Bowling alone, dying together: The role of social capital in mitigating the drug overdose epidemic in the United States

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A B S T R A C T

Background: Drug overdose deaths have risen precipitously over the last fifteen years. Substantial geographic variation, beyond a simple rural-urban dichotomy, exists in the concentration of overdose deaths, suggesting the existence of as-yet unidentified environmental variables that predict resilience (or vulnerability) to drug overdoses. Motivated by reports highlighting the role of community fragility in the opioid epidemic, we explore whether social capital attenuates overdose death rates.

Methods: We conducted an ecologic temporal trends study from 1999 to 2014 to investigate the association between mortality due to drug overdose and social capital. Data from multiple sources were compiled at the county-level to produce an analytic dataset comprising overdose mortality, social capital, and a host of potentially confounding variables indicated by the literature (N = 49,664 county-years). Multinomial logistic regression was used to estimate the likelihood that a county falls in low (<4 deaths per 100,000), moderate, or high (>16 deaths per 100,000) categories of annual overdose mortality.

Results: We observed a strong and statistically significant inverse association between county-level social capital and age-adjusted mortality due to drug overdose (p < 0.01). Compared to the lowest quintile of social capital, counties at the highest quintile were 83% less likely to fall in the “high-overdose” category and 75% less likely to fall in the “moderate-overdose” category.

Conclusion: This study finds large-sample evidence that social capital protects communities against drug overdose. This finding could help guide policymakers in identifying where overdose epidemics are likely to occur and how to ameliorate them.

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1. Introduction

A recent editorial noted that the year 2014 marked the “highest number of individuals considered to have opioid addiction since statistics began to be collected in the late 19th century” (Olsen, 2016). More than ten million Americans report non-medical use of prescription opiates and two million non-medical users of opiates meet criteria for substance use disorders (Olsen, 2016). Climbing rates of opiate use and abuse have precipitated increases in morbidity and mortality. Over the last 20 years, drug overdose fatalities have increased throughout the United States (US) for all gender, age, and racial/ethnic subgroups (Rosen et al., 2016). In 2014, almost 50,000 Americans fatally overdosed on drugs; opiates accounted for about 60% of total drug poisonings, the nation’s leading cause of accidental death (Rudd et al., 2016). Age-adjusted death rates for all-drug poisonings have doubled in the last fifteen years, from 6.1 per 100,000 in 1999 to 14.7 per 100,000 in 2014 (Rudd et al., 2016).

Epidemiologic evidence suggests that temporal increases in overdose deaths are due to both prescription opioids and, more recently, illicit opioid use, particularly heroin. These trends are interrelated since most people who have initiated heroin use recently report doing so after being prescribed analgesic opiates (Rudd et al., 2016). Furthermore, opioid use and abuse is most pronounced among non-Hispanic (NH) whites, the group with the largest increases in overdose death rates since 1999 (Rosen et al., 2016). The deleterious effects of increased opiate prescriptions have prompted the Centers for Disease Control and Prevention (CDC) to issue new, more stringent guidelines about their use (Dowell et al., 2016). Moreover, policymakers at all levels of government have attempted to deal with the opiate epidemic. Congress has extended funding for states’ Prescription Drug Monitoring Programs through 2020 and required Veterans Affairs’ opiate prescriptions to use state monitoring programs (United States
Congress, 2016a) and significantly expanded funding for opiate prevention efforts and law enforcement targeting the trafficking of opiates (United States Congress, 2016b). At the state level, almost all states have passed legislation expanding access to Naloxone (Davis and Carr, 2015). Despite these efforts, the crisis shows few signs of abating (Olsen, 2016).

Both scholarly articles (McLean, 2016; Sundquist et al., 2016) and popular press reports (Achenbach and Keating, 2016) often cite the role of community fragility in contributing to the opiate epidemic. A recent New York Times article (Kolata and Cohen, 2016) notes that "the nation is seeing a cohort of whites who are isolated and left out of the economy and society and who have gotten ready access to cheap heroin and to prescription narcotic drugs." Indeed, the spike in opiate overdoses drives the finding that absolute mortality among middle-aged (45−54 years) whites has increased since 1999 (Case and Deaton, 2015). Substantial geographic variation, beyond a simple rural−urban dichotomy, exists in the concentration of overdose deaths (Rosen et al., 2013), suggesting the existence of as−yet unidentified environmental variables that predict resilience (or vulnerability) to overdoses.

One potentially protective factor is social capital—the extent and depth of social trust, norms, and networks (Sirianni and Friedland, 2001). The central premise of social capital is that social networks matter (Field, 2008). More concretely, social capital consists of five characteristics: (1) the density of community and personal networks; (2) civic engagement and participation; (3) a sense of belonging in the community; (4) reciprocity and cooperation with fellow citizens; (5) trust in the community (De Silva et al., 2005). Neighborhood associations, religious congregations, and civic organizations are sources of social capital. Research from political scientist Robert Putnam posited that high levels of social capital can predict a variety of social outcomes, such as lower crime levels, higher rates of volunteerism, and longer life expectancy. Drawing on several national surveys of membership and participation in civic organizations over three decades, Putnam argued that levels of social capital have been declining in the US since 1950, a phenomenon he described as “bowling alone” (Putnam 2000).

Scholars have long used social capital to explain variation in health outcomes between communities. State−level measures of social capital have been associated with better self−reported health (Kawachi et al., 1999) and reduced mortality (Kawachi et al., 1997; Weaver and Rivello, 2006). At the county level, social capital has been shown to explain the “rural paradox”−the observation that rural communities experience lower all−cause death rates (Yang et al., 2011) and infant mortality (Yang et al., 2009) than their poorer socioeconomic indicators and health behaviors would predict. Social capital is thought to explain the link between inequality and worsened health (Yamaguchi, 2014), and neighborhood income inequality is associated with fatal drug overdoses in New York City (Galea et al., 2003). In contrast, scholars found no relationship between regional measures of “civicness”, a concept similar to social capital, and drug overdoses in Italy after controlling for income; instead, provincial wealth was the primary driver of overdose fatalities, with wealthier provinces experiencing more overdose deaths (Gatti et al., 2007). In this paper, we address a gap in knowledge by leveraging multiple data sources to explore whether social capital moderates drug overdose deaths.

2. Methods

2.1. Study design

We conducted an ecologic temporal trends study from 1999 to 2014 to investigate the association between drug overdose mortality and social capital. Data from multiple sources, primarily federal organizations, were compiled at the county−level to produce an analytic dataset comprising (1.) age−adjusted drug overdose mortality, (2.) social capital, (3.) availability of drug abuse treatment centers, (4.) prescription drug claims prescribed by health care providers, (5.) population demographics, (6.) urbanicity, and (7.) socioeconomic status.

2.2. Data sources and measures

2.2.1. Drug overdose mortality. County−level estimates of overdose (drug poisoning) deaths from 1999 to 2014 were obtained from the CDC’s National Vital Statistics System and Health Indicators Warehouse (Rosen et al., 2016). Deaths were classified using the International Classification of Diseases, Tenth Revision (ICD−10) and overdose deaths were defined as an underlying cause−of−death code in the X40−X44 (unintentional poisoning), X60−X64 (intentional/suicidal poisoning), X85 (homicidal poisoning), or Y10−Y14 (poisoning from an undetermined intent) range. Age−adjusted overdose rates (deaths per 100,000 U.S. standard population for 2000) were calculated using the direct method, and small−area estimation techniques (Rosen et al., 2013) were used to calculate stable estimates of county−level death rates each year, particularly for counties in which data are sparse due to small population size. An advantage of employing this data is its comprehensiveness: first, death certificates are issued to more than 99% of all legal residents over the age of one, and second, counties were not excluded due to privacy concerns or statistical instability of infrequent occurrences. The final estimated outcome (smoothed, county−level, age−adjusted overdose mortality rate) was initially captured as an ordinal variable with 11 categories ranging from 0 to 2 overdose fatalities per 100,000 people to >20 deaths per 100,000 (Rosen et al., 2016).

2.2.2. Social capital. County−level measurements of social capital for the years 1997, 2005, and 2009 were obtained from Rupasingha et al. (2006). The social capital index is generated at the county level using the following four factors: (1.) the density of civic associations and non−profit organizations in the county; (2.) the percentage of county adults who voted in presidential elections; (3.) the county’s response rate to the census; and (4.) the number of tax−exempt non−profit organizations in the county. Principal components analysis was used to create a single index from these four variables; based on our data we estimated that this single index captures 55% of variation in the four factors in 1997, 48% of the variation in 2005, and 45% in 2009. Our use of direct measures of county−level variables, rather than aggregated individual survey−data, avoids biases resulting from the ecological fallacy (Best and Radcliff, 2005). Values for intermediary years were interpolated from the surrounding years, and values for the years 2010−2014 were extrapolated from the surrounding years using linear forecasting. In panel data, county correlates of the social capital index were found to be consistent across time (Rupasingha et al., 2006).

2.2.3. Sociodemographic characteristics. Median household income and poverty data were obtained for each county−year from the US Census Bureau’s Small Area Income and Poverty Estimate (SAIPE). The SAIPE estimates were mostly absent for the years 2005 and 2006, so these values were interpolated from 2004 and 2007 values, respectively. Racial/ethnic characteristics were obtained for each county−year from the US Census Bureau’s county characteristics population estimates. The Census Bureau’s designation of a county on the Rural−Urban County Continuum (RUCC) provides a nine−level classification scheme representing the degree of urbanization, in which 1 is densest and 9 is least dense. RUCCs are only updated each decennial (2003 and 2013); therefore, for 1999–2006 we used the 2003 county−level measure, and for later years we
used the 2013 county-level measure (there were few differences between the two measurements).

2.2.4. Availability of substance abuse treatment. To create an indicator representing the availability of specialized substance use treatment per capita, we obtained the locations of all substance use treatment centers listed on SAMSHA’s Treatment Locator tool (Substance Abuse and Mental Health Services Administration, 2016). The tool, updated regularly, lists “private and public facilities…approved for inclusion by their State substance abuse agency” as well as “treatment facilities administered by the Department of Veterans Affairs, the Indian Health Service, and the Department of Defense.” Using a Python script incorporating the Geopy library and Open Street Map API, we obtained the latitude and longitude coordinates for each center and passed them to the Federal Communications Commission’s Census Block Conversion API (Federal Communications Commission) to obtain the county FIPS code corresponding to the location of each treatment center. To calculate the county-level indicator of treatment facility density, the number of treatment centers was totaled for each county, divided by the total county population, and expressed as centers per 100,000 people.

2.2.5. Prescribing practices. Lastly, we obtained county-level data regarding opiate prescription claims from the Medicare Part D Opioid Drug Mapping Tool (Centers for Medicare and Medicaid Services, 2015). Provided by the Centers for Medicare and Medicaid Services (CMS), this measure indicates, for each county, the percentage of prescriptions written and then submitted to be filled under Medicare Part D (which represent two-thirds of Medicare prescriptions) for opiate analogs in 2013. Though Medicare primarily covers those aged 65 and older, opiate prescriptions through Medicare Part D have been shown to predict overdose deaths among both the elderly and younger Americans (Powell et al., 2015).

2.3. Statistical analysis

Descriptive statistics including frequencies, percentages, means, and standard deviations were used to describe the distribution of social capital and other county-level characteristics, overall and across counties with different levels of mortality due to drug overdose. Drug overdose mortality was classified into three categories of low (0–6 per 100,000), moderate (6.1–16 per 100,000), and high (≥16 per 100,000). Social capital was grouped into quintiles based on the distribution across all counties in all years of the study. Also, to improve interpretability of study results, other county-level characteristics originally reported on a continuous scale (e.g., percentage of population living in poverty) were discretized into three or more distinct categories. As part of our descriptive analyses, we generated nationwide, county-level choropleth maps for both age-adjusted overdose mortality rates and level of social capital over time. This process facilitated a visual examination of the degree of overlap between areas of high overdose mortality and low social capital, and vice-versa. It also identified counties that displayed positive deviance (few overdoses despite low social capital) and negative deviance (many overdoses despite high social capital). Furthermore, since there were significant increases in both individual (Fig. 1) and county-level overdose mortality over time, we investigated the mean age-adjusted mortality due to drug overdose across levels of social capital, in four-year time intervals. Finally, we used multinomial logistic regression to estimate adjusted odds ratios (OR) and 95% confidence intervals representing the associations between age-adjusted mortality due to drug overdose, social capital, and other county-level characteristics. We constructed three models: (1) a model with social capital as the only independent variable; (2) adding sociodemographic variables (racial/ethnic composition, median household income, education, and rural urban status) to model 1; and (3) adding to model 2 the density of substance abuse centers and the percentage of opioid prescriptions written and then submitted to be filled under Medicare Part D in the county. In this paper, we present adjusted measures of association for only the full-adjusted models since they represent the best statistical fit to the data. In all models, year was included as a covariate since overdose rates have changed substantially over time. The fully adjusted model was then used to estimate the adjusted probability of low, moderate, and high rates of age-adjusted mortality due to drug overdose across levels of social capital. Statistical analyses were performed with either SAS, version 9.4 (SAS Institute, Inc., Cary, NC), or Stata/MP 13.1 (StataCorp LP, College Station, TX). We assumed a 5% type I error rate for all hypothesis tests (two-sided).

3. Results

There were 3135 counties/county equivalents in the US between 1999 and 2014 that had an annual estimate of overdose mortality. We excluded 31 counties (1%) without data on social capital, leaving 3104 counties and 49,664 county-years included in the analysis. During the study period, there was a substantial increase in age-adjusted mortality due to drug overdose, from 6.1 to 14.7 per 100,000, with differences across race/ethnic groups. This was primarily attributable to NH-whites who experienced a three-fold increase, from 6.2 to 19.0 overdose-related deaths per 100,000, whereas NH-blacks and Hispanics experienced relatively smaller increases in mortality (Fig. 1).

Table 1 displays the distribution of social capital and other county-level characteristics during the study period, overall and across counties with low (37.8%), moderate (51.1%), and high (11.0%) levels of mortality due to drug overdose. Compared to counties with high rates of overdose mortality, those with low rates tended to be rural (with less than 2500 population), to have <25% of their populations who were non-white and <5% who were Hispanic, and to have >20% with less than a high school education. Low overdose mortality counties were also more likely to have populations with a median household income <$35,000 (43.3% vs. 31.0%), but had a lower proportion of residents who live in poverty. The higher the level of overdose mortality in a county, the higher was the percent of all Medicare Part D prescription claims that were for opiate analogs. We did not observe a consistent trend between overdose mortality and the density of substance abuse treatment centers.

We observed a crude inverse association between social capital and mortality due to drug overdose. During the study period, nearly 35% (20.0% + 34.9%) of low mortality counties were in the highest two quintiles of social capital; the same was true for 32% of moderate mortality and less than 25% of high mortality counties (Table 1). Fig. 2 visualizes the distribution of social capital and overdose rates in 2005 and 2009. The maps highlight some notable overlapping regions that are reflective of a crude, county-level association between social capital and age-adjusted overdose rates. Counties in Appalachia appear red in both figures, indicating that they have both low social capital and high overdose rates. Conversely, the Great Plains region in the central US enjoys both high levels of social capital and low levels of overdose rates. However, this inverse relationship is absent in certain areas of the country. For example, southwest Texas has relatively low social capital but also few overdoses. New York is another anomaly; throughout the state, overdose death rates are uniformly low, despite low-to-moderate levels of social capital. Notably, there were not only increases in overdose mortality between 2005 and 2009 (Fig. 2),
but also dramatic increases throughout the study period. However, throughout the study period, age-adjusted rates of overdose deaths were notably lower in counties with more social capital (Fig. 3). The results of our multivariable, multinomial logistic regression modeling revealed relatively strong county-level associations between both sociodemographic and prescribing characteristics and age-adjusted mortality due to drug overdose (Table 2). Compared to counties with 40% or more non-white residents, those with higher proportions of whites were 4–50 times more likely to have high, rather than low, overdose mortality. Similarly, compared to counties with Hispanics making up 25% or more of the population, those with fewer Hispanics had approximately 3–7 times increased odds of higher vs. lower overdose mortality. In the fully adjusted model, higher mortality was associated with lower median house-
Table 1
Distribution of social capital and other county-level characteristics, overall and across counties with different mortality due to drug overdose, United States, 1999–2014.

<table>
<thead>
<tr>
<th>Social capital quintile</th>
<th>Overall (n = 49,664, 100%)</th>
<th>Low Mortality (n = 18,792, 37.8%)</th>
<th>Moderate Mortality (n = 25,402, 51.1%)</th>
<th>High Mortality (n = 5,470, 11.0%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n²</td>
<td>%</td>
<td>n²</td>
<td>%</td>
</tr>
<tr>
<td>Lowest quintile</td>
<td>9932</td>
<td>20.0</td>
<td>3027</td>
<td>16.1</td>
</tr>
<tr>
<td>2nd quintile</td>
<td>9933</td>
<td>20.0</td>
<td>2728</td>
<td>14.5</td>
</tr>
<tr>
<td>3rd quintile</td>
<td>9933</td>
<td>20.0</td>
<td>2731</td>
<td>14.5</td>
</tr>
<tr>
<td>4th quintile</td>
<td>9934</td>
<td>20.0</td>
<td>3752</td>
<td>20.0</td>
</tr>
<tr>
<td>Highest quintile</td>
<td>9932</td>
<td>20.0</td>
<td>6554</td>
<td>34.9</td>
</tr>
<tr>
<td>Social capital, mean ± SD</td>
<td>0.00</td>
<td>1.40</td>
<td>0.48</td>
<td>1.67</td>
</tr>
</tbody>
</table>

Percent non-white
- <10%: 31,481 (63.4), 12,800 (68.1)
- 10–25%: 9490 (19.1)
- 25–<40%: 4798 (9.7)
- ≥40%: 3895 (7.8)

Percent Hispanic
- <5: 33,389 (67.2)
- 5–9.9: 6765 (13.6)
- 10–24.9: 5686 (11.4)
- ≥25: 3824 (7.7)

Median household income ($)
- <35,000: 16,570 (33.4)
- 35,000–49,999: 25,122 (50.6)
- ≥50,000: 7972 (16.1)

Percent living in poverty
- <10: 9505 (19.1)
- 10–14.9: 17,837 (35.9)
- 15–24.9: 18,776 (37.8)
- ≥25: 3546 (7.1)

Percent with high school education
- <10: 7040 (14.2)
- 10–19.9: 23,424 (47.2)
- ≥20: 19,200 (38.7)

Rural-urban status
- Metro, ≥1 million: 6736 (13.6)
- Metro. 250,000: 5576 (11.2)
- Metro. <250,000: 5600 (11.3)
- Non-metro: 21,488 (43.3)
- Rural, <2500: 10,264 (20.7)

Percent claims opioid
- <3: 1680 (3.4)
- 3–4.9: 16,784 (33.8)
- 5–7.9: 27,408 (55.2)
- ≥8: 3296 (6.6)

Substance abuse centers per 100,000 population
- None: 27,744 (55.9)
- <1: 1424 (2.9)
- 1–3: 9224 (18.6)
- ≥3: 11,272 (22.7)

Note: Unless otherwise stated, data are presented as the frequency and percentage.

- Smoothed county age-adjusted death rates (per 100,000 population).
- Sum of all groups may not add up to the total and percentages may not add to 100 due to missing data. Percentages displayed are column percentages to show the distribution of each characteristic across mortality groups.
- Percentages displayed are column percentages to show the distribution of each characteristic across mortality groups. Percentages may not add to 100 due to missing data.

Although we found no evidence of a dose-response relationship, counties with substance abuse treatment centers tended to have higher overdose rates than counties without them. Finally, we found a statistically significant reduction in the odds of high (vs. low) mortality due to drug overdose with each increasing quintile of social capital; compared to the lowest quintile, counties with the second through fifth quintiles experienced a 29%, 48%, 66%, and 87% lower odds of high mortality, respectively. To improve interpretability of our findings, we then used the parameter estimates from our full model to esti-
mate the adjusted probability (i.e., the average marginal effect at observed values) of low, moderate, and high rates of mortality due to drug overdose across levels of social capital (Fig. 4). Counties in the lowest quintile of social capital had a 32% probability of low mortality (0–6 per 100,000) and an almost 15% of high mortality (≥16 per 100,000). In stark contrast, counties in the highest quintile of social capital were much more likely (52.7%) to have low mortality and less likely (8.3%) to have high mortality.

We also performed a sensitivity analysis in which results were generated separately for large, metropolitan counties (the 6764 county-years whose Census designation on the RUCC indicates a metropolitan area with ≥1 million population) and all other counties. No changes in the direction, statistical significance, or substantive interpretation of any study variable were observed.
Table 2
Odds ratios and 95% confidence intervals representing the associations between age-adjusted mortality due to drug overdose, social capital, and other county-level characteristics, United States, 1999–2014.

<table>
<thead>
<tr>
<th>Social capital quintile</th>
<th>Moderate vs. Low Mortality</th>
<th>High vs. Low Mortality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Crude OR (95% CI)</td>
<td>Adjusted OR (95% CI)</td>
</tr>
<tr>
<td></td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>Lowest quintile</td>
<td>1.07 (1.01, 1.15)</td>
<td>0.96 (0.88, 1.04)</td>
</tr>
<tr>
<td>2nd quintile</td>
<td>1.04 (1.07, 1.12)</td>
<td>1.00 (0.92, 1.09)</td>
</tr>
<tr>
<td>3rd quintile</td>
<td>0.64 (0.59, 0.68)</td>
<td>0.67 (0.62, 0.73)</td>
</tr>
<tr>
<td>4th quintile</td>
<td>0.14 (0.13, 0.15)</td>
<td>0.25 (0.23, 0.28)</td>
</tr>
<tr>
<td>Highest quintile</td>
<td>1.24 (1.14, 1.35)</td>
<td>1.05 (0.99, 1.10)</td>
</tr>
<tr>
<td>Percent non-white</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;10%</td>
<td>1.59 (1.47, 1.72)</td>
<td>4.70 (4.24, 5.22)</td>
</tr>
<tr>
<td>10–25%</td>
<td>3.88 (3.55, 4.25)</td>
<td>12.35 (10.18, 14.98)</td>
</tr>
<tr>
<td>25–40%</td>
<td>2.26 (2.65, 2.49)</td>
<td>3.46 (2.77, 4.30)</td>
</tr>
<tr>
<td>≥40%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Hispanic</td>
<td></td>
<td></td>
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<tr>
<td>&lt;5</td>
<td>1.16 (1.08, 1.26)</td>
<td>1.12 (0.99, 1.27)</td>
</tr>
<tr>
<td>5–9.9</td>
<td>2.02 (1.83, 2.22)</td>
<td>1.86 (1.60, 2.16)</td>
</tr>
<tr>
<td>10–24.9</td>
<td>1.61 (1.46, 1.78)</td>
<td>1.48 (1.27, 1.73)</td>
</tr>
<tr>
<td>≥25</td>
<td></td>
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<tr>
<td>Median household income ($)</td>
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<tr>
<td>&lt;35,000</td>
<td>0.84 (0.79, 0.90)</td>
<td>0.96 (0.85, 1.09)</td>
</tr>
<tr>
<td>35,000–49,999</td>
<td>0.91 (0.86, 0.97)</td>
<td>1.01 (0.92, 1.10)</td>
</tr>
<tr>
<td>≥50,000</td>
<td></td>
<td></td>
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<tr>
<td>Percent living in poverty</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;10</td>
<td></td>
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</tr>
<tr>
<td>10–14.9</td>
<td>1.39 (1.32, 1.48)</td>
<td>1.66 (1.54, 1.79)</td>
</tr>
<tr>
<td>15–24.9</td>
<td>2.12 (2.00, 2.25)</td>
<td>2.60 (2.35, 2.88)</td>
</tr>
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<td>≥25</td>
<td>0.99 (0.90, 1.09)</td>
<td>2.01 (1.71, 2.33)</td>
</tr>
<tr>
<td>Percent &lt; high school education</td>
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<tr>
<td>&lt;10</td>
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<tr>
<td>10–19.9</td>
<td>1.83 (1.72, 1.96)</td>
<td>1.66 (1.53, 1.80)</td>
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<td>≥20</td>
<td>2.11 (1.96, 2.26)</td>
<td>1.86 (1.68, 2.06)</td>
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<tr>
<td>Rural-urban status</td>
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<tr>
<td>Metro, ≥1 million</td>
<td>5.62 (5.20, 6.08)</td>
<td>3.76 (3.37, 4.19)</td>
</tr>
<tr>
<td>Metro, 250,000</td>
<td>5.66 (5.20, 6.16)</td>
<td>2.69 (2.42, 2.98)</td>
</tr>
<tr>
<td>Non-metro, &lt;250,000</td>
<td>3.93 (3.63, 4.25)</td>
<td>1.68 (1.52, 1.85)</td>
</tr>
<tr>
<td>Rural, &lt;2500</td>
<td>3.03 (2.86, 3.21)</td>
<td>1.73 (1.61, 1.85)</td>
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<tr>
<td>Percent claims opioid</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3–4.9</td>
<td>2.59 (2.29, 2.94)</td>
<td>1.76 (1.53, 2.02)</td>
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<td>5–7.9</td>
<td>8.73 (7.70, 9.90)</td>
<td>4.97 (4.33, 5.71)</td>
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<tr>
<td>≥8</td>
<td>17.23 (14.71, 20.20)</td>
<td>9.04 (7.60, 10.76)</td>
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<td>Substance abuse centers per 100,000 population</td>
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<td></td>
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<tr>
<td>&lt;1</td>
<td>3.29 (2.85, 3.79)</td>
<td>1.69 (1.43, 2.00)</td>
</tr>
<tr>
<td>1–3</td>
<td>3.46 (3.25, 3.67)</td>
<td>2.28 (2.11, 2.46)</td>
</tr>
<tr>
<td>≥3</td>
<td>1.77 (1.68, 1.86)</td>
<td>1.59 (1.49, 1.69)</td>
</tr>
</tbody>
</table>

a Generated from a multinomial logistic regression model with level of overdose mortality (low, medium, high) as the outcome, the specified county-level covariate as the independent variable, and adjusted only for year.

b Generated from a multinomial logistic regression model with level of overdose mortality (low, medium, high) as the outcome, and including year and all of the variables listed in the table as independent variables.

c Odds ratios are statistically significantly different from the null value (1).

4. Discussion

We found a strong and statistically significant inverse association between county-level measures of social capital and age-adjusted drug overdose rates. Although our analyses are based on a county-level, ecologic investigation, there are several plausible mechanisms by which social capital may ameliorate overdose mortality, including the ability for social capital to (1) prevent the initial onset of drug-taking, (2) aid in the recovery of drug users and abusers, and (3) reduce the case-fatality rate of drug overdose.

Social capital may help lower the likelihood of initiating opiate or other drug use. The Monongahela Valley of Pennsylvania experienced a substantial increase in drug overdoses after steel factories, the economic engine of the region, closed. Interviews with heroin addicts in the region suggest that some users turn to drugs to cope with the hopelessness, social isolation, and lack of opportunity that followed the region’s economic deterioration (McLean, 2016). Social capital may act as a two-fold buffer against this syndrome. First, the economics literature suggests that social capital acts as a lubricant for economic growth by promoting investment in education and rule of law (Bjornskov, 2012). Second, social capital itself embodies connectedness between people, the antithesis of social isolation, and thus could interrupt the process of isolation and hopelessness that culminate in drug-taking. Social capital may lead to better pediatric and adolescent mental health (McPherson et al., 2014), though evidence for a general effect of social capi-
tal on mental health is inconclusive (De Silva et al., 2005; Kawachi and Berkman, 2001). In our study, social capital and percent opiate prescriptions were somewhat correlated; counties with lower social capital have a higher percent opiate prescriptions (Pearson’s r = −0.2392; p < 0.001). Social capital could plausibly affect opiate prescriptions both through reducing the desire to take drugs and discouraging illicit behaviors, such as doctor shopping and selling prescriptions.

Social capital may also facilitate recovery from addiction. Interviews with former drug addicts who recovered without formal treatment underscore the importance to recovery of social connections and the psychological and material resources provided by social networks (Granfield and Cloud, 2001). Since overdose deaths are a function of the frequency, duration, and severity of drug use, the likelihood of recovery plausibly influences mortality. Some addicts cite the fear that people they care about will discover their drug habit as an impetus to quit. Other recovery stories highlight the role played by friends or family members who intervened (Granfield and Cloud, 2001). Therefore, communities with higher levels of social capital may be more resilient to cycles of recovery and relapse. Conversely, low social capital may make addiction more persistent. As one interviewed patient at a treatment facility noted: “There is no sense of community here. Not one, not one iota of community here. Not one. So, left to your own devices, somebody that’s drinking and drugging is gonna continue drinking and drugging…” (McLean, 2016).

Last, social capital may increase the propensity to seek medical help in the event of an overdose, reducing the case-fatality rate. While overdoses often occur in the presence of other people, bystanders seek medical help in fewer than half of fatal overdoses (Zador et al., 1996). This hesitation to seek help could stem from a “fear of criminal prosecution or a general mistrust of authority suggesting erosion of social capital” (Galeta et al., 2003). Moreover, proximity to other people can itself be protective against overdose. Interviews with residents at a treatment facility in Pennsylvania detail stories of people who “overdosed while using alone, yet were saved by friends or family who were somehow alerted to the danger,” such as by hearing the thud of a body falling on the bathtub floor (McLean, 2016). This suggests that overdose deaths would be more frequent in areas with less social capital even if the underlying rate of drug overdose were similar.

4.1. Limitations

Measuring social capital has proven difficult, and the index used in this study captures the concept of social capital imperfectly and for limited years, requiring the potentially hazardous use of interpolation and forecasting methods, especially for the years 2010–2014. Furthermore, little attention has been given to cultural differences that may contribute to measurement error. Notably for our study, the relationship between social capital and drug overdose rates was not evident in predominantly Hispanic regions of the country, as illustrated in the choropleth maps (Fig. 2). This may be due to imprecision or measurement error in the social capital index among these populations. These errors suggest that the effect of social capital was most likely underestimated; that we nevertheless observed a strong dose–response association may speak to the magnitude of the true effect that social capital may have on overdose mortality. Future research could address this problem by improving measurement of social capital, specifically among Hispanics, such as through noting the size and intergenerational presence of households or through analyzing the spatial density of Hispanic churches.

Furthermore, issues remain with the appropriateness of the county as a unit of measuring social capital for large metropolitan counties (Rupasingha et al., 2006). For example, a large metropoli-

tan county may have, on average, high levels of social capital but it may be distributed unequally across the county, resulting in measurement error. However, there is no a priori reason to think that these measurement errors would systematically bias the estimates in one particular direction. A county could have an area of concentrated low-level of social capital that brings the average level down or a concentration of very-high levels of social capital, bringing the average up. Therefore, the net effect on the results of our study is likely minimal.

Additionally, the inability to disaggregate overdose deaths by subtype is another limitation. A smoothed and geographically comprehensive dataset for subsets of overdose deaths was not available, resulting in our using an aggregation of all overdose deaths. The relative rarity of overdose deaths for some drugs (fewer than 1500 overdose deaths in the US in 2014 involved illicit drugs other than cocaine and heroin) precludes ecologic, county-level analyses (National Center for Health Statistics, 2015). For the reasons indicated, we believe that social capital should mollify overdose deaths from all drugs, so it is reasonable to employ an aggregate measure of overdose deaths. Nevertheless, we hope that this research can serve as the impetus for subsequent work targeting overdose deaths at the individual level and focused on overdose subtypes.

Although we have attempted to control for many important contextual factors, our analysis relies on linkage of disparate data sources that could have omitted potential county-level and individual-level confounders. However, the magnitude of the relationship observed between social capital and drug overdose mortality suggests it is unlikely the entire association is due to unmeasured confounding. Finally, there may be endogeneity in our model estimates to the extent that social capital affects or is affected by other control variables. For example, if social capital affects overdose rates by reducing drug use, we may have underestimated the effect of social capital by including the prescription data as a covariate without accounting for the correlation between social capital and opiate prescription rates. Future studies employing more comprehensive panel data can further elucidate the potentially complex interplay between individual-, neighborhood-, and county-level factors.

4.2. Conclusion

Our analyses demonstrated a strong inverse relationship between a county’s social capital and overdose fatalities, even after controlling for potential confounders. As this was an ecological study, the usual reservations about causal inferences at the individual level apply. Nevertheless, this research adds to a growing literature showing that social isolation contributes to drug use and that strong communities offer resilience against drug epidemics. Viewed through this lens, the fact that social capital may be declining in the US makes the recent growth in drug overdosees particularly striking (Putnam, 2000).

Scholars have increasingly noted the role played by environmental and contextual determinants of health (Mamot and Wilkinson, 2006). This study enhances understanding of the opiate epidemic by suggesting that social capital promotes community resilience. This research can inform policymaking towards the opiate epidemic in two ways. First, since social capital may mollify drug epidemics, policymakers would be well-advised to consider how to facilitate its growth. Second, communities with little social capital are particularly vulnerable to drug epidemics, and treatment and prevention efforts should be targeted accordingly.

Conflict of interest

No conflict declared.
Role of funding source

Nothing declared.

Contributors

Mr. Zoorob conceived the study, identified and linked together the study's disparate data sources, performed exploratory geospatial analyses, and drafted the paper's Introduction and Discussion. Dr. Salemi directed meaningful categorization of study variables, performed statistical analyses, and drafted the paper's Methods and Results sections. Both Mr. Zoorob and Dr. Salemi provided critical revisions to the paper and both approve the final version of the manuscript.

References

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