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RESEARCH ARTICLE

Association of Poor Mental-Health Days With COVID-19 Infection Rates in the U.S.

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Introduction: Limited evidence exists about the association between prior prevalence of poor mental health at the area level and subsequent rates of COVID-19 infections. This association was tested using area-level nationwide population data in the U.S.

Methods: A nationwide study including 2,839 U.S. counties was conducted. Poor mental health was the age-adjusted average number of days within the past 30 days that adults reported poor mental health, including depression, stress, and problems with emotions, from the Behavioral Risk Factor Surveillance System. COVID-19 infection rates were cumulative confirmed cases between January 22 and October 7, 2020 per 100,000 people in the general population. Bayesian spatial mixed-effects regression estimated the relationship between COVID-19 infection and poor mental-health days at the county level in 2019 and change in poor mental health between 2010 and 2019, adjusted for several covariates.

Results: Poor mental-health days in 2019 were positively associated with higher COVID-19 infection rates (RRR=1.059, 95% credible interval=1.003, 1.117). Change in mental health was not significantly associated with COVID-19.

Conclusions: Prior rates of poor mental health in a county were associated with a higher burden of COVID-19 infection. Interventions that improve well-being and strengthen mental-health systems at the community and other geographic levels are needed to address post-COVID-19 mental health problems.

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INTRODUCTION

Before the coronavirus disease 2019 (COVID-19) pandemic, mental health conditions accounted for 21%−32% of total years lived with disability, and between 7% and 13% of total disability-adjusted life years, globally.[1,2] Specific mental health conditions such as depression, mood disorders, and alcohol and drug abuse, are the largest contributors to poor health.[3]

Poor mental health has emerged as a massive public health threat during the COVID-19 pandemic and is an ongoing global problem.[4] Several studies have shown that exposure to or infection with COVID-19 is associated with higher anxiety, post-traumatic stress disorder, depression, suicide, and substance use problems in patient/clinical, general, adolescent, older adult, school student, and healthcare worker populations around the world.[5−7]

Few studies have examined whether prior poor mental health is associated with increased risk of COVID-19 infection. The available evidence so far has been from studies conducted at the individual level among segments of the population. One large study of 62,354 COVID-19 patients in the U.S. found that people who

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had a psychiatric disorder 1 year before the COVID-19 outbreak had a 65% higher risk of COVID-19 infection (compared with matched controls without disorders), adjusting for an extensive range of physical health and socioeconomic risk factors.[8] In another study among individuals, a past-year depression diagnosis had the strongest effect (7-fold risk compared with controls) on COVID-19 infection adjusting for age, sex, ethnicity, and extensive medical comorbidities.[9] In one study from the United Kingdom, among people aged 40−69 years, people with the highest psychological distress scores (relative to those with a 0 score) had a 37% higher risk of hospitalization for COVID-19 and a 76% higher risk of COVID-19 mortality, adjusted for several sociodemographic, economic, and clinical biomarkers.[10,11]

Evidence of an association between mental health and COVID-19 infection, however, is mixed and not all studies found significant associations. In a nationwide study of individuals aged ≥20 years who tested for COVID-19 in South Korea, a diagnosis of a mental illness was not significantly associated with increased risk for a COVID-19 infection, but some evidence suggested that poor mental health was related to a slightly higher risk of severe clinical outcomes among those who were infected.[12] Although some studies included an extensive set of explanatory covariates, potential explanations for the association between mental health and COVID-19 infection are speculative, especially as these associations vary by mental health condition.[8,9] Empirical analyses of mechanisms expected along a causal pathways are scarce.[12]

Though there is some evidence linking COVID-19 infection and mental health among individuals, the authors found no prior evidence about this potential association at the geographic area or community level. The direct and indirect harms of the COVID-19 pandemic are not distributed equally across state populations. Therefore, it is important to evaluate the association between these harms at the county level to identify counties to target for federal funding and prevention resources.[13] For instance, the Ending the HIV Epidemic Initiative used surveillance data to identify 57 counties to prioritize with additional resources for HIV prevention.[14] There is an urgent need for empirical evidence to identify those counties most impacted by these twin crises of mental health and COVID-19 across the U.S. to help deploy resources in the most efficient manner.

Poor prior mental health in a geographic community may be related to higher risk of COVID-19 infection according to environmental stress and system overload theories.[15,16] For instance, higher rates of mental illness in a community may economically and socially burden that community. These burdens may disrupt proper neural functioning in the brain and increase allostatic load stress (e.g., hypothalamic−pituitary−adrenal axis dysregulation) on everyone,[17,18] leaving the community members more susceptible to COVID-19 infections. One quarter (23.7%) of adults with any clinical mental illness in the U.S. reported they were not able to receive treatment for their illness.[19] Higher rates of dysregulated neural circuit function and allostatic load among people without sufficient medical care, therefore, leaves community members more susceptible to COVID-19 infections and correspond to an increase in the population rate of those who succumb to infectious and other diseases.[20,21]

Given the emerging conversations about the role of community mental health care as a strategy to mitigate current and post-COVID-19 effects on health,[22,23] the authors evaluated whether the prevalence of prior poor mental-health days was associated with higher rates of COVID-19 infection using nationwide general population data. The hypothesis is that prior prevalence of poor mental health would be positively associated with higher rates of COVID-19 infections at the county level.

METHODS

Study Sample

The raw number of COVID-19 infection cases between January 22, 2020 and October 7, 2020 for counties in the contiguous U.S. were obtained from the Johns Hopkins University Resource Center dashboard (https://coronavirus.jhu.edu). The analysis was restricted to 2,839 counties (90.3% of 3,143 counties total) where the covariates, mental-health prevalence in 2019, and mental health change between 2010 and 2019 were complete.

Measures

County-level mental-health data were from the Behavioral Risk Factor Surveillance System—the nation's vanguard and longest continuously running health survey system that collects data on health-related risk behaviors and chronic diseases among U.S. residents. Poor mental health was operationalized as the county-level age-adjusted average number of days, in the past 30 days, that adults reported poor mental health, including depression, stress, and problems with emotions. The primary exposure was poor mental-health days in 2019. The secondary exposure was the change in poor mental-health days between 2010 and 2019, calculated by subtracting the average number of poor mental-health days in the past 30 days in 2010 from that in 2019.

The analyses accounted for several county-level variables shown in previous studies to influence COVID-19 prevalence and that might also be associated with poor mental health at the county level.[24,25] The 2019 American Community Survey 5-year estimates were used to obtain the percentage of each county that was Black/African American, Hispanic/Latino, male, and aged 35−64 years; population density per square mile; percentage of uninsured adults aged <65 years; and socioeconomic deprivation (created from principal-component analysis of 4 variables with a Cronbach's α0.84: percentage of the population aged <25 years with less than a high-school diploma, median household income, unemployment rate among the population aged ≥16 years, and percentage of the population aged 18−64 years living in poverty.) Analyses adjusted for the impact of population mobility on mental health by including the daily average number of people not staying at home during the study period, derived from the Bureau of Transportation Statistics. The violent crime rate per 100,000 people in 2019 was from the Federal Bureau of Investigation Uniform Crime Reporting Program. Income inequality, operationalized as the Gini coefficient, was from the Decennial Census 2010. The County Health Rankings & Roadmaps Program was used to obtain the percentage of households with at least 1 of 4 housing problems: overcrowding, high housing costs, lack of kitchen facilities, or lack of plumbing facilities. The analyses controlled for Census region by incorporating a 4-category region variable with the South as the reference group.

Statistical Analysis

Bayesian spatial mixed-effects regression models computed the relationship between COVID-19 infection and poor mental-health prevalence and change, accounting for potential covariates. The model was specified as Oi ~ Binomial(pi, Ni) and $\text{logit}(p_i) = \alpha + \sum_{m=1}^{K} \beta_m X_{im} + s_i + state[ID[i]]$, where Oi, pi, and Ni are raw numbers of observed COVID-19 infection cases, the underlying COVID-19 infection rate, and total population at the ith county (i=1,2,. . .,2,839), respectively. α represents the average COVID-19 infection rate over the entire nation; X_{im} is the mth (m=1,2,..,K) centered and standardized mental-health variables and other county-level covariates in the ith county with corresponding coefficient β_m; s_i is the spatial random effects term that captures unexplained spatial variations. In the binomial models, Ni accounts for the underlying population variation. A Leroux conditional autoregressive prior,[26] which accounts for both spatial clustering and spatial heterogeneity between neighboring counties with a spatial correlation parameter (with a uniform prior between 0 and 1), was assigned to s_i. A spatial correlation parameter with a value equal to 0 indicates independence, whereas a value approaching 1 suggests strong spatial clustering. Counties sharing at least a vertex were considered neighbors, a simple, common, and effective approach to define neighborhoods,[27] and state (ID[i]) is a random effects term that captures state-level variations. Two different models were fitted to explore the impact of average days of poor mental health on COVID-19 infection. Model 1 explored the impact of poor mental health in 2019 on COVID-19 infection rates in 2020, adjusting for prior mental health values in 2010 and covariates. Model 2 explored the impact of change in poor mental health between 2010 and 2019. Two random coefficient models were fitted to examine whether the impacts of mental-health variables on COVID-19 infection varied by state (via adding a random effect term to β_m). Models were implemented by the computationally efficient algorithm integrated nested Laplace approximation using the integrated nested Laplace approximation package in R, version 3.6.2. A copy of the R script is available in the Appendix (available online). The default Gaussian prior with mean and precision equal to 0 was assigned to α, and a Gaussian prior with mean 0 and precision 0.001 was assigned to β_m and state (ID[i]). Model performance was assessed with leave-one-out cross-validation. The Watanabe−Akaike Information Criterion was used to compare model fit; a lower value indicates better model fit.[28]

This study used county-level data and therefore is not considered Human Subjects Research, and was thus is exempt based on the guidelines from Yale University Institutional Review Board (IRB).

RESULTS

The mean county-level COVID-19 infection rate was 207 per 10,000 people and the average number of age-adjusted poor mental-health days in the past 30 days was 4 (SD=0.62) days in 2019. The unadjusted Spearman correlation between poor mental-health days in 2019 and COVID-19 rates at the county level in 2020 was 0.12 days (p<0.001). This result is illustrated in the choropleth maps in Figure 1. Darker shades (poor mental-

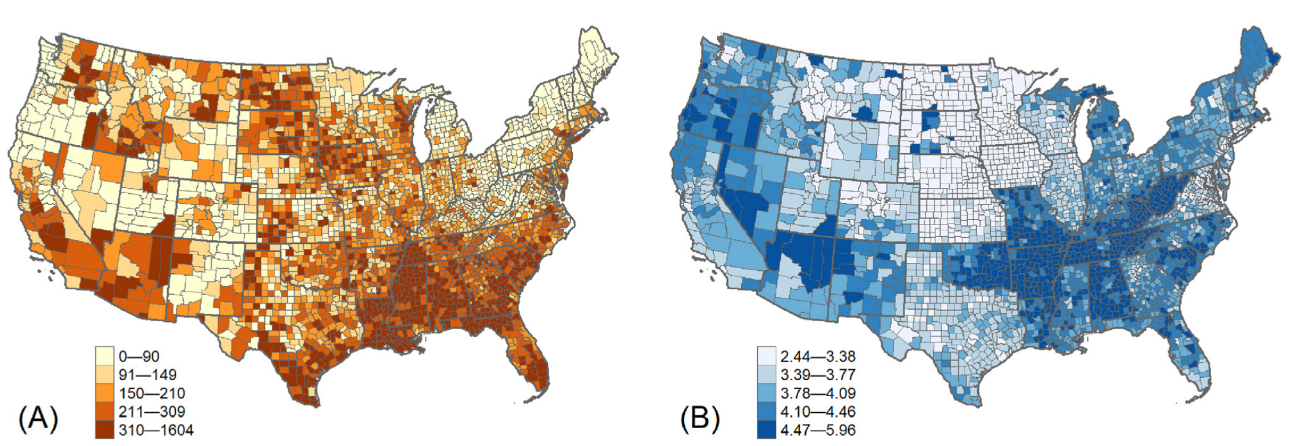

Figure 1. Geographic distribution of COVID-19 diagnosed cases between January 22, 2020 and October 7, 2020, per 10,000 persons in the U.S. (A) and age-adjusted average number of days adults were in poor mental health (B).

Note: The correlation is (Spearman ρ=0.12, p<0.001) evidenced by some overlap across counties shaded in dark between the 2 maps.

health days and higher COVID-19 cases) appeared to cluster in specific counties. A global Moran's *I* test of crude COVID-19 infection rate and poor mental-health days suggested that these 2 measures were significantly, spatially auto-correlated, with a Moran's *I* value 0.52 (p<0.001) and 0.79 (p<0.001), respectively. Spatial coclustering of COVID-19 infection was also indicated by the spatial correlation parameter (0.93, 95% credible interval=0.86, 0.98) from the statistical model, which suggested strong spatial autocorrelation.

Results from the multivariable analysis indicated that a higher average number of poor mental-health days in 2019 was significantly and positively associated with COVID-19 infection rates at the county level, adjusting for potential covariates (Model 1, Table 1). The covariates explained 57% of the variance in COVID-19 infection rates. On a standardized scale, a 1-unit SD increase in the average number of days of poor mental-health days in the past 30 days (mean=4 days, SD=0.62 days) corresponded to a 6% higher rate of COVID-19 infection (RR=1.059, 95% credible interval=1.003, 1.117). Converting the results back to an uncentered and unstandardized scale, a 1-day increase in the average number of poor mental-health days in the past 30 days resulted in a 9% increase in the rate of COVID-19 infection across counties. Between 2010 and 2019, a total of 2,172 counties (77%) experienced an increase in the average number of poor mental-health days (p-trend<0.0001, results not shown); however, this increase was not significantly associated with COVID-19 infection risk (Model 2, Table 1). Model fit was improved with the random coefficient models that examined variation in the mental health −COVID-19 infection association at the state level. For models using poor mental-health days in 2019 and mental health changes as the predictor, respectively, the Watanabe−Akaike Information Criterion decreased by 26.4 (28,297.61 vs 28,271.21) and by 41.3 (28,297.17 vs 28,255.87). These results indicated that the poor mental-

Table 1. Association Between Poor Mental-Health Days and COVID-19 Infection Rates, U.S.

Variables	Descriptive results, mean (SD)	Model 1 results, RRR (95% CrI)	Model 2 results, RRR (95% CrI)
Poor mental-health days, 2019	3.94 (0.62)	1.059 (1.003, 1.117)	N/A
Poor mental-health days, change between 2010 and 2019	0.48 (0.87)	N/A	1.013 (0.995, 1.031)
% Black/African American[a]	9.01 (14.34)	1.087 (1.043, 1.132)	1.084 (1.041, 1.129)
% Hispanic/Latino[a]	8.48 (12.20)	1.393 (1.341, 1.448)	1.383 (1.331, 1.437)
% male[a]	49.92 (1.98)	1.043 (1.024, 1.063)	1.041 (1.022, 1.061)
% Age 35−64 years[a]	38.45 (2.77)	0.947 (0.926, 0.967)	0.945 (0.925, 0.965)
% Uninsured under age 65 years[a]	12.77 (5.62)	1.000 (0.960, 1.043)	1.008 (0.967, 1.050)
Population density per square mile[a]	288.31 (1,885.21)	1.034 (1.007, 1.062)	1.034 (1.007, 1.062)
Socioeconomic deprivation[a,b]	−0.07 (1.61)	1.017 (0.984, 1.051)	1.000 (0.973, 1.028)
Income inequality[c]	0.43 (0.04)	1.048 (1.025, 1.071)	1.048 (1.026, 1.072)
Housing problem[d]	14.43 (4.30)	1.053 (1.022, 1.085)	1.058 (1.028, 1.090)
Human mobility[e]	88,258 (258,189)	1.009 (0.989, 1.031)	1.008 (0.987, 1.029)
Violent crime rate per 100,000 population[f]	253.46 (189.92)	1.002 (0.979, 1.025)	1.004 (0.981, 1.027)
Poor mental-health days, 2010	3.46 (1.03)	0.987 (0.967, 1.008)	N/A
Northeast Census region	N/A	0.541 (0.308, 0.927)	0.524 (0.292, 0.920)
Midwest Census region	N/A	1.033 (0.728, 1.427)	0.996 (0.702, 1.375)
West Census region	N/A	0.525 (0.333, 0.819)	0.509 (0.318, 0.808)

Note: Model 1: primary predictor is the number of poor mental-health days in 2019. Model 2: primary predictor is the change in the number of poor mental-health days between 2010 and 2019. All variables (except Census region) in the model are z-scored standardized to facilitate comparison on the same scale. The South Census region is the reference group for the Census variable.
[a]Data are from the ACS 2019 5-year estimates.
[b]A PCA of 4 variables: percentage of the population under age 25 years with less than a high-school diploma; median household income; unemployment rate among the population aged ≥16 years; and percentage of the population aged 18−64 years in poverty, yielding a Cronbach's α of 0.84.
[c]Represents the Gini coefficient, retrieved from the Decennial Census 2010.
[d]The percentage of households with at least 1 of 4 housing problems: overcrowding, high housing costs, lack of kitchen facilities or lack of plumbing facilities, retrieved from County Health Rankings & Roadmaps Program.
[e]The daily average number of people not staying at home during the study period (collected with mobile devices), from the Bureau of Transportation Statistics.
[f]Violent crime is composed of 4 offenses: murder and non-negligent manslaughter, forcible rape, robbery and aggravated assault. *Violent crimes* are defined in the FBI UCR Program as those offenses which involve force or threat of force. Data are from 2019.
ACS, American Community Survey; CrI, credible interval; FBI, Federal Bureau of Investigation; N/A, not applicable; PCA, principal-component analysis; UCR, uniform crime reporting.

health days with COVID-19 infection association were significant only in Arizona, Montana, and Utah, whereas changes in mental health (insignificant at the national level) were significant in Arizona, Colorado, Nevada, New Mexico, and Utah.

DISCUSSION

Based on the evidence to date, this is the first study to use national population-level data to show that prior poor mental-health days at the county level were associated with higher rates of COVID-19 infection. A small but statistically significant association was found, indicating a 9% increased rate of COVID-19 infections in response to a 1-day increase in the average number of days of poor mental health in the past 30 days in 2019. The RR coefficient estimates for poor mental health are clinically meaningful in the context of other established economic exposures, such as income inequality and structural issues like housing problems.

In addition to the biological pathways discussed earlier, poor economic and living conditions create a syndemic of social vulnerability. The burden of stressors in association with social vulnerability contribute to higher rates of COVID-19 infections.[29,30] Socially vulnerable communities are also at increased risk for poor mental health owing to underinvestment in mental health treatment, psychiatric services, and wellness care,[31] which also likely increase risk of COVID-19. These associations were significant in the Pacific Southwestern states. The findings from these states may be partially supported by poor overall rankings of mental illness and access to mental health care (e.g., Utah ranking 46th and Arizona 40th among the 50 states and District of Columbia).[19]

This study has implications for public health practice and policy. Community-based mental health services and community organizations and government partnership models (e.g., ThriveNYC and Social Prescribing in Ontario) can be critical for supplementing individual-level care to improve mental health at the population level.[32–35] Secondary prevention measures that target the upstream drivers and causes of poor mental health as well as viral susceptibility to diseases like COVID-19 are needed.[36] For example, in one national report that examined mental health and COVID-19 in 2020, a total 24% of respondents reported financial problems were contributing to their mental health currently and 27% were worried about COVID-19.[19] Particular attention will also need to be paid to this association among subgroups, such as Black Americans (who have highest rates of poor mental health and COVID-19 infections and deaths) who were also dealing with the mental health effects of racial unrest in response to police brutality.

Based on these findings, one next actionable step could be to use data such as County Health Rankings & Roadmaps (e.g., countyhealthrankings.org) along with Behavioral Risk Factor Surveillance System to identify counties with exceedingly high rates of poor mental health and then match those counties with data on the rates of COVID-19 outcomes including diagnosis and vaccination. After those areas are identified, one could determine which strategies (i.e., policies and programs that work) could be implemented.

There are also long-term implications to consider. Mental health is underdiagnosed in the population because people may not come forward for help given the external stigma that is prevalent in communities. According to the Framework for Excellence in Mental Health and Well-being,[37] interventions may fall into promotion/prevention, treatment, and maintenance. Based on that framework, one recommendation for a promotion intervention could include projects that build neighborhood belongingness, civic engagement, and social cohesion whereby neighbors check in with each other and strengthen social bonds.[37,38] Social cohesion is necessary to reduce social isolation, which is a major upstream as well as proximate risk factor for poor mental health.[4] Social cohesion may also be channeled to deliver resources to mitigate COVID-19-induced poor health, in the long term, through mechanisms that include redistributing economic resources among individuals, increased support for individuals with identified stress, and greater assistance in gaining access to mental health services.[22,39]

Limitations

This study has several caveats. Each county differs by healthcare policies and other important determinants. Therefore, it is possible that other factors could have influenced the mental health and COVID-19 infection association, such as rurality /urbanicity, ethnic enclaves, noise, and other environmental conditions.[40] To mitigate these factors, additional statistical adjustments were made for an extensive range of well-known sources of health risk factors such as violent crime, income inequality, housing problems, and residential instability/mobility. In addition, the Bayesian statistical model includes a parameter to account for uncertainty caused by unobserved covariates and missing data by borrowing strength from counties with complete data. Taken together, these findings appear robust.

Mental health was assessed in a very specific way via the county-level age-adjusted average number of days in the past 30 days of self-reported poor mental health. A key strength of this specific measure is how simple it is to assess in household surveys. It is also a well-validated marker of population health[41] used to monitor progress toward national health policy goals, such those outlined in *Healthy People 2020*. One limitation of these county-level mental health estimates, however, is that they were derived from small area estimation models that aggregate individuals' responses from the Behavioral Risk Factor Surveillance System.[42] These responses can contain measurement error outside of the study's control.

It is possible that other mental-health indicators measured with clinical diagnostic instruments such as the DSM-5 major depressive disorder might have produced different associations with COVID-19 infection rates. However, county-level estimates of those other mental health measures are unavailable.[43] This analysis was conducted at 1 ecologic level (i.e., the county). According to the modifiable areal unit problem, the size or significance of the associations observed at 1 geographic level may not be observed at another level (e.g., ZIP or postal code). Available COVID-19 data during a specific time were used. However, during this period, diagnosis guidelines, vaccine availability, and prevention ordinances (e.g., dates lockdowns started) varied. Despite these limitations, a key study strength is a nationwide analysis using robust population-level data such as cases of COVID-19 that reflect all data reported across the U.S. during the assessment period.

CONCLUSIONS

Using nationwide population-level data, this study revealed that prior poor mental health at the county level had a positive and significant association with COVID-19 infection rates. This study provides empirical evidence to support ongoing conversations about the urgent need for mental health care to be delivered at the community level. Future studies should replicate this analysis with other psychiatric health measures and will need to identify and estimate mechanisms that potentially explain why prior mental health is associated with subsequent COVID-19 infection at the county level.

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CREDIT AUTHOR STATEMENT

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SUPPLEMENTAL MATERIAL

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