Research Article

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Social factors related to depression during COVID-19

https://doi.org/10.1515/ohe-2022-0030
received September 17, 2022; accepted December 18, 2022

Abstract
Background – Depression can impact both the administration and efficacy of vaccines. Identifying social factors that contribute to depression, especially during a pandemic, is important for both current and future public health issues. Publicly available data can help identify key social factors contributing to depression.
Method – For each US state, information regarding their change in depression as measured by the Patient Health Questionnaire 2, predominant political affiliation, coronavirus disease 19 cases/100k, and lockdown severity were gathered. Structural equation modeling using latent change scores was conducted to assess the longitudinal relationships among depression, cases/100k, and state social restrictions.
Results – Higher initial levels of lockdown severity and depression predicted rank-order decreases in themselves over time. Correlations among the latent change variables reveal that changes in lockdown severity are negatively related to changes in cases/100k and changes in lockdown severity are positively related to changes in depression after controlling for the other variables.
Conclusion – Significant rank-order decreases in depression from T1 to T2 in blue states (who tend to vote for Democrats) vs red states (who tend to vote for Republicans) suggest that decreases in depression may be impacted by the population density and/or political views of that state. Rank-order increases in lockdown measures were negatively associated with rank-order increases in COVID-19 infections, demonstrating strong evidence that lockdown measures do help decrease the spread of COVID-19. Political affiliation and/or population density should be measured and assessed to help facilitate future public health efforts.

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Keywords: depression, social factors, COVID19, politics, population density

1 Introduction

The coronavirus disease 2019 (COVID-19) pandemic has impacted the health, safety, and well-being of a variety of communities across the globe. The negative impact of future pandemics can be mitigated by the observations and data currently collected. We have seen that COVID-19 has disproportionately impacted minorities [1] and is associated with increased mental health issues [2]. Additionally, mental health issues are also related to increased likelihood of contracting COVID-19 [3], while those already suffering from depression and anxiety are far more likely to exhibit increases in suicidal ideation and traumatic symptoms related to post-traumatic stress disorder (PTSD) under strict lockdown measures to mitigate its spread [4]. A systematic review on the mental health outcomes of the general population in China, Spain, Italy, Iran, the US, Turkey, Nepal, and Denmark found significant increases in symptoms of anxiety (6.33–50.9%), depression (14.6–48.3%), and PTSD (7–53.8%) [5]. Using a chain mediation model, Wang and colleagues [6] revealed that both a need for health information and the perceived impact of the pandemic were sequential mediators between mental health outcomes (i.e., anxiety, depression, and stress) and physical symptoms related to COVID-19 infections across three continents: America, Asia, and Europe. Additionally, those in middle-income countries (e.g., China, Iran, Malaysia, Pakistan, Philippines, Thailand, and Vietnam) revealed several risk factors, including age (i.e., <30), high education background, being single or separated, discrimination from other countries, and contact with those infected with COVID-19 [7]. Government response on process and procedures for mitigating the spread of COVID-19 may also influence mental health outcomes. For example, timing of government response is important as Lee and colleagues [8] found that countries with stringent policies exhibited less depressive symptoms, when those policies were enacted promptly. The type of lockdown and other social factors, including marital status, education level, family size, employment status, and contact with those possibly infected with COVID-19, seem to also contribute, as Vietnam had enacted a partial lockdown during the COVID-19 pandemic and revealed a low prevalence of depression (4.9%), anxiety (7.0%), and stress (3.4%) [9]. That said, Vietnam still saw an increase in reported mental health and health-related problems with anxiety and depression, for those whose lowered income was related to social distancing measures [10]. Other precautionary measures, like mask-wearing, have revealed a protective factor in psychological outcomes as can be seen in comparing China and Poland in the initial stages of the COVID-19 pandemic [11]. Polish respondents who were significantly less likely to wear face masks (Poles: 35% and Chinese: 96.8%) were more likely to report anxiety, depression, and stress [11]. Even with prompt protective measures put in place, in any pandemic, exposure is a possibility.

During the many phases of the COVID-19 pandemic, exposure to COVID-19 often involved quarantine to avoid infecting others [12]. Quarantine can have negative mental health consequences, especially for healthcare workers [13]. Additionally, research has suggested that these quarantine restrictions surrounding pandemic-related health issues may negatively impact mental health, in the general population [14,15]. However, as evident in the many previous studies already cited [6,9,11], the impact protective measures have on mental health may also be mitigated by other risk factors. For the future physical and mental health of communities around the world, it is important to identify and explain the role that certain social factors have between protective measures and mental health during pandemics.

One social factor, political affiliation, may influence the impact of mental health issues during a pandemic. Those who identify as conservative tend to be more likely to eschew public health messages [16]. Additionally, those states that primarily voted for Republican candidates, otherwise known as “red states,” were less likely to implement social restriction measures than their “blue state” peers or those who voted primarily for Democratic candidates [17]. If one’s political affiliation is related to ignoring public health measures, then these areas could experience more disease and additional mental health issues associated with care taking, disease, and the loss of family members and loved ones. On the other hand, not having social restrictions could decrease the rates of depression for those in red states [18]. Another factor to consider is the ecological difference between the blue and red states, namely that blue states tend to be more urban and red states tend to be more rural [19,20]. Urban settings tend to have greater population density and naturally more opportunities to participate in various social engagements [21,22]. For those that are high on extraversion, urban settings may provide exceptional opportunities to engage in social activities [23,24]. On the other hand, urban settings can also lead to crowding and invasion of personal space, which can also lead to more experiences of depression, anxiety, and stress [25,26]. Whether one lives in urban or rural areas, social restrictions can help prevent the spread of highly contagious disease; however, the impact of social restrictions on disease spread may be greater for those living in urban areas and subsequently blue states. One of the costs associated with implementing these necessary social restrictions in urban areas may be an increase in prevalence of depression. Political affiliation or population density may be influencing the relationship between social restrictions and mental health.

Previous studies have already revealed the impact political affiliation can have on the attempts to mitigate the impact of infectious diseases. For example, in the US, right-wing conservatism is related to doubting the impact of pandemic severity and mitigation efforts [27]. Conservatives in many countries are less likely to have favorable responses to mask wearing and those wearing masks to mitigate infectious spread [28]. It is also evident that safety measures to mitigate spread are related to adverse mental health outcomes, as already cited above. This study was conducted to provide a model, illustrating the relationship between political affiliation, safety protocols/social restrictions, and mental health. In the US, we tested three social factors by state: social restrictions, politics of state, and positive cases of COVID-19 per 100k in an area to identify the strongest predicting factors of increased depression. Such a model could be used to inform psychological monitoring procedures during outbreaks, with consideration to political affiliation and population area.

2 Methods

2.1 COVID-19 – 2020 state social restrictions

Data regarding the timing of state COVID-19 stay-at-home orders were taken from Moreland and colleague’s paper [29]. Their ratings were based on the extent to which the stay-at-home orders applied to people within the state with no order, advisory, and mandatory for persons at increased risk in certain counties, mandatory for persons at increased risk, mandatory for all in certain counties, or were mandatory for all. We ranked each state at different time periods with a Likert scale of 1 for "no order" up to 6 for "mandatory for all." The state social restriction ratings' first time period covered days from April 21 to May 6, 2020 (T1) and the second time period covered days from May 26 to May 31, 2020 (T2).

2.2 COVID-19 – 2020 measure of depression

The National Center for Health Statistics [30] partnered with the Census Bureau to deploy the Household Pulse Survey in 2020. This 20-min online survey included the Patient Health Questionnaire (PHQ-2).

The PHQ-2 asks, "Over the last 2 weeks, how often have you been bothered by the following problems?" [31]. This was modified in the CDC Pulse questionnaire to ask, "Over the last 7 days,[…]" [12]. The problems listed are "Little interest or pleasure in doing things" and "Feeling down, depressed or hopeless." The possible responses and scores are "Not at all," (0) "Several days," (+1) "More than half the days," (+2) and "Nearly every day" (+3). The scores for the two questions are summed, and in the CDC Pulse data, the percentage of scores that summed to 3 or more was reported as positive [12].

We accessed the data for all 50 states plus the District of Columbia at three CDC Pulse time intervals centered on the date at which the state social restrictions were evaluated by Moreland and colleagues [29], April 23 to May 5, 2020 (T1) and May 28 to June 6, 2020 (T2) from the CDC (2020d).

2.3 COVID-19 – 2020 positive cases per 100k

The New York Times [32] maintains a dataset containing the cumulative counts of coronavirus cases in the United States since January 21, 2020. We accessed these data and computed the average number of new cases per day in each state plus the District of Columbia for the first time period of April 21, April 26, May 1, and May 6, 2020 (T1) and the second time period of May 31, 2020 (T2) to match the time period in the CDC Pulse Data and the estimates of the state's social restrictions. To control for population in each state and in the District of Columbia, these averages were converted to new cases per day per 100,000 people using 2019 population estimates from the US Census Bureau [33].

2.4 Politics of state

Each state was characterized as a blue or red state depending on whether Biden or Trump received more votes in that state in the 2020 presidential election. Data were downloaded through The Cook Political Report [34].

2.5 Analytic approach

A set of autoregressive cross-lagged models were analyzed to assess the longitudinal relationships in the data, but these models did not fit the data well. Therefore, we estimated a Latent Change Score (LCS) model to test our hypotheses. Figure 1 is an illustration of an LCS from T1 to T2. Figure 2 presents the final model with all variables considered simultaneously: politics of state, cases/100k, lockdown severity, depression at T1 (April 21 to May 6, 2020), and changes between T1 and T2 (May 28 to June 2, 2020) and their respective standardized coefficients. For this final model, the change from T1 to T2 is represented as the latent variable whose change is being predicted by observed variables at T1.

3 Results

Averaged across all time points from April 21 to May 31, 2020, the states ranked as most restrictive were California, Hawaii, Michigan, and New Jersey. Their average across all

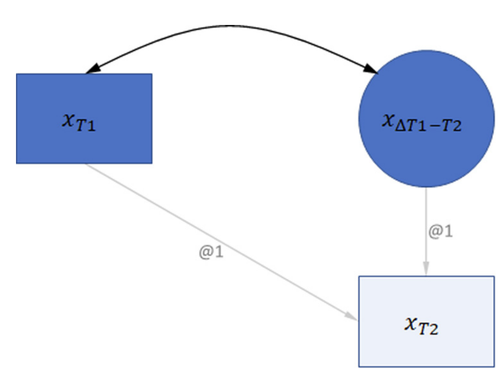

Figure 1: LCS illustration.

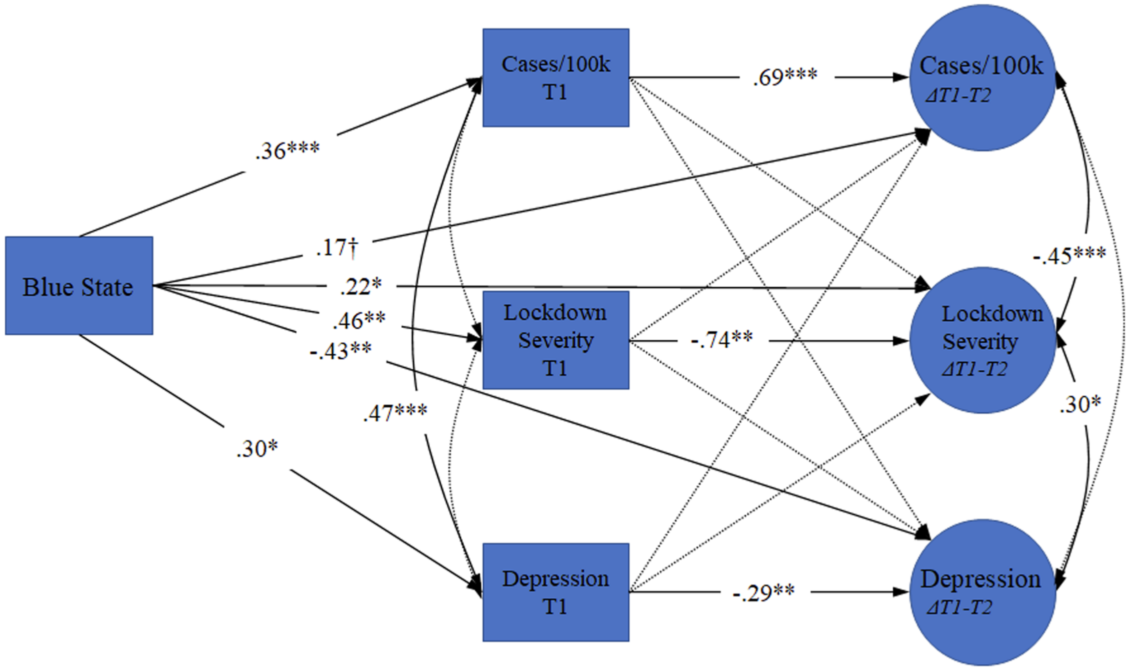

Figure 2: LCS model of red state vs blue state predicting cases/100k, lockdown severity, and depression at T1 (April 21 to May 6, 2020) and changes between T1 and T2 (May 28 to June 2, 2020). The paths and double-headed arrows represent standardized coefficients (i.e., betas and correlations). Dotted lines are non-significant.

time points remained at "6" or "mandatory for all." The states ranked as the least restrictive were Wyoming, North Dakota, Nebraska, Arkansas, and Connecticut. Their average across all time points remained "1" or "no order." From September 16 to October 26, 2020, the prevalence of depressive symptoms as indicated by the PHQ-2 was 24.54% (SD = 3.00). The states with the lowest and highest prevalence of depressive symptoms during this period were South Dakota (18.57%) and Kentucky (30.57%).

During that same time period, the mean number of new coronavirus cases in US states per day was 1021.52 (SD = 993.56), and the mean number of new coronavirus cases in US states per day per 100,000 people was 19.91 (SD = 14.04). The states with the lowest and highest mean number of new cases per day during this period were Vermont (*M* = 9.29) and Texas (5261.73). The states with the lowest and highest mean number of new cases per day during this period were Vermont (*M* = 1.49) and North Dakota (70.99).

The path coefficients in Figure 2 reveal that blue states in general had higher cases/100k at T1, higher lockdown severity for both T1 and T2, and higher depression at T1, but greater rank-order decreases in depression from T1 to T2, than red states. The standardized coefficients from initial status (at T1) to change (from T1 to T2) reveal a positive relationship between cases/100k at T1 to changes in cases/100k at T2. There were negative relationships between initial lockdown severity (at T1) and changes in lockdown severity (between T1 and T2) as well as initial depression (at T1) and changes in depression (between T1 and T2), indicating that higher initial levels of these variables predicted rank-order decreases over time. Finally, the correlations among the latent variables reveal that changes in lockdown severity (T1 to T2) are negatively related to changes in cases/100k (T1–T2) and changes in lockdown severity (T1 to T2) are positively related to changes in depression (T1–T2) after controlling for the other variables.

4 Discussion

The COVID-19 pandemic has resulted in increased challenges to health and welfare. Twenge and Joiner [2] have reported an increase in both depression and anxiety across the US after COVID-19 lockdown measures. Our model revealed that there are social factors to consider when measuring the impact of lockdown measures on mental illness. First, the predominant politics of an area as defined as democrat or republican might impact the degree of mental illness and the spread of illness during a pandemic. Blue states ranked higher in both depression and proportion of cases at T1 compared to red states. Given that blue states tend to be more metro or urban than rural [19], the sheer population density may explain the relationship of these variables. That being said, there were significant rank-order decreases in depression from T1 to T2 in blue states vs red states, suggesting that decreases in depression may be impacted by either the population density and/or political views of that state as pandemic mitigation protocols are enforced. Additionally, rank-order increases in lockdown measures were negatively associated with rank-order increases in COVID-19 infections, demonstrating strong evidence that lockdown measures do help decrease the spread of COVID-19. We also see a significant relationship between rank-order increases in lockdown measures and rank-order increases in depression. Considering that mental illness is associated with poorer health outcomes and pandemic-related safety measures, it may be important to consider mitigating the anticipatory mental health issues that lockdowns can impose. The model did not demonstrate any significant relationship between depression changes and changes in cases per 100k. However, future public health issues should consider social factors (e.g., isolation, political affiliation, and population density of an area) as they impact the mental health and spread of disease.

4.1 Limitations and future directions

We see two major limitations with this study. First, we conducted secondary data analyses at the state level. Ideally, individual-level data would be analyzed since relationships at one level (e.g., states) do not necessarily generalize to other levels (e.g., individual people). Future studies should collect and analyze data on individuals to confirm that the relationships identified in this study generalize to the person-level. Second, although the results are theoretically consistent with a causal interpretation, this was "correlational" (i.e., non-experimental) data, which limit our ability to establish causal relationships. Although we used a longitudinal design, which strengthens causal inference (because causes do not work backwards in time), future studies could use randomized controlled experiments to establish the causal relationships hinted at in this study.

In this study, the impact protective measures and political affiliation have on mental health was measured at the first wave of the COVID-19 pandemic. Since then, the impact COVID-19 has had on mental health may still be evident and we are still just learning about post COVID-19 syndrome and its impacts on depressive symptoms [35]. Future pandemic public health considerations may want to also consider monitoring mental health as the pandemic continues or enters into an endemic phase.

Given that other countries have different political systems and social factors, we recognize this model may be limited to countries with similar political and social structures. For example, China does not have a two-party political system of democrat or republican. Additionally, their mental health outcomes, at a similar time comparison to this study, revealed very little change in depressive and anxiety symptoms [36]. China also adopted a zero-COVID policy which was very different from many places throughout the world. Public health policies like the zero-COVID policy may be just beginning to reveal its impact on mental health, as recent research by Lau and colleagues [37] suggests a relationship to burnout and non-support for zero-COVID policy. Future studies could sample globally and consider the degree of social restrictiveness or infectious spread intolerance as a factor when modeling the relationship between political identity and mental health.

Acknowledgments: We would like to acknowledge Kristin Gray and Robert Alex Blake who took time to read through and implement edits in this manuscript.

Funding information: The authors state no funding involved.

Conflict of interest: The authors state no conflict of interest.

Ethical approval: The conducted research is not related to either human or animal use.

Data availability statement: The data that support the findings of this study are available from the Center for Disease Control, The National Center for Health Statistics and Prevention, The New York Times, and The Cook Political Report, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with the permission of the Center for Disease Control, The National Center for Health Statistics and Prevention, The New York Times, and The Cook Political Report.

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