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RESEARCH ARTICLE

Factors Associated With County-Level Differences in U.S. Drug-Related Mortality Rates

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Introduction: Over the past 2 decades, drug-related deaths have grown to be a major U.S. public health problem. County-level differences in drug-related mortality rates are large. The relative contributions of social determinants of health to this variation, including the economic, social, and healthcare environments, are unknown.

Methods: Using data from the U.S. Centers for Disease Control and Prevention Multiple-Cause of Death Files (2006–2015, analyzed in 2017); U.S. Census Bureau; U.S. Department of Agriculture Economic Research Service; Agency for Healthcare Research and Quality; and Northeast Regional Center for Rural Development, this paper modeled associations between county-level drug-related mortality rates and economic, social, and healthcare environments. Spatial autoregressive models controlled for state fixed effects and county demographic characteristics.

Results: The average county-level age-adjusted drug-related mortality rate was 16.6 deaths per 100,000 population (2006–2015), but there were substantial geographic disparities in rates. Controlling for county demographic characteristics, average mortality rates were significantly higher in counties with greater economic and family distress and in counties economically dependent on mining. Average mortality rates were significantly lower in counties with a larger presence of religious establishments, a greater percentage of recent in-migrants, and counties with economies reliant on public (government) sector employment. Healthcare supply factors did not contribute to between-county disparities in mortality rates.

Conclusions: Drug-related mortality rates are not randomly distributed across the U.S. Future research should consider the specific pathways through which economic, social, and healthcare environments are associated with drug-related mortality.

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INTRODUCTION

From 2006 to 2015, a total of 515,060 people in the U.S. died from drug overdoses and other drug-related causes.[1] A large share (42.3%) involved opioids, but other drugs, including benzodiazepines (12.1%) and cocaine (12%), also contributed.[1] The economic, social, and emotional tolls of these deaths are substantial, but some parts of the U.S. are bearing heavier burdens than others.[2–5] Empirical explanations for this geographic heterogeneity are lacking. Most existing studies of drug mortality examine temporal trends rather than geographic differences,[3–7] and those that examine geographic disparities are largely descriptive, emphasizing data challenges[8] or differences in population composition (e.g., age, race) rather than the "fundamental" social determinants of health[9] known to contribute to geographic differences in other types of mortality and morbidity.[10–14]

This study employs the WHO social determinants of health[15] and socioecological[16] frameworks to develop hypotheses about factors that contribute to between-

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county disparities in drug-related mortality rates. Social determinants of health are the structural conditions in which populations live, work, and socialize that influence stress, relationships, health behaviors, and mortality, including economic resources, the social environment, and the healthcare infrastructure. Based on these frameworks, this study tests the hypothesis that counties' economic, social, and healthcare environments contribute to between-county variation in drug-related mortality rates.

Environmental features can be derived or integral.[17] Derived measures capture aggregate characteristics of individuals, families, and households, reflecting county composition. But they also shape residents' health environments. Economic disadvantages like unemployment, poverty, low education, and housing challenges are associated with increased risk of family conflict, social isolation, stress, and substance misuse.[18–23] Concentrated economic disadvantage can contribute to collective frustration and hopelessness,[24] out-migration, community disinvestments, and social disorders like substance misuse.[24–31] Therefore, counties with greater economic, housing, and family distress should have higher drug-related mortality rates.

Integral measures capture structural (contextual) characteristics external to individuals. Features like the healthcare environment and opportunities for social interaction are inversely associated with all-cause mortality,[10–13] whereas unstable labor markets and manually labor-intensive occupations have been found to be associated with mental health problems, injuries, and chronic pain.[14,15,21] Studies have yet to examine whether these same factors contribute to geographic differences in drug-related mortality rates. Counties reliant on heavy manual labor industries, like mining and manufacturing, that have suffered substantial employment downturns and wage stagnation in recent decades, may have higher drug-related mortality rates.[23,32] Opportunities for social interaction through community associations, recreational facilities, and churches facilitate trust, goodwill, and social cohesion, which may buffer against isolation, depression, and substance misuse.[33,34] Therefore, counties with more of these social capital–promoting establishments may have lower drug-related mortality rates. Access to physical health care may help protect against injury risk or long-term chronic pain and disability for which opioids are commonly prescribed. Access to mental health care may facilitate necessary substance abuse treatment. Counties lacking these services may have higher drug-related mortality rates.

Ultimately, distinguishing which (if any) of these social determinants of health contribute to geographic disparities in drug-related mortality is an essential step toward developing place-level targeted interventions. Therefore, these analyses test associations between county-level social determinants of health and drug-related mortality rates.

METHODS

Study Sample

A pooled cross-section of county-level mortality rates (2006–2015) were extracted from the U.S. Centers for Disease Control and Prevention's Wide-Ranging Online Data for Epidemiologic Research (WONDER) multiple cause-of-death (MCD) files.[1] Categorization of drug-related deaths used ICD-10 codes, including accidental poisoning, intentional self-poisoning, and poisoning of undetermined intent by exposure to drugs, drug-induced diseases, drugs in the blood, and mental/behavioral disorders due to drugs. Appendix A (available online) provides specific codes.

There are practical and conceptual reasons for using MCD versus underlying cause-of-death files. Data suppression for counties with <10 deaths results in suppressed mortality rates for more than one third of counties in the underlying cause-of-death data, even when pooling 10 years of data. Suppressed counties have smaller populations. Excluding them would limit study generalizability and could bias results. Because all contributing causes of death are included in the MCD files, fewer counties have suppressed mortality rates in the MCD data (note that deaths were counted only once, even if multiple drug-related causes contributed to the death). Second, using MCD data reduces risk of undercounting because of misclassification, which has been especially pronounced for drug-related suicides.[35,36] Third, identifying a single factor as the underlying cause of death is an oversimplification of the clinical and pathologic processes that led to death[36] and ignores the possibility that the death may not have occurred if drugs were not involved (e.g., motor vehicle accident).

Measures

County-level predictors were selected based on the social determinants of health[15] and socioecological frameworks.[11,16] When possible, analyses used measures for the working-age population because drug-related mortality rates are highest in that group, and that age group makes the largest contributions to county economies. Data availability prevented matching age ranges for some variables. Analyses used measures that captured conditions pre-2006 to reduce reverse-causality bias (i.e., possibility that high drug abuse rates created the county-level conditions used as predictors). Sensitivity analyses were conducted using variables that captured more recent county conditions.

The economic environment was measured with indicators for county economic distress, housing distress, and labor market structure. Economic distress included the U.S. Census 2000[37] percentage aged 25–54 years in poverty, aged 25–54 years unemployed/not in labor force, aged 21–64 years with disability affecting employment, aged ≥25 years with less than 4-year college degree, households with supplemental security income, households with public assistance income, Gini coefficient of income inequality, and aged 18–64 years without health insurance in 2008.[38] Housing distress included the percentage of vacant housing units and renter-occupied housing units spending >30% of income on rent in 2000.[37] Industrial dependence came from the U.S. Department of Agriculture Economic Research Service's economic dependency typology that categorizes counties as dependent on manufacturing, mining, farming, services, public sector (government), or nonspecialized based on the sector's contribution to the county's economy.[39] Social environment was measured with family distress (residents aged ≥15 years separated/divorced and single-parent families in 2000)[37]; percentage of residents living in a different county 5 years earlier in 2000[37]; and social capital–promoting establishments (religious establishments, nonprofit organizations, membership associations, and sports/recreation establishments per 10,000 population) in 2005.[40] The social capital measures were not normally distributed (even when logged), so they were recoded into quartiles. Healthcare environment included indicators from the Area Health Resource Files designating the county as a primary healthcare or mental healthcare professional shortage area in 2000–2004 and number of active patient care physicians per 10,000 population in 2000.[41] Ideally, analyses would have included the supply of mental health and substance abuse professionals/facilities, but those data are not available for all counties for the necessary years. The Area Health Resource Files capture county-level counts of specific types of healthcare providers (e.g., psychiatrists, psychologists), but prior to the 2013–2014 Area Health Resource Files release, counties with missing values were designated with values of zero. Therefore, users are unable to identify which counties have missing counts versus which counties truly have none.

Control variables were demographic factors likely to be related to geographic differences in mortality rates, based on existing literature[4,42–44]: metropolitan status; racial composition (percentage non-Hispanic black, Hispanic, American Indian); age composition (percentage aged ≥65 years); and percentage of residents in the military/veterans.[12,13] The racial composition variables were highly skewed, leading to heteroscedasticity, so they were recoded into quartiles. All continuous variables were standardized (mean 0, SD=1) to enable comparisons of regression coefficient magnitude across predictors. Appendix B (available online) provides details about all data sources.

Statistical Analysis

Analyses included 3,106 of the 3,143 U.S. counties. All counties in Alaska (29) and Hawaii (5) and Loving County, Texas, were excluded because of lack of data. Broomfield County, Colorado, and Bedford City, Virginia, were excluded because of county boundary changes. Mortality data were suppressed for 623 counties (20%). Therefore, analyses used multiple imputation with the Markov-chain Monte Carlo method (Appendix C, available online).[45] Sensitivity analyses compared results from multiple imputation models with those from models that excluded suppressed counties (i.e., complete case analysis). Minor differences between these models are described in Appendix D (available online).

Exploratory spatial data analysis revealed significant spatial autocorrelation in mortality rates (Moran's I of 0.560). Generalized spatial two-stage least squares autoregressive models were used to model logged county-level mortality rates. These models accounted for correlated residuals between neighboring counties by fitting the model with a correlation parameter of the residuals. The spatial weight matrix was based on first order queens contiguity. Spatial lag models for the dependent variable and continuous independent variables were also tested, but the spatial lag coefficients were not significant in the fully adjusted models.

The first stage of analyses involved separately regressing each predictor on the logged mortality rate to assess each variable's independent relationship with mortality. Models controlled for state fixed effects to adjust SEs that are downwardly biased because of the clustering of counties within states and account for unobserved state-level differences in factors that may influence drug mortality. Several variables were strongly correlated, preventing their inclusion in multivariate regression models (Appendix E, available online). Confirmatory factor analysis was used to create factor-weighted indices combining the economic distress variables (α=0.891) and family distress variables (α=0.784). Factor loadings are presented in Appendix F (available online). Maps showing the geographic distribution of index values are presented in Appendix G (available online). Variables that did not load highly onto factors (≥0.40) and were not collinear with other variables were included in the regression models as individual predictors. The second stage of analysis involved fitting a multivariate regression model that simultaneously incorporated all three groups of predictors (economic, social, and health care), while controlling for demographic characteristics and state fixed effects.

Sensitivity analyses included models on only nonsuppressed counties (n=2,484) and models with temporally overlapping predictors from the 2010–2014 American Community Survey rather than the temporally prior variables from 2000. Coefficients for all models are presented in Appendix D (available online).

Statistical significance is reported at $p<0.05$. Regression analyses were conducted in Stata/SE, version 15.1. Analysis of secondary data is exempt from IRB review by Syracuse University.

RESULTS

The mean county-level age-adjusted drug-related mortality rate (AAMR) 2006–2015 was 16.6 deaths per 100,000 population (min=2.8, max=102.5). There was significant spatial variation in rates (Figure 1). A Local Indicator of Spatial Association map revealed high mortality rate clusters in Appalachia, Oklahoma, parts of the Southwest, and northern California. Low mortality rate clusters were observed in parts of the Northeast, the Black Belt, Texas, and the Great Plains. There was also substantial within-state variation (Figure 2), with West Virginia having the largest disparity between the highest and lowest rate counties. A null multilevel model with counties nested within states was run to assess how much variation in rates was due to state- versus county-level differences. Imputation models produced an average intraclass correlation coefficient of 0.32, indicating that about a third of county-level variation in drug mortality rates was due to differences between states.

Table 1 shows that nearly all of the hypothesized economic and social variables were significantly associated with county-level drug mortality rates, controlling

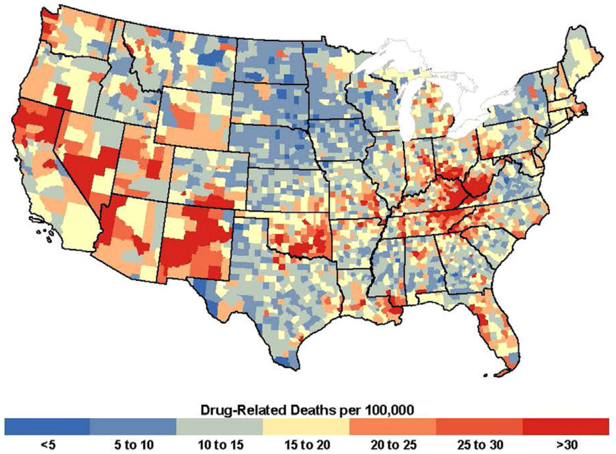

Figure 1. County-level age-adjusted drug-related mortality rates, 2006–2015.

for state fixed effects. The healthcare environment variables were not statistically significant.

Table 2 presents coefficients from the fully adjusted multivariate model. Among the economic variables, economic distress, rental stress, and labor market dependence were significant. An SD increase in economic distress was associated with a 6.4% increase in the AAMR ($p<0.001$), whereas an SD increase in rental stress was associated with a 3.9% increase in the AAMR ($p=0.001$). Compared with diversified economies, mining-dependent counties had a 13% higher average AAMR ($p=0.001$), and public sector–dependent counties had an 11.8% lower average AAMR ($p<0.001$). Manufacturing and farming dependence were also associated with lower AAMRs, but the p-values fell just short of the $p<0.05$ threshold. Among the social factors, family distress, recent in-migration, and religious establishments were significant. Net of all other factors, an SD increase in family distress was associated with a 13.6% increase in the AAMR ($p<0.001$). Counties with higher percentages of residents living in a different county 5 years earlier had significantly lower AAMRs. More religious establishments was associated with significantly lower AAMRs; compared with counties with the fewest religious establishments per capita (Quartile 1), those with the most (Quartile 4) had an 8% lower average AAMR. None of the other social capital variables, or the healthcare environment variables, were significant.

DISCUSSION

This is the first national study to identify specific economic and social factors contributing to between-county differences in U.S. drug-related mortality rates. Consistent with recent research on drug overdose trends,[2,3,5] this study found significant geographic disparities, including large within-state disparities, in drug-related mortality rates. Average drug-related mortality rates were higher among counties characterized by greater economic and family distress, including rates of poverty, unemployment, disability, no college degree, public assistance, rental stress, divorce/separation, and single-parent families. This is consistent with research showing associations between county-level economic deprivation and drug use[31,46] and research on SES as a major social determinant of health and fundamental

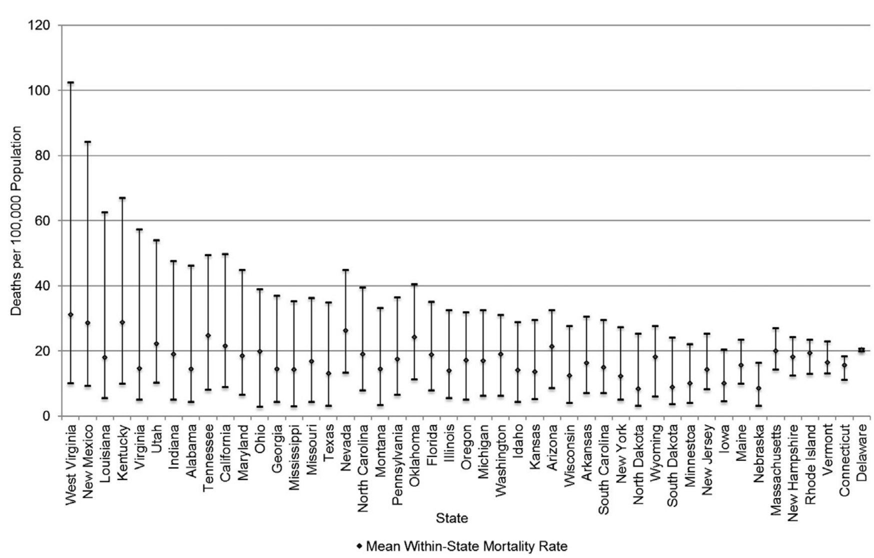

Figure 2. Within-state range between counties with highest and lowest drug-related mortality rates, 2006–2015.
Note: States are ordered by magnitude of difference between highest and lowest county mortality rates. Line caps represent county maximum and minimum drug-related mortality rates in each state.

Table 1. Variables Included in Regression Analysis With Summary Statistics and Bivariate Regression Results

	Summary statistics		Bivariate regression results	
Variable	**M (SD)**	**Range**	**Est. (SE)**	***p*-value**
Drug-related mortality rate (deaths per 100,000)	16.6 (8.9)	2.8 to 102.5	NA	
Drug-related mortality rate, logged	2.7 (0.5)	1.0 to 4.6	NA	
Economic environment				
Economic distress index	0.0 (4.5)	−11.7 to 23.8	**11.53 (1.11)**	$<$**0.001**
Population below the poverty line, age 25–54 years, %	11.3 (5.7)	1.7 to 53.1	**8.57 (1.06)**	$<$**0.001**
Civilian non-institutionalized population unemployed or not in labor force, age 25–54 years, %	24.4 (8.2)	5.3 to 66.3	**5.70 (1.06)**	$<$**0.001**
Civilian non-institutionalized population with a work disability, age 21–64 years, %	13.0 (3.6)	3.7 to 33.9	**9.60 (1.01)**	$<$**0.001**
Population with $<$4-year college degree, age ≥25 years, %	83.5 (7.8)	36.3 to 95.1	**6.64 (0.85)**	$<$**0.001**
Households with supplemental security income, %	5.1 (2.7)	0 to 26.6	**10.81 (1.16)**	$<$**0.001**
Households with public assistance income, %	3.4 (1.9)	0 to 18.6	**9.53 (0.97)**	$<$**0.001**
Population without health insurance, age 18–64 years, %	20.9 (6.6)	4.1 to 50.9	1.35 (1.64)	0.410
Gini coefficient	43.3 (3.6)	32.6 to 60.1	**2.70 (0.90)**	**0.003**
Housing distress				
Vacant housing units, %	14.1 (9.5)	1.5 to 77.0	**3.23 (1.04)**	**0.002**
Renter-occupied housing units with rent ≥30% of household income, %	29.6 (7.2)	0 to 56.1	**5.41 (1.08)**	$<$**0.001**
Labor market dependence, %				
Services	10.8		2.14 (2.62)	0.413
Public sector	11.9		**−11.70 (2.51)**	$<$**0.001**
Manufacturing	29.0		**−4.86 (1.98)**	**0.014**
Mining	4.0		**9.67 (4.29)**	**0.024**
Farming	14.1		**−16.34 (3.89)**	$<$**0.001**
Non-specialized (ref)	30.2			
Social environment				
Family distress index	0.0 (1.8)	−6.9 to 7.3	**16.29 (1.16)**	$<$**0.001**
Persons separated/divorced, age ≥15 years, %	11.3 (2.3)	3.7 to 21.2	**15.66 (1.15)**	$<$**0.001**
Families with children headed by single parent, %	26.1 (7.3)	2.5 to 63.0	**13.51 (1.10)**	$<$**0.001**
Social capital	0.0 (1.8)	−3.3 to 11.2		
Religious establishments per 10,000 population (Q4 vs Q1)	9.4 (5.1)	0 to 49.3	−5.13 (2.79)	0.066
Nonprofit organizations per 10,000 population (Q4 vs Q1)	59.8 (34.6)	1.7 to 360.3	0.48 (3.23)	0.883
Membership associations per 10,000 population (Q4 vs Q1)	3.0 (2.5)	0 to 29.2	**10.26 (2.54)**	$<$**0.001**
Sports establishments per 10,000 population (Q4 vs Q1)	2.0 (1.6)	0 to 18.0	−3.07 (2.51)	0.221
Residents living in different county 5 years ago, %	20.0 (6.8)	4.8 to 71.2	**−5.92 (0.90)**	$<$**0.001**
Healthcare environment				
Physicians per 10,000 population	12.0 (13.6)	0 to 204.0	0.94 (0.75)	0.210
County designated as a primary healthcare professional shortage area	63.3		0.46 (1.60)	0.775

(continued on next page)

Table 1. Variables Included in Regression Analysis With Summary Statistics and Bivariate Regression Results *(continued)*

	Summary statistics		Bivariate regression results	
Variable	**M (SD)**	**Range**	**Est. (SE)**	***p*-value**
County designated as a mental healthcare professional shortage area	55.0		3.47 (1.94)	0.074
Population characteristics				
Nonmetropolitan county	62.7		−1.11 (1.75)	0.524
Age ≥65 years, %	14.8 (4.1)	1.8 to 34.7	**6.28 (1.07)**	<**0.001**
Veterans or currently in armed forces, %	14.3 (3.7)	3.3 to 69.3	**4.61 (0.88)**	<**0.001**
Black population, % (Q4 vs Q1)	8.7 (14.5)	0 to 86.1	−1.85 (3.53)	0.601
Hispanic population, % (Q4 vs Q1)	6.1 (12.0)	0 to 98.1	−1.52 (3.33)	0.648
American Indian population, % (Q4 vs Q1)	1.6 (6.3)	0 to 93.7	**14.04 (3.10)**	<**0.001**

Note: Boldface indicates statistical significance ($p < 0.05$). Coefficients are from spatial autoregressive models with spatial error and control only for state fixed effects. Regression coefficients represent the percentage change in the age-adjusted mortality rate (AAMR, deaths per 100,000 population). All interval-ratio variables (except the four social capital variables, percentage non-Hispanic black, percentage Hispanic, and percentage American Indian) are standardized at a mean of 0 and SD of 1, so the coefficient represents the percentage change in the AAMR for a 1-SD increase in the predictor variable. The four social capital variables, percentage non-Hispanic black, percentage Hispanic, and percentage American Indian were not normally distributed, so they were transformed into quartiles for regression analysis to avoid problems with non-normality of residuals. For those seven variables, the coefficient estimates represent the percentage difference in the AAMR between quartile 4 (the top 25th percentile) and quartile 1 (the bottom 25th percentile). In the interest of space, the coefficient estimates are not shown for quartiles 2 and 3. The coefficients for the labor market dependence categories represent the percentage difference in the AAMR between each respective category and counties with nonspecialized economies.
Est., estimate; NA, not applicable; Q, quartile.

cause of preventable disease disparities.[14,47,48] Although the causal mechanisms driving these associations are unclear, economic insecurity contributes to family breakdown and social disorganization,[21,25,27,30–32] undermining important supports against depression and substance misuse.

Drug-related mortality rates were also higher in counties with labor markets dependent on mining, but lower in counties dependent on the government sector. The mining industry has experienced significant declines in recent decades, displacing many workers, but also adversely impacting secondary service industries in these areas.[24,30] Macro-level labor market stressors are community-level traumas that can manifest in collective psychosocial distress[22,34] and social disorders, like substance misuse.[31–35] The proliferation of illicit high-volume opioid clinics (i.e., pill mills) and aggressive OxyContin marketing throughout the 1990s and 2000s likely contributed to drug deaths in these same counties,[30,49,50] but lack of historic prescribing data prevents testing this hypothesis. Public sector employment is often more stable than other industries and involves less physical stress and injury than manual labor–dependent jobs, which may explain lower average mortality rates in public sector–dependent counties.

This study also demonstrates that economic conditions alone do not fully explain geographic differences in drug-related mortality. Social factors are important. Specifically, counties with a larger presence of religious establishments have lower drug-related mortality rates. Opportunities for fellowship and civic engagement through religious organizations may facilitate social interactions, trust, and social cohesion, and increase residents' sense of belonging.[32,33] The other social capital establishment measures were not significant in the fully adjusted model. Future research should examine whether these institutions are more protective in specific types of counties (e.g., low-income, rural) or in different regions. Percentage of residents living in a different county 5 years ago was associated with lower AAMRs. In-migration may reflect community vibrancy, including good employment and social opportunities, and strong public service infrastructure that can help buffer against widespread substance misuse.

Healthcare supply factors were not significant. County designation as a mental health professional shortage area was associated with higher AAMRs, but it did not meet the threshold for significance ($p < 0.05$). Future research should incorporate more comprehensive indicators of mental health and substance abuse treatment, when/if such indicators become publicly available for all counties.

State-level differences accounted for about a third of the between-county variation in mortality rates. State policy and economic contexts structure residents' lives and influence the ability of counties to provide services.[11,14] Current evidence is mixed on whether state-level factors like prescribing regulations, medical cannabis laws, and insurance treatment mandates are

Table 2. Multivariate Regression Results From Spatial Autoregressive Model

Variable	Model 1 Est. (SE)	*p*-value
Economic environment		
Economic distress index	**6.39 (1.68)**	**<0.001**
Housing distress		
Vacant housing units, %	−0.12 (1.26)	0.924
Rent >30% of household income, %	**3.90 (1.19)**	**0.001**
Labor market dependence		
Services	1.91 (2.62)	0.466
Public sector	**−11.81 (2.59)**	**<0.001**
Manufacturing	−3.53 (1.90)	0.064
Mining	**13.05 (4.03)**	**0.001**
Farming	−6.62 (3.69)	0.093
Nonspecialized (ref)	0.00	
Social environment		
Family distress index	**13.56 (1.46)**	**<0.001**
Residents living in different county 5 years ago, %	**−2.79 (1.11)**	**0.012**
Social capital (all per 10,000 population)		
Religious establishments (Q4 vs Q1)	**−8.14 (2.97)**	**0.006**
Nonprofit organizations (Q4 vs Q1)	−4.28 (3.90)	0.273
Membership associations (Q4 vs Q1)	3.50 (2.75)	0.204
Sports establishments (Q4 vs Q1)	−1.89 (2.61)	0.468
Healthcare environment		
Physicians per 10,000 population	0.42 (0.86)	0.624
Primary healthcare professional shortage area	−2.32 (1.52)	0.126
Mental healthcare professional shortage area	1.50 (1.85)	0.417
Spatial autocorrelation parameter	**0.547 (0.03)**	**<0.001**

Note: Coefficients are from a generalized spatial two-stage least squares autoregressive model with a spatial lag of the error. Average pseudo-*R*-square from multiple imputation models=0.50. Boldface indicates statistical significance ($p<0.05$). Regression coefficients represent the percentage change in the age-adjusted mortality rate (AAMR, deaths per 100,000 population). Economic distress, housing distress, family distress, % residents living in different county, and physicians per 10,000 population are standardized (mean of 0 and SD of 1), so the coefficient represents the percentage change in the AAMR for a 1-SD increase in the predictor variable. The coefficients for the labor market dependence categories represent the percentage difference in the AAMR between each respective category and counties with nonspecialized economies. The coefficients for the four social capital variables represent the percentage difference in the AAMR between quartile 4 (the top 25th percentile) and quartile 1 (the bottom 25th percentile). In the interest of space, the coefficients are not shown for quartiles 2 and 3, but all coefficients are shown in the Appendix (available online). The spatial autocorrelation parameter represents the correlated residuals from neighboring counties. It has a range of −1 to 1, with 0 representing no spatial autocorrelation.
Est., estimate; Q, quartile.

associated with overdose rates.[51–55] Identifying the relative contributions of these and other state factors to between-county differences in drug-related mortality rates was beyond the scope of this study. Future research should examine specific state laws and other factors, such as Medicaid generosity, prescription drug–monitoring programs, and austerity measures that may explain the pathways through which states influence county-level differences in rates. The magnitude and significance of the spatial error term representing correlated residuals among neighboring counties reflects the importance of correctly accounting for spatial autocorrelation in analyses on county-level differences in mortality rates. Analyses that do not correct for spatial autocorrelation risk producing biased or inaccurate results.

Limitations

Analyses were ecologic and cannot account for decedent characteristics, including duration of county residence. Data suppression prevented disaggregating by race/ethnicity, sex, and age. There is significant demographic variation in drug-related mortality.[56] Associations between the factors considered here and mortality rates may vary across groups. Likewise, suppression prevented examining changes in drug mortality and comparing potentially related types of mortality (e.g., suicide, alcohol-related). The necessity to pool multiple years of data prevented exploring possible cohort effects across years. Given the rapid increase in deaths in recent years (e.g., 2014, 2015), these years may be driving geographic variation in rates. Death certificates may misclassify causes of death. Using MCD files reduces the likelihood of undercounting because of misclassification.[36] Results may be biased by heterogeneity in cause-of-death reporting, but state-level reporting variation was controlled with state fixed effects. State fixed effects also accounted for heterogeneity in state programs/policies that may affect drug access. A non-exhaustive list of variables was used to represent social determinants and surely did not capture all relevant factors. County-level data on opioid prescriptions, drug arrests, and other potentially important factors associated with drug supply are unavailable at the national level. There is also heterogeneity within counties that cannot be accounted for in these analyses. Moreover, associations between county environments and mortality rates likely play out over an extended period, but these analyses incorporated only recent county conditions and did not consider temporal changes in environments. Finally, the specific types of drugs and the underlying mechanisms driving drug-related mortality may play out differently across different regions of the country. Future research should examine geographic heterogeneity in the relationships between drug-related mortality and the social determinants considered here.

CONCLUSIONS

Drug deaths are not randomly distributed across the U.S. Failing to consider the substantial geographic variation in drug-related mortality rates may lead to failure to target the hardest-hit areas. Social and economic environments are important for prevention because they affect stress, healthcare investment, residents' knowledge about and access to services, self-efficacy, social support, and opportunities for social interaction.[57] Findings from this study suggest that communities with significant economic and family distress are important targets for interventions. Moreover, religious establishments may play an important social capital–promoting role in the fight against the current U.S. drug epidemic.

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SUPPLEMENTAL MATERIAL

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