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Associations between lockdown intensity and suicide mortality in US states

Konstantinos Christopoulos

University of Piraeus, 80 Karaoli & Dimitriou Street, Piraeus, 185 34, Greece

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ABSTRACT

The COVID-19 pandemic, along with oppressive government interventions, placed a heavy burden on mental health. Suicide mortality is an outcome that may have been affected by the stringency of these lockdown measures. The aim of this study is to examine the association between lockdown intensity, measured by the Stringency Index, and suicide mortality rates in US states from March 2020 to December 2021. To this end, Bayesian methods were used for the estimation of the association for the total population, as well as by gender, and by race. Results show a small negative association between lockdown intensity and suicide mortality rates which applies to most of the examined populations. Future research will determine if this relationship remains the same after the pandemic.

1. Introduction

Suicides are one of main causes of death in the United States and have been on the rise, with rates converging between regions and demographic groups (Christopoulos & Eleftheriou, 2020; Kitenge et al., 2019). Their co-existence with the COVID-19 pandemic, and its subsequent measures, has been characterised as 'a perfect storm' (Reger et al., 2020). The rationale behind this claim is a series of disruptions in risk and protective factors of suicide behaviour.

The pathways to suicidal behaviour presented next—in the context of the COVID-19 pandemic—are based on the expositions of Reger et al. (2020) and Zalsman et al. (2020). They accord with several suicide theories; from those of Durkheim (Taylor, 1982) and Rubinstein (1986) which focus mainly on social relationships and social integration, to Joiner's interpersonal theory of suicide (Joiner et al., 2005) and the 'three-step theory' by Klonsky and May (2015), which focus on simultaneous exposures that can lead from suicidal ideation to action. For a discussion on suicide theories and the COVID-19 pandemic see Banerjee et al. (2021).

Lockdown measures involving social distancing and confinement disrupt social relationships and may make social integration more difficult for some groups. Moreover, economic factors, such as unemployment (see Kawohl and Nordt (2020) for a discussion) and financial distress at the household level, create additional work-related stress and frustration, especially for health professionals. The fear of loss of loved ones places an extra burden to mental health.

Increases in domestic violence and withdrawal syndrome in drug and alcohol users may also deteriorate mental health. The deterioration of mental health may lead to increased substance use, as well as increased firearms sales—the most common suicide instrument/method in the United States. The lockdown measures also reduced access to health care which in turn may had a direct effect on mental health in patients with mental health problems, or indirectly, when individuals with other medical conditions do not receive the optimal treatment. Less obvious are the effects of modification in lifestyle factors, including exercise and nutrition, which might have suffered during the lockdown period.

All (or some) of these factors combined can lead to depression, loneliness, existential issues, and a sense of hopelessness about future. This can trigger suicidal ideation—as an 'escape' from this situation—which may become a suicide attempt and ultimately a completed suicide.

There may be a lagged effect on suicide rates as was the case in previous disasters and wars (Lester, 1994; Zalsman et al., 2020). Or even a positive effect from the shared experiences that may create social cohesion and add value to life and health in general (Reger et al., 2020). Nevertheless, surveys from the US and the UK confirm the increased frequency in suicidal thoughts and behaviours during the pandemic (Ammerman et al., 2021; Iob et al., 2020). Studies also suggest increased mental distress in younger US adults (Twenge & Joiner, 2020), as well as suicide mortality disparities between genders and racial minorities in the time of COVID-19 (Iob et al., 2020; Mitchell & Li, 2021).

The aim of this study is to examine the associations between the lockdown intensity and suicide mortality in the US at the State level. To this end, data from March 2020 to December 2021 were analysed for the total population, as well as by sex, and by race. To the best of our knowledge, lockdown intensity has not been studied for its effect on

E-mail address: kchrist@unipi.gr.

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suicide mortality.

2. Material & methods

2.1. Data

The data used concerns the period March 2020–December 2021. January and February 2020 were excluded because the pandemic was at an infant stage and suicides of that period cannot be attributed to the lockdown measures that were very much absent. More recent suicide mortality data were not available at the time.

Suicide mortality counts were extracted from the Centers for Disease Control and Prevention (CDC) WONDER underlying cause of death database (2021) using the ICD-10 codes X60–X84 (intentional self-harm) and Y87.0 (sequelae of intentional self-harm). To adjust for pre-pandemic factors affecting State suicide mortality rates, while simultaneously avoiding post-treatment bias, the suicide mortality counts of the previous isochronous period (March 2018–February 2020) were extracted and converted into rates.

The respective populations were extracted from the US Census Bureau (USCB, 2020). The intensity of the States' interventions was measured using the Oxford Stringency Index (SI) (Hale et al., 2020). SI takes values from 0 to 100 and is calculated based on data regarding school, workplace, and public transport closures; cancellation of public events and restrictions on public gatherings; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls (Hallas et al., 2021).[1] The mean of the aforementioned period (March 2020–December 2021) was taken in order to obtain a stringency intensity estimate for each State.

Descriptive statistics for the mortality counts and rates of this period are shown in Table 1. Moreover, the geographic distribution of the crude suicide mortality rates for the total population and the mean SI can be seen on Fig. 1.[2]

Table 1
Descriptive statistics for suicide mortality and the Stringency Index from March 2020 to December 2021 ($N = 51$).

	Median	IQR	Min.	Max.
Mean Stringency Index (%)	38.59	44.25–33.14	15.62	63.06
Total population				
Suicide mortality	1234	2236–592	77	7578
Crude suicide rates (per 100,000)	29.15	36.69–25.28	11.17	59.98
Male				
Suicide mortality	972	1792–477	63	5990
Crude suicide rates (per 100,000)	48.87	60.12–41.91	18.91	95.86
Female				
Suicide mortality	267	498–115	14	1657
Crude suicide rates (per 100,000)	11.51	14.99–9.93	3.80	22.99
Hispanic origin				
Suicide mortality	60	131–19	2	1850
Crude suicide rates (per 100,000)	14.64	19.35–10.67	5.74	36.13
American Indian or Alaskan Native				
Suicide mortality	9	24–2	0	198
Crude suicide rates (per 100,000)	23.79	42.44–6.45	0	119.62
Asian				
Suicide mortality	17	52–6	0	746
Crude suicide rates (per 100,000)	13.27	18.68–11.33	0	66.79
Black or African American				
Suicide mortality	78	194–18	0	621
Crude suicide rates (per 100,000)	18.34	25.04–14.06	0	42.16
Native Hawaiian or other Pacific Islander				
Suicide mortality	1	4–0	0	29
Crude suicide rates (per 100,000)	21.41	34.40–0	0	225.73
White				
Suicide mortality	1055	2006–512	39	6600
Crude suicide rates (per 100,000)	37.69	43.21–31.66	14.28	73.87

Notes: IQR=Interquartile range.

2.2. Statistical analysis

2.2.1. Bayesian methodology

Suicide mortality counts were analysed with Bayesian Poisson models using Hamiltonian Monte Carlo (HMC) sampling as implemented in *Stan* version 2.31. Specifically, three models were employed: 1) A Bayesian Poisson regression with a spatial quadratic kernel Gaussian process. The quadratic kernel converts the distance matrix into a covariance matrix which is used for the estimation of the varying intercepts. The Gaussian noise was added to account for rate heterogeneity as well as to control for spatial dependence, that is, common unobserved geographic features between States. 2) A Bayesian Gamma-Poisson regression for comparison, and 3) a Bayesian zero-inflated Poisson regression when many zeros were present.

A choice of somewhat informative priors was done due to the Poisson models, although the number of observations (51) are large enough to overcome any priors. Markov Chain convergence and sampling were inspected with traceplots and ranked traceplots, as well as with $\widehat{R}$ and *Stan*'s estimate of effective number of samples. HMC's divergent transitions warnings were also taken into account.

Model selection was based on Pareto-Smoothed Importance Sampling Cross-Validation (PSISCV) and Widely Applicable Information Criterion (WAIC). The results are presented graphically with posterior distribution densities and posterior predictive simulations, as well as with posterior means and 89% Highest Posterior Density Intervals (HPDI). Given the small number of observations (N = 51), the Bayesian methods allow the estimation of the quadratic kernel covariance matrix whose intercept parameters equal the number of observations. For a discussion on the advantages of the Bayesian methods used in this study we refer the reader to McElreath (2020).

The creation of the distance matrix and the Bayesian analysis were performed using *R* packages '*terra*' and '*rethinking*', respectively. The details of the statistical models are presented next.

2.2.2. Statistical models

The main Bayesian statistical model used in the analysis of the data is the following:

$$S_i \sim Poisson(\lambda_i) \tag{1}$$

where S_i the count of suicide deaths for each State i,

$$log\ \lambda_i = log\ \pi_i + \alpha + k_{STATE[i]} + \beta_1 SI_i + \beta_2 LS_i$$

where $log\ \pi_i$ is the offset and π_i is the population of State i. The intercept is made of a fixed part, α, and a varying part, $k_{STATE[i]}$ that is estimated by the following squared distance Gaussian process.

$$k_i \sim MVNormal(\mu_i, \mathbf{K})$$

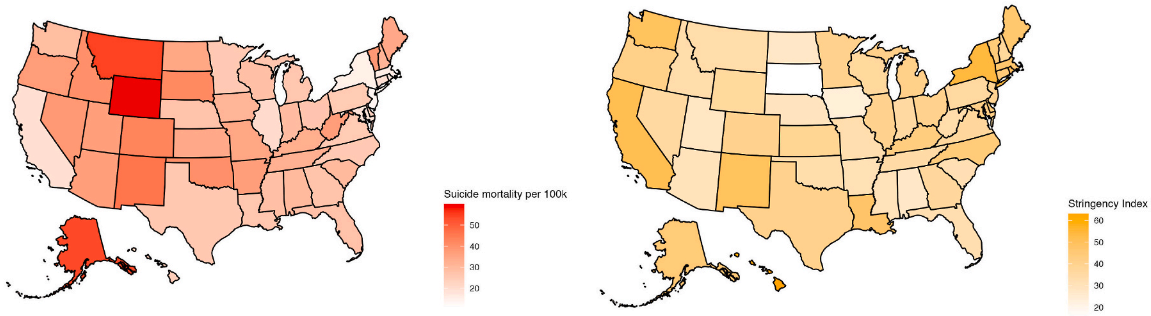
where k_i is a vector of 51 States, μ_i is a vector of zeros, and $\mathbf{K}$ is the quadratic kernel covariance matrix which takes the following form

$$K_{ij} = \eta^2 e^{-\rho^2 D_{ij}} + \delta_{ij}\sigma^2$$

where η is the maximum covariance between States i and j, ρ^2 is the rate of decline, D_{ij} is the distance between States i and j, and $\delta_{ij}\sigma^2$ provides for the within covariance—which does not apply to these single level data. SI_i is the standardised Stringency Index and LS_i is the standardised crude

[1] For more details on the measurement and calculation of the stringency index we refer readers to the following link https://www.bsg.ox.ac.uk/sites/default/files/Calculation%20and%20presentation%20of%20the%20Stringency%20Index.pdf.

[2] The maps were created with *R* packages '*usmap*' and '*ggplot2*'. The rates were calculated using the 2020 population.



(a) Crude suicide mortality rates per 100,000 (b) Mean Stringency Index

Fig. 1. Choropleth maps for suicide mortality rates (left) and mean Stringency Index (right) from March 2020 to December 2021.

suicide mortality rate of the isochronous pre-pandemic period.

The priors selected for the parameters[3] are the following:

$$\alpha \sim Normal(-8, 1)$$

$$\beta_{1,2} \sim Normal(0, 1)$$

$$\eta^2 \sim Exponential(3)$$

$$\rho^2 \sim Exponential(1)$$

Additionally a much simpler Gamma-Poisson model was developed for robustness

$$S_i \sim Gamma - Poisson(\lambda_i, \varphi) \tag{2}$$

$$log\ \lambda_i = log\ \pi_i + \alpha + \beta_1 SI_i + \beta_2 LS_i$$

with scale parameter $\varphi \sim Exponential(1)$. Finally, for the American Indians or Alaskan Natives (AIAN) and Native Hawaiian or other Pacific Islanders (NHPI) the following zero-inflated Poisson model was also considered:

$$S_i \sim ZIPoisson(p_i, \lambda_i) \tag{3}$$

$$logit(p_i) = \gamma + \delta_1 LS_i + \delta_2 log\ \pi_i$$

$$log\ \lambda_i = log\ \pi_i + \alpha + \beta_1 SI_i + \beta_2 LS_i$$

where p_i is the probability of observing zero suicide deaths and $\gamma \sim Normal(-2, 1)$ for the AIAN and $Normal(0, 1)$ for the NHPI. $\delta_1 \sim Normal(0, 1)$ and $\delta_2 \sim Normal(-1, 0.5)$.

3. Results

This section contains the empirical results from the analysis of the population as a total, by gender, and by race. Because SI is standardised, it is worth mentioning the its mean is 38.5, its standard deviation (SD) is 8.43, and results are plotted with the x axis ranging from 13 to 63, approximately. States with extreme values have been given labels and the points are proportional to Pareto k values[4] when a posterior prediction is plotted from a single model. A summary of the results is presented in Fig. 2.

3.1. Total population

For the total population, SI appears to have a very small negative association with suicide mortality. Fig. 3a presents the posterior density of the SI coefficient (β_1). Most of the mass is below zero in both specifications with mean -0.04, standard error (SE) 0.02, and 89% HDPI -0.06 to -0.01 for the Gaussian process model, and mean -0.04, SE 0.03 and 89% HDPI -0.10–0.01 for the Gamma-Poisson model. Fig. 3b and c present the posterior predictions for the average suicide mortality rates per 100,000 and 89% prediction intervals as a function of SI for Model (1) and Model (2), respectively. Model (1) performs better predictive-wise according to PSISCV and WAIC, but this is no surprise since it has 52 parameters more than Model (2).

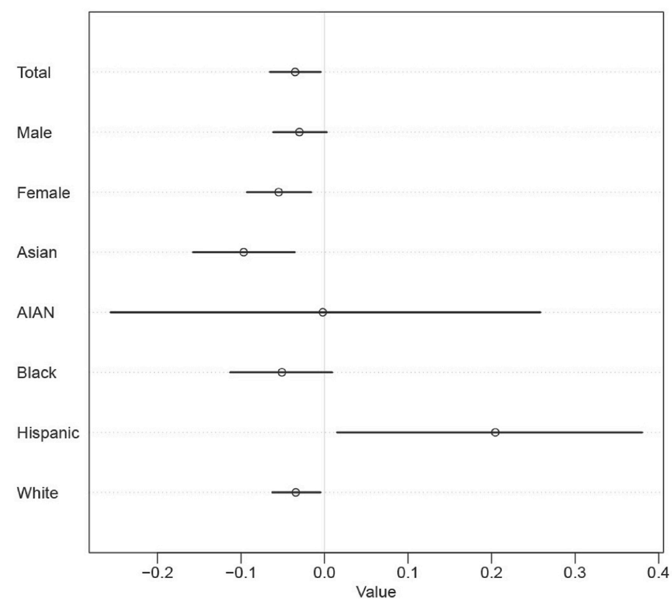


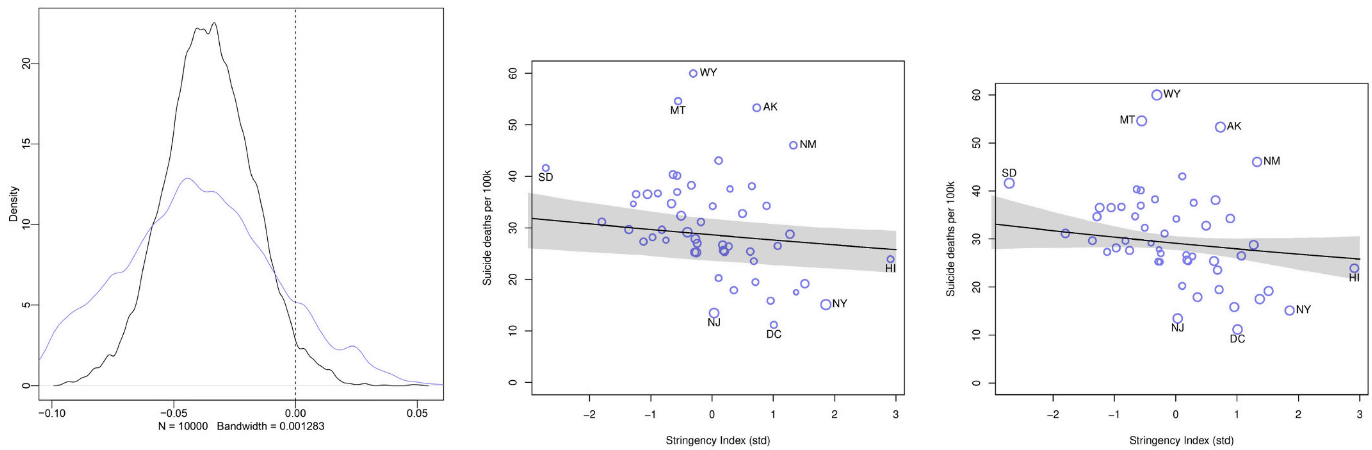
Fig. 2. Forest plot for the SI coefficients and 89% HPDI from Model 1.

3.2. By gender

We rely to Model (1) for the gender analysis—the Gamma-Poisson produced almost identical estimates. The β_1 for the males was very similar with that of the total population with posterior mean -0.03, SE 0.02, and 89% HDPI -0.06–0.00. For females, the posterior mean was -0.05 with SE 0.02, and 89% HDPI -0.09 to -0.02. Fig. 4a presents the posterior densities of the SI coefficient β_1 for males (black) and females (blue). Again, most of the mass is below zero and there is a large overlap between the two distributions. Fig. 4b and c present the posterior predictions for the average suicide mortality rates per 100,000 and 89% prediction intervals as a function of SI for males and female, respectively.

[3] The mean for the prior of the constant α varied from -8 to -9 depending on the model.

[4] The larger the Pareto k values the more influential the point.

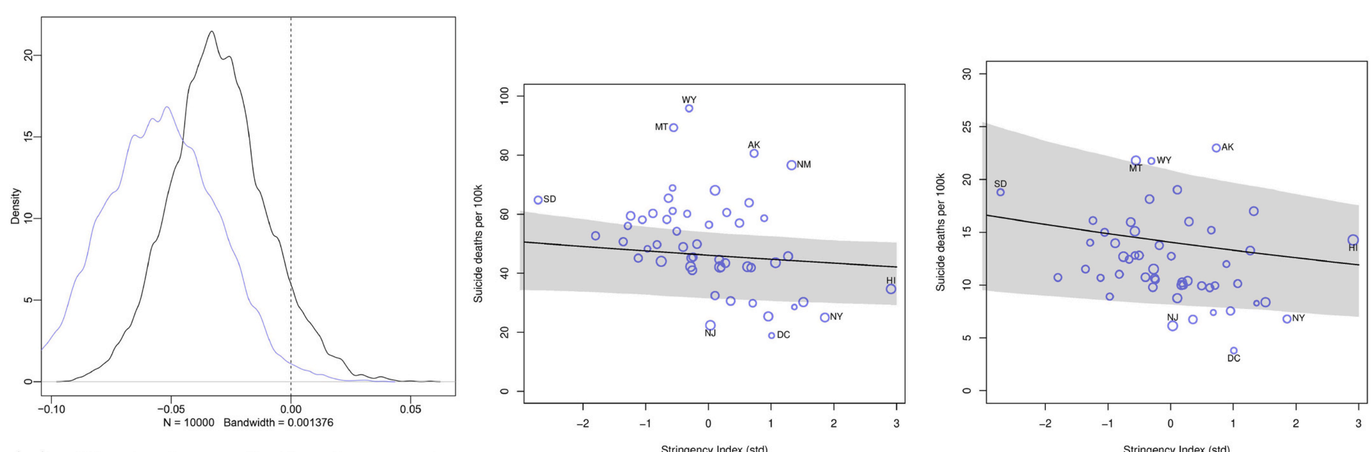


(a) Posterior of β_1. Model 1 (black), Model 2 (blue)

(b) Model 1

(c) Model 2

Fig. 3. Posterior distributions of SI coefficients (a) and posterior predictive simulations for SI for both models (b,c).



(a) Posterior of β_1 for males (black) and females (blue)

(b) Male

(c) Female

Fig. 4. Posterior distributions of SI coefficients (a) and posterior predictive simulations for SI by gender (b,c). Samples are from Model 1.

3.3. By race

Racial analysis also relies on Model 1. Estimates from other models are mentioned when discrepancies occur. Fig. 5 presents the posterior predictions for the average suicide mortality rates per 100,000 and 89% prediction intervals as a function of SI for Hispanics, American Indians or Alaskan Natives, Asians, Black or African Americans, and Whites.[5]

For the Asian population, the posterior mean was -0.10 with 0.04 SE and 89% HDPI from -0.16 to -0.03. Similar were the estimates for the white: mean -0.04, SE 0.02, 89% HDPI -0.06 to -0.01 and black population: mean -0.05, SE 0.04, 89% HDPI -0.11–0.01. Hispanic population data produced a discrepancy between Models (1): mean 0.20, SE 0.12, 89% HDPI 0.01–0.38 and (2) : mean -0.29, SE 0.15, 89% HDPI -0.52 to -0.05. Thus direction of the association remains unclear. From Fig. 5d we observe that Model (2) makes very unrealistic predictions for low SI. The high suicide mortality rates in New Mexico, Colorado, and Alaska probably create these modelling issues.

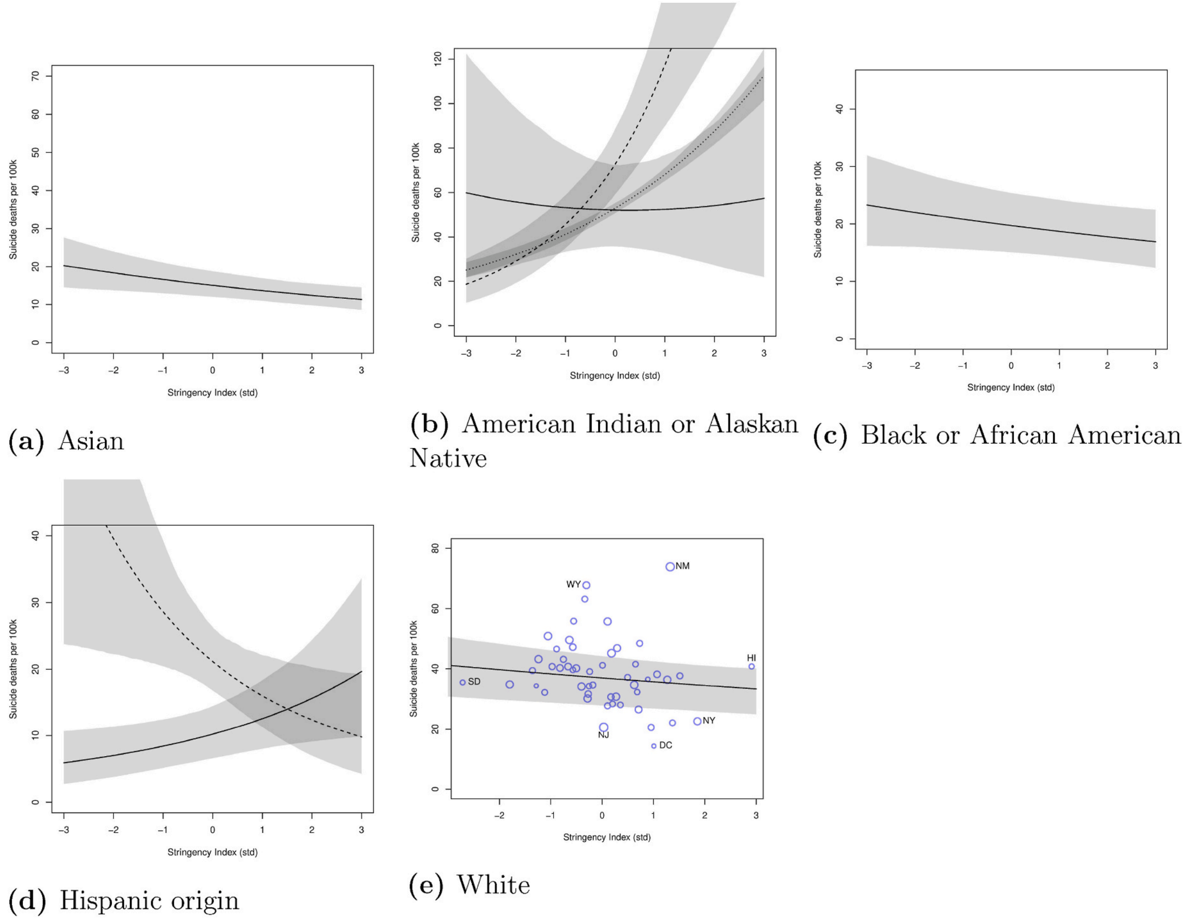
For AIAN there were there discrepancies between Model (1) and (2), albeit of quantitative nature. Since there were six zero values Model (3) was also used. The estimates are: for Model 1 mean 0.00, SE 0.16, 89% HDPI -0.25–0.26; for Model 2 mean 0.47, SE 0.11, 89% HDPI 0.30–0.64; for Model 3 mean 0.25, SE 0.02, 89% HDPI 0.22–0.29. As is evident in Fig. 5b, Models 2 and 3 produce very unrealistic predictions for high SI values. Finally, we were unable to model the suicide mortality of NHPI in any meaningful way. The combination of multiple zero values (n = 20) and very large dispersion in suicide mortality rates—probably with a lot of error, since these populations are very small—led to the decision to not include a graph.

4. Discussion

This study focused on the association between lockdown intensity and suicide mortality rates in US states from March 2020 to December 2021. A very small negative association was observed for the total population. This was also the case in males and females, where no heterogeneous association was found, although a slightly more negative association was observed for females. The great gender disparity in suicide mortality—also evident in our data—was probably not affected by the lockdown stringency, at the least in the short-run.

In the racial analysis, similar results were found for Asians, Black or

[5] Unfortunately, the points for all races except whites are not plotted due to CDC's data confidentially restrictions.



(a) Asian

(b) American Indian or Alaskan Native

(c) Black or African American

(d) Hispanic origin

(e) White

Fig. 5. Posterior predictions of average suicide mortality rates per 100,000 and 89% prediction intervals as a function of SI by race. Model (1) solid, Model (2) dashed, and Model (3) dotted line.

African Americans, and Whites. The negative association was clearer for Asians who are the race with the lower suicide mortality rate (see Table 1). An emerging pattern is that populations with lower suicide rates (females, Asians) exhibit a more negative association. The results were mixed for Hispanics and AIAN, with no, or very small association being the most probable scenario. The rationale behind this claim is that Hispanics also exhibit low suicide mortality rates, and therefore the most likely scenario is that of a negative association, despite the mixed results. For AIAN, results should be interpreted with caution since these populations are very small in most States. More disaggregated, or ideally, individual-level data would be necessary to study these populations. The same applies to NHPI were no conclusions could be drawn.

It appears, at least for this early period, that stringency intensity did not play a significant role in suicide mortality. The original hypothesis of lockdown intensity being associated with higher suicide mortality rates was very much rejected. This is perhaps a counterintuitive result given the numerous potential mechanisms through which lockdown measures can affect mental health and suicidal behaviour. It may be the case that the positive effects of the pandemic on prophylactic factors such as social cohesion and life valuation, neutralised the various risk factors. Or perhaps this is another case were the storm will hit after and not during the event. Another explanation is that suicide attempts may have been more common in younger or female individuals who have lower odds of succeeding (Conwell et al., 1998; Mościcki, 1994), and therefore are not included in the mortality database.

These hypotheses as well as the post-pandemic effect are topics for future research. The role of social cohesion, measured for example by the social capital (see Kawachi et al. (2000) for a discussion on these concepts), presents an opportunity for a mediation analysis—especially in the scenario where social cohesion changes during the pandemic—that is outside the scope of this research, which was to capture the total association of SI and suicide mortality rates.

This is an ecological study that suffers from limitations. Data are aggregated temporally and spatially. A more dynamic and spatially disaggregated study may produce different results. Nevertheless, the effect of stringency on mental health and suicidal behaviour may be lagged, and a dynamic analysis may not capture the potential effect at all. Since SI is measured on the State level, a more disaggregated unit of analysis might lead to a larger ecological fallacy risk. Regarding residual confounding, no traditional confounders were identified, but it is always possible in observational studies. The lagged suicide mortality rates in the model (*LS*)—which serves as an antecedent of factors affecting them—was added because outcome predictors are necessary in generalised linear models. Lastly, some measurement error is unavoidable when creating rates from small populations such as the AIAN and NHPI.

Regarding the transportability of the results, this study focuses on a regional level. This helps reduce confounding but does not allow the extrapolation of the findings outside the US. Lockdown measures were very similar across the globe but their effect on the suicide mortality rates of other populations is not expected to be homogeneous. While it is safer to assume that developed countries may exhibit similar patterns with US, not much can be said about developing countries. This is another topic for future research.

In conclusion, lockdown intensity may have a very small negative association with suicide mortality in US states. No clear disparities were found between genders and races. More research is necessary to monitor the situation in the aftermath of the pandemic.

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Ethical statement for SSM population health

Hereby, I Konstantinos Christopoulos consciously assure that for the manuscript "Associations between lockdown intensity and suicide mortality in US states" the following is fulfilled:

1) This material is the authors' own original work, which has not been previously published elsewhere.
2) The paper is not currently being considered for publication elsewhere.
3) The paper reflects the authors' own research and analysis in a truthful and complete manner.
4) The paper properly credits the meaningful contributions of co-authors and co-researchers.
5) The results are appropriately placed in the context of prior and existing research.
6) All sources used are properly disclosed (correct citation).
7) All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.
8) This research uses ecological data and therefore is not subject to review by an ethics committee.

CRediT author statement

Konstantinos Christopoulos: Conceptualization, Methodology, Software, Data curation, Writing-Original draft preparation, Visualization, Software, Validation, Writing-Reviewing and Editing.

Declaration of competing interest

No competing interests.

Data availability

The data and code used for the analysis are available from: https://github.com/KonstantinosChristopoulos/Christopoulos-SSMPH-2013

References

Ammerman, B. A., Burke, T. A., Jacobucci, R., & McClure, K. (2021). Preliminary investigation of the association between COVID-19 and suicidal thoughts and behaviors in the U.S. *Journal of Psychiatric Research, 134*, 32–38.

Banerjee, D., Kosagisharaf, J. R., & Sathyanarayana Rao, T. (2021). 'the dual pandemic' of suicide and COVID-19: A biopsychosocial narrative of risks and prevention. *Psychiatry Research, 295*, Article 113577.

CDC. (2021). Centers for Disease control and prevention. In *National Center for Health Statistics. National Vital Statistics System, Mortality 2018-2021 on CDC WONDER Online Database, released in 2021. Data are from the Multiple Cause of Death Files, 2018–2021, as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program*. Available from http://wonder.cdc.gov/ucd-icd10-expanded.html.

Christopoulos, K., & Eleftheriou, K. (2020). Premature mortality in the US: A convergence study. *Social Science & Medicine, 258*, Article 113141.

Conwell, Y., Duberstein, P. R., Cox, C., Herrmann, J., Forbes, N., & Caine, E. D. (1998). Age differences in behaviors leading to completed suicide. *American Journal of Geriatric Psychiatry, 6*(2), 122–126.

Hale, T., Webster, S., Petherick, A., Phillips, T., & Kira, B. (2020). *Oxford COVID-19 government response tracker (OxCGRT)*, 8 (p. 30). Available from: https://github.com/OxCGRT/USA-COVID-policy.

Hallas, L., Hatibie, A., Majumdar, S., Pyarali, M., & Hale, T. (2021). Variation in US states' responses to COVID-19. *University of Oxford*. Available from www.bsg.ox.ac.uk/COVIDtracker.

Iob, E., Steptoe, A., & Fancourt, D. (2020). Abuse, self-harm and suicidal ideation in the UK during the COVID-19 pandemic. *The British Journal of Psychiatry, 217*(4), 543–546.

Joiner, T. E., et al. (2005). *Why people die by suicide*. Harvard University Press.

Kawachi, I., Berkman, L., et al. (2000). Social cohesion, social capital, and health. *Social epidemiology, 174*(7), 290–319.

Kawohl, W., & Nordt, C. (2020). COVID-19, unemployment, and suicide. *The Lancet Psychiatry, 7*(5), 389–390.

Kitenge, E., Alam, M. R., & Sameem, S. (2019). Convergence of US suicide rates: What does it imply? *Economic Analysis and Policy, 62*, 300–306.

Klonsky, E. D., & May, A. M. (2015). The three-step theory (3st): A new theory of suicide rooted in the "ideation-to-action" framework. *International Journal of Cognitive Therapy, 8*(2), 114–129.

Lester, D. (1994). Suicide rates before, during and after the world wars. *European Psychiatry, 9*(5), 262–264.

McElreath, R. (2020). *Statistical rethinking: A bayesian course with examples in R and stan*. CRC press.

Mitchell, T. O., & Li, L. (2021). State-level data on suicide mortality during COVID-19 quarantine: Early evidence of a disproportionate impact on racial minorities. *Psychiatry Research, 295*, Article 113629.

Mościcki, E. K. (1994). Gender differences in completed and attempted suicides. *Annals of Epidemiology, 4*(2), 152–158.

Reger, M. A., Stanley, I. H., & Joiner, T. E. (2020). Suicide mortality and coronavirus Disease 2019—a perfect storm? *JAMA Psychiatry, 77*(11), 1093–1094.

Rubinstein, D. H. (1986). A stress-diathesis theory of suicide. *Suicide and Life-Threatening Behavior, 16*(2), 182–197.

Taylor, S. (1982). *Durkheim and the study of suicide*. Springer.

Twenge, J. M., & Joiner, T. E. (2020). Mental distress among US adults during the COVID-19 pandemic. *Journal of Clinical Psychology, 76*(12), 2170–2182.

USCB. (2020). Demographic data for US states. Available from https://data.census.gov.

Zalsman, G., Stanley, B., Szanto, K., Clarke, D. E., Carli, V., & Mehlum, L. (2020). Suicide in the time of COVID-19: Review and recommendations. *Archives of Suicide Research, 24*(4), 477–482.