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# Disparities in opioid related mortality between United States counties from 2000 to 2014

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ABSTRACT

*Background:* The general increase in opioid-related deaths is well documented, and disparities by geographic regions and demographic characteristics have been observed as well. However, the distribution of opioid-related deaths among U.S. counties and the trends in that distribution have not been fully explored. This study examines the inequality in opioid death rates to assess convergence or divergence in opioid-related mortality between counties.

*Methods:* Using mortality data from the NVSS for 2000–2014, this study examines the Gini coefficient of the county opioid mortality distribution.

*Results:* The distribution of opioid mortality became more equal, with the Gini coefficient falling from 0.81 in 2000 to 0.61 in 2014. Counties with lower initial opioid mortality rates experienced faster growth in mortality than counties with high initial mortality.

*Conclusions:* Counties have experienced a convergence in opioid mortality rates. This poses potential challenges for addressing the crisis, as measures must become much broader in scope and be implemented in areas in which the dangers of the opioid crisis are not as apparent.

## 1. Introduction

Drug poisoning deaths have risen dramatically over the past several years, with prescription opioids and heroin being the primary driver of this increase in drug-related mortality (Rudd, 2016). Increases in adverse outcomes due to opioid use have been well-documented and include increasing emergency department use (Cai et al., 2010), substance use treatment admissions (Ling et al., 2011), and hospitalizations (Owens et al., 2006). While a number of policy solutions, such as naloxone distribution programs (McClellan et al., 2018; Rees et al., 2017) and prescription drug monitoring programs (PDMP) (Ali et al., 2017), offer promising results, opioid related deaths remain high. Additionally, focus on national measures of the absolute growth in opioid mortality may mask important differences in relative changes between regions; opioid mortality may not be increasing uniformly across the nation. A deeper understanding of the patterns of the crisis is needed to inform policymakers in devising and implementing responses to the crisis. In particular, understanding the geographic inequalities in opioid mortality and how those inequalities have shifted over the course of the crisis informs the distribution of resources to address the problem and could allow preemptive action in places at risk of large increases in opioid mortality.

Some aspects of the epidemic's patterns have been studied. There is evidence that the growth in opioid use and overdose mortality is disproportionately distributed among socio-demographic groups. While Case and Deaton (2015) notably have shown an increasing share of drug poisonings among the white middle-aged population, other studies have found differential patterns in opioid use by gender, race, and education (Carpenter et al., 2017), in opioid prescribing by race and ethnicity (Pletcher et al., 2008; Singhal et al., 2016), and in treatment by age and urbanicity (Cicero et al., 2014). However, limited work has been conducted on the disparities in opioid mortality between geographic regions. This study gives additional insight into the evolution of the opioid epidemic by providing a concise measure of the distribution of opioid mortality among U.S. counties.

While there has been some study of the geographic dispersion of opioid mortality (Buchanich et al., 2016; Cerdá et al., 2017; Rossen et al., 2013; Stewart et al., 2017), changes in the relative share of opioid mortality among U.S. counties has yet to be fully explored. Most prior literature has focused more on the actual geographic patterns (e.g., the urban vs. rural divide) in opioid mortality. Using advanced geo-spatial methods, these studies identify "hot spots" of opioid activity and examine how these concentrations spread over space and time (Rossen et al., 2013).

While these studies show specific differential trends between certain areas, they do not provide a concise characterization of the relative

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changes in the opioid mortality distribution across counties. A more recent study (Dwyer-Lindgren et al., 2018) does briefly examine the relative distribution of drug mortality and finds an increase in opioid death inequality. However, this study relies on an inequality measure, the 90/10 ratio, which only focuses on changes in relative mortality rates between the 90th and 10th percentiles. As a result, the measure does not capture the full distribution of mortality rates or changes in relative rates between other percentiles, thereby potentially mischaracterizing the changes in county opioid death inequality. It remains unclear if the rise in opioid mortality is uniform across counties or if areas with high initial levels of opioid mortality have experienced greater increases in mortality than areas with initially low opioid mortality (or vice-versa).

Understanding the changes in the distribution of opioid mortality can inform efforts to address the epidemic. Sharper rises in mortality concentrated in a small number of counties, resulting in increasing opioid mortality inequality, would suggest the need for highly targeted interventions in these areas (Davidson et al., 2003). In this case, increased access to medication-assisted treatment and increasing naloxone distribution may be preferable strategies (Hawk et al., 2015; Wheeler et al., 2012). However, broader increases in mortality may call for more general policies that can be widely implemented, such as state or national laws mandating stricter PDMP programs or more liberal naloxone distribution regulations (Ali et al., 2017; McClellan et al., 2018). The different policy responses to these different patterns have implications for the level of resources needed to respond to the epidemic. More diffuse increases would suggest the need for greater resource expenditures, as the response would necessarily be targeted over a wider area and have fewer economies of scale.

Additionally, understanding if county-level opioid mortality is converging or diverging may be indicative of potential mechanisms of opioid mortality. For example, converging mortality rates may suggest the proliferation of more potent opioids or riskier use patterns to areas which are less prepared or aware than areas with already high mortality. Areas in which people are unfamiliar with opioid dangers in particular may be at higher risk of opioid misuse (Arria et al., 2008). Such a result would indicate the need for measures, such as educational or social marketing campaigns, to stop proliferation of opioid misuse to areas with low opioid mortality (Kolodny et al., 2015).

This study aims to characterize the extent of convergence or divergence in county opioid mortality rates from 2000 to 2014. To examine the question of divergence and convergence, Gini coefficients, an established measure often used to examine the inequality of the distribution of an outcome (Giorgi and Gigliarano, 2017), are used to describe changes in the distribution of opioid mortality. However, comparison of Gini coefficients only provides an ad hoc examination of convergence in opioid mortality rates. To examine further potential relative changes in mortality, this study conducts a differential trend analysis using a Poisson regression framework, providing a more formal sensitivity analysis for the results.

## 2. Data and methods

Mortality counts for this study come from the National Vital Statistics System's (NVSS) Multiple Cause Mortality data for 2000–2014. Following prior work (Rudd et al., 2016), opioid-overdose deaths were classified using the International Classification of Diseases, Tenth Revision (ICD-10). For cases with drug overdose coded as the underlying cause of death, the type of opioid involved was indicated by the following ICD-10 multiple cause-of-death codes: opioids (T40.0, T40.1, T40.2, T40.3, T40.4, or T40.6), natural and semi-synthetic opioids (T40.2), methadone (T40.3), synthetic opioids other than methadone (T40.4), and heroin (T40.1). Cases for which the underlying cause of death was coded as suicide (X60-64) were excluded, as the focus is on unintentional deaths, and trends between unintentional and intentional deaths are likely to be different (O'Donnell et al., 2017). There is evidence that synthetic opioids, such as fentanyl, are becoming an increasingly important factor in opioid morality; therefore, the analysis is also stratified by prescription (T40.2 and T40.3) and synthetic opioids (T40.4) (Jones et al., 2018).

The unit of analysis for this study was the U.S. County, the smallest geographic breakdown available in the NVSS data. A county unit is a sub-state administrative division that can vary widely in both geographic size and population. However, due to their relative compactness, complete coverage of the United States, and public health and government infrastructure, counties are often used for public health analysis (Remington et al., 2015) and are a particularly relevant geography for opioids, as many programs are implemented at a county-level (Bennett et al., 2011; Clark et al., 2014).

Counts of opioid mortality were generated by county, year, and five-year age group then paired with population estimates provided in the NVSS's bridged-race population estimates based on Census data to obtain age-specific crude rates for 3,143 counties or county-equivalent areas. This results in 47,145 county-year observations. The crude rates were then adjusted by the year 2000 population to obtain age-adjusted mortality rates for each county-year. Estimates of small area mortality rates can be unstable (Rossen et al., 2013), and work has been conducted to produce more stable county-level estimates of drug poisonings (Rossen and Bastian, 2017). In unreported results, the main analysis was conducted with these stable estimates to examine the sensitivity of the analysis to the choice of mortality rate estimation. While the results using the more stable county-level estimates are qualitatively similar to the main results of this analysis, the available stable estimates are binned and truncated, creating a significant loss of information on the variation of mortality rates across counties. As a result, the preferred estimates use the age-adjusted mortality rates described above.

To examine the distribution of opioid mortality among U.S. counties, Gini coefficients (and associated Lorenz curves) were calculated for each year. While Gini coefficients are typically used to examine relative distributions of wealth and income, they can be used to examine any outcome that can be concentrated among discrete units and have been used in health research to study a variety of outcomes (Moskowitz et al., 2008) including provider distribution (Brown, 1994; Chang and Halfon, 1997), dental health (Tickle, 2002), and even prescription drug use (Hallas and Støvring, 2006). In examining statistical dispersion and inequality, the Gini coefficient is often considered a gold standard, partly because it characterizes the entire distribution of interest and is a unitless measure. With respect to opioid mortality, these properties mean the Gini coefficient gives a concise measure by which to gauge the spread of the opioid crisis, allowing direct comparison across years for the purposes of this study regardless of the absolute growth in opioid mortality.

The relative dispersion of opioid mortality can be graphically shown with a Lorenz curve (Gastwirth, 1971; Wagstaff et al., 1991). After sorting counties from lowest to highest according to mortality rates, the Lorenz Curve plots the cumulative share of opioid mortality by the cumulative percentage of counties. A perfectly equal distribution of mortality, such that 1% of the counties accounted for 1% of deaths, 50% accounted for 50% of deaths, and so on, would result in a linear Lorenz Curve of 45 degrees. In contrast, Lorenz Curves depicting less equal distributions of mortality would result in a concave curve falling below the 45-degree line of perfect equality. The Gini coefficient is the ratio of the difference between the absolute equality line and the Lorenz Curve and the total area under the absolute equality line.

In practice, the Gini coefficient can be calculated as half the mean absolute difference in mortality for all pairs of counties divided by the average county mortality to normalize for scale (Sen, 1973). Gini coefficient calculations were bootstrapped to estimate confidence intervals for each year. The bootstrap procedure built an approximating distribution for the Gini coefficient by first re-sampling with replacement the original data and then recalculating the Gini coefficient from

the re-sampled data. This procedure was repeated 10,000 times to produce the bootstrapped empiric distribution of the Gini coefficient. Bias-corrected 95% confidence intervals were then calculated from the empiric distribution (Efron and Tibshirani, 1997).

Gini coefficients are thus a summary measure of the concentration, or inequality, of opioid mortality rates. The measure is bounded between 0 and 1, with values closer to 1 indicating higher concentrations of opioid deaths, while values closer to 0 indicate a more equitable distribution of deaths. For example, if all opioid deaths were concentrated in a single county, the Gini coefficient would be 1. Conversely, a Gini coefficient of 0 would indicate every county has the exact same age-adjusted opioid mortality rate.

To further examine the changes in the distribution of opioid mortality, each county was categorized into one of five groups based on each county's mortality level at the beginning of the study period, the year 2000. The first group of counties were ones in which there were no reported opioid poisonings in 2000, while the other counties reporting opioid deaths in 2000 were divided by quartile. Trends in average opioid mortality in the subsequent 14 years for the five groups of counties were then graphically inspected. Additionally, a Poisson regression on the age-adjusted mortality rates was used to fit linear trend terms for each grouping to provide a statistical test of potential differences in trends. The linear trend coefficients give estimates of the average annual change in age adjusted mortality for each group. A Poisson model was preferred since the underlying measure of the mortality rate is the count of opioid deaths in a county, and this is necessarily truncated at zero and left-skewed. The model included separate intercepts for each group but was otherwise unadjusted by county characteristics, and robust standard errors were calculated. Since this study was a secondary analysis of a public data set, no IRB approval was required.

## 3. Results

Table 1 provides summary statistics for county opioid-related mortality. Overall deaths spiked from 8,556 in 2000 to 26,799 in 2014, which are estimates consistent with other work (Rudd et al., 2016). Age-adjusted mortality rates also reflect this surge in mortality; however, the increase is slightly more pronounced in counties below the median mortality rate in 2000, with an increase of 6.47 percentage points, than in counties above the median mortality rate, which experienced a 5.41 percentage point increase. A similar pattern emerges for both prescription and synthetic opioid deaths, where counties below the median mortality rate experienced slightly higher percentage point increases in mortality. When calculated as percent increases, the growth of mortality in below-median counties is much higher than that of above-median counties (1787.57% vs. 75.68%, respectively). This suggests a convergence of opioid mortality, which can be further examined with the main analysis.

Fig. 1 compares the Lorenz curves for county opioid mortality for 2000 and 2014. In 2000, opioid deaths were relatively concentrated in a small number of counties. There were no reported opioid deaths in 65.83% of counties, while the top 1% of counties in terms of opioid mortality rates accounted for 15.55% of opioid deaths. In contrast, there were significantly more counties reporting opioid poisonings in 2014, and only 34.71% of counties had no cases. Similarly, the share of opioid mortality in the top 1% of counties fell to 8.02%. These changes are apparent in Fig. 1, where the Lorenz curve for 2000 remains at zero for a large proportion of the counties then increases sharply. However, by 2014 the portion of the Lorenz curve indicating zero deaths is much shorter and the increase for counties with opioid mortality much shallower. The comparison of these two curves indicates counties became more equal over time in terms of opioid mortality.

To assess the trajectory of this convergence toward equality, Fig. 2 plots the Gini coefficient of opioid mortality for each year from 2000 to 2014. In 2000, the Gini coefficient was 0.81 (95% CI: 0.8-0.83), indicating a significant amount of inequality in overdose deaths. Over the study period, the Gini coefficient steadily declines with the exception of a small reversal in 2010. The reason for this temporary reversal is an open question for research. As the share of opioid mortality became more equal across counties, the Gini coefficient declined to 0.61 (95% CI: 0.6-0.63) in 2014. Confidence interval estimates indicate that the difference between Gini coefficients for 2000 and 2014 is statistically significant at conventional levels.

The pattern of falling inequality in opioid mortality among counties is consistent by opioid type as well. Fig. 3 repeats the analysis in Fig. 2 for prescription and synthetic opioids. While inequality in synthetic opioid mortality began near perfect inequality at 0.97 (95% CI: 0.96-0.97), by 2014 it fell to 0.84 (95% CI: 0.83-0.85) with a particularly large decrease in the Gini coefficient between 2013 and 2014. Likewise, prescription opioid mortality became more equal, starting at 0.87 (95% CI: 0.86-0.89) in 2000 and falling to 0.7 (95% CI: 0.69-0.72) in 2014. As with overall opioid mortality, equality steadily increased with the exception of a slight reversal around 2010 for both prescription and synthetic opioids.

Fig. 4 plots the average county opioid mortality rate per 100,000 individuals from 2001 to 2014 by groups of counties based on year 2000 opioid mortality rates. As expected, all five groups exhibited an upward trend in mortality rates; however, the groups with lower initial mortality appear to grow faster than those with higher initial mortality,

**Table 1**
Summary statistics of county opioid related mortality.

| | Counties Below 2000 Median Mortality Rate | | | Counties Above 2000 Median Mortality Rate | | | Overall | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2000 | 2014 | All Years | 2000 | 2014 | All Years | 2000 | 2014 | All Years |
| Total Deaths | 1,948 | 14,723 | 123,948 | 6,608 | 12,076 | 126,071 | 8,556 | 26,799 | 250,019 |
| Mean Unadjusted Mortality Rate | 0.358 | 6.19 | 3.865 | 6.801 | 11.735 | 8.2 | 1.473 | 7.15 | 4.616 |
| | (0.783) | (8.02) | (6.606) | (5.35) | (11.71) | (9.276) | (3.376) | (9.016) | (7.326) |
| Mean Age-Adjusted Mortality Rate | 0.362 | 6.833 | 4.182 | 7.154 | 12.568 | 8.701 | 1.538 | 7.825 | 4.964 |
| | (0.794) | (9.238) | (7.456) | (5.667) | (12.521) | (10.012) | (3.56) | (10.118) | (8.139) |
| Mean Prescription Opioid Age-Adjusted Mortality Rate | 0.181 | 3.626 | 2.732 | 4.073 | 6.65 | 5.705 | 0.855 | 4.149 | 3.246 |
| | (0.542) | (6.269) | (5.928) | (4.812) | (9.265) | (8.148) | (2.533) | (6.974) | (6.466) |
| Mean Synthetic Opioid Age-Adjusted Mortality Rate | 0.043 | 1.221 | 0.627 | 0.772 | 2.031 | 1.076 | 0.169 | 1.361 | 0.704 |
| | (0.24) | (3.783) | (2.477) | (3.011) | (3.252) | (2.71) | (1.3) | (3.708) | (2.525) |

Notes: NVSS Mortality Data. Mortality rates per 100,000 people. Standard Deviations given in parentheses. Age adjusted mortality rate based on 2000 standard population. Median 2000 mortality rate calculated exclusive of counties with zero deaths in 2000. Prescription opioid deaths defined as deaths with underlying cause codes of T40.2 and T40.3 and synthetic opioids as T40.4. Prescription and synthetic opioid categories are not exhaustive categorizations of potential opioid related mortality.

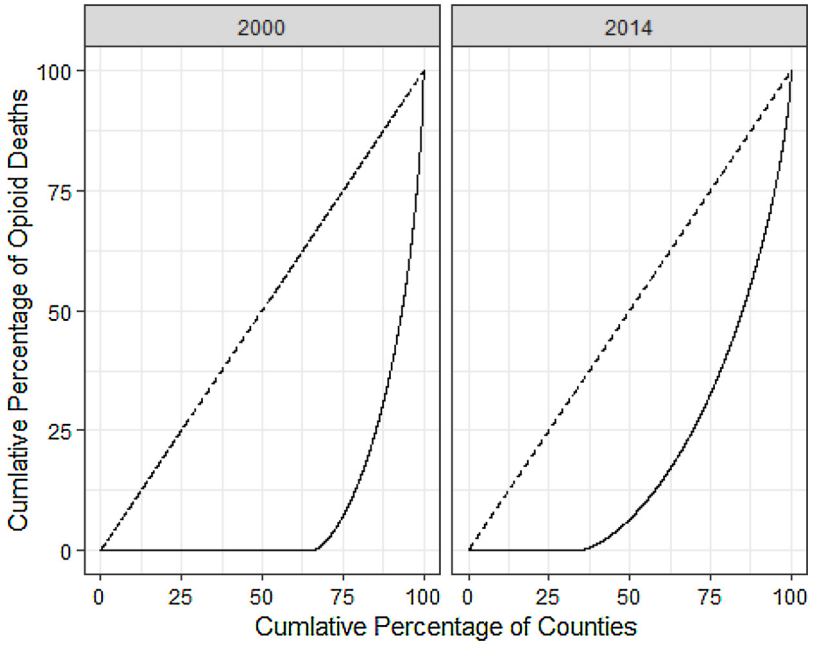


**Fig. 1.** County opioid mortality Lorenz curves: 2000 and 2014.
Notes: The 45-degree dashed line indicates the hypothetically perfectly equal distribution of deaths, where 1% of counties account for 1% of opioid related deaths. The solid curves falling below the 45-degree line indicates the actual distribution of deaths.

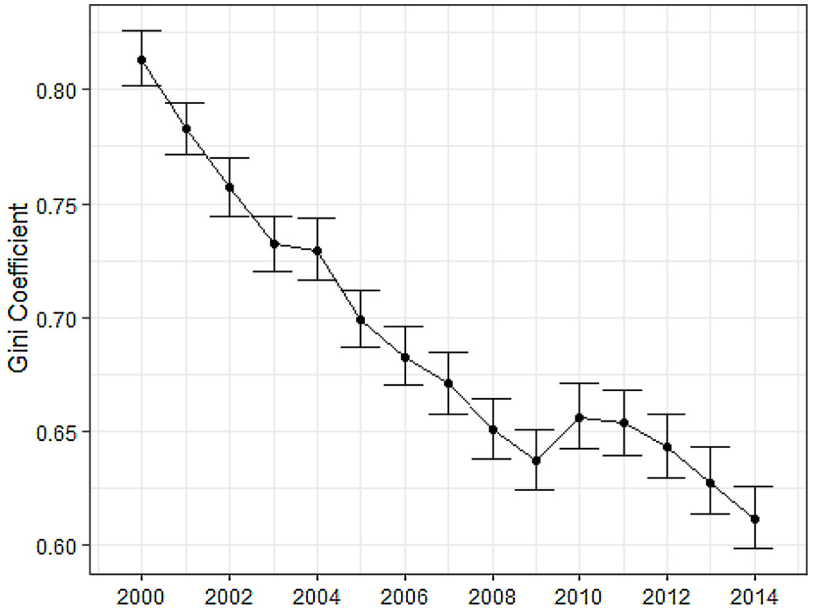


**Fig. 2.** U.S. opioid mortality Gini coefficients:2000–2014.
Notes: Estimates of the Gini are indicated by points, while the 95% confidence interval is denoted by the horizontal bars bounding the estimate point. The solid line shows the trend in Gini coefficients over time.

thus creating the convergence indicated above.

While Fig. 4 is graphically informative, the differential trends can be more precisely quantified by the regression analysis reported in Table 2. The top panel of Table 2 reports the coefficient on each group's trend term from the Poisson regression. The relationship between beginning mortality and mortality growth is readily apparent from these trends. For counties with no opioid deaths in 2000, opioid mortality grew at 9.07 (95% CI: 8.54–9.59) percent per year. The growth rate in opioid mortality remained statistically unchanged or declined by initial mortality level group and bottomed out at 5.52 (95% CI: 4.66–6.39) percent per year for the counties with the highest initial opioid mortality rates.

Testing of the difference in trends (Panel 2) indicates a statistically significant difference in opioid mortality growth between most groups. Opioid mortality rates rose 3.54 (P-value: 0.000) percent per year faster in the group of counties with no opioid deaths than in the counties with the highest rate of opioid deaths in 2000. With the exception of the comparison between the group with no initial mortality and the first quintile, and the second and third quintile, the trend difference between any given county group with fewer initial deaths and a county group with more initial deaths is positive and statistically significant at the 1% level.

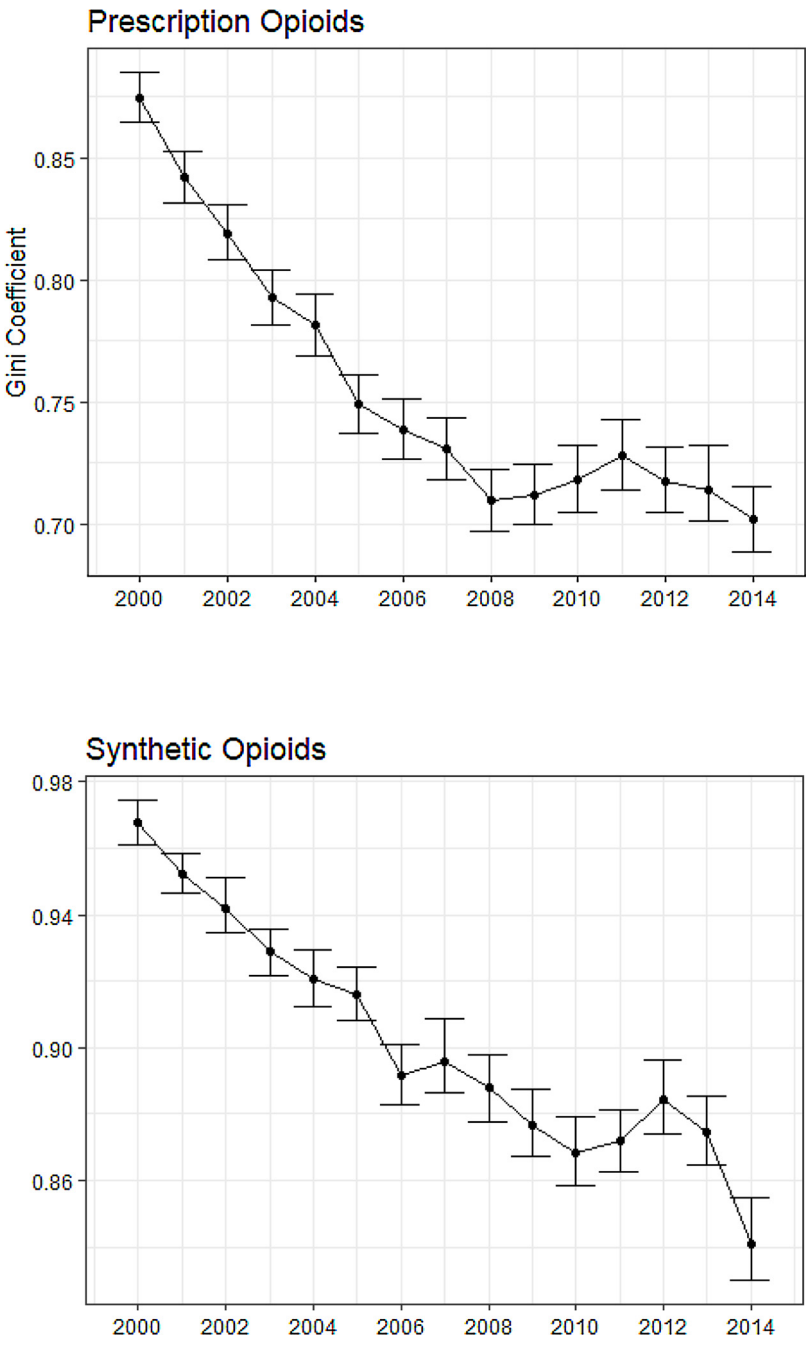


**Fig. 3.** U.S. opioid mortality Gini coefficients by opioid type:2000–2014.
Notes: Estimates of the Gini are indicated by points, while the 95% confidence interval is denoted by the horizontal bars bounding the estimate point. The solid line shows the trend in Gini coefficients over time.

## 4. Discussion

While the general increase in opioid overdose deaths has been widely recognized, the dynamics of the crisis have not been fully examined. This study provides insights into the rise in opioid related mortality by showing that areas with low opioid mortality in 2000 experienced disproportionate increases in deaths. Additionally, these results add to the existing opioid mortality literature by giving a concise measure of the distribution of opioid mortality among U.S. counties.

While the inequality in opioid deaths is still relatively high, it has persistently declined since 2000 as county opioid death rates have converged. Inequality in opioid deaths between U.S. counties, as measured by the Gini coefficient, fell from 0.81 in 2000 to 0.61 in 2014. This finding is consistent with other geo-spatial based analyses that have found higher increases in opioid mortality in rural counties but higher initial mortality in urban counties (Paulozzi and Xi, 2008; Piercefield et al., 2010; Rossen et al., 2013; Wunsch et al., 2009), which implies a convergence between areas with high and low initial mortality.

The decline in opioid-related mortality inequality was consistent across opioid types, with prescription and synthetic opioids exhibiting similar trends. However, synthetic opioids showed a larger decrease in inequality between 2013 and 2014, possibly due to the increasing availability of fentanyl (Gladden, 2016).

The differential trends could be particularly problematic in that most attention and prevention effort could be focused on highly visible

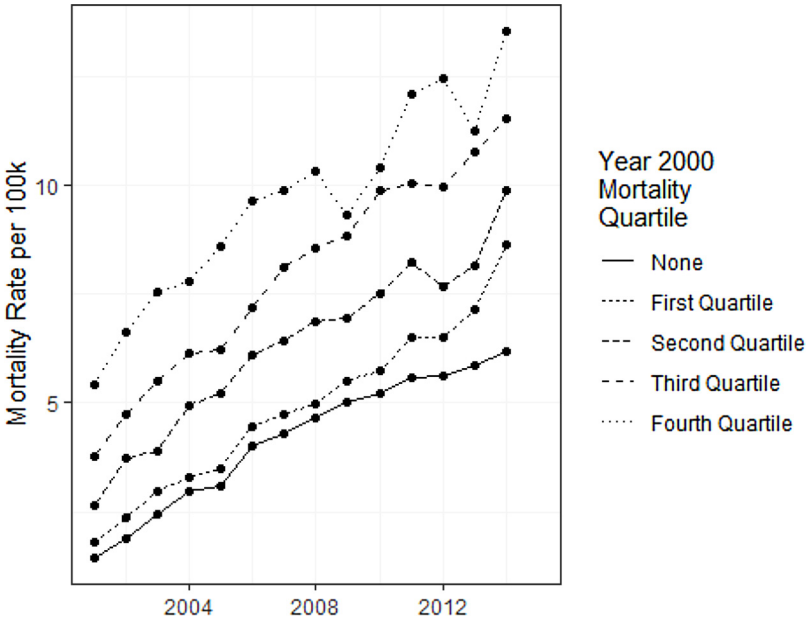


**Fig. 4.** Trends in county opioid mortality:2001–2014.
Notes: Five groups are plotted corresponding to those counties with no reported opioid deaths and those in the first, second, third, and fourth quartiles for year 2000 opioid mortality rates.

**Table 2**
Trends in county opioid mortality by beginning quartile:2001–2014.

| | 2000 Opioid Mortality Quartile | | | | |
|---|---|---|---|---|---|
| | Zero | First | Second | Third | Fourth |
| Average Mortality Rate-2001 | 1.44 | 1.79 | 2.63 | 3.78 | 5.42 |
| *Possion Regression Results* | | | | | |
| Group Trends in Mortality | 0.091*** | 0.098*** | 0.076*** | 0.073*** | 0.055*** |
| | (0.003) | (0.003) | (0.004) | (0.004) | (0.004) |
| *Tests of Differences in Trends* | | | | | |
| Zero | – | – | – | – | – |
| First | −0.008 | – | – | – | – |
| | (0.004) | | | | |
| Second | 0.014* | 0.022*** | – | – | – |
| | (0.004) | (0.005) | | | |
| Third | 0.018** | 0.026*** | 0.004 | – | – |
| | (0.005) | (0.005) | (0.005) | | |
| Fourth | 0.035*** | 0.043*** | 0.021** | 0.017* | – |
| | (0.005) | (0.006) | (0.006) | (0.006) | |

Notes: The top panel reports the coefficient for the trend terms from a Poisson regression of age adjusted mortality rates on group trend terms and intercepts by quartile of 2000 opioid mortality. Robust standard errors are reported in parentheses. The second panel tests if the difference of the two trend estimates is statistically different from zero using a linear combination of the two estimates. Statistical significance denoted at the 5%, 1%, and 0.1% level denoted by *, **, *** respectively.

areas affected by the opioid crisis, while the more significant increases in opioid mortality occur in areas that receive less attention. Prior efforts to address overdose deaths, such as naloxone distribution programs, are often focused in areas with high rates of use and mortality (Wheeler et al., 2012). Though such efforts, by virtue of mitigating overdose deaths in high mortality areas, may be part of the reason for the convergence in mortality rates, the decline in overdose death inequality suggests broader efforts may be needed, such as more emphasis on drug diversion prevention or moving from metropolitan-based surveillance systems to statewide surveillance systems (Paulozzi and Xi, 2008). However, even state-level policies, such as prescription drug monitoring programs, which collect data on potentially inappropriate prescribing behaviors (Ali et al., 2017), are broad approaches that do not differentiate between areas of low and high opioid mortality. These blanket approaches do not offer the opportunity to differentiate responses to specific types of areas which may be at higher risk, such as low opioid mortality areas as suggested by these results.

The convergence of opioid mortality between counties poses unique policy challenges when addressing the opioid crisis. The results of this study possibly suggest that more targeted approaches aimed at stopping the spread of opioids to areas in which they have not been pervasive may be more efficient at slowing the overall growth in opioid related deaths. Such interventions may include educational and public awareness efforts to promote responsible opioid use (Franklin et al., 2012; Walley et al., 2013) in areas in which the opioid epidemic has seemingly not escalated yet. Other policies, such as expanding drug courts, which provide alternative sentencing including treatment and supervision for justice-involved individuals (Mitchell et al., 2012) and access to medication-assisted treatment (Schwartz et al., 2013), might also be considered in areas with low mortality rates despite a possible perceived lack of need for such measures in these areas.

Policies designed for prevention in low opioid mortality areas may also present fiscal challenges for policy makers. While little information is available on the costs of implementing state-level interventions (Haegerich et al., 2014), narrow interventions in a limited number of opioid mortality hot spots are likely to be less resource-intensive than broader prevention measures in areas that have not yet been affected by the crisis. Targeted interventions such as naloxone distribution in high opioid mortality areas have been found to be very cost-effective (Coffin and Sullivan, 2013); however, extending these programs to low opioid mortality areas would certainly lower that cost-effectiveness. Additionally, there are more counties with no or low opioid mortality than counties with very high mortality. This would suggest prevention efforts would need greater funding to reach all areas fully.

While this analysis gives insights about the dynamics of the increase in opioid mortality, it does not provide any indicators of other risk factors beyond initial opioid mortality that may inform prevention efforts. Beyond age, the study does not control for factors which may drive opioid mortality (King et al., 2014). As such, these results should

be taken as a characterization of prior patterns with limited inferential power. Additionally, as a descriptive analysis, this study does not examine potential reasons for the differential growth in opioid mortality. As outlined above, it is possible that interventions and policies in opioid mortality hot spots are drivers of this convergence.

The data also have some limitations. The classification of opioid overdoses often falls to the professional judgement of local coroners and medical examiners and thus may be subject to misclassification bias (Warner et al., 2013). A similar pattern of convergence could happen if medical examiners in jurisdictions with seemingly low initial mortality improve their classifications of opioid mortality, thus creating an exaggerated growth rate. Similarly, differences in classification between jurisdictions could result in differential growth rates; however, the consistent pattern of convergence across opioid types suggests different classification systems are not problematic. Next, poisoning deaths often remain pending after the publication of the mortality data, possibly creating underestimation of opioid mortality (Rossen et al., 2013). Such under-reporting could affect these results, particularly if the under-reporting issues are resolved over time, creating changes in trends.

Additional research into the evolution of the opioid crisis is needed to further understand its dynamics. This study provides a concise measure of the distribution of opioid mortality that shows the increases in opioid mortality are not uniform across U.S. counties. While the mechanisms of this disparity in opioid death trends are not explored, they could include low information on opioid risks in relatively unaffected areas or more intense resource allocation and interventions in hot spots. Counties with no or low levels of opioid mortality need particular attention to prevent the further spread of the opioid crisis.

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## Contributors

C. McClellan was responsible for all stages of analysis and manuscript preparation and approved of the final version of the manuscript.

## Conflict of interest

No conflict declared.

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None.

## References

Ali, M.M., Dowd, W.N., Classen, T., Mutter, R., Novak, S.P., 2017. Prescription drug monitoring programs, nonmedical use of prescription drugs, and heroin use: evidence from the national survey of drug use and health. Addict. Behav. 69, 65–77.
Arria, A.M., Caldeira, K.M., Vincent, K.B., O'Grady, K.E., Wish, E.D., 2008. Perceived harmfulness predicts nonmedical use of prescription drugs among college students: interactions with sensation-seeking. Prev. Sci. 9, 191.
Bennett, A.S., Bell, A., Tomedi, L., Hulsey, E.G., Kral, A.H., 2011. Characteristics of an overdose prevention, response, and naloxone distribution program in Pittsburgh and Allegheny county, Pennsylvania. J. Urban Health 88, 1020–1030.
Brown, M.C., 1994. Using Gini-style indices to evaluate the spatial patterns of health practitioners: theoretical considerations and an application based on Alberta data. Soc. Sci. Med. 38, 1243–1256.
Buchanich, J.M., Balmert, L.C., Pringle, J.L., Williams, K.E., Burke, D.S., Marsh, G.M., 2016. Patterns and trends in accidental poisoning death rates in the US, 1979–2014. Prev. Med. 89, 317–323.
Cai, R., Crane, E., Poneleit, K., Paulozzi, L., 2010. Emergency department visits involving nonmedical use of selected prescription drugs in the United States, 2004–2008. J. Pain Palliat. Care Pharmacother. 24, 293–297.
Carpenter, C.S., McClellan, C.B., Rees, D.I., 2017. Economic conditions, illicit drug use, and substance use disorders in the united states. J. Health Econ. 52, 63–73.
Case, A., Deaton, A., 2015. Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century. Proc. Natl. Acad. Sci. U. S. A. 112, 15078–15083.
Cerdá, M., Gaidus, A., Keyes, K.M., Ponicki, W., Martins, S., Galea, S., Gruenewald, P., 2017. Prescription opioid poisoning across urban and rural areas: identifying vulnerable groups and geographic areas. Addiction 112, 103–112.
Chang, R.-K.R., Halfon, N., 1997. Geographic distribution of pediatricians in the United States: an analysis of the fifty states and Washington, D.C. Pediatrics 100, 172–179.
Cicero, T.J., Ellis, M.S., Surratt, H.L., Kurtz, S.P., 2014. The changing face of heroin use in the United States: a retrospective analysis of the past 50 years. JAMA Psychiatry 71, 821–826.
Clark, A.K., Wilder, C.M., Winstanley, E.L., 2014. A systematic review of community opioid overdose prevention and naloxone distribution programs. J. Addict. Med. 8, 153–163.
Coffin, P.O., Sullivan, S.D., 2013. Cost-effectiveness of distributing naloxone to heroin users for lay overdose reversal. Ann. Intern. Med. 158, 1–9.
Davidson, P.J., McLean, R.L., Kral, A.H., Gleghorn, A.A., Edlin, B.R., Moss, A.R., 2003. Fatal heroin-related overdose in San Francisco, 1997–2000: a case for targeted intervention. J. Urban Health 80, 261–273.
Dwyer-Lindgren, L., Bertozzi-Villa, A., Stubbs, R.W., Morozoff, C., Shirude, S., unutzer, J., Naghavi, M., Mokdad, A., Murray, C.J.L., 2018. Trends and patterns of geographic variation in mortality from substance use disorders and intentional injuries among US counties, 1980-2014. JAMA 319, 1013–1023.
Efron, B., Tibshirani, R., 1997. Improvements on cross-validation: the 632+ bootstrap method. J. Am. Stat. Assoc. 92, 548–560.
Franklin, G.M., Mai, J., Turner, J., Sullivan, M., Wickizer, T., Fulton-Kehoe, D., 2012. Bending the prescription opioid dosing and mortality curves: impact of the Washington state opioid dosing guideline. Am. J. Indust. Med. 55, 325–331.
Gastwirth, J.L., 1971. A general definition of the Lorenz curve. Econometrica 1037–1039.
Giorgi, G.M., Gigliarano, C., 2017. The Gini concentration index: a review of the inference literature. J. Econ. Surv. 31, 1130–1148.
Gladden, R.M., 2016. Fentanyl law enforcement submissions and increases in synthetic opioid–involved overdose deaths—27 states, 2013–2014. MMWR Morb. Mortal. Wkly. Rep. 65.
Haegerich, T.M., Paulozzi, L.J., Manns, B.J., Jones, C.M., 2014. What we know, and don't know, about the impact of state policy and systems-level interventions on prescription drug overdose. Drug Alcohol Depend. 145, 34–47.
Hallas, J., Støvring, H., 2006. Templates for analysis of individual-level prescription data. Basic Clin. Pharmacol. Toxicol. 98, 260–265.
Hawk, K.F., Vaca, F.E., D'Onofrio, G., 2015. Focus: addiction: reducing fatal opioid overdose: prevention, treatment and harm reduction strategies. Yale J. Biol. Med. 88, 235.
Jones, C.M., Einstein, E.B., Compton, W.M., 2018. Changes in synthetic opioid involvement in drug overdose deaths in the united states, 2010-2016. JAMA 319, 1819–1821.
King, N.B., Fraser, V., Boikos, C., Richardson, R., Harper, S., 2014. Determinants of increased opioid-related mortality in the United States and Canada, 1990–2013: a systematic review. Am. J. Public Health 104, e32–e42.
Kolodny, A., Courtwright, D.T., Hwang, C.S., Kreiner, P., Eadie, J.L., Clark, T.W., Alexander, G.C., 2015. The prescription opioid and heroin crisis: a public health approach to an epidemic of addiction. Ann. Rev. Public Health 36, 559–574.
Ling, W., Mooney, L., Hillhouse, M., 2011. Prescription opioid abuse, pain and addiction: clinical issues and implications. Drug Alcohol Rev. 30, 300–305.
McClellan, C., Lambdin, B.H., Ali, M.M., Mutter, R., Davis, C.S., Wheeler, E., Pemberton, M., Kral, A.H., 2018. Opioid-overdose laws association with opioid use and overdose mortality. Addict. Behav. 86, 90–95.
Mitchell, O., Wilson, D.B., Eggers, A., MacKenzie, D.L., 2012. Assessing the effectiveness of drug courts on recidivism: a meta-analytic review of traditional and non-traditional drug courts. J. Crim. Justice 40, 60–71.
Moskowitz, C.S., Seshan, V.E., Riedel, E.R., Begg, C.B., 2008. Estimating the empirical Lorenz curve and Gini coefficient in the presence of error with nested data. Stat. Med. 27, 3191–3208.
O'Donnell, J.K., Gladden, R.M., Seth, P., 2017. Trends in deaths involving heroin and synthetic opioids excluding methadone, and law enforcement drug product reports, by census region—United States, 2006–2015. MMWR Morb. Mortal. Wkly. Rep. 66, 897.
Owens, P., Barrett, M., Weiss, A., Washington, R., Kronick, R., 2006. Hospital Inpatient Utilization Related to Opioid Overuse Among Adults, 1993–2012: Statistical Brief #177. Agency for Health Care Policy, Rockville, MD.
Paulozzi, L.J., Xi, Y., 2008. Recent changes in drug poisoning mortality in the United States by urban-rural status and drug type. Pharmacoepidemiology and drug safety 17, 997–1005.
Piercefield, E., Archer, P., Kemp, P., Mallonee, S., 2010. Increase in unintentional medication overdose deaths: Oklahoma, 1994–2006. Am. J. Prev. Med. 39, 357–363.
Pletcher, M.J., Kertesz, S.G., Kohn, M.A., Gonzales, R., 2008. Trends in opioid prescribing by race/ethnicity for patients seeking care in US emergency departments. JAMA 299, 70–78.
Rees, D.I., Sabia, J.J., Argys, L.M., Latshaw, J., Dave, D., 2017. With a Little Help from My Friends: the Effects of Naloxone Access and Good Samaritan Laws on Opioid-related Deaths. National Bureau of Economic Research, Cambridge, MA.
Remington, P.L., Catlin, B.B., Gennuso, K.P., 2015. The county health rankings: rationale and methods. Popul. Health Metr. 13, 11.
Rossen, L.M., Bastian, B., 2017. Drug Poisoning Mortality: United States, 1999–2015. Available from. National Center for Health Statistics, Hyattsville, MD. https://www.cdc.gov/nchs/products/databriefs/db273.htm.

Rossen, L.M., Khan, D., Warner, M., 2013. Trends and geographic patterns in drug-poisoning death rates in the US, 1999–2009. Am. J. Prev. Med. 45, e19–e25.
Rudd, R.A., 2016. Increases in drug and opioid-involved overdose deaths—United States, 2010–2015. MMWR Morb. Mortal. Wkly. Rep. 65, 1445–1452.
Rudd, R.A., Aleshire, N., Zibbell, J.E., Gladden, R.M., 2016. Increases in drug and opioid overdose deaths–United states, 2000-2014. MMWR Morb. Mortal. Wkly. Rep. 64, 1378–1382.
Schwartz, R.P., Gryczynski, J., O'Grady, K.E., Sharfstein, J.M., Warren, G., Olsen, Y., Mitchell, S.G., Jaffe, J.H., 2013. Opioid agonist treatments and heroin overdose deaths in Baltimore, Maryland, 1995–2009. Am. J. Public Health 103, 917–922.
Sen, A. (Ed.), 1973. On Economic Inequality. Clarendon Press, Oxford.
Singhal, A., Tien, Y.-Y., Hsia, R.Y., 2016. Racial-ethnic disparities in opioid prescriptions at emergency department visits for conditions commonly associated with prescription drug abuse. PLoS One 11, e0159224.
Stewart, K., Cao, Y., Hsu, M.H., Artigiani, E., Wish, E., 2017. Geospatial analysis of drug poisoning deaths involving heroin in the USA, 2000–2014. J. Urban Health 94, 572–586.
Tickle, M., 2002. The 80:20 phenomenon: help or hindrance to planning caries prevention programmes? Commun. Dent. Health 19, 39–42.
Wagstaff, A., Paci, P., Van Doorslaer, E., 1991. On the measurement of inequalities in health. Soc. Sci. Med. 33, 545–557.
Walley, A.Y., Xuan, Z., Hackman, H.H., Quinn, E., Doe-Simkins, M., Sorensen-Alawad, A., Ruiz, S., Ozonoff, A., 2013. Opioid overdose rates and implementation of overdose education and nasal naloxone distribution in Massachusetts: interrupted time series analysis. BMJ 346, f174.
Warner, M., Paulozzi, L.J., Nolte, K.B., Davis, G.G., Nelson, L.S., 2013. State variation in certifying manner of death and drugs involved in drug intoxication deaths. Acad. Forensic Pathol. 3, 231–237.
Wheeler, E., Davidson, P.J., Jones, T.S., Irwin, K.S., 2012. Community-based opioid overdose prevention programs providing naloxone—United States, 2010. MMWR Morb. Mortal. Wkly. Rep. 61, 101.
Wunsch, M.J., Nakamoto, K., Behonick, G., Massello, W., 2009. Opioid deaths in rural Virginia: a description of the high prevalence of accidental fatalities involving prescribed medications. Am. J. Addict. 18, 5–14.