California's Department of Health Care Services in developing its

Mental Health Services Act (MHSA) allocation methodology for FY 2017-18.[3] The first phase involved calculating a need for services for each county based on each county's share of the population, the poverty level, and the prevalence of mental illness. The second phase involved adjusting the need for services based on the cost of being "self-sufficient" and other resources available to each county.
In consultation with VDBHDS, a decision was made to limit the scope of the CSH project to the first phase, *assessing need*, and to defer the determination of resources to future work by VDBHDS. That is, the CSH project would aim to devise a procedure to estimate the burden of suffering from mental illness across CSB jurisdictions but would not attempt to either assess the level of resources already available to the CSBs or to make recommendations on how to allocate resources. The position of CSH was that levels of need, although of great importance to resource allocation, was not the only factor to consider in funding formulas and that VDBHDS was better positioned—based on its statutory authority and access to data—to weigh those considerations.

In developing a methodology for measuring the level of need, the primary interest of CSH was to determine the behavioral health morbidity of the populations served by the CSBs. The ideal approach—to examine prevalence rates for psychosocial issues to mental illness, substance abuse, and other needs—was not an option because reliable data on the true prevalence of mental health conditions are unavailable in Virginia and much of the nation. No population-representative surveys are undertaken in the Commonwealth to accurately ascertain the prevalence of any mental illness or substance abuse disorder at the county or city level. Although some epidemiologic data are collected by CSBs[4], these do not provide population-representative rates (the prevalence of the conditions in the catchment area served by the CSB), nor are they collected systematically across the Commonwealth.

CSH therefore opted to devise a proxy measure for prevalence, called the Behavioral Health Index (BHI), which could be used to predict the prevalence of mental health needs in CSB jurisdictions. CSH considered various outcome measures and statistical techniques to estimate need, including both the accuracy of the methods and the ease with which users could understand and communicate the results. The final outcome measure and statistical approach were selected to maximize predictability, applicability, and communicability. The next section describes the methods in more detail; the appendix includes supplemental analyses that tested a different modeling technique, Weighted Quantile Sum regression, to answer additional behavioral health questions.

Early in the project, CSH established a procedure for engaging DBHDS officials for guidance and for soliciting input from other stakeholders. The principal investigator conducted multiple briefings with agency heads and staff to review the planned approach and solicit advice. Briefings were also conducted with the Virginia Association of Community Services Boards. Among the major feedback themes was the inability of any dependent variable to accurately reflect the prevalence of the diverse clinical conditions that present to CSB providers or the nuances that influence demands on each agency. An understanding among the researchers and the staff was that the proposed Behavioral Health Index could serve only as an imperfect measure, with known limitations, but would nonetheless represent an advance over the

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[3] The California methodology can be accessed at:
https://www.dhcs.ca.gov/services/MH/Documents/FMORB/FY17-18_MHSA_Distribution_Methodolody.pdf

[4] The All-Payer Claims Database could provide data on claims for behavioral health services. This database, managed by the Virginia Department of Health, holds claims data for Virginia residents with commercial, Medicaid and Medicare coverage. However, CSH did not anticipate having access to this database in the short term and such data would reflect the prevalence in populations received care, not in the entire population in the catchment area.

existing approach, known for its reliance on historical allocations and population size, and would represent a first step toward a more elegant and sophisticated funding formula.

METHODS

INDICATORS

Dependent Variable: Mentally Unhealthy Days

In the absence of accurate prevalence data from population-representative surveys (see above), the research team explored several alternative methods to estimate illness burden. The original choice for the dependent variable, the local mortality rate for "stress-related" conditions—an aggregate of death counts for drug overdoses, alcohol intoxication, alcoholic liver disease, and suicides—did not perform well as a proxy indicator and was replaced by a more global measure, the number of mentally unhealthy days. Specifically, the average number of mentally unhealth days in the past month was obtained from the 2017 Behavioral Risk Factor Surveillance Survey (BRFSS), which is administered in Virginia and asks the following question: *"Now thinking about your mental health, which includes stress, depression, and problems with emotions, how many days during the past 30 days was your mental health not good?"* These data are available at the state level and also for the populations in each of the 35 Health Districts managed by the Virginia Department of Health. Data were weighted to adjust for the probability of respondent selection and post-stratified to reflect 12 demographic dimensions representative of the distribution of the adult population in Virginia.

Place-based predictor variables

Indicators and data source

The researchers sought to identify a set of place-based indicators for each CSB jurisdiction that could predict the number of mentally unhealthy days and serve as the basis for the Behavioral Health Index. The process involved two steps: to first identify a set of candidate indicators and to then cull the list to a smaller number of variables that could be entered into linear regression equations. The researchers identified 35 candidate variables for which data were available at the county level[5] from the US Census Bureau and other sources (Table 2). These 35 county-level characteristics were chosen on the basis of three criteria: (1) established association with mental health or substance abuse disorders based on published research; (2) data quality; and (3) data availability. Indicator years were selected to align with or precede the 2017 BRFSS data.

Table 2. Candidate county-level prediction indicators

Variable	Definition	Data Source
Avoidable hospitalization (preventable hospital stays)	Rate of hospital stays for ambulatory-care sensitive conditions per 1,000 Medicare enrollees.	County Health Rankings
Diabetes management	Percentage of diabetic Medicare enrollees ages 65-75 that receive HbA1c monitoring.	County Health Rankings
Primary care shortage	Ratio of population to primary care providers (internists, family physicians, physician's assistants, nurse practitioners)	HRSA Data Warehouse

[5] CSBs are composed of one more counties or cities, allowing county-level data to be aggregated to produce estimates for the entire CSB jurisdiction. When necessary, data for Bedford City were added to data for Bedford County, as these localities were combined during the years when data for some indicators were collected.

Mental care shortage	Ratio of population to mental health providers	County Health Rankings
Uninsured	Percent of civilian noninstitutionalized population who are uninsured	American Community Survey
Private insurance	Percent of civilian noninstitutionalized population with private health insurance	American Community Survey
Public Insurance	Percent of civilian noninstitutionalized population with public health insurance	American Community Survey
Rehospitalization	Percent of acute hospital readmissions: (inpatient readmissions within 30 days of an acute hospital stay)	Dartmouth Atlas of Health Care
Opioid prescription rate	Rate of opioid prescriptions per 100 residents	PolicyMap
Proximity to parks	Percent of population living within a half mile of a park	National Environmental Public Health Tracking Network
Commuting by public transit	Percent of population who take public transport (bus, train, subway) to work	American Community Survey
Commuting by motor vehicle	Percent of population who take a car, taxi, or motorcycle to work	American Community Survey
Commuting by walking/cycling	Percent of population who walk or bike to work	American Community Survey
Severe housing disrepair	Percent of households having at least one of the following conditions: 1) lacking complete plumbing facilities, 2)lacking complete kitchen facilities, 3) with 1.01 or more occupants per room, 4) selected monthly owner costs as a percentage of household income greater than 30 percent, and 5)gross rent as a percentage of household income greater than 30 percent.	American Community Survey
Overcrowding	Percent of households with 1.01 or more occupants per room	American Community Survey
Housing vacancies	Percent of housing units that are vacant	American Community Survey
Distance to highways	Percent of population living within 150m of a highway	National Environmental Public Health Tracking Network
Violent crime rate	Number of reported violent crime offenses per 100,000 population.	County Health Rankings
Married	Percent of population 15 years and older now married (excluding those who are separated)	American Community Survey
Employment	Percent of population ages 25-64 years who are unemployed	American Community Survey
Housing cost burden at 30% of income	Percent of households paying more than 30% of income on housing	American Community Survey
Extremely housing cost burden at 50% of income	Percent of households paying more than 50% of income on housing	American Community Survey
Median household income	Median annual household income	American Community Survey
Child in single-parent households	Percent of children living in households headed by a single parent	American Community Survey
Poverty (children)	Percent of population under age 18 living below the poverty line	American Community Survey
Poverty (adults)	Percent of population ages 18-64 years with household incomes below the poverty level	American Community Survey
Food insecurity (households)	Percent of food insecure households	USDA Food Environment Atlas
Median home value	Median home value of owner occupied units	American Community Survey
Preschool enrollment	Percent of 3- and 4-year-olds not enrolled in school	American Community Survey

High school diploma/higher	Percent with a high school diploma or higher	American Community Survey
Bachelor's degree/higher	Percent with Bachelor's degree or higher	American Community Survey
Public assistance	Percent of households receiving public assistance income	American Community Survey
Religious organizations	Number of establishments in religious organizations per 10,000 population	Penn State Social Capital Measures
Civic and social organizations	Number of establishments in civic and social associations per 10,000 population	Penn State Social Capital Measures
Voter participation	Percent of voting age population who participated in the 2012 presidential election	Penn State Social Capital Measures

Variable reduction

Variable reduction methods, derived from previous work, were used to arrive at a shortened list of eight indicators, the number of variables considered suitable for regression calculations. The prior work had examined bivariate correlations between the 35 indicators and all-cause mortality, a proxy for general population health. The number of variables was reduced by selecting the indicator with the highest absolute correlation and then removing other endogenous indicators that correlated highly ($R^2 \geq 0.70$) with the selected indicator. This process was repeated until the list was reduced to 10 indicators were selected as the leading county predictors of population health. From that list of 10, the eight variables that were most suitable for aggregation at the health district level were selected. The final list of eight place-based indicators, which was used in the regression analysis, is provided in Table 3. The county data for these indicators were then aggregated to produce estimates for two larger geographies: the x health districts and the 40 CSB jurisdictions. To perform the aggregation, any indicator that was presented as a numerator and denominator was converted to a percentage (numerator divided by denominator). Data were then aggregated to the health district level via population weighted averaging and converted into a Z-score.

Table 3. Final eight predictor variables and their bivariate correlations with the number of mentally unhealthy days

Variable	r
Avoidable hospitalization (preventable hospital stays)	0.368
Uninsured	0.417
Commuting by motor vehicle	0.065
Violent crime rate	0.239
Poverty (adults)	0.509
Median home value	-0.325
Public assistance	0.472
Voter participation	-0.239

Missing data

Data were often lacking for one indicator, preventable hospitalizations, either because the numerator and denominator were not reported or because small numerators (N < 10) were suppressed for data privacy. When the numerator and denominator were missing for unknown reasons, *k-nearest neighbors*

(KNN) imputation was performed to create an "almost complete" dataset. When the numerator was suppressed, KNN was performed on this almost complete dataset to impute the missing numerator; imputed values greater than 9 were re-imputed to 9 in order to accurately represent the reason for their absence.

A sensitivity analysis was performed to test the impact of the imputation methods. Specifically, when the data were missing for unknown reasons, both the numerator and denominator were drawn from a uniform distribution, where the lower and upper bounds were set to be the minimum value of the imputed values multiplied by 1 - δ and the maximum value of the imputed values multiplied by 1 + δ, respectively. The value of δ was increased from 0.1 to 0.9 by increments of 0.1 to determine the impact of increasingly drastic changes to the imputed values:

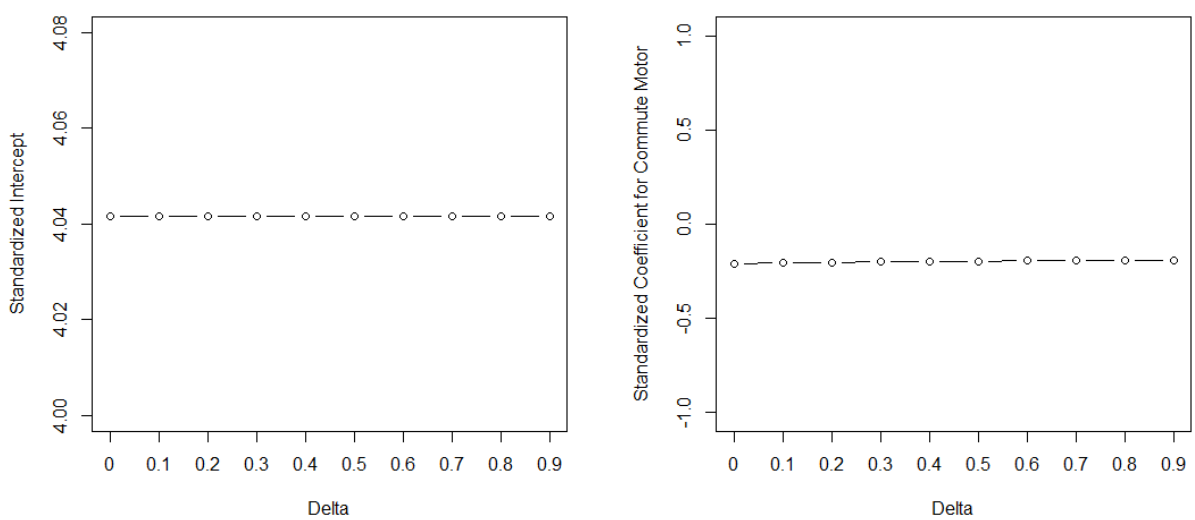
$$Num_{l,miss,unk} \sim Unif\ (min(imputed\ num_{miss,unk}) * \delta_{low}, max(imputed\ num_{miss,unk}) * \delta_{high})$$
$$Den_{l,miss,unk} \sim Unif\ (min(imputed\ den_{miss,unk}) * \delta_{low}, max(imputed\ den_{miss,unk}) * \delta_{high})$$
$$l = 1, 2, \ldots number\ of\ observations\ missing\ for\ unknown\ reasons$$
$$(\delta_{low}, \delta_{high}) = (1 - \delta, 1 + \delta)$$
$$\delta = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9$$

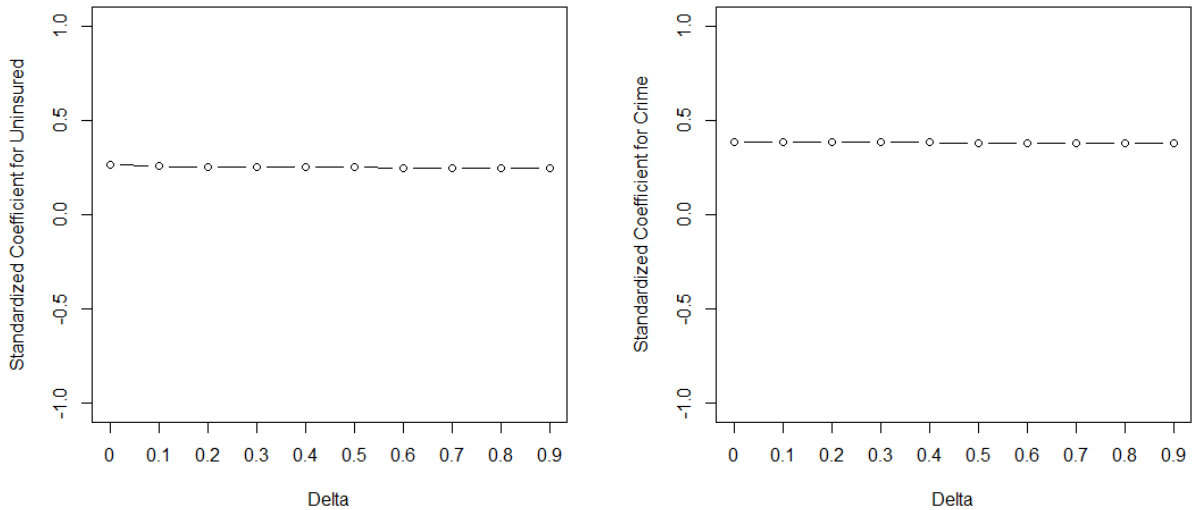
Numerators that were missing due to suppression were drawn from a uniform (0, 9) distribution to account for the limited range of possible values:

$$Num_{m,miss,supp} \sim Unif(0, 9)$$
$$m = 1, 2, \ldots, number\ of\ observations\ missing\ due\ to\ suppression$$

The sensitivity analysis (Figure 1) demonstrated that the change in coefficients was negligible, indicating that the imputation methods were robust.

Figure 1. Sensitivity Analysis: Changes in coefficients with changes in imputation*





*δ=0 represents the value for the coefficient from the original analysis

Regression analysis

Using linear regression methods, the health district-level place-based indicators were regressed on the number of mentally unhealthy days. Best subset regression was performed to select the combination of five indicators (out of the eight available indicators) that produced the highest R^2.

$$\widehat{Mentally\ Unhealthy\ Days_J} = \hat{\beta}_{0,j} + \hat{\beta}_{1,j}X_{1,j} + \hat{\beta}_{2,j}X_{2,j} + \hat{\beta}_{3,j}X_{3,j} + \hat{\beta}_{4,j}X_{4,j} + \hat{\beta}_{5,j}X_{5,j},$$
$$j = 1, 2, \ldots, number\ of\ health\ districts$$

This produced standardized β coefficients for each of the five selected indicators (Table 4). These coefficients were then applied at the CSB jurisdiction level to derive the Behavioral Health Index.

Table 4. Standardized β coefficients used in Behavioral Health Index

	Standardized β	p-value
Intercept	4.042	<0.001**
Commute to work by motor vehicle	-0.212	0.226
Uninsured	0.266	0.143
Violent crime	0.386	0.032*
Avoidable hospitalizations	1.019	<0.001**
Voter participation	0.351	0.113

Adjusted R^2=0.500

**p<0.01; *p<0.05

Behavioral Health Index Computation

To predict the number of mentally unhealthy days for each CSB, the standardized CSB-level indicators were multiplied by the respective standardized β coefficients obtained from the health district analysis and added to the overall standardized intercept from the health district analysis:

$$\widehat{Mentally\ Unhealthy\ Days_i} = \hat{\beta}_{0,j} + \hat{\beta}_{1,j}X_{1,i} + \hat{\beta}_{2,j}X_{2,i} + \hat{\beta}_{3,j}X_{3,i} + \hat{\beta}_{4,j}X_{4,i} + \hat{\beta}_{5,j}X_{5,i},$$

$$i = 1, 2, \ldots, number\ of\ CSBs$$

To ease interpretation, the predicted number of mentally unhealthy days was transformed to a scale of 0-100. To enhance communicability, the Behavioral Health Index (BHI) was derived by "flipping" (inverting) these values so that a higher index score would correspond with a more optimal health state (i.e., a lower number of mentally unhealthy days).

$$BHI_i = 100 - \left(\frac{Mentally\ \widehat{Unhealthy}\ Days_i - \min\left(Mentally\ \widehat{Unhealthy}\ Days_i\right)}{\max\left(Mentally\ \widehat{Unhealthy}\ Days_i\right) - \min\left(Mentally\ \widehat{Unhealthy}\ Days_i\right)} * 100 \right),$$
$$i = 1, 2, \ldots, number\ of\ CSBs$$

RESULTS

Table 5 provides the Behavioral Health Index for each CSB, along with the data for the five predictor variables from which it was derived. Maps 1-6 plot the results at the state level and for each of the five CSB Regions. In general, CSB districts serving suburban areas of Hampton Roads, metropolitan Richmond, and Northern Virginia had higher BHI values, whereas those serving rural southwestern districts or urban centers (e.g., Richmond City, Norfolk City) had lower BHI values.

Table 5. Behavioral Health Index and Predictor Values by CSB

		Predictor Variables				
Community Service Board	**BHI Score**	**Commute by motor vehicle**	**Uninsured**	**Violent crime rate (per 100,000)**	**Avoidable hospitalizations rate (per 1,000)**	**Voter participation**
Alexandria	64.0	68%	15%	176.2	49.4	68%
Alleghany Highlands	65.4	96%	11%	135.8	85.8	66%
Arlington	84.1	61%	11%	146.5	32.9	70%
Blue Ridge	82.1	94%	11%	256.0	50.5	70%
Chesapeake	71.9	95%	9%	374.5	53.6	72%
Chesterfield	87.8	94%	10%	127.6	45.5	76%
Colonial Behavioral Health	100.0	91%	7%	119.7	40.7	75%
Crossroads	60.9	93%	16%	172.6	64.0	71%
Cumberland Mountain	0.0	96%	14%	170.4	151.3	61%
Danville-Pittsylvania	73.6	95%	13%	193.5	58.4	70%
Dickenson	29.9	96%	12%	136.3	129.6	61%
District 19	41.9	94%	14%	289.9	79.0	71%
Eastern Shore	68.0	91%	19%	165.6	52.4	68%
Fairfax-Falls Church	94.0	83%	12%	90.0	37.4	72%
Goochland-Powhatan	91.5	93%	7%	69.4	41.7	82%
Hampton-Newport News	81.5	90%	14%	350.3	41.4	66%
Hanover	91.1	92%	6%	120.9	40.8	82%
Harrisonburg-Rockingham	61.0	88%	15%	134.9	67.5	70%
Henrico	81.8	94%	12%	171.6	43.3	77%
Highlands	45.1	94%	13%	175.8	94.7	67%
Horizon	77.6	93%	12%	194.6	54.4	72%
Loudoun	83.6	88%	9%	85.0	52.0	76%
Middle Peninsula-Northern Neck	79.9	92%	13%	113.2	49.3	75%
Mount Rogers	67.0	96%	14%	132.7	76.8	65%
New River Valley	70.8	88%	11%	176.8	70.8	67%

Norfolk	35.4	82%	17%	559.8	58.2	67%
Northwestern	57.7	93%	13%	137.2	80.3	69%
Piedmont	65.8	95%	15%	216.9	59.7	71%
Planning District One	27.1	96%	14%	168.1	124.0	61%
Portsmouth	63.1	91%	13%	569.3	37.4	71%
Prince William	76.8	89%	15%	175.3	49.1	70%
Rappahannock Area	64.1	91%	11%	184.8	69.8	72%
Rappahannock-Rapidan	80.6	91%	12%	100.3	55.5	72%
Region Ten	82.9	86%	11%	174.4	47.6	72%
Richmond	38.8	83%	17%	630.9	51.4	65%
Rockbridge Area	80.3	89%	13%	89.6	61.0	68%
Southside	70.1	94%	15%	195.8	60.0	69%
Valley	84.1	93%	12%	155.9	48.3	72%
Virginia Beach	97.8	91%	10%	160.2	50.9	65%
Western Tidewater	73.9	95%	11%	248.6	54.4	74%

LIMITATIONS AND APPLICATIONS

The Behavioral Health Index was developed as a short-term proxy for estimating levels of need across CSB jurisdictions, but the limitations of the data sources and computations must be considered in interpreting this index or linking it to policy decisions. For example, the dependent variable—the average number of mentally unhealthy days—is a global self-reported health measure and cannot substitute for reliable data on the prevalence of specific clinical conditions. The prevalence of serious mental illnesses, substance abuse disorders, and other psychosocial needs addressed by CSBs vary across jurisdictions and may not always correlate proportionally with the Behavioral Health Index. Areas with a high index may have great needs in certain clinical areas, and the reverse may hold in areas with a low index. The dependent variable is reported for the entire population of respondents and does not consider how needs vary by age, gender, race-ethnicity, socioeconomic status, and rural and urban settings.

The place-based data provided by the US Census Bureau has inherent limitations, and the aggregated and imputed values are weighted estimates for CSB jurisdictions. These estimates may mask important geographic variations within CSB jurisdictions, especially those serving large areas. Research has shown that health, and the social determinants of health, sometimes vary dramatically across counties and smaller geographic areas (e.g., zip codes, census tracts). Averages for the CSB jurisdiction may not reflect more or less favorable conditions that exist across the catchment area.

The five indicators used in the model are characteristics of *place* and not of *individuals*. They do not necessarily exert a causal influence on behavioral health. The model chose these data points based on their mathematical performance in predicting the number of mentally unhealthy days, not necessarily because they act as causal agents in mental health. For example, the inverse correlation between public assistance and mental health is not causal but mathematical; individuals on public assistance are more likely to have past or present exposures that affect mental health.[6] Similarly, voting participation is itself

[6] Similarly, the inverse correlation between violent crime rates and mental health should be interpreted with caution. That people in jurisdictions with higher crime rates report a larger number of mentally unhealthy days may represent the psychological trauma resulting from exposure to violence but is more likely to reflect the high correlation between neighborhood crime and local socioeconomic and demographic characteristics. The local

an unlikely causal influence on mental health but is an established marker for social capital and connectedness, which have been shown to affect psychological wellbeing.

An important corollary is that the absence of certain indicators from the model has no bearing on their causal importance to behavioral health. For example, although educational attainment was not retained in the model, extensive research documents the important influence of education (and the economic deprivation resulting from limited education) on the prevalence of stress, hopelessness, and substance abuse. Some indicators of great importance to mental health, such as a history of childhood trauma or exposure to adverse childhood events (ACEs), are absent from the model because county-level data are unavailable in Virginia. Often, the variables retained in the regression model are highly correlated with education, ACEs, and other important determinants of behavioral health and are serving as mathematical surrogates for these determinants.

Bearing these caveats in mind, the Behavioral Health Index provides a useful starting point for raising awareness about the geographic variation in behavioral health needs across the Commonwealth and for moving beyond population counts as the basis for allocating resources. It is only a starting point, however; more work is needed to identify richer data sources that replace the need for crude estimates of prevalence. More sophisticated methods are needed for describing variation across and within CSB jurisdictions and for clarifying health inequities among priority populations served by CSBs.

In addition, estimating prevalence or needs (the focus of this project) is only one of many factors that DBHDS and policymakers should consider in allocating resources for behavioral health providers and agencies. Populations and caseload numbers are important and have been emphasized in the past. Funding formulas should also adjust for other factors, such as local and other sources of revenue (e.g., Medicaid) reaching the CSBs, the existing local infrastructure (e.g., office space, personnel, transportation services), the demands on agencies to compensate for local shortages in private mental health professionals outside the CSBs, the socioeconomic status of communities and clients, and the proportion of the population that is uninsured or covered under Medicaid, among others. Funding formulas for some states adjust for the percentage of the population with incomes below 200% of the poverty threshold. Local funding is the third largest source of CSB funding, and interest has grown in considering local ability to pay as an adjustment to local match requirements.

In the short term, until more refined funding formulas are developed, areas with low BHI scores deserve special attention in allocating resources. More sophisticated models will ultimately be needed to fully assess levels of need.

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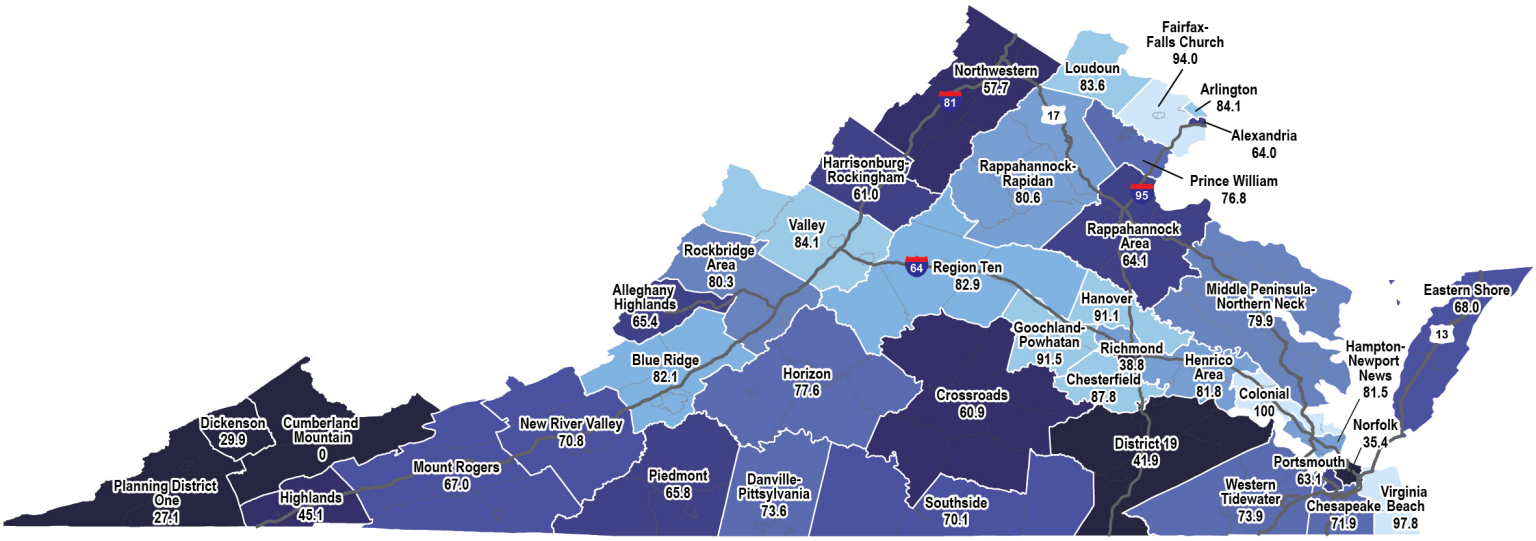
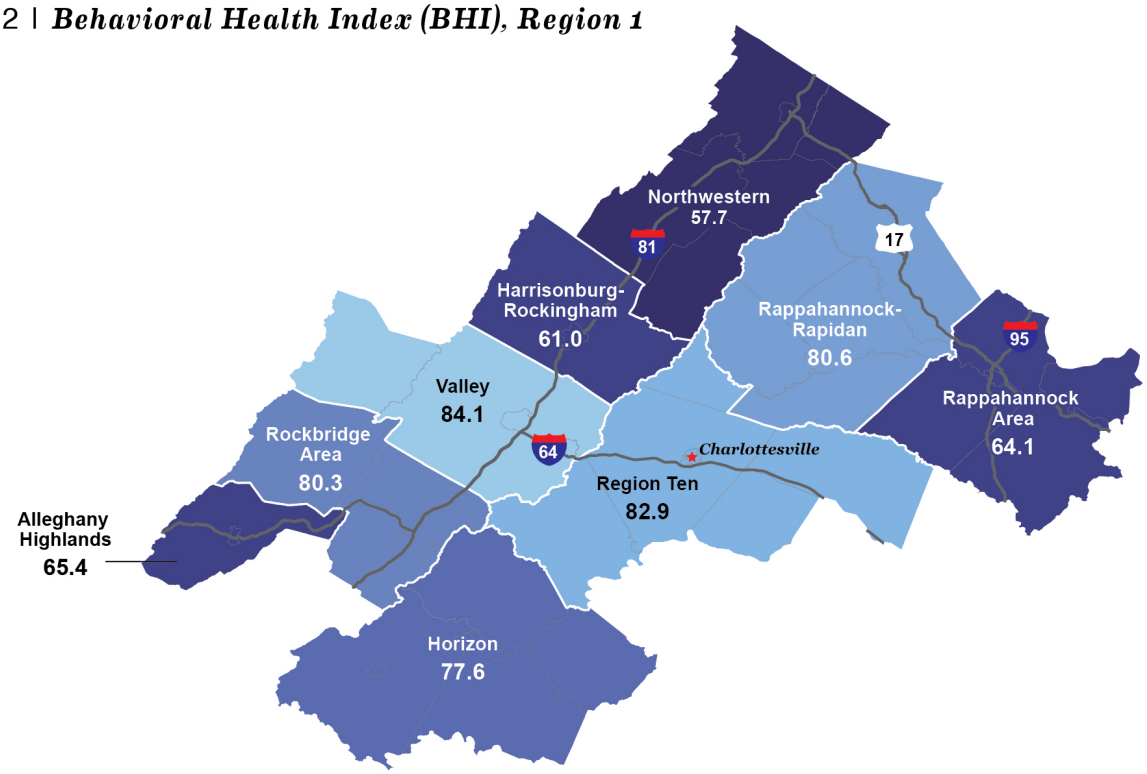
crime rate may act as a proxy for these important influences on mental health. The reverse causal pathway is not supported by the data; people with mental illness are more likely to be victims, and not perpetrators, of crime. The correlations reported here should not be misinterpreted to suggest otherwise.

MAP 1 | ***Behavioral Health Index (BHI), by CSB***



MAP 2 | ***Behavioral Health Index (BHI), Region 1***

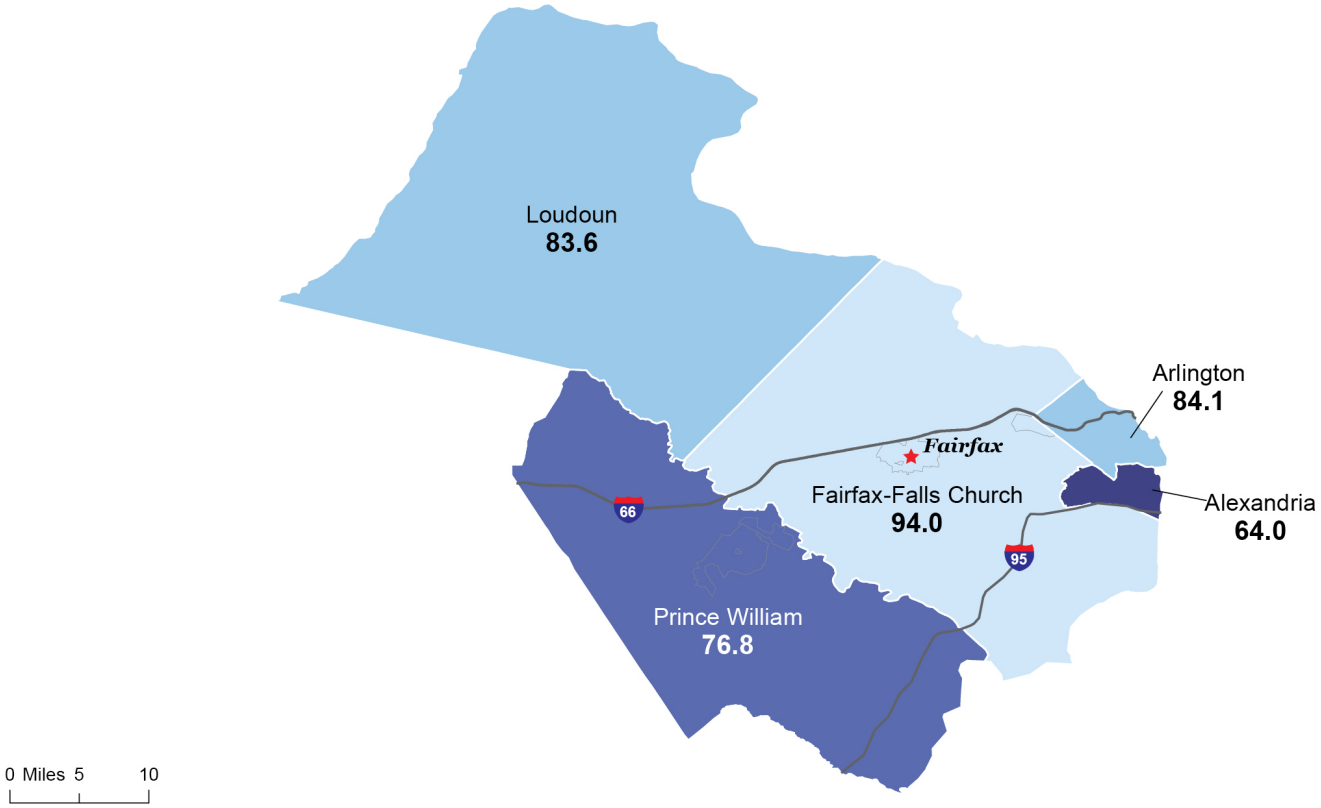


0 Miles 30 60

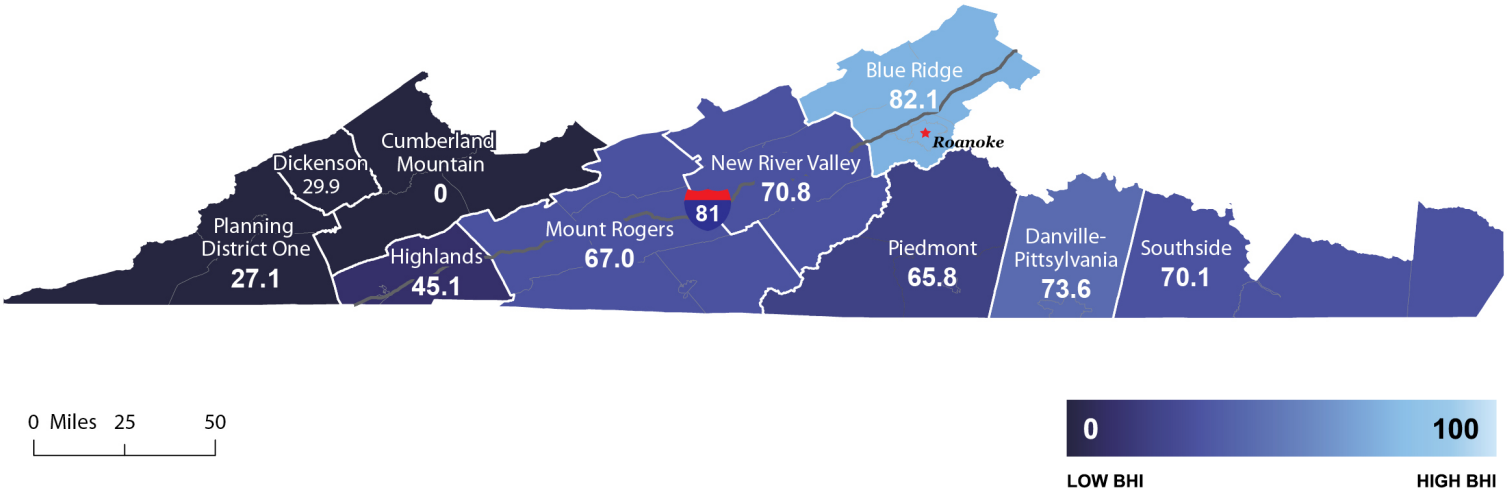
0 100

LOW BHI HIGH BHI

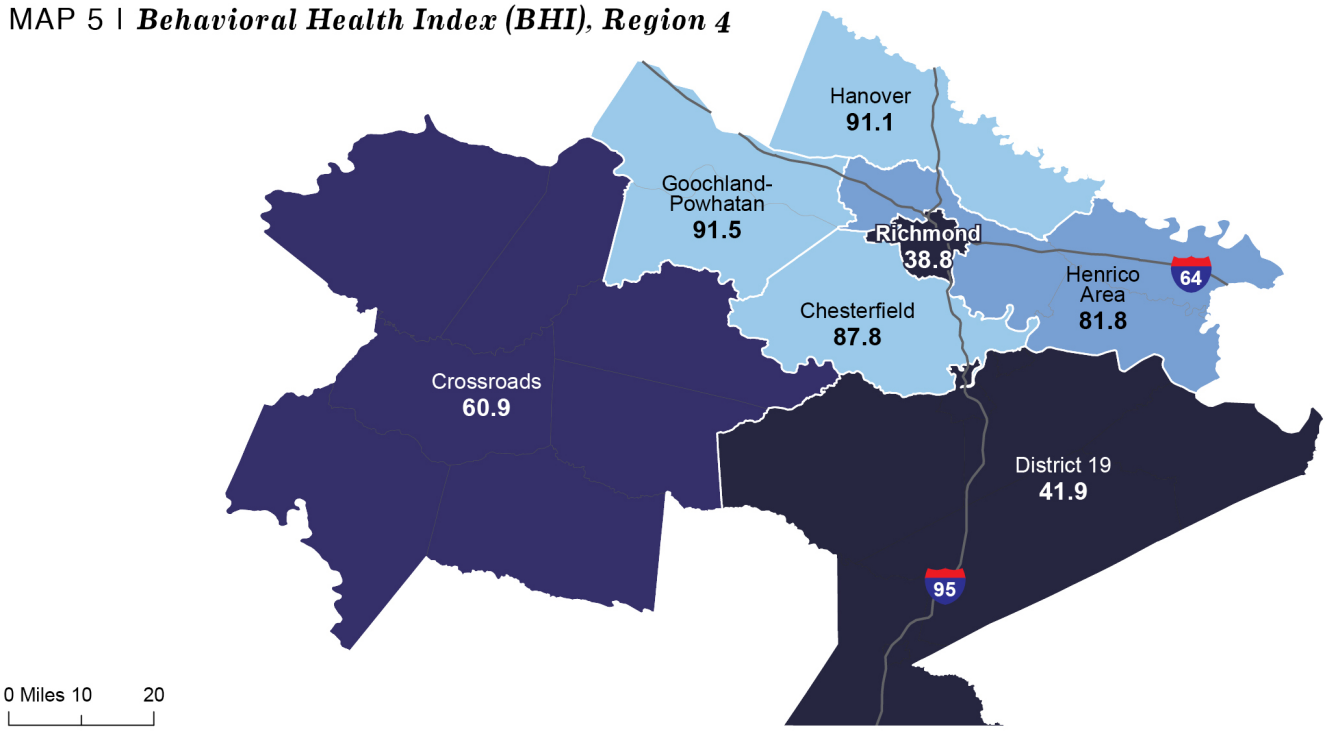
MAP 3 | ***Behavioral Health Index (BHI), Region 2***



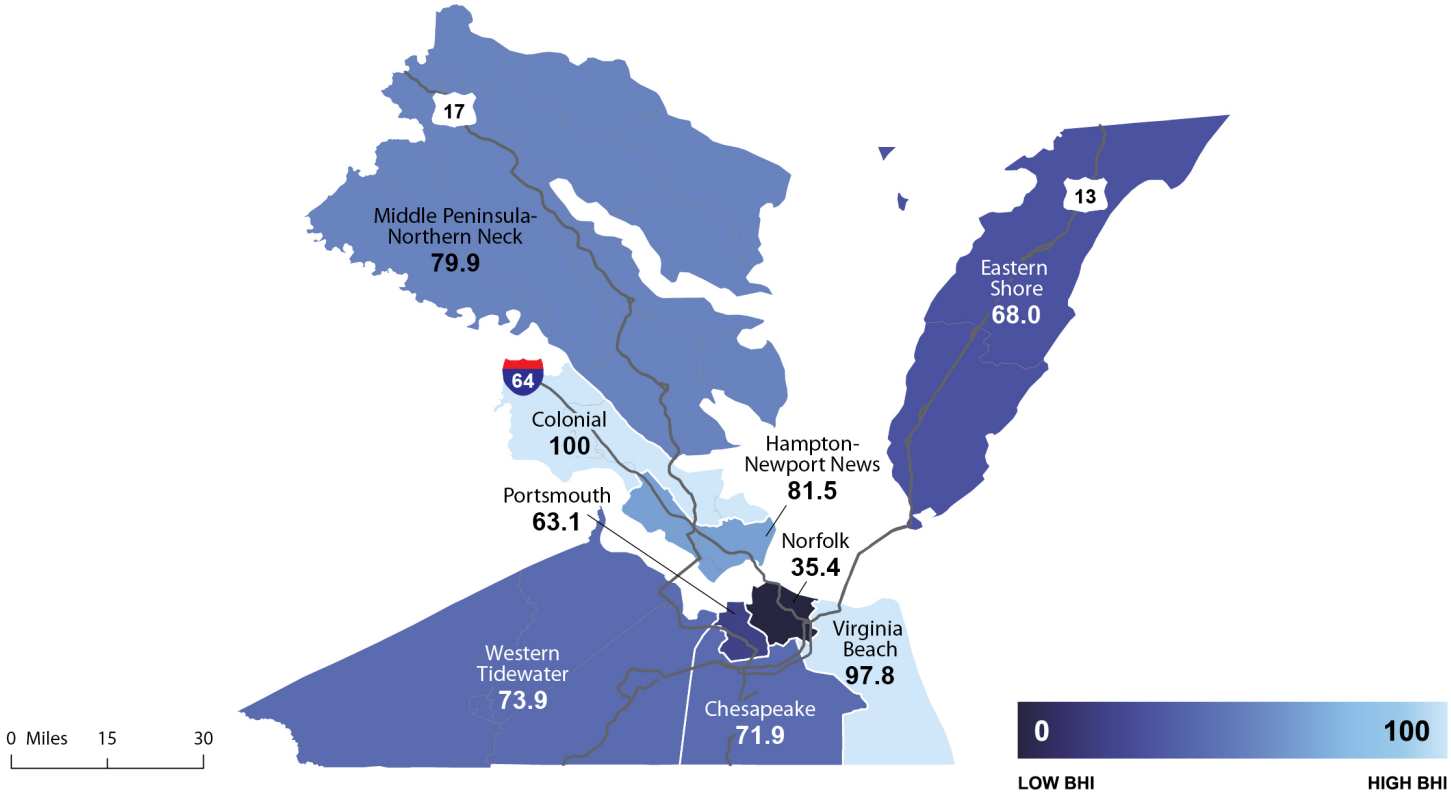
MAP 4 | ***Behavioral Health Index (BHI), Region 3***



MAP 5 | ***Behavioral Health Index (BHI), Region 4***



MAP 6 | ***Behavioral Health Index (BHI), Region 5***



APPENDIX: WEIGHTED QUANTILE SUM REGRESSION

In an analytic exercise that preceded the linear regression equations described above, the researchers also tested the use of Weighted Quantile Sum (WQS) regression methods to predict the dependent variable. The methods and results of that exercise are shared here for interest and reference but should not be used as a basis for setting policy.

METHODS

The indicators were calculated as previously described. The dependent variable was mortality from stress-related conditions—an aggregate of death counts from (1) accidental drug poisoning (ICD-10 codes X40-X44), (2) accidental alcohol poisoning (X45.0), (3) alcoholic liver disease (K70), and (4) suicides (U03, X60-84, and Y87.0). Mortality rates were calculated based on 2007-2017 death and population data obtained from CDC Wonder. All mortality rates were age-adjusted using the 2000 U.S. standard population. Indicators were coerced to be positively associated with the outcome in the same direction, in some cases by multiplying indicators by -1.

For the WQS analysis, missing data were handled at the FIPS level based on the final presentation of each variable. Indicators that were presented as percentages or rates in the final model were calculated at the FIPS level prior to the handling of missing data. KNN imputation was used for any missing values. A quality check was performed to ensure that imputed values did not fall outside of plausible ranges (i.e., that all percentages fell between 0 and 100).

WQS regression was then performed at the county level using 5 quantiles. This least squares regression model was weighted and constrained, assigning weights to each indicator such that the maximum amount of variation in the outcome was explained. Indicators that explained more variation in the outcome were assigned a higher weight. All indicator weights included in the model summed to one, such that the proportional importance of an indicator variable was represented by its weight. This analysis produced the following results at the county level:

$$SRC\ \widehat{Mortality}_j = \widehat{w}_{1,j}q_{1,j} + \widehat{w}_{2,j}q_{2,j} + \widehat{w}_{3,j}q_{3,j} + \widehat{w}_{4,j}q_{4,j} + \widehat{w}_{5,j}q_{5,j} + \widehat{w}_{6,j}q_{6,j} + \widehat{w}_{7,j}q_{7,j} + \widehat{w}_{8,j}q_{8,j} + \widehat{w}_{9,j}q_{9,j},$$

$$\sum_{k=1}^{9} w_k = 1$$

$$j = 1, 2, \ldots, number\ of\ health\ districts$$

RESULTS

Table A1 displays the weights from this county-level analysis, indicating that all indicators made varying contributions in predicting mortality from stress-related conditions.

Table A1. Weights for indicators from the weighted quantile sum regression*

Indicator	Weight
Opioid prescription rate	0.189
Married	0.180
Rehospitalization	0.073

Housing cost burdened	0.060
Child poverty	0.054
Voter participation	0.050
Severe housing disrepair	0.045
Adult poverty	0.037
Diabetes management	0.033
Avoidable hospitalizations	0.031
Religious organizations	0.030
Violent crime rate	0.029
Distance to highways	0.028
Mental health provider ratio	0.026
Public health insurance	0.022
Preschool enrollment	0.020
Bachelor's degree or higher	0.019
Unemployment	0.011
Overcrowded	0.010
Primary care provider ratio	0.008
Single parent household	0.007
Extremely housing cost burdened	0.006
Commute to work by public transportation	0.006
Private health insurance	0.006
Commute to work by motor vehicle	0.005
Median home value	0.005
Vacant housing	0.004
Uninsured	0.004
Median household income	0.002
Access to parks	0.001
Commute to work by walking/biking	<0.001
Public Assistance	<0.001
High school diploma or higher	<0.001
Household food insecurity	<0.001

$R^{2=}$ 0.2964