Mortality and Longevity

Quantifying the Effects of Mental Health on U.S. Suicide and Mortality Rates

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Quantifying the Effects of Mental Health on U.S. Suicide and Mortality Rates

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Quantifying the Effects of Mental Health on U.S. Suicide and Mortality Rates

Executive Summary

Understanding how mental health influences mortality is increasingly important for actuaries involved in pricing, reserving, and population risk assessment. This study quantifies the relationship between mental health indicators, socio-economic conditions, and both suicide and all-cause mortality across U.S. counties from 2010 through 2023.

Using a Bayesian hierarchical spatiotemporal model with a conditional autoregressive (CAR) structure, mortality and suicide patterns are estimated by age, sex, and geography. The framework incorporates county-level data on education, income, housing, marriage, race, household size, unemployment, and multiple measures of mental health, including rates of severe depression, suicidal ideation, and self-reported poor mental health days.

Key findings include:

- Strong geographic clustering: Neighboring counties show highly correlated mortality and suicide outcomes, confirming that regional social and economic context meaningfully influences risk.
- Socio-economic disparities: County-level education, housing prices, and marriage rates are among the strongest predictors of suicide risk, though effects differ by age and sex. Higher education and home values are generally associated with reduced suicide risk for men but have mixed or opposite effects for women in later life.
- Mental health as a leading indicator: County-level mental health distress is consistently associated with higher mortality and suicide rates. The relationship is most pronounced among youth and young adults.
- Temporal persistence: Spatial and temporal correlations suggest stable, long-term regional patterns in both overall mortality and suicide.

These results demonstrate the value of integrating mental health surveillance data into traditional mortality modeling. Doing so can improve experience studies, risk segmentation, and forecasting for life, disability, and group health portfolios. The findings also highlight potential areas for designing interventions that address both mental health and underlying socio-economic factors.

Section 1: Introduction

There is a clear and ongoing need for accurate models of human mortality, and for centuries actuaries have been working to improve their precision and usefulness. As summarized by Lewin and Valois (2003), the history of mortality modeling reflects continuous refinement, from early life tables to sophisticated stochastic and statistical frameworks. These advances have been driven by improvements in data collection, the development of richer mathematical formulations, and the incorporation of new types of covariates into predictive models.

Accounting for spatial and temporal effects in mortality modeling is not new. Since at least 1992 (Lee and Carter 1992), researchers have developed increasingly intricate methods to incorporate spatial and temporal dynamics into mortality projections. These enhancements have led to more robust and reliable actuarial analyses. However, the explicit integration of mental health data alongside socio-economic factors into mortality modeling is relatively recent. Most of this work has emerged in the past decade, and very few studies have attempted to unify spatial, temporal, and mental health effects within a single coherent modeling framework.

The increasing availability of detailed mental health surveillance data, combined with advances in Bayesian computational methods, now provides actuaries with an opportunity to bridge this gap. In this study, a Bayesian hierarchical model is applied with a conditional autoregressive (CAR) structure to U.S. county-level mortality and suicide data. This approach captures spatial and temporal dependencies while incorporating mental health and socio-economic indicators as predictors of variation in mortality outcomes. Specifically, both total deaths and suicides are modeled across combinations of age group and sex, allowing for more granular and interpretable patterns of risk.

Integrating mental health indicators into mortality models has important implications for actuarial practice and public policy. This approach has potential to enable actuaries to:

- Enhance predictive accuracy in mortality and longevity modeling by including behavioral and psychological dimensions of population risk.
- Identify regional risk clusters where socio-economic and mental health conditions interact to elevate mortality risk.
- Support targeted interventions by recognizing at-risk populations that may benefit from early prevention, counseling, or community-based support.
- Improve pricing and reserving assumptions for life, health, and disability insurance, especially as mental health-related conditions increasingly affect claims experience.
- Inform public policy and resource allocation by linking mortality risk to measurable, region-specific indicators of well-being.

By supplementing traditional actuarial models with mental health and socio-economic data, this framework expands the actuarial toolkit for understanding mortality in the modern era. It supports not only more accurate projections but also a deeper understanding of the social and behavioral determinants that shape mortality outcomes across the United States.

The remainder of the paper is organized as follows: Section 2: Literature Review discusses some of the previous work done on the spatiotemporal modeling of mortality curves and how mental health and socio-economic variables can be related to mortality rates; Section 3: Data describes the mortality data, mental health data, and socio-economic covariates used in this study; Section 4: Models and Methods explains the statistical models and assumptions utilized in the analysis; Section 5: Results and Discussion presents and discusses the results; and finally, Section 6: Conclusion gives some concluding remarks.

Section 2: Literature Review

2.1 MODELING SPATIAL AND TEMPORAL TRENDS IN MORTALITY

The foundation for modern mortality modeling was established by the Lee-Carter model, which decomposed mortality rates into age-specific components and time trends, providing a widely adopted framework for demographic forecasting (Lee and Carter 1992). Subsequent extensions of the Lee-Carter model have introduced greater flexibility in age and cohort effects; see Booth and Tickle (2008) or Lee (2000) for discussions of such methods. Building upon this foundation, researchers developed Bayesian hierarchical models that extended mortality modeling to incorporate spatial dimensions alongside temporal patterns. For example, Alexander et al. (2017) demonstrated how Bayesian approaches could estimate subnational mortality by pooling information across geographic space while smoothing over time, using principal components to capture age patterns. Goicoa et al. (2019) used splines to model and smooth age-space-time patterns of mortality, specifically studying breast cancer mortality in Spain.

The spatial-temporal framework was further refined through models that treat both area-specific intercepts and trends as correlated random effects, allowing for explicit modeling of space-time variation in mortality risk (as in Bernardinelli et al. 1995). These Bayesian spatiotemporal models typically incorporate structured priors that account for spatial correlation through conditional autoregressive specifications (Besag et al. 1991) or Gaussian process frameworks (Banerjee et al. 2003). Saavedra et al. (2021) used a Bayesian spatiotemporal model in order to estimate excess deaths in Spain due to COVID-19. The computational challenges inherent in these complex hierarchical models have been addressed through the development of Integrated Nested Laplace Approximations (INLA), which offer significant advantages over traditional Markov chain Monte Carlo (MCMC) methods in terms of computational efficiency and implementation ease for Bayesian spatial modeling (Rue et al. 2017; Lindgren and Rue 2015).

Recent methodological advances have focused on handling large spatial datasets through nearest-neighbor Gaussian process models (Datta et al. 2016) and dynamic linear model frameworks that capture county-level spatiotemporal mortality patterns (Gibbs et al. 2020). These developments have enabled more sophisticated analyses of mortality patterns across geographic scales, from neighborhood-level studies (Wen et al. 2023) to national-scale investigations (Dwyer-Lindgren et al. 2016).

2.2 THE IMPACT OF MENTAL HEALTH AND SOCIO-ECONOMIC FACTORS ON MORTALITY

Suicide deaths have long been theorized to be caused by both internal factors (see De Beurs et al. 2019) and external factors (see Mueller et al. 2021), with a complex interaction between individual psychological processes and broader sociocultural factors (see Comtois et al. 2025). For example, a recent review of meta-analyses found that death by suicide was best predicted in part by involvement in the justice system, foster care experience, and unemployment (Na et al. 2025). Beyond individual-level factors, county-level characteristics have also been found to be predictive of suicide deaths. Liu et al. (2023) used an aggregate index of socio-economic factors (including demographics, health care access, housing availability, education, unemployment rate, etc.) to predict county-level suicide rates. They found that social vulnerability increased suicide rates between 56% and 82%. These studies illustrate two important considerations when predicting suicide deaths: first, predictions that incorporate internal and external processes are likely more powerful, and second, predictors can be found at both the individual and the community level.

Research also consistently demonstrates a strong association between mental health disorders and increased mortality risk across multiple causes of death. A comprehensive systematic review and meta-analysis of 203 studies across 29 countries revealed that individuals with mental disorders face more than double the mortality risk of the general population, with mental disorders contributing to an estimated 14.3% of deaths worldwide—approximately 8 million deaths annually (Walker et al. 2015). This elevated mortality stems from both natural and unnatural causes, with cardiovascular diseases representing a major contributor to reduced life expectancy among individuals with severe mental illness and some finding that those with severe mental illness are twice as likely to die from infectious diseases (Jayatilleke et al. 2017).

Notably, even suicidal ideation without suicide death appears to serve as an indicator of broader health vulnerability, as individuals experiencing such thoughts demonstrate increased mortality from natural causes (Batterham et al. 2013). The COVID-19 pandemic has further highlighted these vulnerabilities, with patients having mental health disorders such as schizophrenia and bipolar disorder showing significantly higher COVID-19-related mortality compared to those without mental health conditions (Fond et al. 2021).

The geographic dimension of mental health and mortality has gained increasing attention in recent research. Song and Luan (2022) employed Bayesian spatiotemporal models to examine associations between mental illness, substance use mortality, and unemployment across U.S. counties, revealing distinct regional risk clusters. Similar approaches have been applied internationally, with studies in South Korea (Kim and Kim 2024) using geographically weighted regression to identify spatial clusters of high suicide rates, and research in Chicago (Lotfata and Hohl 2023) employing multi-level models to examine spatiotemporal associations between mental distress and socio-economic factors.

Fontanella et al. (2018) demonstrated the utility of Bayesian conditional autoregressive models for mapping suicide mortality in Ohio, finding strong associations between socio-economic deprivation, healthcare provider density, and suicide clusters. These spatial approaches have been enhanced through empirical Bayes methods that stabilize mortality estimates in sparsely populated areas (Manton et al. 1989; Clayton and Kaldor 1987), addressing a key challenge in spatial mortality analyses.

Socio-economic factors are closely tied to both mortality and mental health patterns, with income, education, and employment status identified as having important relationships with mortality rates (Chetty et al. 2016; Barbieri 2022). Geographic variation in mortality has been extensively documented, with studies revealing substantial disparities across U.S. counties (Dwyer-Lindgren et al. 2016) and highlighting how these disparities have evolved over time (Ezzati et al. 2008). The use of multi-level geographic approaches has proven essential, as analyzing health outcomes at only one geographic scale can obscure important patterns (Kim and Subramanian 2016).

International comparisons have shown that while mortality inequality exists globally, its patterns vary significantly by country and region (Mackenbach et al. 2008; Atalay et al. 2023). These findings underscore the importance of considering local contextual factors when modeling mortality patterns and suggest that hierarchical Bayesian models are particularly well-suited for capturing these multi-level geographic effects.

From an actuarial perspective, the integration of mental health factors into mortality modeling represents both an opportunity and a challenge. Traditional actuarial models have increasingly incorporated socio-economic variables and epidemic effects (Biffis 2005; Cairns et al. 2024), but the systematic inclusion of mental health indicators remains limited. The COVID-19 pandemic has highlighted the need for more sophisticated mortality models that can account for the complex interactions between mental health, socio-economic factors, and infectious disease mortality (Delbrouck and Alonso-García 2024).

Recent work has begun to address these challenges through the development of cause-specific mortality models that can be decomposed by contributing factors (Villegas et al. 2025) and copula-based approaches that capture changing dependence structures across causes of death (Li 2023). These methodological advances provide a foundation for incorporating mental health variables into actuarial mortality models while maintaining computational tractability.

Despite significant progress in both spatial mortality modeling and mental health research, the integration of these fields remains underdeveloped. Most existing studies focus on either spatial / temporal mortality patterns or mental health associations with mortality, but few have attempted to create unified models that simultaneously capture spatial dependencies, temporal trends, and mental health effects. The development of such integrated models represents a significant opportunity to advance both academic understanding and practical applications in public health and actuarial science.

Section 3: Data

3.1 MORTALITY DATA

Mortality data for this study were obtained from the Division of Vital Statistics within the National Center for Health Statistics (NCHS), a division of the Centers for Disease Control and Prevention (CDC) (National Center for Health Statistics 2023). These data include demographic details and mortality records for all individuals who died in the United States between 2000 and 2023, disaggregated by year, age group, sex, and county of residence.

To estimate population-based mortality rates, population exposures for each demographic group were sourced from annual estimates provided by the U.S. Census Bureau. These estimates were derived from the most recent decennial census and adjusted annually to reflect changes due to births, deaths, and migration. Age was grouped into 18 five-year intervals, ranging from 0–4 to 85 and older, and separate models were developed for each combination of age group and sex, resulting in a total of 36 models.

Several preprocessing steps were applied to prepare the data for modeling. Counties with population estimates of zero for a given age group, or (in rare cases) with more reported deaths than estimated population, were merged with the neighboring county with the largest population to preserve spatial structure while maintaining stable mortality estimates. (Throughout this study, the term “county” is used broadly to refer to sub-state geographic regions, including those in the state of Louisiana, which uses the alternative term “parish” for their sub-state subdivisions.)

To ensure consistency across the full 24-year span, a small number of county names and boundaries were standardized to reflect their configuration as of 2023. Alaska, Hawaii, and U.S. territories were excluded from the analysis due to the difficulty in establishing meaningful spatial adjacency with the contiguous United States, leaving a total of 3,100 counties before combining. After data cleaning and aggregation, the final dataset included 2,974 counties.

3.2 MENTAL HEALTH AMERICA DATA

The bulk of the mental health data used in this analysis was obtained from Mental Health America (MHA), a nonprofit organization dedicated to promoting mental health, preventing mental illness, and improving the overall mental well-being of all Americans (Mental Health America 2025).

While most individuals access MHA Screening organically, MHA has 200 affiliate organizations and multiple partner organizations that often refer users to the MHA Screening Program. Individuals who took a screening test and were referred by one of these affiliates were excluded from the dataset to reduce referral-related bias. In addition, counties with fewer than five positive screening results for a given screen and year were excluded to reduce instability in rate estimates. In this paper, a “positive screening result” is calculated based on the criteria defined for each instrument, as described below.

- Depression: Data on severe depression were obtained from MHA’s Depression dashboard, which uses the Patient Health Questionnaire-9 (PHQ-9), a validated screening tool. The PHQ-9 includes nine items that assess the frequency of depressive symptoms over the past two weeks. Respondents rate each item on a four-point scale from “not at all” (0) to “nearly every day” (3). Severe depression is defined as a total score between 20 and 27, indicating frequent experience of multiple symptoms. The number of individuals meeting this threshold was reported by MHA.

- **Suicidal Ideation:** These data come from MHA's Suicide dashboard, which also uses the PHQ-9. Suicidal ideation is measured using item nine of the PHQ-9: *"Thoughts that you would be better off dead, or of hurting yourself."* Individuals who responded "more than half the days" or "nearly every day" were classified as experiencing frequent suicidal ideation.

- **PTSD:** MHA's PTSD dashboard reports results from the Primary Care PTSD Screen for DSM-5 (PC-PTSD-5), a five-item instrument. Respondents are asked whether they have experienced symptoms such as intrusive thoughts, avoidance, hypervigilance, emotional detachment, or guilt related to a traumatic event. A screen is considered positive if the respondent answers "Yes" to three or more of the five items.

- **Psychosis Risk:** Data on clinical high risk for psychosis were obtained from MHA's Psychosis dashboard, which is based on the Prodromal Questionnaire–Brief Version (PQ-B). This 21-item tool asks about unusual thoughts, feelings, or perceptions over the past month, with Yes/No response options. If "Yes," respondents are prompted to rate the level of distress associated with the experience on a five-point Likert scale. These distress scores are summed, with scores of 24 or higher considered indicative of elevated risk for psychosis.

To construct the model covariates, the Positive Screening Rate (PSR) for each screen was computed, defined as the number of individuals who screened positive divided by the total number of completed screens for that instrument, by county and year. For example, if 10 participants in Maricopa County screened positive for severe depression in 2020 out of 1,000 total depression screens, the PSR would be 0.01. Analogous rates for each of the mental health outcomes described above were calculated and these values used as county-level covariates in the model. Figures 1a and 1b compare county-level PSRs for severe depression and frequent suicidal ideation in 2023.

3.3 BEHAVIORAL RISK FACTOR SURVEILLANCE SYSTEM (BRFSS) AND PLACES DATA

In addition to screening data from Mental Health America, the researchers incorporated county-level estimates of self-reported mental health from the Behavioral Risk Factor Surveillance System (BRFSS), as distributed through the *PLACES* project (Centers for Disease Control and Prevention (CDC) 2023). BRFSS is a nationally representative, state-based telephone survey conducted by the CDC that collects detailed information on health-related risk behaviors, chronic health conditions, and use of preventive services (Centers for Disease Control and Prevention 2022).

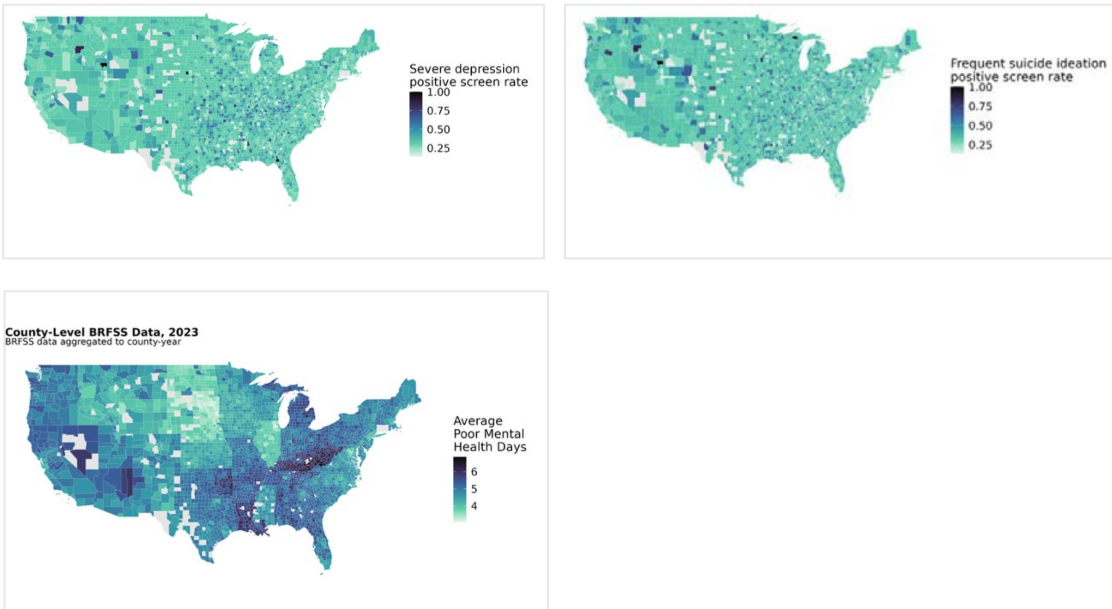
This study specifically used the PLACES dataset, which provides model-based estimates of population health indicators for U.S. counties and census tracts. These estimates are generated through a multi-level regression and poststratification approach that combines BRFSS survey data with demographic and geographic information from the U.S. Census and American Community Survey (ACS). This modeling approach allows for more reliable small-area estimation, particularly in sparsely sampled regions (Centers for Disease Control and Prevention 2023).

From this dataset, the researchers extracted the indicator corresponding to the proportion of adults in each county who reported having 14 or more days of poor mental health in the past 30 days, a variable referred to as `MENTHLTH_GE14D`. This variable is derived from a count question in the original BRFSS survey, which asks respondents to report the number of days (0–30) during which their mental health was not good. PLACES dichotomizes this count at a clinically meaningful threshold of 14 days to indicate *frequent mental distress*, a measure widely used in public health surveillance and epidemiologic studies (Centers for Disease Control and Prevention 2004).

PLACES data used in this study were drawn from the 2023 release and are based on BRFSS responses collected in 2021. These model-based estimates complement this study's screening-derived indicators by capturing a broader population-representative perspective on mental health burden. Figure 1c displays model-based 2023 estimates of the proportion of respondents whose number of poor-mental-health days exceeded the BRFSS threshold.

Figure 1

COUNTY-LEVEL POSITIVE SCREENING RATE (PSR) FOR MENTAL HEALTH FACTORS, 2023



Positive Screening Rates for county-level mental-health indicators in 2023: (a, top left) severe depression, (b, top right) frequent suicidal ideation, and (c, bottom left) frequent mental distress. Counties with insufficient data are shaded light grey. PSR Values are calculated as described in Section 3.2.

3.4 SOCIO-ECONOMIC DATA

Several socio-economic variables were considered in the analysis, as many of them have previously been shown to be related to mortality and mental health, as discussed in 2.2 The Impact of Mental Health and Socio-Economic Factors on Mortality:

- **Alcohol Consumption:** Per capita alcohol consumption data was collected at the state level for each year by the National Institute on Alcohol Abuse and Alcoholism at the National Institutes of Health (Slater and Alpert 2024).
- **Education:** Level of educational attainment was collected at the county level for each year by the U.S. Census Bureau as a part of the American Community Survey (U.S. Census Bureau 2023). The researchers used the percentage of adults with at least a bachelor's degree as the measure of educational level.
- **House Price Index:** House price indices (HPI) were calculated at the state level for each year by the Federal Housing Finance Agency, based on mortgage data from Fannie Mae and Freddie Mac (Federal Housing Finance Agency 2024).

- **Marital Status:** The percentage of adults who were married was collected at the county level for each year by the U.S. Census Bureau as a part of the American Community Survey (U.S. Census Bureau 2023).

- **Household Size:** The average household size was collected at the county level for each year by the U.S. Census Bureau as a part of the American Community Survey (U.S. Census Bureau 2023).

- **Unemployment:** Unemployment rate was collected at the county level for each year by the U.S. Bureau of Labor Statistics (U.S. Bureau of Labor Statistics 2023).

- **Race:** To measure the impact of race, the percentage of heads of households who identify as white was used. This data was collected at the county level for each year by the U.S. Census Bureau as a part of the American Community Survey (U.S. Census Bureau 2023).

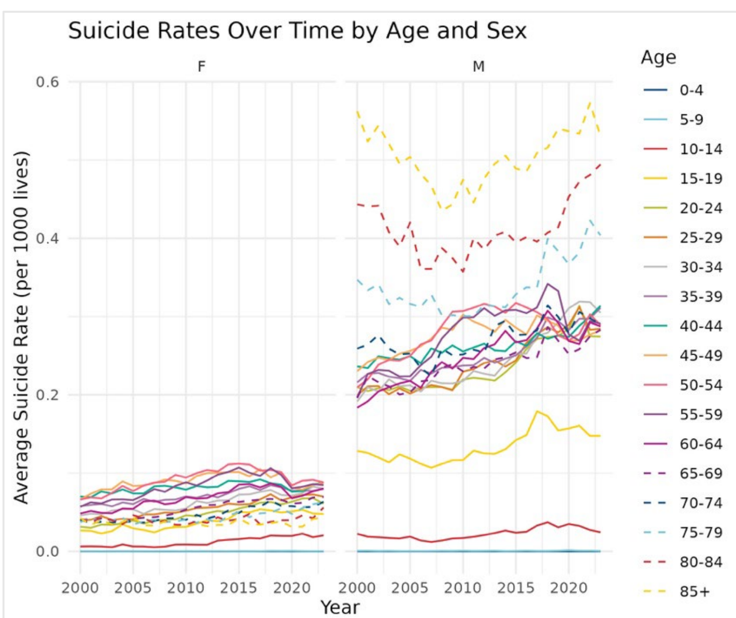
To address missing and inconsistent data prior to analysis, additional preprocessing steps were applied. For the socio-economic data, linear interpolation was used to fill in missing years. In the MHA survey data, counties with missing values for either the number of positive responses or total responses were imputed using the national average, calculated from all available, non-missing county-level responses. Counties with insufficient mortality data after this process are depicted in gray in the exploratory data analysis (EDA) maps, indicating the absence of reliable estimates.

3.5 EXPLORATORY DATA ANALYSIS OF SUICIDE TRENDS

To contextualize the subsequent modeling, the researchers examined temporal trends in age- and sex-specific suicide rates from 2000 to 2023. Figure 2 presents average suicide rates stratified by sex and five-year age groups.

Figure 2

SUICIDE RATES OVER TIME BY AGE AND SEX



Average suicide rates over time, stratified by sex and five-year age group. Trends in age- and sex-specific suicide rates in the United States, 2000–2023, based on mortality data from the National Center for Health Statistics. Rates are expressed as deaths per 1,000 person-years within each age-sex group.

For females, the highest suicide rates occur between the ages of 40–59. The rates are very close to zero for girls under 10 years old, with an increase in rates during the teenage years. For many of the age groups, there appears to be an increasing trend over the observed time period. Many age groups experienced a decline in suicide rates in the year 2020, the same year as the inception of the COVID-19 pandemic.

The highest suicide rates overall are among older males (75+). For those ages, the suicide rates decreased between 2000 and 2009 and have been increasing since then. For all ages older than 15, female suicide rates are much smaller than male suicide rates. Male rates are essentially zero for children and then increase for teenagers and increase further for young adults. The rates are similar for adult males (20–75), with a fairly consistent increasing pattern throughout the study period. Figures 11 and 12 in Appendix B show the plots separately for the younger and older nine age groups for easier comparison.

Section 4: Models and Methods

To evaluate how mental health and socio-economic conditions relate to mortality outcomes across the United States, a Bayesian hierarchical spatiotemporal model was employed similar to that described by Gibbs et al. (2020). This framework captures both geographic clustering and temporal trends while allowing for the inclusion of explanatory variables that vary by county and year.

The model can be understood as having three primary components:

Spatial Variation: Counties that are geographically adjacent often share social, economic, and environmental characteristics. This captures local clustering in mortality risk and stabilizes estimates for counties with smaller populations.

Temporal Dynamics: Mortality rates evolve over time due to changing conditions such as economic cycles, policy shifts, or public health events. The model incorporates a temporal effect that allows each county's rate to follow a linear trend, capturing gradual changes and persistent time patterns.

Fixed Effects: These represent measurable, county-level predictors such as socio-economic indicators or mental health variables. The analysis quantifies how specific characteristics—such as education levels or depression screening rates—relate to mortality outcomes after accounting for spatial and temporal dependence.

All three components were estimated jointly within a Bayesian framework, producing results that reflect both local variation and broader population-level uncertainty.

The analysis was organized around two related families of models, each designed to answer a distinct research question. Both used the same spatiotemporal structure described above, differing only in outcome variable and covariate set.

4.1 SOCIO-ECONOMIC MODELS OF SUICIDE

Outcome: Annual county-level suicide mortality (2010–2023).

Covariates: Educational attainment, housing price index, marital status, racial composition, household size, unemployment, alcohol consumption, indicator variables for the COVID-19 pandemic (2020–2021) and post-pandemic period (2022–2023), and the Behavioral Risk Factor Surveillance System (BRFSS) measure of "poor mental health days."

Structure: A single unified model where all the covariates are used at once.

Purpose: To assess how socio-economic and behavioral conditions influence suicide mortality across counties and over time.

This model isolates the contribution of long-term social and economic conditions to suicide risk while controlling for spatial clustering and time trends.

4.2 MENTAL HEALTH MODELS OF TOTAL DEATHS AND SUICIDE

Outcomes: All-cause mortality and suicide mortality.

Covariates: Positive screening rates from Mental Health America (MHA) for severe depression, suicidal ideation, PTSD, and psychosis risk, supplemented by the BRFSS indicator for frequent mental distress.

Structure: Due to the strong collinearity between these covariates, the models were fit with one covariate at a time, leading to a series of models, each isolating a unique predictor-covariate pair.

Purpose: To determine how community-level mental health indicators correspond to broader mortality outcomes and whether these associations are stronger for suicide-specific mortality.

By comparing results across both outcomes, the analysis evaluates whether mental health indicators serve as general predictors of poor population health or are uniquely tied to suicide mortality.

4.3 SUMMARY

Together, these two model families provide complementary perspectives on the relationship between social context, mental health, and mortality. The socio-economic models establish a baseline of long-term structural influences on suicide, while the mental health models test whether emerging behavioral health patterns offer additional explanatory power.

Section 5: Results and Discussion

This section presents the results of the analyses and discusses some of the most important implications of these findings. These results enable the assessment of spatial and temporal dependence among counties and quantify the impact of the various mental health and socio-economic variables (described above) on all-cause and suicide-specific mortality . These effects were considered for males and females separately, and across all age groups; this is important, since the effects often vary strongly by both age and sex.

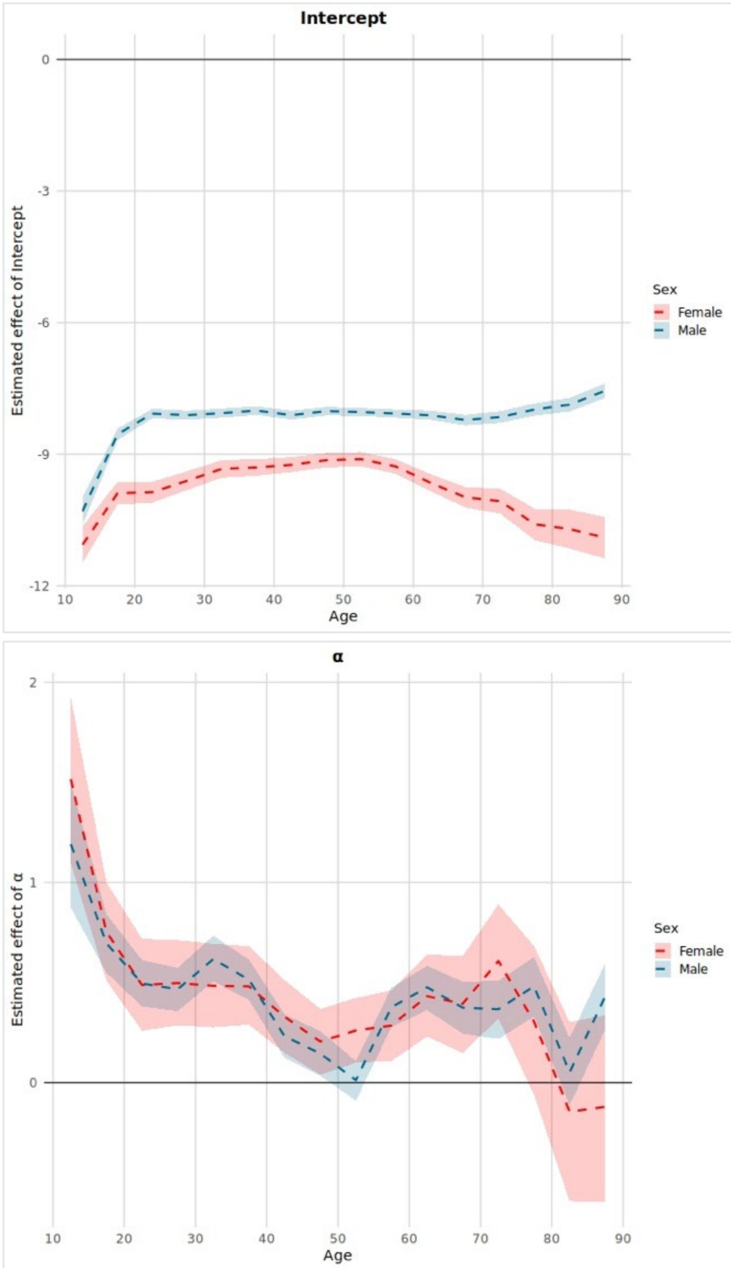
5.1 SOCIO-ECONOMIC EFFECTS ON SUICIDE

This section presents the estimated parameters from the spatiotemporal model using suicide as the target variable and several socio-economic indicators as covariates. It begins by examining model structure parameters and explores what those mean about the nature of the data by age group, time, and location. It then takes a closer look at the specific covariate effects. In all, 36 models were fit, one for every age group and gender combination. These plots aggregate the results of all the models to get a clear picture of general trends.

5.1.1 TEMPORAL AND SPATIAL TRENDS

Figure 3

INTERCEPT AND TIME TREND ESTIMATES BY AGE AND SEX



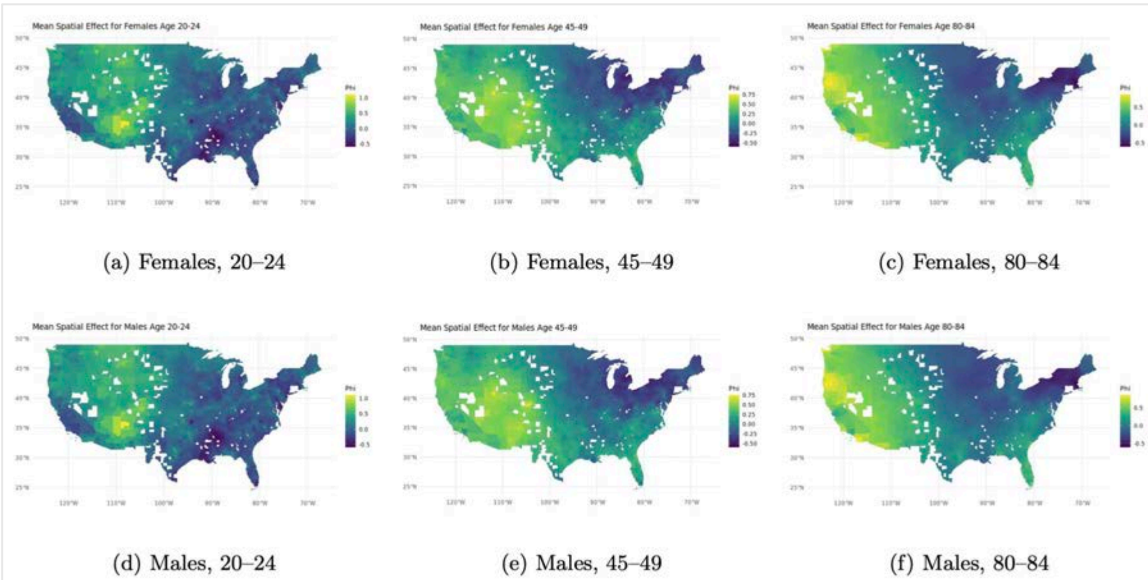
Comparison of intercept and time trend estimates by age and sex. Estimates and 95% credible intervals are given for each sex and age group, calculated for the model described in Section 4.1. Note that the scales of the vertical axes differ between the two panels.

The intercept comparison plot, shown in the top panel of Figure 3, illustrates the general pattern of suicide rates by age and sex. In all age groups, men consistently exhibit higher suicide rates than women. Among men, rates remain relatively high throughout adulthood and show a slight increase after age 70. Among women, suicide rates gradually increase until around age 50 and then gradually decline with increasing age.

The model parameter α reveals whether suicide rates have increased or decreased over time. Positive values indicate increasing rates, while negative values indicate decreases. In the bottom panel of Figure 3 it is observed that in general, the results suggest that suicide rates have increased over time, with the highest increases observed among younger age groups. For women 80 years and older, there is some indication of decline. For men, small declines are visible in the age groups 45–54 and 80–84.

Figure 4

COUNTY-LEVEL SPATIAL EFFECT BY GENDER AND AGE GROUP



County-level spatial effect on suicide rates for selected combinations of age and sex. Plots show estimated posterior means of this parameter, calculated for the model described in Section 4.1.

The model results strongly support the existence of correlation of suicide rates between nearby regions. Figure 4 visualizes the posterior mean of the spatial intercept φ_k, which captures county-specific deviations in baseline suicide risk after adjusting for socio-economic covariates and temporal trends. Across all age groups a broad corridor of elevated φ_k values extend from the Rocky Mountain states through the northern Great Plains, a region commonly referred to as the suicide belt. Counties in Utah, Wyoming, Montana, and neighboring areas exhibit the largest positive departures, whereas much of the eastern seaboard and parts of the Midwest display negative or near-zero effects. These maps highlight enduring geographic inequities in baseline suicide risk and underscore the need for region-specific strategies.

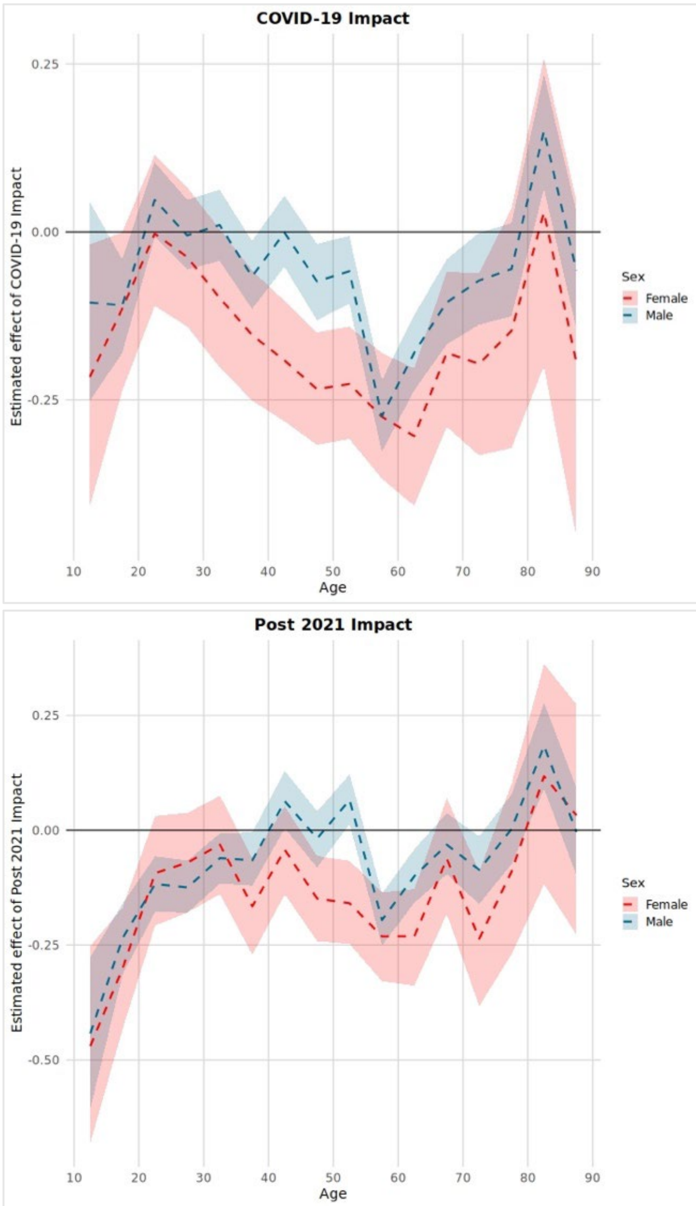
A COVID variable is included (indicating years 2020–2021) and a “Post 2021” variable (indicating years 2022–2023) to account for nationwide shifts affecting suicide and mortality. There is evidence that suicides decreased during the pandemic, as shown in Figure 5, particularly among women aged 30–70. This may relate to higher overall mortality during the pandemic or to changes in social or environmental factors that benefitted some individuals with pre-existing mental health challenges. The post 2021 effect also seems to be related to a decrease in suicide rates for many age groups. Notably, the youngest age groups, which have the most severe increase of suicide rates over time, have a strong negative post 2021 effect.

While the data do not allow for drawing conclusions regarding what these factors might be, some research indicates, for example, that during times of widespread crisis, individuals and communities pull together in their efforts to manage the catastrophe. In a study of undergraduate students after a significant flood, Gordon et al. (2011) found that contributing to the crisis response decreased a sense of burdensomeness and increased a sense of belonging (both of which are predictors of suicide in the interpersonal theory of suicide; Joiner et al., 2010). It is also possible that increased time at home due to initial lockdown measures were a protective factor for some, increasing oversight for those with preexisting suicidality and increasing regular social contact. Supporting this possibility, in a study of 8 million helpline calls from over 19 countries, Brülhart et al. (2021) found that complaints regarding relationship issues, violence, and suicidal ideation all decreased during the early stages of the pandemic. Additionally, they found that complaints regarding economic problems decreased, potentially pointing to the ameliorating effects of financial help from the government during the crisis. An increased sense of community purpose, increased home time and social contact, and governmental financial support may at least partially explain the decrease in suicide deaths.

5.1.2 SOCIO-ECONOMIC EFFECTS

Figure 5

COVID-ERA (2020–2021) AND POST–2021 EFFECTS BY AGE AND SEX



Estimates and 95% credible intervals for the effect of COVID (2020–2021) and post 2021 (2022–2023) on suicide by sex and age, calculated for the model described in Section 4.1. Note that the scales of the vertical axes differ between the two panels.

There were nine additional socio-economic or demographic variables included as predictors for each model. Of those, six have interesting patterns worth discussing while three consistently showed little to no effect for all age groups. Figure 6 summarizes how the six significant covariates relate to suicide risk across the life-course, separately for men (blue) and women (red).

- **Educational Attainment (% with a Bachelor's Degree):** Among men, a greater county-level share of adults holding a bachelor's degree is strongly associated with lower suicide rates, with the largest protective association concentrated in early to mid-adulthood (roughly ages 20–40). In contrast, the female pattern reverses across the life course. The association is negative at younger ages but steadily weakens after age 40 and turns positive by about age 50, indicating that in later life, women living in more highly educated counties experience higher suicide rates than their peers elsewhere. Educational attainment therefore represents the clearest point of divergence between the sexes. While most other covariates show only modest male–female differences in magnitude, none display the pronounced change in sign seen for education. This may be due to a cohort effect, where women in highly educated counties in their 50s have similar cultural interactions with education or midlife challenges. Further research is needed, however, to clarify this finding.

- Housing Price Index: Across most of the life course, higher county-level housing values are linked to lower suicide rates for both sexes, and the strength of this inverse association remains fairly stable. Among males, the effect becomes even stronger at the age extremes. Adolescents and early adults (<20 yrs) and older ages (≥80 yrs) have a more negative effect whereas for females the coefficients taper toward zero in those same bands. Outside these margins, male and female estimates are nearly the same.

- Marriage Rate: County-level marriage rates have a very interesting trend. For the youngest age group shown (10–14) higher marriage rates are associated with lower suicides (though the suicide rate for this age group is very small, ~1/60,000), but the effect quickly spikes, and the relationship becomes positive starting at age 15. For females, the relationship becomes negative again for ages 30+ while for males it becomes negative at 35+ and it remains significantly negative until about age 70 where the effect for both males and females disappears.

- Percent White: The percentage of white heads of households in a county shows almost an inverted effect from marriage rates. For the lowest age group, it is positively associated with suicide rates but then drops to negatively associated between ages 15 to 30. After which the effect becomes strongly positive again. The effect tapers slightly by age but remains significantly positive through older ages.

- Household Size: The average number of members per household has little to no effect for the youngest age groups but then becomes significantly negative after about age 20 for both males and females. The effect is nearly constant past age 20 and is about the same for both males and females.

- Mental Health Days: The results of the BRFSS on mental health are positively associated with suicide rates. This effect is constant, and while significant, it is actually not far from zero. In fact, the confidence interval for females contains zero for most age groups and does for males for some ages. Starting at age 60 the effect becomes stronger for females than it does for males.

There were three variables that showed little to no association with suicide rates. Alcohol consumption shows a weak, non-significant tendency toward higher suicide rates across ages. Neither crime rates nor unemployment rates display any consistent or significant association with suicide rates in this analysis. Figure 7 shows these variables, and while there may be some signal or interpretation from specific components of these plots, it is hard to say with certainty that there is a significant effect.

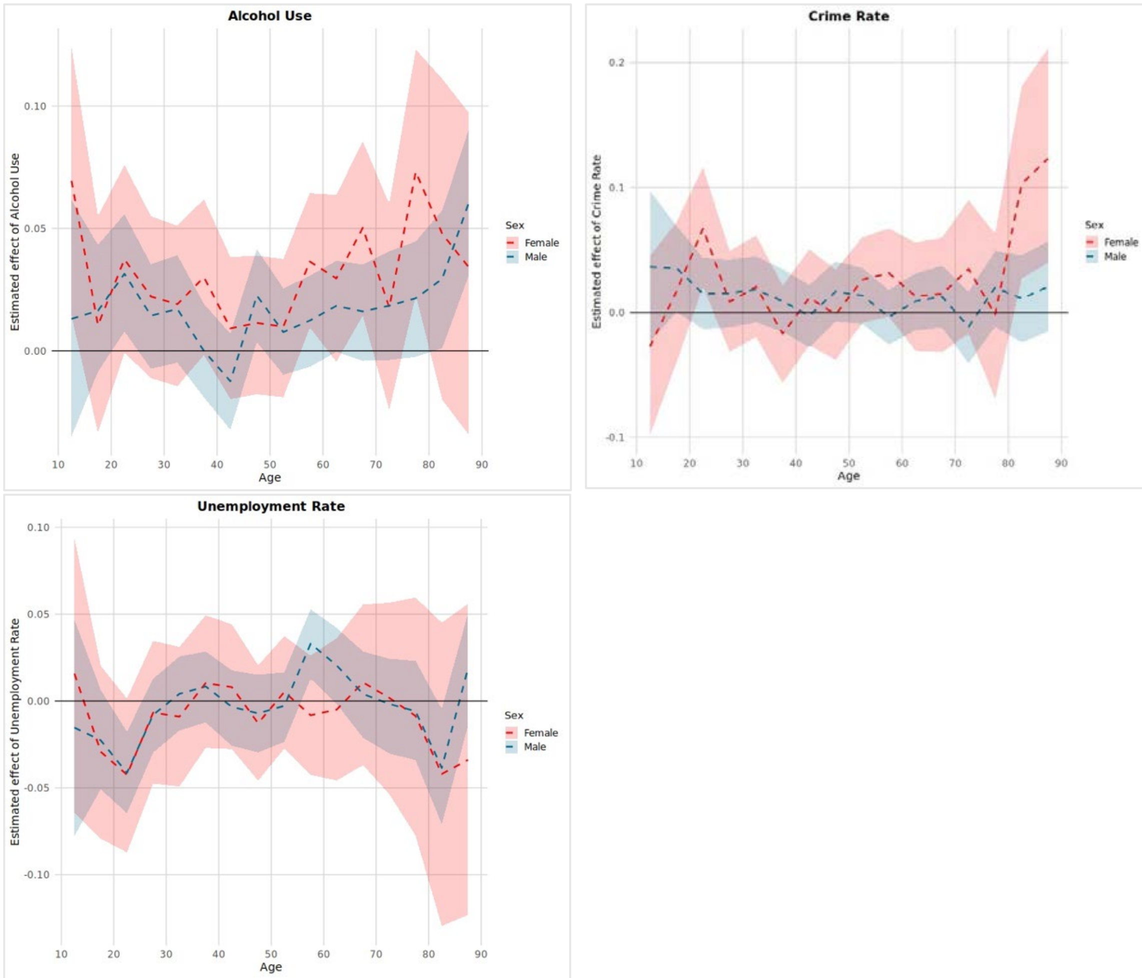
It is important to note that these data were not collected at the individual level, but at the aggregate level, so these cannot be interpreted at the individual level. When correlations and relationships are discussed, the reference is to county aggregates, which still hold very valuable information when it comes to trends and relationships. Each of the predictors was ranked in each model, and the rankings were aggregated overall and by gender. Tables in Appendix A show the average rankings. Lower rankings indicate higher significance. Percent white was the most significant predictor in both the female and male model, as well as overall.

Figure 6

COVARIATE COEFFICIENT ESTIMATES FOR MORE SIGNIFICANT COVARIATES

Estimates and 95% credible intervals for six significant covariates on suicide by sex and age, calculated for the model described in Section 4.2. Note that the scales of the vertical axes differ between the six panels.

Figure 7
COVARIATE COEFFICIENT ESTIMATES FOR LESS SIGNIFICANT COVARIATES



Estimates and 95% credible intervals for the effect of Alcohol Consumption, Crime Rates, and Unemployment Rates on suicide by sex and age, calculated for the model described in Section 4.2. Note that the scales of the vertical axes differ between the three panels.

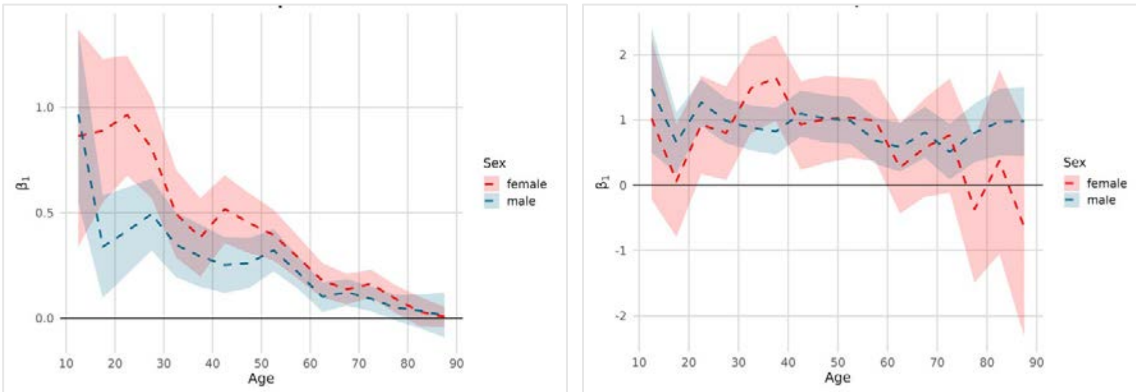
5.2 MENTAL HEALTH INDICATORS AND MORTALITY OUTCOMES

To evaluate how county-level mental health relates to mortality, results are presented from models that pair each mental health indicator with two outcomes: all-cause mortality and suicide. This organization directly addresses the second research question by comparing whether associations seen at the population level are broad (all-cause) or more specific to suicide. For each indicator, male/female estimates are shown across age groups with 95% credible intervals.

5.2.1 DEPRESSION AND ALL-CAUSE MORTALITY / SUICIDE

Figure 8

COEFFICIENT FOR SEVERE DEPRESSION PSR FOR ALL-CAUSE MORTALITY (LEFT) AND SUICIDE DEATHS (RIGHT)



Estimated effect of the severe depression positive screening rate on mortality by age group and sex, calculated for the model described in Section 4.2. Shaded bands represent 95% credible intervals. Note that the scales of the vertical axes differ between the two panels.

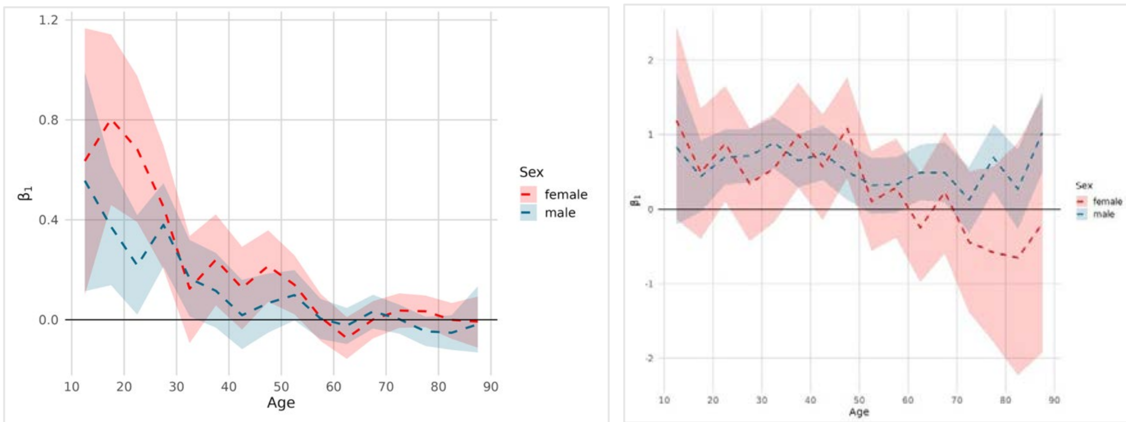
The left panel of Figure 8 shows the estimated effect (β_1) of the severe depression positive screening rate on mortality across age groups, stratified by sex. For both males and females, a positive association in most age groups is observed, suggesting that higher rates of severe depression at the population level are linked with increased mortality risk. The estimated effect is highest among adolescents and young adults, with the largest coefficients observed for individuals under 20. However, the wide credible intervals in these youngest groups reflect greater uncertainty, likely due to lower death counts and smaller sample sizes in these strata.

Across all ages, females tend to exhibit slightly higher effect sizes than males, although there is substantial overlap between the sexes. The magnitude of the association appears to decline steadily with age, becoming close to zero in the oldest age groups. It is important to note that this model estimates mortality at the county-year level and hence should not be interpreted as evidence of individual-level causality between severe depression and death. Nonetheless, the population-level association suggests that areas with elevated rates of severe depression may also face higher overall mortality risk, particularly among youth and middle-aged adults.

5.2.2 SUICIDAL IDEATION AND ALL-CAUSE MORTALITY / SUICIDE

Figure 9

COEFFICIENT FOR SUICIDAL IDEATION RATE ON ALL-CAUSE MORTALITY (LEFT) AND SUICIDE DEATHS (RIGHT)



Estimated coefficient for the association between the positive screen rate for frequent suicidal ideation and mortality outcomes, stratified by sex and age group, calculated for the model described in Section 4.2. Shaded regions represent 95% credible intervals. Note that the scales of the vertical axes differ between the two panels.

Figure 9 (left panel) displays the estimated regression coefficients (β_1) for the association between the positive screen rate (PSR) for frequent suicidal ideation and mortality rates across age groups, stratified by sex. A positive coefficient indicates that higher rates of suicidal ideation in a county are associated with increased mortality rates in that demographic group.

The association is strongest among younger age groups, particularly for individuals under age 25. For both males and females, the effect size is largest in childhood and adolescence, with credible intervals suggesting a significant positive relationship. Among females in particular, the association peaks in the 10–14 age group before declining steadily with age. After age 40, the estimated coefficients approach zero, and the 95% credible intervals widen and generally include zero, indicating increasing uncertainty and decreasing evidence of a consistent relationship in older age groups.

These results suggest that frequent suicidal ideation, as measured by community screening, may be a particularly important correlate of mortality risk in younger populations. The wide intervals in early childhood may also reflect small sample sizes or less stable estimates for those groups.

Figure 9 (right panel) displays the estimated effects of the county-level positive screening rate (PSR) for frequent suicidal ideation on suicide counts, stratified by age and sex. In contrast to the model with all-cause mortality as the outcome, this figure directly links suicidal ideation rates with suicide-specific mortality. For both sexes, the coefficients are generally positive in early adulthood and middle age, with point estimates frequently exceeding 0.5. These results suggest that higher screening rates for suicidal ideation in the population are positively associated with suicide rates.

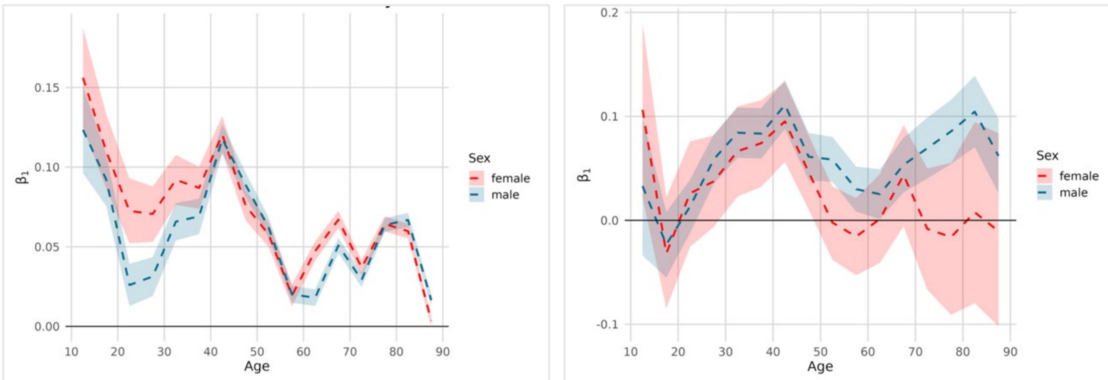
However, the uncertainty is notable, especially among females. The credible intervals widen substantially in older age groups and cross zero frequently, reflecting limited data and potential variability in the relationship across counties and time. The female estimates decline steeply in older ages, becoming negative in the 70+ range with wide uncertainty, which may stem from small sample sizes or complex age-related reporting dynamics. Male estimates remain more consistent across the lifespan, with point estimates staying near or above 0.5 in most age groups.

These results support the use of community-level mental health screening data as an informative indicator of suicide risk, particularly in younger populations.

5.2.3 BRFSS MENTAL HEALTH DAYS AND ALL-CAUSE MORTALITY / SUICIDE

Figure 10

COEFFICIENT FOR MENTAL HEALTH DAYS ON ALL-CAUSE MORTALITY (LEFT) AND SUICIDE DEATHS (RIGHT)



Estimated coefficient for the association between average number of poor mental health days (past 30 days; BRFSS 2010–2023) and mortality outcomes, stratified by age group and sex, calculated for the model described in Section 4.2. Shaded regions represent 95% credible intervals. Note that the scales of the vertical axes differ between the two panels.

Figure 10 (left panel) shows the estimated association between the average number of mentally unhealthy days reported in the past 30 days and mortality rates, using Behavioral Risk Factor Surveillance System (BRFSS) data from 2010 to 2023. As with previous models, estimates are stratified by age group and sex, with shaded regions denoting 95% credible intervals.

The results suggest a modest but consistently positive association between reported mental health burden and mortality, especially in younger age groups. For both sexes, the association peaks in early adolescence (age group 10–14) and declines steadily through midlife. This pattern aligns with previous findings indicating that self-reported mental distress is more prevalent and perhaps more impactful on broader health outcomes during adolescence and early adulthood.

Interestingly, both males and females show a secondary peak in association around the 45–49 age group, particularly in males, before declining again in later life. In the oldest age groups (70+), the estimated effects are smaller and less certain, as indicated by wider credible intervals.

These findings support the use of the BRFSS mental health measures as a meaningful covariate in population-level mortality modeling.

Figure 10 (right panel) displays the estimated relationship between the average number of poor mental health days (reported in the past 30 days) and suicide counts across U.S. counties. Unlike previous models focused on all-cause mortality, this model isolates suicide as the outcome of interest, providing a more targeted view of how self-reported mental health burden correlates with suicide risk.

Overall, the estimated associations are smaller in magnitude compared to those seen in the mortality model, and they demonstrate more variability across age groups. For both sexes, coefficients are generally positive through midlife, suggesting that higher rates of poor mental health days in the population are associated with higher suicide rates. However, many of these associations are not statistically distinguishable from zero, as reflected in the wide credible intervals, especially in younger and older age groups.

Among males, the association becomes more pronounced in later age groups (ages 60+), while the trend for females appears relatively flat or slightly negative in older adulthood. This divergence may point to gendered differences in how mental health distress manifests in suicide outcomes later in life. Additionally, the wide intervals highlight uncertainty in these estimates, which may be due in part to smaller suicide counts relative to all-cause deaths and greater year-to-year variation.

As with all ecological models, these results reflect population-level associations and should not be interpreted as direct individual-level causal effects.

Section 6: Conclusion

This research has examined the relationships between mental health status and overall mortality and suicides at the county level in the continental U.S. It first assessed socio-economic covariates in predicting suicide. While the results vary considerably by age and sex, it was found that the county-level educational attainment, housing prices, marriage rates, racial composition, household size, and poor mental health days all have significant relationships with suicide rates. To further contextualize these findings, Appendix A: Variable Importance Rankings presents the ranked importance of each variable across all fitted models, highlighting the relative influence of demographic, economic, and behavioral factors on county-level suicide risk.

The research also examined the impact of various mental health indicators on all-cause and suicide-specific mortality and found that the strongest effects are observed in younger populations. The spatial and temporal correlation structures revealed substantial regional clustering and time-consistent trends in both all-cause mortality and suicide rates, supporting the use of spatiotemporal methods. The findings highlight the value of integrating mental health surveillance data into mortality models to better identify emerging risk areas and vulnerable populations. This approach has the potential to inform public health policy, resource allocation, and targeted interventions aimed at reducing disparities in mortality and suicide across U.S. communities.

There are many directions in which this work might be extended in the future. As noted above, the covariates are measured at the county level. Thus, while they are helpful in indicating associations, it is difficult to use them to make individual-level causal statements; more granular data might help to clarify some of these relationships. It is also important to note that some of the mental health data only comprises a few years of information, making it difficult to disentangle any COVID-19 (and post 2021) effects. Finally, while the model is able to capture both spatial and temporal effects, more flexible models might be able to discover more complex patterns in the data.

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Appendix A: Variable Importance Rankings

Table 1

VARIABLE RANKING ACROSS ALL SOCIO-ECONOMIC MODELS

Variable	Mean Rank
Percent White	2.68750
Post 2021	3.90625
COVID-19	3.96875
% with a Bachelor's Degree	4.68750
Household Size	4.75000
Marriage Rate	5.25000
Mental Health Days	6.43750
Housing Price Index	6.59375
Crime Rate	8.90625
Alcohol Consumption	8.96875
Unemployment Rate	9.84375

Mean ranks of socio-economic predictors across 32 age–gender suicide models (ages 10–14 to 85+) across both male and female models. Variables are ordered by the absolute magnitude of their effects.

Table 2

VARIABLE RANKING ACROSS FEMALE MODELS

Variable	Mean Rank
Percent White	3.0625
Post 2021	3.1250
COVID-19	3.5000
Marriage Rate	5.3125
% with a Bachelor's Degree	5.4375
Household Size	5.6250
Mental Health Days	5.8750
Housing Price Index	7.0000
Crime Rate	8.3125
Alcohol Consumption	8.7500
Unemployment Rate	10.0000

Mean ranks of socio-economic predictors across 16 age–gender suicide models (ages 10–14 to 85+) for female models. Variables are ordered by the absolute magnitude of their effects.

Table 3

VARIABLE RANKING ACROSS MALE MODELS

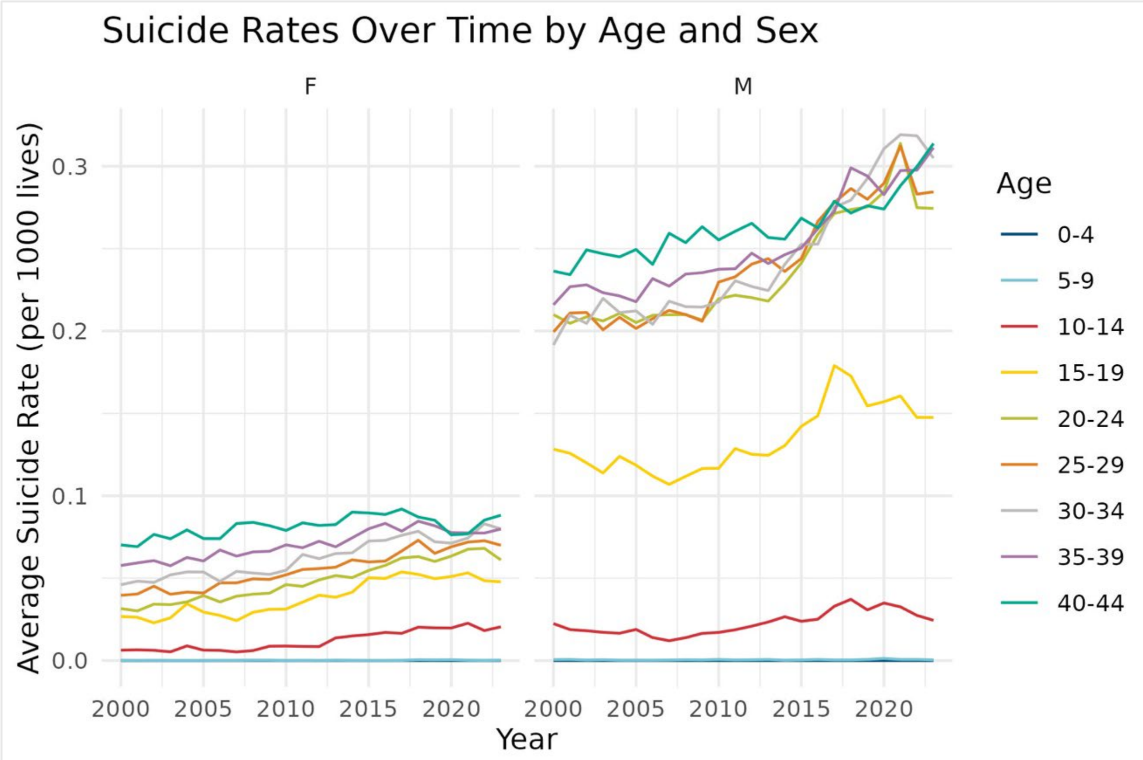
Variable	Mean Rank
Percent White	2.3125
Household Size	3.8750
% with a Bachelor's Degree	3.9375
Post 2021	4.3125
COVID-19	4.8125
Marriage Rate	5.1875
Housing Price Index	6.1875
Mental Health Days	7.0000
Alcohol Consumption	9.1875
Crime Rate	9.5000
Unemployment Rate	9.6875

Mean ranks of socio-economic predictors across 16 age–gender suicide models (ages 10–14 to 85+) for male models. Variables are ordered by the absolute magnitude of their effects.

Appendix B: Suicide Rates Over Time by Age and Sex

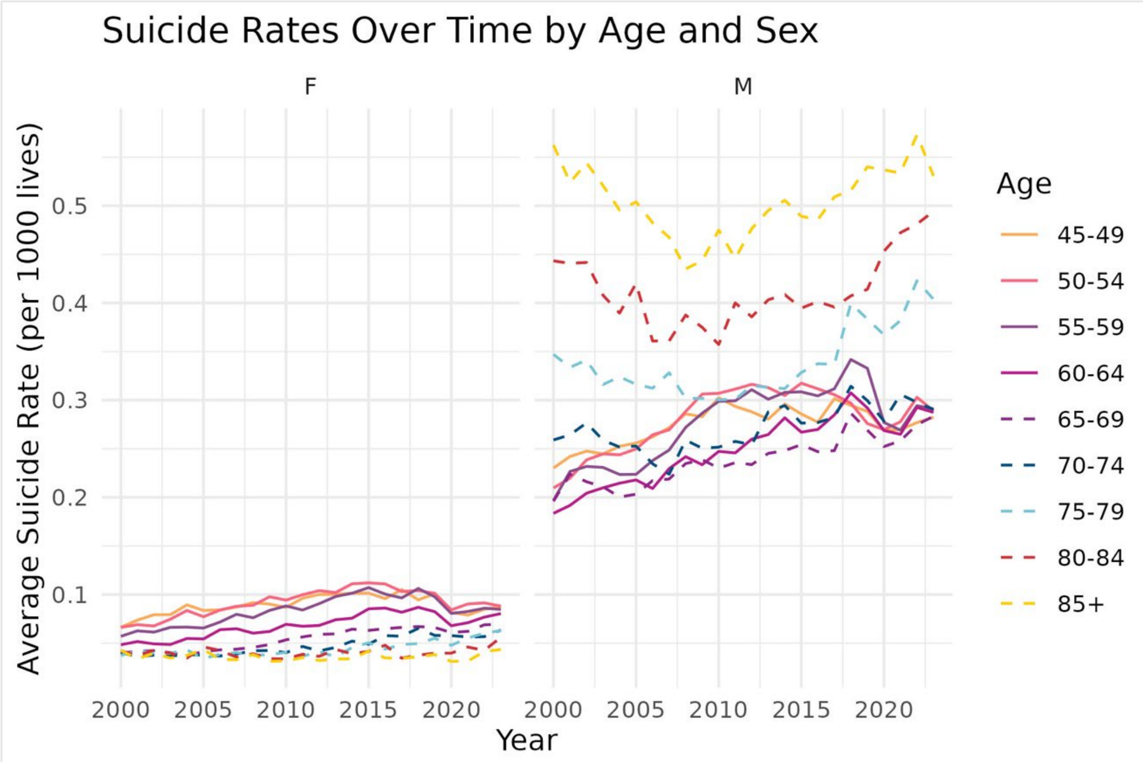
Figure 11

SUICIDE RATES OVER TIME FOR INDIVIDUALS UNDER AGE 45



Trends in age- and sex-specific suicide rates in the United States, 2000–2023, based on mortality data from the National Center for Health Statistics. This graph shows the average suicide rates over time for individuals under age 45. Rates are expressed as deaths per person-year within each age-sex group.

Figure 12
SUICIDE RATES OVER TIME FOR INDIVIDUALS AGE 45+



Trends in age- and sex-specific suicide rates in the United States, 2000–2023, based on mortality data from the National Center for Health Statistics. This graph shows the average suicide rates over time for individuals aged 45 and older. Rates are expressed as deaths per person-year within each age-sex group.

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