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RESEARCH ARTICLE

County-Level Trends in Suicide Rates in the U.S., 2005–2015

Lauren M. Rossen, PhD, MS,[1] Holly Hedegaard, MD, MSPH,[2]
Diba Khan, PhD,[3] Margaret Warner, PhD[1]

Introduction: Understanding the geographic patterns of suicide can help inform targeted prevention efforts. Although state-level variation in age-adjusted suicide rates has been well documented, trends at the county-level have been largely unexplored. This study uses small area estimation to produce stable county-level estimates of suicide rates to examine geographic, temporal, and urban–rural patterns in suicide from 2005 to 2015.

Methods: Using National Vital Statistics Underlying Cause of Death Files (2005–2015), hierarchical Bayesian models were used to estimate suicide rates for 3,140 counties. Model-based suicide rate estimates were mapped to explore geographic and temporal patterns and examine urban–rural differences. Analyses were conducted in 2016–2017.

Results: Posterior predicted mean county-level suicide rates increased by >10% from 2005 to 2015 for 99% of counties in the U.S., with 87% of counties showing increases of >20%. Counties with the highest model-based suicide rates were consistently located across the western and northwestern U.S., with the exception of southern California and parts of Washington. Compared with more urban counties, more rural counties had the highest estimated suicide rates from 2005 to 2015, and also the largest increases over time.

Conclusions: Mapping county-level suicide rates provides greater granularity in describing geographic patterns of suicide and contributes to a better understanding of changes in suicide rates over time. Findings may inform more targeted prevention efforts as well as future research on community-level risk and protective factors related to suicide mortality.
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INTRODUCTION

Suicide is a complex public health problem, influenced by multiple individual, community, and societal risk and protective factors.[1] Since 2008, suicide has ranked as the tenth leading cause of death in the U.S.,[2] and in 2015 accounted for more than 44,000 deaths.[3]

State differences in age-adjusted suicide rates (SRs) have been well documented, with Western states generally showing higher rates.[4,5] Although a more detailed understanding of geographic variation may be useful, attempts at estimating county-level SRs have been limited because the majority of counties report fewer than 20 suicide deaths per year. Direct estimates of SRs based on small numbers can be unstable and highly variable year to year, making it difficult to discern trends.[6] To produce stable estimates, studies[7] and web-based mapping tools[3,8] often aggregate over multiple years or states, potentially masking important trends and within-state variation, including urban–rural differences.[9,10]

From the [1]Division of Vital Statistics, National Center for Health Statistics, Centers for Disease Control and Prevention, Hyattsville, Maryland; [2]Office of Analysis and Epidemiology, National Center for Health Statistics, Centers for Disease Control and Prevention, Hyattsville, Maryland; and [3]Division of Research Methodology, National Center for Health Statistics, Centers for Disease Control and Prevention, Hyattsville, Maryland

Address correspondence to: Lauren M. Rossen, PhD, MS, Division of Vital Statistics, National Center for Health Statistics, Centers for Disease Control and Prevention, 3311 Toledo Road, #5422, Hyattsville MD 20782. E-mail: lrossen@cdc.gov.

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Previous studies have described urban–rural gradients in SRs and suggested that urban–rural differences may be widening, with SRs increasing more rapidly from 2000 to 2015 in less urban areas compared with more urban areas.[10] However, county-level variation in SRs remains largely unexplored. More detailed examination of county-level patterns and trends, including urban–rural differences, can shed light on where SRs may have increased more rapidly and inform more targeted prevention efforts at the community level.[1]

Small area estimation methods[11–14] can be used to produce stable estimates of mortality rates at the county level, borrowing strength from nearby counties and over time, and overcoming limitations related to aggregating data over time or larger geographic units. The objective of this study is to apply these methods to generate estimates of annual county-level SRs for 2005 through 2015[15] in order to examine how SRs vary across counties in the U.S. and whether these patterns are consistent over time. Additionally, this study describes urban–rural disparities and trends, and the percentage of counties within each urban–rural category reporting larger or smaller increases in SRs over time.

METHODS

Details about the statistical models and the advantages of the methods used are described elsewhere.[15] A short description is provided below.

Data

The 2005–2015 National Vital Statistics System Underlying Cause of Death Files[3] were used to extract the number of suicides by county of residence and year. Suicide deaths were identified using the ICD-10 underlying cause codes U03, X60–X84, Y87.0. Annual county-level population denominators were drawn from the U.S. Census intercensal (2005–2009), decennial (2010), and postcensal (2011–2015) population estimates.[16]

To ensure a consistent set of geographic boundaries across the study period (2005–2015), several counties in Alaska were merged and Bedford City, Virginia was merged with Bedford County, Virginia, resulting in a combined national file that included 3,140 counties.[17]

Urbanization level was determined using the National Center for Health Statistics Urban–Rural Classification Scheme for Counties from 2006 (applied to data years 2005–2012) and 2013 (applied to data years 2013–2015).[18] The six levels of urbanization include four metropolitan and two nonmetropolitan categories (Appendix Table 1, available online) representing a continuum from most urban to most rural. From the most urban to the most rural, the categories are: large central metro (most urban), large fringe metro (i.e., suburban), medium metro, small metro, micropolitan, and noncore. Hereafter, urban refers to the four metropolitan categories (large central, large fringe, medium, and small metro).

Hierarchical Bayesian models were developed to generate annual county-level estimates in SRs.[15] Models included a set of time-varying county-level covariates representing risk factors demonstrated previously to be associated with SRs. These covariates included demographic and economic factors (e.g., median age, mean household size, median household income, racial/ethnic distribution, education distribution, percent of the county that is urban, unemployment levels, foreclosure rates),[19–24] divorce rates,[25] prevalence of illicit drug or alcohol abuse/dependence, and prevalence of mental health conditions (e.g., major depressive episode, serious mental illness, suicidal thoughts and behaviors).[26] More detailed descriptions of the covariates and data sources can be found elsewhere,[15] and are outlined in the Appendix (available online).

Although most values for covariates were measured at the county level, some were measured at the substate level (groupings of counties, e.g., the prevalence of drug use or mental health conditions).[27]

Statistical Analysis

A series of hierarchical Bayesian spatiotemporal models were fit, using the INLA package for R, version 3.4.2.[15,28,29] These models borrow strength across neighboring counties and adjacent years to produce stable estimates of SRs. Delaunay triangulation, a spatial weighting method, was used to ensure that each county has at least one neighbor, but the number of neighbors is determined empirically based on the spatial distribution of the counties.[30]

The hierarchical Bayesian models included several terms to account for spatial and temporal dependence.[15] Annual county-level SRs were modeled as a function of the following:

1. a spatial random effect, which accounts for county-level spatial dependence (e.g., clustering) of SRs;
2. a non-spatial random effect, which accounts for any residual county-level variation that is not spatially structured;
3. an overall temporal random effect, which allows for the value in any given year to depend on the value in a prior year, plus an error term (i.e., type I random walk), accounting for temporal correlation in the data; and
4. a county- and year-specific random effect, accounting for any residual spatiotemporal variation.

Model fit was evaluated using the Deviance Information Criterion with lower values indicating better fit.[31] The best-fitting model included the four random effects described above, plus several county-level covariates. Broadly, factors predictive of SRs at the county level included demographic characteristics (e.g., racial/ethnic distribution, percent of the county that is urban, divorce rates), socioeconomic factors (e.g., median household income, education distribution, unemployment rates), as well as health- and crime-related characteristics (e.g., number of property crimes, prevalence of illicit drug or alcohol abuse/dependence). Additional details about covariates, alternative models, and various model checks can be found elsewhere[15] and in the Appendix (available online). Posterior predicted mean county-level SR estimates from 2005 to 2015 from the best-fitting model, including spatial and temporal random effects as well as several covariates, were mapped. Temporal trends were examined for the U.S. overall and by county urban–rural classification. Coefficients of variation (i.e., relative SEs) were used to describe the degree of uncertainty around the model-based SR estimates. All results refer to model-